SMART MACHINE HEALTH MONITORING SYSTEM & USING CLOUD TECHNOLOGIES

S. SURYAPRAKASH B.E.,

Department Of Mechanical Engineering , St. Joseph's Institute of Technology, Chennai, India

Abstract

The Smart Machine Health Monitoring System helps monitor the condition of industrial machines in real time. The system framework is developed using cloud-based IoT architecture, with the principles of Industry 4.0 for smarter, data-driven manufacturing. It uses various sensors to collect important data like vibration, temperature, and machine speed (RPM). These readings are gathered using different types of sensors and a microcontroller. The collected data is stored and sent to the cloud through AWS IoT Core using the microcontroller. Once the data reaches the cloud, it is processed using AWS Lambda and then securely stored in DynamoDB. We use AWS QuickSight to visualize this data in the form of charts and graphs, making it easier to understand machine performance. If the system detects any unusual activity, it immediately sends alerts to the user through AWS SNS. This intelligent monitoring setup reflects the goals of Industry 4.0 by enabling predictive maintenance, reducing downtime, and enhancing overall operational efficiency in the manufacturing process.

Keywords :

Cloud-based IoT Architecture, Industry 4.O, Machine Health Monitoring, IoT, Cloud Technologies, Industrial Automation.

1. INTRODUCTION

Many recent studies have shown how IoT and cloud technology are improving machine monitoring in industries. With Industry 4.0 ,With the growing demand for uninterrupted production, the continuous monitoring of machine health has become a critical aspect [1]. Unexpected failures in machines during operation can lead to costly downtimes, production delays, and potential safety hazards [2]. Hence, the implementation of a reliable and intelligent machine monitoring system is essential in modern industries.

Machine health monitoring involves the real-time observation of key operational parameters such as vibration, temperature, and rotational speed (RPM) [3]. These parameters serve as early indicators of possible mechanical issues. Traditional maintenance methods, including scheduled or reactive servicing, often lack the efficiency to detect faults at an early stage [4]. As a result, there is an increasing need for smart systems that provide real-time insights into the condition of industrial machines [5].

To overcome these limitations, a Smart Machine Health Monitoring framework has been developed using a cloud-based IoT architecture [6]. This system utilizes sensors connected to an ESP32 microcontroller to measure critical machine parameters. The collected sensor data is transmitted to the AWS IoT Core platform. Cloud-based processing is carried out

through AWS Lambda functions, and the structured data is stored in AWS DynamoDB. The processed data is then visualized using AWS QuickSight dashboards, enabling effective monitoring and analysis [7].

Furthermore, the system integrates AWS Simple Notification Service (SNS) to deliver instant alerts when sensor readings indicate abnormal machine behavior [8]. This allows for timely intervention and fault prevention. The proposed solution supports predictive maintenance strategies, minimizes equipment downtime, and enhances the overall efficiency of industrial operations [9]. Its practical applicability extends to a wide range of manufacturing sectors, particularly in environments utilizing traditional machinery such as center lathes [10].

1.1 LITERATURE REVIEW

The recent advancements in industrial automation have significantly transformed the functioning and maintenance of machinery in various manufacturing environments[1]. machines are now connected with sensors that collect real-time data such as temperature, vibration, and speed. This allows continuous observation of machine performance without manual checks or downtime[2].

Cloud platforms are widely used to store large amounts of sensor data. This data can be analyzed using machine learning techniques to detect unusual behavior and predict possible failures[3]. Early warnings can help in scheduling maintenance at the right time and reduce the chances of unexpected breakdowns[4].

Research also highlights the use of short-term data analysis to understand the current condition of machines and estimate their future performance [5]. Edge computing is used in some systems to process data quickly at the device level. This reduces the amount of data sent to the cloud and provides faster insights[6] .

Combining data from different machines on the cloud helps build stronger models for detecting and predicting faults more accurately[7] . These technologies are helping industries save time, reduce repair costs, and improve overall machine reliability.

1.2 SYSTEM QUALITY & RELIABILITY

Monitoring System ensures high quality and reliability by using IoT sensors to monitor key data like temperature, vibration, and RPM. Real-time data is processed in the cloud for easy access and quick analysis [1].

Predictive maintenance is another key feature, allowing the system to forecast potential failures and reduce downtime [2]. The cloud infrastructure efficiently handles large amounts of data, ensuring smooth performance without any delays. Additionally, the system triggers alerts to notify maintenance teams of abnormal conditions, enabling quick action before problems escalate.

By improving machine efficiency, reducing costs, and extending the lifespan of equipment, the system adds significant value to industrial operations [3]. This results in enhanced productivity and operational reliability.

2. OBJECTIVES OF THE STUDY

The primary objective of the Smart Machine Health Monitoring System is to enhance the operational efficiency of industrial machines by monitoring their health in real-time. The key goals of this study are as follows:

- **Real- time Monitoring** : To continuously track machine parameters such as vibration, temperature, and rotational speed (RPM) using IoT sensors, providing instant insights into machine condition.
- **Predictive Maintenance**: To use the collected data and analyze it to predict potential machine failures before they occur, enabling timely maintenance and reducing unexpected downtimes.
- **Cloud Integration**: To integrate the system with cloud platforms like AWS, which will allow for efficient storage, processing, and visualization of sensor data, ensuring scalability and accessibility.
- **Data Visualization**: To provide a user-friendly interface for operators and engineers to visualize real-time machine data and identify patterns or anomalies that may indicate a failure.
- **Alert System**: To implement an alert system using AWS SNS, which will notify maintenance teams in case of any abnormal readings or potential issues detected by the system.
- **Improved Machine Lifespan:** The system helps improve machine lifespan by using real-time data to detect early signs of issues. This allows for timely maintenance, preventing major failures and reducing unexpected downtime.This leads to increased reliability and cost savings in industrial operations.
- **Efficiency**: To improve the overall operational efficiency of industries by ensuring machines are in optimal working condition.

By achieving these objectives, the system aims to improve maintenance planning, reduce operational costs, and extend the lifespan of industrial machines, leading to enhanced productivity and minimized downtime in industries like manufacturing and construction.

3. PROBLEM STATEMENT

In many industries, machines are essential for smooth and efficient operations. However, sudden machine failures can lead to unexpected production stops, high repair costs, and safety risks. A smart and automated system is needed to monitor machines in real time and alert users when issues are detected. This helps reduce downtime, plan maintenance better, and improve overall performance.

3.1. CONSTRUCTION & WORKING

The system is built using key components such as an ESP32 microcontroller, temperature sensor (DHT11), vibration sensor (SW-420), and IR sensor for speed (RPM) measurement. These sensors are connected to the ESP32, which collects the data from the machines.

The ESP32 sends the sensor data to the cloud using **AWS IoT Core**. Once the data reaches the cloud, it is processed by **AWS Lambda**, stored in **DynamoDB**, and visualized using **AWS QuickSight**. If any abnormal values are detected, an alert is sent to the user through **AWS SNS**. This allows operators to take quick action.

3.2. CALCULATIONS

The vibration sensor (SW-420) and the temperature sensor (DHT11) directly provide their values. But the speed sensor does not give the RPM value directly. So, a speed calculation formula is necessary to get the correct value.

3.2.1 SPEED CALCULATION :

RPS (Revolution Per Second) :

$$\textbf{RPS} = \frac{\textbf{Pulse Count}}{\textbf{Time Travel (in seconds)}}$$

RPM (Revolution Per Minute) :

$$\textbf{RPM} = \textbf{RPS} * 60$$

------------------- Or Directly--------------------

$$\textbf{RPM} = \left(\frac{\textbf{Pulse Count}}{\textbf{Time Interval (In Sec)}} \right) * 60$$

Example:

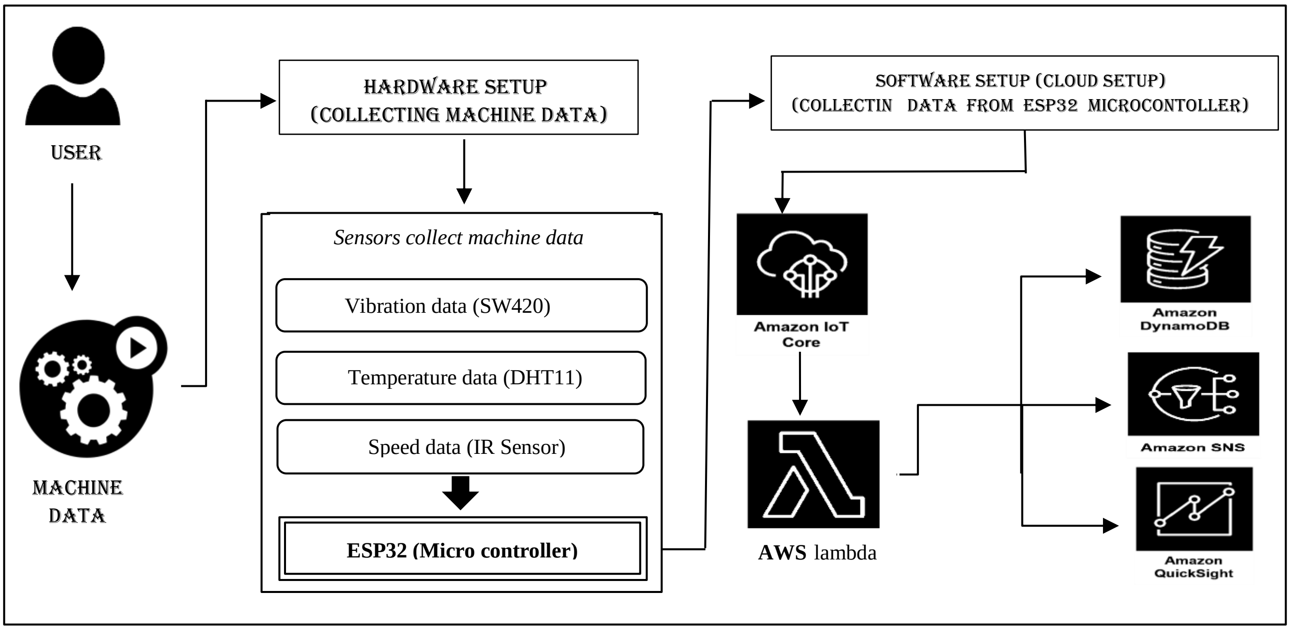
If the IR sensor detects **10 pulses in 2 seconds**, then:

- RPS = 10 / 2 = **5 RPS**
- RPM = 5 × 60 = **300 RPM**

(OR)

- RPM = (10 / 2) * 60 = **300 RPM**

4. FLOW OF THE SYSTEM :



4.1 BLOCK DIAGRAM EXPLANATION :

This system starts with three main sensors: the SW420 vibration sensor, DHT11 temperature sensor, and an IR sensor to monitor the machine's speed. These sensors are fixed to the machine and constantly collect real-time data related to its health and performance [1]. The ESP32 microcontroller is used to collect data from all the sensors. It acts as the brain of the system, combining all the readings and preparing them for cloud transfer [2].

Once the data is ready, the ESP32 sends it wirelessly to **AWS IoT** Core, where the values are received and securely handled in the cloud [3]. This cloud platform helps to manage device communication and ensures reliable data transfer. The moment data reaches **AWS IoT, AWS Lambda** is triggered. This service processes the data in real time, helping to identify any unusual readings like a sudden rise in vibration or temperature [4].

After processing, the cleaned and structured data is stored in **Amazon DynamoDB**, a cloud database designed to handle fast and scalable storage needs [5]. If any value crosses a predefined safety limit, **AWS SNS** instantly sends alert messages to the maintenance team or user's mobile phone. This ensures quick attention and prevents possible machine damage [6].

To help users monitor everything easily, **AWS QuickSight** is used. It gives a neat and interactive dashboard to visualize temperature, vibration, and speed data live. This allows machine operators to make smart decisions based on real-time information [7].

Overall, this system connects sensors, microcontrollers, and cloud services in a smooth and efficient way. It not only tracks the condition of machines but also helps to predict failures, reduce downtime, and support better maintenance planning [8].

4.2 SENSOR PARAMETER RANGES AND THRESHOLDS :

To ensure accurate monitoring and fault prediction, the Smart Machine Health Monitoring System tracks essential machine parameters within defined ranges. These thresholds help identify early signs of malfunction, wear, or overload conditions.

Various machines are designed with different operating parameters depending on their function and build. For example, the following parameter ranges are based on a center lathe machine, which is commonly used in manufacturing environments:

Parameter	Low Range	High Range	Remarks
Vibratioin (HZ)	10 – 20 Hz	60 - 120Hz	Normal vibration should be below 1.0 g. Above 2.0 g may indicate issues like imbalance, misalignment, or component wear.
Speed (RPM)	100 – 300 RPM	1200 – 2000 RPM	Speed range depends on operation Exceeding limits can lead to

			overheating&tool damage.
Temperature (*C)	30°C – 40°C	60°C – 80°C	Monitored at the tool or bearing. Temperatures over 80°C may cause thermal damage without proper cooling mechanisms.

Monitoring these parameters in real time helps maintain machine health, reduces wear, and supports predictive maintenance planning. The system sends alerts when any parameter crosses its defined threshold, ensuring quick response to potential faults.

4.3 DATA TABLE STRUCTURE & STORAGE FORMAT :

The Smart Machine Health Monitoring System collects real-time data from multiple sensors such as temperature, vibration, and speed sensors. This data is structured and stored in a cloud database—AWS DynamoDB. Each record in the table includes important fields like timestamp, machine ID, sensor type, sensor value, and unit of measurement. This format helps to organize the data efficiently for quick access and analysis.

The system records data at regular intervals, ensuring that every change in machine condition is logged. By maintaining a well-structured table, it becomes easy to filter and analyze specific sensor data for any machine during a certain time period. This structured storage also supports real-time dashboards and alert triggers based on defined thresholds.

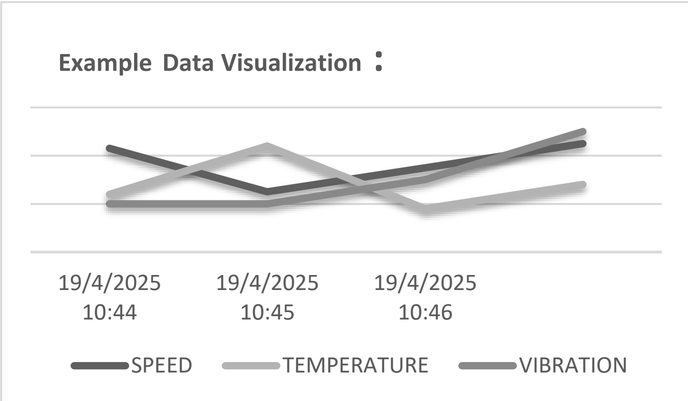
Here is a sample table format:

Timestamp	Machine ID	Sensor Type	Value
2025-04-19 10:45:32	MCH001	Temperature	47.2 *C
2025-04-19 10:45:32	MCH001	Vibration	32.8 Hz
2025-04-19 10:45:32	MCH001	Speed	1430 RPM

4.4 DATA VISUALIZATION USING AWS QUICKSIGHT :

In this system, AWS QuickSight is used to visualize sensor data in a meaningful way. It helps monitor machine health by showing temperature, vibration, and speed trends over time. QuickSight automatically pulls data from DynamoDB and displays it using various charts such as line graphs and pie charts. Line charts are used to show how temperature or RPM changes over time, while pie charts help in analyzing machine status like Normal, Warning, or Critical conditions.

These visuals allow maintenance teams to quickly identify problems and take action. Real-time updates ensure that decisions can be made based on the most recent data. By using filters and custom dashboards, users can view data for a specific machine or time range. This improves understanding, boosts efficiency, and supports predictive maintenance.

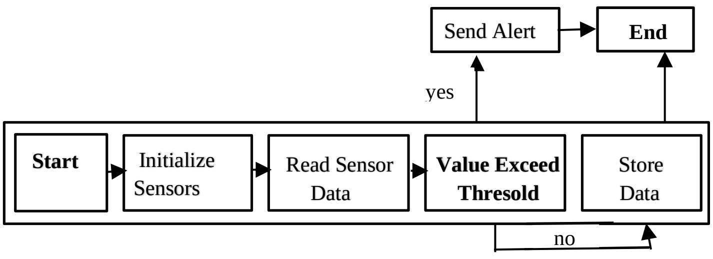


5. FINAL SYSTEM OVERVIEW :

The system begins by collecting data from various sensors that monitor important machine health parameters. These sensors send the collected data to a microcontroller, which then forwards it to the cloud for further processing.

In the cloud, the data is received and processed in real time. It is securely stored in a database, and if any abnormal values are detected, an alert is immediately sent to notify the concerned team.

The data is also visualized through dashboards that display clear graphs for easy understanding. This overall setup helps monitor machine conditions, detect faults early, and support timely maintenance actions.



6. CONCLUSION :

The Smart Machine Health Monitoring System provides an effective solution for real-time monitoring of industrial machines. By using cloud-based IoT architecture, the system collects, processes, and stores sensor data efficiently. This setup helps detect issues early, reduces unexpected machine failures, and supports better maintenance planning. The alert system ensures quick response to abnormal conditions, improving machine reliability and performance. Overall, the system helps industries save time and cost, while also increasing the safety and productivity of their operations. In addition, the centralized cloud storage enables easy access to historical data for performance analysis and predictive maintenance. The system's scalability makes it adaptable to different types of machines and industrial environments, allowing for widespread implementation. As industries continue to adopt smart technologies, this system plays a crucial role in driving digital transformation and sustainable manufacturing practices.

7. FUTURE ENHANCEMENT :

In the future, the Smart Machine Health Monitoring System can be further improved by integrating advanced technologies such as Machine Learning (ML) for predictive analytics. By training models on historical sensor data, the system can predict potential failures before they occur, enabling even smarter maintenance decisions. Another enhancement would be the addition of a mobile or web dashboard with real-time graph visualization and machine status updates. This would allow engineers and technicians to monitor machines remotely and take action immediately when needed. The system can also be upgraded to support multiple machines simultaneously, making it suitable for large-scale industrial environments. Integration with Augmented Reality (AR) could assist maintenance teams by providing visual guidance during troubleshooting. Regular software updates and cloud service optimizations will also ensure long-term efficiency, scalability, and security of the system.

REFERENCES :

[1]. Çınar, Zeki Murat, Abubakar Abdussalam Nuhu, Qasim Zeeshan, Orhan Korhan, Mohammed Asmael, and Babak Safaei. "Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0." *Sustainability* 12, no. 19 (2020): 8211.

[2]. Erameh, Andrew A., Nurudeen A. Raji, Rasheed O. Durojaye, and Abiodun A. Yussouff. "Process capability analysis of a centre lathe turning process." *Engineering* 8, no. 03 (2016): 79.

[3]. Feng, Q., Zhang, Y., Sun, B., Guo, X., Fan, D., Ren, Y., ... & Wang, Z. (2023). Multi-level predictive maintenance of smart manufacturing systems driven by digital twin: A matheuristics approach. *Journal of Manufacturing Systems*, *68*, 443-454.

[4]. Patel, Hiren, and I. A. Chauhan. "A study on Types of Lathe Machine and Operations." *International Journal* 8, no. 4 (2020): 286-291.

[5]. Pech, M., Vrchota, J., & Bednář, J. (2021). Predictive maintenance and intelligent sensors in smart factory. *Sensors*, *21*(4), 1470.

[6]. Cerquitelli, Tania, Nikolaos Nikolakis, Niamh O'Mahony, Enrico Macii, Massimo Ippolito, and Sotirios Makris. *Predictive maintenance in smart factories*. Springer Singapore, 2021.

[7]. Anandan, R., Suseendran Gopalakrishnan, Souvik Pal, and Noor Zaman, eds. *Industrial internet of things (IIoT): intelligent analytics for predictive maintenance*. John Wiley & Sons, 2022.

[8]. Ogunfowora, Oluwaseyi, and Homayoun Najjaran. "Reinforcement and deep reinforcement learning-based solutions for machine maintenance planning, scheduling policies, and optimization." *Journal of Manufacturing Systems* 70 (2023): 244-263.

[9]. Dosluoglu, Taner, and Martin MacDonald. "Circuit Design for Predictive Maintenance." *arXiv preprint arXiv:2211.10248* (2022).

[10]. Filios, Gabriel, Ioannis Katsidimas, Sotiris Nikoletseas, Stefanos H. Panagiotou, and Theofanis P. Raptis. "Agnostic learning for packing machine stoppage prediction in smart factories." *arXiv preprint arXiv:2212.06288* (2022).

[11]. Wong, T. K., Mun, H. K., Phang, S. K., Lum, K. L., & Tan, W. Q. (2021). Real-time machine health monitoring system using machine learning with IoT technology. In *MATEC Web of Conferences* (Vol. 335, p. 02005). EDP Sciences

[12]. Selcuk, Sule. "Predictive maintenance, its implementation and latest trends." *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture* 231, no. 9 (2017**):** 1670-1679.

[13]. Woodbury, Robert S. "The origins of the lathe." *Scientific American* 208, no. 4 (1963): 132-143.

[14]. Franse, J., Roblee, J.W. and Modemann, K., 1991. Dynamic characteristics of the Lawrence Livermore National Laboratory precision engineering research lathe. *Precision engineering*, *13*(3), pp.196-202.

[15]. Compton, Alfred George, and James H. De Groodt. *Advanced Metal-work: The speed-lathe*. Wiley, 1898.