2023 International Conference on Power Energy, Environment & Intelligent Control (PEEIC)

2023 International Conference on Power Energy, Environment & Intelligent Control (PEEIC) | 979-8-3503-5776-9/23/$31.00 ©2023 IEEE | DOI: 10.1109/PEEIC59336.2023.10450639

Utilization of DS18B20 Temperature Sensor for Predictive Maintenance of Reciprocating Compressor

Devesh Bora
Department of Mechanical Engineering
Graphic Era Hill University
Bhimtal, India
dbora@gehu.ac.in

Devendra Singh
School of Computing
Graphic Era Hill University
Bhimtal, India
dsingh@gehu.ac.in

Bharat Negi
Department of Mechanical Engineering
Graphic Era Hill University
Bhimtal, India
bharatnegiengg@gmail.com

Abstract— The temperature sensors DS18B20 and Raspberry Pi based platform are used to collect the data for the compressor machine elements. Sample data is being analyzed using Machine Learning for predicting health of the compressor, Real-time data collection and analysis will be used in scheduling and optimizing the maintenance requirements of the compressor.

Keywords— Raspberry Pi, DS18B20, ARIMA, Machine Learning, Reciprocating Compressor.

I. Introduction

The concept of Predictive maintenance was reported to be around since 1940. However, its rudimentary version, where an experienced maintenance person tours the premise and uses his or her senses of seeing, hearing, smelling and touching to detect a sign of a problem, dates further back and it is still being widely practiced because it is still very valuable in many cases [1] [2].

Predictive maintenance of mechanical equipment involves the scheduling of maintenance activity based on the current condition/status of equipment. When we discuss Predictive Maintenance Utilizing Machine Learning, we generally refer to Automated Anomaly Detection [3]. IoT sensor data that is recorded over time or in real-time is used by machine learning models to establish the normal behavior of the metric stream. In the subsequent phase, aberrant data and events are automatically identified, correlations are found, and precautionary advice is given. In the long run, this saves a lot of money and time [4]. Because it can understand what happens in real-time, flexibly react to new data, and recognize and alert staff to key issues, machine learning is wonderful. Traditional maintenance methods do not involve manual threshold sets, data selection, or configuration.

Forecasting to determine when a machine needs to be repaired or replaced, predictive maintenance only requires mathematical calculations, which enables timely and efficient maintenance to be performed. Additionally, facility managers will have more time to concentrate on important duties rather than making educated guesses. The proposed scheme can be seamlessly put into practice through the utilization of intelligent software modules, which are developed to facilitate communication among themselves, as well as with sensors, the mechanical equipment, and the human operator. This interconnected system ensures a proactive and efficient approach to maintaining mechanical equipment in optimal working condition [5].

DS18B20 temperature sensor and Raspberry Pi 4 B is used to record the live data of compressor in every 2 hour and machine learning model is used to analyze the data for Reciprocating compressor. ARIMA module is used to predict the temperature of compressor, these predicted data are used for predictive maintenance. Predictive maintenance for mechanical equipment revolves around strategically scheduling maintenance activities based on the current condition and status of the equipment. To effectively implement this maintenance approach, it is crucial for in-process monitoring and diagnostic procedures to align with it. Consequently, this paper presents a comprehensive architecture for predictive maintenance in mechanical equipment, integrating in-process monitoring and diagnosis. Furthermore, the paper delves into the theoretical criteria guiding the setup of a Predictive Maintenance Programme, emphasizing condition-based maintenance (CBM). CBM, a maintenance approach rooted in condition monitoring, encompasses data acquisition, processing, and maintenance decision-making. The paper reviews recent developments in diagnostics and prognostics within CBM, focusing on models, algorithms, and technologies for data processing and decision-making. With the increasing use of multiple sensors in condition monitoring, the authors explore various techniques for sensor data fusion. The abstract concludes with a brief discussion on current practices and potential future trends in CBM [6].

II. Reciprocating Compressor

A reciprocating compressor or piston compressor is a positive-displacement compressor that uses pistons driven by a crankshaft to deliver gases at high pressure [7] [8]. The intake gas enters the suction manifold, then flows into the compression cylinder where it gets compressed by a piston driven in a reciprocating motion via a crankshaft and is then discharged. Applications include oil refineries, gas pipelines, oil and gas production drilling and well services, air and nitrogen injection, offshore platforms, chemical plants, natural gas processing plants, air conditioning, and refrigeration plants.

A. Root Couse of failure of reciprocating Compressor

I. High suction pressures
II. Low discharge pressure
III. High discharge temperature

There are many more reason for the failure of the reciprocating compressor but here we took temperature for analysis purpose. The compressor's bottled pressure is to blame for overheating. By installing temperature sensor at the heads temperature can be taken to prevent the failure of compressor. Here we utilized DS18B20 temperature sensor.

III. EQUIMENT USED

DS18B20 temperature sensor, Raspberry Pi 4B+ model, wires, HDMI cable, Power supply and Breadboard.

A. Benefits of using DS18B20

The DS18B20 Temperature Sensor's Fig 1 primary advantage lies in its compact size, making it exceptionally versatile and suitable for use in various settings. Additionally, its metal casing not only shields it from environmental factors like water and direct heat but also serves as a conductive element for the sensor's temperature readings. A key reason for its widespread use, especially following the DHT11 sensor capable of measuring temperature and humidity concurrently, is its single-pin data output. Unlike many other temperature sensors that require isolation to prevent inaccuracies, the DS18B20's overall structure ensures durability, distinguishing it from others in the market.

B. Temperature Range

When choosing a temperature sensor for an application, the temperature range should be taken into account first. Different temperature ranges will suit various temperature sensors better. NTC thermistors are suitable for a variety of applications because they work well in temperatures ranging from -50° to +250°C. Thermocouples can measure temperatures up to 2000°C but are less accurate at lower temperatures.

C. Accuracy

Another crucial factor is the required accuracy. Despite their low cost, thermocouples lose accuracy over time more frequently than a thermistor temperature probe. The most

accurate range for NTC thermistors and thermistor probes is between -50C and +150°C. If they are glass-encapsulated, they can also be very accurate at 250°C.

D. Stability

Depending on how they are made, what materials they are made of, and how they are packaged, temperature sensors may lose some of their effectiveness over time. Depending on whether it is hermetically sealed or not, a thermistor can fluctuate between 0.02°C and 0.2°C over the course of a year. Over the course of a year, a thermocouple can vary by 1 to 2 degrees Celsius. Here we used two DS18B20 temperature sensors. In the long-term procedure the kind of temperature sensor that is employed will be impacted by this factor.

TABLE. I. DS18B20 TEMPERATURE SENSOR (SOURCE: ROBU.IN)

IV. METHODOLOGY

Various methods are employed for the predictive maintenance of reciprocating compressors [9] [10]. In this paper the process Fig 2, initiates by affixing a temperature sensor to the compressor heads within a laboratory setting. Subsequently, data is collected using a Raspberry Pi 4B+, and the collected data undergoes filtration. The refined data is then transmitted to the feature extraction platform, ARIMA, for comprehensive analysis, storage, and the prediction of future data trends. The temperature data serves as a crucial factor in forecasting potential causes of failure due to temperature-related issues. This predictive information is then cross-referenced with the compressor's rating to ensure the preemptive maintenance of critical equipment, which, if neglected, could lead to production delays or halts in the future [11].

The implemented approach has successfully reduced the probability of failure, prolonging the compressor's lifespan by predicting the timely need for maintenance. Furthermore, it facilitates the identification of the optimal timing for preventive maintenance, contributing to the overall efficiency and reliability of the compressor.

preventive maintenance, contributing to the overall efficiency and reliability of the compressor.

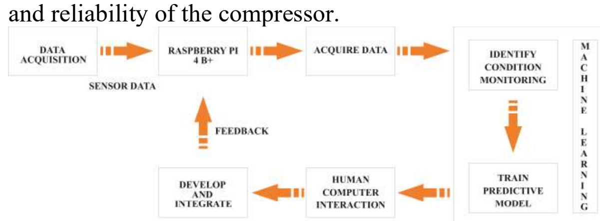

TABLE. II. Research Methodology

V. EQUIPMENT PREPARATION AND DATA COLLECTION

A. Equipment Preparation

Sensor were placed in reciprocating compressor for determining its temperature, sensor is connected with raspberry Pi with one wire output with the help of breadboard and wires. A resistor is attached to signal wire Fig 3.

Data Collection

Table 1 represent the DS18B20 temperature sensor data in 2-hour interval i.e., T1, T2, T3, T4 for half month and with help of machine learning model ARIMA one yaer data is predicted and this temperature data will be used to prevent failure in compressor before causing any severe fault. Temperature is taken in celcius and taken from 10 am to 4 pm daily for half month. T1, T2, T3, T4 is temperaure in hour variaton. T1 is temperaute at 10 am, T2 is temperaute at 12 pm, T3 is temperaute at 2 pm and T4 is temperaute at 4 pm.

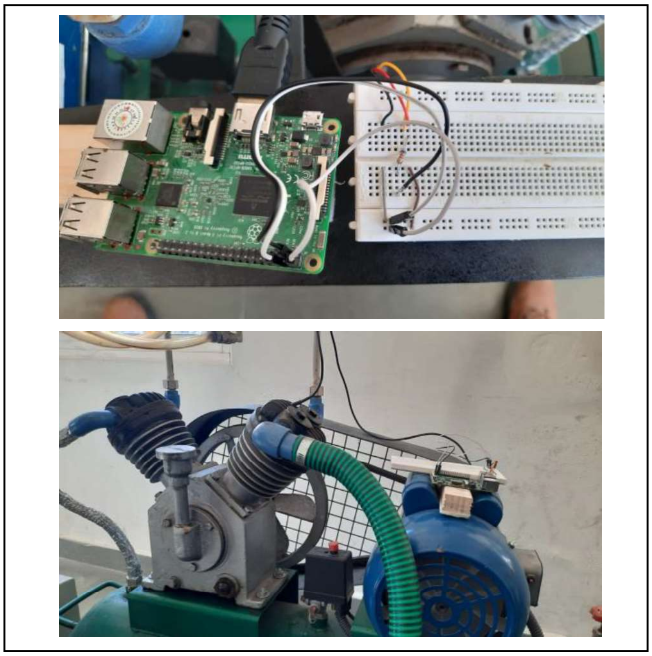

TABLE. III. Implant of Ds18b20 Temperature Sensor With Raspberry Pi On Reciprocating Compressor

TABLE. IV. TEMPERATURE READING

Date	DS18B20 Temperature sensor		
	Time	***Time Interval 2 hrs.***	***Temperature in Celsius***
4/8/2022	10 am to 4pm	T_1, T_2, T_3, T_4	C_1=19.875, C_2=20.187, C_3=20.000, C_4=20.000
5/8/2022	10 am to 4pm	T_1, T_2, T_3, T_4	C_1=41.125, C_2=36.437, C_3=27.875, C_4=41.125
6/8/2022	10 am to 4pm	T_1, T_2, T_3, T_4	C_1=40.875, C_2=79.062, C_3=80.312, C_4=80.312
8/8/2022	10 am to 4pm	T_1, T_2, T_3, T_4	C_1=19.875, C_2=20.187, C_3=20.000, C_4=20.000
9/8/2022	10 am to 4pm	T_1, T_2, T_3, T_4	C_1=69.875, C_2=79.062, C_3=80.312, C_4=80.312
10/8/2022	10 am to 4pm	T_1, T_2, T_3, T_4	C_1= 97.587, C_2= 68.00, C_3=67.77, C_4= 63.050
12/8/2022	10 am to 4pm	T_1, T_2, T_3, T_4	C1=40.875, C2=79.062, C3=80.312, C4=80.312
13/8/2022	10 am to 4pm	T_1, T_2, T_3, T_4	C_1=43.875, C_2=67.766, C_3=60.987, C_4=70.876
16/8/2022	10 am to 4pm	T_1, T_2, T_3, T_4	C_1= 62.937, C_2= 62.93, C_3=55.986, C_4= 62.937
17/8/2022	10 am to 4pm	T_1, T_2, T_3, T_4	C_1=19.875, C_2=20.187, C_3=20.000, C_4=20.000
18/8/2022	10 am to 4pm	T_1, T_2, T_3, T_4	C_1=21.875, C_2=42.276, C_3=76.976, C_4=8.987
20/8/2022	10 am to 4pm	T_1, T_2, T_3, T_4	C_1= 68.789, C_2=0000, C_3= 67.775, C_4= 68.000
22/8/2022	10 am to 4pm	T_1, T_2, T_3, T_4	C_1=19.875, C_2=20.187, C_3=20.000, C_4=20.000
23/8/2022	10 am to 4pm	T_1, T_2, T_3, T_4	C_1=91.875, C_2= 62.487, C_3= 61.137, C_4= 62.487
24/8/2022	10 am to 4pm	T_1, T_2, T_3, T_4	C_1= 62.937, C_2= 62.93, C_3=55.986, C_4= 62.937

Fig 4 shows the temperature with respect to time interval of 2 hours. Half-month data is represented in the graph. This is the temperature variation in Celsius of reciprocating compressor in condition. In Fig 5 Training and tested data is represented in this graph, data is analyzed and tested with the help of ARIMA model. This real data is compared with machine learning data. Firstly, 15 days' temperature data was taken with help of DS18B20 temperature sensor to predict the next 10 days' temperature data from one month using machine learning. In Fig 6 predicted data for whole one year is represented with the help of ARIMA and the Mean absolute percentage error score is checked. MAPE score was 15% which is very good prediction.

This temperature reading now then used for predicting temperature related errors in compressor as in industries breakdown of compressor can stop/delay the production. To reduce this proper maintenance is required time to avoid breakdown. We took temperature of heads of compressor and studied the fluctuation in temperature and after this predicted the timely maintenance for compressor.

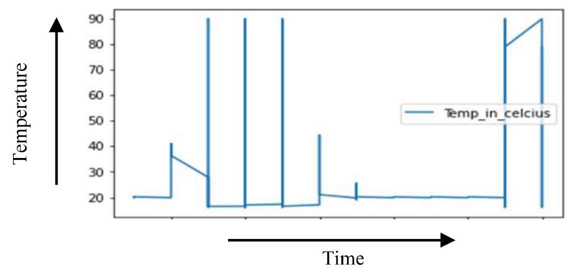

TABLE. V. Temp Data In Celcius

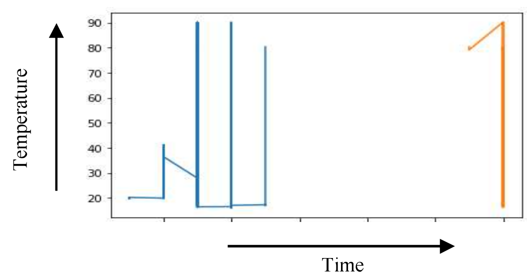

TABLE. VI. Training and Tested Temp Data in Celcius

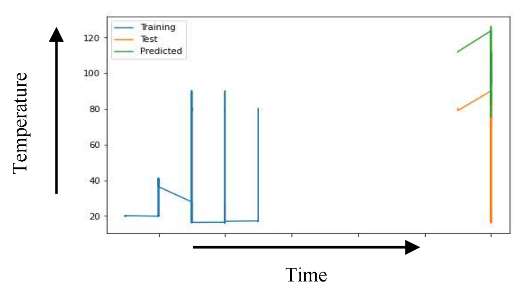

TABLE. VII. Training, Predicted And Tested Temp Data In Celsius

VI. RESULT AND DISCUSSION

Half-month temperature data from DS18B20 temperature sensor is extracted with the help of Raspberry Pi 4B+ model, here raspberry Pi is acting as interface between sensor and user it is providing real time data of sensor. Extracted data now used to predict the future data with the help of machine learning module ARIMA and all the parameter related to weather condition were applied. Firstly, 15 days' data was taken to predict the next 10 days' data and after analysis output, 10 days were compared with collected data and MAPE score was 15% which is good score and also tells the accuracy of prediction. These whole year temperature data allowed us to keep proper eye on fluctuation caused by temperature in reciprocating compressor. The DS18B20 temperature sensor has proven to be incredibly beneficial for acquiring real-time and accurate data, making it a valuable resource for analysis purposes. The DS18B20 temperature sensor offered numerous advantages, such as its compact size and metallic tip, enabling versatile placement even in confined spaces and high-temperature environments. This capability proved instrumental in assessing critical and preventive maintenance requirements for compressors, mitigating the risk of failure. The one-wire data output of the DS18B20 simplified its usage, allowing for the seamless integration of multiple sensors in a series. This arrangement facilitated the collection of data from various crucial equipment, supporting predictive maintenance efforts associated with temperature-related failures in other systems.

VII. CONCLUSION

Predictive maintenance for reciprocating compressors involves a systematic process. Initially, a temperature sensor is affixed to the compressor heads within a controlled laboratory environment. The Raspberry Pi 4B+ is then utilized to collect and filter the obtained data. The refined dataset is subsequently forwarded to an ARIMA-based feature extraction platform for comprehensive analysis, storage, and the generation of future predictions.

Examining the temperature data over an entire year provides insights into potential future failure causes attributed to temperature variations. This predictive data is compared against the compressor's rating to ensure proactive maintenance of critical equipment, thereby averting potential production delays or stoppages.

Through this methodology, we've effectively reduced the likelihood of failures, extended the compressor's operational life, and accurately determined the timely requirements for both corrective and preventive maintenance measures. This paper addresses the strategic decision-making involved in establishing a Predictive Maintenance Programme (PMP) and the lack of comprehensive analysis regarding its setup, management, and control. A novel evaluation system is proposed, integrating operational research tools such as the Analytic Hierarchy Process, decision rules, and Bayesian tools. This system serves as a valuable aid for PMP managers, enhancing the implementation of such programs and preventing their failure. Tested in both a petrochemical plant and a food industry, the Evaluation System incorporates technological, organizational, and control considerations that were previously underexplored in PMP research.

REFERENCES

[1] Alexandros Bousdekis, Katerina Lepenioti, Dimitris Apostolou, Gregoris Mentzas." Literature Review and Research Agenda for Industry"; IFAC PapersOnLine 52-13 (2019) 607–612.

[2] Prajapati A, Bechtel J and Ganesan S. Condition based maintenance: a survey. J Qual Mainten Eng 2012; 18(4): 384–400.

[3] T. I. Ogedengbe*, S. O. Abadariki and T. M. Adamolekun, "Predictive Maintenance of Mechanical Equipment Through Inprocess Monitoring And Diagnosis"; Hosted by the Nigerian Institution of Mechanical Engineers Akure, Nigeria October 23-25, 2013.

[4] Sezer, E.; Romero, D.; Guedea, F.; Macchi, M.; Emmanouilidis, C. An Industry 4.0-Enabled Low Cost Predictive Maintenance Approach for SMEs. In Proceedings of the 2018 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC), Stuttgart, Germany, 17–20 June 2018; pp. 1–8.

[5] MaCarmen Carnero, "Evaluation of the setting up of a predictive maintenance programme"; Reliability Engineering & System Safety, 2005.

[6] Jardin AKS, Lin D and Banjevic D. A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mech Syst Signal Pr 2006 .

[7] Bloch, H.P. & Hoefner, J.J. (1996). Reciprocating Compressors, Operation and Maintenance. Gulf Professional Publishing. ISBN 0-88415-525-0.

[8] Reciprocating Compressor Basics". www.machinerylubrication.com. Retrieved 2015-12-02.

[9] Amruthnath, N., and Gupta, T. (2018). A research study on unsupervised machine learning algorithms for early fault detection in predictive maintenance. In 2018 5th International Conference on Industrial Engineering and Applications (ICIEA) (pp. 355-361). IEEE

[10] Xiao Wang , Deyi Xu ,Na Qu ,Tianqi Liu ,Fang Qu and Guowei Zhang. "Predictive Maintenance and Sensitivity Analysis for Equipment with Multiple Quality States"; Volume 2021, Article ID 4914372.

[11] Sule Selcuk, "Predictive maintenance, its implementation and latest trends"; DOI: 10.1177/0954405415601640, 2016.