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ORIGINAL ARTICLE

# An Industry 4.0 implementation of a condition monitoring system and IoT-enabled predictive maintenance scheme for diesel generators

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**KEYWORDS**

Diesel Generator (DG);
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Remote monitoring;
Decision Support System (DSS).

**Abstract** In most business and residential organizations, Diesel Generators (DG) is a viable supplementary power source for ensuring an undisturbed power supply. The DG is a hybrid machine that generates electrical energy using a Diesel Engine (DE) and an Electric Generator (EG). By routinely monitoring crucial machine parameters, alternative power source efficiency can be improved. Furthermore, Condition Monitoring Systems (CMS) based on the Internet of Things (IoT) have supplanted the traditional equipment maintenance method. Predictive maintenance is also an important building block of Industry 4.0, whose entire process and performance can be fully understood by using IoT-enabled Remote Monitoring (RM) schemes. Firstly, this paper introduces a remote monitoring and data acquisition scheme to realize the concept of predictive maintenance. Secondly, this article discusses a strategy for real-time observation of DG parameters as well as a comprehensive analysis of various metrics. Thirdly, this research article includes a monitoring and analysis scheme of crucial factors in a DG, like the speed of an engine, voltage output, the current produced, power factor, coolant required, fuel consumption, and battery health. Different mathematical models are formulated by correlating experimental data and estimating the coeffi-

*Abbreviations*: DG, Diesel Generator; EG, EletricGenerator; CMS, Condition Monitoring Systems; IoT, Internet of Things; RM, Remote Monitoring; DSS, Decision Support System; PVM, Preventive Maintance; PM, PredictiveMaintance; CMA, Condition Monitoring Application; ML, Machine Learning; FBG, Fiber Bragg Grating; MQTT, Message Queuing Telemetry Transport.

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cients. Finally, to create suitable real-time warnings under critical circumstances, a fuzzy logic-based Decision Support System (DSS) and web-based integration elements are presented.



## 1. Introduction

Industrial manufacturing processes require raw materials and handle the end-to-end production process. The first industrial revolution (Industry 1.0) began in the 18th century, with the adoption of steam power. The second industry revolution (Industry 2.0) began with the advancement of electricity and its integration into production and mass production started at that point. In the'70 s, partially automated industries employing computers and memory-programmable controls kicked off the third industrial revolution (Industry 3.0). Finally, the fourth industrial revolution (Industry 4.0) delivers smart manufacturing practices by leveraging the concept of a cyber-physical system and supports the manufacturing operator with fewer errors as well as high reliability [1]. Similarly, maintaining industrial machinery is a difficult undertaking because most modern industrial machines use both mechanical and electronic systems to operate. As a result, regular maintenance of large industrial devices is essential to avoid concerns such as decreased productivity, increased production costs, and job losses [1,2]. In addition, machine maintenance is divided into three categories: "Reactive Maintenance (RM)," "Preventive Maintenance (PVM)," and "Predictive Maintenance (PM)," among others. Reactive Maintenance is the type of attention and concern given when something isn't working properly. Reactive maintenance allows the equipment to operate to its fullest potential whereas repairs are only undertaken once the machine has failed. Light bulbs and home fans are examples of low-cost systems where the reactive maintenance technique is ineffective. Repairing badly damaged parts on aircraft engines, on the other hand, is quite expensive. Preventive maintenance, on the other hand, is a type of routine maintenance performed to avoid loss. Many institutions strive to prevent failure before it occurs by performing routine equipment inspections [3]. One of the biggest challenges with preventive maintenance is determining when it should be performed. Because the time of breakdown is always unknown, the operator must plan for important safety machinery with caution. In the early phases of maintenance schedules, consumers are losing equipment life that is still usable, which increases operational costs. In a similar theme, predictive maintenance is a type of maintenance where the schedule of repair is decided by system monitoring and analytics [4]. Predictive maintenance not only foresees future failures but also pinpoints faults in complicated machinery and aids in the identification of specific sections that require repair.

Escalators, power plants, manufacturing facilities, and vehicles are just a couple of small areas where electric motors are being used. The two aspects of electric engine failures are electrical and mechanical. Because they link the stator and rotor, bearings are among the most critical and susceptible to damage in electric motors [9]. Potential malfunctions must be avoided, financial losses must be kept to a minimum, and industrial operations must be run securely. Because of this, accurate condition monitoring of electric engines is vital and involves a lot of attention [10]. In continuous condition monitoring, data is periodically acquired by the operating machine's sensors and compared to a predefined threshold.

Similarly, online Condition Management Systems (CMS) have grown in popularity recently, where the role of IoT and IIoT is very much important. The idea of IIoT is to provide more convenient and reliable maintenance using low-cost CMS and Industry 4.0. It is made up of three broad sections such as the establishment of experiment setup, IIoT-based Condition Monitoring Application (CMA), and the assessment of Machine Learning (ML) models. Further, it is important to detect faulty bearings in any rotating machine before they cause rotational instability [5]. The CMA can use mobile devices to notify maintenance team supervisors through SMS and email if critical criteria are exceeded [6]. Also, CMA enables real-time monitoring and recording of data that is wirelessly delivered from the setup on a mobile device using the Android operating system.

Similarly, the CMS of a DG unit has several other physical parameters that define the performance and efficiency level of the hybrid machine. In a fully effective CMS, various more crucial parameters of a DG must be monitored. The vibration of the generator shaft, the temperature of the shaft, the noise level, and so on are some of the characteristics. Many studies have shown the use of fiber optic sensors in machine monitoring applications, such as the Fiber Bragg Grating (FBG) sensor. These sensors are passive and are typically used in applications requiring high-precision sensing [8]. In the same way, Table 1 lists some additional significant DG parameters and sensing principles behind the sensor devices.

Some of the most vital and expensive elements of DG include the battery, fuel, and coolant oil. Any CMS for DGs must keep track of the coolant oil's condition, especially coolant temperature, fuel level, and battery voltage. The sensor technology has advanced to a point where it can now accurately measure the tank's gasoline level. In the majority of DGs, these parameters may be retrieved via the external interface of the DG electric panel. A full grasp of the appropriate communication protocols is required to develop IoT-enabled data collection and analysis systems [7]. The suggested CMS is illustrated in Fig. 1 of this article. The suggested architecture is a three-layer method that uses the electric control panel and appropriate sensors to remotely monitor DG parameters. The first layer is the machine layer where the IoT devices are connected to the DG sets and various real-time parameters are acquired from the DG control panel. The IoT device communicates with the DG control panel via RS485 bus architecture and sends the acquired information to the cloud storage vi 2G/3G/4G network connection. The second layer of the proposed architecture is the cloud computing system which is responsible for data analytics, diagnostics, data management, visualization, and machine control. Further, the third layer is the DSS layer which runs the Fuzzy Inference System (FIS)

**Table 1** Additional significant DG parameters and sensing principles.

| Sl. No. | Other Important Parameters | Type of Principle for Sensing |
|---|---|---|
| 1. | Particulate Matter (PM) | Quantitative chemical analysis (Gravimetric method) |
| 2. | Sulphur Dioxide ($SO_2$) | Electrochemical principle (Barium Perchlorate/Thorin titration indicator) |
| 3. | Oxides of Nitrogen ($NO_x$) | Non-Dispersive IR (NDIR), Non-Dispersive UV (NDUV), Chemiluminescence (high-temperature device for continuous measurement) |
| 4. | Carbon Monoxide (CO) | NDIR |
| 5. | Oxygen ($O_2$) | Paramagnetic measurement (Electrochemical principle) |
| 6. | Non-Methane Hydro-Carbon (NMHC) | Gas Chromatograph type measurement (Flame Ionisation Detector – FID) |
| 7. | Engine Vibration | Vibration sensor (Piezoelectric type devices, or Accelerometers) |
| 8. | Noise level | Micro Electro Mechanical System (MEMS) type microphones |
| 9. | Engine temperature | Temperature sensors (Resistive, or Optical type principle) |

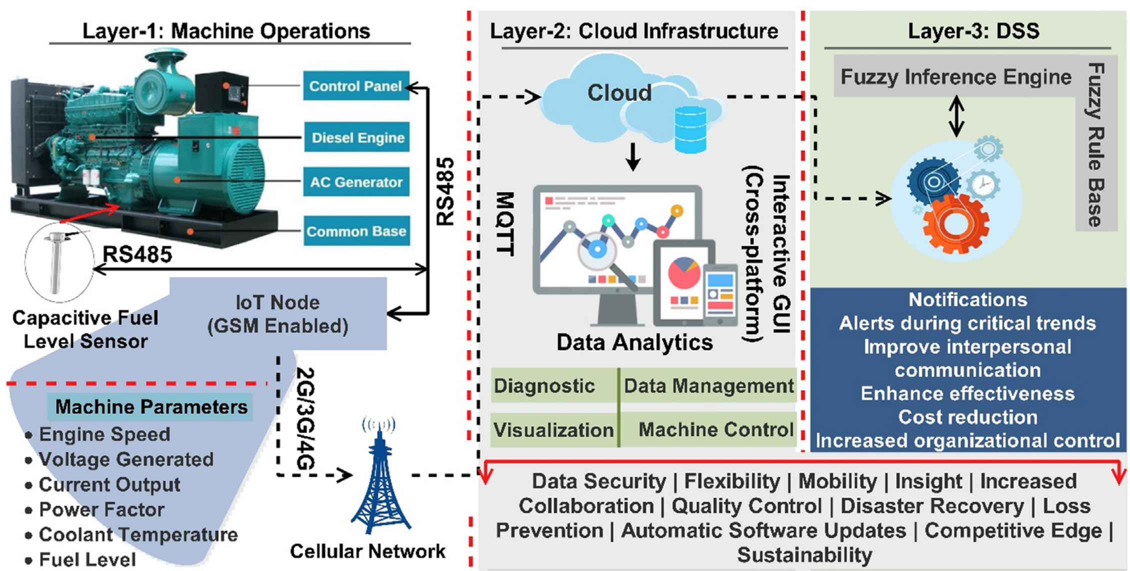


**Fig. 1** A 3-layer design for the IoT-enabled CMS for DG monitoring and predictive analysis.

and the required suggestions/notifications are generated using this stage.

The step-by-step approach of the proposed IoT-enabled CMS is portrayed with its experimental implementations. The novelty of this approach is to quantify the instantaneous specification of different useful components of any DG unit. The overall efficiency of any machine depends on the individual component efficiencies and the overall efficiency can be improved by enhancing individual efficiencies. Further, the rated efficiency is always defined by the manufacturer and the deviation in rated efficiencies can be estimated by acquiring real-time parameters using IoT-enabled devices. The usefulness of various theoretical models are discussed in the next section which is followed by every DG designer. All these aspects are well discussed in this article and the complete experimental analysis is discussed in the results section of this article.

This article is divided into seven different sections to emphasize the relevance of an IoT-enabled CMS. The performance parameters of the diesel engine and the parameters related to battery charging efficiency are discussed in the second section of the article. Similar to this, the third, fourth, and fifth sections of the article cover the details of the experimental procedure, data collection process, and hypothesized DSS model. The outcomes from the experimental study are presented in the sixth part of this article. The findings of this suggested experimental endeavour are detailed in the article's conclusion section, which is followed by the reference section.

## 2. Diesel generator model

Diesel-electric generators are important assets in any power generation industry and these machines provide guaranteed backup or emergency power whenever needed. The generator efficiency is always calculated to evaluate the efficiency parameter using input and output quantities. The generator efficiency ($\eta_g$) is expressed as in Equation (1).

$$\eta_g = \frac{generatoroutput}{generatorinput} X100 \tag{1}$$

The output power delivered by the generator is alternating electrical power and the energy supplied to the generator as input is mechanical power. In general, the losses in the copper, the core, and the mechanical components prevent the generators from producing all the energy that is fed into devices. After accounting for all generating losses, the net electrical power is what is available at the generator output. Therefore, equation (1) can be redefined as a combination of losses. Similarly, Equation (2) and Equation (3) define the generator efficiency as a function of power supplied to the generator, available output power, and loss components.

$$\eta_g = \frac{generatoroutput}{generatoroutput + generatorlosses} \times 100 \tag{2}$$

$$\eta_g = \frac{generatorinput - generatorlosses}{generatorinput} \times 100 \tag{3}$$

Similarly, the generator efficiency in terms of input power supplied to the generator ($P_{in}$) and output power available at the output of the generator ($P_{out}$) can be expressed as in equation (4). This generator's efficiency is always in terms of percentage.

$$\eta_g = \frac{P_{out}}{P_{in}} \times 100 \tag{4}$$

The expression for generator efficiency as shown in Equation (4) can also be expressed in terms of generator losses as in Equation (5) and Equation (6).

$$\eta_g = \frac{P_{in} - P_{losses}}{P_{in}} \times 100 \tag{5}$$

$$\eta_g = \frac{P_{out}}{P_{out} + P_{losses}} \times 100 \tag{6}$$

Where, $p_{losses}$ is the generator losses due to several internal factors as discussed above.

Moreover, the fuel consumption of any diesel engine is also an important parameter and it is directly related to the efficiency of the engine. The hourly consumption of any DG unit can be represented as a linear model using equation (9) [8]. This hourly consumption of fuel in the DG unit is expressed as Liter/hour.

$$D_t(t) = \alpha_D P_{Dg}(t) + \beta_D P_{Dgr} \tag{7}$$

Where $D_t(t)$ represents the hourly fuel consumption of the DG in Liter/hour; $P_{Dg}(t)$ is the hourly generated power by the DG unit (KW); $P_{Dgr}$ is the rated power of the DG unit (KW); $\alpha_D$ and $\beta_D$ are the coefficients of the fuel consumption curve.

In general, the coefficients of the fuel consumption curve are 0.246 and 0.08145 [9].

In a similar context, the battery is used as a storage buffer and the supplied electric current is passed through the battery according to Peukert's law which can be used to predict the battery discharge by considering the nonlinear properties of the battery as per Equation (8). Also, the nominal battery capacity can be evaluated in Ahr to charge in Coulumb as shown in Equation (9).

$$t_{discharge} = H\left(\frac{C}{IH}\right)^k \tag{8}$$

$$C_{capacity} = 3600 Kp_{nom} K_1(cycle) K_2(temp) \tag{9}$$

Where, $Kp_{nom}$ is the nominal capacity in Ahr, $K_1(cycle)$ is the correction factor for several charge–discharge cycles, $K_2(temp)$ is represented as an ambient temperature correction factor [9].

Similarly, coolant temperature has a large effect on the volumetric efficiency of the diesel engine. Volumetric efficiency is an overall measure of engine effectiveness along with its intake and exhaust system. The volumetric efficiency ($\eta_{vol}$) can be expressed as the engine speed ($\eta$), mass flow rate ($m_a^*$), engine displacement ($V_d$) and density ($\rho_a$) as shown in Equation (10).

$$\eta_{vol} = 2m_a^*/(\rho_a V_d \eta) \tag{10}$$

Waleed et al. (2002) reported an experimental analysis of the coolant temperature of a four-stroke cycle engine. The experimental analysis shows a clear understanding of the effect of coolant temperature on volumetric efficiency. The experimental results show that the volumetric efficiency decreases with the increase in coolant temperature [10]. The increase in coolant temperature also raises the temperature of the cylinder wall, which increases the amount of heat that is transferred from the wall to the comparatively cold charge during the intake stroke, raising the temperature. Additionally, this lowers the density and mass flow rate, which lowers the engine's volumetric efficiency. Additionally, the fuel efficiency and brake thermal efficiency are significantly impacted by the coolant temperature. According to Equation (11), the conversion of fuel energy to brake power by the brake thermal efficiency is well expressed [10].

$$\eta_{bth} = (brakepower)/(fuelmassflowrate \times fuellowheatingvalue) \tag{11}$$

## 3. Experimental setup

To create an experimental unit, a DG (Cummins Diesel Generator Set B3.3 Series, 50–62.5 kVA, 40–50 kWe Prime, 150 Litre) with GPRS connectivity (TraDe GPRS) is installed. Leveraging the RS485 interface of the DG motherboard, external device integration with the main control board in the electric panel is implemented. The RS485 protocol makes it possible to create a multi-hop and low-cost local network via twisted pair cables. In addition, the fuel tank's gasoline level

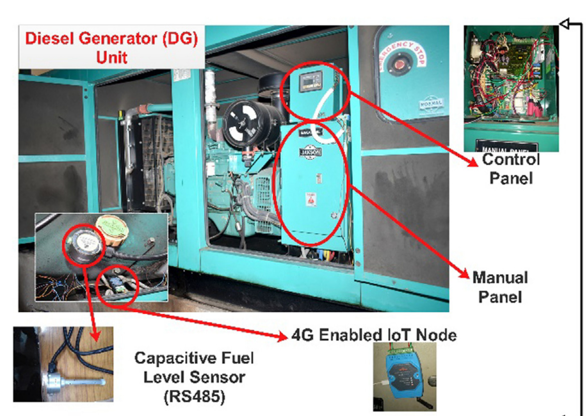


**Fig. 2** Experimental setup of IoT node installed at a Diesel Generator (DG) unit.

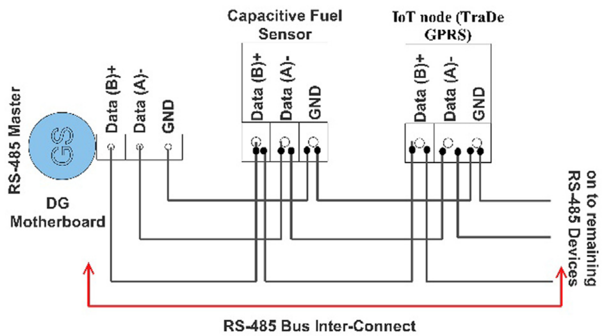


**Fig. 3** RS485 bus interfacing scheme for IoT node and capacitive fuel sensor.

is measured using a capacitive fuel level sensor with an RS485 interface. Utilizing an RS485 communication interface, the TraDe unit and fuel sensor unit are linked to a common communication bus. Fig. 2 shows the IoT node interface and the installation of a capacitive fuel level sensor in the DG unit. Fig. 3 illustrates the RS485 bus interface. Through the GPRS-enabled IoT node, the necessary data are retrieved from the DG control panel and fuel sensor. A cloud framework receives the data and performs in-depth data analytics on it. The findings and analysis part of the article discuss the DG unit's real-time data analysis.

In this experimental work, a DOE (Design of Experiment) approach is used to identify the factors that affect the performance of the system and to optimize the system based on the results of the experiments. Here are some steps that can be taken to conduct a DOE in DG monitoring using IoT:

a) Define the objectives: In this step, the objective is defined. The main objective of this experimental work is to identify and analyze various DG parameters for optimizing efficiency, system reliability, or maintenance costs.
b) Identify the factors: The next step is to identify the factors that may affect the performance of the DG monitoring system. These factors include real-time data collection using IoT nodes and smart fuel sensors for the analysis of diesel consumption.
c) Design the experiment: Based on the identified factors, a set of experiments are carried out. A continuous recording of real-time data was performed and data segregation is done for the next level of analysis.
d) Conduct the experiment: The data collected using the IoT node is analyzed using preprocessing techniques to determine the effect of each factor on the performance metrics. The results section describes the techniques applied to each parameter of the DG set.
e) Analyze the results: In this step, the most important parameters affecting the DG performance are identified and analyzed. The most important parameter of the DG unit which affects maintenance is coolant condition, engine speed, and battery condition.
f) Validate the results: Finally, the results are validated to ensure that the improvements in performance are sustained over time.

## 4. Data sources

The diesel generator is a combination of a diesel engine and an electric generator to generate electric energy. The electric generator is often known as an alternator which converts mechanical energy to electrical energy in the form of alternating current [12]. There are several internal parameters of a diesel generator unit including both mechanical as well as electrical parameters. The main control board of the DG unit collects all this information from different sub-sections and sensors attached to the individual units. In this article, a set of major parameters such as Coolant Temperature (CT), Engine Speed (ES), Fuel Level (FL), Oil Pressure (OP), Battery Voltage (BV), Voltage (V), Current (I) generated and Frequency (F), etc. are acquired from the DG using the GPRS TraDe unit. A small subset of the real-time data recorded in the cloud platform is shown in Table 2.

The dataset shown in Table 2 contains a small set of entire real-time parameters considered in the proposed analysis technique. The DG status implies the running condition of the generator at a particular instance. These data points are helpful to establish individual mathematic models for the estimation of performance parameters such as the Rate of fuel consumption (liter/min), Rate of decrease of coolant temperature (°C/min), Rate of decrease of battery voltage (V/min) and Rate of change of oil pressure (Pa/min). The results and analysis of the proposed predictive maintenance model are discussed in the subsequent section of the article.

**Table 2** Real-time DG parameters acquired using IoT Device.

| Sl. No. | CT (°C) | ES (RPM) | BV (Volt) | FL (Liter) | V (Volt) | I (Amp.) | F (Hz) | P (Pa) | DG Status |
|---|---|---|---|---|---|---|---|---|---|
| 1. | 30 | 1498 | 12.6 | 273.093 | 409 | 2.1 | 46.67 | 51 | ON |
| 2. | 33 | 1503 | 12.5 | 271.44 | 414 | 2.2 | 50 | 51 | ON |
| 3. | 36 | 1499 | 12.5 | 271.411 | 414 | 3.1 | 49.9 | 50.3 | ON |
| 4. | 32 | 0 | 12.8 | 271.411 | 0 | 0 | 0 | 0 | OFF |
| 5. | 32 | 0 | 12.8 | 271.411 | 0 | 0 | 0 | 0 | OFF |
| 6. | 31 | 0 | 12.9 | 271.411 | 0 | 0 | 0 | 0 | OFF |
| 7. | 30 | 1498 | 12.6 | 269.12 | 409 | 3.6 | 49.9 | 51 | ON |
| 8. | 34 | 1503 | 12.5 | 269.062 | 414 | 3.8 | 49.8 | 51 | ON |
| 9. | 39 | 1499 | 12.5 | 269.004 | 414 | 3.7 | 50 | 50.3 | ON |

## 5. Decision Support System (DSS)

The Decision Support System (DSS) is an informational tool that helps decision-makers to apply judgment, make a choice, and follow a certain approach. Large volumes of structured or unstructured data are processed by the information system, which also gathers data that may help with problem-solving and decision-making [13,14]. A DSS can be automated, controlled by people, or be a combination of both. There are five categories of DSS models used in various applications. Fig. 4 shows a list of various types of DSS models used in different real-time applications [15,16].

In this work, a DSS model is established to perform three basic tasks such as estimation of parameter variations, evaluation of critical trends or trips during the running of the DG unit, generation of adequate notifications or alerts, etc. The proposed DSS model is a knowledge-driven system where conditions-based decisions are generated for the performance analysis of the DG unit. A fuzzy logic-based DSS model is implemented and adequate notifications are generated using real-time DG parameters. The detailed operation of the DSS model to perform the above tasks is shown in Fig. 5. The proposed DSS model will help the operation manager to take the necessary steps during the running of the DG unit.

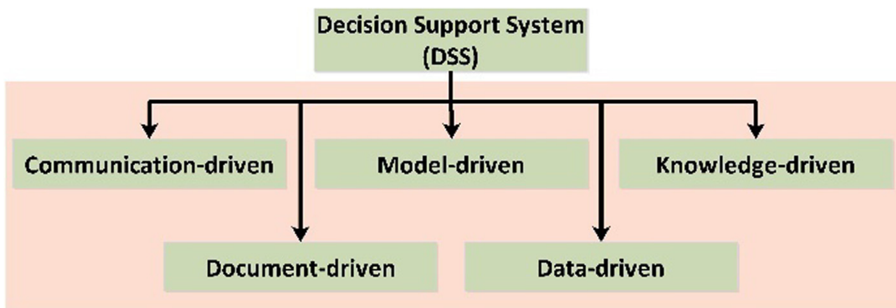


**Fig. 4** Types of Decision Support System (DSS).

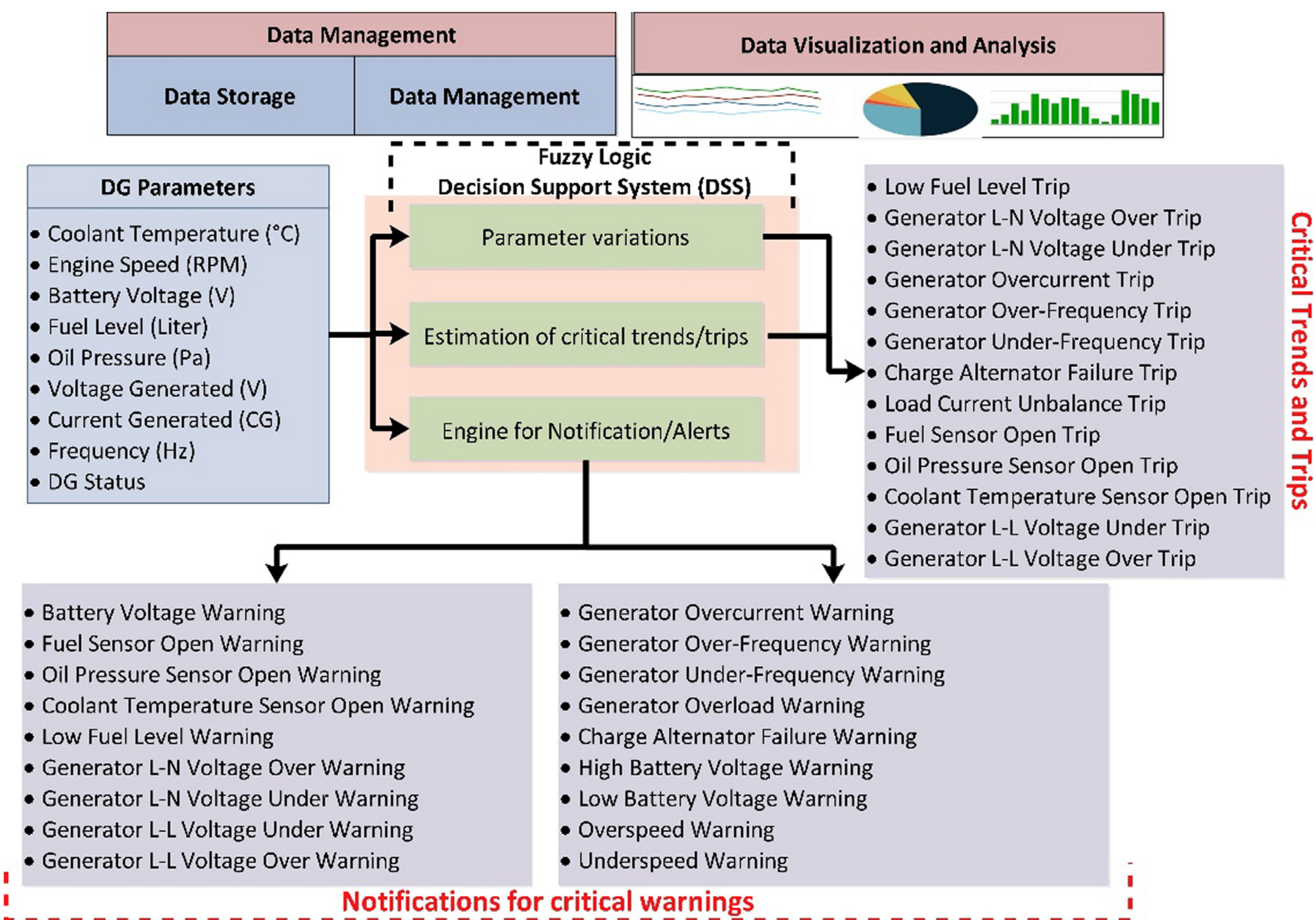


**Fig. 5** Decision Support System (DSS) for data management, critical trends, and warnings.

**Table 3** Parameter specific analysis and estimation techniques.

| Sl. No. | DG Parameters | Short Notation | Analysis & Estimation Method |
|---|---|---|---|
| 1. | Coolant Temperature (°C) | CT | • Variation in CT concerning ES<br>• Notification during alarm scenario<br>• Rate of decrease of CT (°C/min) |
| 2. | Engine Speed (RPM) | ES | • Variation in ES for different DG running state<br>• Notification during critical trends |
| 3. | Battery Voltage (V) | BV | • Variation in BV concerning DG running state<br>• Notification during alarm scenario<br>• Charging/discharge rate of battery |
| 4. | Fuel Level (Liter) | FL | • Variation in FL<br>• Fuel rate of the engine<br>• Notification during critical trends |
| 5. | Oil Pressure (Pa) | OP | • Variation in OP<br>• Over/under pressure notification |
| 6. | Voltage Generated (V) | VG | • Estimation of average voltage generated |
| 7. | Current Generated (CG) | CG | • Estimation of average current generated |
| 8. | Frequency (Hz) | F | • Variation in F |
| 9. | DG Status | DGS | • Alert notification during every DGS |

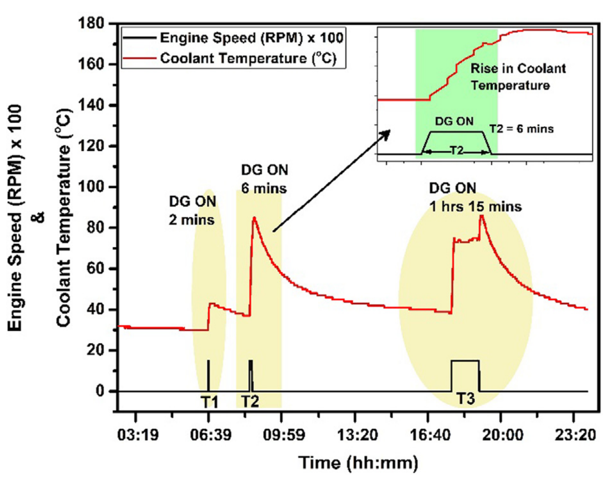


**Fig. 6** Variations in coolant temperature (°C) and engine speed (RPM) for a period of 24Hrs.

## 6. Results analysis

The DG unit's real-time parameters are stored in a cloud framework (datoms.io) where the IoT node performs the communication using the MQTT protocol. The data management and analysis are performed in the cloud framework. A detailed analysis of the DG performance is discussed in this section. Apart from the data management and analysis, the proposed DSS is also presented in the subsequent section of this research article. The detailed list of parameter-specific analysis and estimation techniques incorporated in this proposed research work is enumerated in Table 3.

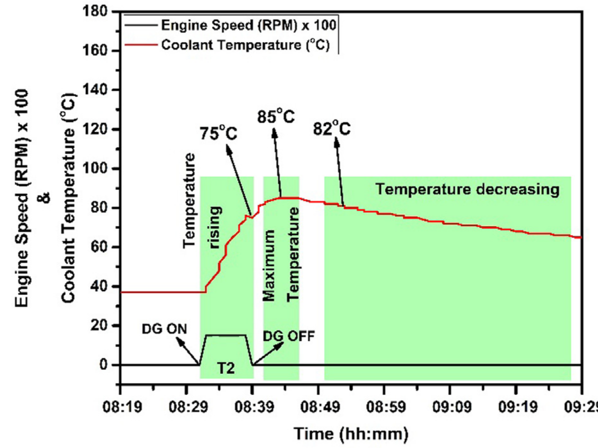


**Fig. 7** Variation of coolant temperature (°C) and engine speed (RPM) for the 2nd DG ON condition.

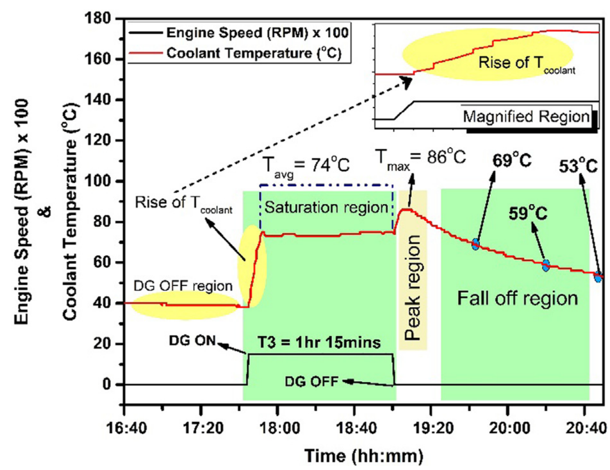


**Fig. 8** Variation of engine speed (RPM) and coolant temperature (°C) during the 3rd DG ON state.

**Table 4** Maximum coolant temperature and rate of decrease.

| Sl. No. | DG ON/OFF condition | Maximum Temperature (°C) | Rate of decrease (°C/min) |
|---|---|---|---|
| 1. | T2 | 85 | −0.2027 |
| 2. | T3 | 86 | −0.2119 |

Note: The above values are evaluated from the DG after filling the new coolant during maintenance.

The coolant temperature (°C) and engine speed (RPM) of the DG unit under test are examined initially. Fig. 6 depicts the changes in coolant temperature and engine speed (RPM)

**Table 5** Maximum coolant temperature and rate of decrease (after 24 months).

| Sl. No. | Case | Maximum Temperature (((C) | Rate of decrease (r) °C/min | Average Rate of decrease (r) °C/min |
|---|---|---|---|---|
| 1 | Case-1 | 89 | −0.1196 | −0.1226 |
| 2 | Case-2 | 91 | −0.1256 | |

throughout 24 h. The DG was turned on three times during the day, and the real-time fluctuations were recorded using the IoT node. The coolant temperature rises following the DG ON condition, as can be shown in Fig. 6. When the coolant temperature exceeds 95 °C, the DG performance may suffer. The coolant temperature should not exceed 90 °C, according to industry standards. As a result, an alarm condition must be created in the IoT dashboard. The user will be notified of the alarm conditions. The proposed DSS is designed to meet the above requirement and performs the alarm operation whenever required.

In a similar context, a theory is also developed about the variations in coolant temperature (°C) and DG engine speed (RPM). The discrepancy between coolant temperature and engine speed may be seen in Fig. 6. The coolant temperature rises to about 85 °C at a steady engine speed of 1500 RPM. As a result, there is no connection between the rise in coolant temperature (°C) and engine speed. Further, the rate of increase of the coolant temperature is required to be analyzed and a mathematical interpretation of the rate of increase is established by observing the characteristics as shown in Fig. 7 and Fig. 8. It is reported that 40% of all diesel engine problems are due to inadequate coolant maintenance. Though its primary purpose is to maintain the engine's internal working temperature, the coolant also transports valuable nitrites to the cylinder sleeve liner's outside [11]. The fluid's inertia causes small vacuum pockets, and vapor bubbles to grow on the liner wall. This is controlled by the vibration of a vertically pounding piston and a spinning crankshaft. The liner vibrates back through the vacuum pockets, which causes the bubbles to collapse under pressure, ripping tiny portions off the liner. Those little bits may eat into a hole if they go undetected and have enough time. Newer coolants have an ingredient that acts as a barrier, preventing the liner wall from cavitating. There are two major types of additives Nitrites/Borate and Mobdylate/Phosphate used to maintain the coolant function in the engine. It is not always possible to measure the condition of the coolant by utilizing laboratory-based chemical tests. Therefore, the rate of decrease in coolant temperature is the most useful parameter to evaluate the coolant conditions in the diesel engine [11,12].

The rate of increase and decrease of coolant temperature is evaluated by establishing a mathematical model between temperature and time duration. The increase in coolant temperature for the 2nd DG ON condition is portrayed in Fig. 7. The highest peak of coolant temperature is observed at 85 (°C) which is within the safety limit. In a similar context, the variations of coolant temperature for a constant engine speed in the 3rd DG ON condition are portrayed in Fig. 8.

The rate of decrease of coolant temperature for two different DG ON/OFF conditions is listed in Table 4. It is found that the rate of decrease of coolant temperature for two different DG ON/OFF conditions remains nearly equal. The coolant was replaced two days before the measurement readings were collected from the DG unit. Therefore, it can be concluded that the rate of decrease listed in Table 4 is the reference value and a suitable condition-based checkpoint can be established to identify the status of coolant oil present inside the DG unit. This condition-based model is established in the proposed DSS model for DG predictive maintenance.

It is obvious that the rate of decrease of coolant temperature always changes after the adequate running interval of the DG unit and this is a good indicator to notify the user about the requirement for coolant oil replacement. Table 5 shows the maximum coolant temperature and rate of decrease reached for two different cases.

It is observed that the maximum coolant temperature is reached at nearly 90 °C for two different cases and the rate of decrease of the coolant temperature is reduced as compared to the rate mentioned in Table 4. Further, a mathematical model is established to predict the rate of decrease in the coolant temperature from the maximum temperature reached during the DG running. Equation (12) shows the established non-linear model from the recorded readings of the DG unit.

$$CT = CT_m e^{-rt} \tag{12}$$

Where CT is the coolant temperature (°C), r is the rate of decrease of coolant temperature (°C/min) and t is the time.

The estimated rate of decrease in coolant temperature and the actual rate of decrease is plotted in Fig. 9. This represents

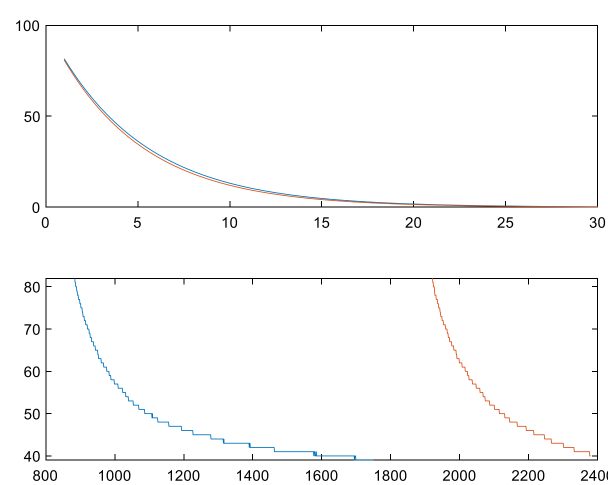


**Fig. 9** Rate of decrease of coolant temperature (°C).

**Table 6** Dimension of the fuel tank.

| Sl. No. | Parameters | Dimension |
|---|---|---|
| 1 | Shape | Rectangular |
| 2 | Width | 1006 mm |
| 3 | Length | 1743 mm |
| 4 | Height | 185 mm |
| 5 | Usable capacity | 300 Liters |

a non-linear model for the rate of decrease of coolant temperature with a maximum temperature ($CT_m$) of 100 °C. It is observed that the decrease of coolant temperature for a particular time interval can easily be estimated using equation (12).

Further, fuel consumption is an important parameter to check the performance of the DG unit. The capacitive fuel transmitter is interfaced with the IoT node using an RS485 bus connection. The fuel level is measured as a percentage of available fuel and finally, it is converted to the actual fuel level inside the tank. The tank capacity is 300 Liters and the complete dimension of the tank is listed in Table 6.

The fuel level presented in Fig. 10 is the calculated fuel level present in the DG unit for 24 Hrs where the DG was switched ON thrice that day. The rate of fuel consumption is also estimated from the real-time fuel data which can be seen in Fig. 11. It can be observed that the rate of fuel consumption (Liters/Hr) is varying from 11 Liters/Hr to 12 Liters/Hr. The average fuel rate estimated using the real-time fuel sensor data is around 12 Liters/Hr. This average rate of fuel consumption lies within the standard limit as per the company specification. Equation (13) represents the rate of fuel consumption of the DG unit. As per the standard limit, a 160 KVA DG unit will have a rated fuel consumption of 16 Liters/Hr for ø load. Further, equation (13) shows a fitted model of the rate of decrease in the fuel level which is established using the real-time fuel data captured using the IoT node.

$$FL = 100e^{-f_r t} \tag{13}$$

Where FL is the fuel level inside the tank (Liters), $f_r$ is the rate of decrease in fuel level (Liters) and t is the time.

As shown in Fig. 10, the fuel level is gradually decreased due to the consumption done by the DG unit. The fuel level in the fuel tank and the rate of fuel consumption is directly related to each other. It is observed that the fuel level is gradually reducing concerning the duration of the DG running. A mathematical model is established to predict the rate of fuel consumption and remaining fuel inside the fuel tank. Similarly, the fuel rate variations for a specified time interval can be studied in Fig. 11 and the time-specific suggestions can be generated from the proposed DSS model. A detailed description of the proposed DSS model is portrayed in the subsequent section of the article.

Similarly, the battery unit in the DG is a crucial part, and its condition directly affects maintenance costs. As a result, DG predictive maintenance includes the monitoring of the battery unit as a key component. Additionally, the IoT node from the DG motherboard interface was used to record the DC voltage level of the DG battery (12 V/90 Ah) unit. Fig. 12 depicts the voltage level of the DG battery unit about the engine speed for 24 h while using various ON/OFF settings. As previously noted, the DG unit was started three times during the day's 24-hour period. However, the battery voltage drops below 13 V and reaches approximately 12 V in every running situation. The drop in battery voltage to a level of 12 V is within the rated specification of the DG battery unit. Therefore, it can be determined that the battery unit is in good condition and meets the requirements from the time of purchase. It also doesn't need any maintenance. The charging time (hours) of a lead-acid battery is related to the battery capacity (mAh) and the amount of charging current (mA) as per equation (14).

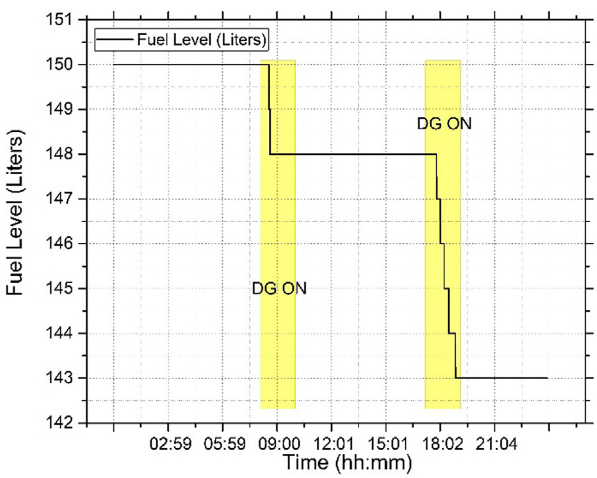


**Fig. 10** Variation of fuel level (Liters) for a period of 24Hrs.

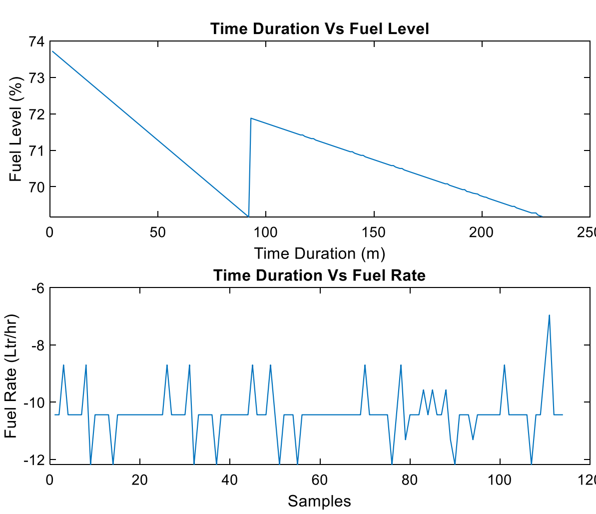


**Fig. 11** Fuel rate (Liters/Hr) variation of the DG unit under test.

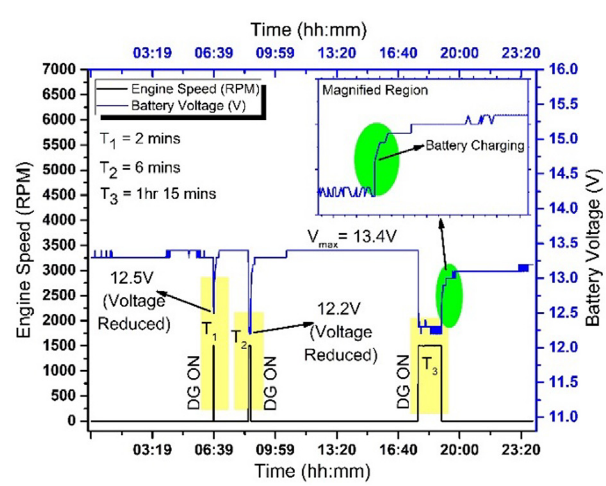


**Fig. 12** DG Battery charging and discharging concerning the engine speed for 24 h.

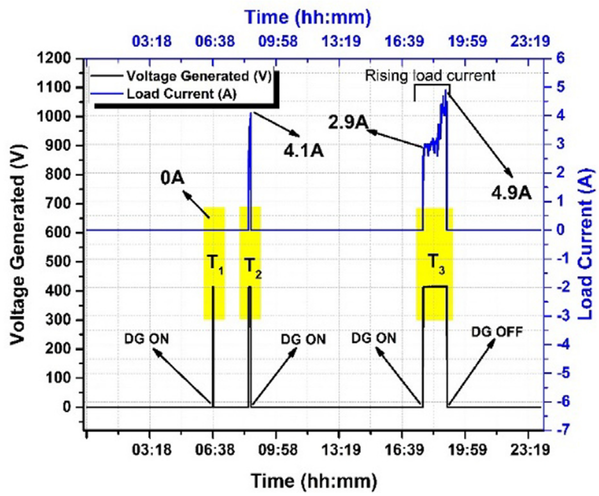


Fig. 13 Voltage and current generation from the DG unit under different ON/OFF conditions.

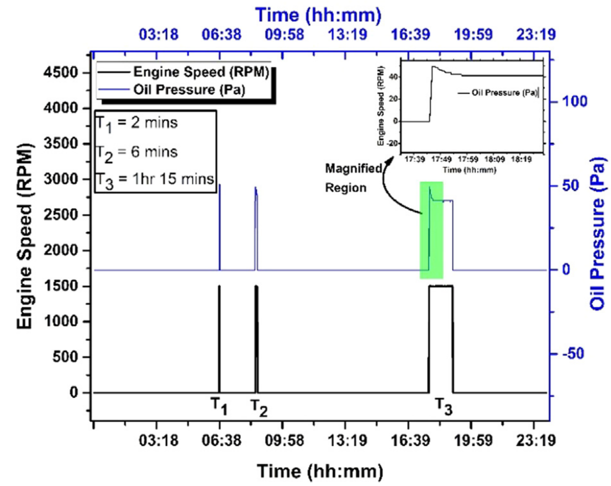


Fig. 14 Variations in oil pressure (PSI) vs the engine speed (RPM).

**Table 7** Generation of current (A) during both loading and unloading conditions.

| Sl. No. | Current (A) | Time (hh: mm) | Running Status of the DG |
|---|---|---|---|
| 1. | 04.12 | 08:38 | Sudden ON and DG was in OFF condition |
| 2. | 02.91 | 18:03 | Initial DG start condition |
| 3. | 04.92 | 18:57 | Full load condition |

$$BatteryCharingTime(h) = \frac{BatteryCapacity(mAh)}{ChargingCurrent(mA)} \tag{14}$$

The rate of charging or discharging of a battery device is referred to as C-rating. A battery's capacity is often rated and labeled at the 1C Rate (1C current), which indicates that a completely charged 90Ah battery should be able to supply 10 Amps for nine hours. The battery unit is continuously monitored and the battery voltage level is recorded. Fig. 12 shows DG Battery charging and discharging characteristics concerning the engine speed for 24 h.

Fig. 13 also shows how the DG generates a voltage (V) and current (A) during loading and unloading occurs. Table 7 indicates the instantaneous peak current (A) produced by the DG in loading and unloading scenarios. According to Table 7, the DG produces a peak current of 4.1A during an abrupt ON at 08:38 h, while the peak current is zero during an OFF condition. Similarly, the peak current at starting is around 3.0 A and gradually increases to 4.9 A under maximum loading conditions. As a result, it may be stated that when the DG starts, the current saturates after a specific time. It can also be postulated that the coolant temperature has a good link with the DG current generation both at the loading and unloading conditions. A similar pattern can be observed in Fig. 6 where the coolant temperature follows a similar pattern as the current generated from the DG unit. At maximum loading and current generation, the coolant temperature reaches its maximum. At each operating period, the voltage generated by the DG unit stays constant. As a result, it has no connection to the present generation or coolant temperature. The engine speed, on the other hand, is proportional to the voltage created by the DG when it is operating.

Additionally, the oil pressure is a crucial metric to consider while evaluating the condition of a DG unit. When the flow of fuel is restricted, the oil pressure rises. These issues arise because of a barrier in the fuel flow, component failure, or an issue with the oil itself. Under normal circumstances, the usual oil pressure ranges from 25 PSI to 65 PSI. The oil pressure fluctuations are obtained utilizing the IoT device from the DG control panel. Fig. 14 depicts the oil pressure (PSI) with engine speed (RPM) for a 24-hour recording. Peak oil pressure is around 50 PSI, which is much below the maximum permissible limit. During the DG's startup phase, the oil pressure maintains at 50 PSI, then drops to 42.5 PSI after a while. This is a favorable quality for the DG because the oil flow is unrestricted in the flow channel. As a result, the DG under test does not require any oil pressure maintenance.

The proposed predictive maintenance scheme for remote DG monitoring and analysis is well understood by acquiring real-time DG parameters using IoT architecture.

Various real-time data were captured and used for further analysis to understand the in-depth operational efficiency of the DG unit. The equations discussed in the second section of this article are very much useful to get insight information about the machine. The usefulness of equation (1) to equation (9) can be understood by correlating real-time DG parameters collected using IoT-based architecture. A hypothetical analysis is presented below to portray the usefulness of these mathematical equations.

a) The generator efficiency ($\eta_g$) is expressed in different forms as shown in Equation (1), Equation (2), Equation (3), Equation (4), Equation (5), and Equation (6). To quantify the parameter $\eta_g$, suitable independent parameters like input power, output power, and loss component of the power are required. Moreover, the proposed IoT-based architecture measures the power delivered to the load by acquiring real-time data from the DG motherboard. However, the input power of any DG unit remains the same as the output power for the ideal scenario with no loss component in it. This condition is not always feasible as the power loss component is an inherent quantity in any distribution system. By introducing and compressing air and fuel into the engine separately, diesel generators can achieve greater power output with less fuel consumption. When operating within its designed optimum range, a typical diesel generator can attain an efficiency level of around 40 percent, which can go up to 80 percent of its total load capacity. As the rated efficiency varies within a range, the efficiency equations mentioned above can be used to calculate the instantaneous efficiency by using power quantities from the DG motherboard.

b) Similarly, fuel consumption is another important factor that needs to be analyzed in any DG unit. Equation (7) shows the hourly fuel consumption of the DG unit in Liter/hour. It can be observed that the coefficients of the fuel consumption curve ($\alpha_D$ and $\beta_D$) and the rated power of the DG unit are constant. Equation (7) is very much useful to estimate the hourly fuel consumption using an empirical model and correlating with the data obtained by the IoT based data analytics architecture. The IoT node is also collecting the fuel information from the DG motherboard and calculating the hourly fuel consumption using the fuel sensor data. However, the Equation (7) shows an empirical model based on the power generated by the DG unit which is related to the fuel consumption. This experimental work is carried out by using the commercial grade IoT node (TraDe node) which has it's own dashboard. For better user experience, the dashboard contains a comparative view on the empirical model as well as the instantaneous fuel consumption collected from the DG motherboard and the fuel sensor unit.

c) Further, battery capacity must be monitored continuously in any DG unit. A similar approach is carried out to predict the battery discharge using an empirical non-linear model and estimate the nominal battery capacity in Ahr-Coulumb. As the nominal battery capacity is also an important parameter in any DG unit, a correlation with the empirical model must be established and this is done by collecting real-time battery status along with some important aspects such as battery charging/discharging rate estimated from the real-time data collected from IoT node.

Subsequently, the implementation of a DSS model is discussed with in-depth concepts and corresponding results are portrayed for analysis. The DSS model used in this research work is developed using a fuzzy logic-based approach where comparative decisions are taken using equipment-specific rated specifications from the manufacturer. A set of rated specifications of 50–62.5 kVA diesel generators are incorporated in the conditions-based DSS model as listed in Table 8. The major DG parameters considered in this work are compared with the rated threshold levels from the manufacturer. Real-time data recording and processing can also be performed using a distributed computing environment like Big Data-enabled platforms [13,14]. This will help the users to have a common platform for data storage, management, analytics, and decision-making [15,16]. Generating adequate notifications and giving alerts to the user is the most important aspect which needs to be considered in any CMS. The corresponding notifications or alerts generated using the DSS model are also listed in Table 8. The decision logic of the proposed DSS model is established using a fuzzy logic-based approach and adequate

**Table 8** Threshold level of various DG parameters and notifications.

| Sl. No. | Real-time DG parameters | Notation | Threshold value | Notifications |
|---|---|---|---|---|
| 1 | Coolant Temperature (°C) | CT | CT ≥ 90 °C | • Variation in CT concerning ES<br>• Notification during alarm scenario<br>• Rate of decrease of CT (°C/min) |
| 2 | Engine Speed (RPM) | ES | ES ≥ 1500 RPM | • Variation in ES for different DG running state<br>• Notification during critical trends |
| 3 | Battery Voltage (V) | BV | 12 V | • Variation in BV concerning DG running state<br>• Notification during alarm scenario<br>• Charging/discharge rate of battery |
| 4 | Fuel Level (Liter) | FL | 30% of the tank capacity (300 Liters), i.e. 90 Liters | • Variation in FL<br>• Fuel rate of the engine<br>• Notification during critical trends |
| 5 | Oil Pressure (Pa) | OP | 10–15 psi per 1000 RPM and 55–65 psi for full speed (1500 RPM) | • Variation in OP<br>• Over/under pressure notification |
| 6 | Voltage Generated (V) | VG | 400 V for 50–62.5 kVA diesel generator | Estimation of average voltage generated |
| 7 | Current Generated (CG) | CG | 4 A (Average current generated) | Estimation of average current generated |
| 8 | Frequency (Hz) | F | 48 Hz to 50 Hz | Variation in Frequency (F) |
| 9 | DG Status | DSG | On-board status (Any error status from the main board) | Alert notification during every DGS |

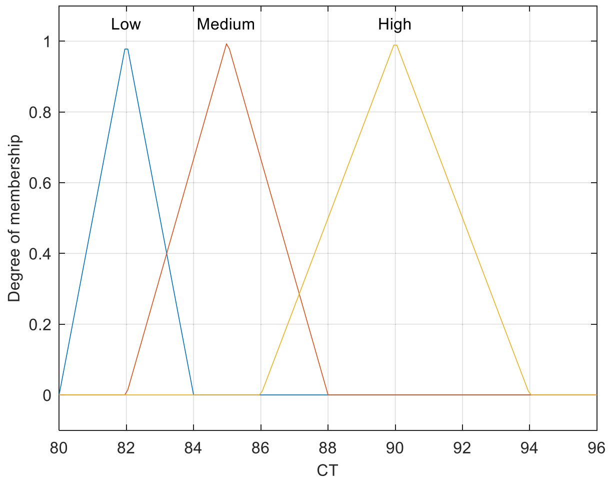


**Fig. 15** Fuzzy logic input membership function for CT.

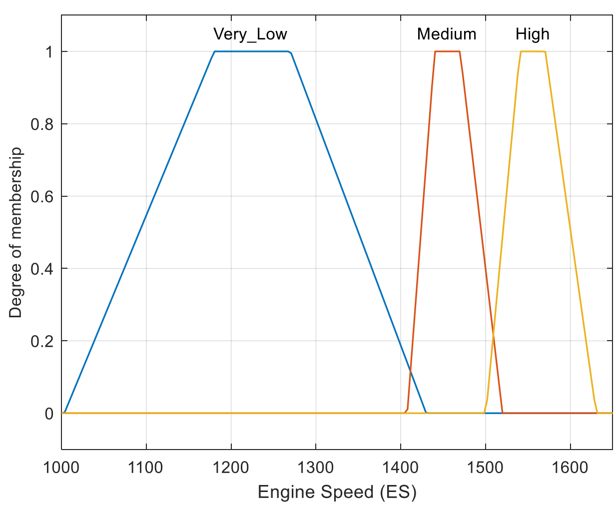


**Fig. 16** Fuzzy logic input membership function for ES.

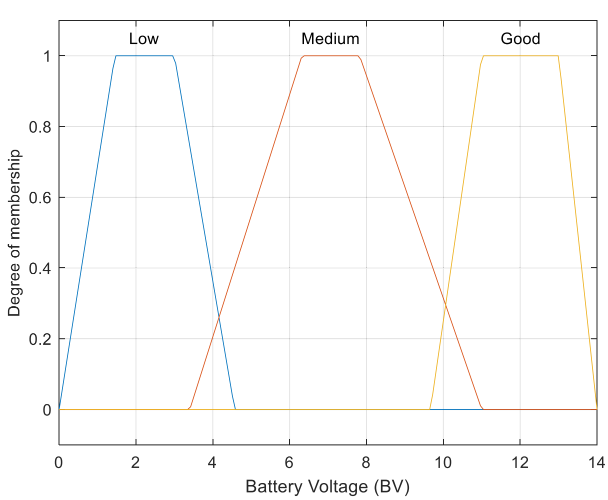


**Fig. 17** Fuzzy logic input membership function for BV.

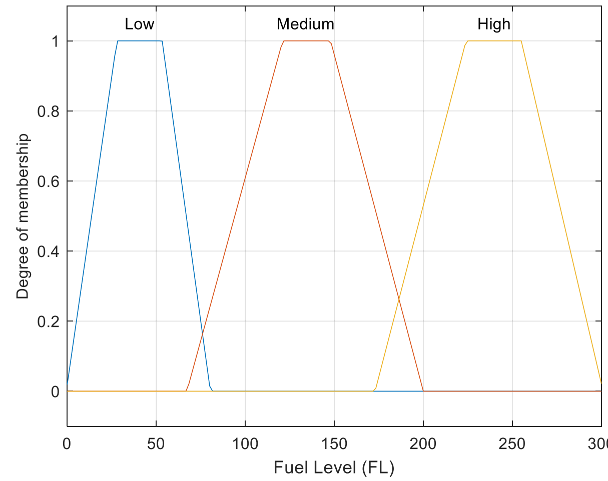


**Fig. 18** Fuzzy logic input membership function for FL.

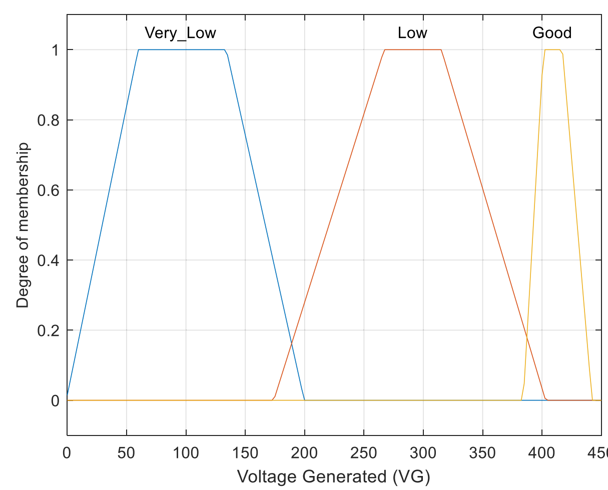


**Fig. 19** Fuzzy logic input membership function for VG.

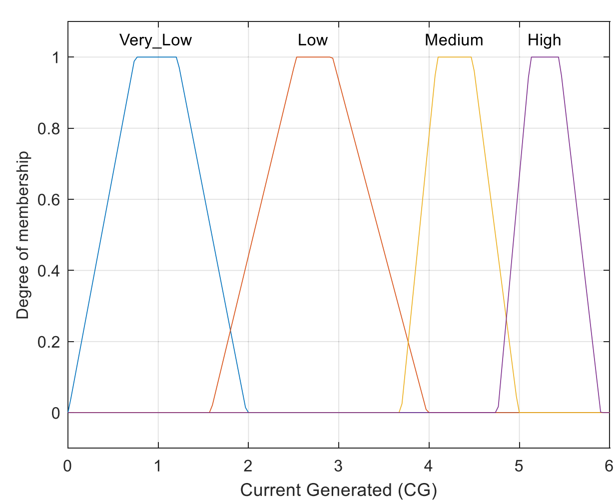


**Fig. 20** Fuzzy logic input membership function for CG.

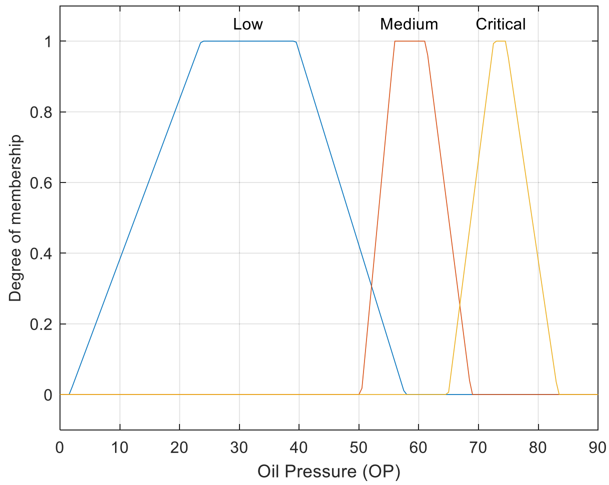


**Fig. 21** Fuzzy logic input membership function for OP.

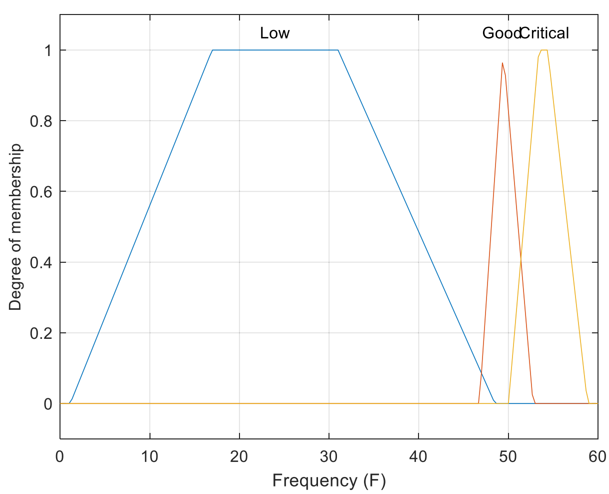


**Fig. 22** Fuzzy logic input membership function for F.

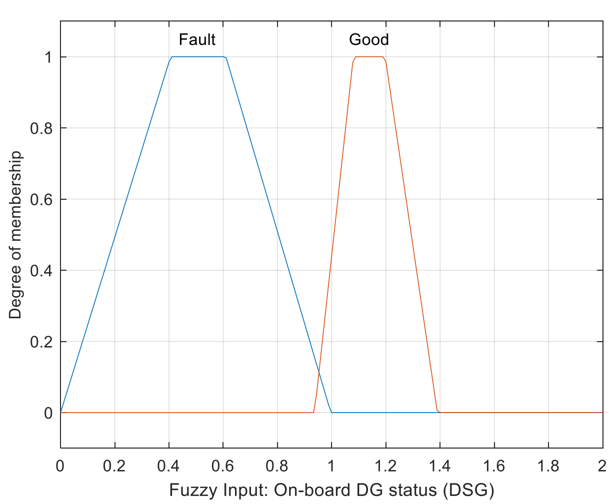


**Fig. 23** Fuzzy logic input membership function for DSG.

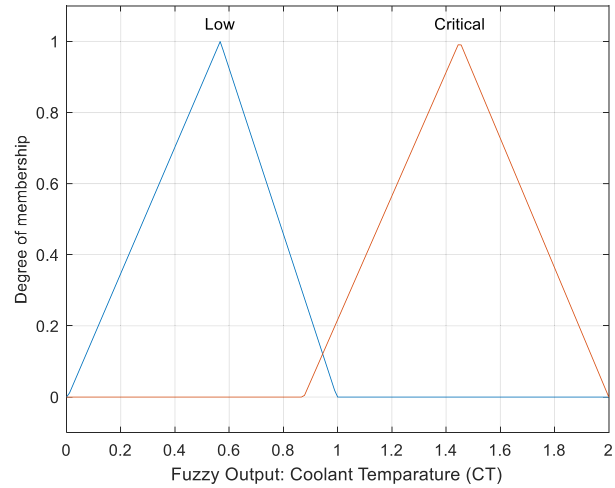


**Fig. 24** Fuzzy logic output membership function for CT.

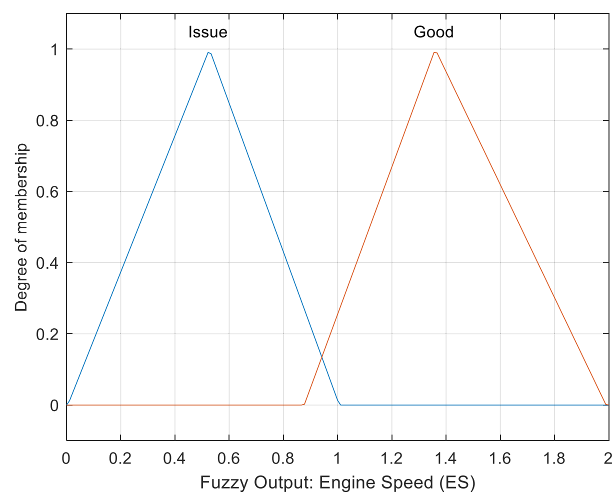


**Fig. 25** Fuzzy logic output membership function for ES.

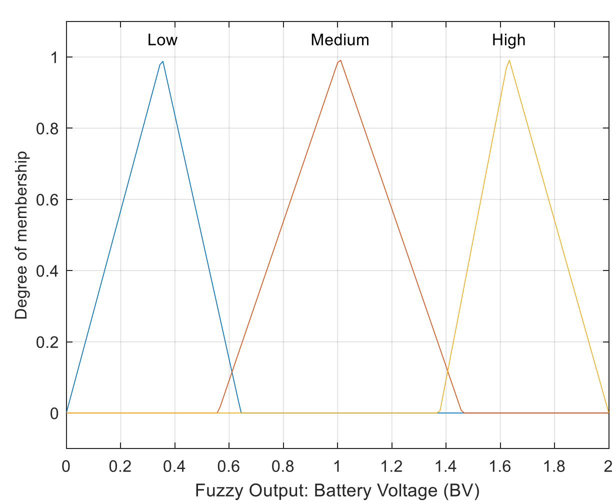


**Fig. 26** Fuzzy logic output membership function for BV.

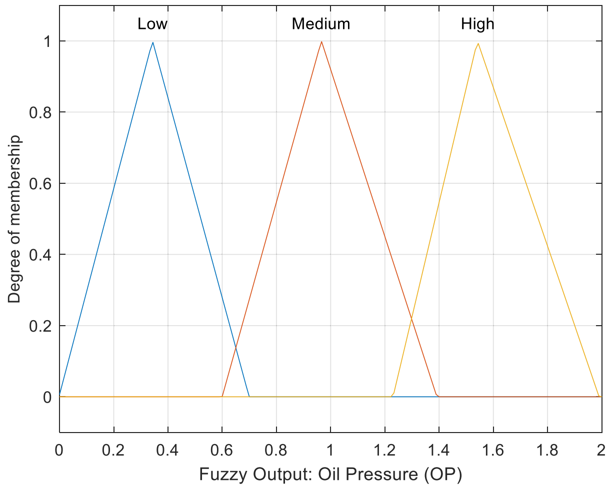


**Fig. 27** Fuzzy logic output membership function for OP.

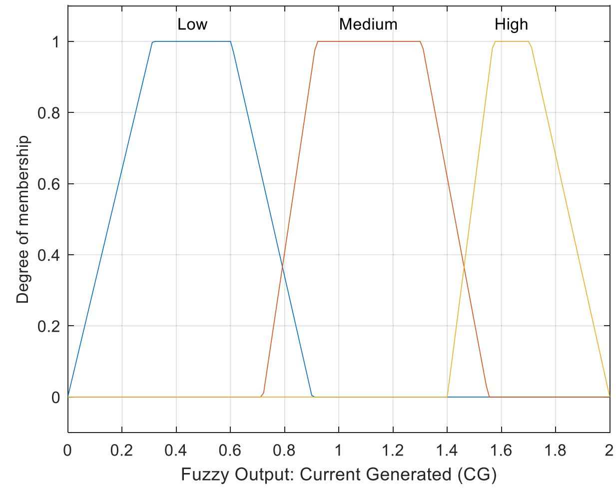


**Fig. 30** Fuzzy logic output membership function for CG.

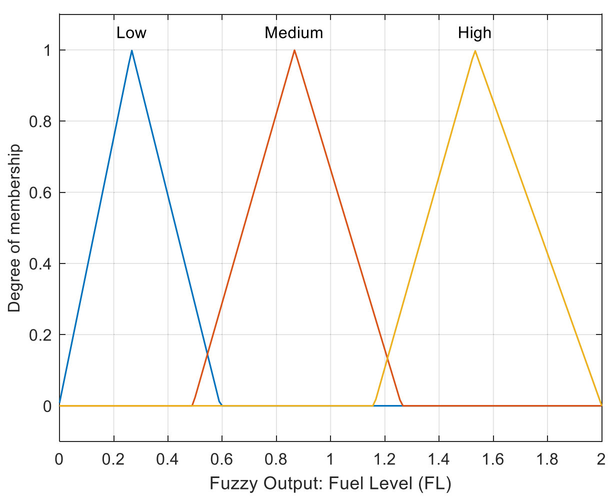


**Fig. 28** Fuzzy logic output membership function for FL.

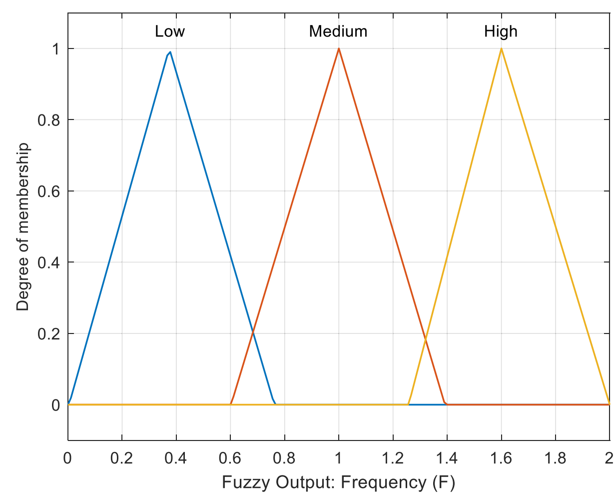


**Fig. 31** Fuzzy logic output membership function for F.

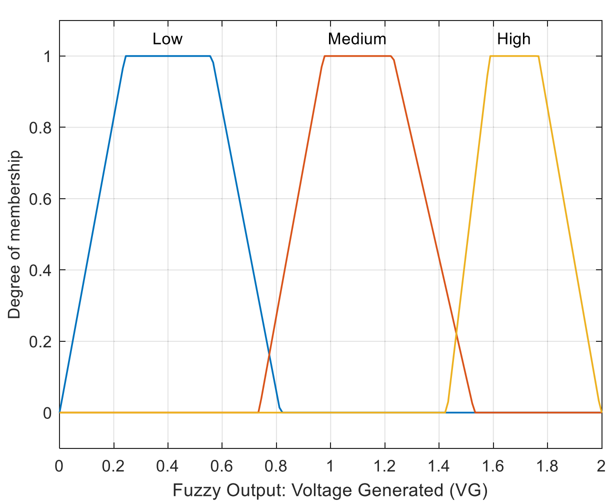


**Fig. 29** Fuzzy logic output membership function for VG.

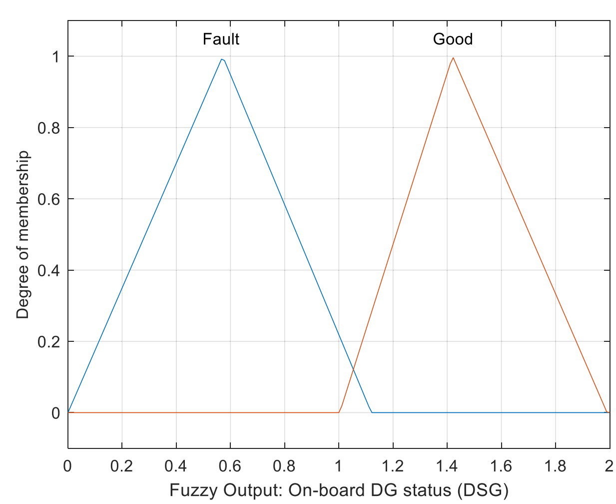


**Fig. 32** Fuzzy logic output membership function for DSG.

condition-based notifications are generated to identify machine issues. Fig. 15, Fig. 16, Fig. 17, Fig. 18, Fig. 19, Fig. 20, Fig. 21, Fig. 22, and Fig. 23 depict the input membership functions of the fuzzy logic model. Further, Fig. 24, Fig. 25, Fig. 26, Fig. 27, Fig. 28, Fig. 29, Fig. 30, Fig. 31, and Fig. 32 depict the output membership functions of the proposed fuzzy-based decision model similarly. Table 9 contains a list of the setup settings for the input and output fuzzy membership functions.

By combining a set of language rules derived from DG operational circumstances, the Mamdani fuzzy inference system generates appropriate notifications. Each fuzzy rule in the Mamdani fuzzy inference system produces a fuzzy set as its output. This Mamdani-based fuzzy inference system was chosen because the fuzzy rule base is more comprehensible and intuitive. Additionally, it works best for expert system applications where the fuzzy rules are generated from subject-matter expertise held by humans.

The output of each rule is a fuzzy set created using the output membership function and implication approach of the Fuzzy Inference System (FIS). These output fuzzy sets are combined into a single fuzzy set via the FIS's aggregation process. The final crisp output value is then calculated from the combined output fuzzy set by defuzzifying it using one of the techniques described in Defuzzification Methods. Depending on the range of the associated parameter, triangular and trapezoidal functions are used to produce the individual membership functions.

**Table 9** Fuzzy membership functions with a range.

| Sl. No. | Real-time DG parameters | Notation | Function Type | Membership Range | Membership Values |
|---|---|---|---|---|---|
| 1. | Coolant Temperature (°C) | CT | Triangular | Low | [80 82 84] |
| | | | | Medium | [82 85 88] |
| | | | | High | [86 90 94] |
| 2. | Engine Speed (RPM) | ES | Trapezoidal | Very Low | [1003 1180 1270 1430] |
| | | | | Medium | [1408 1440 1470 1520] |
| | | | | High | [1501 1541 1571 1631] |
| 3. | Battery Voltage (V) | BV | Trapezoidal | Low | [0 1.452 3 4.57] |
| | | | | Medium | [3.4 6.32 7.82 11] |
| | | | | Good | [9.666 11 13 14] |
| 4. | Fuel Level (Liter) | FL | Trapezoidal | Low | [-0.549 27.9 53.32 80.4] |
| | | | | Medium | [67.2 121 147.9 200] |
| | | | | High | [172.9 224 255 301] |
| 5. | Oil Pressure (Pa) | OP | Trapezoidal | Low | [1.54 23.6 39.45 57.7] |
| | | | | Medium | [50.4 55.96 61.2 68.8] |
| | | | | Critical | [64.95 72.55 74.59 83.31] |
| 6. | Voltage Generated (VG) | VG | Trapezoidal | Very Low | [-0.874 59.8 134 199.7] |
| | | | | Low | [174 267 315.2 403] |
| | | | | Good | [384.2 401.3 417.2 442.2] |
| 7. | Current Generated (CG) | CG | Trapezoidal | Very Low | [0.00289 0.742 1.21 1.978] |
| | | | | Low | [1.58 2.53 2.93 3.976] |
| | | | | Medium | [3.69 4.087 4.48 4.99] |
| | | | | High | [4.761 5.121 5.443 5.901] |
| 8. | Frequency (Hz) | F | Trapezoidal | Low | [1.13 16.95 31 48.5] |
| | | | | Good | [46.77 49.43 52.75] |
| | | | | Critical | [50.01 53.4 54.38 58.83] |
| 9. | DG Status | DSG | Trapezoidal | Fault | [0 0.406 0.6099 0.997] |
| | | | | Good | [0.937 1.08 1.197 1.39] |

**Table 10** Symbolic representations of the fuzzy rules.

| | |
|---|---|
| '1 3 3 0 0 3 0 2 2, 1 0 0 0 0 0 0 0 0 (1): 1 ' | '0 0 0 3 0 0 0 0 2, 0 0 0 3 0 0 0 0 2 (1): 1 ' |
| '2 3 3 0 0 3 0 2 2, 1 0 0 0 0 0 0 0 0 (1): 1 ' | '0 3 0 0 1 0 0 0 2, 0 0 0 0 1 0 0 0 2 (1): 1 ' |
| '3 3 3 0 0 3 0 2 2, 2 0 0 0 0 0 0 0 0 (1): 1 ' | '0 3 0 0 2 0 0 0 2, 0 0 0 0 2 0 0 0 2 (1): 1 ' |
| '0 3 3 0 0 3 0 2 2, 2 2 0 0 0 0 0 0 0 (1): 1 ' | '0 3 0 0 3 0 0 0 2, 0 0 0 0 3 0 0 0 2 (1): 1 ' |
| '0 1 3 0 0 3 0 2 2, 2 1 0 0 0 0 0 0 0 (1): 1 ' | '0 3 0 0 0 3 3 0 2, 0 0 0 0 3 2 0 0 2 (1): 1 ' |
| '0 2 3 0 0 3 0 2 2, 0 1 0 0 0 0 0 0 0 (1): 1 ' | '0 3 0 0 0 2 3 0 2, 0 0 0 0 3 1 0 0 2 (1): 1 ' |
| '0 0 3 0 0 0 0 0 2, 0 0 3 0 0 0 0 0 2 (1): 1 ' | '0 3 0 0 0 1 3 0 2, 0 0 0 0 3 1 0 0 2 (1): 1 ' |
| '0 0 2 0 0 0 0 0 2, 0 0 2 0 0 0 0 0 2 (1): 1 ' | '0 3 0 0 0 3 3 0 2, 0 0 0 0 0 2 2 0 2 (1): 1 ' |
| '0 0 1 0 0 0 0 0 2, 0 0 1 0 0 0 0 0 2 (1): 1 ' | '0 3 0 0 0 3 3 2 2, 0 0 0 0 0 0 0 2 2 (1): 1 ' |
| '0 0 0 1 0 0 0 0 2, 0 0 0 1 0 0 0 0 2 (1): 1 ' | '0 3 0 0 0 3 3 0 1, 0 0 0 0 0 0 0 0 1 (1): 1 ' |
| '0 0 0 2 0 0 0 0 2, 0 0 0 2 0 0 0 0 2 (1): 1 ' | '0 3 0 0 0 3 3 2 2, 0 0 0 0 0 0 0 0 2 (1): 1 ' |

**Table 11** Test inputs and notifications generated from the Fuzzy DSS model.

| Inputs to the Fuzzy DSS model [CT, ES, BV, FL, OP, VG, CG, F, DSG] | Outputs of the Fuzzy DSS model [CT, ES, BV, FL, OP, VG, CG, F, DSG] | Notifications Generated |
|---|---|---|
| [87, 1510, 13, 121, 96, 400, 4.2, 50, 1.1] | [1.45, 0, 0, 0, 0, 0, 0, 0, 0] | Coolant Temperature is Critical |
| [60, 1541, 13, 121, 96, 400, 4.2, 50, 1.1] | [1, 0.527, 1, 1, 1, 1, 1, 1, 1] | Engine Speed is Critical |
| [60, 1510, 13.2, 119, 74.59, 402, 4.1, 50, 1.1] | [1, 1, 1, 1, 1.9, 1, 1, 1, 1] | Oil Pressure is Critical |

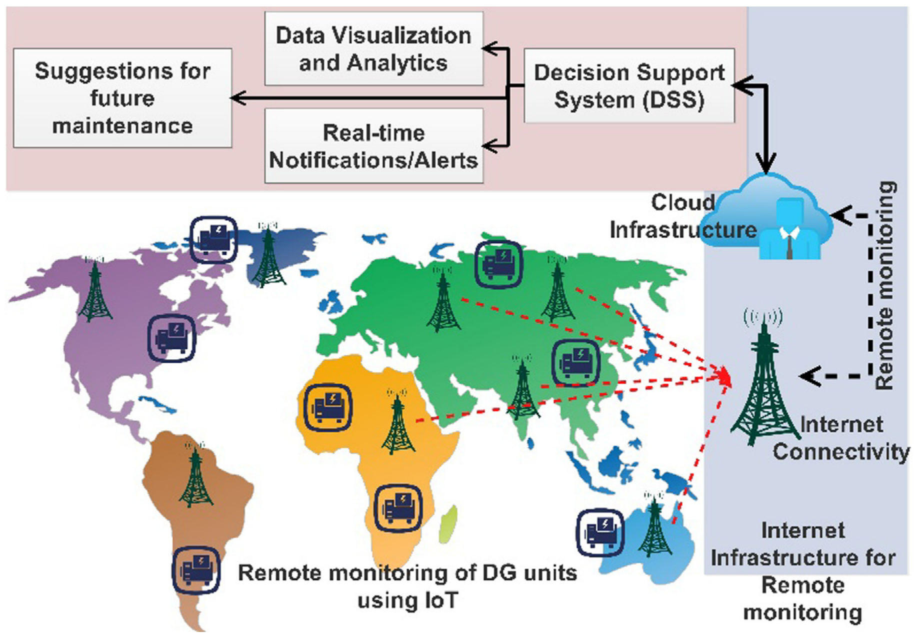


**Fig. 33** Scalable architecture of the remote DG monitoring using IoT.

The proposed DSS is tested with different standard inputs to the fuzzy model and desired notifications are generated. The symbolic representations of the fuzzy rules are listed in Table 10. The test inputs and notifications generated from the fuzzy DSS model are listed in Table 11. These test notifications will be helpful for the maintenance engineers during the operation of the DG unit.

A similar approach to remote monitoring of DG units can be adapted on a large scale and a wide variety of such machines can be monitored using a common cloud framework. A scalable architecture of the remote DG monitoring using IoT-enabled technologies is depicted in Fig. 33. Important decisions and remote analysis based on real-time parameters can also be performed by utilizing internet-connected machines on a large scale.

## 7. Conclusion

Machine predictive maintenance tools like CMS facilitated by the Internet of Things (IoT) are a difficult area in the present technical advancements associated with Industry 4.0. The proposed research work showcases the utilization of smart decision-making methodology by incorporating real-time machine data using IoT-enabled devices. Experimental implementations, analysis, and decision-making are used to emphasize the proposed research works described in this article. The most significant DG unit metrics were successfully recorded, and the findings were analyzed. The significance of this research effort stems from the capacity to use IoT-enabled technologies to monitor critical DG characteristics such as engine speed, voltage, the current generated, power factor, coolant, fuel, and battery status, among others. The consequences of irregularities in these parameters are indicated, as well as their safe operating range. Some of the major analyses performed to monitor the DG performance are maximum CT, rate of decrease of CT, the instantaneous rate of fuel consumption, rate of variation of fuel consumption during DG running condition, battery charging rate, etc. This will assist users in making appropriate maintenance decisions for the discovery of new information. Finally, a Fuzzy-DSS model is implemented and tested to generate appropriate alerts/notifications for the user. The configuration settings of the Fuzzy logic model as well as the rule base are well documented in this article.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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