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# Industry 4.0-Based Predictive Maintenance System for an Automated Bottle Inspection System

**Maitree Pazare[1], Vishal Jaiswal[2]**

[1]Student, Department of Electronics and Telecommunication, G. H. Raisoni College of Engineering and Management, Nagpur, India

[2]Assistant Professor, Department of Electronics and Telecommunication, G. H. Raisoni College of Engineering and Management, Nagpur, India

**Abstract**

Nowadays in the industry, moving from reactive maintenance to predictive one is necessary for increasing reliability of the machinery and reducing failures in the production. This task can be solved using predictive maintenance that implies continuous machine monitoring. However, existing systems usually employ expensive condition-monitoring sensors. This research project aims at creating and deploying efficient low-cost cloud-based PdM system at the Testing Station of MAPS-6S2. The Siemens S7-1200 PLC (CPU 1215C) programmed by the TIA Portal V19 software controls the process and gathers real-time data. Operational data include cycle time, the number of products manufactured, rejection of the particular types of bottles (short height and metallic ones), the state of the machine and timestamps of process variables. The Node-RED is used as the communication gateway of the industrial process when process variables are collected, processed and safely uploaded to the cloud service named ThingSpeak. The historical data received from the cloud are analysed in the MATLAB environment by means of KPI analysis. Thus, it was found out that the efficient PdM can be achieved using the data of PLC operations alone. Therefore, the developed approach combines the concepts of industrial automation, edge routing, cloud computing, and analytics into the scalable Industry 4.0 architecture, setting the stage for the future implementation of complex machine learning predictive models.

**Keywords:** Predictive Maintenance, Industry 4.0, Siemens S7-1200, Node-RED, ThingSpeak, MATLAB, IIoT, Automation Systems, CPS

## 1. Introduction

The progress of Industry 4.0 has resulted in the transformation of classical manufacturing systems into smart, connected production facilities able to monitor operations in real time, make autonomous decisions, and optimize processes. The implementation of IIoT, PLCs, cloud computing, and data analysis have helped industries move from reactive maintenance to predictive maintenance, increasing efficiency and reliability of their equipment and production processes.

Predictive maintenance became an important part of modern automation since it allows detecting degradation of equipment and anomalies in the processes before the failure occurs. In contrast to preventive maintenance following fixed schedule, predictive maintenance continuously evaluates the state of machines and processes using process data collected from sensors and control systems. It minimizes unplanned downtimes, optimizes maintenance planning, extends the service life of the equipment and reduces the expenses related to maintenance at the expense of production efficiency.

Automated production systems operate under constant monitoring of process parameters to maintain high product quality and reliability. Parameters like cycle time, pneumatic pressure, bottle height, conveyor speed, production count, rejection count, and actuator performance can give useful information about process stability and condition of equipment. Any changes in process parameters indicate mechanical wear, degraded sensors, leaks, or inefficiency; thus, they can be used as the basis for predictive maintenance solutions.

This study describes the design and development of a cloud-enabled predictive maintenance system for an automatic bottle inspection and sorting production line based on the Modular Automated Production System (MAPS). The designed system is built around a Siemens S7-1200 programmable logic controller (PLC), which is used to collect process data from sensors and actuators on the production line.

Operational parameters are gathered in real-time mode and then sent to the cloud via Node-RED and saved in a time-series database to facilitate centralised process monitoring, data analysis, and predictive evaluation of equipment performance.

The designed solution is aimed at creating a scalable and affordable monitoring system that will enable efficient maintenance decisions. A live monitoring dashboard allows for visualisation of process parameters, production statistics, and equipment states in order to perform remote monitoring of system operation and detect abnormal operation modes. Historical process data also allows conducting analysis of data trends, detecting anomalies and performing preventive maintenance.

By means of integrating automation technology with Industrial IoT solutions, the designed system represents a practical example of Industry 4.0 technologies application for intelligent manufacturing.

## 2. Literature Review

### 2.1 Modular Mechatronic Training Platforms

Modular systems such as MAPS (MTAB Modular Automation Production System) simulate industrial-scale bottle handling, quality checking, and sorting activities in a miniature format. Past literature suggests using these modules for teaching individualized mechatronics skills proximity detection, analog manipulation, and pneumatic sorting prior to system integration.

### 2.2 Direct Driver Architecture against OPC UA

Whereas the OPC UA protocol is mandatory in Industry 4.0 for semantic data representation, it imposes immense CPU and memory consumption on edge devices. The memory of compact controllers, such as Siemens S7-1200, is very limited by nature (100–200 KB). According to literature, utilizing native S7 TCP/IP driver or Modbus TCP polling directly instead of introducing an OPC UA server removes protocol translation delays, decreases the payload size, and keeps important PLC computing resources for automation logic.

### 2.3 Ingestion into Edge Middleware

Node-RED provides a flow-based, lightweight middleware layer that acts as an OT-to-IT connectivity solution. Mapping global PLC data block (DB) variables, Node-RED becomes a nonintrusive translator. Edge telemetry is locally streamed, structured in JSON format, and sent through lightweight protocols such as MQTT and RESTful API to the cloud side.

### 2.4 Cloud Analytics & Predictive Maintenance

Predictive maintenance (PdM) is made possible by cloud-based historization rather than individual readings. With conventional time series systems (such as ThingSpeak) and computational systems (like MATLAB), it is possible to perform a statistical analysis of factors like cycle times and rejection rates without additional condition monitoring hardware. Rolling averages and drift measures enable detection of gradual pneumatic or sensor degradation even before the device fails. In sophisticated setups, the RUL determined through analytics becomes an input for job scheduling systems

## 3. Bottle Testing Station: Mechanical and Sensing Architecture

The Testing station performs three sequential checks on each incoming bottle: presence and position confirmation, height measurement, and material verification, before the PLC issues an accept or reject decision. Table 1 summarises the principal sensing and actuation components involved and their roles in this sequence; Figure 1 depicts the sequence as a flow of discrete stages.

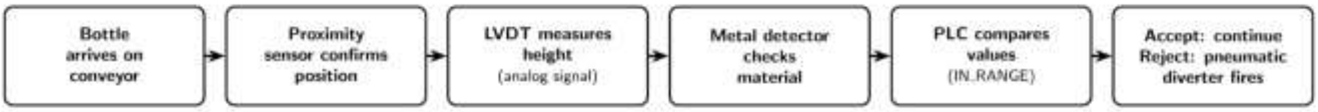
**Table 1: Sensing and Actuation Components of the MAPS-6S2 Testing Module and Their Function in the Bottle-Inspection Cycle**

| Component | Function | Signal Type | Role in Inspection Cycle |
|---|---|---|---|
| Proximity sensor (inductive/capacitiv) | Detects presence and correct positioning of the bottle before measurement | Digital (24 V DC, ON/OFF) | Gates the start of the LVDT measurement step; prevents false readings on an empty fixture |
| LVDT (Linear Variable Differential Transformer) | Measures bottle height via mechanical displacement of a probe | Analog (typically conditioned to 0-10 V or 4-20 mA) | Provides the continuous value compared against upper/lower limits using an IN_RANGE-type check |
| Metal detection sensor | Verifies material composition of the bottle/cap | Digital (24 V DC, ON/OFF) | Confirms the workpiece matches the expected non-metal/metal specification |
| Pneumatic cylinder and solenoid valve | Executes the reject action for non-conforming bottles | Digital output (24 V DC coil) | Actuated by the PLC when a reject condition is latched |
| Conveyor drive | Transports bottles between distribution, testing, and processing stations | Digital output / motor starter contact | Synchronised with sensor states so bottles stop at the correct inspection position |

### 3.1 Proximity Sensing and Position Confirmation

An inductive or capacitive proximity sensor confirms that a bottle has arrived and is correctly seated in the test fixture before any measurement is attempted. This is a simple but essential interlock, as without it the LVDT stage could register a spurious reading against an empty fixture, and the PLC's accept/reject logic could act on invalid data. The sensor's digital ON/OFF output is read directly into a PLC digital input and typically gates the start of the height-measurement sub-routine within the control program.

**Figure 1: Sequential stages of a single bottle-inspection cycle on the Testing module, from arrival to the accept/reject decision.**




### 3.2 Height Measurement via LVDT

Bottle height is measured using a Linear Variable Differential Transformer (LVDT), a well-established electromechanical transducer that converts linear displacement of a probe into a proportional analog electrical signal. As the bottle displaces the LVDT's spring-loaded probe, the transducer outputs a voltage or current signal that is digitised by the PLC's analog input channel. The measured value is then compared against upper and lower acceptable limits, conceptually an IN_RANGE-type check, to classify the bottle as within specification or defective.

### 3.3 Material Verification via Metal Detection

A metal detection sensor performs a binary check on the bottle's material composition, distinguishing metallic from non-metallic (or correctly capped versus incorrectly capped, depending on the exact MAPS6S2 build) workpieces. Like the proximity sensor, this produces a simple digital signal that the PLC logic combines with the height-check result to reach a final accept/reject decision.

### 3.4 Pneumatic Rejection

On receiving a reject command from the PLC, the solenoid valve directs compressed air to extend the cylinder, diverting the non-conforming bottle into a separate collection point before the conveyor carries it further downstream. Pneumatic actuation is favoured in this type of application for its speed, mechanical simplicity, and tolerance of the repetitive duty cycle typical of a teaching station used across many student sessions.

### 3.5 Conveyor Synchronisation

A linear conveyor transports bottles between the Distribution, Testing, and Processing stations. Correct synchronisation, that is, stopping a bottle precisely at the proximity sensor's detection point, holding it during the LVDT and metal-detection checks, and only then restarting the conveyor, is itself a control-logic function, typically implemented as a short state machine within the PLC program (see Section 6.4). Additional sensors placed along the conveyor path may provide supplementary position feedback, depending on the specific MAPS-6S2 build.

## 4. Siemens S7-1200 CPU 1215C: Hardware Platform

The testing station MAPS-6S2 utilised in the design of this project employs the Siemens SIMATIC S7-1200 CPU 1215C (DC/DC/DC type) controller, which is programmed using TIA Portal V19 software. This is a transistor output PLC with compact size intended for small and medium-sized automation systems wherein the digital and analogue inputs, two PROFINET interfaces, and the CPU all exist in one module. Two aspects of the hardware employed in this project are crucial for its application in the process of bottle testing. First, since there are analogue input channels on the module (0-10V DC), the LVDT signal could be measured directly without employing any extra analogue modules, provided the conditioner of the transducer has a similar input range. Second, while the PROFINET interfaces ensure a real-time deterministic field I/O traffic, they also provide the capability of asynchronous S7 Ethernet communication based on TCP/IP protocol. Hence, the edge gateway could access the variables of the optimised data blocks (DBs) asynchronously without interference with real-time traffic.

## 5. Proposed Methodology

The suggested methodology includes creating an industry 4.0 predictive maintenance system for the automated MAPS bottle testing station using such techniques as industrial automation, IIoT, cloud computing, and data analysis integrated into one single system. The main goal of this system is to receive the information regarding the work of the station, transfer the information to the cloud infrastructure and analyse historical tendencies in order to make decisions regarding the predictive maintenance. The overall structure of the suggested methodology is illustrated in Figure 2 and includes five consecutive stages: MAPS bottle testing station, data collection by PLC, communication via Node-RED, cloud-based data storage and visualization, and predictive maintenance analysis. All these stages guarantee proper collecting, transmitting, storing, and analysing of the information received from the industrial process..

**Figure 2. General methodology of the proposed cloud-integrated predictive maintenance system.**


Methodology begins at MAPS-6S2 Testing Station, where bottles are tested during transportation on the conveyor belt. At this stage, the sensors and pneumatics are employed to determine the bottle height and its material, as well as sort out the malfunctioned bottles. As a result, certain production indicators are constantly generated: cycle time, bottle height, number of manufactured bottles, number of rejected bottles, machine status and conveyor status. The data can be considered not only as the indicator of the production efficiency but also as the machine status, and, thus, be used as the input for predictive maintenance system.

$$CT_i = t_{\text{completion},i} - t_{\text{arrival},i}$$

where:

- $CT_i$= Cycle time of the $i^{th}$bottle.
- $t_{\text{arrival},i}$= Time when the bottle enters the testing station.
- $t_{\text{completion},i}$= Time when the bottle exits (accepted or rejected, depending on your logic).

Control process at the inspection station is carried out using Siemens SIMATIC S7-1200 PLC (CPU 1215C). The program for controlling the process was made with the help of software package TIA Portal version 19. Along with control process itself, PLC permanently receives operational data from the sensors and actuators. Process variables acquired by the PLC are stored in PLC Data Blocks, which allow easy and reliable connection for subsequent external communication. As compared to traditional prediction maintenance systems, which use special condition monitoring sensors, the suggested system operates based on the operational data from the PLC. In order to ensure connectivity with the cloud, the PLC should be connected to Node-RED, which is used as the data acquisition and communication gateway. Particularly, Node-RED collects process variables from the PLC and formats and packages data for cloud platform. This is the middleware technology responsible for efficient data communication and transfer from industrial control environment to the cloud.

To enable the connectivity within IIoT, Node-RED is utilized as a middleware solution in the process of creating connection between the PLC and the cloud platform. Node-RED constantly reads the process variables of the PLC using the Siemens S7 communication protocol, prepares the acquired information, puts timestamps, and transfers it to the cloud platform. The usage of such middleware ensures scalability and reliability of the communication as well as the reduction of the computation load of the PLC.

The structured data is fed into the ThingSpeak cloud service in which it is stored in form of time-series data and is presented with the help of real-time dashboards. The cloud service enables continuous monitoring of the machine performance, remote access to the data and archiving of the past production data. Moreover, with the help of built-in MATLAB Analytics, one can conduct statistical analysis and trend analysis of past performance data.

The last part of the analysis of the stored process data is the analysis of the predictive maintenance state of the process. The past trends of the process variables like cycle time, number of production, number of rejection, bottle height, and machine state are constantly analysed for any deviations which could be used as an indication of any process degradation or instability. By comparing the present working conditions with the historical behaviour of the process, potential problems can be identified and maintenance can be scheduled to prevent equipment failure.

The proposed methodology serves as an efficient platform for Industry 4.0 implementation by integrating the collection of PLC data, communication using Node-RED, cloud computing through ThingSpeak and analysis using MATLAB to form a predictive maintenance system. The utilization of production-related KPIs rather than any additional monitoring devices makes the proposed solution efficient not only in machine diagnostics but also in production monitoring.

## 6. System Implementation

The above-mentioned predictive maintenance system was developed for use in the Modular Automated Production System (MAPS-6S2) Testing Station for testing bottles according to their height and material properties. Cloud-integrated industrial automation, cloud computing, and IIoT technologies were used in the system implementation to allow real-time monitoring, storage of historical data, and predictive maintenance analysis. The architecture of the system includes four levels: the industrial process level, control level, communication level, and the cloud analytics level.

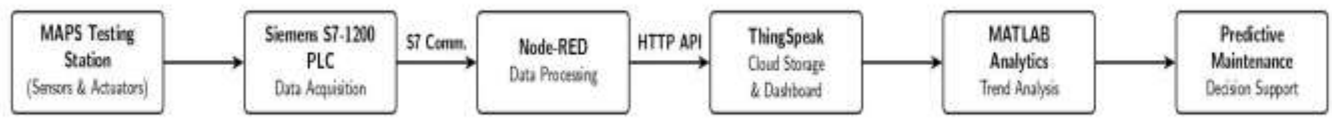



**Figure 3. Architecture of the proposed predictive maintenance system implementation.**

### 6.1 Industrial Process and Data Collection

The MAPS-6S2 Testing Station is used as an industrial platform for data collection and monitoring of the process. The bottles are moved along the testing station conveyor in which several industrial sensors examine each bottle before the latter moves to the next step. The examination process includes detection of the bottle presence, measuring its height by means of the LVDT sensor, and material examination using a metal detection sensor. On the basis of these examination results, the PLC decides whether the bottle meets the predefined quality requirements or is to be rejected with the help of the pneumatic rejection system.

The Siemens SIMATIC S7-1200 CPU 1215C PLC operating with TIA Portal V19 program is used to control the entire process of bottle examination. Besides controlling the automation process, the PLC collects operational parameters that represent machine performance and production quality. The main process parameters collected from the PLC are enlisted in the following table.

**Table 2: Operational Parameters Monitored on the MAPS-6S2 Testing Station**

| Parameter | How to Measure | Why It Matters |
|---|---|---|
| Cycle Time | Timer between consecutive bottle detections | Detects slower machine operation |
| Moving Cycle Time | Average or moving average of cycle times | Smooths fluctuations and shows long-term trends |
| Production Count | Counter | Measures throughput |
| Short Height Reject Count | Counter | Indicates quality or sensor issues |
| Metal Reject Count | Counter | Detects contamination events |
| Reject Rate | Reject Count divided by Production Count, multiplied by 100 | Shows quality degradation |
| Machine Status | PLC logic (Running/Stopped/Fault) | Identifies operational state |

### 6.2 PLC-Based Process Monitoring

The PLC becomes the core controller of the predictive maintenance system as it performs both process control and process monitoring operations simultaneously. The digital and analogue input signals from the field sensors are analysed through the PLC program to monitor the process status.

Unlike traditional predictive maintenance systems, which require additional vibration sensors and current sensors, the proposed predictive maintenance system makes use of data already available from the PLC system. Thus, this greatly lowers the cost of implementing the system and provides enough data for assessing the performance of the machinery.

The PLC continually monitors the monitored variables during each manufacturing process cycle. The monitored variables become an important source of information concerning the efficiency of the process performed by the machine.

### 6.3 Node-RED Communication Gateway

To achieve the connectivity of the IIoT network, the Node-RED was implemented as the middleware layer between the Siemens PLC and the cloud infrastructure. The middleware software collects the process variables from the PLC continuously by the Siemens S7 protocol, processes the received data, and converts the data into appropriate format that is suitable for cloud uploading. By avoiding the use of OPC UA protocol, which consumes the unnecessary CPU resources of the controllers, the Node-RED directly interfaces with the Siemens SIMATIC S7-1200 CPU 1215C with native S7 Ethernet TCP/IP protocol. The gateway collects the process parameters from the configured PLC Data Blocks (DBs) on a regular basis at a configurable polling interval, packages the payload into JSON format, and securely transfers it to the ThingSpeak Cloud via HTTP REST API POST request.

### 6.4 Cloud-Based Storage of Data Using ThingSpeak

The collected operational data are sent to the ThingSpeak cloud platform from Node-RED by making use of the HTTP REST API. The process variables that have been collected from the Siemens S7-1200 PLC are formatted in Node-RED and then are sent to the corresponding ThingSpeak channel fields through HTTP requests with the help of the channel Write API. The cycle time, production count, rejection count, bottle height, and machine status are among other parameters that get assigned to specific fields in the cloud channel for collecting time-series process data.

ThingSpeak cloud platform is designed for real-time visualisation, storing of historical data, and machine performance monitoring. Each data entry made into the platform is time-stamped, thus helping analyse the trends at various time intervals. The historical data stored in the cloud is used for further trend analysis of machine performance to plan for predictive maintenance with the help of the built-in MATLAB Analytics environment.

### 6.5 MATLAB Based Trend Analysis

ThingSpeak provides an integrated **MATLAB Analytics** environment for analysing historical operational data without requiring additional software. The time-series data collected from the automated bottle testing station are processed using statistical and trend-based techniques to evaluate machine performance. Key operational parameters, including **cycle time, production count, rejection count, bottle height, and machine status**, are continuously monitored to identify changes in process behaviour and overall system performance.

The analytical process includes moving average calculation, trend identification, process deviation analysis, and production performance evaluation. By comparing current operational data with historical trends, the proposed framework detects abnormal operating conditions that may indicate equipment degradation or process instability. This enables maintenance activities to be planned proactively, thereby reducing unplanned downtime, improving machine reliability, and enhancing the overall efficiency of the production system.

## 7. Experimental Setup

The proposed predictive maintenance system was experimentally designed and tested using the Modular Automated Production System (MAPS-6S2) Bottle Testing Station. In this case, the experiment included the use of Siemens SIMATIC S7-1200 PLC (CPU 1215C) that had been programmed using TIA Portal V19 for monitoring the bottle inspection process and recording operational data of the production line. This testing station contained industrial sensors, pneumatic actuators and a conveyor system for conducting the automated bottle inspection process in accordance with predefined quality criteria.

The operational data recorded throughout the bottle inspection process, such as cycle time, production count, rejection count, metal bottle count, short-height bottle count, bottle height and machine status were continuously recorded by the PLC in Data Blocks. Moreover, the acquired operational data were periodically sent to the cloud via Node-RED using the Siemens S7 communication protocol and the HTTP REST API, allowing continuous collection of data into the ThingSpeak cloud database. Finally, historical data were analysed using MATLAB Analytics to assess machine behaviour and conduct predictive maintenance.

In order to validate the above-mentioned methodology, the testing station of bottles was put to operation in normal production environment through several production cycles. Data collected from these operations were utilized to confirm the effectiveness of the data collection process, cloud connection and the historic data storage process. The test setup created all the needed prerequisites for conducting the performance evaluation of the machine by means of operational parameters which are described in the following section.

## 8. Results and Discussion

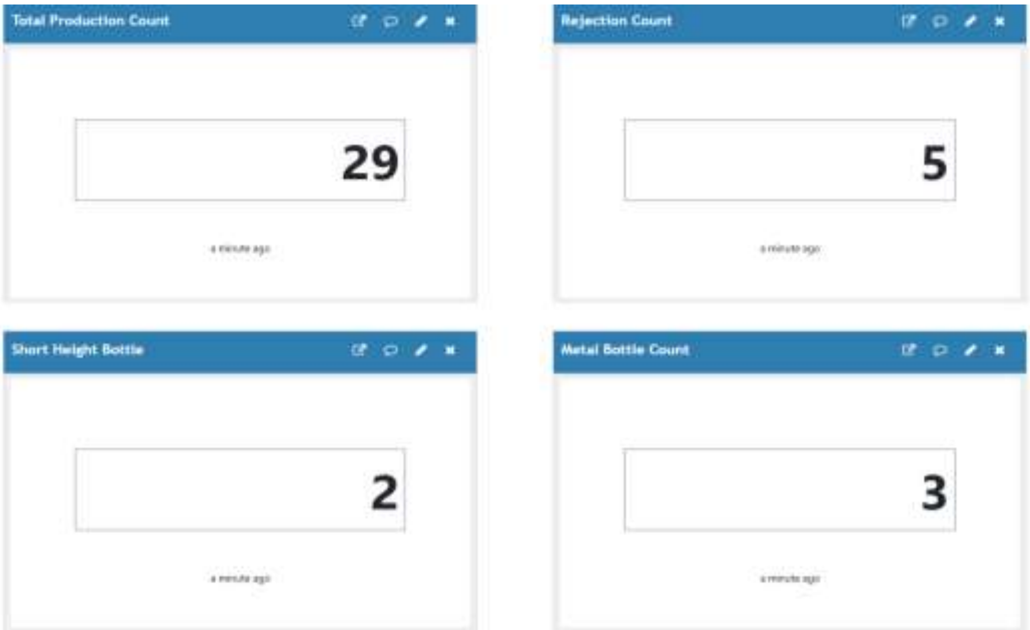
The implemented Industry 4.0-based predictive maintenance system was experimentally tested with the help of the Modular Automated Production System (MAPS-6S2) Bottle Inspection System. It has been successfully proved that the integration of industrial automation and cloud monitoring is possible due to the possibility of constant acquisition, transmission, storing, and processing of data. The process variables received via Siemens SIMATIC S7-1200 PLC have been transferred to the cloud storage ThingSpeak with the help of Node-RED using HTTP REST API protocol. Time-series data are stored and analysed in the cloud environment.

### 8.1 Real-time Monitoring and Cloud Dashboard

The monitoring dashboard developed using the ThingSpeak platform enables the visual representation of the data collected from the automated bottle inspection system in real-time. Figure 9 illustrates the monitoring dashboard used for monitoring the machine performance in the experimentation process. The dashboard shows the current values of production count, rejection count, metal bottle count, short height bottle count, along with the real-time changes in cycle time and machine status. Such information allows operators to monitor the state of operations of the production machine in real-time and keep a history of the machine's behaviour.

The cloud-based dashboard offers a centralised tool for monitoring the production parameters without having to access the industrial control system directly.

**Figure 4. ThingSpeak dashboard for real-time monitoring of the Industry 4.0-based predictive maintenance system.**




**8.2 Historical Data Analysis for Predictive Maintenance**

The historical data about the operation stored in the ThingSpeak platform were analysed through MATLAB Analytics integrated into the platform to analyse the behaviour of the machine over time. Important process parameters such as cycle time, production, rejection, bottle height, and machine state were constantly monitored to detect any trend and deviation from normal operations. Trend analysis makes it possible to monitor changes in the machine performance gradually and make assessments of the machine condition before its failure that can lead to interruptions in production.

As opposed to traditional maintenance techniques that are based on regular inspection, the proposed solution provides continuous monitoring of production-oriented operational parameters collected through the PLC. The possibility of having historical process data makes it possible to conduct long-term assessment of machine performance and plan preventive actions.

**8.3 Predictive Maintenance Analysis and Alert Generation**

The operational data of the past machine operations have been analysed using MATLAB Analytics to understand the performance of the machine and abnormal machine operations. At each iteration, the MATLAB code collects the latest operational data from the cloud and analyses certain process variables like the bottle height, cycle time, number of productions, number of rejections, and machine operation. A rule-based trend analysis method is used for the predictive maintenance algorithm to analyse the operational data of each succeeding run by comparing it with certain threshold values and moving average metrics. For experimental purposes, two different cases of machine maintenance have been considered. The first one is based on bottle height and concerns detecting progressive sensor drift or detecting the presence of a cluster of low bottle height, which shows a drastic reduction in consecutive bottle heights **<2.5** This shows the possibility of calibration and alignment problems with the LVDT sensors. The second case involves increasing the drift trend of cycle time over time. If the machine operates in any kind of abnormal operating conditions or negative drift trends that fulfil the criteria of predictive maintenance, then the MATLAB program will give an alert signal through ThingSpeak API. An e-mail shall immediately be sent to the maintenance crew regarding the unusual condition of operation and the necessary maintenance work to be done

**Figure 5. An automatic email notification received after detecting an abnormal operating condition using the designed predictive maintenance system**


### 8.4 Discussion

Experimental data show that the developed Predictive Maintenance System, which is based on the principles of Industry 4.0, manages to unite industrial automation, cloud computing, and analytics within one maintenance system. It was possible to monitor the system operation continuously, analyse historical data and send notifications about maintenance automatically without stopping the production process due to the reliable interaction of the PLC, Node-RED, ThingSpeak, and MATLAB Analytics.

As opposed to other predictive maintenance systems that require dedicated vibration or current sensors, the developed system relies on production-related parameters that are used by the PLC, such as cycle time, bottle height, production count, rejection count, and machine state. The combination of continuous cloud monitoring, rule-based trend analysis, and automatic email notifications allows detecting abnormal conditions early on and helps to plan maintenance activities proactively.

## 9. Future Scope

The proposed Predictive Maintenance System based on Industry 4.0 is a sound solution for monitoring and maintenance in an automated bottle inspection system. Even though the current design relies on a rule-based trend analysis of anomalies and maintenance requests, future improvements to the system could include the application of machine learning methods to develop predictive models that will help detect machine failures in advance. The algorithms used might be decision trees, support vector machines, random forests, and LSTM networks; they will be developed based on historical data to improve classification and predict machine degradation.

Moreover, the system can be improved by adding other condition monitoring sensors like vibration sensors, temperature sensors, pressure sensors, and motor current sensors to provide a more complete picture of the machine state. The combination of measurements of condition monitoring parameters and production-based operational parameters will help in fault diagnosis. In addition, the proposed framework can be integrated with digital twin technology; this integration will allow developing a virtual model of the inspection system, which would help test maintenance solutions in a virtual environment before their use in a real-world scenario.

Additionally, future work may explore edge computing for real-time computation of data and real-time decision-making, while still using cloud computing for storing data in order to conduct analytics in the long run. Integration with Manufacturing Execution System (MES) and Computerised Maintenance

Management System (CMMS) would provide automation in terms of maintenance scheduling and creation of work orders. Ultimately, this framework may be tested on a large-scale industrial manufacturing production line consisting of several machines in order to validate its scalability.

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