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Research article

IIoT Based Anomaly Detection and Maintenance Management of an Industrial Rotary System

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Abstract

Keywords

industrial internet of things;

machine learning algorithm;

anomaly detection;

optimal decision-making process

Numerous challenges are being faced by implementing the Industrial Internet of Things (IIoT), which enables anomaly detection and optimal maintenance management of industrial production systems and their critical machines. Industries have started adopting this revolutionary technology along with other allied technologies to reap the full benefits out of Industry 4.0 environment. The objectives of this research work were to use the IIoT to develop a continuous monitoring system of the behavior of bottleneck facilities in a production system, to predict and avoid all possible failures, and to improve the overall productivity of the manufacturing system. The proposed prognostic health monitoring system employs IIoT sensors to measure the current values of the operating parameters of a machine, using built-in intelligent decision support mechanism to compare with optimal ranges of values, and to message the appropriate alarming signals as per the severity of the deviation. The system developed was tested with a prototype model comprising the Internet of Things, internet communication technology, and a machine learning algorithm, MEMS with standard input, output, storage and display of components, which was developed in a laboratory but implemented in a case study in a real industrial production plant. After the successful implementation of the developed system, the performance of the critical machine was evaluated in terms of metrics such as the average number of failures, average downtime and average service time spent. It was found that after the implementation, the downtime has decreased by nearly 22% and for the performance in terms of its output, the flow rate exhibited a steady increase with the passage of time.

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1. Introduction

Nowadays, the implementation of the fourth revolution of industry (Industry 4.0) in small and medium-sized enterprises (SMEs) is the most significant activity around the world. It can be achieved through the utilization of the recently introduced key terms and technologies of the industry 4.0 such as Industrial Internet of Things (IIoT), data mining (DM), cyber-physical production system (CPPS), internet Communication technology (ICT), machine learning (ML), and the like. Most multinational corporation (MNC) production systems that currently include computer technology are being enhanced by a network connection and have a digital twin on the internet, allowing for man-machine interaction. These capabilities enable communication with other facilities as well as the production of data about themselves. This is the present state of production automation. All-systems networking leads to CPPS and hence smart factories, in which production systems, their components and stakeholders interact through ICT and the production is almost autonomous. In this era, the IIoT has been advancing.

In our work, the primary focus was on the maintenance and service management system of a typical smart factory supported with optimal decision-making processes. Industrial rotary systems are the most significant components in the manufacturing systems of any industry. Hence, in this work, an industrial hydraulic pump was investigated in order to develop a new smart maintenance and service framework with optimal decision-making process. In fact, a real time industrial case study was undertaken in a SME that had a major industrial rotary system in its manufacturing process. The traditional maintenance management activities being carried out in the SME were converted into a partially autonomous or smart maintenance management system. This conversion was achieved through the application of a MEMS (micro-electronic mechanical sensor) which captured the actual values of performance, and these data was transmitted using the IIoT via Arduino board [1]. Subsequently, these data were tested against standard (of desired performance) values by the application of a Fast Fourier Transformation program, ML techniques, an optimal decision support system, along with the ICT/WiFi/Cloud storage, and a computing system for the smart maintenance function in industry. An overview of the proposed architecture of the smart maintenance management system, comprising task real-time monitoring, data collection, analysis, decision-making, and maintenance planning is shown in Figure 1.

Some of important research work related to smart manufacturing, predictive/preventive maintenance management, and optimal decision-making systems carried out in the past that have relevance to our research work are; recent developments, challenges, applications, and trends in IIoT for smart factories, smart homes, smart commercial used products, and agriculture functions as demonstrated through the real-time case study [1]. Regarding smart healthcare systems with the utilization of various sensors for monitoring the regular activity of the people, human health parameters were monitored with the help of IoT devices and useful information was shared with health trainers or doctors in order to save lives [2]. Development of a prototype for in-line health monitoring systems of aircraft hydraulic pumps and motors for diagnosing any behavioral changes while in operating condition was reported [3]. Fenton *et al.* [4] examined the effectiveness and the remaining life cycle prediction through the utilization of the Bayesian network. They developed a model to identify the number of residual defects in rotary components and to organize the optimal decision-making for the service and maintenance activity. An investigation of DC microgrid fault detection under fluctuating flow using an artificial neural network (ANN) to enhance maintenance decisions based on the analysis of actual DC microgrid conditions was studied [5]. Vibration based fault detection of a centrifugal pump by Fast Fourier Transform and adaptive neuro-fuzzy inference mostly around the issue of vibration-based condition checking of divergent pumps was undertaken [6]. A fault diagnosis of pump-motor set, using an IoT condition monitoring technique and current

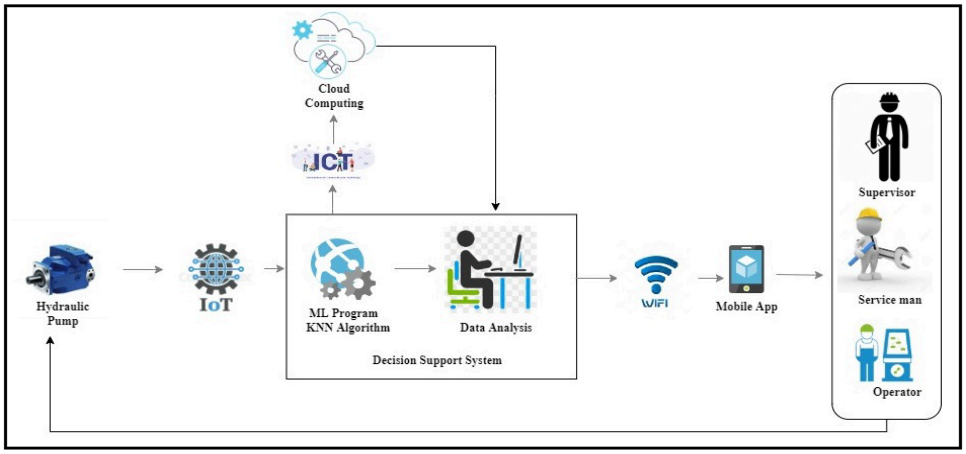

Figure 1. System architecture of prognostic health monitoring system

signature analysis techniques in order to identify the vibrational and temperature rise faults in an industrial centrifugal pump where the sensors were installed at respective locations to monitor misalignment, impeller, and divergent head [7, 8]. An automatic fault detection and isolation of the power distribution network was investigated through the utilization of the decision support method and support vector mechanism. In this research, optimal fault detection was achieved based on real-time observation of distribution network variation. This model was implemented for the identification of the fault and to initiate the appropriate corrective actions in the power distribution center to achieve the optimal results [9, 10]. The remaining useful life prediction of the power plant machines, and their critical components was investigated through the application of conventional neural network analysis techniques and the performance of the machine was measured with root mean square error values of the analysis results [11]. Intelligent prognostic and health monitoring systems of a centrifugal pump with the utilization of the vibration signal variations and the support vector mechanism was studied and the predicted model was applied to detect the anomaly conditions of the centrifugal pump, and the efficiency of that developed method has been verified [12]. An optimal decision model for the supplier selection process, which was a framework organized through the fuzzy hybrid decision model in the industry was reported [13]. Customer necessity-based real-time problems were investigated to facilitate minimum delivery time of mass-customized ordered products by an optimal flexible scheduling process in the industry. The minimization of the lead time of products in the steel industry with non-value-added activities was also analyzed through the application of the value stream mapping approach [14, 15]. The fault detection of an industrial rotary system through the application of soft computing techniques was explained. Analysis and identification of anomaly conditions of the motor and pump were achieved by the utilization of ANN approaches. A comparison of the actual time date with standard values for the proposed optimal decision making of the fault identification in the industry was studied [16, 17]. A fault identification of the petrol engine was described through a smart monitoring system for vibration control as well as a knowledge-based decision support system of the machine maintenance activities was presented [18-20]. Digital control system of maintenance and manufacturing industry securities issues and challenges was described in detail via a sample model [21]. Vibration monitoring of damage assessment of RC building life validity through a retro filled RC frame model was also explained in a real time case study of a construction project [22]. A critical overview of a smart maintenance management system and factor analysis of the implementation of a digital and optimal maintenance management system were illustrated [23, 24]. Through this analysis, optimal maintenance management activities were initiated. Based on the above critical literature review of smart health monitoring, optimal maintenance management systems in various industries, this work attempted to develop a prognostic health monitoring system for bottleneck facilities in the production line of SMEs.

2. Materials and Methods

Most of the manufacturing system of SMEs are complex with networks of numerous subsystems, and the uptime of such a system is decided by bottleneck/critical subsystems, and thus the maintenance function of the system starts with identifying those critical subsystems. Identification of critical subsystems based on the availability prediction analysis by employing the Markov decision model and MATLAB R2019a software was already done in our previous research work [25-27]. Our earlier research is vital to the industrial case study undertaken in this work. As per the output of the above-mentioned analysis, a heavy-duty rotary system found in the manufacturing system of the SME of interest was identified as the critical subsystem and considered for further study in this work. The specifications of the rotary system are shown in Table 1.

Table 1. Specifications and optimal operating range of parameters of the rotary system

S. No	Parameters Description	Specification
1	Geometric Displacement	63 Cm^3/Rev
2	Drive Speed RPM	Maximum 1800 RPM
3	Volumetric Efficiency	Approximately 91%
4	Operating Pressure	350 - 450 bars
1	Optimal Range for displacement	60 - 62 Cm^3/Rev
2	Optimal range for speed	1700 - 1750 RPM

One of the objectives of any production system is to achieve maximum availability of its bottleneck facility. This involves maintaining the failure rate of the facility below a pre-determined minimal (optimal) level such that the repair time is kept to a minimum level, and the Mean Time Between Failures to a desired maximum level. To achieve these objectives, the operating parameters of the critical bottleneck facility are required to be maintained within an acceptable/desired (optimal) range, taking into account its current behavior and age of service. This exercise was already done exclusively in previous research work by the same authors, and is in the process of publication. Based on the previous research study, the optimal range for the operating parameters of the rotary systems, namely the flowrate/displacement in cm^3/revolution and the speed of the motor in revolutions per minute, were determined and are shown in Table 1.

In this work, a real-time, continuous health monitoring system of the rotary system type was implemented as per the requirements of the autonomous maintenance management for smart factory systems, in order to ensure that the operating parameters of the rotary system were maintained within the acceptable/optimal range, thereby maximizing the uptime of the production line. The proposed smart maintenance management system involved a continuous health monitoring and prognostic framework, designed for critical components, and the rotary system of the manufacturing process of SMEs is shown in Figure 1. The logical flow chart of the decision support system built into smart maintenance management system is shown in Figure 2.

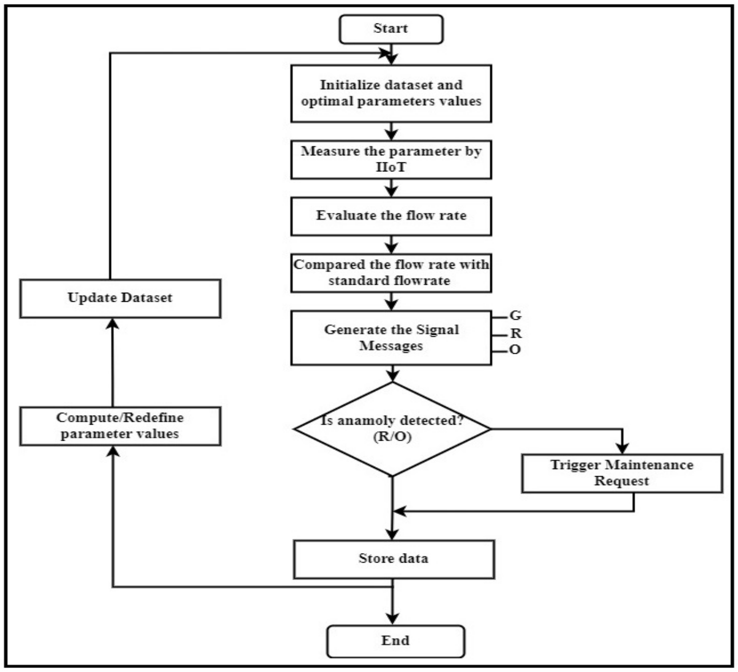

Figure 2. Logical flowchart of the decision support system

In the proposed system, IIoT sensors (for speed and displacement) were installed to monitor the real time behavioral changes of the rotary system found in the SMEs. The actual time series data, that is, the actual values of the two operating parameters namely the speed in rpm and the displacement in cm^3 per revolution measured by the IIoT sensors were recorded, and the corresponding instantaneous flow rate of the pump in liters per minute was computed and stored in an unified data storage device for further analysis by the coded programs of the smart system. The optimal/desired range of operating parameter values and other necessary initial parametric values were fed into the database of the system.

Machine learning algorithms can be employed to train the smart system, using collected data from the dataset, to compare real-time observed parameter values/estimated (predicted) flow rates with the desired/optimal range of parameters/flow rates stored in the database, and to classify the real time output of the system into either desirable/acceptable or alarming/warning output [28, 29]. The system can further classify the alarm out based on the degree of deviation of the output from the acceptable level and generate corresponding messages to the operating and/or service personnel. The MLA, through the application of ICT, can also identify and contact the right maintenance personnel for ensuring minimum delay in maintenance activity, which in turn minimizes the downtime of the rotary system.

The proposed system will drastically minimize the unnecessary manufacturing downtime and service time delay that is observed in the existing traditional maintenance system of the SMEs. The other eventual benefits will include increase in remaining life of the machines/facilities and increase in productivity of the manufacturing system and quality of the product/service produced. The proposed system through optimal decision-making process will also result in improved planning and scheduling of maintenance activities and effectiveness in deployment of maintenance workforce. The effectiveness of the proposed system can further be enhanced by augmenting with wireless/Bluetooth connectivity along with access to cloud computing.

2.1 Exprimental setup

An SME, a sensor and switch manufacturing company in the southern region of Tamil Nadu state of India were chosen for the case study that was the implementation of a smart maintenance management system. Based on availability prediction analysis, the critical subsystem of the manufacturing process and heavy-duty rotary system was a HP-HVV102-63 type gear pump. The technical specifications of this heavy-duty hydraulic gear-pump are given in Table 1. The experimental set-up, which conformed to the system architecture shown in the Figure 1, was as follows:

1. An Arduino board, an open-source micro controller device fitted with PCB, USB ports and basic features
2. The IIoT module, ICT module with Bluetooth/WiFi connectivity, and LCD display circuit, which were installed onto the board.
3. An IoT displacement sensor fitted to the rotary pump and connected to the IIoT module to measure the instantaneous flow rate in cm^3 per revolution
4. An IoT speed sensor fitted with the rotary pump and connected to the IIoT module to measure the instantaneous speed of the motor in rpm
5. The dataset format shown in Table 2 was fed into the board. The PLC was programmed to compute the actual flow rate of the pump based on the data generated by the IoT sensors and to store in this database as per the format.
6. The LRA algorithm [28, 29] was coded into the PLC of the board to classify the output into either acceptable or requiring concern for maintenance work
7. The decision support algorithm as shown in Figure 2 was fed into the PLC to generate messages for different maintenance service requests
8. The KNN algorithm [28, 29] was coded into the PLC for identifying the right maintenance hand to carry out the preventive/repair work activities.

2.2 Initialization of dataset

The standard static data related to performance of the pump including maximum and minimum permissible speed, maximum and minimum permissible displacement, design displacement and speed were recorded into the corresponding columns (2-12 and 22-24) of the dataset.

2.3 Continuous monitoring and data collection

The IIoT sensors were used to continuously measure the instantaneous values of the operating parameters, namely the speed and the displacement of the pump. Each of the observation, the sensed data, was recorded with a corresponding timestamp in column 1 of the dataset, and stored in the unified data storage device of the system. The measured values are entered into the data set under columns 14 and 15.

2.4 Computation of flow rate

The performance of the rotatory system, the flow rate in litres per minute is computed and stored in column 16.

Table 2. Structure of dataset for the decision support system

Column No.	Field	Variable Name	Type	Value
1	Date and Time	DT	V	
2	Component	Pump	F	HP-PVV102
3	Design Displacement	d_{sp}	F	63 cm^3/rev
4	Design Rotating Speed	N_{sp}	F	1800 rpm
5	Maximum Displacement	d_{max}	F	62 cm^3/rev
6	Minimum Displacement	d_{min}	F	62 cm^3/rev
7	Mean Displacement	d_{tar}	F	61 cm^3/rev
8	Maximum Speed	N_{max}	F	1750 rpm
9	Minimum Speed	N_{min}	F	1700 rpm
10	Design Flow rate	Q_{sp}	F	103.19 L/min
11	Maximum Permitted Flow Rate	Q_{max}	F	98.74 L/min
12	Minimum Permitted Flow Rate	Q_{min}	F	92.82 L/min
13	Mean Flow Rate	Qtar	V	
14	Measured Displacement	d_{ob}	V	
15	Measured Speed	N_{ob}	V	
16	Measured Flow Rate	Q_{ob}	V	
17	Deviation	Q_D	V	Q_{tar}-Q_{ob}
18	State	S_t	V	1 or 0
19	Limit for Orange	SO	V	
20	Limit for Green	SG	V	
21	Signal	SIG	V	R/O/G
22	Mobile of M/H 1	M_{01}	F	
23	Mobile of M/H 2	M_{02}	F	
24	Mobile of M/H 3	M_{03}	F	
25	Identified M/H	MH	V	M_{01}/ M_{02}/ M_{03}
26	Efficiency	EFF	V	

2.5 Computing the deviation from the average/expected performance

The difference between the actual performance and the expected performance was computed and stored in column 17.

2.6 Decision-making

If the deviation is zero or negative, the rotary system is considered to be in safe operating condition, and it is recoded with 1 (otherwise 0) in column 18 and a green signal is recorded in column 21. If the deviation is positive, and if the deviation is more than the specified limiting value recorded in column 19, an orange alarm signal is recorded in column 21, otherwise a red alarm signal is recorded in column 19. The decision scheme for messaging the alarming signal is depicted in Figure 3.

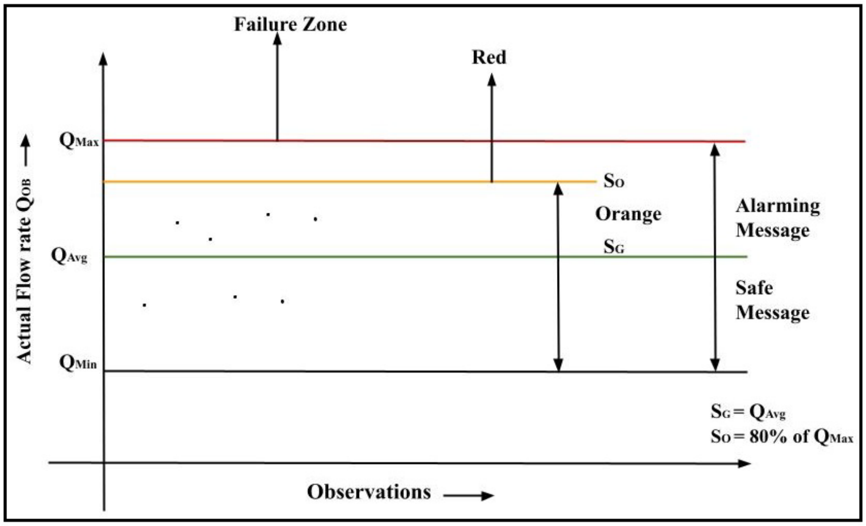

Figure 3. Decision scheme for signaling deviations

2.7 Choosing the right maintenance hand

Using the KNN algorithm [28, 29], among the available service men, the nearest service man to attend the maintenance activity is identified, using the GPS tracing system of the mobile phones of the servicemen, messaged, and recorded in column 25.

Before implementing the proposed system, a prototype, as shown in Figure 4, was developed with the hardware, circuit designs and coding of logics with the designed dataset as explained above. It was tested with a similar small size pump in the laboratory. An online interface application CLOUD MQTT, the webpage of which is shown in Figure 5, was used to connect and communicate between the entities of the proposed architecture through the IIoT, and the WiFi module in the Arduino board. The behavioral pattern of the industrial rotary system used in the case study industry was studied in detail, using the data collected from the maintenance department of the plant. A real time environment was simulated in the prototype by changing the flow rate of laboratory pump manually, and letting the prototype act autonomously with updating of data in the dataset as per the design.

With the installation of the wireless communication module of the Audrino board, this autonomous health monitoring and control management was made accessible at any time and from anywhere in and around the production plant through the access of the cloud storage data using mobile phone and laptop.

3. Results and Discussion

The prognostic health management system developed in this work was successfully implemented and tested during the first half of the year 2021, in a SME engaged in manufacturing sensors and switches for the automobile industry, which was situated in southern part of India. The heavy-duty rotary gear pump was installed with the smart maintenance management system as per the architecture shown in Figure 1 with the decision support system as exhibited in Figure 2.

Prior to the implementation of the developed system for the pump described above, a detailed study about failure occurrence patterns, mean time to repair, mean time between failure and availability for useful production of the heavy-duty pump, was undertaken and statistics are shown in Table 3. The variation of the predicted efficiency and the observed flow rate of the rotary system is shown in Table 4. The plant was suffering due to the high failure rate and high downtime of the critical bottleneck machine. In order to improve the functioning of the system it was necessary to run the machine at the predetermined values of the critical operating parameters, and to continuously monitor those parameters, and then adapt predictive maintenance and preventive measures to minimize the failures to an acceptable level.

At first, the proposed architecture of the smart maintenance management system was developed as a prototype as shown in Figures 4 and 5, and tested with a functionally similar but a smaller rotor system as suggested by SME. After the successful trial with the prototype, the developed system was implemented. The two critical operating parameters, the speed and displacement of the heavy-duty rotary gear pump were monitored/measured using the IIoT sensors and the real time behavior of the pump, which was recorded once every five minutes in the dataset, and computations as shown below were carried out by the built-in decision support system and recorded in the dataset. The average statistics were computed in every 24 hours and every month. The sample dataset with computed values is shown in Table 5.

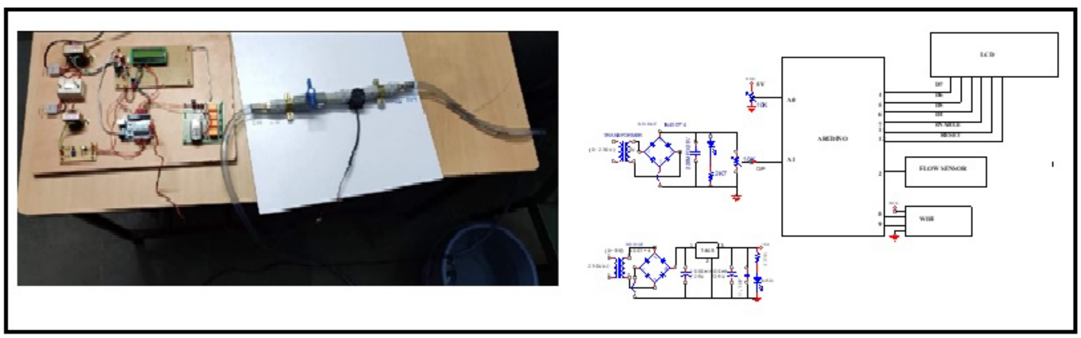

Figure 4. Prototype of proposed smart maintenance system

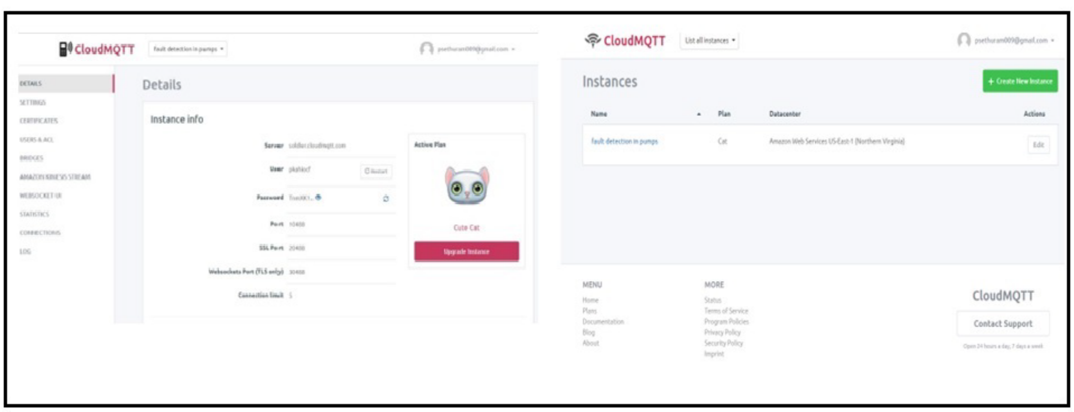

Figure 5. Cloud interface for proposed system

Table 3. Performance of the proposed prognostic health monitoring system

Before Implementation					After Implementation				
Month	**Avg. Flow rate**	**Avg. Breakdown**	**Avg Down time (Hrs.)**	**Avg. Service Man Hrs.**	**Month**	**Avg Flow rate**	**Avg Break down**	**Avg Down time Hrs.**	**Avg Service Man Hrs.**
Jun-20	92.5	20	8.4	28	Jan-21	92.8	12	10	30
Jul-20	95.4	18	10	31	Feb-21	93.7	10	8.3	25
Aug-20	90.2	16	9.7	25	Mar-21	94.1	10	8	20
Sep-20	93.4	17	10	26	Apr-21	94.8	8	6.6	16
Oct-20	92.7	16	8.6	20	May-21	95.0	6	5.2	12
Nov-20	90.8	16	9	20	Jun-21	95.8	6	5	9
Avg	92.5	17.16	9.28	25		94.4	8.66	7.18	18.66

Table 4. Efficiency variation of the rotary system

Month	Efficiency	Avg Flowrate observed
Jan-21	87.84	92.82
Feb-21	90.64	93.76
Mar-21	92.05	94.10
Apr-21	92.45	94.89
May-21	93.14	95.04
Jun-21	93.65	95.83
Avg.	91.62	94.40

$$Design\ \text{Flowrate}\ (Q_{sp}) = \frac{d_{sp} \times N_{sp} \times \epsilon}{1000} = \frac{63 \times 1800 \times 0.91}{1000} = 103.194\ L/min \qquad (1)$$

$$Maximum\ \text{Flowrate}\ (Q_{Max}) = \frac{d_{Max} \times N_{Max} \times \epsilon}{1000} = \frac{62 \times 1750 \times 0.91}{1000} = 98.735\ L/min \qquad (2)$$

Where:

d_{sp}- Geometric Displacement in Cm^3/Rev
N_{sp}- Drive Speed in RPM
€- Volumetric Efficiency = 0.91
Q_{sp}- Design Flowrate (L/min)
Q_{Max}- Maximum Flowrate (L/min)

Table 5. Sample records of dataset for a month

Time - Date	Q_{tar}	d_{ob}	N_{ob}	Q_{ob}	Q_D	St	SO	SG	SIG	MH	EFF
01.01.2021	95.78	61.76	1701	95.60	0.18	1	96.96	95.78	G	MH1	99.94
02.01.2021	95.78	60.84	1741	96.41	-0.63	0	96.96	95.78	O	MH 2	99.19
03.01.2021	95.78	61.41	1716	95.90	-0.13	0	96.96	95.78	O	MH 1	98.99
04.01.2021	95.78	60.98	1750	97.08	-1.30	0	96.96	95.78	R	MH 1	98.61
05.01.2021	95.78	60.43	1734	95.38	0.40	1	96.96	95.78	G	MH 3	99.00
06.01.2021	95.78	60.50	1733	95.44	0.34	1	96.96	95.78	G	MH 2	99.76
07.01.2021	95.78	61.98	1708	96.35	-0.58	0	96.96	95.78	R	MH 1	98.56
08.01.2021	95.78	60.80	1747	96.65	-0.87	0	96.96	95.78	R	MH 3	98.57
09.01.2021	95.78	60.76	1739	96.16	-0.38	0	96.96	95.78	O	MH 3	99.65
10.01.2021	95.78	61.03	1746	96.98	-1.20	1	96.96	95.78	G	MH 3	98.04
11.01.2021	95.78	61.29	1732	96.59	-0.81	1	96.96	95.78	G	MH 1	97.72
12.01.2021	95.78	61.07	1714	95.22	0.55	1	96.96	95.78	G	MH 3	99.02
13.01.2021	95.78	60.63	1703	93.98	1.79	1	96.96	95.78	G	MH 1	99.81
14.01.2021	95.78	61.69	1747	98.04	-2.27	0	96.96	95.78	O	MH 2	99.07
15.01.2021	95.78	60.35	1736	95.33	0.45	1	96.96	95.78	G	MH 3	99.90
16.01.2021	95.78	61.58	1740	97.49	-1.71	1	96.96	95.78	G	MH 1	99.30
17.01.2021	95.78	61.23	1727	96.22	-0.45	1	96.96	95.78	G	MH 1	99.83
18.01.2021	95.78	61.47	1724	96.44	-0.66	0	96.96	95.78	R	MH 1	97.61
19.01.2021	95.78	61.55	1739	97.40	-1.62	1	96.96	95.78	G	MH 3	97.92
20.01.2021	95.78	60.15	1726	94.47	1.30	0	96.96	95.78	O	MH 1	99.78
21.01.2021	95.78	61.70	1749	98.20	-2.42	0	96.96	95.78	O	MH 3	98.81
22.01.2021	95.78	60.73	1736	95.94	-0.16	0	96.96	95.78	O	MH 2	99.67
23.01.2021	95.78	61.41	1727	96.50	-0.72	1	96.96	95.78	G	MH 3	98.12
24.01.2021	95.78	61.15	1701	94.67	1.11	0	96.96	95.78	O	MH 3	98.90
25.01.2021	95.78	60.17	1723	94.35	1.43	0	96.96	95.78	R	MH 2	98.56
26.01.2021	95.78	60.32	1725	94.70	1.07	1	96.96	95.78	G	MH 3	99.32
27.01.2021	95.78	61.79	1744	98.07	-2.29	1	96.96	95.78	G	MH 3	98.93
28.01.2021	95.78	60.42	1738	95.57	0.20	0	96.96	95.78	O	MH 1	99.87
29.01.2021	95.78	60.44	1742	95.79	-0.01	0	96.96	95.78	R	MH 3	98.36
30.01.2021	95.78	60.18	1731	94.79	0.99	1	96.96	95.78	G	MH 1	98.17
31.01.2021	95.78	61.49	1750	97.91	-2.13	1	96.96	95.78	G	MH 2	98.84

The accuracy analysis of the heavy-duty hydraulic pump flow rate was measured with the help of the proposed flow rate variation data. The efficiency in terms of how close the observed flow rate was with respect to the target/expected flow rate is calculated as below.

$$Deviation = \frac{Observed\ flowrate - Tarket\ flowrate}{(Tarket\ flowrate\ )} = \left[\frac{94.07-95.78}{(95.78)}\right] = 0.0178 \quad (3)$$

$$Efficiency = (1 - Deviation) * 100 = (1 - 0.0178) * 100 = 99.9\% \quad (4)$$

The sample predicted efficiency values are shown in the last column and first row of Table 5.

The observation was continued for six consecutive months and the failure rate and downtime statistics of the system after the implementation of the proposed continuous prognostic health monitoring system were computed and tabulated in Table 3. It can be seen from the Table that the average failures, average down time, and average maintenance manpower utilized to restore/upkeep this rotor system progressively decreased. Over the span of initial six months, the number of break down decreased by 49%, the downtime decreased by 22%, maintenance manhours decreased by 25%, and the output of the pump, the average flow rate increased by 1.9%. It was also found that the efficiency in terms of percentage of closeness of the actual/observed output to the expected output also progressively increased, as can be seen in Table 4 and Figure 6.

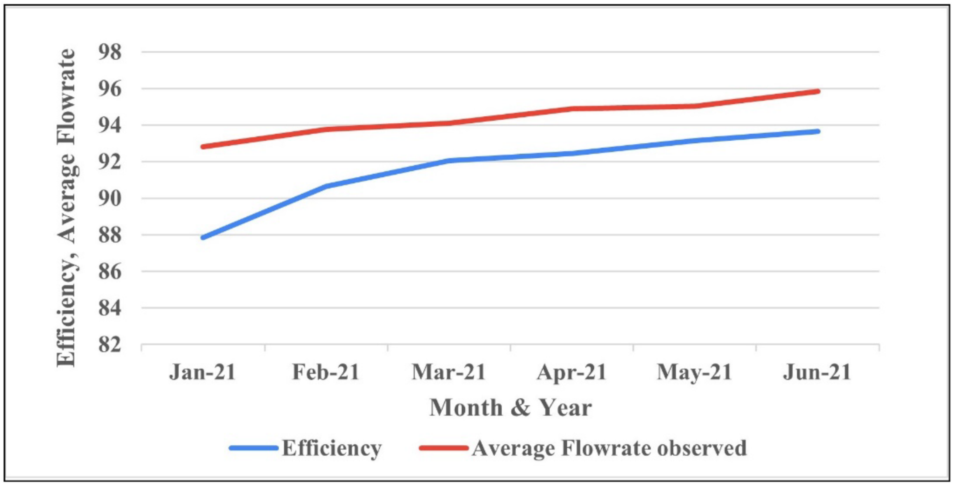

Figure 6. Performance improvement

4. Conclusions

Most of the SMEs are required to implement technologies like the Industrial Internet of Things (IIoT), data mining (DM), cyber-physical production system (CPPS), internet communication Technology (ICT), and machine learning (ML) to reap the benefits of Industry 4.0, most of which involve real-time capturing of data, which allows continuous monitoring of the behavior of critical machines in the production line, predict of unavoidable failures, and the adoption of preventive measures to avoid larger downtime. With built in decision support system, such system provides a smart maintenance management system which results in improved health and longevity of bottleneck facilities, and also better utilization of maintenance crew and reduced repair/service time at the time of failures. In this work, a framework for a prognostic health management system for a bottleneck facility in the production line, employing a MEMS coupled with IIoT sensors, other required hardware, and an in-built decision support system, was developed. Before implementing the developed system in the actual production line, it was tested by building a protype in the laboratory with similar set-up. After successful trials with the protype, the developed continuous prognostic health management system was implemented for a heavy-duty gear pump, which was a critical facility in the case study SME (which was a business producing sensors and switches for automobiles). The objective of the study was to establish a smart maintenance management system under a typical Industry 4.0 environment. The performance of the pump in terms of maintenance metrics like the average number of failures, average downtime, average service manhours was measured after implementing the proposed system, and it was found to be much better compared to the performance before implementation. Also, the performance was observed to be progressively improve with the passage of time.

The developed prognostic health management system was also tested by implementing with another rotor system in another case study SME produced tyres and tubes for automobiles. The results are being observed and appear to be very encouraging. In the future, we hope to develop a unified kit for the smart health monitoring of critical machines in the SMEs through the further application of our recent technologies.

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