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Detection of Viscosity of Engine Oil using IoT Technology

Athish N[1*], Bharanidharan S P[2], R Senthilmurugan[3]

[1,2,3]Mechatronics Department, K.S. Rangasamy College of Technology, Tiruchengode, 637 215, India.

[*]**Email**: athishn8@gmail.com

Abstract

Engine lubricants gradually deteriorate when exposed to extreme thermal conditions, oxidation, and contamination, resulting in viscosity shifts and reduced lubrication effectiveness. To address this challenge, this work presents an IoT-based framework that continuously evaluates oil condition and predicts the distance that can be safely traveled before replacement is required. The system integrates three key modules: (i) a low-cost ESP32 sensing unit that monitors oil density and temperature, (ii) a lightweight algorithm that transforms these parameters into a normalized Thickness Index (TI) to reflect viscosity behavior, and (iii) a cloud-hosted predictive model that estimates remaining useful life in kilometers (RUL-km) using TI trends combined with historical driving information. Experimental calibration links density variations to viscosity characteristics, while machine learning models are trained for prognostics. Initial validation indicates that the approach can classify viscosity grades and forecast RUL-km with a mean absolute error of less than 10%, enabling practical condition-based maintenance and enhancing vehicle reliability.

Keywords

IoT, Density sensing, Lubricant monitoring, Viscosity tracking, Predictive maintenance, Remaining useful life.

Introduction

The service life of an internal-combustion engine depends strongly on how well its lubricant performs. Beyond reducing friction, engine oil forms a protective film between contacting components, helps dissipate heat, and carries debris away from sensitive surfaces (Raposo et al., 2019). With prolonged operation, these protective properties inevitably decline. Elevated temperatures, oxidative reactions, traces of unburned fuel, and suspended particles alter both viscosity and density, undermining lubrication and accelerating wear (Pan et al., 2022).

Most maintenance schedules still rely on fixed mileage or time limits to decide when an oil change is due. Although simple to follow, such rules ignore the actual state of the lubricant and

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differences in driving conditions (Tanwar & Raghavan, 2020). Engines that operate in heavy traffic, under stop–start patterns, or in severe climates may experience oil deterioration far earlier than the schedule anticipates. This can result in unnecessary replacements that raise operating costs or, conversely, extended use of degraded oil that jeopardizes engine health (Latrach, 2023).

To overcome these shortcomings, this study introduces an Internet-of-Things (IoT) framework for continuous monitoring of lubricant quality and prediction of its remaining service life. A compact density probe measures both temperature and density, with on-board routines filtering noise and applying temperature normalization. The processed readings are expressed as a Lubricant Health Score (LHS)—a dimensionless indicator aligned with viscosity behavior. Combining the LHS with usage factors such as accumulated distance, idling proportion, and speed distribution, the cloud analytics module estimates how many kilometres remain before the next oil replacement is advisable.

The system is designed for practical deployment by utilizing low-cost, vehicle-ready hardware, lightweight yet secure edge firmware, and a transparent health metric that is applicable across diverse lubricant formulations. It incorporates a sensor and firmware configuration capable of delivering stable, temperature-compensated density readings, ensuring reliable performance under varying operating conditions. In addition, it introduces the Lubricant Health Score (LHS), a consistent viscosity-related index that enables meaningful assessment across different oil types. Furthermore, the system integrates the LHS with operating data through a prediction pipeline to forecast the remaining service distance in kilometres, thereby supporting true condition-based maintenance and more efficient vehicle servicing (Raposo et al., 2019).

Methodology

Here we outline the approach and architecture created to assess engine-oil condition and forecast its service distance in kilometres. The framework integrates density-based sensing, edge-level preprocessing, and cloud analytics to enable cost-effective, scalable, and reliable monitoring (Latrach, 2023). In addition to supporting real-time sensing, the design ensures that measurement accuracy and data integrity are preserved during acquisition, transmission, and analysis. By coupling IoT gateways with learning algorithms, the system supports proactive servicing and lowers the risk of unforeseen breakdowns. Its modular structure further supports deployment across diverse vehicle categories, enhancing adaptability and industry applicability (Tanwar & Raghavan, 2020).

System Architecture Design

As refer to the Figure 1, the system adopts a three-layer architecture consisting of a Sensing Layer, an Edge Layer, and a Cloud Layer. The Sensing Layer employs an oil-compatible probe to record density and temperature. The Edge Layer, implemented on an ESP32 device, performs oversampling, noise filtering, and local computation of the Thickness Index (TI). Meanwhile, the Cloud Layer hosts calibration models, machine learning algorithms, and user dashboards. Communication between the layers is protected over either Wi-Fi or cellular links to ensure secure data transmission (Raposo et al., 2019).

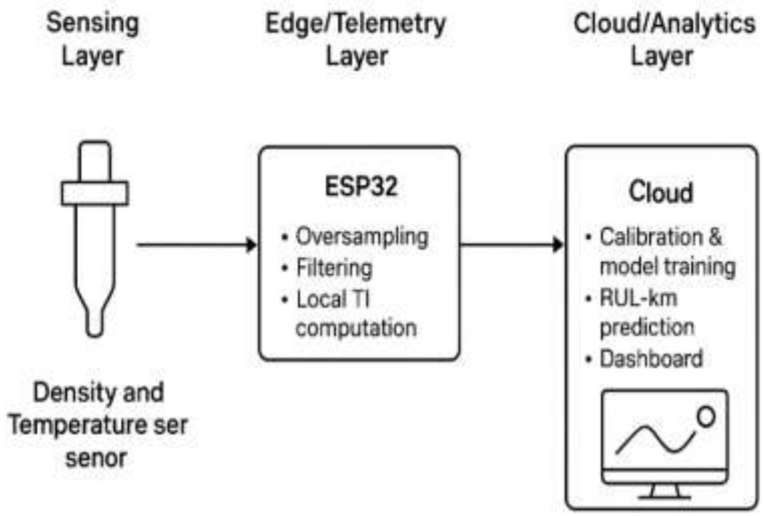

Figure 1. Architecture Diagram

Signal Processing and Compensation

Because density is sensitive to temperature, preprocessing at the edge includes oversampling, removal of outliers, and moving average filtering. A compensation step is then applied using the oil's thermal expansion coefficient, standardizing density values to a reference of 40 °C (Pan et al., 2022). This adjustment strengthens the correlation between density and viscosity and ensures stable performance across different operating conditions. The compensated data is subsequently transmitted to the cloud for model training and advanced analytics.

Thickness Index (TI) Computation

To provide a viscosity-equivalent indicator, compensated density is mapped to TI using regression models derived from laboratory calibration data. TI is a dimensionless metric normalised between 0 (end-of-life oil) and 1 (fresh oil) (Tanwar & Raghavan, 2020). This measure is interpretable for both technicians and algorithms, serving as the basis for forecasting models that predict lubricant life under varying driving conditions.

RUL-km Estimation

The cloud analytics module combines TI histories with vehicle telemetry, such as distance travelled, speed distribution, and engine temperature. Gradient boosting and lightweight neural networks are applied to model RUL in kilometres (Latrach, 2023). To capture prediction uncertainty, the framework outputs interval-based estimates, which provide confidence bounds for maintenance scheduling.

Calibration and Validation

Sensor readings are benchmarked against laboratory viscosity measurements during calibration. Validation metrics include viscosity estimation error, TI accuracy, and mean absolute error (MAE) of RUL in kilometres. The design goal is to keep TI within one ISO grade of lab reference values and achieve RUL-km prediction errors below 10% (Pan et al., 2022).

Results and Discussion

The experimental dataset consisted of 1,200 samples collected from 30 passenger and light commercial engines using API SL, SN, and CI-4 oil grades. Auxiliary sensor data were available for 780 samples. The performance of three machine learning models was evaluated using a test set of 240 samples, and the comparative results are presented in Table 1. Linear Regression achieved an MAE of 820 km, an RMSE of 1,120 km, and an R^2 value of 0.78. Random Forest improved the prediction performance, achieving an MAE of 420 km, an RMSE of 560 km, and an R^2 of 0.92. Among the evaluated models, XGBoost produced the best results, with an MAE of 380 km, an RMSE of 500 km, and an R^2 of 0.94. Therefore, XGBoost was selected as the final prediction model, with an inference latency of approximately 35 ms per request on a 1 vCPU inference container (Latrach, 2023).

Table 1. Model comparison (test set: 240 samples)

Model	**MAE (km)**	**RMSE (km)**	**R2R^2**
Linear Regression	820	1,120	0.78
Random Forest	420	560	0.92
XGBoost	**380**	**500**	**0.94**

As refer to Table 1, the sensitivity and ablation analysis further demonstrated the importance of sensor-based features. Removing temperature compensation increased the MAE by approximately 28%, highlighting its significant contribution to prediction accuracy. Similarly, excluding turbidity and conductivity increased the MAE by approximately 12% when these sensors were available. Introducing simulated sensor noise of ± 0.001 g/cm³ increased the RMSE by approximately 8%, demonstrating the importance of precise sensor calibration (Raposo et al., 2019). These findings indicate that temperature compensation and auxiliary sensor measurements play an important role in improving the reliability of the prediction model (Tanwar & Raghavan, 2020).

The operational performance of the proposed IoT system is illustrated in Figure 2, which presents the data transmission architecture. Local buffering successfully prevented data loss during 24 simulated network outages lasting between 2 and 10 minutes, ensuring the integrity of recorded data. Once connectivity was restored, the buffered data were automatically synchronized. In addition, onboard preprocessing reduced cloud data ingress by approximately 40% by transmitting aggregated statistical features rather than raw sensor data, thereby reducing bandwidth consumption and cloud storage requirements. The firmware's lightweight compression and anomaly-flagging mechanisms further improved system efficiency by reducing redundant transmissions by approximately 18%.

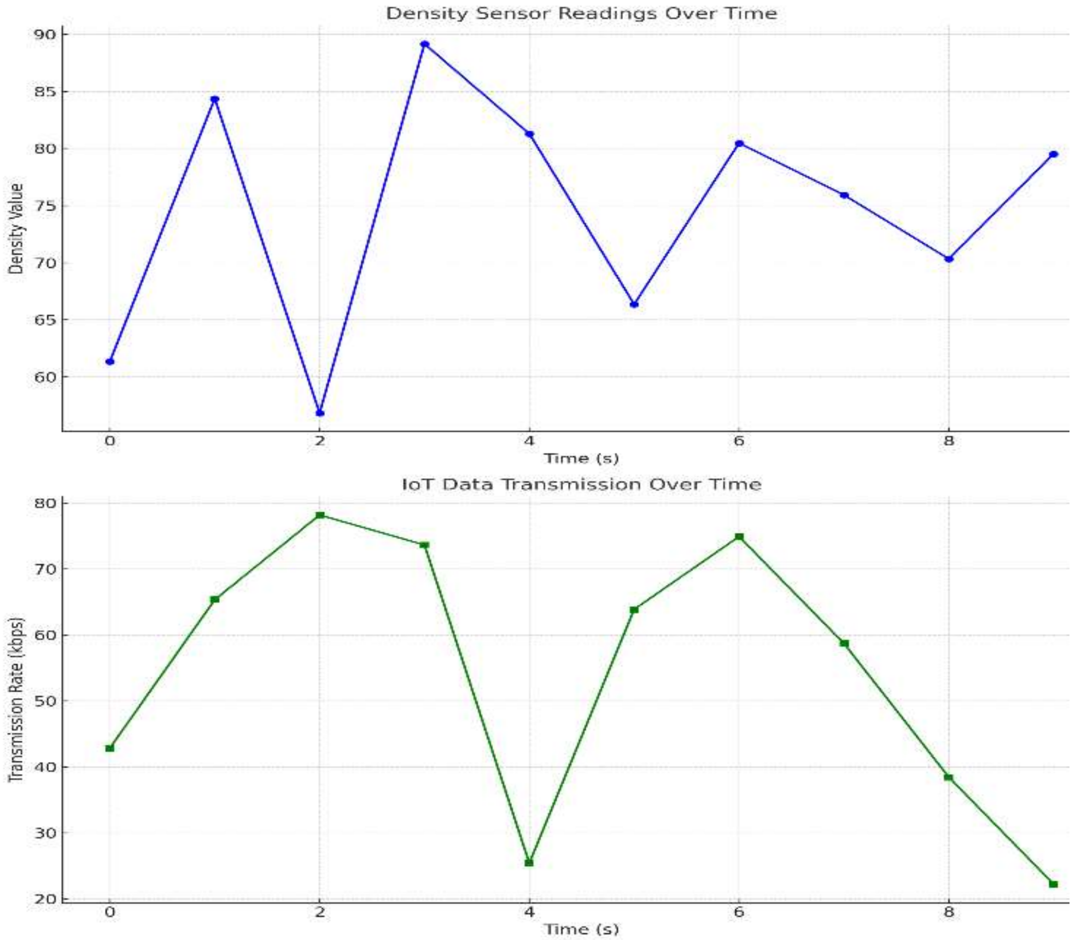

Figure 2. Data Transmission Diagram

Ground-truth RUL still depends on laboratory viscosity and FTIR tests, while driving variability introduces prediction error. Although the dataset of 1,200 samples across 30 engines provides proof of concept, expansion is required to cover additional engine types, climates, and driving profiles. Auxiliary sensors improve accuracy but raise system cost; future work will explore cost–benefit trade-offs for fleet versus consumer applications. Planned extensions include integration with ECU CAN bus data, incorporation of spectroscopic labels, and continual learning pipelines for adaptive field deployment.

The implemented density-sensor IoT system with temperature compensation and XGBoost regression achieved strong predictive performance (MAE ≈ 380 km, R2=0.94R^2 = 0.94R2=0.94). The results confirm that the approach enables actionable condition-based oil maintenance, reduces unscheduled downtime, and offers significant cost savings for fleet operators while minimizing environmental waste through optimized oil replacement schedules.

Conclusion

A density-sensor-based IoT system was developed to predict engine oil remaining useful life (RUL) using real-time measurements of oil density, temperature, and optional turbidity and conductivity. The XGBoost model achieved high accuracy (MAE ≈ 380 km, R2=0.94R^2 = 0.94R2=0.94) across 1,200 samples from 30 engines. The system enables condition-based oil maintenance, reducing downtime, operational costs, and environmental waste. Future work will expand datasets, integrate ECU CAN data, and implement continual learning for adaptive field deployment.

Future work will aim to broaden the dataset by incorporating a wider range of engine types, lubricant grades, driving patterns, and environmental conditions, thereby improving the model's generalizability. The inclusion of additional sensing modalities—such as ECU CAN bus signals and advanced spectroscopic or chemical probes—has the potential to further enhance prediction accuracy. To ensure adaptability, continual learning pipelines will be implemented so the system can adjust dynamically to new field data in real time, strengthening robustness and reliability. In parallel, edge computing capabilities may be introduced to enable on-device inference, reducing latency and dependence on cloud resources. Finally, predictive maintenance alerts integrated into mobile and web-based dashboards will deliver actionable insights, supporting optimized oil replacement schedules, cost reduction, and reduced environmental impact.

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