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A LiDAR and IoT Integrated Approach for Intelligent Monitoring of Lubricant Liquid Levels: A Lab Scale Study on Petronas Products

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ABSTRACT

This study investigated the development of an Internet of Things (IoT) based lubricant level monitoring system. Monitoring lubricant levels is essential for maintaining the reliability, efficiency, and longevity of industrial machinery. Conventional lubricant level inspection methods are often manual, time-consuming, and unsuitable for continuous monitoring. To address this limitation, this study develops the system integrates a Light Detection and Ranging (LiDAR) LiDAR sensors and IoT technology using an ESP32 microcontroller for real-time lubricant level measurement and remote data monitoring. The proposed system continuously measures lubricant levels and transmits the collected data through an IoT platform, enabling users to access monitoring information remotely. Laboratory tests were carried out using two Petronas products. They are base oil, known as ETRO 6+ and product, termed as Syntium 800 10W-40. Five measurement tests were performed for each lubricant to evaluate the stability and consistency of the monitoring system. The collected data were analysed using statistical parameters, including mean and standard deviation. The test results showed stable performance with standard deviations of 10.6 mm and 9.27 mm, respectively. The proposed system offers a practical solution for predictive maintenance applications. Future work should focus on evaluating the system under actual industrial environments involving vibration, temperature fluctuations, and other operational disturbances to further validate its industrial applicability and long term reliability. These findings indicate that the developed LiDAR-IoT monitoring system is capable of providing accurate and continuous lubricant level monitoring under controlled laboratory conditions.

Keywords: Industrial automation, IoT, LiDAR sensor, lubricant level monitoring, real-time data

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INTRODUCTION

Advances in Industrial Revolution 4.0 technology have created technology such as sensors, from the ordinary to the best, such as the integration of light detection sensors (LiDAR). A LiDAR is often used in navigation mapping because of its precise, contactless nature, which is suitable for measuring lubricating oil levels (Epelle & Gerogiorgis, 2020; Manish et al., 2022). LiDAR sensor intelligence has been integrated with a robust IoT framework to create a transformative approach towards real-time measurement of the residual lubricant level in a tank (Tanati et al., 2023). In the case of this study, the LiDAR sensor system is to measure the fluid level in the tank and send the data through a microcontroller (ESP32) and upload it to a cloud platform via Wi-Fi or MQTT.

The setup is enabled with real-time monitoring and alert systems to prevent machine failure. Continuous data collection, remote or close observation and prompt decision making allow for the concentration of sensors in high resolution with any proper digital connection (Xin et al., 2024), which improves operational performance and reduces reliance on unscheduled maintenance. The lubricating systems have self-adjusting control and optimisation based on real-time operating conditions, which have been significantly enhanced by recent developments in sensor attenuation, wireless communication protocols, and artificial intelligence (AI) (Liu et al., 2024).

Traditional monitoring methods usually rely on manual inspections or simple sensors such as float-based systems that are often exposed to inaccuracies, delayed responses, and human error (Sparham et al., 2014). These traditional methods lack the swiftness in detecting any abnormal situations early, which leads to system production shutdown and any unnecessary problems. Most industries still practice manual or basic monitoring methods due to limitations in awareness and the use of technology. This method will usually lead to issues such as unexpected shortage of lubricant stock, resulting in shutdowns in the production line (Zhang et al., 2025). With the advent of industrial technology, the industry is beginning to realise the need to introduce smart technology to reduce risks, as well as increase efficiency and optimise resource utilisation (Benziane et al., 2025).

As a result, improvement with the use of intelligent monitoring is a critical step towards better predictive maintenance and operational efficiency. Failure to maintain lubrication levels is often associated with a lack of routine maintenance, especially in machinery and motor equipment (Chen et al., 2020). Therefore, continuous monitoring of lubricant levels is a must to ensure operational reliability and extend the service life of equipment (Hanaysha, 2016; Quinchia et al., 2014).

The transformation of smart monitoring technology has revolutionised the way industrial systems manage operations in production, in addition to maintenance and sustainability (Varalakshmi et al., 2025). This is because one of the branches of this transformation is the Industry Internet of Things (IIoT), where industry players are shifting from a reactive maintenance approach to predictive maintenance and automation methods.

In this study, the LiDAR and IoT framework is a good system that can be used in the oil and gas industries (demonstrates significant potential for application in the oil and gas industry). Radar, Lidar, and Photocells-based method systems typically involve higher initial costs due to the sophisticated technology employed, but they offer real-time and accurate data, justifying their investment (Lo Castro et al., 2024). The study focuses on the development and validation of LiDAR-IoT integrated monitoring systems for lubricant level measurement (the study focuses on the development and validation of an integrated LiDAR-IoT monitoring system). An intelligent system with a LiDAR sensor for level monitoring, which is contactless, can significantly improve the performance of the lubricating system, especially in ensuring smooth and more efficient mechanical operation (The intelligent contactless monitoring system performance by ensuring smoother and more efficient mechanical operations). The study makes direct comparisons with other sensing technologies (Direct comparisons with other sensing technologies), such as ultrasonic, capacitive, and float-based systems (float-based systems), which are beyond the scope of the study.

The literature review highlights several key factors that influence its design and effectiveness. These factors include operational efficiency, security and reliability, cost reduction, scalability, and sustainability. Hence, this study establishes a performance standard for next-generation smart lubrication management systems while addressing the gaps in the current systems (Wilińska et al., 2025). A comprehensive benchmarking analysis of conventional sensing technologies is recommended as future research to further evaluate the relative performance, accuracy and practicality of the proposed system.

The research gap and novelty have been strengthened by highlighting those existing studies on liquid level monitoring that focus on conventional sensing technologies, whereas the integration of LiDAR with IoT for lubricant level monitoring remains underexplored. Furthermore, limited studies have investigated the feasibility of LiDAR-based monitoring specifically for Petronas lubricant products, incorporating real-time cloud-based visualisation and remote monitoring capabilities. Internet of Things (IoT) technology has emerged as a promising solution for addressing these challenges (Ahlawat & Rana, 2021; Boddu et al., 2023).

Efficiency in operation is defined as the ability of the system to convert the input into a desired output with minimal loss. In lubrication management, the efficiency of the system depends on the accuracy of the system configuration, timely feedback and continuous monitoring to avoid mechanical failure. In traditional inspection methods that rely heavily on manual reading, which lack consistency and are prone to human error, this often leads to delayed maintenance and the incurrence of huge losses due to a stop in production.

Therefore, the novelty of this work lies not only in overcoming the limitations associated with conventional methods but also in the development and validation of an integrated LiDAR via an IoT framework for intelligent lubricant level monitoring applications, which remains insufficiently explored in existing literature.

It mirrors the real-world counterpart and allows simulation, monitoring, and analysis. Combining machine vision with IoT sensor data, cloud storage, and machine learning algorithms can proactively enhance the accuracy of measurement prediction, machining responses and schedule maintenance (Kaur et al., 2020; Liu et al., 2022).

LiDAR sensors provide superior spatial stability, response time and non-contact measurement capabilities. The LiDAR is resistant to surface pollution or turbulence, making it a good tool for continuous and stable monitoring. However, many existing studies focus on environmental or hydrological applications, such as flood monitoring and terrain mapping, rather than lubrication systems that differ significantly in properties such as viscosity and optics (Mast et al., 2024). Therefore, a more reliable monitoring system is the LiDAR and IoT that help to improve efficiency in production operations and the overall supply chain.

Safety and reliability are two important factors of a monitoring system used in the industry. Failure to provide lubricant stock will cause many to be affected because the decline in stock level and supply will cause the machine to shift and line shutdown due to overheating, and lead to catastrophic mechanical failure (Shi et al., 2021). IoT-based monitoring technology provides a preventive and early warning system that reduces risk and ensures safe operations. LiDAR, with its non-contact measuring ability and optical properties, enhances the system's predictability by eliminating issues related to corrosion, electrical interference and mechanical wear associated with sensors such as in non-contactless sensor systems

On the other hand, when integrated with IoT platforms, LiDAR data can trigger automatic alerts and predictive maintenance responses, reducing shutdown time in unplanned production (Hatta Antah et al., 2021). Despite these advantages, the environmental factors such as oil mist, reflective surfaces, and particulate matter can affect the quality of the signal, underscoring the need for advanced calibration and adaptive algorithms to maintain accuracy in real-world industrial settings (Schneider et al., 2021).

In addition, cost saving is another factor that is the main driver for using this type of tape monitoring system (Muneeswaran et al., 2023). Intelligent maintenance powered by IoT can reduce maintenance costs and minimise maintenance losses due to line and unplanned shutdowns. Although LiDAR was once considered a more expensive technology than ultrasonic sensors, advances in solid-state LiDAR have significantly reduced costs. When considering its long-term durability, minimal maintenance requirements and high reliability, smart LiDAR systems offer an excellent return on investment. However, existing studies rarely provide comprehensive cost-benefit analyses that compare LiDAR with conventional sensors in smart monitoring of the lubricant level, suggesting research opportunities to evaluate technoeconomic to offset performance, cost, and long-term value (Castro et al., 2024).

Scalability is another important aspect, in addition to features that are suitable for modern industrial systems. Scalable systems can evolve and adapt to meet growing operational needs without the need for a complete redesign (Rashidifar et al., 2022). For IoT Frame protocol support, communication protocols such as MQTT are indeed the preferred choice as they allow multiple sensors to work more efficiently and seamlessly within a unified framework. LiDAR sensors are one of the best sensors that have been designed to be compatible with common microcontrollers such as Arduino, ESP32 and Blynk Apps that are suitable and easily integrated into larger systems. But it will become more difficult in terms of finding compatibility in terms of latency, power management and data transmission as sensors increase.

Machine vision systems have demonstrated the capability to perform non-contact and real-time tool condition monitoring through both direct and indirect measurement approaches. These systems can effectively detect tool wear and machining conditions, reducing dependence on manual inspection while improving monitoring efficiency in manufacturing operations (Pimenov et al., 2024). Meanwhile, the various techniques, including image enhancement, feature extraction, machine learning, and deep learning algorithms, for evaluating tool wear, surface quality, and defect detection reported that these approaches enable automated monitoring and quality control, contributing to improved measurement accuracy and manufacturing reliability (Ercetin et al.,2024). Several algorithms for flank wear assessment have been reported to have high measurement accuracy and repeatability. The study found that the effectiveness of machine vision systems for automated, non-contact, and real-time monitoring supports predictive maintenance and productivity improvement in modern manufacturing environments (Makhesana et al., 2025).

These studies demonstrate the growing adoption of intelligent sensing, machine vision, and automated monitoring technologies in Industry 4.0 applications. Although previous research primarily focused on tool condition monitoring and machining performance assessment, the findings highlight the advantages of non-contact sensing for real-time industrial monitoring. The advantages of these developments, the present study proposes a LiDAR sensor integrated with IoT technology for continuous lubricant level monitoring. The proposed system provides real-time data acquisition and remote monitoring capabilities, offering a practical solution for predictive maintenance and smart manufacturing environments.

METHODOLOGY

A prototype simulation of a laboratory-scale level monitoring system has been developed, made of smart liquids using the integration of LiDAR and IoT, specifically for smart lubricant tanks. This prototype is a replica of the existing tank in the industry but has been reduced in size to allow conditions to mimic the actual lubricant storage operation. The test setup aims to evaluate the ability of LiDAR sensors to accurately detect fluid levels and transmit data through IoT networks using microcontrollers.

Based on the research flow chart shown in Figure 1, this test was conducted in two different phases, namely hardware installation and software implementation phases. The hardware installation phase begins with a study on the design and fabrication of laboratory-scale prototypes. Several suitable tank designs were identified to be used as a prototype, and the PUGH matrix was employed to determine the most suitable design alternative

Based on the matrix, we chose the cylinder-shaped tank design. The prototype was developed, taking into consideration the material as well as measurement to ensure its performance behaviour closely resembles real-world operating conditions. The conversion from a full-scale industrial system to a compact laboratory setup allows experiments to be conducted under controlled conditions. In doing so, it minimises external interference temperature and environmental changes. This allows for a reliable testing and validated data collection process. In the software installation phase, ESP32 and Blynk were used to create a physical dashboard monitoring system. This system is then connected with the LiDAR sensors, enabling real-time collection, transmission, and display of the lubricant

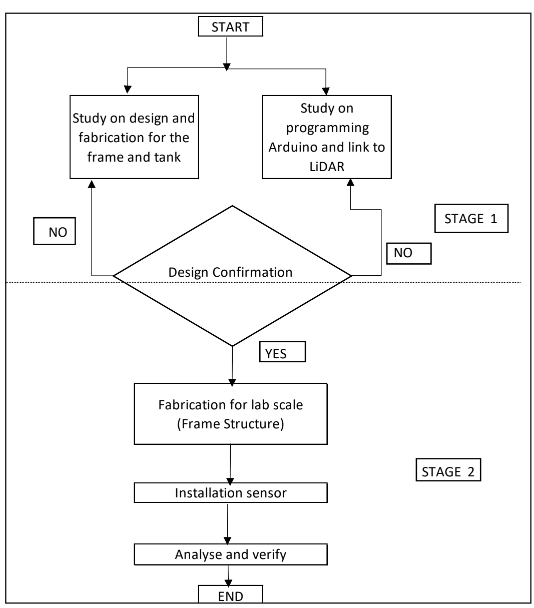


Figure 1. Research flow chart

level. The integration of the monitoring system with an IoT connection allows for two-way communication between physical hardware and a cloud-based monitoring interface. This allows users to observe, record, and analyse system performance remotely through mobile or web applications. Automation of data synchronisation helps to provide timely updates and reduce latency in sensor readings.

After which, a trial of the integrated monitoring system was carried out to validate its mechanical system's performance, accuracy of the sensors installed, as well as the IoT-based monitoring capabilities for potential customisation in an industrial lubrication management application.

During the test period, the usability of the LiDAR sensor was evaluated. Environmental parameters, such as temperature and laboratory conditions, were not considered; they remained constant under controlled experimental conditions as the prototype was built to gauge the readings of the lubricant level in the tank, as shown in Figure 2.

To facilitate the test, two different PETRONAS lubricant samples were used: the raw lubricant, identified as PETRONAS ETRO6+ base oil, and the final product, derived from the same base oil, PETRONAS Syntium 800 10W-40. These samples were tested to observe the standard deviation between the two samples, focusing on the expected variations arising from the inherent characteristics of LiDAR sensors, which differ significantly from conventional ultrasonic sensors commonly used in lubricant level monitoring. The prototype system shown in Figure 3 was tested under controlled laboratory conditions. The following experimental parameters, namely laboratory temperature, surrounding environment, fluid velocity, and viscosity, were kept constant.

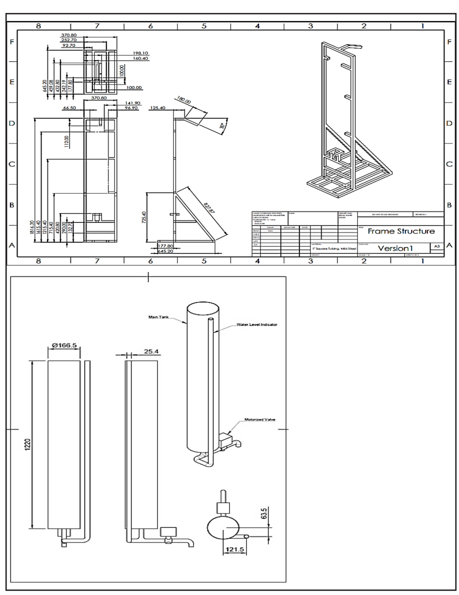


Figure 2. 2D Drawing of the prototype: top: frame; bottom: tank

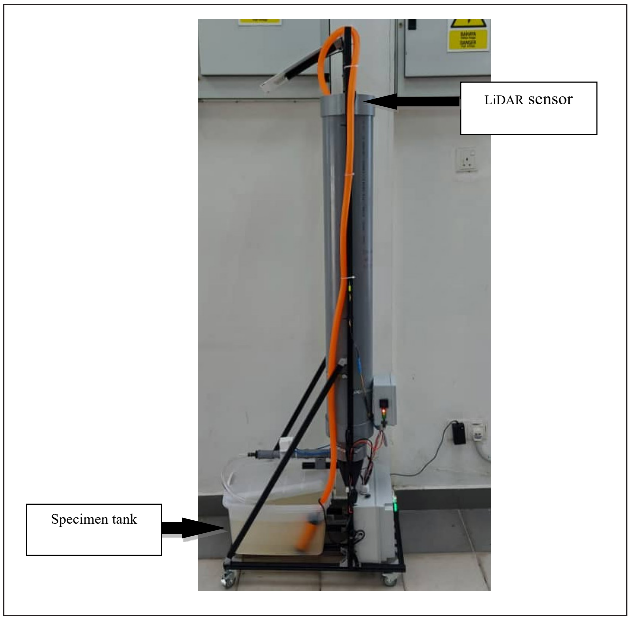


Figure 3. Prototype system

The system showed reliable performance in monitoring lubricant levels. However, further testing is required to evaluate its performance in real industrial conditions. Two PETRONAS lubricant samples: base oil PETRONAS ETRO 6+ and the finished lubricant product PETRONAS Syntium 800 10W-40 were used to assess accuracy as well as the response rate of the LiDAR sensor. The system is designed to reduce reliance on manual maintenance and prevent lubricant run-out that could compromise machine operation. The experiment was repeated five times to ensure the reliability and validity of the data collected. The repetition principle is important in scientific research because the observational indices are random variables, which require a certain number of samples to reveal their changing regularity. The repetition principle helps stabilise the mean and the standard deviation, thereby enabling sample statistics to more accurately represent population parameters. Thus, the statistical inference will be reliable. This article discussed the repetition principle from the perspective of common sense and speciality with examples. Repeated measurements reduce the impact of random errors, thereby improving data robustness and reliability for subsequent analysis (Hu et al. 2011).

Two different laboratories at two different locations were used for the purpose of this study. The fabrication and development stage was carried out at the Sports Engineering and Artificial Intelligence Centre (SEA-IC) Laboratory, UiTM Shah Alam, while the system calibration testing was carried out at the Fluid Laboratory, UPM. The objective of this study is to find out the standard deviation value of two lubricating oils from Petronas ETRO6+ base oil and compare it with the blended lubricating oil to get the standard deviation, which provides information on the consistency and variation of measurement between the two lubricants. As illustrated in the system circuit diagram shown in Figure 4, the electrical configuration operates under controlled electrical current conditions, and its configuration was carefully developed to ensure both functional performance and operational safety. As the system circuit diagram demonstrates, the electrical configuration operates through controlled electrical current, and its configuration has been carefully developed to ensure not only functionality but also operational safety.

Every single component of the electrical hardware is orderly arranged, systematically connected, to minimise the risk of electric degradation, without compromising on the performance. The integration of electrical circuits with power supplies, switches, resistors, sensors and other essential elements and components is chosen for its distinctive function in ensuring the effectiveness, stability and reliability of the system. The circuit is designed to support the required electrical load while also providing adequate safety features in safety protection in case of an emergency; therefore, it also ensures the safety and longevity of the system. The system technique has been used to build a circuit so that the prototype works properly. The diagrams that have been created provide a clear picture and function as a reference for any changes or future changes. The electrical components are carefully connected to the mechanical system to guarantee they function properly. This organised design allows the prototype to perform as planned and provides a dependable and sturdy solution for its use.

The prototype was designed systematically. The circuit schematics were prepared to have a better understanding and serve as a reference for future modifications or any improvements. The integration of electrical components with the mechanical system was carefully done, so that the components and system complement each other. Hence, creating a robust and reliable system that can be used as intended.

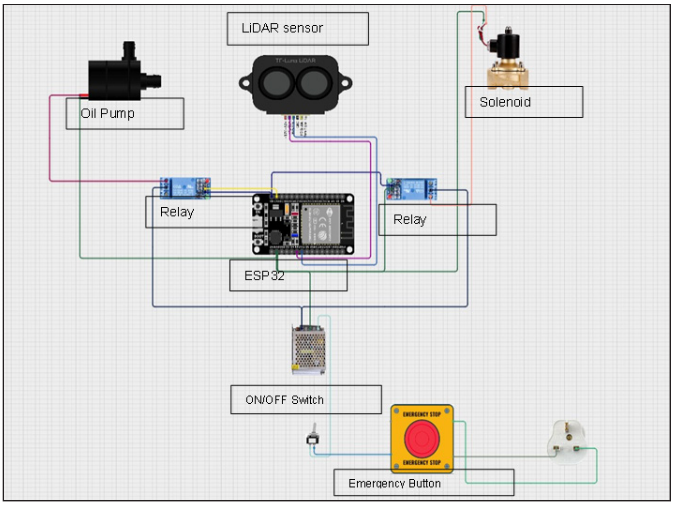


Figure 4. System circuit

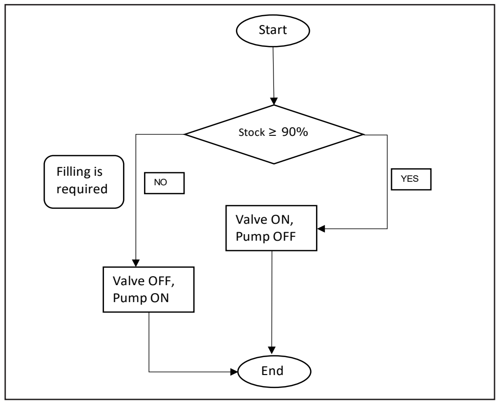


Figure 5. Programming process flow chart

Figure 5 shows the programming flowchart, which explains the logical sequence of the automatic control process. The system starts by continuously monitoring the lubricant level in the tank. It then checks whether the lubricant level is sufficient, based on the tank's full capacity. The flowchart serves to visually explain the logical sequence of the automatic control process.

The monitoring of levels of lubricant in the tank begins with the 'Start' button, where the result notes are used to check if the lubricant levels in the tank are at the optimum level, which is 100 per cent of the tank's capacity. If the reading is at 90 per cent or more, the system will automatically identify it as sufficiently filled. After which, the valve is turned on to release the excess fluid, and the pump is turned off to stop the lubricant from flowing into the tank. On the other hand, if the reading falls below 90 per cent, the pump will be turned on, for lubricants to flow into the tanks, while the valve is turned off, until it reaches its optimal level.

The program for the sensor was developed using the TTGO ESP32 (NodeMCU) microcontroller. It serves as the main controller for the IoT-based lubricant level monitoring system. It is also responsible for sensor startup, real-time data collection, basic signal filtering, and data transmission to the Blynk IoT platform for remote monitoring and visualisation. Also, the program used a modular coding structure to ensure clarity, scalability, and help with future maintenance. The main reason for choosing NodeMCU is its features. The NodeMCU has built-in WiFi, low power consumption and easy sensor integration. This open-source platform is cost-effective and more efficient when compared to alternatives, such as Raspberry Pi and Arduino Mega. The NodeMCU can activate the pump and valve accordingly when the lubricant level reaches a certain threshold. Through IoT monitoring, automatic control guarantees timely fluid management, can prevent overflow or leakage, and enables predictive maintenance.

The following pseudocode shows the sequence and structure of the program's logic. It provides an overview of the functions and operation of the prototype system:

```
BEGIN
  //Initialise Serial Communication
  Initialise Serial
    //Initialise LIDAR sensor with pins (RX, TX)
  Initialise LIDAR communication with pins (RX, TX)
  Initialise the TFMPlus library with the LIDAR device
    //Initialise TFT display
  Initialise TFT display (invert display, set rotation, set text size)
    // Set pin modes for LEDs, relays, and buzzer
  Set pin modes for:
    LED Yellow, LED Red, LED Green
    Relay 1, Relay 2, Relay 3, Relay 4
    Buzzer Pin
      //Initialise Blynk connection for remote monitoring
  Initialise Blynk connection with authentication token
    // Start system operation
  PRINT "System initialisation complete."
    // Main loop
  WHILE true:
      // Read distance, strength, and temperature from LIDAR
    IF LIDAR data is available:
      Read distance, strength, and temperature from LIDAR
        // Display data on TFT screen
    DISPLAY "Distance: " + distance + " cm" on TFT screen
    DISPLAY "Strength: " + strength on TFT screen
    DISPLAY "Temperature: " + temperature + " degC" on TFT screen
        // Send distance value to Blynk app
    SEND distance data to Virtual Pin V1 on Blynk
        // Control LEDs based on distance
    IF distance > 90:
      Turn ON red LED
      Turn OFF the yellow LED
      Turn OFF green LED
      Trigger Buzzer for 3 short bursts (tone)
    ELSE IF distance > 70:
      Turn OFF red LED
      Turn ON yellow LED
      Turn OFF green LED
      Turn OFF Buzzer
    ELSE:
      Turn OFF red LED
      Turn OFF yellow LED
      Turn ON green LED
      Turn OFF Buzzer
    // Control relays based on virtual pin values from Blynk app
    IF Virtual Pin V0 has value:
      Control relay connected to "oren"
    IF Virtual Pin V2 has value:
      Control relay connected to "hitam"
    // Execute Blynk functions for app updates and communications
    RUN Blynk app loop (Blynk Edgentrun)
  END WHILEEND
```

RESULT AND DISCUSSION

During the initial stages, the frame and tank design were developed using both 2D and 3D computer-aided design (CAD) models. These models figured the system's geometry, layout of the component, and structural configuration. These models provide a comprehensive representation of the lubricant monitoring system, ensuring that all mechanical and electronic components can be smoothly integrated into housing and mounting structures.

After this, there is the validation of the prototype, which used Finite Element Analysis (FEA). It measures the mechanical performance, stress distribution and deformation of the prototype when use. The FEA evaluates the maximum, average and minimum stress concentration that causes deformation when the prototype is subjected to mechanical loads and vibrations. FEA is specially chosen as it can provide pertinent insights towards modifications, in terms of the selection of materials, as well as the thickness of the prototype. This is purposefully carried out to ensure structural rigidity, durability, and stability of the prototype. The simulation was carried out using a 3D CAD model prototype. Fixed constraints were placed at the base and distribution loads along the support surface to simulate the actual condition when in use.

As presented in Table 1, it is crucial to evaluate the prototype performance through simulation analysis to ensure compliance with engineering best practices, as well as the principles of precision design and cost-effective prototyping.

Table 1
Finite Element Analysis (FEA) summary table

Analysis Type	Purpose	Key Focus	Findings / Objective
Static FEA (No External Loads)	Assess frame behaviour under self-weight and gravitational force	Structural deformations, stress distribution, stiffness, displacement	Identify areas of potential weakness or stress concentration, ensuring robustness under normal conditions
Static Load Analysis	Evaluate frame response to specific external loads	Local deformation, stress concentrations, and potential failure modes	Determine the frame's ability to resist bending, shearing, or torsional stresses under operational loads
Loaded FEA (With External Loads)	Simulate frame's behaviour under complex loading scenarios (e.g., dynamic, thermal)	Impact of dynamic loads, thermal effects, and vibrations on frame performance	Identify worst-case scenarios, assess performance under transient forces, and consider potential design optimisation
Comprehensive FEA Assessment	Combine static and loaded analyses to evaluate overall structural integrity	Load distribution, material properties, stress analysis across scenarios	Inform design adjustments, including material selection, geometry, and reinforcement for enhanced stability

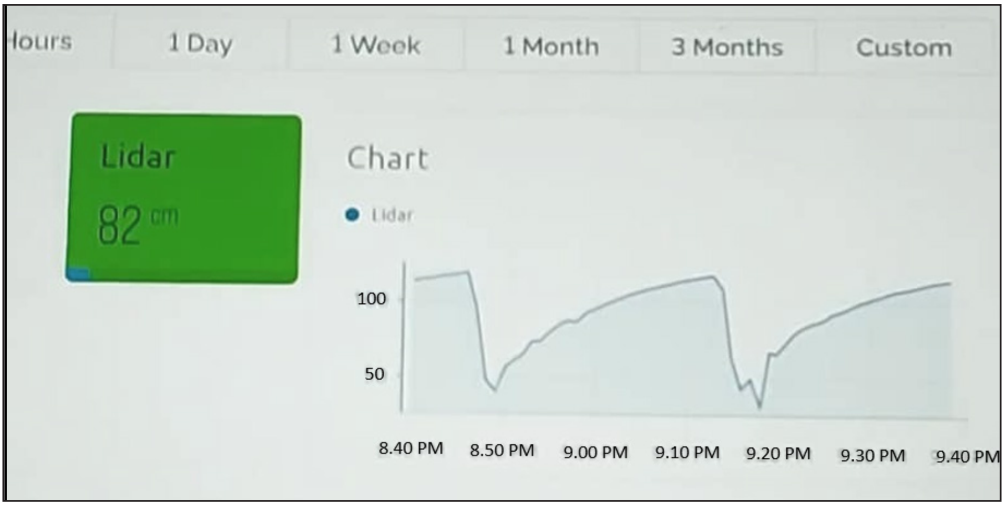


Figure 6. Real-time visualisation of lubricant level data measured by the LiDAR sensor on the IoT dashboard

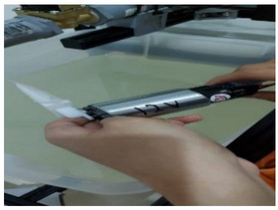
The system and prototype were put to the test and repeated five times, to make sure that the results obtained are valid and reliable. From these repeated measurements, the mean and standard deviation were calculated. The comparison of standard deviation values between the base oil PETRONAS ETRO 6+ and the finished lubricant PETRONAS Syntium 800 10W-40 helps to evaluate the sensor's consistency and sensitivity. It revealed how the difference in fluid viscosity and composition influences LiDAR measurement stability in controlled experimental conditions.

Figure 6 illustrates that the graph and the real data appeared as digital numbers. Calibration is critical, as it helps to make sure that the system is functioning well. Before the experiment, the sensors were calibrated to ensure measurement stability and accuracy during data collection. At the same time, readings were also tested and displayed through the Blynk application.

The calibration process is designed to align the sensor output voltage and distance reading with the actual fluid level in the tank, minimising systematic failure or avoiding any error and ensuring that subsequent measurements reflect actual physical variations rather than sensor interference. At the start of the calibration process, the LiDAR sensor is placed at a fixed height above the tank surface. Distance readings were then recorded as the fluid level changed. Each reading was compared with the actual fluid height measured in the tank.

The test was repeated five times, under the same conditions and prototype. This is done to ensure that the data collected is reliable and valid. Repetition, in taking the measurement, helps in identifying random variation due to sensor sensitivity or acute testing fluctuation. The collected data were then analysed. They were analysed using the cumulative standard

Table 2
Results of loading lube and unloading lube by using two different specimens from two products of PETRONAS: Raw material and end product

No.	Material	Colour	Loading Lube by Using a Pump	Unloading Lube by Using a Solenoid
1	Base Oil, PETRONAS Etro 6+		Low viscosity enables easy pumping	Poor LiDAR detectability due to optical clarity
2	PETRONAS Syntium 800, 10W-40		Higher viscosity may require increased pump pressure	Good LiDAR detectability due to high opacity

deviation (σ), a statistical parameter that measures the difference in reading when compared to the mean value. degree of measurement spread relative to the mean value.

The result of the data analysis from the test carried out, as Table 2, has confirmed the reliability of the LiDAR-based liquid level monitoring system, even when using lubricants with different properties. These findings reinforce the use of LiDAR technology for monitoring of lubricant level at a larger scale, like industrial lubrication. This has happened because of their repeatability, operational efficiency, accuracy and adaptability, which are critical for predictive maintenance and stock levels.

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As shows as Table 3 and 4, by using Equation 1, the Cumulative Standard Deviation (σ) for the PETRONAS ETRO 6+ base oil and product of PETRONAS Syntium 800 10W-40 was derived from five sets of measured data for each specimen. The graphical representations indicate a degree of uniformity and stability in the readings of the sensors, where lower standard deviation values indicate higher value accuracy and consistent sensor performance. A lower Cumulative Standard Deviation (σ) value corre sponds to a more consistent

Table 3
PETRONAS ETRO 6+: Data collection to get sigma value

PETRONAS ETRO 6+					
Sequence, n	1	2	3	4	5
Time taken, (s)	244	260	230	248	257
xi-μ	-3.8	12.2	-18	0.2	9.2
$(xi - \mu)^2$	144	149	317	0	84.6
Cumulative Distribution	0.36	0.87	0.05	0.51	0.81

Table 4
PETRONAS Syntium 800, 10W-40: Data collection to get sigma value

PETRONAS Syntium 800, 10W-40					
Sequence number, Ω	1	2	3	4	5
Time, (second)	195	210	185	205	190
xi-μ	-2	13	-12	8	-7
$(xi - \mu)^2$	4	169	144	64	49
Cumulative Distribution	0.41	0.92	0.1	0.81	0.23

reading, confirming that the system is capable of high repeatability and low measurement uncertainty.

To quantify the static variance in sensor readings, the standard deviation (σ) of the lubricant level measurements was calculated by using the formula in Equation 1.

The formula calculation shall be:

$$\sigma = J\overline{\frac{1}{n-1}\sum_{i=1}^{n}[x_i - \pi]^2} \qquad [1]$$

Sigma, σ = standard deviation
n = total number of observations
x_i = each value from the data
μ = the mean of the data

Then the mean deviation of the value from the mean is determined as: $\sum_{i=1}^{n}[x_i - \pi]^2$

To calculate x_i-μ Every number has to be minus the mean value.
244-247.8 = -3.80, and so on; using the same formulae.

Using the numbers acquired, the mean deviation can be calculated.
Let's use a value as an example: $= \sum_{(i=1)}^{n} 〖(x_i-\mu)^2〗 = (-2)^2 = 4$
By adding all the values from $(x_1-197)^2$ to $(x_n-197)^2$,
The final total of the Sum of Differences is: 430
and the variance of the PETRONAS ETRO 6+ is: 430/5
Thus, the Standard Deviation of PETRONAS ETRO 6+, $\sigma = \sqrt{86} = 9.27$

The graph of the cumulative and sequence for PETRONAS Etro6+ is plotted in Figure 7.

The static evaluation allows for the identification of measurement dispersion and serves as a performance indicator for accuracy, precision and stability of LiDAR sensors. When the accuracy of the system is benchmarked against conventional level monitoring methods such as ultrasonic and capacitive sensors, it demonstrates performance and reliability that is consistent with various environmental conditions, including temperature, viscosity and optical interference. These findings underscore the potential of integrated LiDAR sensors and IoT systems to deliver monitoring accuracy, fast response times, and significant maintenance cost reductions. The sensor calibration in measurement, static verification and comparative tests proves the effectiveness of this system in the management of real-world industrial lubrication.

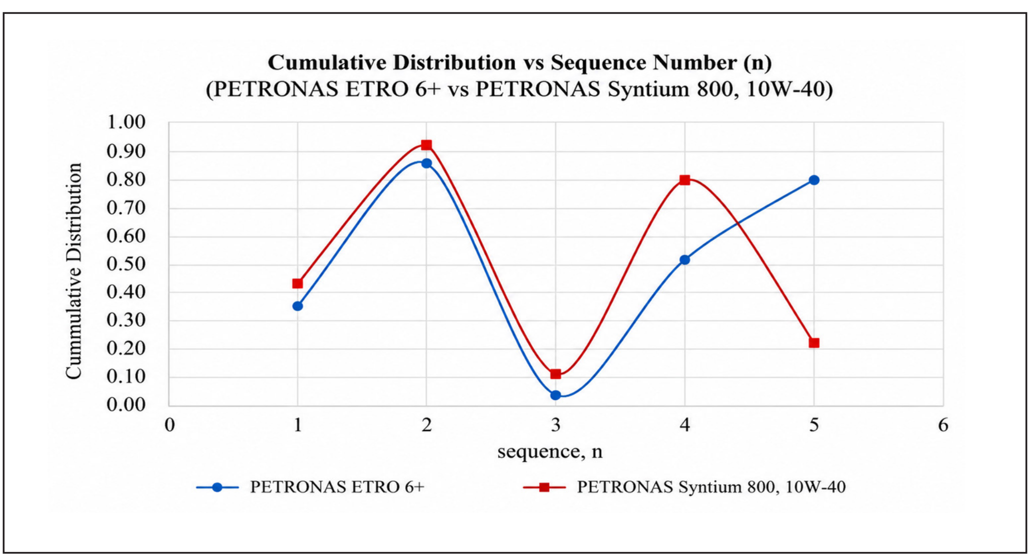

Figure 7. Combined cumulative distribution profiles of PETRONAS ETRO 6+ and PETRONAS Syntium 800 (10W-40)

Table 5
Comparison between PETRONAS 6+ and Syntium 800, 10W-40

Type	PETRONAS ETRO 6+	PETRONAS Syntium 800, 10W-40
Data quantity	5	5
Sum	1239	985
Mean, μ	247.8	197
Subtract from the Mean	564.8	430
Variance, σ^2	112.96	86
Standard Deviation	10.63	9.27

The statistical results summarised in Table 5, which compares PETRONAS ETRO 6+ and PETRONAS Syntium 800 (10W-40). The observed differences in mean, variance, and standard deviation indicate variations in lubricant level measurements, reflecting the distinct monitoring characteristics of the two lubricant samples.

The calculation of both data showed that the difference of standard deviation is 1.36, and by comparing the data of standard deviation, it shows how consistent and reliable the results are in different datasets. The data showed a lower standard deviation, which means that the values are closer to the mean and are less affected by random factors. A higher standard deviation means that the test scores are farther from the mean and thus more influenced by random factors.

Figure 7 shows the combined cumulative distribution profiles of PETRONAS ETRO 6+ and PETRONAS Syntium 800 (10W-40). The graph PETRONAS ETRO 6+ represents in a blue line, the normalised cumulative distribution function derived from the measured lubricant level, providing an overview of the trend variation and stability of the measurements from various experiments. A product of lubricant, PETRONAS Syntium 800 (10W-40), represented in the red line, has properties of higher viscosity and greater optical opacity compared to the PETRONAS ETRO 6+ base oil. The plot captured that the sensor was responding consistently over five measurement sequences by providing a perspective on how fluid characteristics influence LiDAR signal stability and measurement precision.

The inconsistency of the fluctuation curve in the red line indicates of PETRONAS ETRO 6+ that the LiDAR readings in the measurement, this is because the variation reflects the sensor's characteristic capabilities, high transparency and low reflectivity, which can reduce the sensor’s ability to capture consistent reflected light signals from the fluid surface. As LiDAR technology relies on the time of flight (ToF) of laser pulses to determine distance, any reduction in the returned signal strength may lead to minor measurement deviations or signal.

For red lines for PETRONAS ETRO 6+, the fluctuation of the graph shows the cumulative distance values that the sensor captured, a temporary reduction in detection accuracy, such as signal loss caused by the lubricant's optical clarity. On the other hand, the smoother portions of the curve indicate a higher measurement consistency, where the LiDAR readings are more stable and repeatable. The standard deviation (σ) calculated from these readings quantifies the extent of dispersion in the measured lubricant levels. A moderate standard deviation (σ) value indicates that the sensing remains to maintain a level of accuracy even when the degree of measurement variability occurs due to the optical properties of the base oil. This finding is in line with the transparent liquid properties that produce less reliable LiDAR reflections compared to more pigmented lubricants such as PETRONAS Syntium 800 10W-40.

For as PETRONAS Syntium 800 10W-40, the pattern demonstrates two prominent peaks with a relatively smooth transition between sequences, indicating repetitive yet stable measurement behaviour. Even though there are minor fluctuations observed, the overall data trend suggests improved reflectivity and signal reliability, due to lubricant properties and the reduced light transmittance. These optical properties enhance the return intensity of the laser beam, allowing the LiDAR sensor to provide more consistent distance readings.

The comparison between the PETRONAS ETRO 6+ base oil, which exhibited measurement irregularities, was due to its transparency. The PETRONAS Syntium 800 10W-40 data showed narrower dispersion around the mean, resulting in a lower standard deviation (σ) value. This lower standard deviation (σ) indicates greater precision and repeatability, validating that the LiDAR system performs more effectively with opaque or semi-opaque lubricants that minimise beam scattering. The PETRONAS Syntium 800 10W-40 results confirm that higher viscosity and optically opaque lubricants enhance LiDAR detection reliability by strengthening signal reflection. This finding supports the conclusion that fluid optical density plays a key role in determining LiDAR measurement precision. As a result, the use of LiDAR sensors in industrial lubrication monitoring is suggested for the product of lubricants, where consistent level detection is essential for predictive maintenance, efficiency control, and system automation.

The system performance was validated through a series of statistical data collection from experiments by two specimens from PETRONAS ETRO 6+ and PETRONAS Syntium 800 10W-40, which show standard deviations of both are 10.6 and 9.27. These values indicate that both lubricants demonstrated acceptable measurement stability, with

PETRONAS Syntium 800 10W-40 showing slightly higher precision due to its greater optical pigmentation and viscosity.

The validation process encompassed the observation of real-time variations in lubricant levels, pump activation durations, and the total volume of lubricant dispensed. The data has been recorded in the cloud. To ensure that the system is reliable, these measurements have been benchmarked against the data obtained through manual monitoring techniques. Comparative observations confirm that the LiDAR integrated monitoring system performs better in all aspects, such as achieving maximum accuracy, consistency, and operational efficiency, in addition to lowering the probability of human error and response delays typically associated with manual observation. The findings validate that the system has the potential for real-time, contactless monitoring applications, particularly in industrial lubrication management, where measurement precision and automation are critical for predictive maintenance.

The cumulative distribution results confirm that the level monitoring system by using LiDAR based liquid level monitoring system can detect the level of lubricant in the base oil properties. However, signal calibration and optimisation may be required to increase detection stability when measuring optically clear or low viscosity liquids.

CONCLUSION

This study successfully designed, built and tested a prototype experiment on a laboratory scale for a lubricant level monitoring system through IoT, providing information on measurement accuracy, system reliability and operational efficiency for applications, especially in the oil and gas industry. The proposed system has been designed to provide real-time and continuous monitoring of lubricant stock levels in the tank, while reducing the need for manual inspections and minimising human error. The system also delivers data consistently under different environmental conditions and fluid properties. Thanks to the combination of modern sensing technology and IoT connection protocols, there are effective means to facilitate.

Validation of the experiment conducted through data analysis showed that the system's capacity can maintain high accuracy, durability and adaptability to various lubricant parameters. The results also show that the proposed system is not only good at improving monitoring performance but can also help promote predictive maintenance techniques by allowing accurate decisions to be made in a timely and informed manner. This feature is essential for maximising resource utilisation, improving equipment availability, and reducing downtime in industrial environments. Furthermore, analysis from real industry provides a complete picture of the main elements that drive system performance, laying the groundwork for future improvements and scalability.

As this research was limited to a laboratory-scale study, the long-term durability and continuous operational testing were beyond the scope of the present study. In real industrial applications, the system may be exposed to various operating conditions, including mechanical vibrations, temperature fluctuations, dust accumulation, oil mist contamination, and electromagnetic interference, all of which may potentially affect the sensor performance and measurement stability. Nevertheless, the non-contact measurement principle of the LiDAR sensor minimises mechanical wear and reduces direct exposure to the monitored lubricant that may contribute to improved operational longevity. For future research recommendation can focus on extended-duration testing under actual industrial operating conditions to evaluate sensor degradation, calibration drift, system reliability, maintenance requirements, and long-term proposed measurement consistency.

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LIST OF ABBREVIATIONS

IoT	:	Internet of Things
LiDAR	:	Light detection sensor
Wi-Fi	:	Wireless fidelity
MQTT	:	Message Queuing Telemetry Transport
IIoT	:	Industry Internet of Things
TTGO	:	refers to a popular series of ESP32-based development boards
ESP32	:	Espressif 32-bit Microcontroller
NodeMCU	:	Node MicroController Unit

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