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Cloud-Powered Industrial IoT Platform for Continuous Equipment Health Tracking and Failure Alerts

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Abstract. Constantly monitoring the industrial apparatus is essential to keep them in the operation mode, reduce unpredictable accidents, and improve the effectiveness of maintenance. Traditional maintenance schedules that use period reviews or on-repair services usually lead to manufacturing delays and increased cost of operation. This paper provides an IIoT cloud-based platform to be used in continuous monitoring of equipment health and generation of automatic failure signals. The system is designed with many sensors which can help to receive the necessary machine parameters including temperature, vibration, pressure, and current. The obtained information is transported through an edge gateway to a cloud system to store it, process it, and conduct real-time monitoring. The system compares the trend of the parameters against the set threshold values, to determine an anomaly and give early alarms to the maintenance officials. There is experimental evaluation of six pieces of industrial equipment whose operational evaluation shows a significant enhancement. Based on the findings, the efficiency of equipment went up to 87 and system dependability went up to 93, as compared to 68 and 72 respectively. More so, the amount of equipment devoted to downtime dropped to 28 hours per month, and the response time on maintenance was reduced to 33 minutes per month. The quantitative results prove that the offered IIoT monitoring system based on clouds is the solution that has a strong positive effect on equipment reliability, facilitates its proactive maintenance and ensures the increased productivity of the industrial sector in general.

Keywords: Industrial IoT, Cloud computing, Equipment health monitoring, Real-time data analytics, Sensor networks, Operational efficiency

INTRODUCTION

With the introduction of the IIoT, the management and maintenance of equipment have gained a new face in terms of current businesses monitoring its work and operations and offering unprecedented understanding of aspects of its functioning. The traditional forms of maintenance that rely on periodic or reactive maintenance cannot usually prevent unexpected downtimes; hence production losses, higher maintenance costs, and safety risks are experienced. A cloud-based IIoT platform is a groundbreaking proposal since one can monitor equipment health constantly through a network of connected sensors. These sensors retrieve real-time data on parameters like temperature, vibrations, pressure, operating load among others and forwarded to the cloud servers where they are centrally stored and analysed.

The platform, either via trend analysis and anomaly detection, can give early alerts and, therefore, maintenance teams will be able to address potential issues before they evolve into a failure. Besides early diagnosis, the system enables a comprehensive visualisation of equipment performance and, therefore, enables making informed decisions and optimizing resources. There have been significant gains on the reliability of equipment used in industries, the efficiency of operations, and a reduction in cost at various pilot applications. By combining IIoT with cloud technology, enterprises can proceed to the stage of proactive instead of being reactive in their maintenance practices and allow smarter, safer, and more efficient manufacturing processes based on the ideas of Industry 4.0. The paper makes contributions in the following ways:

- **Cloud Based Monitoring Framework:** The article describes a cloud-based Industrial IoT system that allows us to constantly monitor the health of the equipment through acquiring sensor data in real time and processing it centrally in the cloud.
- **Early Failure Detection Mechanism:** This is a system that identifies cases of anomaly in operating parameters through analysis of parameter thresholds, which allows the effective detection of potential equipment failures.

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- **Automated Alert and Notification System:** The system will generate failure alerts and notifications in real situations to be received by maintenance workers enabling quick response and reduction of unexpected preventable downtimes caused by machine failures.
- **Centrally Visualised and Remote-Accessed Visualisation:** With a cloud dashboard, real-time visualisation of equipment state and the trends of past data can be viewed, and the remote equipment can be monitored in various ways to increase maintenance choices.

LITERATURE REVIEW

The mining excavators and construction equipment's should be of high standards to operate effectively in their risky working environment. The issues with the current health monitoring technologies are false alarms and low accuracy of the forecasts [1]. The proposed solution is a dynamic adaptive Transformer with the use of multi-scale attention (better predictions), and dual-stage attention (anomaly detection). The results of the experiment indicate high-performance level and the application in the engineering field. To observe health of equipment in real-time and predict when it is going to malfunction, the proposed study addresses the Industrial IoT architecture based on the Machine Learning [2]. It classifies the status of equipment depending on the information gathered by sensors. A Kaggle dataset was utilized to simulate and verify the use of real-time sensor data in a realistic application of the IoT. This study relies on wavelet transformation to convert the data of the signal of industrial bearings into images without simulating noise to test deep networks [3]. It aims to enhance the diagnostics and monitoring of equipment through categorizing pictures of normal and defects, optimising parameter settings through various means and decision fusion to enhance accuracy. This study will present a novel framework of preventative maintenance to the equipment, used in sectors with a high energy intensive, by merging the concepts of data-driven causal analysis and reinforcement learning (RL) [4]. It was assessed on a Kraft pulp mill case study, and it employs deep learning autoencoders to give health indicators, clustering to identify the underlying causes, and a Petri net model to optimise maintenance activities.

There are the issues associated to the use of multi-sensor fusion on intelligent O&M methods of industrial equipment which include lack of labelled samples and bad generalisation between tasks [5]. This paper introduces MSMNEG, a multi- sensor fusion, to dynamically produce features to perform different tasks. It constructs non-Euclidean graphs based on the experimental validation to represent and optimise data effectively. The proposed study learns Remaining Useful Life (RUL) predicted model as a probabilistic neural network to combine a QR-DQN reinforcement learning agent and a PdM framework (PdM) [6]. It makes the use of maintenance more efficient and reduces lifespan costs by reducing uncertainties and risks of failure; maximising maintenance decisions, and accurately predicting RUL. This work will aim to offer a combined method of deep learning and domain knowledge in the failure detection of industrial equipment [7]. It enhances interpretability and reliability through incorporating expert-determined requirements in the anomaly detection process by LSTM. In a case study regarding drive pumps, its role in tracing the progress of health and the reinforcement of complicated interpretations of equipment conditions had been demonstrated. The article presents the novel technique to identify industrial equipment abnormalities, which defeats the limitations of the existing techniques [8]. As an enhancement to feature fusion, it uses a multi-head shrinkage graph attention network and residual network to obtain features of data obtained using many sensors. It also possesses a multi-condition discriminator so that it could be better generalised to various operating situations.

This study examines the relationship between industrial equipment reliability and predictive analytics, which are guided by AI. It employs a quantitative case-study approach to produce analytical snapshots using signal by integrating signals of condition monitoring with event histories [9]. The main objective is enhancement of the equipment resilience knowledge and significant outcomes consist of frequency, duration, and consequences of failures along with the availability, downtime, and the performance of the equipment in general. Evaluation of research on industrial equipment predictive maintenance in this systematic review, both the usefulness of the expert judgment and text mining of language models were used to evaluate research on predictive maintenance [10]. It used dimensionality reduction and clustering to affect papers on various components and found important methods, including deep learning and classical models. Relevance and quality were addressed by validating it by experts. This model is denoted as TCN-BiLSTM model [11] it can enhance greater accuracy in predicting defects of time-series by incorporating an improved temporal convolutional network with the use of a long short-term memory which is bi-directional. It utilizes the hyperparameter optimisation with Optuna, advancing feature extraction techniques, and industrial data, which have been pre-processed. Monitoring of the industrial equipment should be done in real time to achieve maximum performance. The processes and equipment in a complicated manner communicate with each other and the conventional methods do not discover these links [12]. DiFFNet is a multi-modal data fusion network that combines coarse- and fine-grained features by means of equipment monitoring prediction, which is developed in the current study.

Through deep learning, this study proposes a digital-twin-based unmanned health monitoring system of the industrial equipment that is capable of reciprocal behaving [13]. It enhances the accuracy of monitoring through using simulation tools along with a generative adversarial network. As the results of the experiment demonstrate, the model is more precise and stronger and justifies the applicability of the proposed strategy and minimizes the scope of errors significantly. Efficiency and reduction of cost in the industrial equipments are among the priorities. The most significant points of concern in this research of predictive maintenance by machine learning are data collection, pre-processing and feature engineering [14]. The importance of anomaly detection to diagnose an early failure is highlighted and the issue of using models to simulate the remaining useable life (RUL) is also discussed. Traditional industrial equipment monitoring often uses a single source of data and does not provide the possibility of fault diagnosis and condition verification [15]. In this work, there is a Bayesian fusion method, which consists of sensor data and visual data combining to improve equipment malfunction detection accuracy. This will enhance the management of health and monitoring of condition in complex industries. This research aims at enhancing the performance and efficiency of the industrial equipment, analyzing the innovative methods of detection, prevention, and monitoring [16]. It evaluates methods like vibration, artificial intelligence, audio/image analysis and signal analysis. We will strive to create greater reliance in industrial processes through maximising maintenance, avoiding any break downs, and making such improvements.

Complicated industrial system diagnosis greatly depends on troubleshooting trees. They start with a list of known failures and a system analysis that can offer a systematic approach to problem solving [17]. This research paper provides an approach to creating early trouble shooting trees using product manuals and the study examines the application of generative big language models to process and arrange the information on unstructured texts. The sphere of artificial intelligence (AI) marketing has been observed to be impacted by these developments [18]. This paired with data gathered in real-time by sensors turns the monitoring and maintenance of equipment in an absolute ease. The health management and reliability of industrial equipment can be enhanced through the analysis of huge data with the help of AI-based procedures, including machine learning. Prognostics is based on much on assessing health condition and formal life expectancy. This is not the end yet as there are still barriers to be traded like neglected inter-task correlations, feature extraction challenges and inter-task heterogeneity [19]. To enhance and outsmart former models regarding the aspect of adaptability, task correlation and the ability to extract features, the given study recommends a mixture-of-experts model with adaptive multi-scale feature fusion. The paper presents a preventative maintenance model of industrial equipment in a large scale that employs machine learning to reduce the number of equipment issues and enhance the efficiency of maintenance [20]. It uses sensors to derive information, and this is what enables it to spot anomalies, how long it will last and when it will stop functioning.

The topic of artificial intelligence (AI) in preventive management solutions to industrial equipment is discussed in this study with machine learning (ML) models to predict failures and optimise the maintenance schedule [21]. There is a risk-taking of the transition to AI-assisted maintenance, in which data collection, feature engineering, and application of the various ML techniques to construct models are highlighted. This study is on Predictive Industrial Maintenance with the use of XGBoost and Local outlier factor [22]. Its objectives encompass enhancing the reliability of the industrial processes and forecasting the time when equipment would malfunction. It uses Explainable AI to give light into the decision-making process that is done by the used predictive models. It focuses on predictive maintenance of industrial equipment, and the given research is aimed at comparing four valuable machine learning techniques [23]. To achieve sustainable manufacturing processes, improvement in operational efficiency, and reduction of downtime, it emphasizes on the importance of algorithm decisions. Unplanned equipment breakdowns in the industrial sector cause financial losses and inefficiency of these machines. Predictive maintenance (PdM) with the help of machine learning allows to optimise schedules and extend the life of equipment [24]. Explainable AI is useful in enhancing model transparency. It has been established by research in the energy and industrial sectors that ML can save cost and time down. Dwelling upon the issues of the automation of the machine rate of production, the research explores the applications of the machine learning in the manufacturing sphere [25]. Our results are the analysis of data transmitted by the energy meters on the Modbus by the CART based binary decision tree.

PROPOSED SYSTEM

It is proposed that the IIoT infrastructure based on clouds be used to continuously monitor the equipment status and give instantaneous failures to increase reliability and operational performance in industries. The system has built-in smart sensors, data gathering units on edges, cloud computing, as well as a centralized monitoring dashboard to deliver an all-embracing equipment monitoring framework. First, multiple sensors are installed on several industrial machines which measure the most important parameters of operation like the temperature, vibration, pressure, current consumed, humidity and the speed of rotation. These security feed real-time information which shows the working condition of the equipment. The local data acquisition module or edge gateway gathers sensor data where it acts as a point of contact between the devices and the cloud system.

This gateway takes data through multiple sensors, basic filtering to remove noise or redundant data, and sends the filtered important information to the cloud server over reliable communication systems, including Wi-Fi, Ethernet, industrial communication networks, etc. When the sensor data arrives in the cloud infrastructure, it is stored in a scalable database that can handle great volumes of the streaming industrial data. The cloud platform is used to carry out continuous data processing and data analysis to absorb the state of each unit. With the investigation of previous tendencies and current statistics, the system will identify the aberrant patterns which can represent wear, overheating, imbalance, and the other advance signs of equipment failure. The cloud platform enforces set limits on the threshold level of different metrics depending on the specifications of equipment and requirement to perform its work.

In Figure 1, it is recommended to have a system to monitor industrial equipment by use of sensors that will collect data relating to temperature, vibration and pressure. Information is transmitted through an edge gateway to the cloud platform to store and process information. The system measures working patterns, finds the abnormal conditions, and provides warnings and a centralised interface allows real-time visualisation of the system and provides maintenance support.

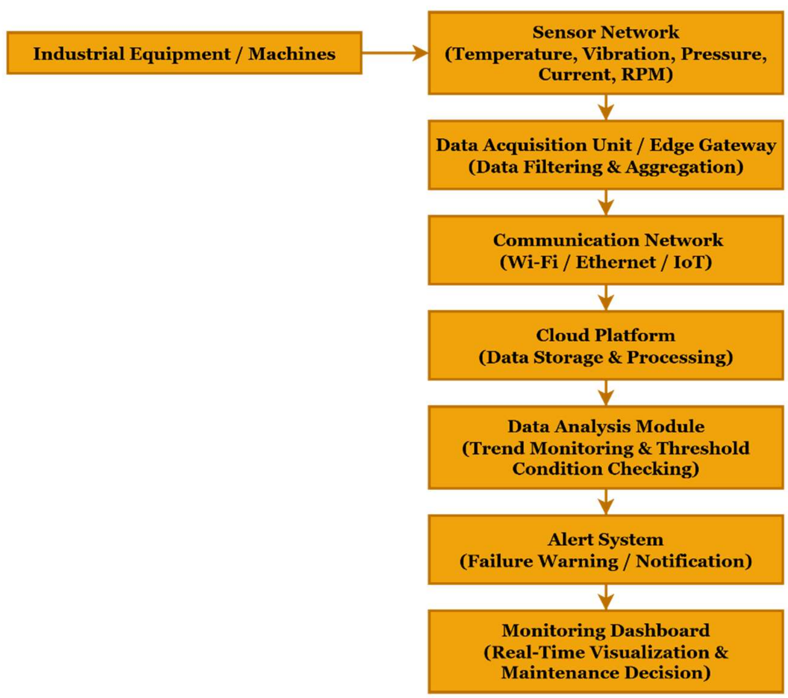

FIGURE 1. Architecture of the proposed IIoT monitoring platform

Once the sensor data at the real time falls below or significantly different to these values the system classifies the occurrence as a likely malfunction or deviant behaviour. The technology makes it possible to provide automated notification of failure in case of abnormal circumstance detection to support proactive maintenance. An alert system is immediately transferred to the maintenance professional through a notification system like mobile apps, email, online dashboard, etc. The warnings are also comprehensive with the machine identification number, parameter that triggered the warning, the measured value and time when it happened all being contained with the warning. This will allow the maintenance staff to quickly determine the root cause of the issue and undertake corrective actions before the complete breakdown of a system occurs. Early notification helps businesses to minimize unexpected downtimes, avoid high-cost repairs, and maintain continuous production processes. The proposed system will provide the centralised visualisation platform through which the plant managers and the maintenance workers will be able to monitor the equipment issues in real time. The dashboard has the graphical displays of sensor data trend, equipment status, and history of alerts. The interface is useful in monitoring the functioning of different machines effectively in numerous manufacturing units. The analysis of historical data enables engineers to understand the long-term operation of equipment, identify the persistent operational issues and upgrade the maintenance plans.

Figure 2 below shows an operating procedure flow chart of the proposed system. Sensors collect real time equipment information and send it to edge gateway to run initial processing. The information is then uploaded into the cloud platform to be stored and analyzed. The system analyzes parameter thresholds, finds out abnormal situations, sends warnings, and replenishes the monitoring dashboard.

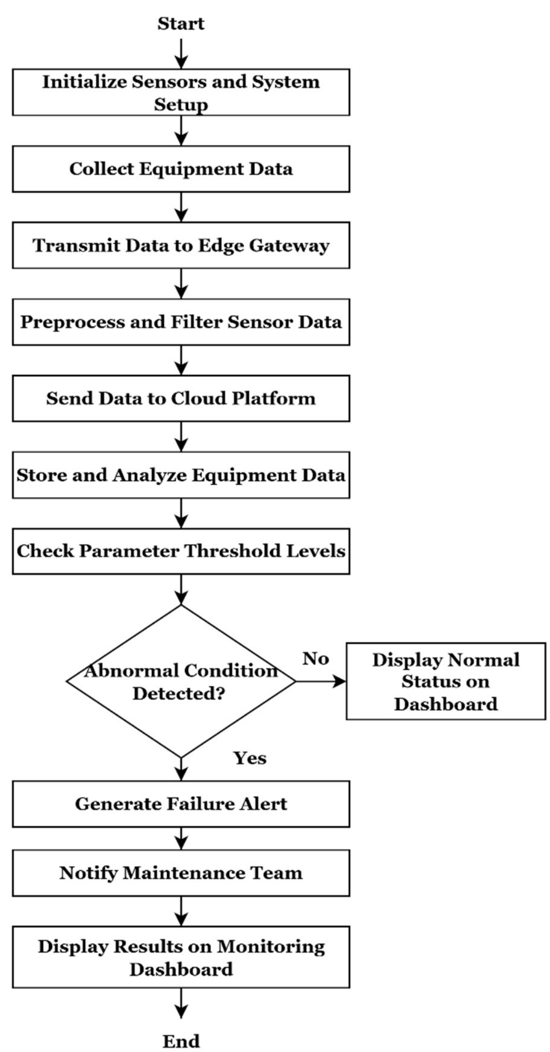

FIGURE 2. Flowchart of the proposed cloud-based IIoT equipment monitoring system

The visualisation tools can be used to aid decision-making due to the ability to provide concise information on the machine usage, the efficiency of performance, and the level of operational risk. One of the most important qualities of the suggested platform is its access remoteness. Since the information is stored and manipulated on the cloud, authorised users could retrieve equipment information in any place through secure log-in authentication. This feature of remote monitoring is most useful to those companies that have several plants or geographically spread locations. Maintenance supervisors can monitor equipment status away and this increases reaction and operational coordination. The system also provides role-based access control which will ensure that vital data pertaining to operations is only made accessible to authorised people.

The proposed system with its architecture will be scalable and flexible to most industrial applications. It is possible to add supplementary machines or sensors to the existing network without making any significant changes to the infrastructure. Resource control of data storage and processing is automated by the cloud environment, which also allows the platform to support large scale industrial implementations. Additionally, the system provides continuity in data representation which allows enterprises to maintain records of maintenance, evaluate the lifespan of equipment, and minimise the safety rules which go with the industrial operations.

RESULTS AND DISCUSSION

The suggested cloud-based Industrial IoT platform was tested within an industrial environment where the viability of the given platform in continuous equipment health monitoring and failure warning generation could be evaluated. Many of the equipment's included sensors to monitor the critical operating rates including temperature, vibration, and current consumption. The obtained data were transmitted to the cloud platform through an edge gateway and stored and analysed to determine how the equipment was functioning and any unusual condition in which it was operating. The results of the experiment prove that the approach contributes greatly to the efficiency of equipment monitoring and minimizing cases of unpredictable machine failures. Throughout the period of assessment, the platform was able to easily identify anomaly fluctuation of parameters before the development of massive equipment failures. As an example, a set of vibration level beyond the required amount of the specified threshold values triggered early warning messages that allowed repair specialists to investigate and fix the issue before it was serious. The system, therefore, reduced the expected system failures and reduced unexpected downtime. The statistical analysis of the obtained data shows that there were fewer downtimes on the equipment, and the maintenance response time improved. In addition, the overall efficiency of the equipment at work became better due to the early detection and timely maintenance.

The cloud dashboard that was centralised played a very vital role in ensuring that the decisions regarding maintenance were made. The actual condition of equipment can be viewed on the real-time basis by the plant operators and engineers through the graphical presentation of sensor data trends. The system-maintained records of the historical data and this allowed the engineers to examine equipment behaviour at a certain period and identify repeating operating patterns. This historical approach thus helped the maintenance teams to develop preventive maintenance programs in a more cost-effective way, reducing unnecessary inspections at the expense of the allocation of resources. The scalability and reliability of a cloud infrastructure is among the notable results of the deployment. The system was able to process incessant machine data streams without reducing its performance. Cloud-based platform enables the introduction of new equipment and sensors in the system with ease and does not require any major changes in the infrastructure.

The proposed solution is suitable to large industrial environments in which multiple units should be tracked at the same time due to its scalability. The automated warning system was demonstrated to be very effective when it came to enhancing response time in maintenance. When the abnormal situation was detected, the notification was quickly sent to the maintenance workers through the monitoring dashboard and the notification system. Quick communication allowed faster correction of measures to curb production and prevented a high threat of equipment damage. The technology increased the safety of the workers; therefore, providing timely information on the potential failure of equipment. Table 1 shows the sensor results of monitoring of six industrial equipment. The parameters that are measured against the threshold values include temperature, vibration, pressure and current to determine the state of equipment and the necessary maintenance tasks.

TABLE I. Sensor-based equipment health monitoring results of industrial machines

Machine ID	Temperature (°C)	Vibration (mm/s)	Pressure (bar)	Current (A)	Threshold Status	Alert Generated	Maintenance Action	Equipment Status
M1	62	3.1	5.4	12.5	Normal	No	Not Required	Stable
M2	78	6.8	5.9	14.2	High	Yes	Inspection	Warning
M3	65	3.9	5.2	11.9	Normal	No	Not Required	Stable
M4	82	7.5	6.1	15.3	Critical	Yes	Immediate Repair	Fault Risk
M5	70	4.2	5.6	13.1	Normal	No	Not Required	Stable
M6	75	6.1	5.8	14.0	High	Yes	Scheduled Check	Warning

Table 2 compares the past performance of the system and that of the system after the introduction of the cloud-enabled IIoT platform. The results reveal differences in the efficiency of equipment, reduction in downtime, speed in responding to repair, and reduction in operating costs.

TABLE II. Performance comparison of the system before and after implementation

Parameter	Before Implementation	After Implementation	Improvement (%)	Observation	Status
Equipment Downtime (hrs/month)	42	28	33.3	Reduced downtime	Improved
Maintenance Response Time (min)	60	33	45.0	Faster response	Improved
Equipment Efficiency (%)	68	87	27.9	Higher productivity	Improved
Failure Detection Rate (%)	61	90	47.5	Early fault detection	Improved
Maintenance Cost (USD/month)	5200	3800	26.9	Cost reduction	Improved
System Reliability (%)	72	93	29.2	Stable monitoring	Improved

The accepted characteristics of equipment behaviour or measurement, comprising temperature, vibration, and current, are in figure 3 being plotted on six industrial machines. The highest temperature (82 0 C) and level of vibration (7.5 mm/s) are registered by machine M4, which can indicate a potential failure mode. Machine M1 and M3 operate in the normal parameters. Based on the investigation, it is noted that high vibration and temperature levels have a strong relationship with early deterioration and maintenance with equipment.

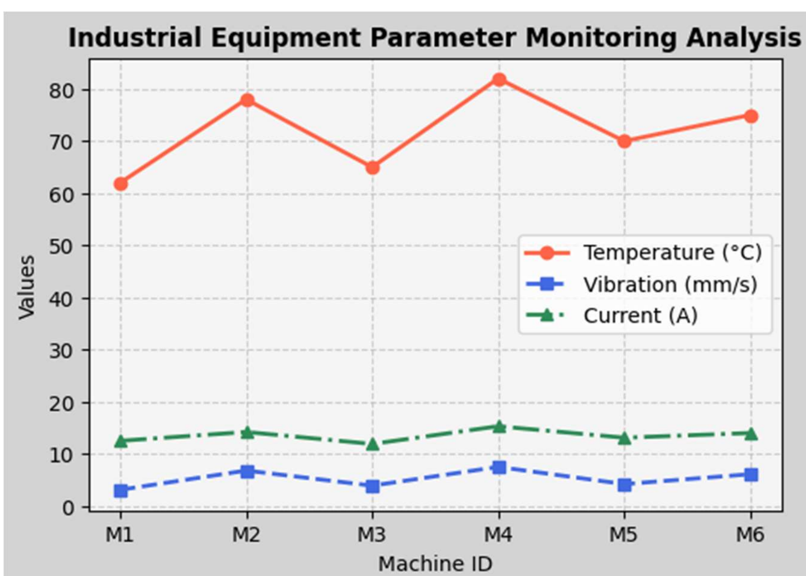

FIGURE 3. Analysis of equipment operational parameters

Figure 4 demonstrates the failure alarm detection time, maintenance response time and the number of minutes the six machines would fail to not to be down. Machine M4 has the shortest detection time of 4 minutes, and it eliminates 4.1 hours off time. M2, M3 and M6 are machines that have timely notifications and effective maintenance processes. As indicated by the analysis, timely warning development results in a significant reduction in downtime and performance durability and stability of equipment.

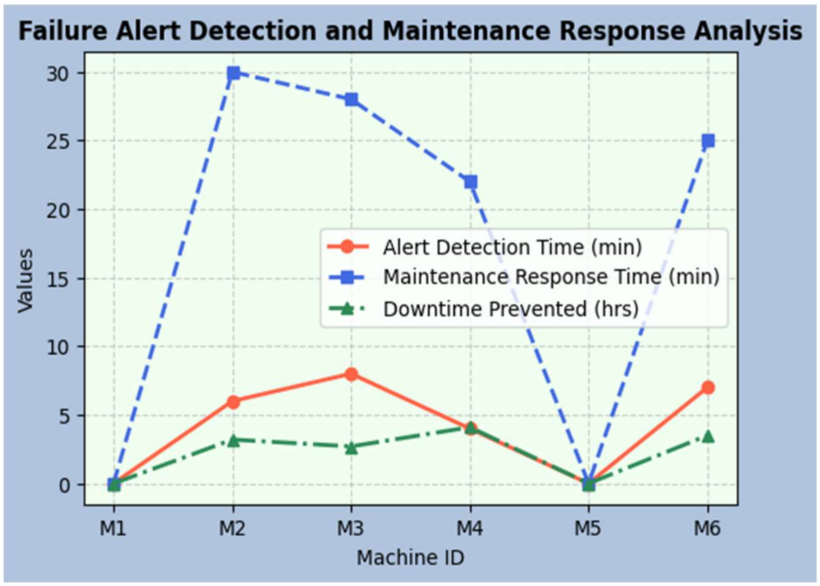

FIGURE 4. Alert generation and maintenance response evaluation

The identification of failure alerts regarding monitored machineries is summarised in Table 3. The system identifies anomalous conditions, including high vibration or temperature level, and these are reported in time, so appropriate maintenance interventions may prevent breakdowns.

TABLE III. Failure alert detection and maintenance action summary

Machine ID	Detected Issue	Alert Time (min)	Maintenance Outcome
M1	Normal Operation	0	No Action
M2	High Vibration	6	Inspection Completed
M3	Temperature Rise	8	Cooling Adjusted
M4	Critical Vibration	4	Immediate Repair
M5	Normal Operation	0	No Action
M6	Current Fluctuation	7	Preventive Maintenance

Although the proposed way has advantages, there are some disadvantages to it. The technology relies a lot on a good internet connection to ensure data is passed continuously to the cloud and this may affect the monitoring of far industrial locations. The initial costs of the installation of the sensors and cloud infrastructure can be quite high. Furthermore, wrong sensor values or malfunctioning of the hardware can cause false alarm that requires frequent calibration and troubleshooting to ensure effective operations of the system.

CONCLUSION

The study proposed a cloud-based IIoT system, which is supposed to be used in continuous monitoring of equipment health and designing of advance warning of failure in the industry context. The proposed system will be a combination of sensor networks, edge gateways, and cloud infrastructure that will be used to collect, transfer, and process real-time operational data of industrial equipment. By continuously checking such important parameters as temperature, vibration, pressure, and current, the platform effectively identifies cases of abnormal operation and provides timely messages to the maintenance personnel. It has been found in the deployment that the system is very effective in terms of efficiency in monitoring equipment and reliability in operations. According to the performance study, there was an increase in efficiency, which went up to 87 percent against 68 percent, system reliability that went up to 93 percent against 72 percent, and decrease in equipment downtime to 28 hours every month against 42 hours. Moreover, the time in which the maintenance should respond was shortened to 33 minutes instead of 60 minutes due to the automatic alarm system. The realised Maintenance decisions were improved by the visualisation and remote monitoring of the cloud dashboard, which made the real-time decision-making process. The proposed IIoT-based monitoring system suggests a cost-effective system of the management of industrial assets, which is scalable. It also helps advance the proactive maintenance approach, reduce operational disruptions, and improve on smart manufacturing technologies and Industry 4.0 ecosystem development.

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