Machine Learning Based Predictive Maintenance Model

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Abstract

The production systems are affected by degradations and failures caused by operational and environmental conditions. Indeed, unplanned, unscheduled maintenance (UUM) practices lead to lower productivity, lost production, expensive labour (call-outs, overtime) and damaged equipments. However, predictive maintenance (PdM) is a condition-based maintenance strategy (CBM) that has become popular among practitioners in recent years that carries out maintenance action when needed, avoiding unnecessary preventive measures or failures. Machine learning (ML) has become an advanced diagnostic approach in maintenance strategy to mitigate those challenges. Despite that, the ML-based PdM strategies are infancy stage due to the immaturity of the Industrial Internet of things (IIoT) which is responsible for data collection and execution. Implementing ML-based PdM is a difficult and expensive process, especially for those companies which often lack the necessary skills and financial and labour resources. Thus, a cost-oriented analysis is required to define when ML-based PdM. The proposed study develops the ML algorithm and provides an intelligent PdM model with a framework for practitioners and researchers considering aircraft industries. The contribution of the paper has twofold. The first is to developing an ML-based predictive maintenance model. The analysis shows that random forest outperformed other models scored 28.63 cycles to predicts Time to failure (TTF) within the average error range of ±28 cycles. While, the research finding helps to monitor that how to execute data wrangling and prepare pandas data frames to define TTF of the airlines engines.

Keywords
Machine Learning, Industrial Internet of things, python, Random Forest Regression, and predictive maintenance.

1. Introduction
With the advent of the fourth industrial revolution, the application of artificial intelligence in the manufacturing domain is becoming prevalent (Pundir et al., 2020b; Mohanty and Ranjana, 2019). Maintenance is one of the essential activities in the manufacturing process, and it requires proper attention. Nowadays, the plant's crucial facilities like monitoring, safety analytics, and predictive quality are mainly driven by predictive maintenance strategies (PdM) (Abishekraj et al., 2020). The viability of those strategies generally used data-driven methodology such as machine learning (ML) techniques (Pundir et al., 2020a). Primarily, concerning the current scenario, the transformation of existing technology into digital technology ensures safety and reliability over the lifetime of the machine components. At the same time, incorporating such strategies into the existing company gains more attention among researchers and practitioners.

The analysis of scheduling problems with PdM mainly considered two processing modes. The first is the non-resumable mode, and another is the resumable mode. Recent development in the Industrial internet of things (IIOT) suggested that ML can incorporate both methods (Maheshwari et al., 2021; Mohanty and Ranjana, 2019).

The IIOT has spread its applications into various verticals such as healthcare, manufacturing, oil and gas (Maheshwari et al., 2021). With ML analytics, vast amounts of data generated from the IIOT sensors fitted on manufacturing assets can be leveraged to detect asset failure in advance (Maheshwari et al., 2022). The objective is to predict failures in advance, thereby increasing equipment uptime.

The research on IIoT-based PdM is still in the preliminary stage (Patel et al., 2019). Earlier literature was mainly centred around Condition Based Maintenance (CBM) strategies and intelligent maintenance systems that estimate the reliability of a plan to detect any failures beforehand (Shah, 2019). It is based on maintenance techniques such as Preventive Maintenance (PM) and CBM strategies. The challenging tasks are researching the latest trends, applications, and how PdM can help improve reliability and efficiency and protect the environment. PdM employs non-intrusive testing techniques, such as thermodynamics, acoustics, vibration analysis, infrared analysis, etc., to monitor and evaluate equipment performance trends.

Implementing Internet of things (IoT) sensor architecture using ML algorithms has not yet been fully exploited (Pundir et al., 2020a). An Intelligent PdM framework (IPdM) can give an initial direction for doing the PdM (Figure 1). The goal is to create and deploy a model for predicting machinery failure using data collected from industrial sensors.
We have used a quantitative analysis method (Gautam et al., 2019). This research will mainly target two objectives first, to obtain the random forest method and root mean square error analysis for PdM, while the other objective function predicts the Time-To-Failure (Figure 1).

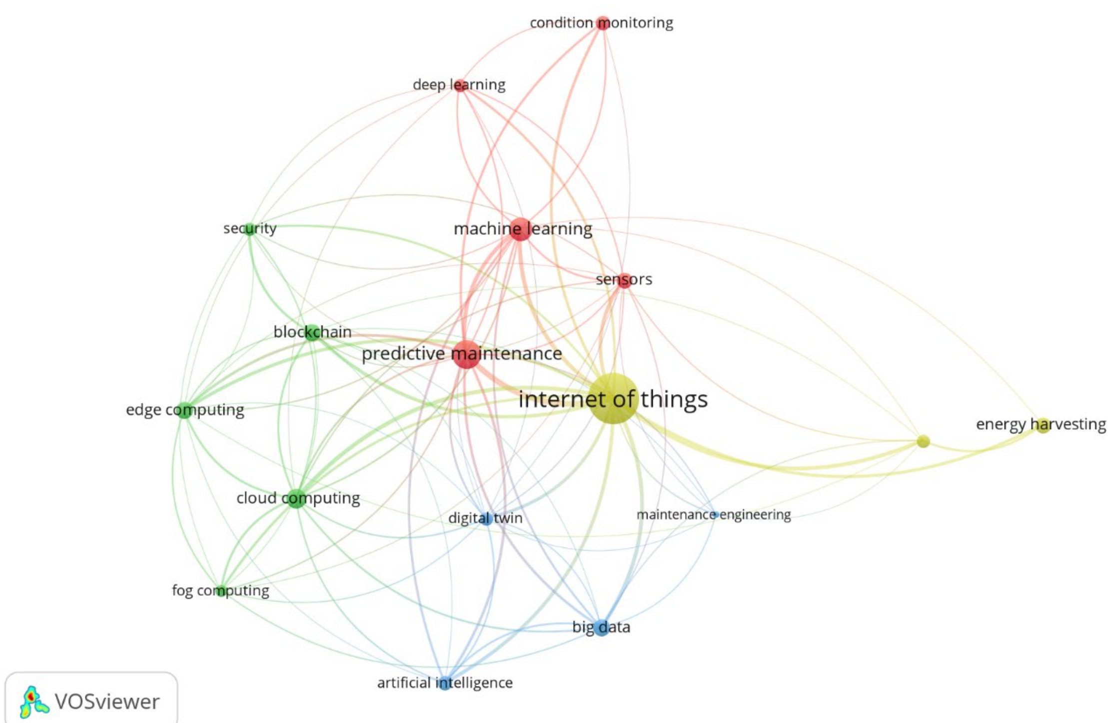

Figure 1. Vos viewer analysis of IIOT and maintenance aspects.

1.1 Research Objectives

The research objects are following-

- To build a model for ML-based predictive maintenance strategies.
- To identify the role of the Industrial Internet of things in predicting the Time-To-Failure of equipment.

The remainder of the paper is that section 2 represents the literature review, section 3 states the methodology, and section 4 has the problem description. Section 5 describes the analysis, followed by section 6 results and implications.

2. Literature Review

The main aim of this paper is to develop the ML algorithm and its application in the maintenance sector. To incorporate this objective, we have identified the potential research paper published in this domain using Scopus and the web of science database. We have adopted the literature review method of Hinz et al. (2018). The literature states three important factors for the ML algorithm: availability, breakthroughs, and advancement in computational power. Furthermore, we have developed the literature review section into two parts.

2.1 Statistics related to predictive maintenance

The widespread use of predictive maintenance increased from 47% in 2017 to 51% in 2018 and is expected to increase by 70% in the next few years. Preventive maintenance is still preferred by 80% of maintenance personnel. In contrast, 80% of manufacturing plants use preventative maintenance, and over half use predictive maintenance with analytical tools. In 2012, the U.S. Bureau of Labor Statistics estimated that the nation would be short 10 million workers over the following six years. Roughly 10% (and maybe even less) of industrial equipment wears out, meaning a considerable portion of mechanical failures can be avoidable. Meanwhile, Predictive analytics yields a tenfold return on investment, resulting in savings of 30% to 40%. Besides that, the most common challenge facilities face a lack of resources, including human, technical, and strategic resources. Historically, total productive maintenance has been shown to increase plant capacity by over 10% and productivity by 50%, but over half of all attempts to implement total productive maintance result in failure. At the same time, 79% of businesses see predictive maintenance as the main application of industrial data analytics.

Working with any new technology requires justifiable investment, and predictive maintenance is no exception. Data scientists must realize the value of their investment and produce quantifiable results as quickly as possible. Software capabilities and tools such as MATLAB can help people new to predictive maintenance get up and running efficiently. By taking advantage of such devices, engineering teams can quickly incorporate predictive maintenance algorithms into operations already in place.

Creating a systematic approach to predictive maintenance puts engineers in the best position to build a real-time system using a predictive model successfully. The five-step workflow can offer guidance when just starting:

- Accessing sensor data – Gather data from databases, spreadsheets, and web archives, and ensure the data is in the correct format and organized.
- Preprocess data – Clean the data by removing outliers, aligning time series, and filtering out noise.
- Extract features – Capture higher-level condition indicators, such as frequency domain or time-frequency domain features, instead of feeding raw sensor data into the model.
- Train the model – Build models that classify equipment as healthy or faulty that can detect anomalies or estimate remaining helpful life for components.
- Deploy the model – Generate code and deploy models as an application on hardware.

Predictive maintenance relies on ML algorithms, and enough data must exist to create an accurate model. This data typically stems from machine sensors. Model success depends on how information is logged: preferably, machines will include logging options that can be modified to record more data, or simulation tools can be used to combine simulated data with available sensor data to build and validate predictive maintenance algorithms. Engineers should avoid a condition where their systems operate in a "feast or famine" mode where little or no data is collected until a fault occurs. To prevent this, companies can change the data logging options to record more data, perhaps on a test fleet if production data is unavailable. It is also possible to generate test data using simulation tools by creating models covering mechanical, electrical, or other physical systems to be monitored and then validated against measured data.
Failure data is a fundamental element of predictive maintenance. Yet this data may not exist if maintenance is performed so frequently that no failures occur. Simulation tools, such as Simulink can help data engineers generate this necessary failure data. Even without failure data, unsupervised techniques can be used to identify normal and faulty behaviour. For example, data could be collected from several sensors on an aircraft engine. A dimensionality reduction technique such as principal component analysis (PCA) could then reduce the sensor data into a low-

dimensional representation for visualization and analysis. In this representation, healthy equipment data may be centred around a specific operating point, while unhealthy equipment may be seen as moving away from normal conditions.

There's a big difference between identifying a failure source and knowing how to predict it. Engineers must clearly define their goals—such as longer cycles and decreased downtime—and consider how a predictive maintenance algorithm affects them. They then should build a framework to test algorithms and estimate their performance so that they can get immediate feedback during design iterations. They can use this framework to test simple models and apply their knowledge of the data to try more complex model types (Table 1a). They should keep things small, validate against data, and iterate until they are confident with their results.

Obstacles aside, data scientists and engineers can take solace in realizing that predictive maintenance is an achievable goal if they can locate the best balance of tools and guidance. The onus is on engineers and data scientists to determine the features, methods, and models that work best for them and keep iterating until they fully master these techniques.

2.2 IIOT in Predictive Maintenance

IIOT connect different hardware devices, software, and communication capability to make any object intelligent so that they can communicate virtually, regardless of physical location. The Radiofrequency identification (RFID) and wireless sensor network concept has been growing and attracting industry and academia. The IIoT ability to connect physical objects and allow them to share information through the Internet may facilitate collecting a significant amount of data that are a powerful strength for the success of any business and future prediction. In the maintenance world, embedded hardware made up of sensors and other intelligent devices powered by IoT is reshaping industrial and manufacturing maintenance processes. The internal equipment outfit is generally unobservable; thus, regular planned preventive maintenance does not provide enough or clear information involving the equipment status to maintainers. When operating without any physical symptoms of depreciation, it is not practically easy to identify whether there is any root to cause the future defect.

Consequently, the routine schedule is retained, and sudden downtime may occur at an unexpected time, perhaps even during a heavy work period. The equipment gradually degrades over time before reaching a complete collapse. The insufficient maintenance accuracy of asset's conditions results in a thorough deterioration that reflects in service deficiency, clients' appointments postponement, and dismay while waiting for the procurement of new spare parts or equipment replacement that always goes together with an increase in cost demand.

Thus, with the power of IoT, the predictive maintenance approach may be influential in this game to integrate the direct monitoring of equipment through collecting continuous real-time data from its physical health parameters.

2.3 Model for predictive maintenance using IIOT

- IoT Sensors: Sensors or Cyber-physical systems can interact and communicate with each other. Sensors capture raw data. Few Popular Industrial IoT Enabled Sensors measure Temperature, Humidity, Pressure, Current, Vibration, Air Quality, Footfall, Gas, and Weight. Another commonly used sensor is the Photoionization Sensor, which measures volatile inorganic compounds and gas levels. The ultrasonic sound sensor is used to translate high-frequency sounds due to leaks.

- Digital Signal: Data from sensors captured in the form of analogue signals is converted into digital signals using an Analogue-digital converter. The digital signal is machine-readable and is used for further analysis.

- Data storage and transfer: Digital data stream generated is stored on the organization's local intranet or a secure, centralized or remote cloud location in a database file. IoT Sensors installed in remote areas without internet connectivity have inbuilt Random Access Memory (RAM) storage space where data is stored. Data from IoT sensors is transmitted to a centralized cloud server or decentralized fog nodes via Wi-Fi or in remote locations through Cellular networks or Bluetooth Low Energy (BLE) technology.

- Cloud Computing: IoT sensors like Arduino, Raspberry PI, ESP8266, and ESP32 have inbuilt computing power. Based on the asset's criticality, PdM algorithms can be processed at Edge, Fog, or Cloud. In Edge devices, the processing is done locally. It is used to provide near to real-time insights into Machine failure. In cloud computing, the server is centralized, having big data centres (Chatterjee et al., 2022). Data generated from the IoT sensors in PdM applications are sent to Cloud for further processing. Processing in Cloud has high latency. Fog Computing has distributed architecture where fog nodes are distributed in many locations over large geographic areas. It is the intermediate layer between Cloud and IoT Edge devices. If a significant distance separates the assets, it is recommended to implement fog architecture over the Cloud due to low latency and higher computing power. The proposed model uses the architecture shown in Figure 2.

Figure 2. Architecture for predictive maintenance using IoT

3. Methodology

The ML is a subfield of computer science that enables computer programs to predict, diagnose, plan, and recognize behaviour patterns by learning from historical data, i.e. without a priori knowledge. Learning can be classified into four main categories: (i) supervised when a set of labelled training data feeds the algorithm; (ii) unsupervised, characterized by an unlabelled training dataset; (iii) semi-supervised, where datasets contain both labelled and unlabelled examples; (iv) by reinforcement, in which the learning system can observe the environment, perform some actions, and get some rewards (negative/positive) based on the selected action.

3.1 PdM Structure Development Methodology

Starting a PdM structure that IoT powers require integrating a new and separate independent design built with the ability to collect data, process them, and make data perceptions sharing across existing systems. The preliminary works before starting the construction of the system for predicting the forthcoming faults, including the different steps:

- Highlighting the equipment in query and conducting its operational assessment.
- It collects its data from maintenance history to discover and describe what type of faults mostly make it traumatized, their impact on the system, and how they were identified.
- Based on the acquired information, highlight the critical components and their physical parameters
- to be monitored as well as the needed materials.

The PdM requires the embedded system powered by the IoT capabilities to keep spotting the continuous streamed sensors data, various linked hardware (microcontroller, sensors, communication module) to process data, and constantly provide feedback.

3.2 Proposed Predictive Maintenance (PdM) Structure Using Internet of Things (IoT)

The PdM structure depends on the queried environment and a predictive analytics tool to discover remarkable insights. Because the data type leads the remaining parts of the prediction, we have developed a data collector prototype before proposing the PdM structure using IoT to help us obtain real-time data to learn a predictive model for our proposed system.

- Generating Data for Predictive Model Construction: Noticing the unavailability of the equipment performance data, we developed a data collector to collect the real-time data to be used in developing the predictive analytics model. The collected data helped to observe data changes versus components' health performance to classify the functional component's health status. Figure 3 illustrates the main components schematic of the data collector used to gather and transmit data.

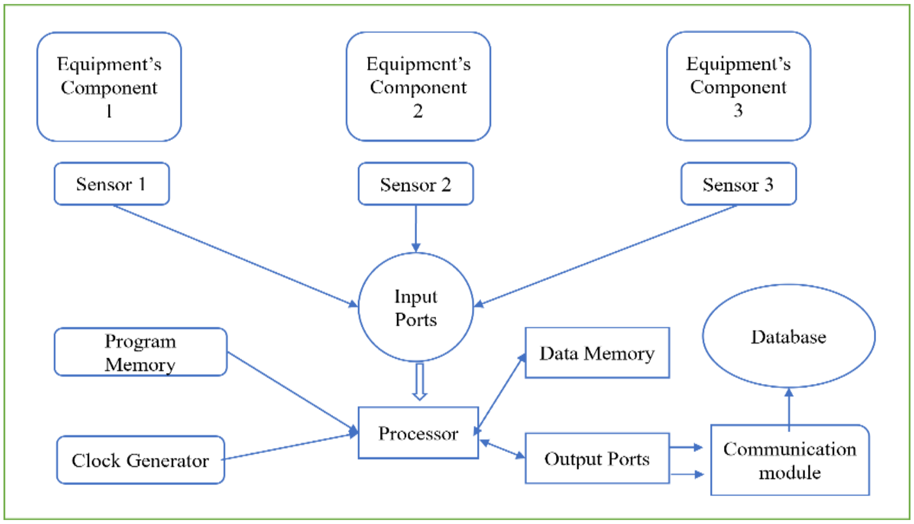

Figure 3. Data collector prototype main components

a. Microcontroller

The program running into the microcontroller to collect and transmit the data is performed through five phases:

- Ports for sensors and communication modules are initialized and configured.
- Read voltage sensor data corresponding to the thermistor resistance.
- Convert voltage into temperature.
- Try to connect to the GSM network
- The data are sent to a remote database if the microcontroller is connected to the GSM network. Otherwise, the microcontroller keeps trying to connect to the GSM network

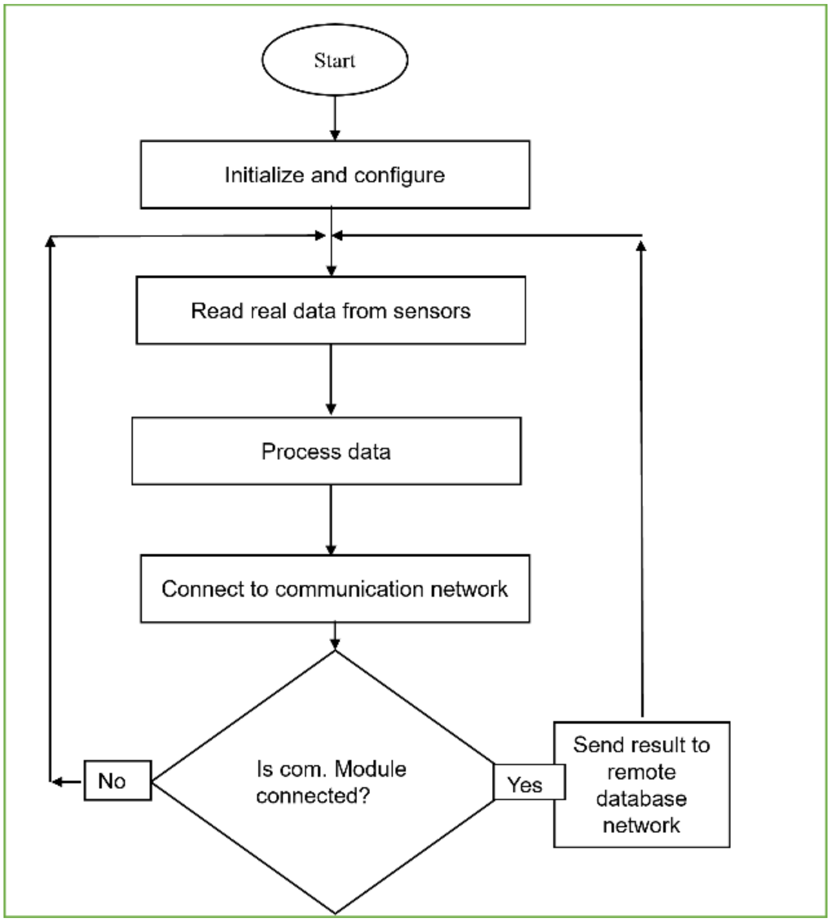

Figure 4. programming algorithm

Figure 4 states the programming algorithm that, based on the real-time data, time dependence significantly influences predictive data analytics since the present time points are likely to be related to the previous time point or a time point in the long past. Such independence can help detect a feature for the present abnormal occurrence, which may be mapped to the previous one.

Predicting the health status of mechanical equipment relies on the unstable long-time dependence performance data. To propose the fitting predictive model, the Seasonal Autoregressive Integrated Moving Average (SARIMA) and LSTM models were used to learn and predict from our real-time collected data, where LSTM performed well with a low root mean square. Error Root-mean-square deviation (RMSE) is 22.89 and 2.9 compared to SARIMA, with 29.97 and 3.68 RMSE, respectively, for different components' univariate data.

On top of the predictive model results, the microcontroller could be programmed, depending on results displayed, such as client access limit, reports generation, alerting message, like a short notification message or email sending, customized dashboard outlook, etc., all for monitoring.

4. Problem Description and analysis

Failure prediction is an important topic in predictive maintenance in many industries. Airlines are particularly interested in predicting equipment failures in advance to enhance operations, cut the cost of time-based preventive care, and reduce flight delays.

Observing the engine's health and condition through sensors and telemetry data is assumed to facilitate this type of maintenance by predicting the Time-To-Failure (TTF) or Remaining Useful Life (RUL) of in-service equipment. This research work is trying to predict the aircraft engine's TTF.

4.1 Exploratory Data Analysis
Feature variability, distribution, and correlation were examined to uncover the underlying structure and extract essential variables. Features with high variability were checked for correlation with other features and regression labels (TTF).

- Training data: Contains aircraft engines' run to failure data. 20,000+ cycle records for 100 engines (Table 1a).
- Test data: Contains aircraft engines' operating data without failure events recorded (Table 2b).

The remaining cycles for each engine are provided in a separate Ground truth data file. Contains the true remaining cycles for each engine in the test data. Whereas ID denotes the engine ID, ranging from 1 to 100. cycle: per engine sequence, starts from1 to the cycle number where failure had happened setting1 to setting3 engine operational settings s1 to s21 sensors measurements.

Steps used to do analysis:

1. Data wrangling: Steps involved in data wrangling are as follows:

a) Source Data: Display and examine a few lines from the top and the bottom of the source data files to prepare for loading the data into Pandas data frames. This will help decide how to load the data, for example, if there are column headers, comments lines at the start or end of the file, empty rows or columns. It will also help identify the field's separator and potential data types.

b) Load data: Considering the above findings, load the data from the source file into Pandas data frame, assign columns names, and remove empty or unwanted columns. Run some Pandas data frame methods to get more information about the loaded data. This includes data frame .describe(), .head(), .tail(), .dtypes etc. For example, the describe() method will reveal insights about numeric column data distribution, e.g. columns with one constant value that could be excluded from further steps in the pipeline.

c) Missing Values: Check for null (NaN) values by running Pandas data frame method .null().sum(), which gives the total of missing values for each data column. Accordingly, some columns may be excluded from the data if they have many missing values. Alternatively, missing values could be replaced by statistical measures like mean, median, mode, or some interpolated value based on domain knowledge. Fortunately, the data set of this project is clean since it mainly contains sensors and machine-generated data.

d) Outliers Detection: For outlier detection, run Pandas data frame .quantile() method, SciPy stats. zscore, or manually by identifying the data points above or below [mean ± n standard deviation], where n can take the value 2 or 3 assuming a normal distribution. Pandas' data frame filtering methods could then be used to remove/replace outliers.

e) Other Data Manipulation: Join or merge data frames based on an index or common key. For example, labels for test data were in the separate source data file. This could be done by using Pandas .concat() and .merge() methods. Regression: Time-To-Failure TTF (no. of the remaining cycle before failure) for each cycle/engine is the number of cycles between that cycle and the last cycle of the same machine (Figure 5).

For test data, TTF is provided in a separate truth data file. These two files were merged, and then classification labels for test data were created in the same way described above

f) Feature extraction: It is applied to the training and test data by introducing two additional columns for each of the 21 sensor columns: rolling mean and rolling standard deviation. This smoothing of the sensor's measurements over time would improve the performance of some MLalgorithms.

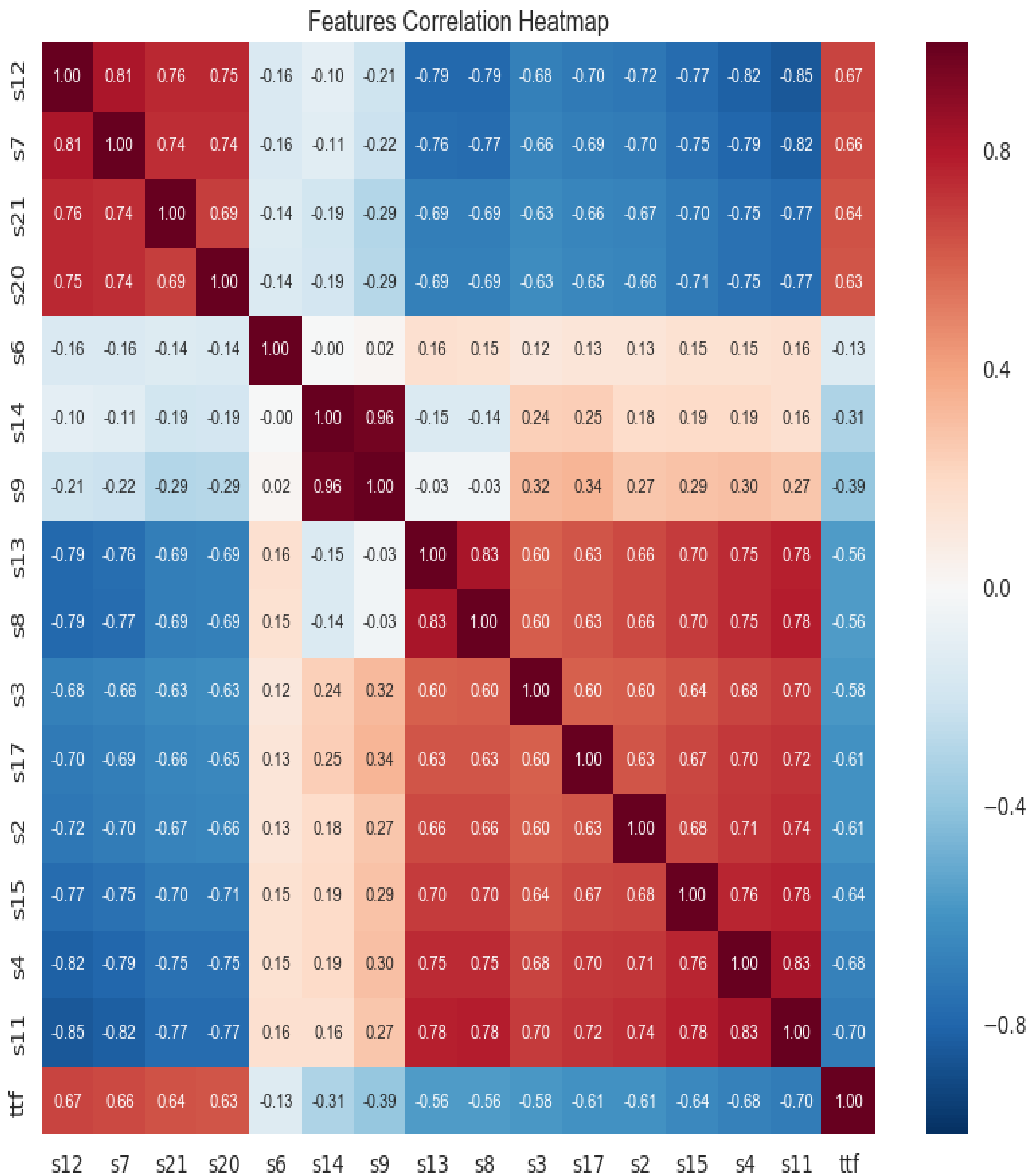

Figure 5. Heat map for the sensors which affect TTF

There is a very high correlation (> 0.8) between some features e.g.: (s14 and s9), (s11 and s4), (s11 and s7), (s11 and s12), (s4 and s12), (s8 and s13), (s7 ands12) (Figure 6).

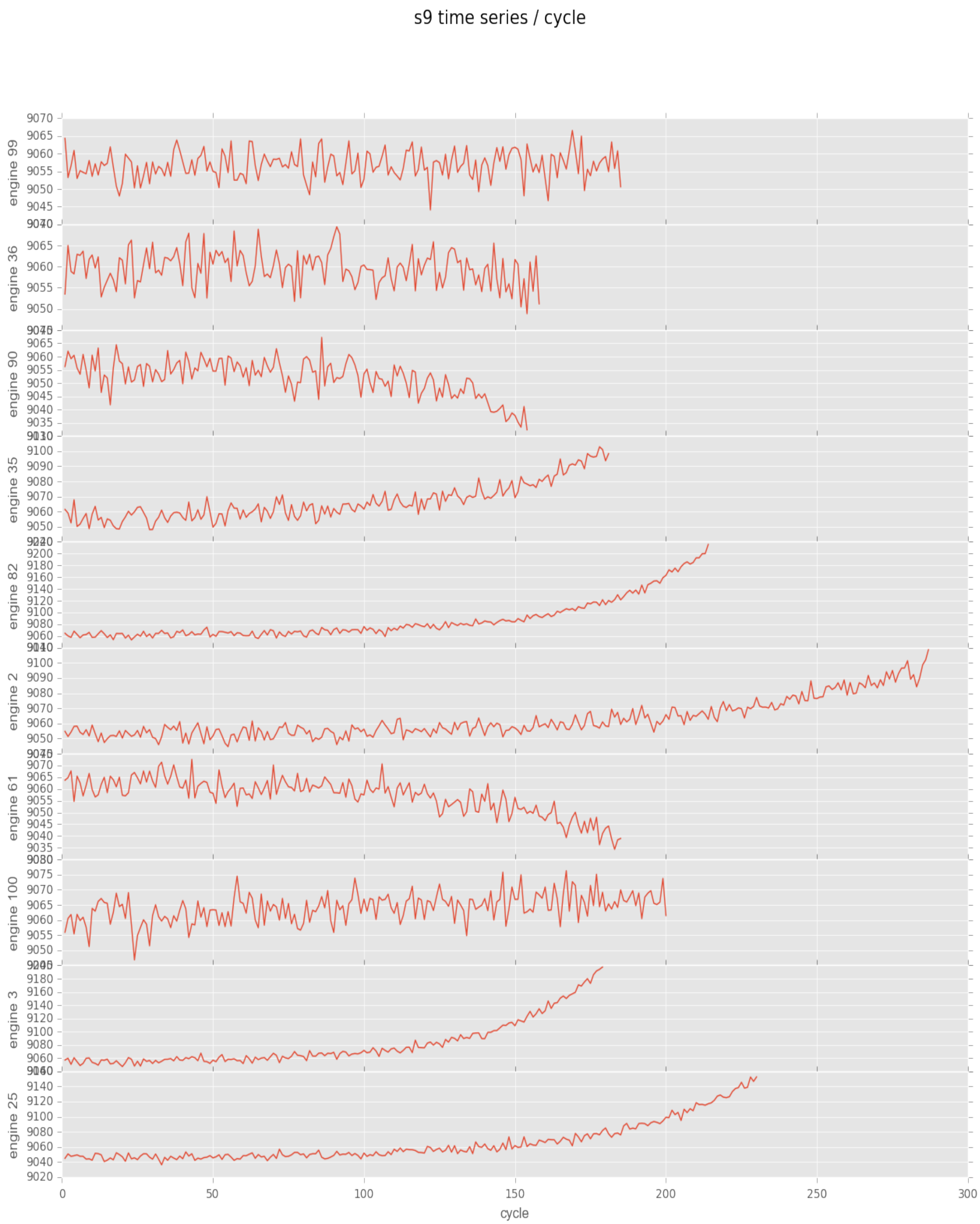

Figure 6. A set of graphs applied to each S9 (sensor) feature individually

4.2 Predicting Engine's Time-To-Failure (TTF)

4.2.1 Regression modelling

To predict the number of remaining cycles before engine failure. The steps involved are:

- **a.** Segment training and test data into features data frame and labels series. To make it easy to train models on a different set of features, a variable to hold the set of features required was used to subset the original data frames
- **b.** Create a helper function to calculate regression metrics (Figure 7)
- **c.** Create a helper function to plot the coefficient's weights or feature importance
- **d.** Create a helper function to plot the regression residuals. Some of the regression models used are as shown:

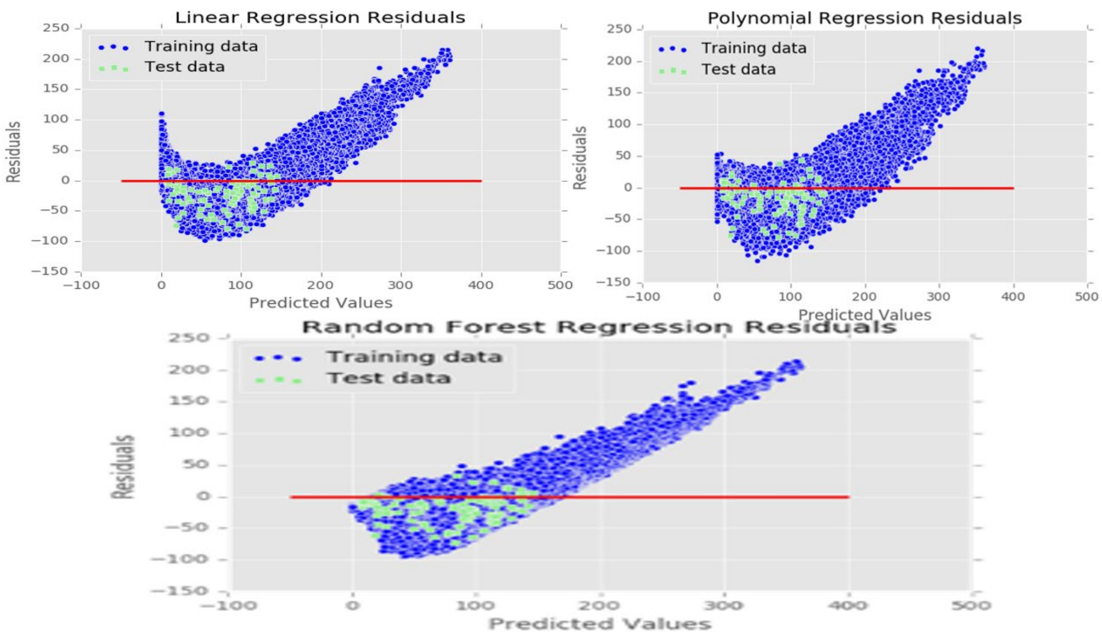

Figure 7. Regression model

5. Results and Discussion

Random Forest outperformed other models scoring RMSE of 28.63 cycles, i.e. the model predicts TTF within the average error range of ±28.63 cycles. The research findings will help the maintenance team members monitor a remote database for storage and virtual access. Users may access the database from anywhere through a computer or mobile application. Through monitoring, the generated reports from the streamed data will be processed and analyzed, the early detected faults shall be triggered, and the user may optimize and act on the maintenance plan. The analysis is in a graphic format for ease of interpretation.

When considering the nature of the maintenance works, maintainers keep moving from one place to another due to different equipment in different locations and may be out of network.

coverage. To obtain warning information promptly proposed system sends a short notification message to their phones for their actions in the case of critical equipment components.

6. Conclusion

Predictive maintenance techniques are designed to help determine the condition of in-service equipment to estimate when maintenance should be performed. This approach promises cost savings over routine or time-based preventive maintenance because tasks are performed only when warranted. Thus, it is regarded as condition-based maintenance carried out as suggested by estimations of the degradation state of an item. The central promise of predictive maintenance is to allow convenient corrective maintenance scheduling and prevent unexpected equipment failures.
Predictive maintenance has several promising outcomes, including reducing machine downtime and avoiding unnecessary maintenance costs while adding revenue streams for equipment vendors with aftermarket services. However, engineers and scientists phase challenges around process and data when incorporating predictive

maintenance technology into their companies' operations. This work can be extended in terms of neural networking and its applications.

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Table 1 a. Data table

id	cycle	setting1	setting2	setting3	s1	s2	s3	s4	s5	s6	s7	s8	s9	s10	s11	s12	s13	s14	s15	s16	s17	s18	s19	s20	s21
1	1	0.0023	0.0003	100	518.67	643.02	1585.29	1398.21	14.62	21.61	553.9	2388.04	9050.17	1.3	47.2	521.72	2388.03	8125.55	8.4052	0.03	392	2388	100	38.86	23.3735
1	2	-0.0027	-0.0003	100	518.67	641.71	1588.45	1395.42	14.62	21.61	554.85	2388.01	9054.42	1.3	47.5	522.16	2388.06	8139.62	8.3803	0.03	393	2388	100	39.02	23.3916
1	3	0.0003	0.0001	100	518.67	642.46	1586.94	1401.34	14.62	21.61	554.11	2388.05	9056.96	1.3	47.5	521.97	2388.03	8130.1	8.4441	0.03	393	2388	100	39.08	23.4166
1	4	0.0042	0	100	518.67	642.44	1584.12	1406.42	14.62	21.61	554.07	2388.03	9045.29	1.3	47.28	521.38	2388.05	8132.9	8.3917	0.03	391	2388	100	39	23.3737

Table 2. b. Data table for testing

id	cycle	setting1	setting2	setting3	s1	s2	s3	s4	s5	s6	s7	s8	s9	s10	s11	s12	s13	s14	s15	s16	s17	s18	s19	s20	s21
1	1	-0.0007	-0.0004	100	518.67	641.82	1589.7	1400.6	14.62	21.61	554.36	2388.06	9046.19	1.3	47.47	521.66	2388.02	8138.62	8.4195	0.03	392	2388	100	39.06	23.419
1	2	0.0019	-0.0003	100	518.67	642.15	1591.82	1403.14	14.62	21.61	553.75	2388.04	9044.07	1.3	47.49	522.28	2388.07	8131.49	8.4318	0.03	392	2388	100	39	23.4236
1	3	-0.0043	0.0003	100	518.67	642.35	1587.99	1404.2	14.62	21.61	554.26	2388.08	9052.94	1.3	47.27	522.42	2388.03	8133.23	8.4178	0.03	390	2388	100	38.95	23.3442
1	4	0.0007	0	100	518.67	642.35	1582.79	1401.87	14.62	21.61	554.45	2388.11	9049.48	1.3	47.13	522.86	2388.08	8133.83	8.3682	0.03	392	2388	100	38.88	23.3739

Biographies

Dr Ashok k Pundir worked as a Professor (Operations Management) and Dean at the National Institute of Industrial Engineering (NITIE) in Mumbai, India, for more than 22 years. He has 39 years of Industrial and Academic experience. He has worked for more than 16 years at The Premier Automobiles Ltd, Mumbai, and was Assistant General Manager(Projects) and the Industrial Engineering Department head. He was actively involved in the restructuring of manufacturing operations. Prof. Pundir's interest areas include Industrial Engineering, Project Management, Manufacturing Systems, Service Operations, and Supply Chain Management.

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Pradeep Prajapati is a management intern at Spence's retails. He completed a bachelor's degree in electrical electronics engineering from the Thapar institute of engineering and technology from 2010-2014. He earned a post-graduate diploma in industrial engineering from NITIE Mumbai during 2019-2021. His research interest includes Industrial electronics.