Data Acquisition Using IoT Sensors for Smart Manufacturing Domain

Pooja Kamat, Malav Shah, Vedang Lad, Priyank Desai, Yaj Vikani, and Dhruv Savani

Abstract

The Internet of things (IoT) showed gigantic development in recent trends of industrial, medical and environmental applications. Due to the huge computational power in the cloud, opportunities for complete industrial device automation have emerged. The uninterrupted monitoring and beforehand fault detection of the machines build efficient process control in the automation process. Analysing data acquired from various IoT sensors with the help of suitable data processing algorithms combined with artificial intelligence (AI) can help achieve predictive maintenance of industrial equipment, production lines as well as home appliances. This will significantly help in improving the service life of appliances as well as reduce the servicing cost by diagnosing active faults. This research paper focuses on developing an IoT-based fault detection system by connecting various sensors to the equipment and capturing their data using the sensors and storing them in the cloud platform for further analysis. Further data analytics applied on the accumulated sensor data can be useful to carry out predictive maintainence of the equipment.

Keywords

IoT • Predictive maintenance • Fault detection • Industry 4.0

1 Introduction

Today, Internet of things is being considered as the second most important advancement in technological world after Internet. It is a type of intelligent system that connects many devices to the Web so that they can communicate and exchange information with each other. Many mechanical industries are currently using IoT for achieving their goals and in increasing their efficiency. IoT can also be seen to play an important part in the environment as well as medical fields. The paper is organized as follows: the following subsections provide further introduction to usage of IoT devices in fault detection and predictive maintenance in machinery.

1.1 Introduction to Fault Detection in Manufacturing Machines

A product manufacturing process consists of various sequential steps. The manufacturing assembly for a product consists of multiple machinery set-ups that works for an extended period. The most elusive yield issues in such huge assembly lines can be intermittent machinery or component failures that randomly occur over time (Iqbal et al. 2019). There is no perceptible consistency in the inability of occurring events, and they happen randomly. It becomes too time-consuming and negatively impacting to find out the faults manually in such huge manufacturing lines (Okaro et al. 2019).

Alternatively, if faulty equipment keeps on running, it may lead to the production of defective products, or it may further damage itself. Due to the incompetence in diagnosing the failure of machines, safety accidents are prone to occur frequently (Kim et al. 2019). An unexpected failure may result in a devastating accident and financial losses depending on the interaction among industrial equipment. This, in turn, may lead to massive loss to industry in terms of

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money, labour and time. Such losses can be prevented by applying techniques like predictive maintenance (He et al. 2019). Early detection and maintenance can help in avoiding the faults that turn into critical problems.

1.2 Introduction to Predictive Maintenance

Predictive maintenance for the industry is a technique used for preventing machine failures by analysing data and patterns to identify the faults beforehand (Sang et al. 2020). Predictive maintenance has shown a lead in a rise in investment return, around 25–30% decrease in maintenance costs, 70–75% reduction in breakdowns and 35–45% decrease in downtime (Fiix. Predictive maintenance. https://www.fiixsoftware.com/maintenance-strategies/predictive-maintenance/). Various technologies, like IoT and cloud platforms combined, help develop predictive maintenance systems.

Cloud computing is the accessibility of computer system resources without direct supervision by the user, especially computing power and data storage. It is mainly used in describing data that is available to a large number of users through the Internet. Nowadays, cloud computing is providing a boost to support IoT by providing computational power which can be dynamically changed according to the requirement (Annamalai et al. 2019).

For collection of data from the mechanical devices, multiple sensors having different functionality are being used. A few of them include temperature sensor, humidity sensor, and accelerometer and vibration sensor. With the help of IoT, we can collect this data accurately and quickly. Combining IoT and cloud computing can be useful in monitoring different services and processing the obtained data for further analysis and computing (Compare et al. 2019).

Artificial Intelligence enabled techniques when applied on mukti-sensor data can assist in performing predictive maintainence of machinery by early detection of faults thereby improving the service life of the machinery (Lee et al. 2019).

1.3 Introduction to Internet of Things (IoT)

The Internet of things can be considered as an intelligent system that interconnects various machines, devices or objects each of which has unique identifiers. They are also capable of conveying data or instructions without the need of any computer or human intervention.

The meaning of IoT has advanced because of the union of various innovations, real-time analytics, machine learning (ML), sensors and embedded systems. Standard fields of remote sensor systems, control structures, embedded systems and robotization add to authorizing the IoT (Bhatter et al. 2020). The manufacturing developments have great significance in the economic development of many countries, and the constant claim for better efficiency with higher quality at a cheaper rate is an important topic these days.

Also, because of the inefficiency in analysing the faults of mechanical hardware in time, relating security mishaps happen quite frequently (Killeen et al. 2019). In an IoT domain, countless mechanical machine data can be gathered in a brief time frame. Many different sensors like temperature and humidity, vibration, acceleration, etc., have been utilized, or various sensors of a similar sort have been consolidated to gather constant operational status information identified within the various pieces of mechanical hardware (Sahal et al. 2020). Given the IoT along with cloud storage and analysing the data collected can significantly increase the accuracy of detecting faults beforehand, this has become a profoundly applicable research subject.

The Internet of things or IoT is never again exploratory; it is standard. Organizations are grasping it for a severe edge and creative contributions. In principle, IoT is the idea of giving machines, objects or individuals the capacity to naturally move information to a system without any correspondence from the PC.

IoT is presently allowing organizations to make smart products, empower improved activities and assist with improving business choices driven by data analytics (Plaza Bonilla et al. 2019). It can alter how organizations follow and oversee business work processes.

2 Literature Review

Dhamandea and Chaudhari (2018) in their research have tried to extract faults in compound gear-bearings. As mentioned in their paper, they have tried to utilize time–frequency method. By using this method, they have experimentally measured the compound deficiencies. Such deficiencies help in finding out faults within the external as well internal parts of the bearing together. Faults like two or three teeth of the gear having corner damage can be easily found out with this. Vibration estimation was done at distinctive speed and load conditions with the help of vibration sensors to improve the effectiveness of the diagnosis (Dhamande and Chaudhari 2018).

Glowacz and Glowacz (Vibration-Based Fault Diagnosis of Commutator Motor, 2018) have researched about fault detection in electric motors based on a commutator. They have tried to determine faults using vibration signals generated by vibration sensor and acoustic sensor. After analysing various vibration signals, they have tried to classify the states of the motor in three distinct categories, namely a healthy working motor with no faults, a motor with a sprocket or tooth damage or a motor where the rotor coil is damaged (Zhao et al. 2019).

Glowacz (Acoustic based fault diagnosis of three-phase induction motor 2018) in his research has written about detection of faults in induction motor with 3 stages. He has utilized acoustic sensors to screen four states of the 3-phase induction motor. These states include a solid induction motor, a motor which has a flawed squirrel cage ring, a motor which has its rotor bar damaged and a motor which has its two rotor bars with a flaw or broken. The achieved results helped develop a fault detection method using acoustic signals (Glowacz and Glowacz 2018).

Pérez et al. (2019) have researched in the field of designing IoT circuits which can be used for monitoring the health of refrigerators that are majorly used for cold chain purposes. They have mentioned about smart monitoring designs using Sigfox and IoT-based sensors. An IoT-based PCB is also outlined in their paper to detect faults in refrigerators that use routine compressors as well as non-inverter technology. Around two thousand refrigerators and coolers that are a part of cold chain were monitored. Sigfox has been used to wirelessly communicate and send data to the servers of the cloud service. The system monitored various aspects which include measure of the internal temperature of the freezer and measure of the power consumption inclusive of voltage and current. It also helped in controlling the compressor with an alarm system for operational failures. It is a low-cost system which can be utilized in routine temperature control systems. The most important part of the circuit is the temperature sensor (Li et al. 2020).

Mahajan et al. (2017) have surveyed the emerging research work on IOT based on home and kitchen appliances and created a smart refrigerator that enables on/off control through mobile application, details of the items to be ordered, indication when ice is ready, detects volume of liquid in bottles, alert system when hot items are placed, energy saving system during winters, indication of open door for long period, overweight sensor, expiry alert of product, and provides temperature reading. They used temperature sensors, proximity sensors, load sensors and gas sensors to achieve the above-mentioned tasks (Glowacz 2018).

Velasco et al. (2019) in their research have effectively created a refrigerator smart inventory observing framework using an Arduino sensor network which comprised 6 weight sensors, a camera and 2 ultrasonic sensors. The main control box was associated wirelessly with an android application through the Web through cloud (Pérez et al. 2019).

3 Implementation and Methodology

The Figure 1 diagram below shows the proposed methodology designed for the implementation of the system. It depicts a process where the sensors are connected to a machinery or a home appliance for acquiring data.

Primarily, we have fetched the temperature and humidity data of the refrigerator cabin with the help of DHT11 sensor controlled by a Raspberry Pi 3B+ which also acts as gateway and helps storing the data locally in a csv file format. Further, the data is also uploaded to Google Cloud Platform where it can be analysed for predictive maintenance. All the important steps about the implementation of methodology design are as below:

- Data acquisition and storing the data in csv format
- Directory monitoring for uploading the data to cloud
- Alerting the user for faulty data (Fig. 1).

The two main components of the designed system include the DHT11 sensor (Fig. 2) and its controller Raspberry Pi 3B+ (Fig. 3). DHT11 is a sensor for measuring temperature and humidity of the surroundings. It contains a capacitive sensing element which has dual electrodes with a substrate which can hold moisture as a dielectric between them. As the humidity changes, a change in capacitance occurs between them. For measuring the temperature, a negative temperature coefficient thermistor is used which causes a decrease in the resistance with rise of temperature. Raspberry Pi 3B+ is used as a microcontroller to control this sensor. It is a Linux-based computer which also contains a set of GPIO pins. These pins allow us to control electronic components including various sensors for physical computing and programming which helps develop various IoT systems.

The trials for the above implementation process were taken on a LG refrigerator which is running for 20 years. The system was implemented using a Raspberry Pi 3B+ as a sensor controller. A DHT11 temperature and humidity sensor was used to acquire the cabin temperature and humidity of the refrigerator. The data acquired was first stored in a local csv file managed by the Raspberry Pi which runs on Raspbian operating system. The data was acquired by

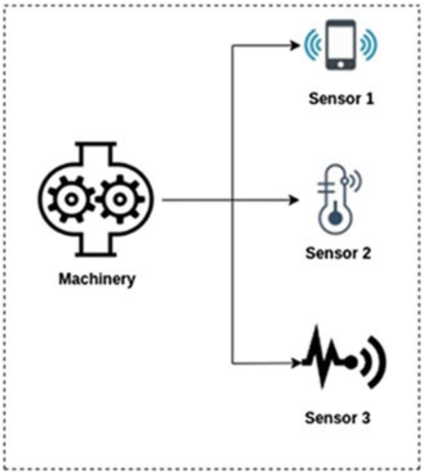

Fig. 1 Process adopted for data acquisition and cloud storage

Fig. 2 DHT11 pinout (https://components101.com/sites/default/files/component_pin/DHT11%E2%80%93Temperature-Sensor-Pinout.jpg)

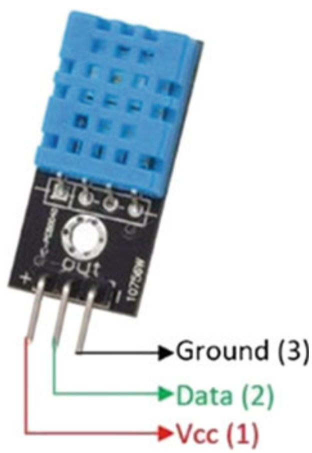

Fig. 3 Raspberry Pi 3B+ (https://aws.robu.in/wp-content/uploads/2018/07/robu-5–7.jpg)

running Python script which also handles the csv file. Further, Python scripts were coded to upload the data simultaneously to the Google Cloud Storage.

4 Results

Below are the results obtained by acquiring data with the help of DHT11 temperature and humidity sensor from a refrigerator.

4.1 Data Overview

The below image shows csv file generated as the data is acquired after the execution of Python script (Fig. 4).

The image below shows the data uploaded to Google Cloud Storage after the data is stored in a csv file using a Python script (Fig. 5).

After the data is stored on Google Cloud Storage, it is further stored in a Google BigQuery Table where it is queried for abnormal data like the temperature of the refrigerator cabin above 4 °C. The following image shows the results after querying the BigQuery Table (Fig. 6).

4.2 Graphical Overview of Data

Normal Temperature Variation The below graph indicates the normal usage of refrigerator where the temperature is usually observed nearer to 1 °C. A few peaks indicate that the refrigerator was used or opened at that moment of time and again the temperature begins to drop from there. The humidity is also observed constant without much variations (Fig. 7).

Faulty Temperature The below graph indicates that the refrigerator has some fault, or it is loaded heavily as the temperature is around 10 °C. The refrigerator is taking a lot

Fig. 4 Data stored in csv file

1	date	time	tempCelsius	tempFarenh	humidity
2	05-13-2020	16:03:30	4	39.2	49
3	05-13-2020	16:04:33	4	39.2	48
4	05-13-2020	16:05:33	4	39.2	77
5	05-13-2020	16:06:34	4	39.2	48
6	05-13-2020	16:07:35	4	39.2	47
7	05-13-2020	16:08:38	4	39.2	47
8	05-13-2020	16:09:38	4	39.2	76
9	05-13-2020	16:10:39	4	39.2	47
10	05-13-2020	16:11:39	4	39.2	46
11	05-13-2020	16:12:40	4	39.2	46
12	05-13-2020	16:13:41	4	39.2	46
13	05-13-2020	16:14:41	4	39.2	46
14	05-13-2020	16:15:42	4	39.2	45
15	05-13-2020	16:16:42	4	39.2	46

Fig. 5 CSV files uploaded to Google Cloud Bucket

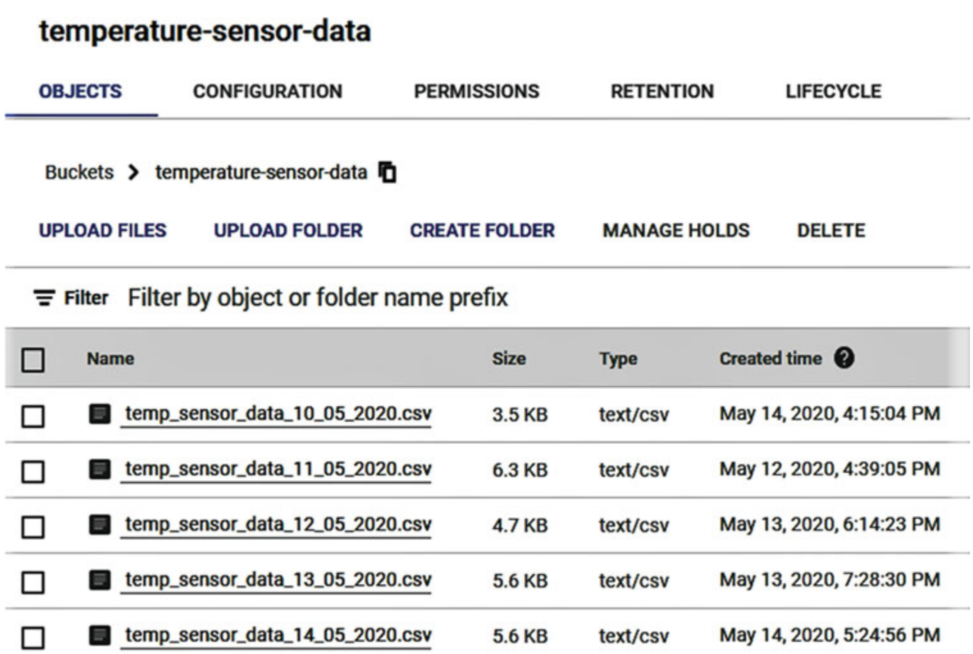

Fig. 6 Result obtained after querying the BigQuery Table

```
Sensor Data when temperature exceeds 4 degree Celsius:
               Date          Time          Celsius          Humidity
               2020-05-11    11:59:00      5                88
               2020-05-11    12:00:00      5                88
               2020-05-11    12:01:00      6                88
               2020-05-11    12:43:00      5                88
               2020-05-11    12:45:00      6                88
               2020-05-11    12:46:00      6                88
               2020-05-11    12:47:00      5                88
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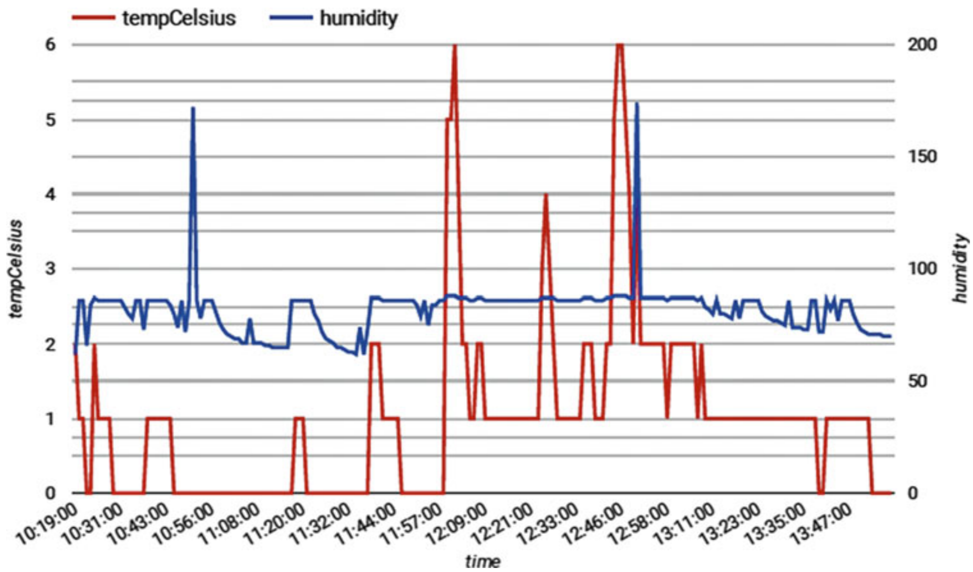


Fig. 7 Normal temperature graph

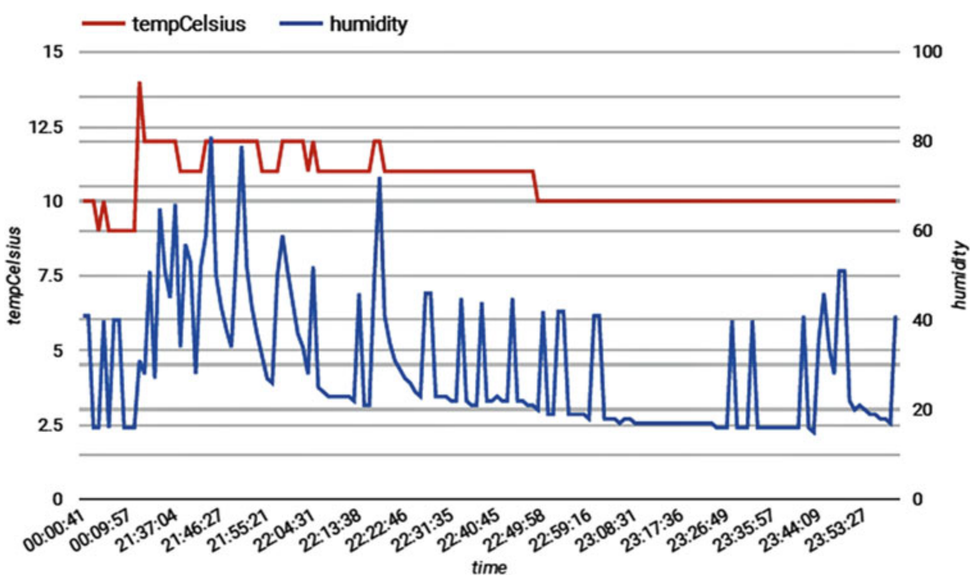


Fig. 8 Faulty temperature graph

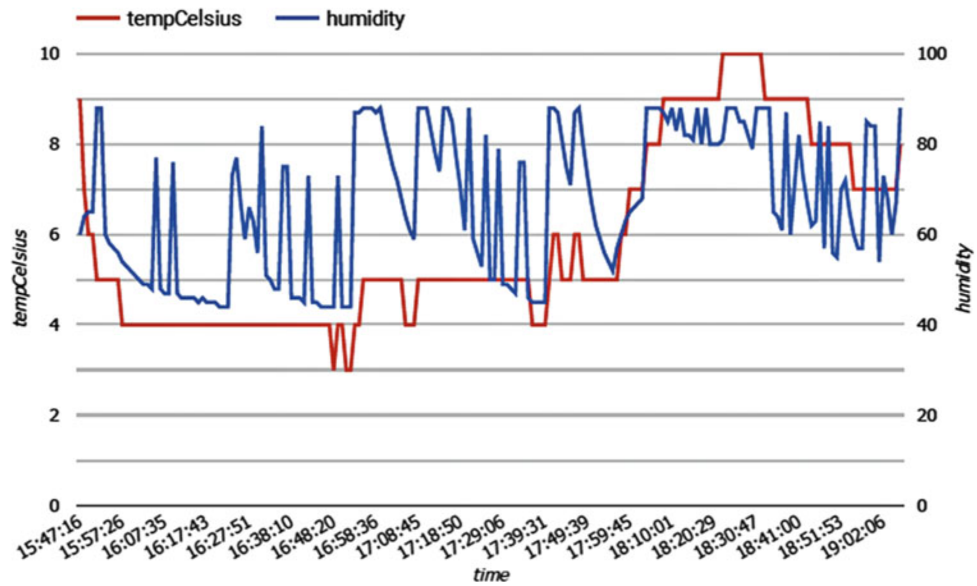
of time to cool down due to overloading or some fault in the cooling system. But the humidity is also variating much which also suggests overloading. This analysis can help detect overloading or active fault (Fig. 8).

Partly Overloaded/Faulty This graph shows a lot of variation in temperature, but the fridge is cooling at a faster rate than the above shown faulty data graph which means that either something warm is kept inside the fridge or the door is opened frequently and maybe there is no fault in the fridge as the cooling time is quicker than the faulty data (Fig. 9).

5 Conclusion and Future Scope

This paper demonstrates the research work and a methodology design for implementing predictive maintenance and fault detection in industrial machinery as well as home appliances. The focus of this research is mainly on designing a system which can be used to generate data using various sensors which can detect faults and store it on a cloud platform for further analysis. Even though most of the modern industries are based on Industry 4.0 principles, it is very important to detect early faults in the production

Fig. 9 Partial faulty temperature graph



machinery which may help saving money and time. Predictive fault detection and maintenance also helps in increasing the life of home appliances like refrigerators.

Our research shows how the data can be generated using various sensors, and it can be uploaded to Google Cloud Storage for further analysis. This methodology if implemented in today's modern era of IoT would definitely bring a change in fault detection and maintenance systems of mega industries.

The system designed in the research also requires some refinements in terms of backing up of data locally if there is an Internet connectivity fault. It also requires a power backup as the controllers and sensors may stop working due to power failure.

This research can be further integrated with a data analysis system which will help analyse the generated data for a more precise fault detection and predictive maintenance. An application can also be integrated with the system for live alerts which would help detect faults spontaneously.

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https://components101.com/sites/default/files/component_pin/DHT11%E2%80%93Temperature-Sensor-Pinout.jpg

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