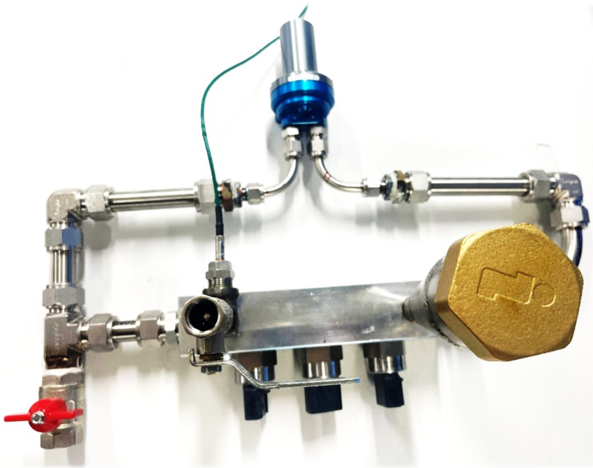

Oil Quality Sensor (OQS)
Sensor performance testing and modelling

Real time condition based maintenance

Master's thesis in Product Development

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DEPARTMENT OF INDUSTRIAL AND MATERIALS SCIENCE
PRODUCT DEVELOPMENT (MPPDE)

CHALMERS UNIVERSITY OF TECHNOLOGY
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Real Time Condition Based Maintenance

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Cover: The image of Oil Quality sensor installed in the oil rig

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Oil Quality Sensor (OQS): Sensor Performance Testing and Modelling for Real-Time, Condition-Based Maintenance.
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Abstract

Engine oil condition in Volvo Group heavy-duty field trucks is currently assessed through fixed interval oil changes supplemented by laboratory sample analysis, a process that takes up to four weeks and cannot detect real time contamination events such as water contamination or fuel dilution before damage occurs. This thesis investigates whether the TE Connectivity FPS2800 Oil Property Sensor measuring viscosity, density, dielectric constant, and electrical resistivity simultaneously is capable of replacing this process with real-time oil monitoring for Volvo VDS-5 engine oil.

The work was carried out in four phases starting with the sensor's temperature dependent properties which were validated on a oil test rig resulting in three of the four proposed models (viscosity, density, dielectric constant) held in line for VDS-5 oil, while resistivity required a corrected Arrhenius cubic model to replace the originally proposed linear one. Fuel dilution models were calibrated at 3%, 6% and 9% and water contamination at 1% and 2% concentrations. further on to second phase where the validated models were applied to three months of CAN-bus data from a Volvo field test vehicle by building a pipeline on Volvo's Data Science Lab. Moving to third phase where the resulting oil condition estimates were validated against Volvo's laboratory reference data which showed agreement for soot, water contamination and oxidation. Finally the fourth phase where the pipeline was deployed end to end with a Power BI dashboard for research and development team.

The results show that the FPS2800, calibrated specifically for VDS-5 oil, can deliver oil condition estimates comparable in accuracy to laboratory analysis for the most critical parameters, furthermore, estimated prototype cost was estimated and business case was made for the sensor. Remaining gaps like oxidation and soot rig calibration are identified as future work ahead of production deployment.

Keywords: oil condition monitoring, FPS2800, condition based maintenance, heavy-duty diesel engines, sensor calibration, real-time monitoring.

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It was enlightening to work on this thesis on the development of an Oil Quality Sensor model. I got a chance to go deeper into the sensor model design and condition based maintenance for Medium Duty Diesel Engines. I am grateful for the opportunity to learn so much about this area of study.

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Mohammed Talha, Gothenburg, 2026

List of Acronyms

The following acronyms are used throughout this thesis. They are listed in alphabetical order and defined at first use in the text.

API	American Petroleum Institute
ASTM	American Society for Testing and Materials
CAN	Controller Area Network
CBM	Condition-Based Maintenance
DSL	Data Science Lab
FTIR	Fourier Transform Infrared Spectroscopy
GLAD	Global Liquid Analysis Database
OQS	Oil Quality Sensor
SAE	Society of Automotive Engineers
TAN	Total Acid Number
TBN	Total Base Number
TTI	Trucks Technology and Industrial Division
VI	Viscosity Index

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1 Introduction

This chapter is an introduction of the project, which starts from the background, then moves towards the definition of the problem. In addition to this, the scope of the project is described here together with research questions. In order to make the reader understand the structure of the report, a brief overview is provided at the end.

1.1 Project Background

This project involves a partnership between Chalmers University of Technology, student at the Master's thesis level and company Volvo Group. The Volvo Group has several divisions such as Volvo Trucks (Heavy and medium truck production), Renault Trucks (Heavy and Medium trucks for Europe), Mack Trucks (For America), Volvo Construction equipment, Volvo Buses, Volvo Penta, Volvo Energy, Volvo Financial Services (VFS), Volvo Autonomous Solutions (VAS), Arquus. Volvo TTI is part of the Volvo group which works on research and innovation, powertrain systems (diesel, electric, hydrogen), vehicle architecture and platforms among others. Volvo Power train is the division which takes care of engine oils.

It has been seen that the Engine oil is one of the most important lubricants that has various roles in the automobile including lubrication, cooling, cleaning, corrosion protection, sealing and many others. Hence, it is very important to ensure that the quality of the oil should be good at all times.

The concept of analyzing oil quality came from new engine testing. While setting up oil change parameters for new engine, it was a constant pain that the engine oil was deteriorating in quality and going unnoticed for weeks before the results of oil analysis came out. This was mainly because of collection, transportation, experimentation and rolling out of the result as a process.

1.2 Problem Analysis

The current method used for engine oil analysis involves taking a sample of the engine oil of approximately few milliliters and conducting multiple tests on it at the chemical lab. The test results takes about four weeks. The output of this process has three parameters which are kilometers traveled, hours of operations and total fuel consumption. The oil change takes place whichever parameter is reached first according to Volvo's standard for oil change interval. There are some disadvantages associated with this kind of oil change process. The first and important one is that the time taken to analyze the oil is four weeks which is too long as delay in results will worsen the situation if it has gone bad. Also, there are various tests needed to be done to determine the parameters and still there is uncertainty regarding the oil change intervals.

1.3 Scope of the project

This project is to determine the feasibility of FPS2800 sensor through performance tests, verification and validation. The deployment of Oil Property Sensor will only be performed for internal research and development activities. The scope of the project is defined in four phases.

1.3.1 Phase 1: Rig Based Sensor Performance Testing

This first stage would consist of testing of the FPS2800 sensor in the lab using an oil test rig that has been designed. The sensor is used to measure viscosity, density, dielectric constant, resistivity and temperature of engine oil as explained in the principle of measurement of this sensor [1]. The purpose of this stage is to find out if the models of physical properties which have been introduced in scientific literature like temperature relationship of viscosity, density, dielectric constant and resistivity of engine oil and various contamination hold true in the particular use case scenario in Volvo Powertrain applications.

1.3.2 Phase 2: Vehicle Data Collection and Model Application

After validation of the rig equations, the models validated are used on real time data obtained from a vehicle fitted with the FPS2800 sensor. Data about the oil properties is obtained using the Controller Area Network (CAN) bus. The data is saved at the Volvo Data Science Lab (DSL). The temperature normalization and filtration technique involving modeling of new oil, current oil and relative evolution is applied on the live data to estimate the condition of the oil in the five parameters of the sensor.

1.3.3 Phase 3: Validation Against Laboratory Analysis

These oil condition estimates based on data from the sensors are verified using the reference laboratory test results carried out on oil samples obtained from the same vehicle during specific time periods. These lab tests includes viscosity, Soot, oxidation, water and fuel content measurement. This verification enables checking the validity of the sensor based model in monitoring oil condition.

1.3.4 Phase 4: Data Integration and Dashboard Development

In the final stage, the data pipeline is represented on a visualization tool. Data from the vehicle CAN bus is collected and analyzed with the help of a Python based pipeline that utilizes the actual results to compute oil condition indicators in near real time. Finally, the processed information is visualized on a Power BI dashboard for easy access to the research and development team.

1.3.5 Delimitations

Project scope refers to the engine oil condition monitoring of the engine under test in a particular powertrain configuration. Modeling and calibration of the model will be done using the oil and varying contamination. However, the project scope does not include hardware modifications beyond the CAN bus infrastructure, as well as oil change notifications.

1.3.6 Research Questions

In relation to the scope of the project as described above, the research questions have been formulated for guiding the project. These research questions are aimed at addressing the key issues of the implementation of real time engine oil monitoring

RQ1: What are the possible critical events that goes unnoticed before changing oil?
RQ2: To what extent do current oil changing interval techniques fail to fulfill the purpose?
RQ3: What are the benefits of having a real time monitoring of engine oils ?
RQ4: What is the value of oil health monitoring when compared to cost and complexity?

By setting out these research questions, the whole project is captured and set a foundation for itself. It is important to have research questions like these when trying to solve such an issue.

1.4 Previous work on the project

Previously, an analysis of several sensors was carried out in a Masters thesis study at Volvo in 2014. Later, Volvo decided to investigate one sensor named FPS2800 using the tuning fork principle. This sensor is now installed in some test trucks to evaluate its performance. All data is recorded and stored in the Data Science Lab of Volvo.

1.5 Overview of report

Finally, the report will cover the design of Oil quality sensor behavior model. This section covers market assessment and analysis of competitors. Customer need assessment is done based on interviews and secondary sources. Further, we explore the testing and implementation of rig test results into vehicle data and finally display the result in Power-Bi. A business case is studied before finishing the report that involve discussion and conclusion and suggestions for future work.

2 Gathering Information

This Chapter contains the literature review that was used to answer the objectives of the thesis. The literature has been selected because of their relevance to gather and analyze the data.

2.1 Primary Research

The primary research was performed using a structured process of stakeholder interviews. The goal of the study was to understand the exact needs and technical specifications, deficiencies in the current oil monitoring practice that the FPS2800 based solution should overcome, as well as the needs of the Volvo company. The following section will present the chosen stakeholders for the interview, methodology, customer needs and secondary research.

2.1.1 Stakeholder Categories and Interview Structure

Three types of stakeholder groups were considered in the process of designing the oil condition monitoring system for medium duty and heavy duty trucks:

1. **Research and Development Team** : The first stakeholder group was internal team from Volvo Group Powertrain who have detailed technical knowledge regarding the ageing of engine oil, sensor placement and powertrain testing processes. This stakeholder group helped in defining requirements based on engineering standards and practices.

2. **Aftermarket and Service Operations**: The stakeholders who are concerned with fleet maintenance, scheduling of oil changes and field services support. These stakeholders gave the requirements that were based on daily operations challanges, cost limitations and acceptable time frame for measurements.

3. **Competitors and Potential Customers**: representatives who know about the market landscape for oil condition monitoring products, which include other requirements from the customers in the transport industry.

A total of four semi structured interviews were carried out from which two of them were from Research and Development and one each from Aftermarket and competitor/Potential Customer categories. Interviews were preferred over questionnaires for being able to dive into follow up questions when technical information came up, but still having a common base of questions for all four interviews.

In compliance with the non-disclosure agreement signed with the Volvo Group, the names and organizations of the interviewees are referred to using their roles alone in this section. Requirements in terms of numbers, obtained from interviews, are stated normally or masked when they involve proprietary operational goals.

2.1.2 Competitor Analysis

Competitor analysis of oil condition monitoring within heavy duty powertrains was done through the literature review and interviews with the relevant stakeholders involved in R&D and the market. Two main strategies have been identified.

1. **Approach 1: Algorithm-Based Oil Life Monitoring (1980s to Present).** The first approach, which has been used by cars. It involves the oil life prediction algorithm using the existing vehicle. It makes use of data related to the engine speed, load cycles, engine and oil temperature and fuel consumption and uses it to predict the remaining oil life without an oil quality sensor. It was introduced and implemented by General Motors in the 1980s using the Oil Life Monitor system and since then has been used by many other vehicles. [2].

   Although computationally cheap and readily implementable within existing systems, there are three limitations of this method that have been found through the stakeholder interviews. First, accuracy will be limited due to the fact that the algorithm uses a proxy signal which means that the oil status is estimated and not measured directly. Second, any contamination like water, fuel, or soot, is not estimated using this method. Third, the algorithm will require calibration for each specific engine which will make it costly and difficult to apply to other engines.

2. **Approach 2: Dedicated Oil Quality Sensor (2020 to Present).** The second approach is the use of an oil quality sensor that directly detects physical properties of the oil. A particular example found in the competitive analysis of the technology is the use of the TANDelta OQS-G2 sensor used by Volvo Penta to measure the Total Base Number (TBN) depletion index (TDN) of the oil using capacitive measurement techniques [3]. Although this technique has greatly improved over the algorithmic technique, the research and development team pointed out that the accuracy of the measurement of contaminants such as Soot and metals are not according to the requirements.

2.1.3 Customer Needs Identification

In order to analyse the four interviews with stakeholders, the method of customer need extraction was employed following Ulrich and Eppinger's approach [4], where interview statements are converted into product need statements and ranked according to their importance. These needs were then classified into two groups, **hard requirements**, that must be met for a product to be considered acceptable, or **wishes**, which are additional value adding features but are not necessary. Each wish statement received a weighting factor between 1 and 5.

Table 2.1 provides the complete customer needs specification obtained through the interviews. As per the conditions set by the NDA, the threshold levels of those requirements which relate to the proprietary Volvo Group operational specifications are provided in the form of normalized directional targets.

Table 2.1: Customer needs specification derived from stakeholder interviews. Requirements are mandatory; wishes are desirable with priority weight 1 to 5.

Requirement	**Target**	**Unit**	**Type**	**Source**
Oil change interval	>threshold	km	Requirement	R&D
Measurement time (lab & field test)	<1	day	Requirement	R&D
Measurement time (customer-facing)	<30	days	Requirement	Aftermarket
Detect and measure soot	≤target	%	Requirement	Aftermarket
Detect metal contamination	≤target	ppm	Requirement	Aftermarket
Detect net oxidation	≤target	A/cm	Requirement	Aftermarket
Measure viscosity	≤target	cSt	Requirement	Aftermarket
Detect fuel dilution	≤target	%	Wish (4/5)	Aftermarket
Detect water contamination	≤target	%	Wish (3/5)	Aftermarket
Soot measurement accuracy	≥95	%	Requirement	Aftermarket / R&D
Oxidation, metal & viscosity accuracy	≥85	%	Requirement	Aftermarket / R&D
Fuel dilution & water accuracy	≥85	%	Wish (4/5)	Aftermarket
Total system cost per unit	≤target	SEK	Wish (4/5)	R&D / Market
Operating temperature range	−30 to 120	°C	Requirement	R&D / TE Connectivity

A number of insights could be gained from the customer need specification. Firstly, it is seen that the accuracy requirements for soot is specified to have a higher accuracy (95%) than oxidation and viscosity (85%). Hence, soot is seen as the major cause of engine failure. The temperature requirement range of between −30°C to 120°C is in line with the FPS2800 sensor specification and Volvo Group powertrain requirements.

The total system cost per unit is a constraint of feasibility and not an engineering necessity. It consists of costs of sensor, mounting, harness, labour cost of installation and software integration cost allocated per unit as illustrated in the business case study in Chapter 6.

2.1.4 Sensor Capability Against Customer Needs

Initial judgment of the measurement capabilities of the FPS2800 sensor with regard to the customer needs was made at this stage to establish feasibility prior to conducting the rig tests. Table 2.2 below shows the needs that can be measured using the sensor and those that cannot. This is mainly because of the sensors capablities as shown in figure 2.1

	Lower Limit	Upper Limit	Resolution
Oxidation	0 A/cm (ASTM D7418)	50 A/cm (ASTM D7418)	2 A/cm (ASTM D7418)
Water Contamination	2000ppm	20000ppm	2000ppm
Coolant Contamination	4000ppm	40000ppm	4000ppm
Fuel Contamination	1%	10%	1%
Soot Contamination	0,2% (ASTM D7418)	5% (ASTM D7418)	0,1% (ASTM D7418)
Metal Contamination	20000ppm	100000ppm	20000ppm
TBN / TAN	Detection of the oil degradation Phases	Detection of the oil degradation Phases	Detection of the oil degradation Phases
Wrong Fluid Detection	Function of fluid type	Function of fluid type	Function of fluid type

Figure 2.1: Sensor capabilities[1].

Table 2.2: FPS2800 sensor coverage against identified customer needs.

Customer Need	**FPS2800 Measurable?**	**Primary Parameter(s)**
Soot contamination	Yes	Viscosity, Dielectric
Net oxidation	Yes	Resistivity, Viscosity
Fuel dilution	Yes	Viscosity, Density
Water contamination	Yes	Dielectric, Resistivity
Wrong fluid detection	Yes	All four parameters
Metal contamination	Partial	Viscosity, Density
TBN/TAN monitoring	Partial	Resistivity (proxy)

Metal contamination and TBN/TAN measurement only being partially addressed which is falling short as described in the FPS2800 white paper [1]. With regard to metal contamination, the instrument is able to detect only high levels of contamination but not to the level of precision required by the customer requirement document. In addition, TBN number loss are trend based on behavior, but it is not quantified in absolute numbers. These limitations are carried forward and are discussed further in Chapter 4.

2.2 Secondary Research

2.2.1 Engine Oil

Engine oil is lubricant that have various purposes such as lubricating, wear resistance, cooling and cleaning. The modern engine oil is designed in a way to increase the efficiency of the car. It comprises of 80 % base oil and 20 % additives.

1. **Base Oil.** Base oil forms the bulk of engine oil. More than 80'% of the oil constitutes base oil. Base oil forms the core of the oil. It gives the basic characteristics of the oil such as viscosity, thermal stability, volatility, lubricity and compatibility with additives. The API classification system classifies the base oils according to paraffinicity and sulfur content of the stocks. API classifications for Group 1 to 5 base stocks are detailed in API Publication 1509, Fifteenth Edition, April 2002.

Group	**Saturates**	**Sulphur**	**Viscosity Index**
Group 1	Below 90%	Over 0.03%	80 to 120
Group 2	90% and Above	0.03% or less	80 to 120
Group 3	90% and Above	0.03% or less	Above 120
Group 4	Polyalphaolefins	-	-
Group 5	Others	-	-

Table 2.3: Classification of base oils according to saturates, sulphur content and viscosity index.

API base oil types are divided into five categories according to their saturation level, sulfur level and viscosity index (Table 2.3). The first category involves conventional base oils, while the second one involves moderately hydrocracked oils, such as catalytically dewaxed oil. Group 3 base oils are cracked waxes, which typically have relatively high viscosity indices and relatively low sulfur levels. The fourth category includes polyalphaolefins (PAOs), which are synthetic base oils, while Group 5 base oils include all others such as synthesized hydrocarbons, olefin oligomers, alkylated aromatics and organic esters.

These classifications are important in deciding what kind of engine tests need to be carried out whenever the base stocks of different groups have to be substituted in the final oil products that hold API licenses. The growing demand for base stocks of Groups 3, 4 and 5 comes from the desire to increase fuel efficiency, decrease oil consumption and extend service as well as oil drain life in passenger car, light commercial and heavy duty diesel engines. For instance, the base stocks of Group 3 help increase fuel efficiency through better pressure-viscosity relationship and improved oxidation stability, with decreased volatility helping decrease oil consumption.

2. **Additives in Engine Oil.**

   Oil additives are those substances which are added to the lubricant in small proportions for enhancing its characteristics. Small portions of base stocks do not fall under the category of additives but form part of blending agents. The current lubricants especially the engine oils have high proportions of additives along with base stocks. The proportion of additive content in premium oil can be around 20%. Given below is the list of additives which are added to enhance the characteristics of the oil. [5]

   (a) **Pour Point Depressants**
   The pour point depressant ensures the reduction in the temperature at which the mineral oil begins to congeal. During the formation of the base oil, wax is stripped from the oil that would hinder its flow since the wax crystallizes into plate-like structures that interlock and form a retaining structure that prevents the flow of oil. As the oil is cooled and the wax begins to settle out, the waxy component of the pour point depressant crystallizes together with the wax from the base oil, but the bulkier naphthalene component disrupts the surfaces of the crystals and prevents further crystallization. [5]

   (b) **Viscosity Modifiers**
   The viscosity modifier improves the viscosity index because they are more soluble in the base stock at high temperatures than in low temperatures. In high temperatures, the polymer chains are solvated, meaning that they are surrounded by the lubricant base-stock molecules, extending into the oil, hindering its flow and thus raising the viscosity significantly. In low temperatures, the polymer is not solvated and will thus attract itself more than the base-stock molecules, forming small coils and clusters of polymer that do not hinder the flow of the oil as much as in high temperatures. Even though the oil has thickened due to the low temperatures, the thickness of the oil as a result of the polymer is not as high as it would be at high temperatures. Olefin copolymer consisting of ethylene and propylene is commonly used as Viscosity Index modifiers[5].

   (c) **Anti-Oxidants**
   Oil undergoes oxidation in the presence of air when heated to high tempera-

tures, resulting in darkening, acidification and formation of sludge. The crude base stock which has been mildly refined consists of some inherent inhibitors or antioxidants which get stripped away through refining.
In the case of earlier motor oils, there was no much refining done to them and therefore, they had their natural inhibitors intact. Motor oil would be changed often since it was extremely inexpensive, as well as being heavily contaminated with by-products of combustion. Early premium motor oils had small amounts of ZDDP added to give it some anti-wear properties, as well as anti-oxidant properties. Presently, Amines and substituted phenols are normally used as Anti-oxidants[5].

(d) **Detergents**
A detergent additive is an additive whose main purpose is to reduce deposits on the engine's hot parts, especially the piston and in the piston ring grooves. A detergent inhibitor is an additive which works as a detergent but it contains components which provide it with inhibition property against oxidation and bearing corrosion. The detergents, especially the sulfonates, also possess some capacity of dispersing soot and other particles within the oil. Majority of detergents being used in the current formulations consist of a metal compound or a combination of metals such as calcium, magnesium, sodium which lead to the formation of metallic ash. Furthermore, since they are sulfurized to form sulfonates or phenates, they contain large amounts of sulfur compounds. A lot of concerns have been raised by many OEMs about the effects of the level of sulfur and metallic additives in the current formulations on the performance of after treatment systems in order to comply with U.S. 2004 heavy-duty diesel emission legislation. They are calling for the production of low-sulfur containing formulation. Thus, the requirement of higher use of zero-low sulfur and ash and low-metallic content detergents is needed[5].

(e) **Dispersant**
As early as the discovery of the sludge problem, it was realized that a new group of additives needed to be developed to cope with what is referred to as "cold sludge." They are the ashless dispersants, whose main role is to disperse water and soot particles so as to make it harmless, though their use is now extended to diesel engines and they can also disperse other substances and work as mild detergents. The "succinimides" that are produced using polyamines are the most common. Other types of dispersants, based on polyhydroxy compounds (such as pentaerythritol) or amino-hydroxy compounds, are also available and are essentially polyisobutenyl succinate esters. They function like the nitrogen-only materials, except that they have a polar head based on oxygen or oxygen plus nitrogen instead of just nitrogen. They were briefly popular and were preferred by some formulators as at least a component of dispersants[5].

(f) **Anti-wear Additives**
In 1941 with the Lubrizol Corporation's invention of Zinc Dialkyl Dithiophosphates (ZDDP). First employed in small quantities (0.1 to 0.25%) to serve as a bearing passivator and oil anti-oxidant, ZDDP was quickly discovered to be very efficient as an anti-wear agent. This is an additive that works against wear from boundary lubrication all through to extreme pressure action in very heavily loaded steel-on-steel mechanisms. Currently, ZDDP is the main anti-wear additive in crankcase oil, although it is a category of additive rather than

just one type of chemistry. The downside with ZDDP is that it has a lot of sulfur species. Due to the fact that there have been complaints from some OEMs regarding the bad influence of sulfur species on the performance of after treatment, there is likely to be minimal sulfur formulations available to meet the requirements of US 2004 heavy duty diesel emission legislation[5].

(g) **Friction Modifiers**
There have been new developments in the area of Friction Modifiers as a result of the increasing interest in improving the fuel economy of vehicles and the realization that these additives can play a relatively minor yet valuable role in achieving this goal. Friction Modifiers are a group of lubricating additives including those in boundary lubrication and further development of this concept to make the components even more "slippery" and decrease the friction coefficients. Suitable chemicals will include long-chain substances that have very polar groups allowing them to attach to the metallic surfaces[5].

(h) **Rust and Corrosion Inhibitors**
It is also essential to prevent corrosion of the engine where the water may accumulate, like the area below the rocker cover and the sump. Some of the metals present in the engine, including aluminum, magnesium and copper alloys, may also tend to corrode in the presence of excess moisture and acidic residues from combustion. The triazoles and thiodiazoles form two categories of modern general purpose corrosion inhibitors[5].

(i) **Anti-Foam Additives**
Many lubricating systems, especially those of the conventional wet sump engine whereby the crankshaft agitates air and oil, may cause the formation of foamy layers in the lubricant, especially if there are detergents and other surface active agents present. For crankcase lubricants, a trace amount of silicone oil in the lubricant can significantly reduce foaming. Silicone oil does not mix with mineral oil and small droplets of silicone oil on a microscale increase the thickness of the oil layer around the air bubbles, thus promoting the quick draining of oil and ultimately leading to the breaking down of the foam. One drawback of using silicone oil is that it causes air entrainment, meaning that it promotes the retention of many small air bubbles in the oil. The formation of some entrained air in motor oils is not detrimental, but for some industrial oils, air entrainment is highly undesirable. In such situations, the anti-foaming agents used are ester polymers which are used in higher concentrations than silicones but are not prone to air entrainment[5].

2.2.2 Performance Standards for Oil

Performance of oils is always relative. Any liquid could probably be used to lubricate an engine in some way for a period of time but this period must be measured in months rather than minutes. The period of life of any oil (between drainages of oil) has constantly grown while life of engines has been also growing. Both factors are due to the growing performance of oils required by the engine manufacturers. With a few exceptions that may be discussed, every next generation of oils requires better performance in some area compared to previous oil specifications.

1. **SAE J300 Standards.** The SAE J300 standard set by SAE International sets forth the viscometric characteristics of both single grade and multigrade engine oils. Among other things, it sets the standards for the most important parameters like kinematic viscosity, high temperature and high shear viscosity (using tapered bearing simulator test) and low temperature characteristics (using cold-cranking simulator test and mini-rotary viscometer test).

   Grade oil with "W" (Winter) designation represents good low temperature characteristic while non-"W" grade represents viscosity at normal engine operating temperature. Single grade oils are known as "straight weight" oils. Winter grade includes viscosity grades: 0W, 5W, 10W, 15W, 20W, 25W, 8, 12, 16, 20, 30, 40, 50 and 60."

   Table 2.4 lists some common winter-grade engine oils (0W to 25W) with their key viscosity properties as per SAE J300. Oil used in engines not during the winters

Grade	Low-temperature CCS viscosity (cP) (max)	Low-temperature pumping viscosity (cP) (max)	Kinematic viscosity (cSt) @100 °C (min)
0W	6,200 @-35 °C	60,000 @-40 °C	3.8
5W	6,600 @-30 °C	60,000 @-35 °C	3.8
10W	7,000 @-25 °C	60,000 @-30 °C	4.1
15W	7,000 @-20 °C	60,000 @-25 °C	5.6
20W	9,500 @-15 °C	60,000 @-20 °C	5.6
25W	13,000 @-10 °C	60,000 @-15 °C	9.3

Table 2.4: Viscosity properties of different oil grades

   is known as straight weight oil. The specification SAE J300 specifies important properties such as kinematic viscosity at 100°C and HTHS (High Temperature High Shear) viscosity at 150°C, which show the resistance to flow of the oil. The important properties of common non-winter grades are shown in Table 2.5.

Grade	Kinematic viscosity (cSt) @100 °C (min)	Kinematic viscosity (cSt) @100 °C (max)	HTHS viscosity (cP) @150 °C (min)
8	4.0	<6.1	1.70
12	5.0	<7.1	2.0
16	6.1	<8.2	2.3
20	6.9	<9.3	2.6
30	9.3	<12.5	2.9
40	12.5	<16.3	2.9 or 3.7
50	16.3	<21.9	3.7
60	21.9	<26.1	3.7

Table 2.5: Viscosity properties of common non-winter engine oils (SAE J300).

2. **Performance Standards for Diesel Engine Oils.** There have been differences between European OEMs with regard to the way lubricants have been classified and approved. The policy that issues lubricant "sequences" but does not approve them is ACEA. It prefers to use the multi-cylinder European engine tests conducted by CEC wherever possible. Sequences exist for gasoline engines, light duty diesel engines and heavy duty diesel engines. There are currently five sequences for gasoline and light

duty diesel engines and four for heavy duty diesel engines.

3. **Volvo Standards for Diesel Engine Oils.** Where Volvo has set its own standards through making their oil standards more stringent due to sustainability, any oil that meets the criteria of the Volvo standards can get certification from Volvo.

2.2.3 Engine Oil Standard Tests

The oil quality for engines can be tested in laboratories using certain test methods that focus on a particular parameter of deterioration. The test methods act as the ground truth against which sensor-based measurements can be validated in this dissertation, knowing about the test method is important to know the capabilities of the FPS2800 sensor.

1. **Viscosity Measurement.**

   The kinematic viscosity is evaluated at 40°C and 100°C in a glass capillary viscometer according to ASTM D445 / ISO 3104. The dynamic viscosity is calculated from the kinematic viscosity and density. For low temperatures, cold-cranking viscosity is estimated in a Cold-Cranking Simulator (CCS) according to ASTM D5293, while pumping viscosity at low temperature is determined in a Mini-Rotary Viscometer (MRV) according to ASTM D4684. These values determine the viscosity grade of the lubricant according to SAE J300 specification.

2. **Fourier Transform Infrared Spectroscopy (FTIR).**

   FTIR spectroscopy is the primary method for quantifying multiple degradation parameters simultaneously from a single oil sample. Analysis is performed per ASTM D7418 (full spectral scan) or ASTM D7214 (carbonyl-specific). The key parameters measurable by FTIR include:

   - **Oxidation**: quantified from the carbonyl absorption peak at 1700 cm^{-1}, expressed in absorbance units per centimetre (A/cm).
   - **Nitration**: absorption at 1630 cm^{-1}, expressed in A/cm.
   - **Soot content**: absorption at 2000 cm^{-1}, expressed as % by mass.
   - **Water content**: absorption at 3400 cm^{-1}, expressed in ppm.
   - **Fuel dilution**: absorption at 812 cm^{-1} for diesel, expressed as % by volume.
   - **Glycol/coolant contamination**: absorption at 1000 cm^{-1}, expressed as ppm.

   FTIR is the reference method used for all oil condition parameters within the Volvo GLAD system and it constitutes the primary ground truth against which the FPS2800 sensor model outputs are validated in Chapters 4 and 5.

3. **Total Base Number (TBN).**

   The TBN value is determined using potentiometric titration in accordance with ASTM D2896 or ASTM D4739 standards, stated in mg KOH/g. It represents the level of alkalinity of the oil as well as its ability to neutralize acids formed during combustion process. Pure VDS-5 oil has TBN within the range of 8-14 mg KOH/g. Volvo has a defined TBN limit for an oil change [1]. TBN degradation is a characteristic of the oil which decreases monotonically.

4. **Total Acid Number (TAN).**

   TAN is determined using potentiometric titration in accordance with ASTM D664 and is reported in units of mg KOH/g. It is an expression of total acidity in the oil, which rises as more oxidation products and combustion acids form. The TBN to TAN ratio is an important measure of the remaining alkalinity reserve of the oil, since the TBN becomes equal to TAN when the oil's acid-neutralising ability becomes exhausted and oil change is critical [1].

5. **Spectrometric Metal Analysis.**

   Concentrations of wear metals and contaminant elements (Fe, Cu, Al, Cr, Na, B, K) are determined by ICP Atomic Emission Spectroscopy (ICP-AES) according to ASTM D5185 / NFT 60 106, in units of mg/kg (ppm by weight). Iron and copper are key parameters for detecting abnormal wear caused by engine components.

6. **Water Content.**

   Total absolute water content is measured by Karl Fisher titration per ISO 12937 / ASTM D1533, expressed in ppm by mass with accuracy to approximately 100 ppm. Alternative methods include FTIR (ASTM D7418) and aquatesting (ASTM D7358).

2.2.4 The FPS2800 Oil Property Sensor

1. **Measurement Principle.**

   The FPS2800 Oil Property Sensor (OPS) made by TE Connectivity operates on the basis of quartz tuning fork resonator technology. The tuning fork consists of a quartz material which vibrates due to the application of voltage while simultaneously producing voltage due to mechanical stress. The tuning fork resonates due to a sinusoidal excitation signal applied to the thin electrodes of the tines and undergoes mechanical bending at a resonant frequency of about 31 kHz in air. The generated current due to such resonance is used to measure the system impedance that depends on the frequency of the excitation signal, elastic properties of the quartz material and properties of the surrounding liquid [1]. The circuit diagram is shown in figure 2.2 .

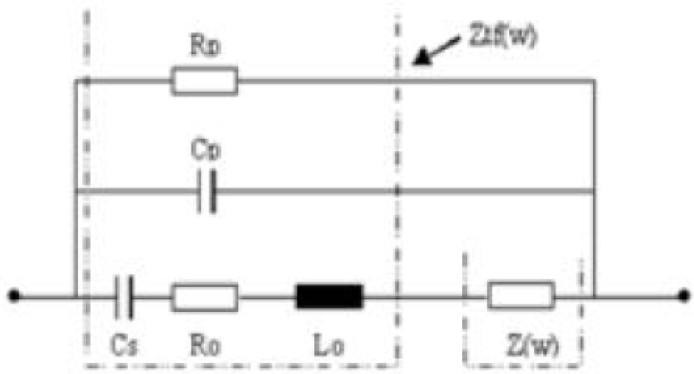

Figure 2.2: The figure shows equivalent circuit diagram of the sensor [1].

When immersed in a fluid, the resonance frequency and amplitude decrease due to increased mass loading and frictional damping by the fluid. The fluid's contribution to the total impedance is described by an additional term in the equivalent electrical circuit model [1]:

$$Z(\omega) = Ai\omega\rho + B\sqrt{\omega\rho\eta}(1+i) \tag{2.1}$$

where ω is the excitation frequency, ρ is fluid density, η is dynamic viscosity and A and B are resonator geometry constants. The dielectric constant ε and electrical resistivity R_p are simultaneously measured via the parallel capacitance C_p and resistance R_p of the tuning fork:

$$C_f(\varepsilon) = (\varepsilon - 1)\frac{\partial C_P}{\partial \varepsilon} + C_{P,\text{vacuum}} \qquad R_p(\mathrm{P}) = \mathrm{P}\frac{\partial R_p}{\partial \mathrm{P}} \tag{2.2}$$

Following a calibration step, the FPS2800 is capable of simultaneously measuring dynamic viscosity η (cP), density ρ (g/cc), dielectric constant ε (dimensionless) and electrical resistivity R_p (Ω) of the oil in which it is immersed [1].

2. **Temperature-Dependent Physical Property Models.**

   The four measured parameters are all temperature dependent. The FPS2800 white paper proposes the following temperature models for clean engine oil [1]:

   Kinematic viscosity follows a double-logarithmic temperature dependence per the ASTM D341 standard:

   $$\log(\log(\mu + 0.7)) = B - C \cdot \log(T + 273.15) \tag{2.3}$$

   where μ is kinematic viscosity (cSt), T is temperature (°C) and B, C are oil-dependent constants.

   Density follows a linear temperature dependence:

   $$\rho = D + E \cdot T \tag{2.4}$$

   Dielectric constant follows a linear temperature dependence, consistent with the Clausius-Mossotti relation linking ε to density:

   $$\varepsilon = F + G \cdot T \tag{2.5}$$

   Resistivity is proposed as linear in the white paper:

   $$R_p = H + I \cdot T \tag{2.6}$$

   The validity of these models for Volvo VDS-5 engine oil is a primary objective of the rig testing phase described in Chapter 4.

3. **Contamination Detection Models.**

   For each contamination type, the FPS2800 white paper provides linear blending models that describe how each of the four measured parameters changes with contamination concentration at constant temperature [1]. The general form for a contamination C at concentration x is:

$$\phi_m = \phi_i \cdot (1 + k_\phi \cdot x) \tag{2.7}$$

where ϕ_m is the measured parameter value, ϕ_i is the fresh oil baseline or the previous condition and k_ϕ is an oil-specific sensitivity constant determined by calibration. The sensitivity constants documented for each contamination type and parameter are presented in Chapter 4, where they are compared against the values obtained from the VDS-5 rig calibration experiments.

4. **Oil Ageing and Detection Capabilities.**

   Without contamination, during the normal aging of oils, viscosity, density and dielectric constant increases but the resistivity follows a different pattern due to depletion and acid generation in the four phases of the oxidation process [1]. The Figure 2.3 has been taken from the white paper of the sensor [1]. The graph shows the aging of new oil (Blue curve) without contamination (Red Curve).

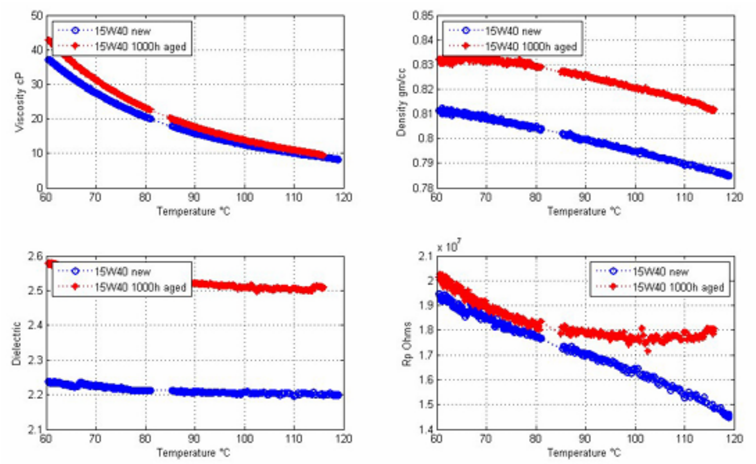

Figure 2.3: The figure shows how new oil(Blue curve) gets changed over a period of time with ageing (Red curves) [1].

   This white paper presents the sensor's ability to detect eight different events which are related to the oil conditions, they are oxidation, water contamination, coolant contamination, fuel dilution, soot contamination, metal contamination, TBN/TAN depletion monitoring and incorrect fluid. Every contamination has its own unique curves in all four parameters, which makes it possible to identify multiple contaminations simultaneously using coupled equations [1].

2.2.5 Data Collection and Analysis Methods for Oil Condition Monitoring

1. **CAN-Bus Data Acquisition.**

   In modern vehicles, the sensor data are transferred through Controller Area Network (CAN) bus that follows the serial communication protocol. The FPS2800 oil quality sensor, for example, provides its data as CAN messages at an adjustable acquisition rate. In this thesis, the logging rate is set to take one record every 30 seconds. Consequently, the amount of data obtained from the sensor during the three months of service period will be over one million records that will surpass the maximum row number of typical desktop analysis software like Microsoft Excel (1,048,576 rows).

2. **Data Filtering Methods.**

   Raw Sensor readings in the vehicle application have structured noise due to cold starts, the settling time of sensors and CAN-bus error frames. There are several filtering methods possible:

   Hard filtering applies a predetermined upper and lower limit for each of the parameters based on the physical specification of the sensor and the operating physical range. Readings outside this physical bound are disregarded.

   RANSAC (Random Sample Consensus) filtering iteratively fits a model to random data subsets and identifies inliers based on a distance threshold [6]. It provides robust outlier rejection without assuming Gaussian noise, making it suitable for rig datasets containing structured, non-random outliers during temperature transitions.

   Savitzky-Golay filtering applies a polynomial smoothing function to preserve signal shape while reducing noise. It is appropriate for continuous, slowly varying signals but is not designed to reject structured outliers and may smooth over genuine contamination events.

3. **Temperature Normalisation.**

   Since all four FPS2800 parameters are temperature dependent, direct comparison of measurements taken at different temperatures is not meaningful without normalisation. Temperature compensation is performed by fitting the fresh oil temperature model (Equations 2.3 2.6) to baseline data acquired after an oil change and subsequently computing the deviation of each measurement from the temperature-predicted baseline at a fixed reference temperature T_1 [1]. This yields temperature compensated relative and absolute evolution values that isolate contamination driven changes from thermally driven ones.

4. **Coupled Equation Matrix Approach.**

   Since each of the four sensor parameters is influenced by multiple contamination sources simultaneously, contamination estimation requires solving a system of coupled equations at each time step. This is formulated as a linear system $\mathbf{M} = \mathbf{A} \cdot \mathbf{C}$, where $\mathbf{M}$ is the vector of measured parameter deviations from baseline, $\mathbf{A}$ is the sensitivity matrix of calibration constants and $\mathbf{C}$ is the vector of unknown contamination levels. The system is solved via matrix inversion $\mathbf{C} = \mathbf{A}^{-1} \cdot \mathbf{M}$ at each time step using numerical linear algebra methods [7, 8]. Slow cumulative parameters (soot, oxidation) are integrated over time to give accumulated estimates, while fast transient parameters (water, fuel dilution) are reported as instantaneous estimates [1].

2.2.6 Soot Surrogates in Laboratory Testing

Controlled Laboratory alternative of soot contamination for sensor calibration is quite difficult as it is impossible to create diesel combustion soot in controlled amounts without the use of an engine. Commercial carbon black is the most common laboratory substitute for diesel soot in studies on sensors.

The Imperial College London research on soot in engine oil examined the use of commercial carbon black as a diesel soot substitute in lubricant studies [9]. It was determined that while both carbon black and diesel soot have similar particle structure of aggregates, their surfaces are quite different chemically. In the case of diesel soot particles, their surface contains oxygen containing functional groups such as carboxyl, hydroxyl and carbonyl groups, which appear as a result of combustion. Such groups react with the polar head of dispersant additives and attach the additive to the particle surface. This keeps the soot suspended in oil. The surface of commercial carbon black is quite inert chemically and contains fewer functional groups, so it tends to agglomerate quickly in oil. [9, 10].

2.3 Chapter Summary

This chapter combined primary and secondary research to create a foundation for the FPS2800-based oil condition monitoring system. The primary research based on four stakeholder interviews from R&D, aftermarket and competitor/customer sectors, found out that there is no solution for contamination detection and identification as well as soot and metals analysis by using algorithmic oil life monitor or single parameter capacitive sensor, such as TANDelta OQS-G2. This lack of solution was transformed into the formal needs specification of customer requirements that FPS2800 met almost completely except partial analysis of metal contamination and TBN/TAN monitoring. Secondary research created the necessary theoretical background in order to understand the functioning of the sensor, composition of engine oil based on API base oil categories and types of additives; performance requirements (SAE J300, ACEA and internal criteria of Volvo), laboratory reference analysis (viscometry, FTIR, TBN/TAN titration, ICP-AES, Karl Fischer), tuning-fork measurement principle of FPS2800, models of temperature and contamination, eight oil condition events detectability, methods of data collection and processing (CAN-bus recording, hard/RANSAC/Savitzky-Golay filtering, temperature normalization, coupled equation matrix estimation) that were used in the following part of thesis, and carbon black as a surrogate of soot in the laboratory.

3 Methodology

This chapter presents the structured methodology followed in this thesis to develop a real-time oil condition monitoring system for engine oils at Volvo. The methodology is a systematic product development practice, following a process that moves from high level system definition through functional decomposition, concept generation, structured elimination and final concept selection. Each step builds on the previous one, ensuring that all design decisions are justified. The selected concept defines the specific implementation choices for the rig design, oil grade selection, contamination method, data analysis tool chain, vehicle selection and data filtering approach used throughout this thesis.

3.1 System Definition : Black Box Model

The starting point of any systematic design process is a clear definition of what the system must do, stated independently of how it should do it. This is achieved using a black box model which is a standard system engineering tool that represents the system purely in terms of its external inputs and outputs, with no assumptions about internal implementation [11]. By defining the system bounds at this broad level, it is possible to ensure that the problem is fully understood before any solution is considered.

As shown in Figure 3.1, the oil condition monitoring system receives two inputs. The primary input is data from the FPS2800 Oil Quality Sensor (OQS), which provides continuous measurements of four physical oil properties: dynamic viscosity, density, dielectric constant and electrical resistivity. The secondary input is data from other sensors installed on the vehicle or test rig. The single output of the system is a real time oil condition estimate, expressed as quantified levels of key oil contaminants and degradation indicators such as soot, oxidation, fuel dilution and water contamination.

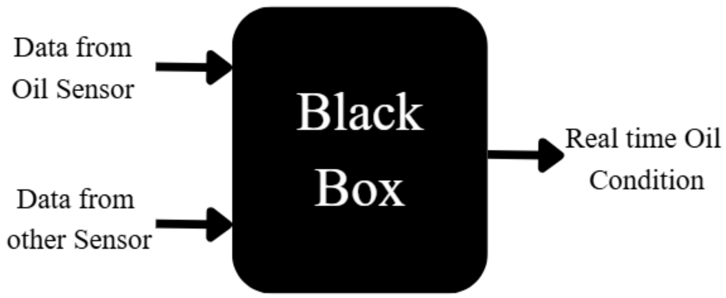

Figure 3.1: Black box model of the oil condition monitoring system.

3.2 Functional Decomposition

With the system boundary defined, the next step was to decompose the top-level system function into a set of sub-functions. This process, known as functional decomposition, is a fundamental technique in systematic engineering design [4]. It transforms a single, abstract requirements of oil condition monitoring in real time into a hierarchical tree of concrete sub-tasks, each of which can be addressed independently. The functional tree also serves as the structural backbone for the morphological matrix, since each branch of the tree becomes a row in the matrix for which solution alternatives are generated.

3.2.1 Top-Level Functional Tree

Figure 3.2 presents the top-level functional tree. The overarching function of oil condition monitoring is decomposed into four primary sub-functions:

1. **Collecting data from sensors**: acquiring raw physical property measurements from the FPS2800 OQS and supporting sensors, from both the laboratory rig and the instrumented vehicle.
2. **Processing sensor data**: cleaning, filtering and normalising the raw data to remove noise, normalise the temperature and establish standard equations from the processed data.
3. **Analyzing data**: applying the contamination models to estimate oil condition, comparing outputs against physics-based equations and literature references and verifying results against independent laboratory tests.
4. **Deploying the monitoring system**: integrating the validated model into a pipeline which connects to a display dashboard for future use.

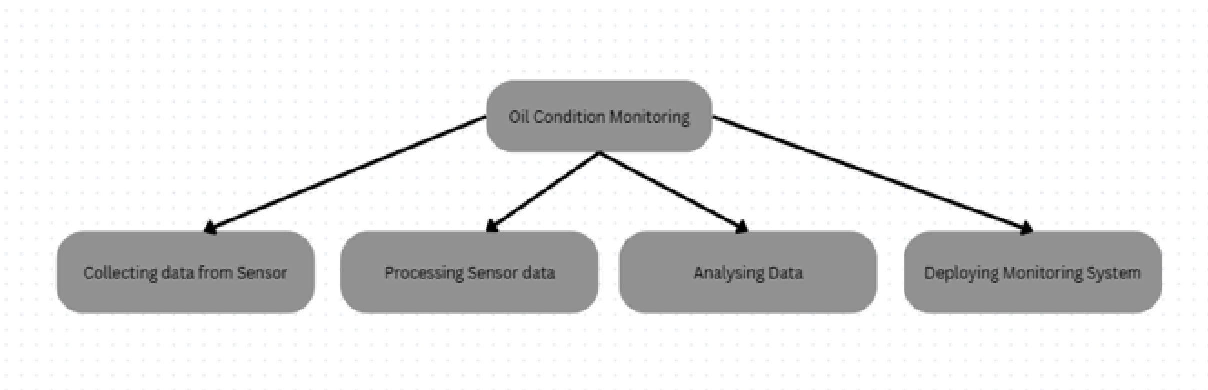

Figure 3.2: Top-level functional tree for the oil condition monitoring system, decomposed into four primary sub-functions.

3.2.2 Data Collection Sub-Functions

Figure 3.3 expands the data collection branch into its constituent sub-functions. Data is collected from two independent and complementary sources.

The first source is the laboratory oil test rig. This involves manufacturing a suitable rig, selecting an appropriate base oil, contaminating the oil with controlled quantities of known contaminants, testing the oil samples under defined conditions and analysing the sensor response. Each of these steps constitutes a sub-function in its own points and displays a design decision point at which multiple solution alternatives exist.

The second source is the vehicle. This branch involves selecting an appropriate vehicle from the Volvo Group test fleet and converting the raw CAN bus data stream into the physical parameter format required by the processing pipeline.

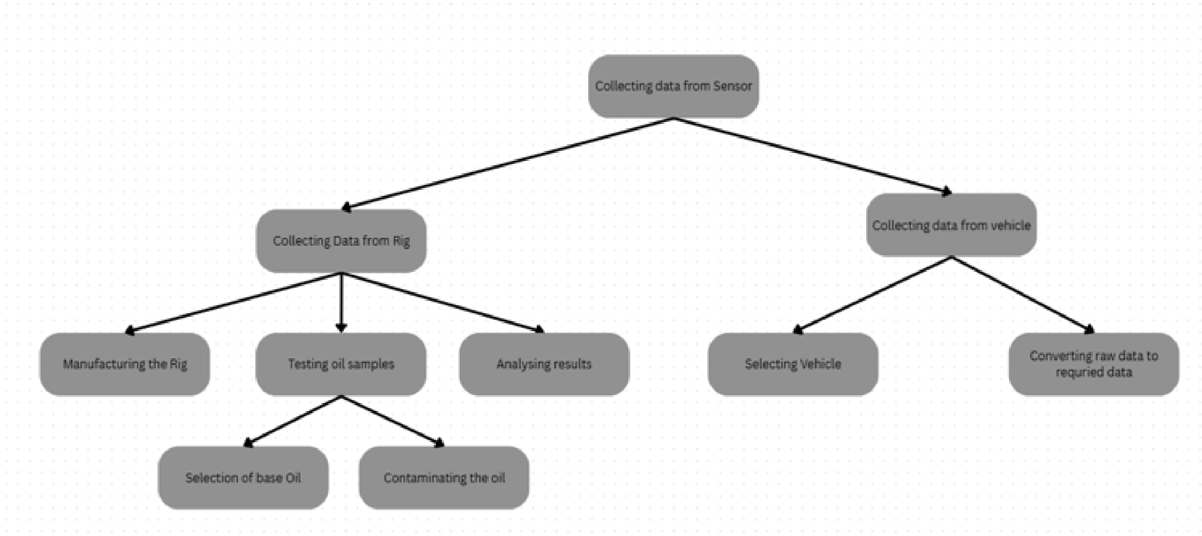

Figure 3.3: Functional tree for the data collection sub-functions, covering both rig-based and vehicle-based data sources.

The two source data strategy is important because it provides controlled calibration data from the rig, which is necessary for model fitting and real world validation data from the vehicle, which provides the operational context in which the model must perform.

3.2.3 Data Processing and Analysis Sub-Functions

Figure 3.4 shows the processing and analysis branches in detail. The processing branch comprises three steps starting with filtering the raw sensor data to remove noise and outliers, then normalising the data for temperature effects so that contamination driven changes can be isolated from thermally driven changes and finally creating the standard model equations that relate sensor outputs to contamination levels.

The analysis branch comprises three parallel activities starting with comparing model outputs against physics-based equations derived from first principles oil property models, benchmarking against trends reported in the research literature and verifying the model outputs against laboratory test results obtained from Volvo's Global Liquid Analysis Database (GLAD).

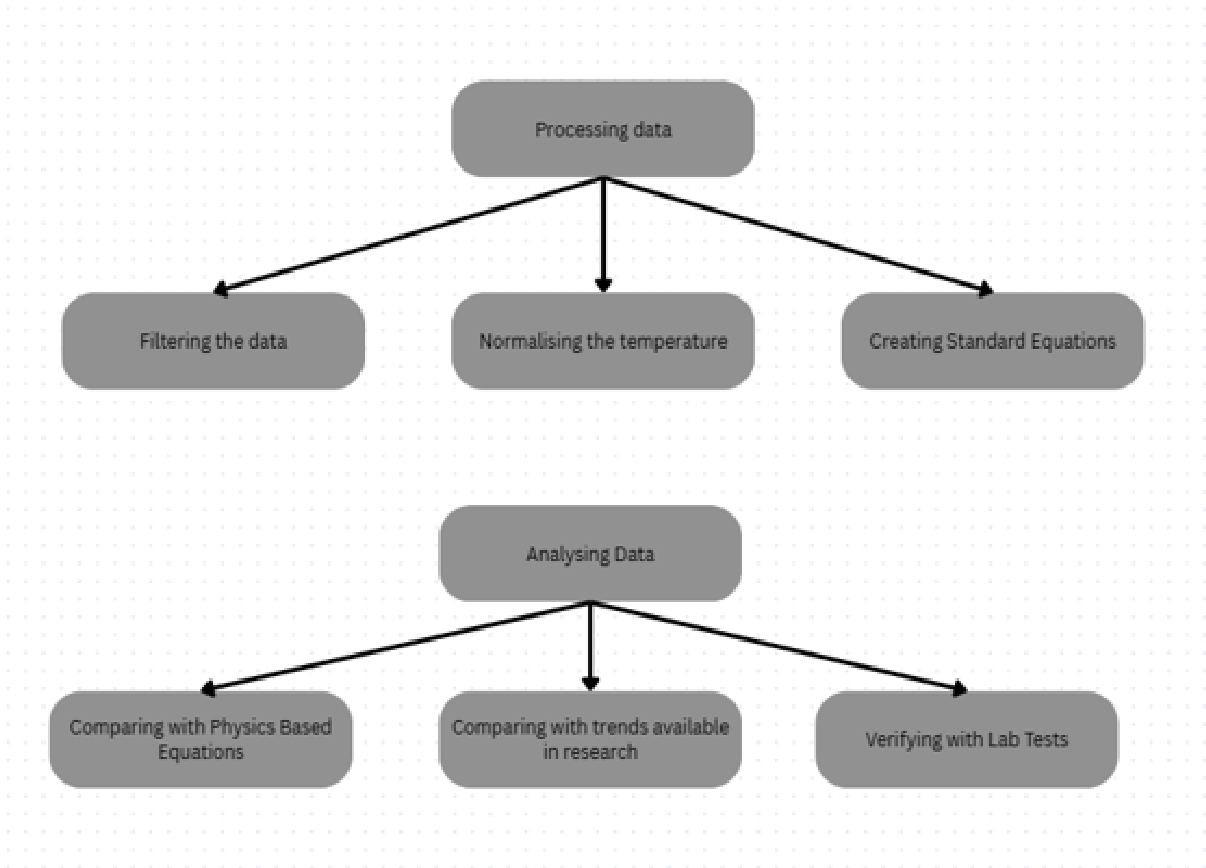

Figure 3.4: Functional tree for data processing and analysis sub-functions, including filtering, temperature normalisation, model creation and multi-source validation.

3.3 Process Flow

To take the functional decomposition forward and get a executable methodology, a process flow diagram was developed. While the functional tree shows what the system must do, the process flow diagram shows how and in what order those functions are executed. Figure 3.5 illustrates the complete process from raw sensor data acquisition to final validated output.

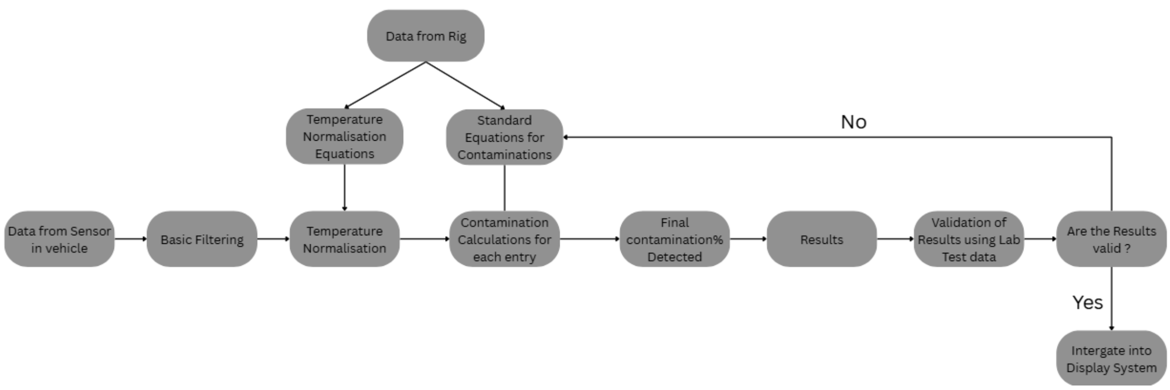

Figure 3.5: Process flow diagram for the oil condition monitoring methodology.

The process begins with raw data acquisition from the FPS2800 sensor. This raw data undergoes filtering and smoothing to remove noise. Temperature normalisation is then applied to isolate contamination-driven deviations from thermally-driven parameter changes. Curve fitting is performed on the processed sensor data and compared against standard curves established from the controlled rig testing phase described in Chapter 4. The standard curves provide the reference model coefficients used to convert the fitted sensor data into physical contamination estimates. The converted estimates are then passed to the output function matrix using contamination equations. The resulting estimates are validated against independent laboratory test results obtained from GLAD. A decision gate is included where if the results are valid, they proceed to the final output stage and if not, the process loops back to the output function matrix for model recalibration. This iterative loop is a critical quality assurance feature, ensuring that no model outputs are accepted without demonstrated agreement with laboratory evidence.

Once validated, the final output is integrated into the display system which will presents the oil condition estimates in a format accessible to everyone without requiring any interpretation of raw sensor data. This final integration step closes the loop between sensor measurement and decision-making.

3.4 Concept Generation : Morphological Matrix

With the sub-functions fully defined through the functional decomposition, the next step was to generate a set of solution alternatives for each sub-function. This was achieved using a morphological matrix, a tool introduced by Zwicky [12] and widely used in systematic product development to ensure that the design space is explored broadly before any concept is selected. The matrix lists all sub-functions as rows and all identified solution alternatives as columns, making the full combine design space visible and preventing premature convergence on a single solution path.

Table 3.1 presents the morphological matrix developed for this project. Eight sub functions were identified from the functional decomposition. For each sub-function, between three and four technically feasible solution alternatives were identified based on a review of available equipment, software tools and industry practice.

Table 3.1: Morphological matrix for the oil condition monitoring system showing all solution alternatives for each sub-function.

Sub-Function	Solution 1	Solution 2	Solution 3	Solution 4
Manufacturing rig	Oven rig	Oven circulating rig	Engine-based rig	Pressure temperature rig
Selection of base oil	VDS-4	VDS-5	VDS-6	–
Contaminating base oil	Mixing contaminants	Buying reference fluids	Field samples	External lab samples
Analysing rig data tools	PyCharm	Excel	Jupyter Notebook	Visual Studio Code
Selection of vehicle	FL286	DL239	FL289	–
Filtering rig data	Hard filtering	Savitzky-Golay filtering	RANSAC filtering	Low-pass filtering
Analysing vehicle data tools	PyCharm	Excel	Jupyter Notebook	Visual Studio Code
Filtering vehicle data	Hard filtering	Savitzky-Golay filtering	RANSAC filtering	Low-pass filtering

The total number of possible concept combinations is the product of the number of alternatives per sub-function: $4 \times 3 \times 4 \times 4 \times 3 \times 4 \times 4 \times 4 = 18{,}432$ possible combinations. The purpose of the elimination and scoring steps that follow is to reduce this space to a single justified concept path in a structured manner.

3.5 Concept Elimination: Screening Matrix

A binary elimination step was applied to remove concepts that fail basic requirements, regardless of their performance criteria. This two-stage approach starting with elimination and followed by scoring is consistent with best practice in systematic design, as it avoids spending evaluation effort on concepts that fail mandatory constraints [13].

The following criteria were used for elimination. A concept alternative is eliminated if it fails any single criterion.

- **C1 Technically feasible within project scope:** achievable within the timeline, budget and equipment available for a master's thesis project at Volvo Group Powertrain.
- **C2 Compatible with FPS2800 measurement principle:** does not interfere with the tuning fork resonator, which requires controlled flow and a non-conductive fluid environment.

C3 Produces controllable and repeatable test conditions: allows contamination levels and operating conditions to be set and repeated accurately.

C4 Scalable to required dataset size: capable of handling datasets exceeding one million rows for the six-month vehicle CAN-bus dataset.

Table 3.2: Concept elimination matrix. '+' = passes, '–' = eliminated, '?' = further investigation needed. Any alternative with at least one '–' is eliminated.

Sub-Function	**Alternative**	**C1**	**C2**	**C3**	**C4**	**Result**
Rig design	Oven rig	+	+	+	+	**Pass**
	Oven circulating	+	+	+	+	**Pass**
	Engine-based rig	−	+	+	+	Eliminated
	Pressure temp. rig	−	+	+	+	Eliminated
Base oil	VDS-4	+	+	+	+	**Pass**
	VDS-5	+	+	+	+	**Pass**
	VDS-6	+	+	+	+	**Pass**
Contamination	Mixing contaminants	+	+	+	+	**Pass**
	Reference fluids	+	+	?	+	**Pass**
	Field samples	+	+	−	+	Eliminated
	External lab samples	−	+	−	+	Eliminated
Rig analysis tool	PyCharm	+	+	+	+	**Pass**
	Excel	+	+	+	−	Eliminated
	Jupyter Notebook	+	+	+	+	**Pass**
	VS Code	+	+	+	+	**Pass**
Vehicle	FL286	+	+	+	+	**Pass**
	DL239	+	+	+	+	**Pass**
	FL289	+	+	+	+	**Pass**
Rig filter	Hard filtering	+	+	−	+	Eliminated
	Savitzky-Golay	+	+	+	+	**Pass**
	RANSAC filtering	+	+	+	+	**Pass**
	Low-pass filtering	+	+	+	+	**Pass**
Vehicle analysis	PyCharm	+	+	+	−	Eliminated
	Excel	+	+	+	−	Eliminated
	Jupyter Notebook	+	+	+	+	**Pass**
	VS Code	+	+	+	+	**Pass**
Vehicle filter	Hard filtering	+	+	+	+	**Pass**
	Savitzky-Golay	+	+	+	+	**Pass**
	RANSAC filtering	+	+	+	+	**Pass**
	Low-pass filtering	+	+	+	+	**Pass**

The elimination step removes eight alternatives from consideration. The engine-based and pressure-temperature rigs are eliminated on feasibility grounds (C1), as both require capital equipment and operational expertise beyond the scope of this thesis. Field samples and external laboratory samples are eliminated because they do not permit controlled, repeatable contamination levels (C3). Excel is eliminated for both rig and vehicle analysis because its maximum row limit of 1,048,576 entries is insufficient for the vehicle dataset (C4). PyCharm and VS Code are eliminated for vehicle analysis because they lack direct integration with the Volvo DSL environment (C4). Hard filtering is eliminated for rig data because for a small, controlled dataset, it discards valid data points during temperature ramp phases (C3).

3.6 Concept Scoring: Pugh Matrix

Following the elimination step, a Pugh concept scoring matrix was applied to the surviving alternatives for each sub-function where more than one option remained [13]. The Pugh matrix uses a reference datum for comparison and assigns scores of '+' (better than datum), 'S' (same as datum), or '–' (worse than datum) for each criterion. Four weighted scoring criteria were used:

- **Model accuracy** (weight 3): how well the solution supports accurate contamination model development and validation.
- **Implementation effort** (weight 2): time and technical effort required within the project timeline.
- **Scalability** (weight 2): suitability for larger datasets and future extension to additional vehicles.
- **Volvo infrastructure compatibility** (weight 3): integration with existing Volvo Group tools and data environments.

Table 3.3: Pugh concept scoring matrix for surviving alternatives after elimination. Datum alternatives are marked (D). Weighted score = $\sum$(criterion score $\times$ weight), where $+1$, 0, -1 correspond to $+$, S, $-$ respectively.

Sub-Function	**Alternative**	**Acc.** *(w=3)*	**Effort** *(w=2)*	**Scale** *(w=2)*	**Compat.** *(w=3)*	**Score**
Rig design	Oven circulating (D)	–	–	–	–	Only survivor
Base oil	VDS-4 (D)	S	S	S	S	0
	VDS-5	+	S	+	+	+8
	VDS-6	S	S	S	–	−3
Contamination	Mixing (D)	S	S	S	S	0
	Reference fluids	S	–	S	S	−2
Rig tool	PyCharm (D)	+	+	+	+	+8
	Jupyter Notebook	S	S	S	S	0
	VS Code	S	S	S	S	0
Vehicle	FL286 (D)	S	S	S	S	0
	DL239	S	S	S	–	−3
	FL289	S	S	S	–	−3
Rig filter	Savitzky-Golay (D)	S	S	S	S	0
	RANSAC	+	S	+	S	+5
	Low-pass	–	S	S	S	−3
Vehicle tool	Jupyter Notebook (D)	S	S	S	S	0
	VS Code	S	S	S	–	−3
Vehicle filter	Hard filtering (D)	S	+	+	S	+3
	Savitzky-Golay	+	–	S	S	+1
	RANSAC	+	–	S	S	0
	Low-pass filtering	–	S	S	S	−3

The Pugh matrix identifies a clear winner for each sub-function with multiple surviving alternatives. VDS-5 scores highest for base oil (+8) because it is the current Volvo-specified grade and directly applicable to the target fleet, giving it advantages on accuracy, scalability and compatibility. Jupyter Notebook scores highest for rig analysis tool (+8) due to its richer documentation capabilities and superior scalability compared to PyCharm, even though both pass elimination. RANSAC filtering scores highest for rig data filtering (+5) due to its superior model accuracy and scalability over Savitzky-Golay. FL286 scores highest among vehicles due to the best combination of data continuity and GLAD sample availability. For vehicle data filtering, hard filtering scored the best as each data is important and only the noise should be eliminated when the sensor readings are completely off.

3.7 Selected Concept Path

The combined elimination and Pugh scoring process produces a single concept path. Table 3.4 summarises the selected solution for each sub-function.

Table 3.4: Final selected concept path for the oil condition monitoring system.

Sub-Function	**Selected**	**Reason**
Rig design	Oven circulating rig	Ensuring laminar flow for FPS2800 with temperature rise
Base oil	VDS-5	Volvo-specified grade for target fleet; highest Pugh score
Contamination	Mixing contaminants	Controlled, repeatable levels required for model fitting
Rig analysis tool	PyCharm	Easier; highest Pugh score
Vehicle analysis	Jupyter Notebook	Only survivor with DSL integration
Vehicle selection	FL286	Best data continuity and GLAD coverage
Rig data filter	RANSAC filtering	Robust to structured outliers; highest Pugh score
Vehicle data filter	Hard filtering	Computationally efficient; physically grounded bounds

3.8 Summary

This chapter has presented a complete, structured methodology for the development of the oil condition monitoring system. Beginning from a high-level black box system definition, the requirements were translated into a functional decomposition covering data collection, processing, analysis and deployment. A morphological matrix was constructed to systematically list down all solution alternatives coming from eight sub-functions, generating a design space of over 18,000 possible concept combinations. A binary elimination step removed eight alternatives that were incompatible with the FPS2800 measurement principle, incapable of producing controlled test conditions, or insufficient in data scalability. A weighted Pugh scoring matrix was then applied to the surviving alternatives to identify the highest-scoring solution for each sub-function.

The resulting selected concept path oven circulating rig, VDS-5 oil, direct contamination mixing, Jupyter Notebook for vehicle data analysis tasks, Pycharm for Rig Data Analysis, vehicle FL286, RANSAC filtering for rig data and hard filtering for vehicle data defines all key implementation decisions carried forward in this thesis

4 Rig Testing and Findings

This chapter presents the experimental setup, testing methodology and findings from the controlled rig-based performance evaluation of the FPS2800 Oil Quality Sensor. The objective of this phase was to validate the physical property models proposed by TE Connectivity [1] for Volvo Group's specific engine oil, identify deviations from expected behaviour and develop corrected models where necessary. Tests were conducted across a temperature range with fresh oil, followed by controlled contamination experiments.

4.1 Rig Design and Setup

The test rig used in this study was designed and assembled at Volvo Group Powertrain, Gothenburg, with reference to an existing rig configuration established at Volvo's facility in France. The rig was built to conduct experiments with repeatable measurement conditions for the FPS2800 sensor under varying temperature and oil contamination scenarios.

The rig comprises the following key components:

1. **Oven enclosure:** An electrically heated oven capable of maintaining oil temperatures up to 120°C, providing a stable and controllable temperature space for the test oil volume.
2. **Gear motor pump:** A gear-driven pump circulates oil through the sensor housing at a controlled flow rate, ensuring laminar flow conditions across all three sensor measurement elements. Laminar flow is critical to avoid turbulence induced measurement artefacts in the tuning fork resonator of the FPS2800. The gear motor pump did not increase pressure but just made sure that the oil is flowing.
3. **Three FPS2800 sensors:** Three sensors were mounted in parallel within the rig, enabling measurements and sensor comparison for each test condition. This configuration also allowed identification of any sensor variability and improved confidence in the measured data.

All sensor outputs like viscosity, density, dielectric constant and resistivity were acquired via the CAN-bus interface and recorded using a Vision Software which was then converted into excel for analysis in Python software called Py-charm.

4.2 Test Oil

All rig experiments were conducted using Volvo VDS-5 engine oil, the grade specified for use in Volvo Group heavy duty powertrain applications. This ensured that the models developed and validated in this study are directly applicable to the target application. The oil was used in its fresh, unused state at the start of baseline tests.

4.3 Temperature Sweep: Baseline Characterization

The first set of experiments involved heating the fresh VDS-5 oil from ambient temperature to 110°C, while the three FPS2800 sensors continuously recorded viscosity (η), density (ρ), dielectric constant (ε) and resistivity (R_p). The purpose of this test was to understand the temperature dependence of each parameter and assess the validity of the models proposed in sensor specifications [1].

4.3.1 Viscosity

The measured viscosity exhibited a strongly non linear decrease with increasing temperature and can be seen in figure 4.1. Each graph represents Viscosity vs Temperature. First collumn with three graphs represents the raw data from three sensors which is then filtered in the second collumn by using RANSAC and finally a curve fitting is carried out in the third collumn where we get the details of the curve. It was consistent with the logarithmic model proposed by TE Connectivity based on the ASTM D341 standard:

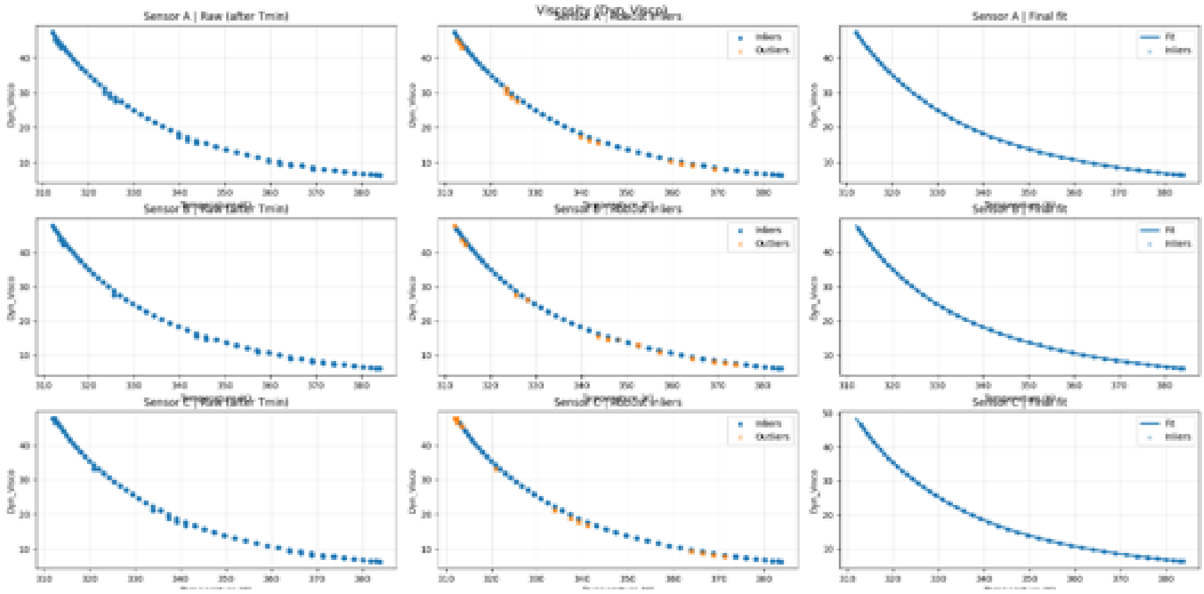

Figure 4.1: Baseline Viscosity vs Temperature

$$\log(\log(\mu + 0.7)) = B - C \cdot \log(T + 273.15) \qquad (4.1)$$

where μ is the kinematic viscosity (cSt), T is temperature (°C) and B and C are oil-dependent constants. Curve fitting using Python (`scipy.optimize.curve_fit`) against the rig data confirmed that this model provides an excellent fit for VDS-5 oil across the full temperature range tested.

4.3.2 Density

Density showed a linear decrease with temperature, It can be seen the cuvre figure 4.2.

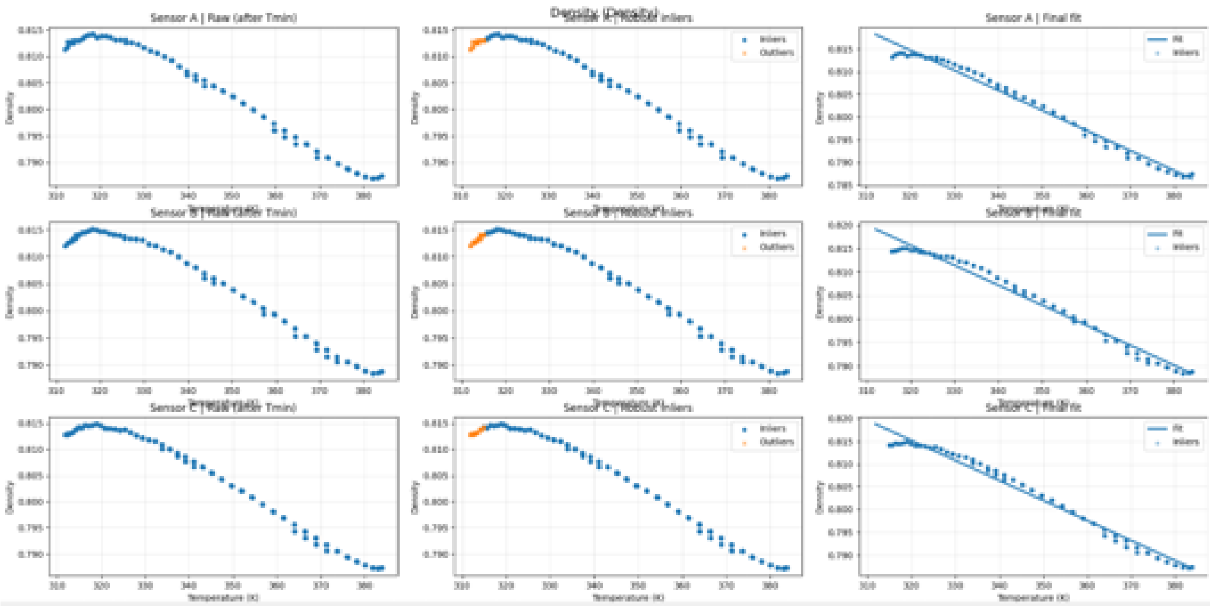

Figure 4.2: Baseline Density vs Temperature

The Equation is well described by:

$$\rho = D + E \cdot T \tag{4.2}$$

where D and E are oil-dependent constants. The linear model proposed by TE Connectivity [1] was confirmed to be valid for VDS-5 oil with a high coefficient of determination ($R^2 > 0.99$).

4.3.3 Dielectric Constant

The dielectric constant exhibited a linear temperature dependence, Figure 4.3 shows the curve.

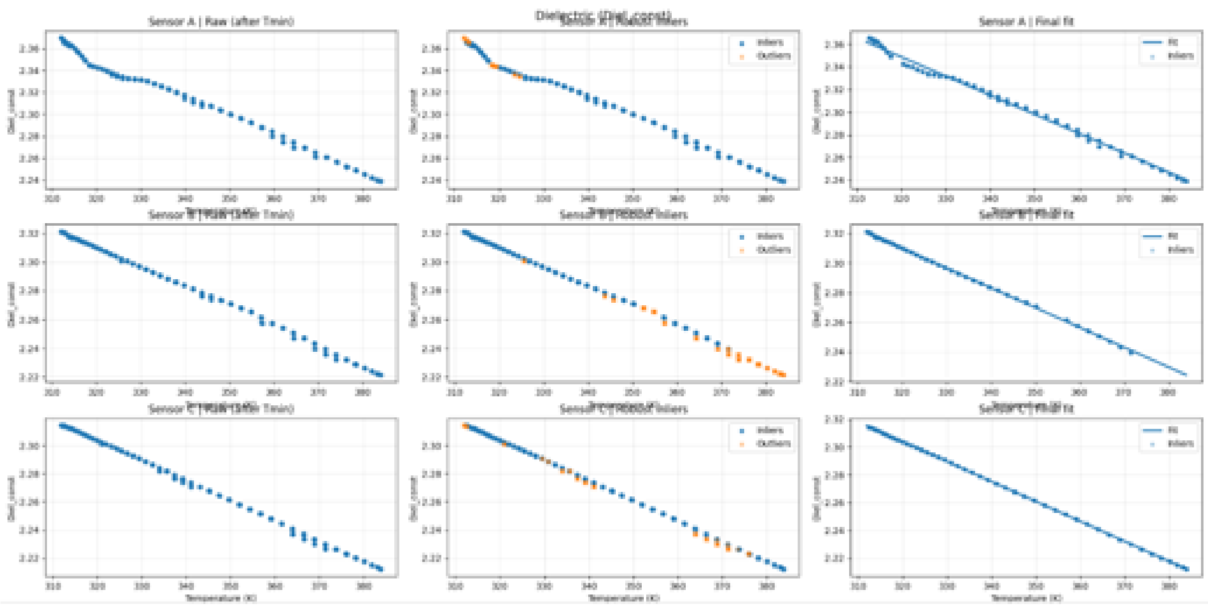

Figure 4.3: Baseline Dielectric vs Temperature

It consistent with the model:

$$\varepsilon = F + G \cdot T \tag{4.3}$$

where F and G are oil-dependent constants. This result is supported by the Clausius-Mossotti relationship, which links the dielectric constant to oil density and molecular polarizability [1] and Carey [14], who demonstrated that dielectric constant in lubricating oils follows a temperature dependent linear trend due to change in density.

4.3.4 Resistivity (Deviation from the Linear Model)

The resistivity measurement showed deviation from the linear model proposed by TE Connectivity [1]:

$$R_p = H + I \cdot T \quad \text{(TE Connectivity model)} \tag{4.4}$$

Visual inspection of the measured resistivity temperature curve showed a non-linear, cubic-like behaviour as seen in the figure 4.4, which the linear model failed to capture. This finding is consistent with the observation in the literature that *"there is no linear correlation between conductivity and temperature, as each oil type has its own conductivity/temperature relationship"* [15]. Furthermore, engine oil electrical conductivity is the inverse of resistivity is governed by ionic charge carrier mobility, which is itself temperature dependent in a manner better described by the Arrhenius equation [16]:

$$\sigma(T) = \sigma_0 \cdot e^{-W/(RT)} \tag{4.5}$$

where σ is electrical conductivity, σ_0 is a pre-exponential constant, W is the activation energy (J/mol), R is the ideal gas constant (8.314 J/mol·K) and T is absolute temperature (K). Since resistivity is the reciprocal of conductivity ($R_p = 1/\sigma$), the Arrhenius framework predicts a non-linear temperature dependence for resistivity. The experimental data from the present rig tests confirmed this behaviour.

To capture this non linearity more accurately while maintaining a practical model form, a combined Arrhenius-cubic polynomial model was evaluated:

$$R_p(T) = A_0 \cdot e^{-E_a/(RT)} + a_1 T + a_2 T^2 + a_3 T^3 \tag{4.6}$$

Python-based curve fitting demonstrated that this formulation provides a better fit to the measured VDS-5 resistivity data compared to the linear model, with a higher R^2 value.

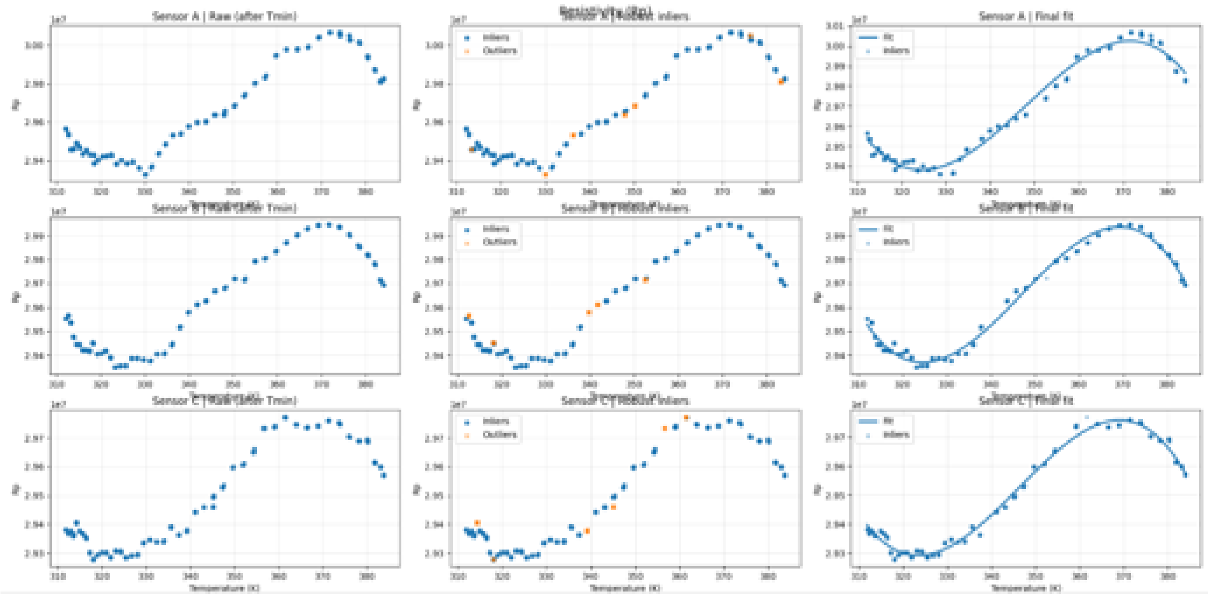

Figure 4.4: Baseline Resistivity vs Temperature

4.4 Fuel Dilution Experiments

Following baseline characterisation, controlled quantities of diesel B7 fuel were blended into the VDS-5 oil at the rig operating temperature. Three fuel dilution levels were tested: 3%, 6% and 9% by volume. For each dilution level, the oil was circulated through the rig and sensor outputs were recorded at steady state.

The results showed that viscosity decreased exponentially with increasing fuel dilution which can be seen in the figure 4.5. .

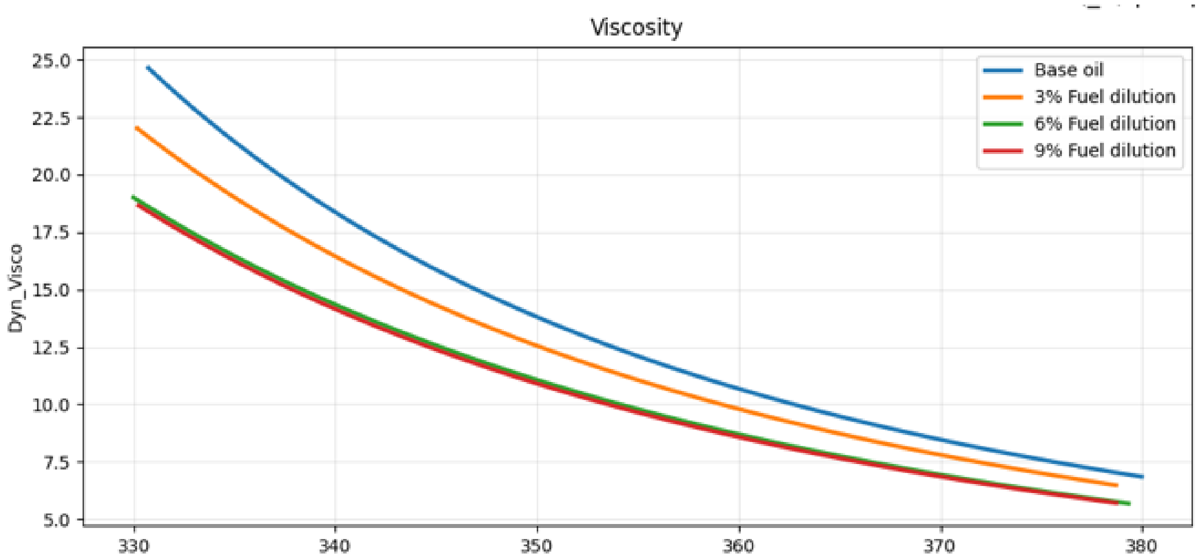

Figure 4.5: Impact on Viscosity with Fuel Dilution

It is consistent with the miscible blending behaviour described by the Refutas method [1]. Density and dielectric constant also changed linearly with fuel concentration, while resistivity showed relatively small changes, consistent with the findings in the TE Connectivity white paper [1].

The figure 4.6 shows input parameters like viscosity etc vs increasing contamination. Red highlighted area is the accuracy bandwidth mentioned in [1]. Red line indicates the whole data set and finally the point on the red line is the average of the points

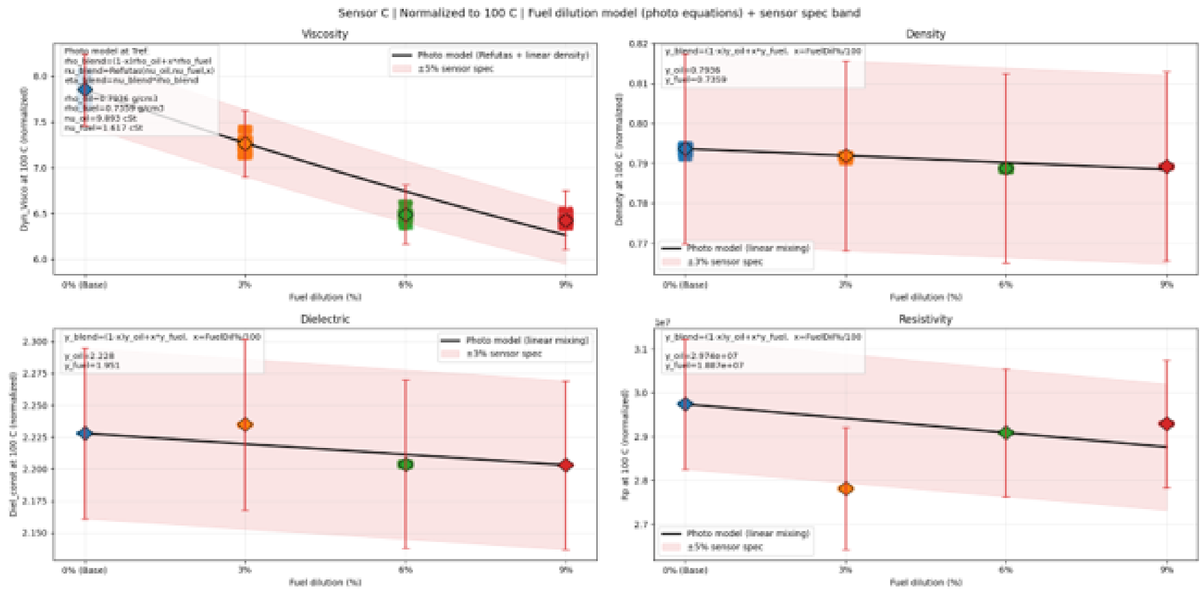

Figure 4.6: Fuel Dilution Models

This was compared to the standard curve for fuel dilution given in [1]. Figure 4.7 shows the curves available in the specifications.

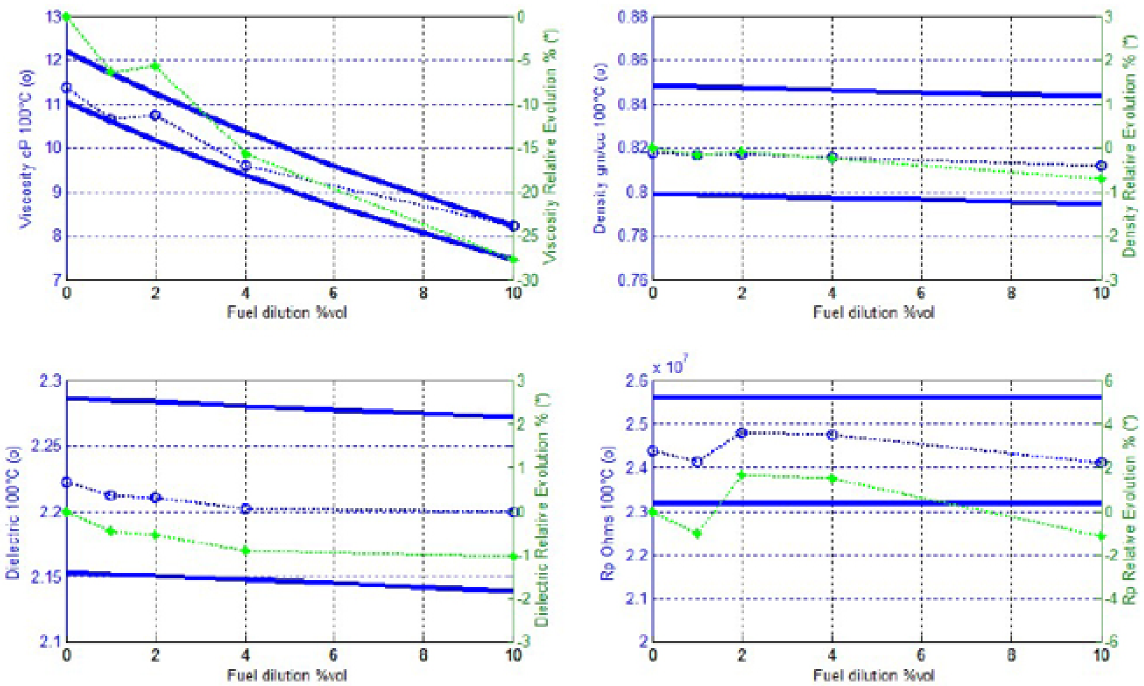

Figure 4.7: Standard curves for Fuel Dilution [1]

The fuel properties at room temperature were measured directly using the FPS2800 sensor and was estimated at 100 degrees by the curve and are summarised in Table 4.1. These values were used as fixed constants in the linear blending models for all four parameters, consistent with the approach described by TE Connectivity [1]. The resulting model fits and sensor measurement are shown in Figure 4.6.The experimentally derived contamination models for fuel dilution in VDS-5 oil are expressed as:

$$\begin{aligned}
\eta_m &= \mu_{\text{oil}} \cdot (1 - \text{FuelDil}_{\%}/100) + \mu_{\text{fuel}} \cdot \text{FuelDil}_{\%}/100 \quad \text{(Refutas blending)} \\
\rho_m &= \rho_{\text{oil}} \cdot (1 - \text{FuelDil}_{\%}/100) + \rho_{\text{fuel}} \cdot \text{FuelDil}_{\%}/100 \\
\varepsilon_m &= \varepsilon_{\text{oil}} \cdot (1 - \text{FuelDil}_{\%}/100) + \varepsilon_{\text{fuel}} \cdot \text{FuelDil}_{\%}/100 \\
Rp_m &= Rp_{\text{oil}} \cdot (1 - \text{FuelDil}_{\%}/100) + Rp_{\text{fuel}} \cdot \text{FuelDil}_{\%}/100
\end{aligned} \tag{4.7}$$

Table 4.1: FPS2800-measured physical properties of diesel fuel used in dilution model (at 100°C)

Parameter	**Value**	**Unit**
Kinematic Viscosity (μ_{fuel})	1.188	cSt
Density (ρ_{fuel})	0.735	g/cc
Dielectric Constant ($\varepsilon_{\text{fuel}}$)	1.951	–
Resistivity (Rp_{fuel})	1.887×10^7	Ω

4.5 Water Contamination Experiments

Water contamination was introduced into the oil at two concentration levels: 1% and 2% by volume, mixed by hand stirring and then magnet stirring followed by the gear pump circulation. As expected from the high dielectric constant of water ($\varepsilon_{\text{water}} = 80$) and its auto ionization properties, the dielectric constant increased and resistivity decreased with increasing water contamination, while viscosity and density remained largely unchanged. Figure 4.8 shows the water dilution cuvres. These findings are consistent with the behaviour reported by TE Connectivity [1] and with the literature on water-in-oil contamination [16].

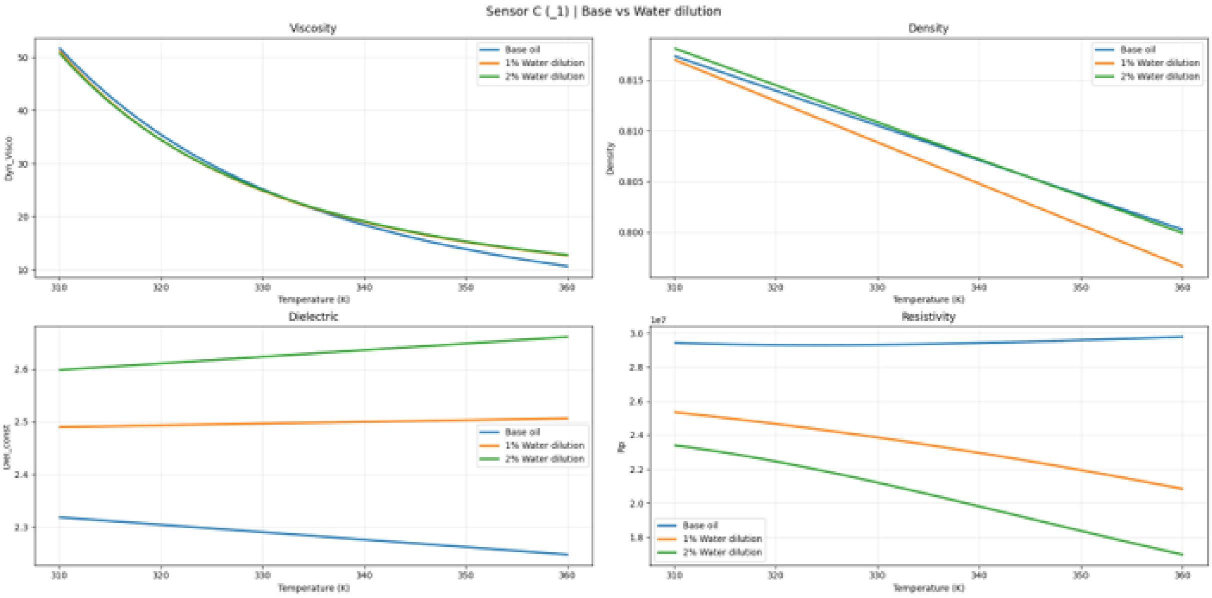

Figure 4.8: Water Dilution curves

The VDS-5 water contamination models derived from rig data are:

$$\varepsilon_m = \varepsilon_i \cdot (1 + k_\varepsilon \cdot \mathrm{WatDil}_{\mathrm{ppm}}) \tag{4.8}$$

$$Rp_m = Rp_i \cdot (1 - k_{Rp} \cdot \mathrm{WatDil}_{\mathrm{ppm}}) \tag{4.9}$$

Figure 4.9 shows the trend of parameters with increasing water contamination.

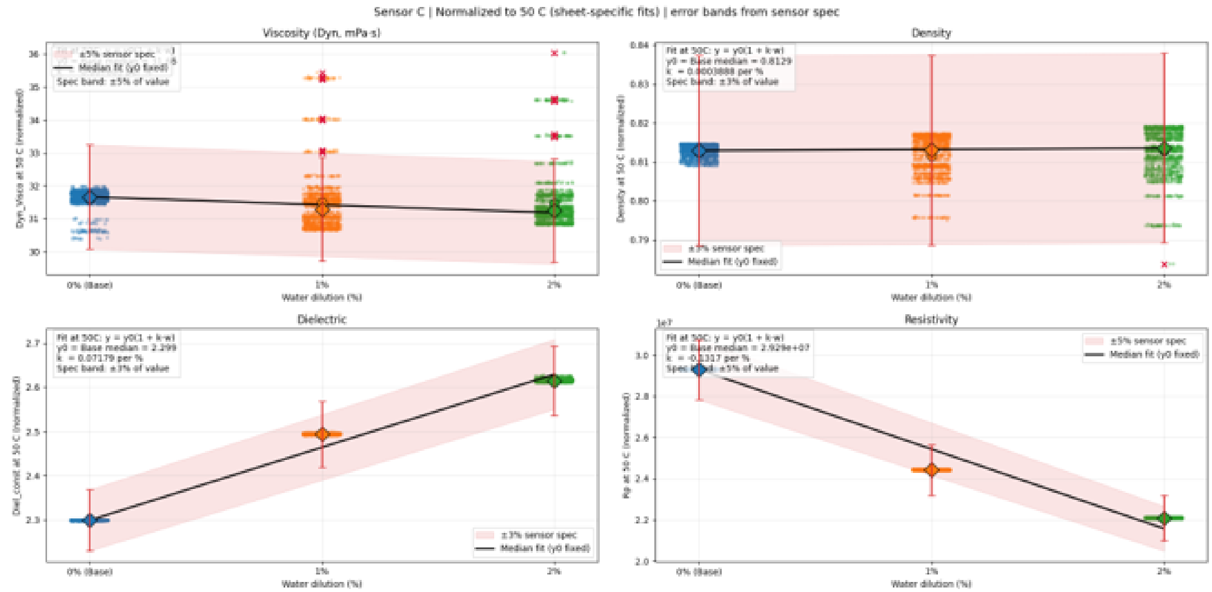

Figure 4.9: Water Dilution Models

This was compared to the standard curves mentioned in the [1]. Figure 4.10 shows the standard curves for water contamination.

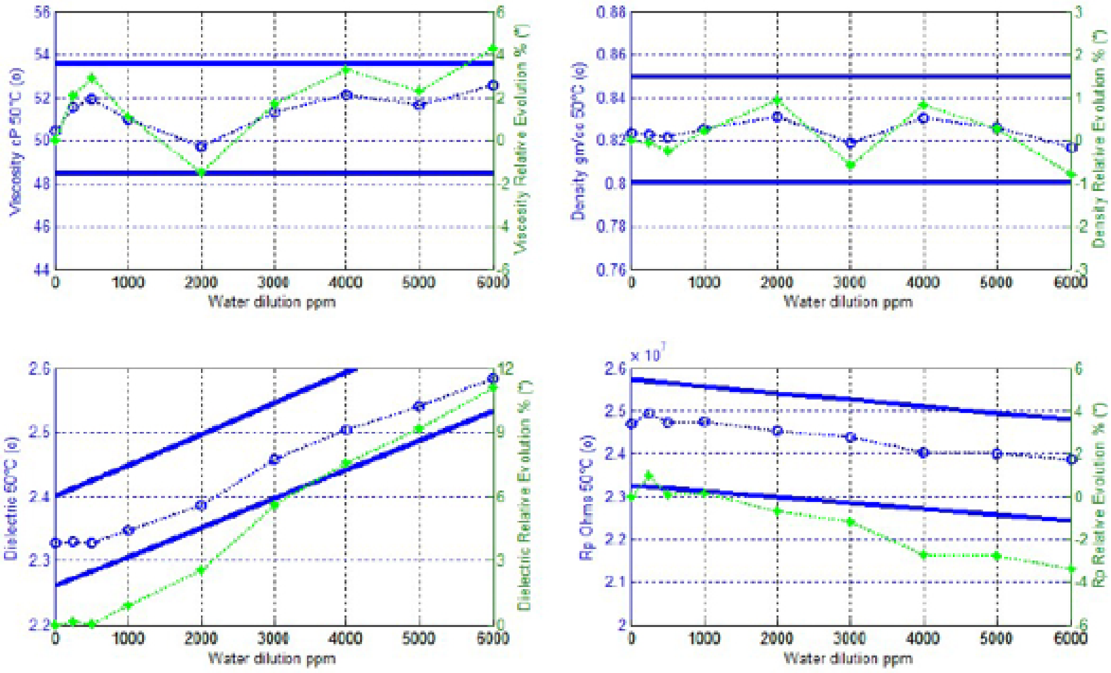

Figure 4.10: Standard curves for Water Contamination[1]

The water contamination models derived from rig curve fitting for Volvo VDS-5 oil are expressed as follows, where all parameters are normalised to their values at 100°C:

$$\eta_m = \eta_i \quad \text{(no change observed)} \tag{4.10}$$

$$\rho_m = \rho_i + Z \times 10^{-8} \cdot \text{WatDil}_{\text{ppm}} \tag{4.11}$$

$$\varepsilon_m = \varepsilon_i \cdot (1 + X \times 10^{-6} \cdot \text{WatDil}_{\text{ppm}}) \tag{4.12}$$

$$Rp_m = Rp_i \cdot (1 - Y \times 10^{-6} \cdot \text{WatDil}_{\text{ppm}}) \tag{4.13}$$

Table 4.2 compares the contamination sensitivity constants obtained from the present rig experiments against the reference values provided by TE Connectivity [1] for a standard 15W40 engine oil. Differences between the two sets of constants are attributed to the different additive package and base oil composition of Volvo VDS-5 oil compared to the reference oil used by TE Connectivity.

Table 4.2: Comparison of water contamination sensitivity constants: TE Connectivity reference values vs. VDS-5 rig measurements

Parameter	**TE Engineering**	**VDS-5 (This Study)**	**Unit**
Viscosity	0	No change	cP/ppm
Density	0	$Z \times 10^{-8}$	(g/cc)/ppm
Dielectric	20×10^{-6}	$X \times 10^{-6}$	−/ppm
Resistivity	-6×10^{-6}	$-Y \times 10^{-6}$	Ω/ppm

The main deviation is observed in the dielectric constant sensitivity, where the VDS-5 oil yields a coefficient is less than half of the TE Connectivity reference value. The resistivity sensitivity is approximately twice as large in magnitude, suggesting that the VDS-5 additive package results in a higher impact on resistivity to water ion release. Viscosity and density show negligible sensitivity to water contamination in both cases, confirming that these two parameters alone are insufficient for water detection and that dielectric and resistivity are the primary indicators.

Figure 4.9 shows the measured sensor data alongside the fitted model curves and the ±3% sensor specification band for all four parameters.

4.6 Soot Contamination (Experimental Limitations)

Attempts were made to characterise the FPS2800 sensor response to soot contamination using acetylene derived carbon black (Carbon Black 99.9%, VWR International, SE) as a soot surrogate at concentrations of 0.2% and 0.4% by mass. Carbon black is widely used as a laboratory surrogate for engine soot, as its surface chemistry has similarities to diesel combustion soot [10]. However, the experiments were ultimately unsuccessful due to two fundamental measurement principle:

1. **Electrical conductivity of carbon black:** Carbon black is an electrically conductive particulate material. When introduced into the oil, it significantly changed the dielectric and resistivity measurements of the FPS2800 sensor in an uncontrolled manner, making it impossible to separate the sensor's actual response to soot as a contaminant from the direct electrical interference of the carbon particles on the tuning fork resonator. This is consistent with findings in the literature that soot particle conductivity [17].

2. **Suspension instability:** Carbon black particulate could not be maintained in a stable, homogeneous suspension in the VDS-5 oil under the rig's gear pump flow conditions. Unlike engine soot, which is kept in suspension by dispersant additives reacting with soot surface functional groups formed during combustion [18], laboratory carbon black lacks these surface functional groups and agglomerates rapidly [10]. Hence, meaningful sensor calibration was not achievable.

It is acknowledged that the suitability of carbon black as a soot surrogate is itself debated in the literature. While some studies report that certain commercial carbon blacks can show the clusturing behaviour [10], others note significant differences in surface composition that limit the use [19]. For the purposes of FPS2800 sensor calibration, these differences are secondary to the conductivity issues faced. Controlled oxidation ageing experiments were similarly not conducted within the scope of this project, as they require long duration of thermal ageing typically conducted at 150°C over 1000 to 3000 hours [1], which was not possible considering the time available for the project. Soot and oxidation modelling therefore represent clear directions for future work, as discussed in Chapter 8.

4.7 Aged Oil Validation

To further validate the sensor and modelling framework, a sample of used engine oil obtained from a Volvo vehicle in service was tested on the rig alongside fresh VDS-5 base oil. This test was done as a validation of the sensor's ability to check and validate the contamination levels independently recorded in Volvo's Global Liquid Analysis Database (GLAD).

4.7.1 Sensor Response to Aged Oil

Figure 4.11 shows the four FPS2800 sensor measurements for fresh base oil and used oil across the tested temperature range (320 to 385 K).

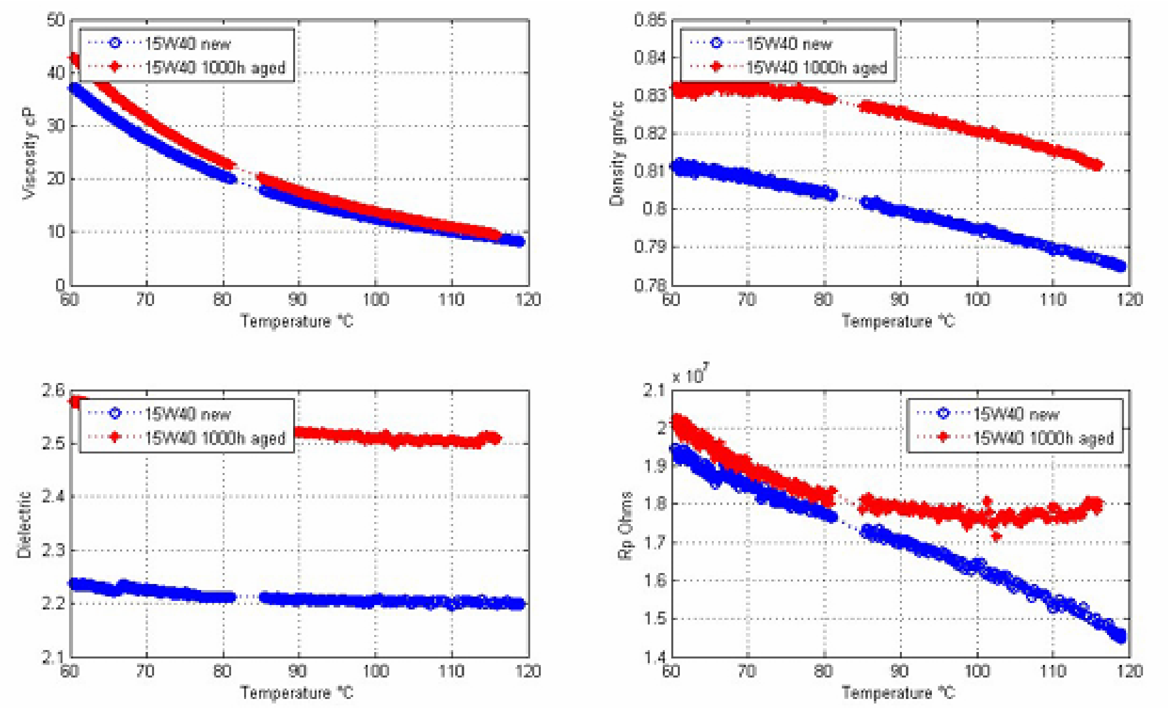

Figure 4.11: Standard Aged Oil[1]

The results are consistent with the ageing behaviour described by TE Connectivity [1]: viscosity, density and dielectric constant are all elevated in the aged oil compared to fresh oil, reflecting the polymerisation of oil molecules and the accumulation of polar degradation compounds during service. Resistivity shows a decrease in the aged oil sample, attributable to the depletion of alkaline additive reserve and the formation of conductive acid by-products over the oil's service life.

These trends confirm that the FPS2800 sensor, when deployed on the Volvo rig, is differentiating between fresh and use oil conditions across all four measured parameters .

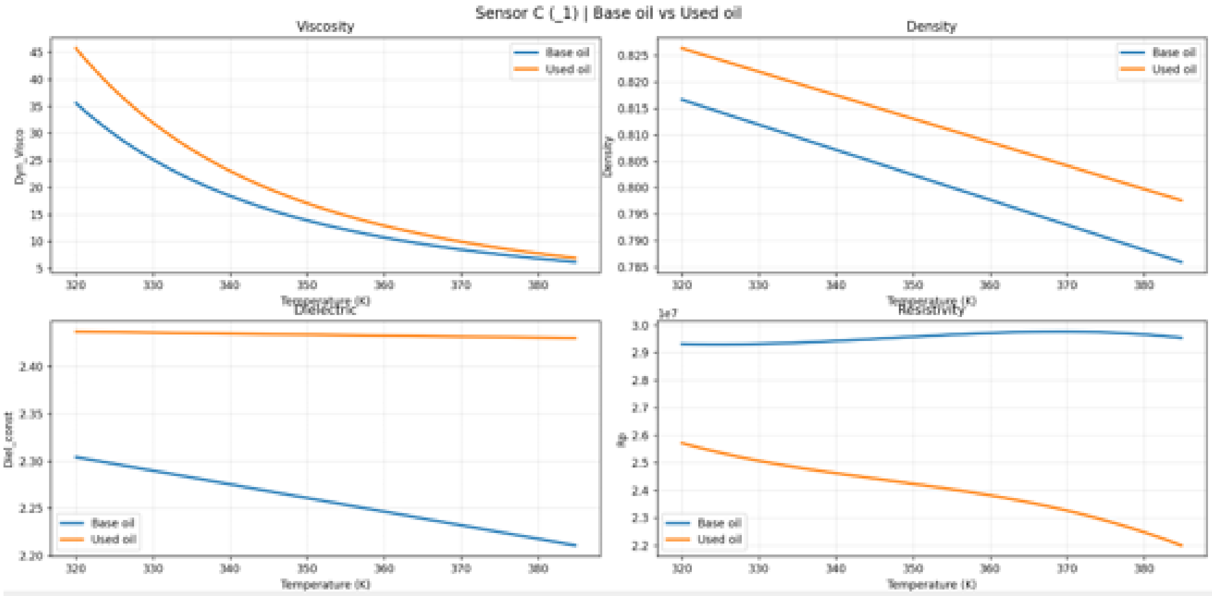

Figure 4.12: Volvo aged oil

4.7.2 Quantitative Comparison Against GLAD Reference Values

The aged oil sample was independently characterised through Volvo's Global Liquid Analysis Database (GLAD), which provides reference laboratory analysis results for oil samples taken from service vehicles. The contamination levels recorded in GLAD were compared with the values calculated by the FPS2800 sensor models and against the reference constants provided by TE Connectivity [1]. The results are summarised in Table 4.3.

Table 4.3: Comparison of contamination levels in aged oil sample: GLAD laboratory reference vs. FPS2800 sensor estimate (values normalised to GLAD reference)

Parameter	GLAD (normalised)	Sensor
Soot	1.000	0.990
Net Oxidation	1.000	0.783
Fuel Dilution	1.000	0.000
Water Contamination	1.000	0.960

The results shows good agreement between the sensor based estimates and the GLAD laboratory reference values for soot and water contamination. Soot content predicted by the sensor deviates by less than 1% from the GLAD reference value, indicating that viscosity and dielectric-based soot estimation is effective for this oil grade despite the unsuccessful controlled soot rig experiments described in Section 4.6.

Water contamination estimated by the sensor is in close agreement with the GLAD reference value, with a relative error of approximately 4%, which is within the FPS2800 sensor specification.

The net oxidation estimate shows underestimation of approximately 22% relative to the GLAD reference value. This is because of the fact that the oxidation model was not recalibrated for VDS-5 oil in this study. The TE Connectivity model constants, derived from 15W40 oil [1], are therefore used as a first case and recalibration for VDS-5 remains a recommendation for future work.

Fuel dilution registers as zero by the sensor which is consistent with the almost zero GLAD reference value, which falls below the sensor's practical detection threshold for fuel contamination as shown in Section 4.4.

4.8 Summary of Rig Findings

Table 4.4 summarises the model validation outcomes from the rig testing phase.

Table 4.4: Summary of FPS2800 model validation for Volvo VDS-5 oil

Parameter	**TE Model**	**Validated?**	**Finding**
Viscosity	Log (ASTM D341)	Yes	Strong fit confirmed
Density	Linear	Yes	Strong fit confirmed
Dielectric	Linear	Yes	Strong fit confirmed
Resistivity	Linear	No	Cubic/Arrhenius model required
Fuel dilution	Refutas/linear	Yes	Validated at 3, 6, 9%
Water contamination	Linear	Yes	Validated at 1, 2%
Soot	Linear	N/A	Experiment unsuccessful
Oxidation	Multi-phase	N/A	Not tested

The key finding of this chapter is that three of the four baseline temperature models proposed by TE Connectivity are valid for Volvo VDS-5 engine oil. The exception is resistivity, for which a cubic polynomial combined with an Arrhenius correction provides a significantly better description of the temperature dependence. Furthermore, validation and formulation of equations for fuel dilution and water contamination is done which is carried forward into the vehicle data analysis in Chapter 5.

[0] Exact numerical values are withheld under a non-disclosure agreement with Volvo Group Powertrain. Relative errors are computed from normalised values.

5 Vehicle Data Analysis and Real-Time Implementation

This chapter describes the complete pipeline developed to apply the validated FPS2800 sensor models from Chapter 4 to real-world vehicle data. The chapter covers the data infrastructure challenges encountered, the Python based processing pipeline developed to overcome them, the model application and accumulation methodology, validation against GLAD laboratory results and the final Power BI dashboard developed for operational use.

5.1 Data Infrastructure and Limitations of Conventional Tools

The FPS2800 sensor installed in the vehicle gives data continuously through the CAN-bus interface. Data is collected for over a three month oil service period, this results in more than a million individual data entries. Initial attempts to process this data using Microsoft Excel had scalability issue as Excel's maximum row capacity of 1,048,576 rows is insufficient to get a full three month sensor data in a single worksheet and even at the row limit, performance was slowed significantly for any computations.

To overcome this, the data pipeline was redesigned to interface directly with Volvo Group's Data Science Lab (DSL). Data was called directly to Jupyter Notebook which was hosted within the DSL. This approach had three advantages:

1. **Scalability:** The full three-month dataset could be called at once and processed in memory without file size constraints.
2. **Reproducibility:** The notebook environment ensured that all data transformations, model applications and outputs were occuring at once and creating a transparent and processing record.
3. **Integration:** Direct DSL access eliminated manual data export steps, reducing the risk of data handling errors introduced during file transfers and save time.

5.2 Data Pre-processing Pipeline

5.2.1 Data Acquisition and Down Sampling

Raw CAN-bus data from the vehicle was called directly from the DSL into the Jupyter Notebook environment. The raw data contained sensor readings, which produced a high volume of entries. To reduce computational load while preserving physically meaningful trends, the dataset was downsampled to one reading per 30 seconds. This downsampling rate was selected as the frequency of sensor.

5.2.2 Noise Filtering and Parameter Bounds

To ensure robustness of the model outputs, a bounds based filtering also known as hard filtering was implemented for each of the sensor parameters. Physical upper and lower bounds were defined for each parameter based on the expected operating range of VDS-5 engine oil. Any reading falling outside these bounds was flagged as an outlier and excluded from computations. This approach effectively eliminates the Sensor error readings during cold start transients, where oil viscosity may temporarily exceed the FPS2800 measurement range and Electrical noise spikes on the CAN-bus.

This filtering methodology is consistent with Function A.1 (Aberrant Data Filtration) and Function A.2 (Application Condition Filtration) described in the TE Connectivity oil condition algorithm framework [1].

5.3 Model Application and Accumulation

5.3.1 Baseline Establishment and Temperature Modelling

Before any contamination estimation can be performed, the pipeline establishes a fresh oil baseline as soon as the oil is changed. This step is critical because all contamination estimates are computed as deviations from fresh oil behaviour. This principle is consistent with the measurement filtration framework described by TE Connectivity [1].

The baseline is constructed from the first stable readings acquired after the oil change, once the cold start transient period has elapsed. Cold start readings are excluded from baseline calculations because during engine warm-up, oil temperature is rising rapidly and the sensor's tuning fork resonator requires a stabilised flow and calibration to produce accurate measurements.

Once valid fresh oil readings are identified, the temperature dependent models for all four parameters (viscosity, density, dielectric constant, and resistivity) are fitted to the fresh oil data using the equations established in Chapter 4. These fitted models represent the expected behaviour of clean VDS-5 oil as a function of temperature and represents the reference baseline against which all other measurements are compared throughout the service period.

5.3.2 Oil life Parameter Trends

Figure 5.1 shows the temperature compensated time series of all four FPS2800 sensor parameters recorded over the three-month vehicle operating period (September to December 2025). This trend is compared to the standard curves given in the specification of sensor and from which it resembled soot contamination as shown in the figure 5.2

Several observations can be made from these trends:

- **Viscosity** shows an overall increasing trend over the service period which shows standard ageing with oxidation and soot contamination [1].

- **Density** shows a minimal changes but a slight drift over the service period, reflecting the accumulation of heavier degradation products and soot particles in the oil, consistent with the behaviour reported by TE Connectivity for aged engine oil [1].
- **Dielectric constant** shows a clear increasing trend from September to December, indicating the progressive accumulation of polar compounds a characteristic signature of oxidative ageing and soot contamination [1].
- **Resistivity** shows a generally decreasing trend, consistent with the depletion of alkaline additive reserve and the formation of conductive acid by-products over the oil service life, as described in Section 4.3.4.

These trends confirm that the sensor is successfully tracking the progressive degradation of the oil throughout its service life, and that the signal contains sufficient information to support quantitative contamination estimation.

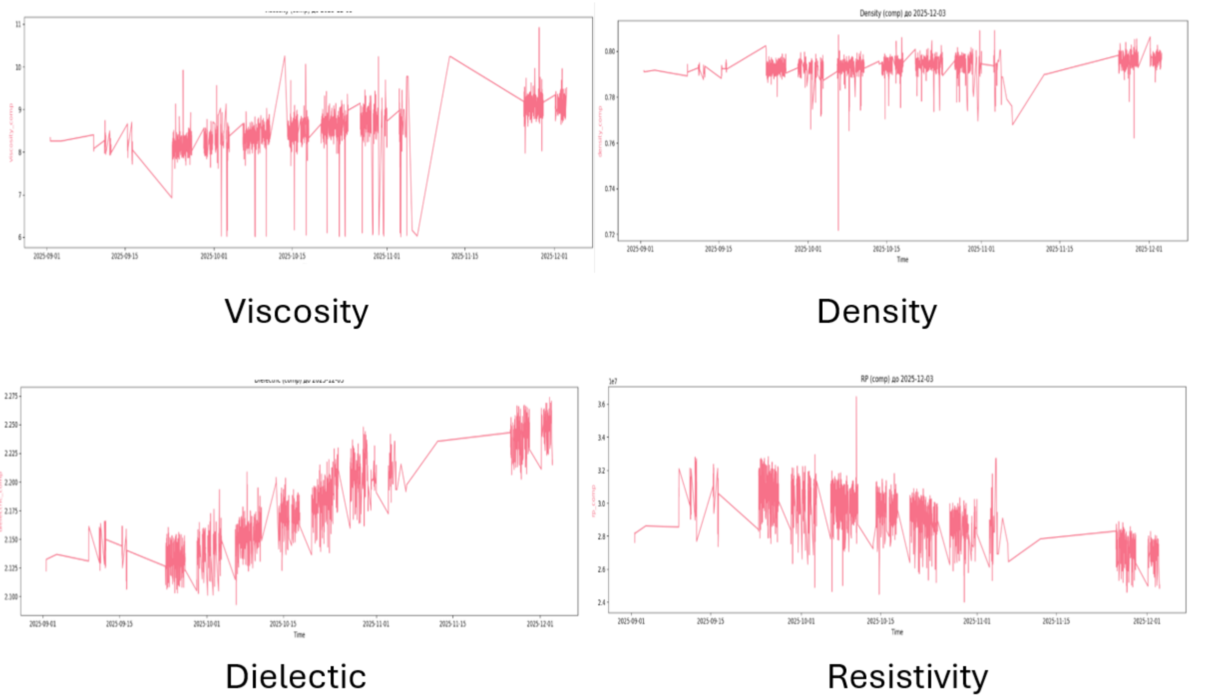

Figure 5.1: Temperature-compensated FPS2800 sensor measurements over the Oil life operating period : viscosity (top left), density (top right), dielectric constant (bottom left) and resistivity (bottom right).

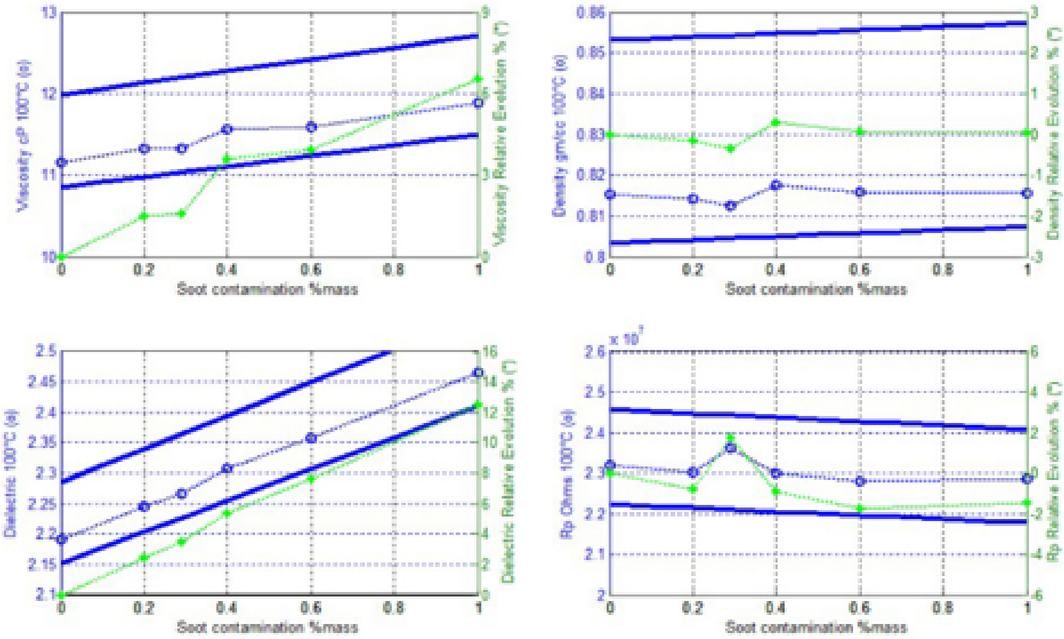

Figure 5.2: Standard soot curve.[1]

5.3.3 Coupled Equation Framework and Matrix Inversion

Each of the four FPS2800 sensor measurements is simultaneously influenced by multiple contamination sources. For example, viscosity is affected by oxidation, soot and fuel dilution; density is affected by oxidation, soot and fuel dilution; dielectric constant is affected by oxidation, soot, water and fuel dilution; and resistivity is affected by oxidation, water and fuel dilution. This interdependence means that a single parameter measurement cannot be used alone to quantify a specific contaminant the system of equations must be solved together.

The contamination estimation is therefore made as a linear system of the form:

$$\mathbf{M} = \mathbf{A} \cdot \mathbf{C} \tag{5.1}$$

where $\mathbf{M}$ is the vector of normalised measured parameter deviations from fresh oil baseline:

$$\mathbf{M} = \begin{bmatrix} \Delta\eta \\ \Delta\rho \\ \Delta\varepsilon \\ \Delta Rp \end{bmatrix} \tag{5.2}$$

$\mathbf{C}$ is the vector of unknown contamination levels to be estimated:

$$\mathbf{C} = \begin{bmatrix} C_{\text{soot}} \\ C_{\text{oxidation}} \\ C_{\text{fuel}} \\ C_{\text{water}} \end{bmatrix} \tag{5.3}$$

and **A** is the sensitivity matrix whose coefficients are the contamination model constants established from the rig tests in Chapter 4:

$$\mathbf{A} = \begin{bmatrix} k_{\eta,\text{soot}} & k_{\eta,\text{ox}} & k_{\eta,\text{fuel}} & 0 \\ k_{\rho,\text{soot}} & k_{\rho,\text{ox}} & k_{\rho,\text{fuel}} & 0 \\ k_{\varepsilon,\text{soot}} & k_{\varepsilon,\text{ox}} & k_{\varepsilon,\text{fuel}} & k_{\varepsilon,\text{water}} \\ 0 & k_{Rp,\text{ox}} & k_{Rp,\text{fuel}} & k_{Rp,\text{water}} \end{bmatrix} \tag{5.4}$$

The contamination vector **C** is then solved at each time step via matrix inversion:

$$\mathbf{C} = \mathbf{A}^{-1} \cdot \mathbf{M} \tag{5.5}$$

This matrix formulation is established with approaches in multi-parameter fluid condition monitoring, where simultaneous measurement of multiple physical properties is used to decompose the contributions of individual contaminants [7, 8].

5.3.4 Temporal Accumulation

Oil condition parameters such as soot and oxidation are cumulative and they increase monotonically over the oil service life rather than fluctuating with instantaneous operating conditions. The pipeline takes a temporary and continuous accumulation approach, where contamination estimates at each time step are summed over the full service period to produce a total. For a parameter C_i estimated at time step i with interval $\Delta t = 30$ seconds, the accumulated value at time t_n is:

$$C_{\text{acc}}(t_n) = \sum_{i=1}^{n} C_i \cdot \Delta t \tag{5.6}$$

Fast-changing contamination like water and fuel dilution are calculated at each time step as they dont grow gradually.

A key design feature of the pipeline is that it flags and stores the accumulated estimates at the exact calendar dates on which laboratory oil samples were submitted to GLAD. This output enables direct comparison between the sensor derived estimates and the independent laboratory results, forming the basis of the validation.

5.4 Data Storage and Database Integration

Once the model pipeline was validated, the oil condition outputs were written to a structured SQL database. A dedicated table was created to store the time series of accumulated contamination, with each row corresponding to a one day interval and containing the fields like timestamp,viscosity, soot content, net oxidation, estimated fuel dilution and estimated water contamination.

The SQL database serves as the data source layer for the Power BI dashboard described in Section 5.5. This architecture ensures that the dashboard always reads from pre-calculated and validated results rather than performing real time model calculations, which improves dashboard responsiveness and reduces the risk of errors.

5.5 Power BI Dashboard

5.5.1 Dashboard Architecture

The Power BI dashboard was developed as the front end visualisation layer for the oil condition monitoring system. The dashboard connects directly to the SQL database described in Section 5.4, fetching the computed oil condition time series for display. In addition, GLAD laboratory analysis results manually downloaded from the GLAD portal and uploaded into Power BI as a reference dataset which are plotted on top of the sensor graphs. This allows everyone to view and compare both the sensor estimate and the laboratory reference at the same place. The figure 5.3 shows the comparision of model calculation and lab measurements.

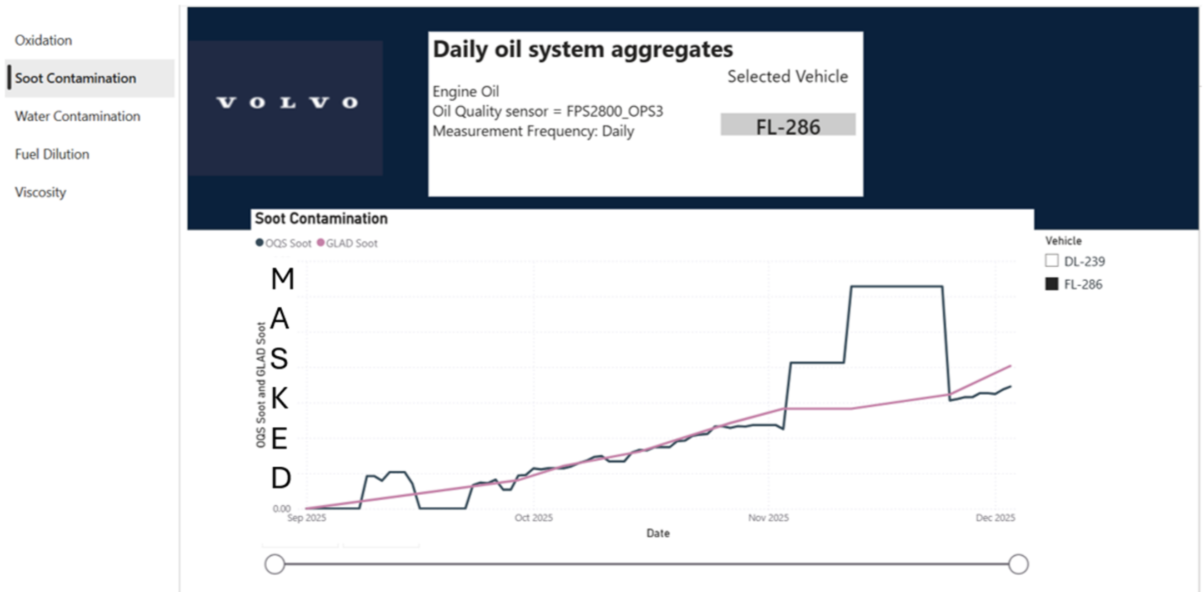

Figure 5.3: PowerBi Dashboard showing measurements of GLAD in pink compared to sensor computed in black for FL286 Vehicle

5.5.2 Dashboard Design and Key Performance Indicators

The dashboard displays the following oil condition indicators as time series plots on the left end side:

- **Viscosity** : Dynamic viscosity trend over the service period
- **Soot content** : Accumulated soot estimate (%)
- **Net oxidation** : accumulated oxidation level (A/cm)
- **Fuel dilution** : estimated fuel dilution (%)
- **Water contamination** : estimated water content (%)

5.6 Summary

This chapter described the complete data pipeline developed for the FPS2800 sensor models used for vehicle condition monitoring. The key contributions of this phase are:

1. A scalable data infrastructure solution using DSL and Jupyter Notebook, overcoming the limitations of conventional desktop tools for large CAN-bus datasets.
2. A robust preprocessing pipeline with downsampling and bounds-based noise filtering, ensuring model input quality.
3. A coupled-equation accumulation framework that produces oil condition estimates aligned to laboratory sampling dates for direct validation.
4. A SQL based Power BI dashboard integrating sensor estimates and GLAD reference data, providing an interface for research and development team.

Together, these components demonstrate that the sensor model developed in Chapter 4 can be successfully deployed on real vehicle data and visualised in a format suitable for operational use at Volvo Group Powertrain research and development facility.

6 Business Case Analysis

This chapter evaluates the commercial use of deploying the FPS2800 Oil Quality Sensor (OQS) as a production level solution across the Volvo Group heavy duty truck. It covers the total cost of installation per vehicle, two concepts representing different customer base, the economic benefits and the overall value proposition for fleet operators. All cost figures are presented in Swedish Kronor (SEK) and represent prototype level estimates. Production volumes would reduce per unit costs considerably.

6.1 Cost Estimation: Per Vehicle Installation

Table 6.1 presents the estimated total cost of deploying one FPS2800 OQS unit on a single heavy-duty truck at the current prototype stage. The cost is decomposed into five categories covering hardware, installation and software.

Table 6.1: Estimated cost breakdown for FPS2800 OQS installation per vehicle (prototype stage).

No.	**Cost Type**	**Amount (SEK)**	**Breakdown**
1	Sensor procurement	Masked	Unit cost of FPS2800-OPS3 sensor
2	Mounting, harness & installation	Masked	Bracket: Masked SEK; vibration and leak-proofing: Masked SEK
3	Installation labour	Masked	Labour cost per hour × time for mounting, harness routing, electrical connection and functional verification
4	Software integration	Masked	Total software development and maintenance cost calculated across the volume of trucks with OQS installation
5	Miscellaneous	Masked	Consumables and costs during maintenances and other factors
	Total	**Masked**	

The dominant cost is sensor procurement at approximately 60% of total, reflecting the current prototype pricing of the FPS2800 OPS3. At production volumes, unit cost is expected to decrease substantially through economies of scale, bringing the total system cost well below the threshold identified by stakeholders as the commercial viability boundary (Section 2.1.3). Installation labour and mechanical hardware together account for less than 25% of total, indicating that the sensor is straightforward fit. The software integration cost per vehicle is low because it represents a one time pipeline development investment across the full installation volume, which improves further as scale increases.

6.2 Deployment Concepts

Two deployment concepts were developed to reflect different customer base. Both concepts share the same sensor hardware (FPS2800-OPS3) and the validated software pipeline described in Chapter 5.

6.2.1 Concept 1: Direct Fleet Deployment (Customer: Internal Volvo use and competitors)

Concept 1 represents the current prototype deployment configuration, in which the FPS2800 sensor is installed directly onto field vehicles by the Volvo TTI test team. The sensor is connected to the vehicle CAN-bus and data is transmitted to the Volvo DSL environment for processing by the Python pipeline. Results are written to an SQL database and visualised on the Power BI dashboard, as described in Chapter 5.

This concept requires manual intervention at some stages. Despite that, Concept 1 is immediately deployable on Volvo Group test fleet vehicles and enables proof of concept validation across a wider range of vehicles and engine configurations.

The primary value of Concept 1 lies in its speed of deployment and low integration overhead. It allows collection of real-world data from multiple vehicles simultaneously, enabling model refinement and reduce feild test and durablity test which are carried out currently at Volvo.

6.2.2 Concept 2: Integrated Production Deployment

Concept 2 represents a deeper integration into the Volvo production architecture, in which the OQS data pipeline is integrated directly with Volvo's existing infrastructure. In this concept, CAN-bus data from the FPS2800 sensor is transmitted via the vehicle's existing telematics unit, eliminating the need for a separate data logging device. The Python processing pipeline runs as a cloud-based service, automatically collecting and processing new data as it arrives from the fleet, computing oil condition estimates and populating results without manual intervention. There are no GLAD references in this as the model will be accrate enough to eliminate the lab tests.

Concept 2 requires significant software integration effort and involvement from Volvo Group IT and connectivity teams, making it a long term development objective rather than an immediate deployment option.

6.3 Benefit Analysis

The economic benefits of real-time oil condition monitoring is still yet to be discovered but currently it is derive from two sources: optimizing the use of engine oil by having variable oil drain interval for vehicles operating in different conditions and prevention of unplanned engine failures caused by undetected contamination events.

6.3.1 Oil Drain Interval Extension

For a heavy-duty truck engine with a current fixed oil drain interval, condition based monitoring will help with the interval to be optimize for vehicles whose accumulated oil degradation as estimated by the sensor model has not yet reached the change threshold. This reduces the number of planned oil changes over the vehicle's lifetime, with associated savings in oil, filter and labour costs.

6.3.2 Prevention of Unplanned Failures

The more significant economic benefit in heavy duty applications is the prevention of unplanned engine failures caused by rapid contamination events like coolant leakage, water contamination, or fuel dilution that are currently undetectable between scheduled laboratory samples. A single unplanned engine failure in a heavy-duty truck can result in costs of unscheduled downtime, towing, emergency repair, and potential warranty claims that far exceed the total installation cost of the OQS system. The FPS2800's ability to detect water and coolant contamination within minutes provides a failure prevention capability that is difficult to quantify in absolute terms but represents the commercial justification for the system.

6.3.3 Environmental Benefit

OPtimising oil change intervals also reduces the volume of waste engine oil generated per vehicle per year, contributing to Volvo Group's sustainability objectives. Reduced oil filter consumption similarly reduces the volume of contaminated filter waste. These benefits align with Volvo Group's commitment to reducing the environmental footprint.

6.4 Limitations and Risks

Several limitations and risks must be tackled before the business case can be fully realised at production scale.

Sensor robustness: The FPS2800 in its current prototype form requires improvements to manufacturing consistency and mechanical robustness for long-term deployment in the vibration and temperature environment of a production truck powertrain.

Placement sensitivity: The sensor requires approximately laminar flow conditions and oil temperatures not exceeding 150°C for accurate measurement. The compressor pipe location used in the FL286 test vehicle provided suitable flow conditions but however, optimal sensor placement must be validated by performing a CFD analysis to identify the optimum installation position.

Initial calibration requirement: The FPS2800 requires a minimum of approximately half an hour of operation to calibrate and provide accurate readings. hence we will have to discard those readings as it might reduce the accuracy sometimes.

Vehicle inactivity: Extended periods of vehicle inactivity like observed with the FL286 vehicle can produce faulty sensor readings due to oil settling and temperature non-uniformity. The current pipeline handles this through hard filtering, but large inactivity remains a source of inaccurate results which are accumulated over time.

6.5 Summary

The business case for the FPS2800 OQS system is summarized in Table 6.2.

Table 6.2: Business case summary for FPS2800 OQS deployment on Volvo Group heavy-duty trucks.

Parameter	Value / Assessment
Total installation cost	Masked SEK per vehicle (prototype; expected to decrease at production volumes)
Dominant cost driver	Sensor procurement (60% of total)
Primary benefit	Detection of rapid contamination events (water, coolant, fuel dilution) with minutes latency vs. four-week laboratory cycle
Secondary benefit	Oil drain interval extension for light-duty cycle vehicles; oil, filter and service savings
Environmental benefit	Reduced waste oil and filter consumption per vehicle lifetime
Deployment readiness	Concept 1 immediately deployable on test fleet; Concept 2 requires IT integration and further validation
Key risks	Sensor robustness, placement validation, model coverage for other oil grades

The business case for FPS2800 is the commercial proposition for Volvo Group fleet applications, provided that sensor robustness is improved for production deployment. The proof of concept results from the FL286 vehicle campaign demonstrate that the system can deliver real time oil condition estimates with accuracy comparable to laboratory analysis for the key parameters like soot and water contamination. The full commercial value of the system is yet to be discovered which is the future scope of the project.

7 Discussion and Conclusion

This chapter consolidates the findings from this thesis starting with the sensor's fundamental measurement capability and limitations, the rig testing results (Chapter 4), followed with the vehicle data analysis and validation (Chapter 5) and then complete pipeline and Power BI dashboard deployment. It also reflects on the implication of the key findings, points out the limitations, states the results with the broader context of oil condition monitoring for heavy duty power trains and summaries the overall conclusions of the thesis.

7.1 Sensor Performance

7.1.1 Measurement Capability: Mechanical and Electrical Response

The main capability demonstrated across both the rig and vehicle testing phases of this thesis is the FPS2800's ability to resolve both the mechanical and electrical response of the oil simultaneously from a single quartz tuning fork resonator. On the mechanical side, the fork's resonance frequency and amplitude under fluid gives a measurement of dynamic viscosity and density (Equation 2.1) and on the electrical side, it gives the dielectric constant and resistivity of the oil (Equation 2.2). This combination of mechanical and electrical sensing helps to create the multi-parameter contamination decomposition which was used throughout the thesis.

7.1.2 Limitations: Metal Contamination and TBN Monitoring

Customer needs also identified metal contamination and TBN monitoring as only partially measurable. For metal contamination, the sensor can detect large quantity but it fails to measure metal particles with the resolution required by the customer needs. For TBN, resistivity trends provide an indirect trend of depletion, but not an absolute value. Meeting this requirements would require changes in sensor sensitivity.

7.1.3 Sensor Variability and Manufacturing Quality

The rig testing setup (Chapter 4) mounted three FPS2800 sensors in parallel for sensor comparison under identical test conditions. This comparison showed that the three units did not always agree with each other. Desppite showing similar trends the equations varied from sensor to sensor for the same oil sample and temperature. sensor variability is a reliability concern rather than a modelling one. No amount of model refinement compensates for a sensor that reads differently from its neighbour under the same conditions. Tighter manufacturing tolerances and a unit calibration or verification check are recommended as prerequisites for fleet scale deployment, so that oil condition estimates remain comparable across vehicles regardless of which physical sensor unit is installed.

7.2 Rig Testing: Temperature Modelling and Contamination Calibration

The rig testing phase addressed two questions: whether the temperature dependent property models proposed by TE Connectivity for generic oil hold for Volvo VDS-5 oil, and whether the contamination blending models could be calibrated for the specific contamination types relevant to the customer needs specification.

7.2.1 Temperature Modelling

The logarithmic ASTM D341 viscosity model achieved strong agreement with the rig measurements across the full temperature range (40 to 110°C), confirming that VDS-5 oil's viscosity vs temperature behaviour follows the logarithmic relationship as the generic reference oil.

Density and dielectric constant both confirmed the linear temperature dependence proposed by TE Connectivity, with fitted constants D, E, F and G that differ from the white paper reference values, reflecting the distinct base oil and additive chemistry of VDS-5 relative to 15W40. The measured resistivity vs temperature curve exhibited distinctly cubic behaviour that the linear model ($R_p = H + I \cdot T$) could not capture properly. A combined Arrhenius cubic polynomial model provided a significantly better fit, consistent with the theoretical expectation that ionic charge carrier mobility in lubricating oils follows an Arrhenius type temperature dependence rather than a linear one [16, 15].

7.2.2 Fuel Dilution

All four sensor parameters for fuel dilution followed the models proposed by TE Connectivity, with the Refutas viscosity blending model providing an accurate prediction of viscosity reduction at 3%, 6% and 9% dilution levels.

The resistivity alone cannot be used to detect fuel contamination, reinforcing the importance of the multi parameter approach. Fuel dilution is mainly detectable through viscosity reduction, with density and dielectric providing incomplete signals.

7.2.3 Water Contamination

The water contamination results revealed some differences between the VDS-5 sensitivity constants and the TE Connectivity reference values for 15W40 oil. The dielectric sensitivity constant for VDS-5 was less than half of the reference value, while the resistivity sensitivity was approximately twice as large in magnitude. Applying the TE Connectivity constants directly to VDS-5 data without re-calibration would have wrong estimation of water contamination. The VDS-5-specific constants derived from this rig testing should replace the white paper reference values in the production model for Volvo applications.

7.2.4 Soot Contamination and Oxidation (Scope Limitations)

The inability to complete controlled soot calibration experiments using carbon black is a limitation of this thesis that warrants discussion. The failure occured mainly because of two reasons i.e. suspension instability and electrical conductivity interference. In the absence of controlled soot calibration, the vehicle soot model relies on the TE Connectivity reference constants for 15W40 oil. Validation against GLAD laboratory data for the FL286 vehicle (Section 4.7) showed less than 1% relative error, suggesting these reference constants are a reasonable first approximation for VDS-5. The recommended approach for soot contamination calibration is to use NIST Standard Reference Material 2975 (diesel particulate matter) for soot calibration, as recommended by TE Connectivity [1]

Furthermore, Controlled oxidation ageing experiments were similarly not conducted within the scope of this project, since they require long duration thermal ageing at 150°C over 1,000 to 3,000 hours [1].

7.3 Vehicle Testing and Model Validation

Before any contamination estimation could be performed on vehicle data, a fresh oil baseline had to be established for the FL286 test vehicle immediately following its oil change and the temperature models for all four parameters were re-fitted to these fresh oil readings (Section 7.2). This step is essential. With the baseline and temperature model established, the validated models were applied to three months of FL286 vehicle CAN-bus data. The GLAD validation results demonstrate close agreement for soot, oxidation and water contamination. Taken together, these results provide a good proof of concept . However, this validation rests on a single vehicle and a single three month monitoring window, which limits how confidently the results can be generalised. The overall confidence level is at approximately 70% on this basis. Current situation does not have sufficient data to support the model and make a fleet wide deployment decisions.

7.4 Power BI Dashboard and Pipeline Performance

The complete pipeline starting from CAN-bus data acquisition, DSL based Python processing, SQL storage and Power BI visualisation was successfully deployed and demonstrated for the FL286 vehicle. The dashboard (Section 5.5) displays the sensor calculated oil condition with the GLAD laboratory reference values for comparison and validation. It allows the team to filter the view by vehicle and by the specific contamination type being monitored, so that results can be inspected at the level of an individual truck or an individual degradation mechanism without requiring any knowledge of the underlying models or Python code. The pipeline translates the theoretical FPS2800 sensor models into an operational tool that research and development team can use directly.

Two operational limitations in the current implementation are that there is no automated connection between the pipeline and Volvo's GLAD laboratory system. GLAD reference values must be manually downloaded from the GLAD portal and uploaded into Power BI before they appear on the dashboard and producing a fresh set of estimates requires manually re-running the Jupyter Notebook processing pipeline rather than this happening automatically as new CAN-bus data arrives. Both of these are manual steps rather than technical dead ends and both are already planned as future work items in Section 8.3.

7.5 Achievement of Research Objectives

Table 7.1 summarises the extent to which each of the four research phases defined in the scope (Section 1.3) was achieved.

Table 7.1: Achievement of research objectives.

Objective	**Status**	**Notes**
Rig-based model validation	Substantially achieved	3/4 temperature models confirmed; resistivity model corrected; fuel dilution and water calibrated. Soot and oxidation not completed
Vehicle data model application	Achieved	Three month dataset processed; all four parameters tracked; coupled solver deployed
GLAD validation	Achieved	Soot <1% error; water <4% error; oxidation <25% underestimation
Pipeline and dashboard deployment	Partially Achieved	CAN → Python → SQL → Power BI fully operational but manual intervention required for refreshing

8 Recommendations and future work

This chapter turns the findings and limitations from the rest of the thesis into a set of next steps for taking the FPS2800 from a working proof of concept to something ready for production across the Volvo Group heavy duty truck fleet. The recommendations are grouped into four areas: model development, hardware and installation, software and pipeline and strategic deployment.

8.1 Model Development

8.1.1 Controlled Oxidation Ageing Experiments

The pending work in rig testing is that there is no VDS-5 oxidation calibration. Right now the model runs on TE Connectivity's reference constants [1] and that is exactly why net oxidation is not accurate compared to lab data. Fixing this will need running a dedicated long duration ageing trial of fresh VDS-5 oil held at 150°C, sampled regularly and checked by FTIR (ASTM D7418) and TBN titration (ASTM D2896) over 1,000 to 3,000 hours, following the same protocol TE Connectivity describes in their white paper [1].

8.1.2 Controlled Soot Calibration Using NIST SRM 2975

As Chapter 4 covers, carbon black did not work as a soot surrogate.It interfered with both electrical and mechanical readings. NIST Standard Reference Material 2975 (diesel particulate matter) is the recommended replacement as suggested by TE engineering.

8.1.3 Calibration for Additional Oil Grades

Everything calibrated in this thesis is specific to VDS-5. Volvo Group trucks also run on VDS-4.5 and will likely run on some other oil in future. The resistivity deviation and the water contamination constants found here already show that these calibration values do not transfer between oil grades, so each additional grade needs its own rig calibration, using the same temperature sweep and contamination as developed in this thesis.

8.1.4 Multi-Vehicle Model Validation

Everything in the vehicle validation comes from one truck over three months period. The GLAD agreement is encouraging, but it is still a single data point in terms of vehicle and operating conditions. Getting confidence needs testing across a large set of vehicles with different duty cycles, different engine variants and models.

8.2 Hardware and Installation

8.2.1 CFD Analysis for Optimal Sensor Placement

The FPS2800 needs roughly laminar flow to get accurate tuning fork readings and the oil at the sensor cannot exceed 150°C. On the FL286 test vehicle, mounting it on the compressor pipe worked well, but that might or might not necessarily be the optimum position . Before locking in a production installation, a proper CFD analysis of oil circuit needs to be done to find a mounting point that satisfies both the flow and temperature requirements across the full operating range, while minimizing noise.

8.2.2 Sensor Robustness Improvements

The FPS2800 in its current OPS3 prototype form is not ready for a production truck. Sensor variability discussed in Chapter 7 needs improvement from TE Engineering.

8.3 Software and Pipeline

8.3.1 Automation of GLAD Data Integration

Right now GLAD reference data has to be downloaded manually and uploaded into Power BI manually. That is a dependency on someone to do it. In future we can make a system which can call data directly from GLAD and upload it in Power-Bi.

8.3.2 Automated Power BI Refresh

The dashboard currently needs a manual refresh to show new data. Setting it up for scheduled automatic refresh would let it update on its own, with no one needing to trigger anything.

8.3.3 Inactivity Handling in the Accumulation Model

The FL286 data showed that when the vehicle sits idle for a while, pushes sensor readings outside the calibrated range. Hard filtering catches these bad readings, but it also leaves a gap in the accumulation record and that gap creates some uncertainty. A cleaner fix is to add an explicit inactivity detection step. Once the vehicle has been stationary past some threshold, pause accumulation and flag it on the dashboard. That would get rid of the inactivity spike seen in the dashboard.

8.3.4 Virtual Sensor Development

A further out idea is a virtual sensor where a model that estimates oil condition purely from existing signals like engine load, speed, temperature history, fuel consumption without a physical FPS2800 fitted at all. Trained on the labelled data from FPS2800 instrumented vehicles and checked against GLAD, a model like this would let oil condition monitoring extend to vehicles that never carry a physical sensor, using the instrumented fleet as the calibration reference for everyone else.

8.4 Summary of Recommendations

Table 8.1 pulls all of the above together in priority order.

Table 8.1: Summary of recommendations and future work in priority order.

Priority	Category	Recommendation
1	Model	Controlled oxidation ageing experiment for VDS-5 (1,000 to 3,000 h at 150°C)
2	Model	Soot calibration using NIST SRM 2975 diesel particulate matter
3	Hardware	CFD analysis for optimal sensor placement per engine variant
4	Software	Automate GLAD data integration via API
5	Software	Implement inactivity detection and accumulation pause logic
6	Model	Calibrate models for VDS-4.5 and VDS-6 oil grades
7	Model	Multi-vehicle GLAD validation (5 to 10 vehicles, diverse duty cycles)
8	Software	Automated Power BI dashboard refresh
9	Software	Virtual sensor model development using existing CAN-bus signals
10	Hardware	Engage TE Connectivity on production-grade sensor robustness specification

Taken as a whole, Table 8.1 sets out a reasonably clear route from where the project stands today to a production ready monitoring system.

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