Developing a real-time sensor data analysis predictive maintenance system powered by the Internet of Things to track the condition of industrial machinery and avert malfunctions

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Abstract:

Predictive maintenance has become a critical strategy for ensuring the optimal performance and longevity of industrial equipment. This research aims to create an IoT-driven predictive maintenance system that monitors the health of industrial equipment in real-time by analyzing sensor data. The system leverages IoT-enabled sensors to collect continuous data on various operational parameters such as temperature, vibration, pressure, and energy consumption. Advanced machine learning algorithms, including time-series analysis and anomaly detection models, are employed to detect early signs of equipment degradation or malfunction. The system's predictive capabilities are enhanced by integrating data from multiple sensors, enabling the identification of complex patterns and potential failures before they occur. Additionally, the platform incorporates a user-friendly interface for operators to receive real-time alerts and actionable insights, facilitating timely maintenance interventions. The system is validated using real-world industrial datasets, demonstrating its effectiveness in reducing downtime, optimizing maintenance schedules, and \ improving overall equipment reliability. Arduino IoT cloud using an ESP32 module and it reads the sensors information like DHT11 sensor is a low-cost, digital sensor that measures both temperature and relative humidity. The MQ2 gas sensor operates on 5V DC and consumes approximately 800mW. It can detect LPG, Smoke, Alcohol, Propane, Hydrogen, Methane and Carbon Monoxide concentrations ranging from 200 to 10000 ppm. Vibration sensors, used in various industries, detect and measure vibrations to monitor machinery, identify potential problems, and enable predictive maintenance, ultimately preventing breakdowns and optimizing performance. The BMP180 was designed to accurately measure atmospheric pressure. Atmospheric pressure varies with both weather and altitude; you can measure both of these using this sensor.

ACS712 Current Sensor is the sensor that can be used to measure and calculate the amount of current applied to the conductor without affecting the performance of the system. ACS712 Current Sensor is a fully integrated, Hall-effect based linear sensor IC. All these dangerous gases, temperature and humidity, atmospheric pressure can be monitored real time in LCD and smartphone using Arduino cloud application. This research aims to improve operational efficiency, lower maintenance costs, and extend the lifespan of critical industrial machinery through proactive monitoring and maintenance.

Keywords: MQ2 gas sensor,DHT11 sensor, Vibration sensor, BMP180, Current sensor, ESP32 controller, LCD display, Arduino IDE, Embedded C, Arduino cloud

1.Introduction:

This study discusses about temperature monitoring system in the goat pen via smart phone. In addition to monitoring, temperature control is also needed to maintain temperature conditions in the goat pen. This system is useful so that goat cultivation produces well by getting a healthy temperature during its growing period[1]. Manual monitoring is time consuming, so a more practical monitoring application is required.

This monitoring application is built using Internet of Things (IoT) technology so that it can be monitored remotely. The temperature data is taken from the DHT11 temperature sensor which is collected on a microcontroller which is then sent to the internet wirelessly. To control the temperature in the goat pen using an SSR relay. Based on the results of this study, the application of temperature monitoring in the goat pen via smartphone with the Internet of Things (IoT) is able to read the temperature value in the goat pen[2], and can adjust the SSR to turn on and turn off the heating element remotely using a smartphone.

2. Block diagram:

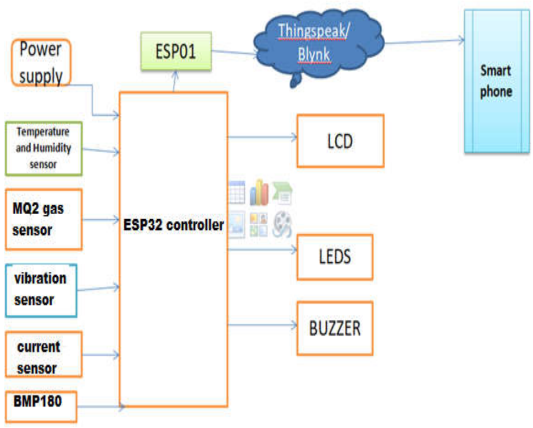


Fig.1. Block diagram of proposed system

2.1. Working process:

IoT cloud using an ESP32 module and it reads the sensors information like DHT11 sensor, it is a low-cost, digital sensor that measures both temperature and relative humidity.

The MQ2 gas sensor operates on 5V DC and consumes approximately 800mW. It can detect LPG, Smoke, Alcohol, Propane, Hydrogen, Methane and Carbon Monoxide concentrations ranging from 200 to 10000 ppm. Vibration sensors, used in various industries, detect and measure vibrations to monitor machinery, identify potential problems[3], and enable predictive maintenance, ultimately preventing breakdowns and optimizing performance. The BMP180 was designed to accurately measure atmospheric pressure. Atmospheric pressure varies with both weather and altitude; you can measure both of these using this sensor[4]. ACS712 Current Sensor is the sensor that can be used to measure and calculate the amount of current applied to the conductor without affecting the performance of the system. ACS712 Current Sensor is a fully integrated, Hall-effect based linear sensor IC. All these dangerous gases, temperature and humidity, atmospheric pressure can be monitored real time in LCD and smartphone using Arduino cloud application.

3. Existing system:

Existing systems, along with the advantage and disadvantages of various technologies and sensor networks[5]. After analyzing the cost and complexity related issues associated with existing scientific solutions for IAQ monitoring.

4.Proposed system:

Environmental air parameters directly affect our daily quality of life, and they can change from day to day or even hour to hour. With rapid industrialization over the past few decades, there is a dramatically increasing demand for people to monitor the local air quality to know how they live and what they breathe[6]. In this work, we proposed an air monitoring system based on the Arduino platform. IoT cloud using an ESP32 module and it reads the sensors information like DHT11 sensor is a low-cost, digital sensor that measures both temperature and relative humidity. TheMQ2 gas sensor operates on 5V DC and consumes approximately 800mW. It can detect LPG, Smoke, Alcohol, Propane, Hydrogen, Methane and Carbon Monoxide concentrations ranging from 200 to 10000 ppm. Vibration sensors, used in various industries, detect and measure vibrations to monitor machinery, identify potential problems, and enable predictive maintenance, ultimately preventing breakdowns and optimizing performance[7]. The BMP180 was designed to accurately measure atmospheric pressure. Atmospheric pressure varies with both weather and altitude; you can measure both of these using this sensor.

ACS712 Current Sensor is the sensor that can be used to measure and calculate the amount of current applied to the conductor without affecting the performance of the system. ACS712 Current Sensor is a fully integrated, Hall-effect based linear sensor IC. All these dangerous gases, temperature and humidity, atmospheric pressure can be monitored real time in LCD and smartphone using Arduino cloud application. This environmental air monitoring with temperature and alert system is designed to provide an efficient, straightforward and robust solution to monitor the air quality continuously and in real-time using IoT technology. It is a portable system that integrates multiple sensors into a single unit and can be placed anywhere[8]. The acquired results are displayed on a screen and can also be saved on a host computer for further analysis.

5. Implementation methods:

• Data Collection: The study involves the collection of data from the operational period of the Bulk Continuous Filament machine which is fundamental to any PdM system. Data collected includes variables related to vibration, temperature, and energy consumption.

• IoT-Based Predictive Maintenance System: The study establishes an IoT based predictive maintenance system. It involves the design and implementation of custom IoT modules for measuring physical variables. These modules collect data from the field, which is then transmitted to a cloud application. This system forms the backbone of the predictive maintenance approach.

• Data Analysis and Optimization: The collected data is analyzed and optimized using machine learning methods. Various algorithms, including Random Forest ensemble learning, Support Vector Machine, Gaussian Process, Decision Tree regressions, and Deep Learning (DL) algorithms, are utilized for this purpose. These algorithms are applied to preprocess and structure the data, and then models are trained and evaluated.

• Alert System: An alert system is implemented based on standard deviation computations. When the system surpasses predefined thresholds, the maintenance team is alerted via email notifications. This step ensures timely response to potential issues detected by the predictive maintenance system[9].

• Evaluation and Model Deployment: The models developed through machine learning techniques are evaluated using metrics to determine their accuracy and performance. The DL algorithm is highlighted as achieving a high accuracy of 96%.

Algorithms:

6. Literature survey:

In literature, the PdM approach applied to textile manufacturing field where ML algorithms are used to predict equipment failures on the production line using real equipment data in an ML module is rare. Quality control to determine the defect issues and machine control are often handled. Elkateb et al. studied on PdM application employing a knitting machine process, and used ML techniques with DT and AdaBoost to classify machine stops accurately and facilitate prompt maintenance actions, and they obtained an accuracy of 0.92. In recent literature, a PdM application on a melt spinning machine that produces an artificial yarn as the material, was employed. In this research, a set of neural networks was trained using historical experimental data to predict multiple quality characteristics and with 2 layers and 20 neurons, they achieved RMSE of 0.097 at best.

The drawbacks of the conventional monitoring instruments are their large size, heavy weight and extraordinary expensiveness. These lead to sparse deployment of the monitoring stations. In order to be effective, the locations of the monitoring stations need careful placement because the air pollution situation in urban areas is highly related to human activities (e.g. construction activities) and location-

dependent (e.g., the traffic choke-points have much worse air quality than average)[10]. IOT Based Air Pollution Monitoring System monitors the Air Quality over a Blynk/Thingspeak using internet and will trigger an alarm when the air quality goes down beyond a certain level, means when there are amount of harmful gases present in the air like CO2, smoke, alcohol, benzene, NH3, NOx and LPG. The system will show the air quality in PPM on the LCD and as well as on webpage so that it can be monitored very easily. Temperature and Humidity is detected and monitored in the system. LPG gas is detected using MQ6 sensor and MQ135 sensor is used for monitoring Air Quality as it detects most harmful gases and can measure their amount accurately[11]. In this IOT project, it can monitor the pollution level from anywhere using your computer or mobile. This system can be installed anywhere and can also trigger some device when pollution goes beyond some level, like we can send alert SMS to the user.

7. Developed Data Acquisition System For PDM Application:

The integration of computer aided PdM systems into businesses has led to the modular availability of essential components for these systems, marketed as IoT technology components.

These modular parts are nowaccessible for businesses, rendering the need for elaborate system installations, such as server systems and database servers for data storage. Cloud technology has enabled the establishment of plugand- play as well as track-and-trace systems, significantly reducing both the financial investment and annual operating costs[12]. Siemens, Eton, and Schneider are now offering energy monitoring and PdM modules for cloud applications, further reducing costs.

In this technological landscape, thousands of microcontroller units (MCUs) and sensors will communicate in the IoT network and considering the diversity and size of the data collected from these devices. Program software and big data storage, and visualization has now been reduced to a few commands by the cutting-edge computer technology[13]. Artificial intelligence, machine learning, data mining and intelligent computing methods will become increasingly pivotal for data optimization, assessment of failure statuses, and prediction of failure probabilities. Machine learning will play a significant role in modeling of future systems and

developing advanced systems through real data from the field.

7.1. IoT-based sensor system:

In this section, we introduce our IoT-based sensor system, a fundamental component of our computer-aided PdM system. The system is designed to acquire data from various sources, specifically eight data points from five distinct sensors situated within an extruder group of an artificial yarn production machine, as depicted in Fig. Our meticulously established system is fully aligned with IoT platform capabilities.

7.2. Optimization of the collected data:

The referred reviews on PdM have revealed that PdM applications primarily utilize data driven models[14]. We adopted data-driven approach for fault prediction, using the data collected from the sensors installed in the BCF machine and its associated components. To refine and optimize the collected data, we employed supervised regression as our ML methodology. We applied RF of Ensemble Tree method, SVM, and DT algorithms, and DL method for predicting regression data effectively. The following subsections give brief explanations of the methods utilized.

8. Algorithms:

8.1. Machine Learning:

Machine learning, a subcategory of AI, is a modeling and algorithm method that extrapolate from measured or available data by means of mathematical and statistical methods andaccurately predict the unknown. Various ML algorithms to make predictions are developed by researchers which are categorized as unsupervised learning and supervised learning. Unsupervised learning methods are utilized to find unknown structures and relationships in the data and model the distribution to find similar sample groups in the data Supervised ML method is used for predicting future outcomes based on the trained past data. In supervised learning process, the training dataset for the ML model is created first. Second, the algorithm for learning process from the trained data is executed, and then this process is controlled by the test data for validation. Supervised ML methods are considered as classification and regression. Supervised regression is an ML method to build functions within certain limits according to the relation between the data. Other goals of the regression algorithm are to plot a best-fit curve between the data and to establish a feed-forward system based on the outputs of the new data entering this function. Supervised classification is a learning method associated to attribute observations to qualitative classifications to model and predict variables. Among supervised ML methods, linear regression, ridge regression, and logistic regression are prominent linear algorithms.

The nonlinear algorithms, DT, Naive Bayes, k-Nearest Neighbors, Gaussian regression, SVM, and Neural Networks (NN) are favored. RF, bagging, and stacking are featured ensemble methods.

8.2. Random Forest:

Random Forest trains multiple decision tree models using the sample dimension and the feature dimension. By integrating the voting results of multiple decision trees, it improves the problem where decision trees tend to overfit. The RF utilizes weaker algorithms, as in DT, by repetitions to improve performance. For regression problems, the RF algorithm tries to predict the data from the base tree.

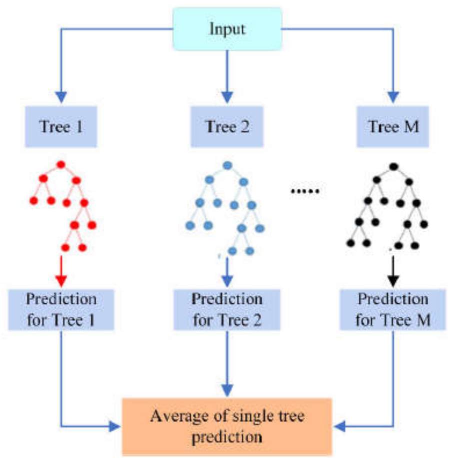


Fig.2. Random F3Support Vector Machine Algorithm for Regression:

The Support Vector Machine algorithm is used for predicting classification and regression data. Operators' object in SVM is to identify a borderline that is called as hyperplane, in a space of K with k features to classify data into separate classes.

This classifier searches for an optimal hyperplane that separates the data points of each class and maximizes the distance between them.

8.3. Decision Tree:

The Decision Tree algorithm generates a decision model that classifies instances by sorting the feature space into subspaces starting at the root node until a termination criterion is met. This algorithm can be used to solve regression problems as well as classification problems. DT is like a tree structure: each node represents a feature in an instance to be classified, and each branch represents a value that the node can adopt.

9. Hardware description:

9.1. ESP32 Controller:

ESP32 is a chip that provides Wi-Fi and (in some models) Bluetooth connectivity for embedded devices – in other words, for IoT devices. While ESP32 is technically just the chip, the modules and development boards that contain this chip are often also referred to as "ESP32" by the manufacturer. The original ESP32 chip had a single core Tensilica Xtensa LX6 microprocessor. The processor had a clock rate of over 240 MHz, which made for a relatively high data processing speed.

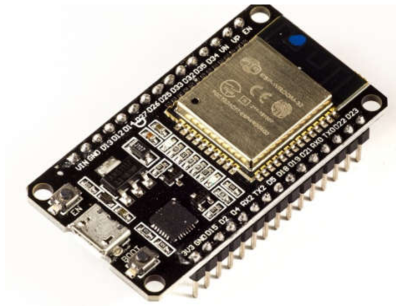


Fig.3. ESP 32 Controller

ESP32 is the SoC (System on Chip) microcontroller which has gained massive popularity recently. Whether the popularity of ESP32 grew because of the growth of IoT or whether IoT grew because of the introduction of ESP32 is debatable.

9.2. Liquid crystal display (lcd):

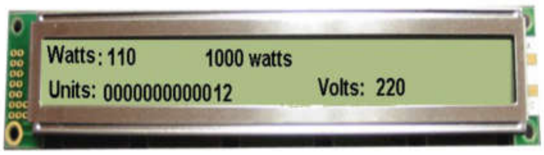
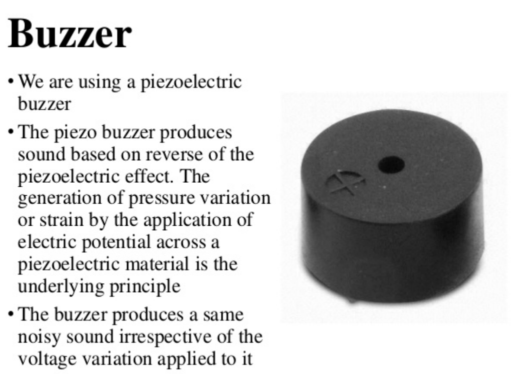


Fig. 4. Liquid Crystal Display

This is the first interfacing example for the Parallel Port. We will start with something simple. This example doesn't use the Bi-directional feature found on newer ports, thus it should work with most, if no all Parallel Ports. A 16 Character x 2 Line LCD Module to the Parallel Port. These LCD Modules are very common these days, and are quite simple to work with, as all the logic required running them is on board. The LCD panel's Enable and Register Select is connected to the Control Port. The Control Port is an open collector / open drain output.

While most Parallel Ports have internal pull-up resistors, there are a few which don't. Therefore by incorporating the two 10K external pull up resistors, the circuit is more portable for a wider range of computers, some of which may have no internal pull up resistors. We make no effort to place the Data bus into reverse direction. Therefore we hard wire the R/W line of the LCD panel, into write mode. This will cause no bus conflicts on the data lines. As a result we cannot read back the LCD's internal Busy Flag which tells us if the LCD has accepted and finished processing the last instruction. This problem is overcome by inserting known delays into our program.

9.3. Buzzer:



9.4. DHT11 Temperature and Humidity sensor:

Do you want to measure temperature and humidity information. So, we have the Grove Temperature & Humidity Sensor (DHT11) especially for you. It can measure temperature as well as humidity at the same time! Its a high quality, low-cost digital temperature and humidity sensor based on the new DHT11 module. It utilizes a DHT11 sensor that can meet the measurement needs for general purposes.DHT11 is the most common temperature and humidity module for Arduino and Raspberry Pi. However, this sensor provides reliable readings when environment humidity condition is in between 20% RH and 90% RH, and temperature condition is in between 0C and 50C.

Fig.5. DHT11 Sensor

9.5. MQ2 Gas sensor:

The MQ-2 sensor is a gas sensor that detects flammable gases and smoke. It has many uses, including detecting gas leaks in homes and industries, and in portable gas detectors.

Fig.6. MQ2 gas sensor

9.6. Current sensor:

Current flowing through a conductor causes a voltage drop. The relation between current and voltage is given by Ohm's law. In electronic devices, an increase in the amount of current above its requirement leads to overload and can damage the device. Measurement of current is necessary for the proper working of devices. Measurement of voltage is Passive task and it can be done without affecting the system. Whereas measurement of current is an Intrusive task which cannot be detected directly as voltage.

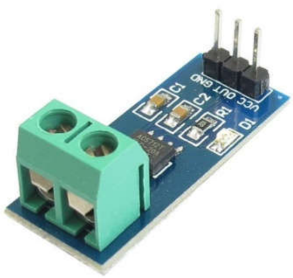


Fig. 7. ACS712 Current sensor

For measuring current in a circuit, a sensor is required. ACS712 Current Sensor is the sensor that can be used to measure and calculate the amount of current applied to the conductor without affecting the performance of the system.

ACS712 Current Sensor is a fully integrated, Hall-effect based linear sensor IC. This IC has a 2.1kV RMS voltage isolation along with a low resistance current conductor.

9.7.Vibration sensor:

Vibration sensors are used to detect and measure vibrations in machinery, equipment, and structures, allowing for condition monitoring, predictive maintenance, and early detection of potential problems.

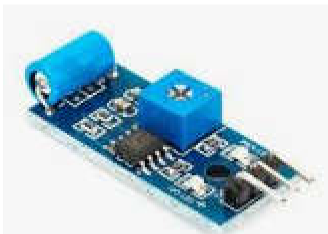


Fig.8. Vibration sensor

9.8. BMP180 sensor:

BMP180 Digital Barometric Pressure Sensor Module is used for measuring barometric pressure and altitude. It also has a temperature sensor for temperature compensation of pressure measurements. It uses push sensors for the BMP180. It offers a pressure measuring range of 300 to 1100 hPa with a relative pressure error of 0.12 hPa. BMP 180 is a barometric pressure sensor with an I2C interface. Barometric pressure sensors measure the absolute pressure of the air around them[13].

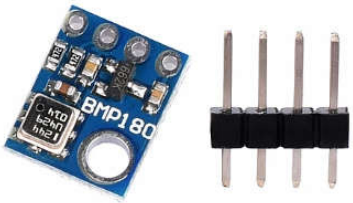


Fig. BMP 180 sensor

First we need to open the Arduino IDE 2.0.

10. Software description:

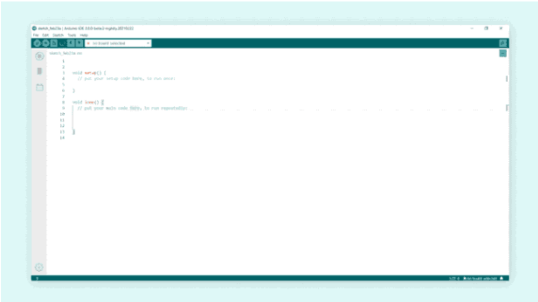
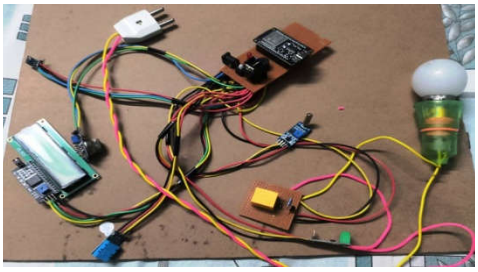


Fig.9. Arduino IDE sketch window



When it has finished uploading, click on the Serial Monitor button, located at the top right corner of the IDE[14]. This will launch the Serial Monitor in the bottom of the IDE, replacing the console section.

11. Advantages:

An IoT-driven predictive maintenance system offers numerous advantages for industrial equipment, including reduced downtime, extended equipment lifespan, cost savings, and improved safety, all achieved through real-time sensor data analysis and proactive maintenance planning.

- Cost Savings:

  Reduced downtime, lower maintenance costs, and optimized resource allocation contribute to significant cost savings for businesses.

- Optimized Resource Allocation:

  Predictive maintenance enables businesses to allocate maintenance resources more efficiently, focusing on equipment that requires attention and minimizing unnecessary maintenance activities.

  3. Enhanced Safety and Risk Management:

- Real-time Monitoring:

  IoT sensors continuously monitor equipment performance and environmental conditions, allowing for the early detection of potential hazards and the implementation of corrective actions.

12. Applications:

IoT-driven predictive maintenance systems use sensors to monitor industrial equipment in real-time, analyze data to predict potential failures, and alert maintenance teams proactively, minimizing downtime and optimizing resource allocation.

Here's a more detailed explanation of the applications:

1. Real-time Monitoring and Early Warning:

- Sensor Deployment:

  IoT sensors are strategically placed on industrial equipment to collect data on critical parameters like temperature, vibration, pressure, and energy consumption.

- Data Collection and Transmission:

  These sensors transmit the collected data wirelessly to a central system for analysis.

- Real-time Analysis:

  Advanced analytics and machine learning algorithms analyze the data in real-time, identifying patterns and anomalies that could indicate potential problems.

- Proactive Alerts:

  The system generates alerts to maintenance teams, allowing them to address potential issues before they lead to major breakdowns.

13. Conclusion:

This research highlights the significance of using real-world sensor data from operational predictive maintenance systems, rather than relying on synthetic or simulated datasets, which is a common practice in many existing papers. This comprehensive approach in development of a PdM system for artificial yarn production machines uses the equipment data via a cost-effective IoT module without the need to invest in commercial IoT devices[15]. The collected field data from this module is a valuable resource for AI and ML applications in predictive maintenance. IoT cloud using an ESP32 module and it reads the sensors information like DHT11 sensor is a low-cost, digital sensor that measures both temperature and relative humidity. The MQ2 gas sensor operates on 5V DC and consumes approximately 800mW. It can detect LPG, Smoke, Alcohol, Propane, Hydrogen, Methane and Carbon Monoxide concentrations ranging from 200 to 10000 ppm.

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Industries are increasingly utilizing IoT data to enhance operational efficiency. Therefore, the expanding role of AI in processing and interpreting data will facilitate better decision-making and predictive capabilities.

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