# Online Industrial Lubrication Oil

# Health Condition Monitoring, Diagnosis and Prognostics

BY

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THESIS

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## DEDICATIONS

I would like to dedicate this thesis to my mom, Jin Zhang, for her unconditional love and encouragement from heaven. My memories of her never fade away throughout the past 17 years since she passed away.

To my dad, Qiucheng Zhu, for being great pillars of my support, for raising me throughout difficult times by himself and for encouraging me to never give up chasing my dreams for a better future.

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Junda Zhu

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## LIST OF ABBREVIATIONS

| | |
|---|---|
| CBM | Condition Based Maintenance |
| CNT | Carbon Nano Tube |
| DAQ | Data Acquisition |
| DC | Dielectric Constant |
| DD | Degree of Degradation |
| EIS | Electrochemical Impedance Spectroscopy |
| EKF | Extended Kalman Filter |
| FTIR | Fourier Transform Infrared Spectroscopy |
| KF | Kalman Filter |
| LDR | Light Dependent Resistor |
| PDF | Probability Distribution Function |
| PF | Particle Filtering |
| PHM | Prognostic and Health Management |
| RUL | Remaining Useful Life |
| SCADA | Supervisory Control And Data Acquisition |
| SIR | Sequential Importance Resampling |
| SIS | Sequential Importance Sampling |
| SMC | Sequential Monte Carlo |
| SOAP | Spectrometric Oil Analysis Program |
| TAN | Total Acid Number |
| TBN | Total Base Number |
| UKF | Unscented Kalman Filter |

## SUMMARY

According to the United States Department of Energy (DOE), wind energy is the most rapidly advancing source of energy worldwide. United States wind power produces as much clean electricity as nearly 10 nuclear power plants without environmental pollution and consumes virtually no water. However, to increase wind energy production rate, there is an urging need to improve the wind turbine availability and reduce the operational and maintenance costs. The safety and reliability of a functioning wind turbine depend largely on the protective properties of the lubrication oil for its drive train subassemblies such as gearbox and means for lubrication oil condition monitoring and degradation detection. In comparison with current vibration based machine health monitoring, online lubrication oil diagnostic solutions provide over 10 times earlier warning of possible machine failure. The purpose of lubrication oil condition monitoring and degradation detection is to determine whether the oil has deteriorated to such a degree that it no longer fulfills its function in real time.

In this dissertation, lubrication oil degradation basic degradation features have been investigated. Lubrication oil degradation is classified into three categories: particle contamination, water contamination and oxidation which are defined as three basic degradation features. A comprehensive review of current state of the art lubrication oil condition monitoring techniques and solution has been conducted. Viscosity and dielectric constant are selected as the performance parameters to model the degradation of lubricant based on the result of the literature review. Physics models have been developed to quantify the relationship between lubricant degradation level and the performance parameters. Commercially available viscosity and dielectric sensors have been acquired and installed in a temperature controlled chamber to validate the developed performance parameter based lubrication oil deterioration physics models. Water and particle contamination are the most common oil deterioration features. Therefore, it is essential to keep monitoring the water and particle content of the lubricant. Particle filtering techniques are introduced and adapted to predict the remaining useful life of lubrication oil based on the developed

physics models. In the particle filtering algorithm, state transition function was constructed to estimate the fault progression. Observation function was assembled based on the output of the sensors (physics model based on state transition function) which are viscosity and dielectric constant, respectively.

The developed prognostic methodology has been implemented into two case studies to test the effectiveness and the robustness of the developed remaining useful life (RUL) prediction algorithm. The first study is an industrial scenario simulation with progressing water contamination. The second case study is an industrial simulation with progressing iron contamination. Temperature compensation module has been integrated to smooth the prediction result. The impact of the number of observations (number of sensors implemented), particle populations have been investigated and compared.

The contributions of the research described in this dissertation are summarized as following:

1) A comprehensive investigation and evaluation on current state of the art oil condition monitoring techniques and solutions has been conducted. The results of the investigation have showed that viscosity and dielectric constant sensors are capable of performing online oil condition analysis. This investigation is the first publication that systematically summarized and evaluated current oil condition monitoring solutions in the industry and academia, commercially available and under development.
2) Physics based models for lubrication oil performance degradation evaluations have been developed. The two most common basic degradation features: water contamination and particle contamination have been both successfully modeled and validated. Commercial available dielectric constant sensor and viscometer have been acquired and utilized in lab based simulation tests to validate the developed physics models. Most oil degradation models reported are data driven, this research is the first one that developed physics based models to describe the degradation of the lubricant and also the first one to use physics based model to perform lubrication oil remaining useful life prediction.
3) With the help of particle filtering technique, the remaining useful life prediction of lubrication oil has been successfully performed. The developed physics models have been integrated into the

particle filtering framework as observation functions. The state transition function can be correlated based on previous experience and data of the system dynamics. Also within the particle filtering algorithm, an *l*-step ahead state parameter prediction and RUL estimator have been developed to enable this technique to perform *l*-step ahead prediction while most of other papers published just show one-step prediction. Therefore the developed RUL prediction technique is capable of providing practical and feasible solution to the current condition based maintenance systems. This is the first time particle filtering technique was successfully implemented to predict the remaining useful life of the lubrication oil.

4) The developed lubrication oil condition monitoring and RUL prediction technique has been validated using two simulation case studies, water contamination case study and particle contamination case study. Within the industrial simulation model, a temperature compensation module has been integrated into the physics model and RUL prediction algorithm. This module enhances the lubrication oil condition monitoring and RUL prediction algorithm so the developed technique can handle highly fluctuating operating temperature conditions with reliable and consistent RUL prediction result.

# CHAPTER 1

# INTRODUCTION

## 1.1. Background and Motivation

According to the United States Department of Energy (DOE), wind energy is the most rapidly advancing source of energy worldwide. United States wind power produces as much clean electricity as nearly 10 nuclear power plants without environmental pollution and consumes virtually no water However, to increase wind energy production rate, there is an urging need to improve the wind turbine availability and reduce the operational and maintenance costs. The reliability and availability of a functioning wind turbine depend largely on the protective properties of the lubrication oil for its drive train subassemblies such as the gearbox and means for lubrication oil condition monitoring and degradation detection. The wind industry currently uses lubrication oil analysis for detecting gearbox and bearing wear but cannot detect the functional failures of the lubrication oils. The main purpose of lubrication oil condition monitoring and degradation detection is to determine whether the oils have deteriorated to such a degree that they no longer fulfill their functions. This thesis describes a research on developing online lubrication oil condition monitoring and remaining useful life prediction using particle filtering technique and commercially available online sensors. It first introduces the lubrication oil condition monitoring and degradation detection for wind turbines. Viscosity and dielectric constant are selected as the performance parameters to model the degradation of lubricants. In particular, the lubricant performance evaluation and remaining useful life prediction of degraded lubrication oil with viscosity and dielectric constant data using particle filtering are presented. A simulation study based on lab verified models is provided to demonstrate the effectiveness of the developed technique.

Lubrication oil is an important information source for early machine failure detection just like the role of the human blood sample testing in order to perform disease detection. In modern industries, lubrication oil plays a critical part in condition maintenance of complicated machineries such as wind turbines. In recent years, health condition monitoring and prognostics of lubrication oil have become significant topics among academia and industry. Significant effort has been put into oil diagnostic and prognostic system development and research. In comparison with vibration based machine health monitoring techniques, lubrication oil condition monitoring provides approximately 10 times earlier warnings for machine malfunction and failure as stated by Poley [57]. The purpose of most research is, by means of monitoring the oil degradation process in real time, to provide early warning of machine failure, extend the operational duration of lubrication oil in order to reduce the frequency of oil changes and most importantly to optimize the maintenance schedule therefore reduce maintenance costs.

Based on current industry standard, there are 3 tiers of oil analysis [57]. Tier 3 is offsite oil analysis. For tier 3, lubrication oil are sampled and sent to remote laboratories for the result of analysis and proper maintenance suggestion. The sampling and analysis delay is from a couple of weeks to a month which makes it impossible to know the actual condition of the lubricant. Tier 2 is onsite oil analysis with portable testing kit while tier 1 is online oil analysis. For this method, engineers will need to climb up the tower and sample the oil. The testing kit will be brought onsite for instant data acquisition. However, these testing kit are usually in portable size and have limited functions. For online lubrication oil analysis, oil health condition information is gathered by sensors that are integrated in the oil circulation system and transferred to remote diagnostics centers. The gathered data is analyzed by special developed algorithms and the result and proper maintenance suggestion is presented in real time.

Currently, wind energy industry mostly uses tier 3 offsite lubrication oil analysis. The lubrication oil in the wind turbine is normally sampled every 6 months and sent to oil analysis labs for feedback on the condition of the oil. The online health monitoring of functional failures of lubrication oil has been an issue that remains to be unsolved. The purpose of lubrication oil online condition monitoring and degradation detection is to determine whether the oil has deteriorated to such a degree that it no longer fulfills its protective function and to provide early warning of the possibility of total failure in real time. The capability of online oil health condition monitoring will leads to better remaining useful life prediction which will results in a much optimized maintenance schedule and less unscheduled maintenance events. Unexpected gearbox or drivetrain repairs often associate with large bills. The cost of wind turbine maintenance crane mobilization costs over $150,000. As one can imagine if many unexpected failure occurs, financial lost will be considerable. The implementation of online lubrication oil health monitoring will also reduce the unnecessary oil change cost. In the current schedule based maintenance, most of the oil was dumped well before it reaches its end of life. According to Machinery Lubrication Magazine [46], the actual cost to change the oil in a rather small system at a power plant requiring 5-gallons of oil (5 dollars per gallon) is $988.70 which is 40 times the price of the new oil. For wind turbines, the oil capacity is normally from 55 to 85 gallons, 45 to 55 dollars per gallon and it takes 150,000 dollars to mobilize the crane. The actual cost of one oil change is enormous. Wind energy industry right now needs the tax incentives from federal government in order to survive. And it also faces the challenge from natural gas industry. The high cost of wind turbines maintenance is emerging as the warranties from the turbine manufactures expires. A great portion of the maintenance bill is from unscheduled maintenance. However, with effective online oil condition based maintenance, the life of oil can extend to close to maximum and unnecessary or unscheduled oil change will be greatly reduced.

As stated by Sharman and Gandhi [66], and many other researchers, the primary function of lubrication oil is to provide a continuous layer of film between surfaces in relative motion to reduce friction and prevent wear, and thereby, prevent seizure of the mating parts. The secondary function is to cool the working parts, protect metal surfaces against corrosion, flush away or prevent ingress of contaminants and keep the mating component reasonably free of deposits. In a lubricated system, variation in lubrication oil physical, chemical, electrical (magnetic) and optical properties change the characteristics of the lubrication oil and lead to its protective property degradation. The main causes of turbine lubricant deterioration are oxidation, particle contamination, and water contamination. These three causes are defined in this thesis as lubrication oil basic degradation features. The parameters that describe the lubrication oil performance or level of degradation are called performance parameters. These parameters include viscosity, water content, total acid number (TAN), total base number (TBN), particle counting, pH value and so forth. Each performance parameter can be measured by certain sensing techniques. The relationship among the basic degradation features, performance parameters, and available oil condition sensors is shown in Figure 1.1. Also, Table 1.1 [62] [1] [2] [66] shows the performance parameters for different kinds of applications and their benchmark for lubrication oil degradation. For example, for water content, it measures the water contamination percentage of the lubrication oil. This performance parameter is necessary and crucial to gearbox, hydraulic system, engine, compressor, and turbine applications. Water content can be measured by a capacitance sensor, viscosity sensor, and water in oil sensor.

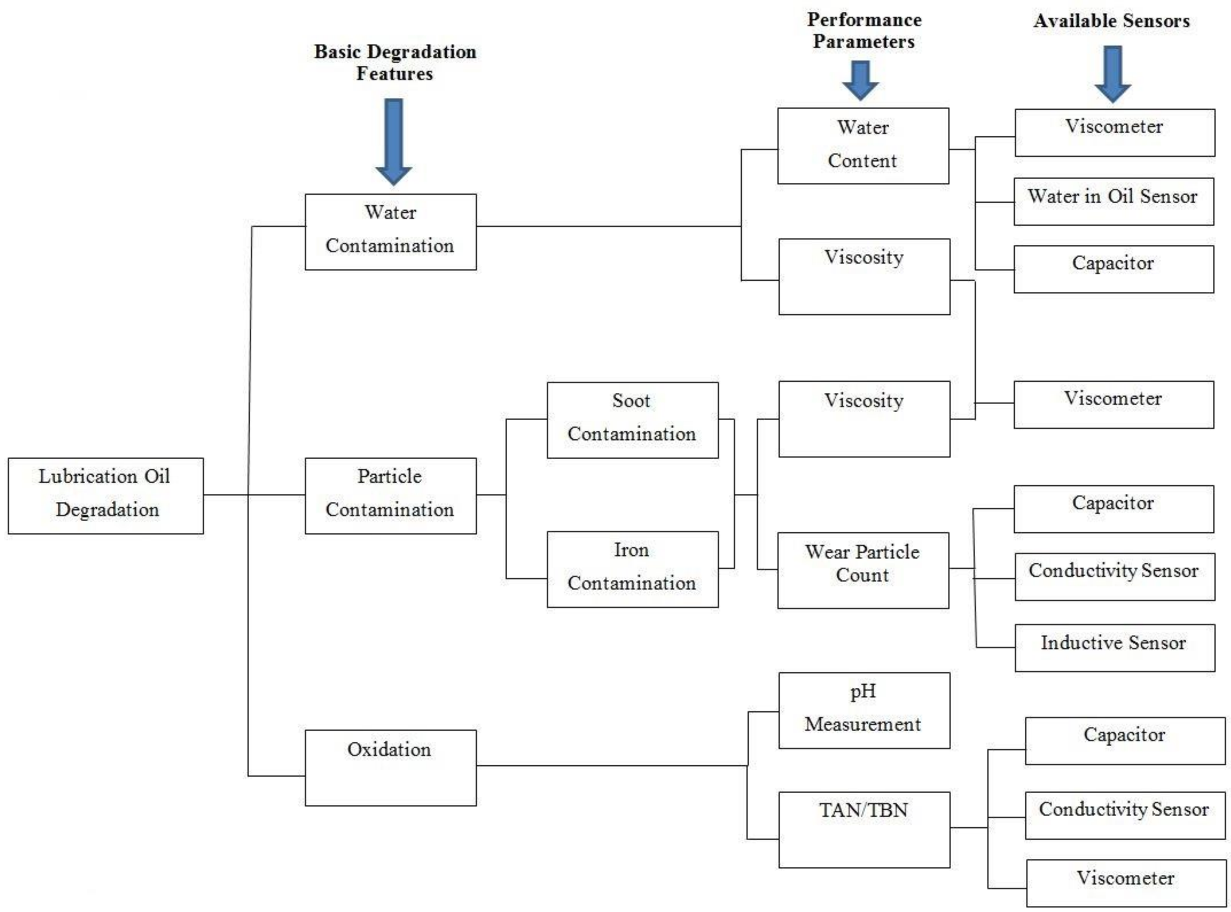


Figure 1.1 The relationship among the basic degradation features, performance parameters, and available oil condition sensors

To find a feasible solution for online lubrication oil health condition monitoring and remaining useful life (RUL) prediction, it is necessary to conduct a comprehensive review of the current oil health monitoring techniques. Over the years, scientists and experts have developed sensors and systems to monitor one or more of the lubrication oil performance parameters in order to monitor the oil condition effectively. These sensors and systems can be summarized into four categories including electrical (magnetic), physical, chemical, and optical techniques. For example, the most effective electrical technique for oil health monitoring is detecting the dielectric constant change of the lubrication oil. According to recent studies, the capacitance or permittivity change can be used to monitor the oxidation, water contamination, and wear particle concentration. On the other hand, for physical techniques, viscosity is most commonly discussed. The lubrication oil oxidation, water contamination, particle concentration, and some other property changes all have certain degree of impact on oil viscosity. Therefore, viscosity measurement is considered an objective mean of oil degradation detection. The final goal of all above mentioned systems is to achieve lubrication oil online health monitoring and remaining useful life prediction in industrial machineries. Note, that most sensing systems are only capable of off-line monitoring in which oil samples are collected from the machinery by specialists and sent to laboratories for oil condition analysis. In this way, the actual condition of the lubrication oil cannot be determined online because of the sampling and analysis delay.

In this thesis, based on the results of a comprehensive investigation of oil condition monitoring techniques, the two most effective online lubrication oil sensors, kinematic viscometer and dielectric constant sensors, were selected to develop an online lubrication oil health monitoring and remaining useful life prediction tool. Kinematic viscosity is the absolute viscosity with respect to liquid density while dielectric constant is the relative permittivity between the lubrication oil and air.

The purpose of this thesis is to present the development of an online lubrication oil condition monitoring and remaining useful life prediction technique based on a particle filtering algorithm and commercially available online sensors. This technique was developed by integrating lubrication oil degradation physics models with the particle filtering algorithm. The physics models were used to simulate the deterioration process of the lubrication oil due to basic degradation features in terms of the kinematic viscosity and dielectric constant. Two simulation case studies based on lab verified models were used to demonstrate the effectiveness of the technique.

Table 1.1 Performance parameters, applications and their benchmark for lubrication oil degradation

| Performance Parameters | Measurement Function | Unit | Benchmark of Degradation | Applications | | | | | Available Measurement Approach |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Gear box | Hydraulic system | Engine | Compressor | Turbine | |
| Viscosity (40 ℃) | Contamination of lubricant by some other oil, oxidation | Cst ($mm^2/s$) | $\geq 55$<br>$\leq 50$ | yes | yes | yes | yes | yes | Kinetic Viscometer |
| Viscosity (100 ℃) | | | $\geq 10$<br>$\leq 8$ | | | | | | Micro-acoustic Viscometer |
| Water Content | Presence of water | % | $\leq 2$ | yes | yes | yes | yes | yes | Capacitance sensor (Dielectric constant) |
| | | | | | | | | | Kinetic Viscometer |
| | | | | | | | | | Water in oil sensor |
| TAN/TBN | Acidity/alkalinity of lubricant (oxidation level) | mgKOH/gm | $\geq 0.6$<br>$\leq 0.05$ | yes | yes | yes | yes | yes | Capacitance sensor (Dielectric constant) |
| | | | | | | | | | Kinetic Viscometer |
| | | | | | | | | | Conductivity Sensor |
| Flash point | Presence of dissolved solvents or gases in the lubricant | ℃ | $\geq 220$<br>$\leq 140$ | no | yes | yes | no | no | Thermometer |
| Wear Particle Count | Wear particles in parts per million | ppm | $\leq 40$ | yes | yes | yes | yes | yes | Capacitance sensor (Dielectric constant), Kinetic Viscometer, Conductivity Sensor, Inductive Sensor |
| Particle Counting | Detect number of particles for sample size of 100cc | mg/L | $\leq 200$ | no | yes | no | no | yes | |

Also in this thesis, a particle filtering algorithm was utilized as RUL prediction tool. For oil condition monitoring, an effective and accurate state estimation tool will be beneficial to reduce machine downtime. An on-line RUL estimator includes two stages: state estimation and RUL prediction. First, in the state estimation stage, even though there are many state estimation techniques, Kalman filter and particle filter are the most utilized ones. However, Kalman filter requires many assumptions such as: 1) zero-mean Gaussian process noise, 2) zero-mean Gaussian observation noise, 3) Gaussian posterior probability density function (pdf), etc. Because nonlinear Kalman filter is linearization based technique, if the system nonlinearity grows, any of linearization (either local or statistical linearization) methods breaks down as reported by Merwe *et al.* [51]. Second, in RUL estimation stage, particle filtering can handle statistic prediction data unlike the other methods (parameter estimation). As a result, particle filtering algorithm provides feasible solutions for a wide range of RUL predication applications. A particle filtering algorithm integrated with physics based oil degradation models will provide a basis to develop practically feasible tools for accurate RUL prediction of lubrication oil.

## 1.2. Literature Review

### 1.2.1. Principles of Lubrication Oil Monitoring Techniques

To understand the principles of lubrication oil monitoring techniques, one has to review the 3 lubrication oil basic degradation features. The Principles of lubrication oil condition monitoring is by means of various sensing techniques to directly or indirectly monitor the lubricant basic degradation features. The basic degradation feature includes oil oxidation, water contamination, and particle contamination. The variation of these features can be detected by a set of oil performance parameters.

<u>Water Contamination and Its Impact on Lubrication Oil Performance</u>

The water contamination source may include the followings as reported by Kittiwake Developments Ltd. [35] and Benner *et al*. [8]:

1) Leakage from oil coolers, charge air coolers and steam heating coils, condensation of atmospheric humidity.
2) Blow-by gases from diesel engine combustion spaces or past compressor ring packs.

3) Leakage at tank vents (especially those exposed to weather).

4) Coolant jacket leaks through cracks or seals.

5) Contamination from top-up oil (especially in systems with a low tolerance to water).

6) Water is a normal product of combustion in gasoline and diesel engines and the normal expansion and contraction of air in the sump will condense water out of the air.

7) The lip seals around rotating shafts may allow water ingression.

When operating in high speed and temperature, the oil and water mixture will form an emulsion which prevents the oil from forming an effective lubrication film between the contact components. Generally speaking, excessive water content leads to insufficient lubrication and subsequently to abrasive wear and corrosion as reported by Kuntner *et al.* [38]. Typical acceptable levels for the water content in engine and transmission oils are in the order of 1 to 2 percent as reported by Jakoby and Vellekoop in 2004 [29]. The water contamination can have the following influence upon oil degradation:

1) Normally, as the lubrication oil ages, the viscosity changes. However, if there is water contamination, the lubricant's viscosity variation rate increases dramatically which will undermine the lubrication oil performance.

2) Water can displace the oil at contacting surfaces, reducing the amount of lubrication and activating surfaces which may themselves act as catalysts for degradation of the oil.

3) Water is an important contaminant in many lubricant oil systems because of its potential to cause failure via a number of mechanisms.

4) Water contamination within lubricating/lube oil storage tanks can lead to microbiological growth, forming yeast, mold and bacteria that will clog filters and very rapidly corrode fuel systems (Kittiwake Developments Ltd., 2011 [35]).

5) Water contamination of motor oils during storage and use in low-temperature conditions cause formation of deposits. These deposits, which consist of asphaltenes and additives, characterize the colloidal stability of the oils. A decrease in the concentration of additives worsens the performance properties of the motor oils as reported by Korneev *et al*. in 2006.

As an example, in terms of permittivity, the capacitance of oil is normally between 2 to 3 while that of water is around 80. The mixture's permittivity can be expressed as:

$\varepsilon_{r,m} = (1 - f)\varepsilon_{r,o} + f\varepsilon_{r,w}$ where subscripts '$m$', '$o$', and '$w$' are the (relative) permittivity of the mixture, oil, and water, respectively, and $f$ is the water fraction by volume. One can see that small fractions of water would yield comparatively large changes in the total (effective) permittivity of the mixture as stated by Jakoby and Vellekoop [29]

Oxidization and Its Impact on Lubrication Oil Performance

Oils consist of long-chain oxidizable hydrocarbons. In an operating engine they are exposed to high temperatures, and this makes them more vulnerable to attack from free radicals. This means that hydroxyl groups may be introduced at random locations along the long-chain oil molecule. Hydroxyl groups damage the lubricating properties of the oils. So to prevent this happening antioxidants are added which scavenge any radicals before they can do damage to the oil. Nevertheless, some oxidation does always take place, and it appears that as a consequence colloidal carbon is formed giving rise to black coloration and solid deposits. A second degradation mechanism has also been found to occur by the Chemistry Department at Reading University by Turner and Austin [71]. For example, at a bearing surface very high shear forces exist, and this can have the effect of physically pulling a long-chain molecule apart and forming two radicals. These may then react either with oxygen to form hydroxyl groups, or with the antioxidants added to the oil. In either case the reaction leads to lower molecular weight components being created in the oils as stated by Turner and Austin [71].

The chemical degradation process is very complicated including many reactants. Reaction families and prototypical reactions for lubricant degradation can be generally described as following stages in terms of chemical reaction equations as stated by Diaby *et al*. in 2010 [16] [17].

Initial Reactions:

1) Primary initiation: $Rh + O_2 \rightarrow R\cdot + HOO\cdot$

2) Bond fission: $ROOH \rightarrow RO\cdot + HO\cdot$

3) Hydroperoxide decomposition: $RH + R'OOH \rightarrow R\cdot + R'O + H_2O$

Propagation Reactions:

1) Oxygen addition: $R\cdot + O_2 \rightarrow ROO\cdot$

2) Alkoxy $\beta$-Scission: $RO\cdot \rightarrow R'C(O)H + R''\cdot$

3) $\beta$-Scission: $\cdot ROOH \rightarrow RO + \cdot OH$

4) Hydrogen Transfer: $ROO\cdot + R'H \rightarrow ROOH + R'\cdot$

Termination Reactions:

1) Disproportionation: A. $2ROO\cdot \rightarrow RO + ROH + O_2$ ; B. $2ROO\cdot \rightarrow 2RO\cdot + O_2$

2) Recombination: $2R\cdot \rightarrow RR$

Other Reactions: $RCOH + RCOOOH \rightarrow 2RCOOH$

The effects of oxidation due to chemical reaction as well as the by-products of combustion produce very acidic compounds inside an engine. These acidic compounds cause corrosion of internal engine components, deposits, change in oil viscosity, varnish, sludge and other insoluble oxidation products that can cause a performance and durability degradation of the engine over a period of time. The products of oxidation are less stable than the original base hydrocarbon molecular structure and as they continue to be attacked by these acidic compounds can produce varnish and sludge. As an engine goes through multiple heating and cooling cycles this sludge can harden and cause other problems such as restricted passageways and decreased component tolerances. Varnish can cause such things as piston ring and valve sticking. The deposits can also affect heat transfer from pistons to cylinder and in extreme cases can cause seizure of the piston in the cylinder. Pistons also have oil return slots machined into them that can become plugged and result in increased oil consumption and additional deposits created on top of the deposits that are already there. Deposits also form on the tops of pistons which over a period of time can cause pre-ignition, increased fuel octane requirements, detonation/pinging and increased exhaust hydrocarbon emissions and an overall destructive effect on the engines internal parts. Deposits also form inside valve covers, timing gear covers, oil pump pickup screens, oil filters and oil passageways as stated by Mann [48].

Particle Contamination and Its Impact on Oil performance

The lubrication oil performance stay stable if the oil temperature is maintained within the manufacture recommended range. In case it is not operating in the required condition, the oil deterioration starts and it reflects the degradation of lubricating oil. As a general thumb rule, 10℃ rise in temperature doubles the oxidation rate and so is formation of oxidation products. Initially these oxidation particles are soft and gummy products. When these particles come in contact with high-temperature zones these lead to formation of hard and abrasive particles. These on contact with the components cause generation of wear particles causing further reduced system performance. Therefore, to control wear and for increased performance, viscosity and contaminants (insoluble) are the contributing performance parameters as reported by Sharma and Gandhi [66].

During operation of a lubricated system, wear particles are generated. These particles can clog the filter, which may even rupture the filter and thus causing contamination level rise to an alarming level, with possibility of reduced performance or a catastrophic failure. In addition, these can block oil holes, causing the oil starvation at the mating contact and it may even lead its seizure, causing a catastrophic failure. The high contamination level (generated, and oxidation and gummy products), particularly in, lubricated systems causes their improper operation due to malfunctioning of the valves. This may also cause internal leakage in the system and if not taken care, lead to external leakage. Particle counting can be used to determine the level present in the system. Spectrometric oil analysis program (SOAP), i.e. spectroscopic technique can be used to identify the metallic element constituting and their level to relate with their source. Environment contamination is also added during maintenance actions, e.g. oil topping up or oil change, due to improper actions and inadequate care and handling. In addition, this may be due to improper care of oil drum in storage. A defective seal due to improper fitting, use of degraded/damaged seal during storage and incompatibility of it with the oil may also allow these. Defective seals/gasket/orings, e.g. in internal combustion engines can allow mixing of fuel or coolant with oil and this causes viscosity decrease. In case this value falls down the recommended value, this may lead to oil leakage or the metal to metal contact causing high friction and wear. This may also cause increase in the water content and for system it may be very critical as mentioned by Sharma and Gandhi, in 2008 [66].

The following subsections illustrate different lubrication oil monitoring techniques in four categories. Most electric (magnetic) and optical approaches are indirect techniques of oil health monitoring. They usually monitor the specific property and correlate the data with that acquired by direct oil degradation feature monitoring approaches while most of the physical and chemical techniques are direct degradation feature monitoring techniques.

### 1.2.2. Electrical (Magnetic) Techniques

Dielectric Constant

Several researches have been reported using special designed capacitors to measure the dielectric constant variation of the target lubrication oil in order to monitoring the oil degradation. It has been proved by Schmitigal and Moyer in 2005 [65] that capacitance sensor is capable of lubrication oil oxidation, water contamination and wears particle contamination detection. Raadnui and Kleesuwan [62] used a grid capacitance sensor (Figure 1.2) to measure the dielectric constant with artificial oil contamination then used statistical method to evaluate the performance parameter importance and interaction. The capacitance of the sensor can be expressed as follows: $C=(\varepsilon_0 \varepsilon_v A)/\sigma$, where $\varepsilon_0$ is the dielectric constant in the vacuum; $\varepsilon_y$ is the dielectric constant of the oil between two poles; $A$ is the available area of poles; $\sigma$ is the distance between two poles; For a fixed sensor, $\varepsilon_0$, $A$ and $\sigma$ are constant, the capacitance of the sensors is determined by $\varepsilon_y$ while the voltage is loaded between the emission pole and the detecting circuit is proportional to the capacitance of the sensor.

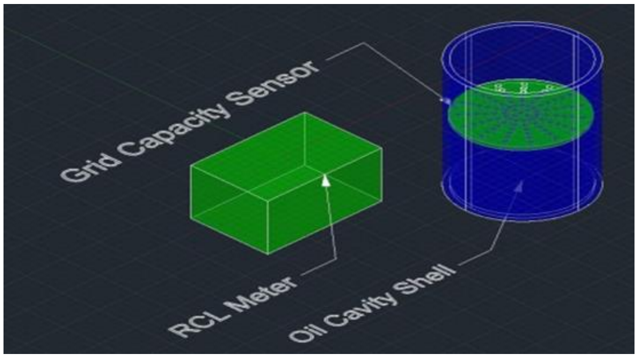

Figure 1.2 Grid capacitance sensor

In this paper, the programmable automatic RCL meter is used and the capacitance readout from the measuring apparatus is directly related to the input frequency which is explained in the following Equation (1.1).

$$C=0.5\pi f X_c \tag{1.1}$$

In Equation (1.1), $C$ is the overall capacitance; $f$ is the input frequency; $X_c$ is an inductive of components; Based on the preliminary measurements of dielectric constant of engine oils, the authors find the value of dielectric constant varied from 6.5 to 10 pF in relation to the input frequency (electric current change rate between the poles).Turner and Austin [71] measured the dielectric constant and magnetic susceptibility then correlate it with viscosity of the lubricant with an interleaved-disc capacitor. The sensor structure is shown in Figure 1.3.

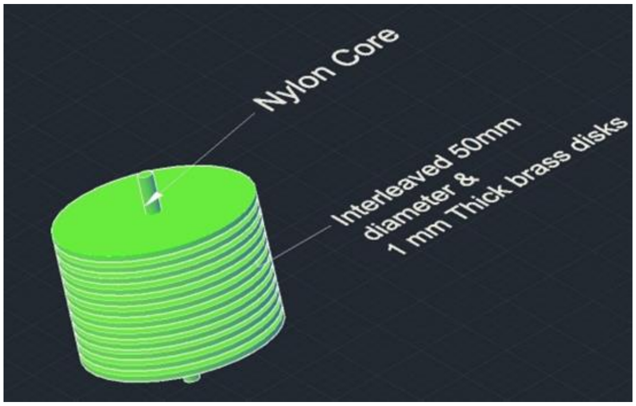


Figure 1.3 Interleaved-disc capacitor for measurement of dielectric constant

The authors first measured the capacitance of the air which was around 170 pF. Then, at 19℃ room temperature, the sensor was dipped into the test oil to measure the capacitance of the oil. The dielectric constant was then calculated as:

$$D=C_{oil}/C_{air} \tag{1.2}$$

Moreover, Cho and Park [14] designed a wireless sending system which transmits lubrication oil capacitance information and energy between sensor and reader for automobiles with a capacitive IDT sensor. The sensor is shown in Figure 1.4.

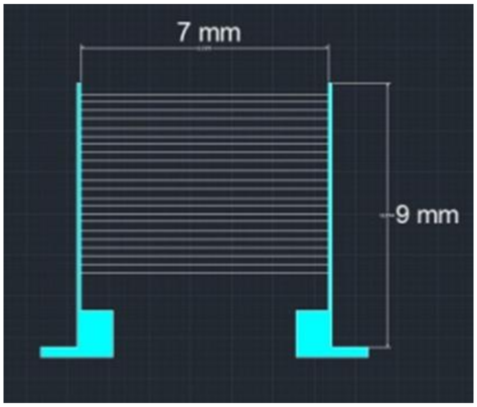


Figure 1.4 Capacitive IDT sensor

For the relationship between the field strength $E$ applied to the dielectric substance and the polarization $P$, the polarization is getting bigger when the field strength increases as shown in Equation (1.3).

$$P = \varepsilon_0 X_e E \tag{1.3}$$

$$\varepsilon_r = 1 + X_e \tag{1.4}$$

And the relationship, which is indicated in Equation (1.4), is established between the relative permittivity $\varepsilon_r$, and the electric susceptibility $X_e$, which presents the degree of polarization caused by the electric field that is applied to a certain substance. The deteriorated oil with polar molecules appear to have a bigger electric susceptibility than the non-deteriorated engine oil with non-polarization, and it is greatly affected the metallic particles and metallic ions that increased due to corrosion and abrasion. Accordingly, it can be identified that the more the engine oil is deteriorated, the more the permittivity of the engine oil is increased. Jakoby and Vellekoop [29] combined permittivity (capacitance) sensor with micro acoustic viscometers in order to detect water-in-oil emulsions. MG (Maxwell-Garnett) rule has been identified as a proper tool to predict the size of the effect. Because of the relative permittivity of oil ($\varepsilon_{r,o}$= 2 - 3) is quite different from water ($\varepsilon_{r,w}$= 80). The effect of water contamination on the permittivity of the mixture can be expressed as:

$$\varepsilon_{r,m} = (1 - f)\varepsilon_{r,o} + f\varepsilon_{r,w} \tag{1.5}$$

Where $\varepsilon_{r,m}$ stands for the relative permittivity of the mixture. They proved that permittivity sensors yield a clear indication of the water content in the oil being moreover to first order independent of the exact permittivity of the contaminating water. Also, the output signal of micro acoustic viscometer is hardly influenced by the water content compared to traditional rotational viscometer. Another paper by Guan *et al.* [21] combined dielectric constant with an analytical method called dielectric spectroscopy to measure the oxidation rate of the lubrication oil. Dielectric spectroscopy (DS) is an analytical technique on the interaction between dielectric material and electromagnetic energy in the radio frequency and microwave range, which is a powerful structural detection technique for dielectric material. This technique is capable of detecting oxidation duration (OD), total acid number (TAN) and insoluble content (IC). The paper proved that DS was the most effective method to extract the dielectric characteristic from dielectric material and could be developed into an efficient oil degradation monitoring technique. The authors believed that the remaining useful life of engine lubricating oil could be predicted based on online or in situ DS data.

Several commercially available sensors developed by Kittiwake Developments Ltd are also capable of online oil quality detection by way of interpreting lubrication oil dielectric property. For example, the Kittiwake on-line oil condition sensor (Figure 1.5) uses a combination of proven Tan Delta dielectric sensing and smart interpretation algorithms to detect lubrication oil oxidation. As mentioned above, TAN is a commonly used performance parameter to describe lubrication oil oxidation. So, by mean of correlating lubrication oil oxidation and the dielectric property variation, online oil oxidation monitoring is achieved. Also, based on similar dielectric property monitoring theoretical base, the Oil Quality Sensor (Figure 1.6) developed by Tan Delta Systems Ltd is capable of water contamination and oxidation online detection. Moreover, a specialized Moisture Sensor (Figure 1.7) developed by Kittiwake Developments Ltd is also commercially available. This sensor uses a combination of proven think film capacitance sensor and special developed algorithm to perform relative humidity detection.

Figure 1.5 On-line oil condition sensor (Kittiwake Developments Ltd)


Figure 1.6 Oil quality sensor (Tan Delta Systems Ltd)

Figure 1.7 Moisture sensor (Kittiwake Developments Ltd)

Since many previous oil conditions diagnostic techniques focus on monitoring the basic degradation features like oxidation and soot concentration. They are not capable of performing online data acquisition. By means of correlating dielectric constant variation data with basic degradation data acquired from traditional lubrication oil condition monitoring sensors, one can achieve online lubrication oil deterioration detection. The advantages of dielectric constant include: all degradation feature coverage, online health monitoring capability, and low data processing complexity and maintenance cost.  The disadvantage is that most of them need special design and fabrication.

Conductivity

Like capacitor, special fabricated lubrication oil electrical conductivity sensor is another direction scientists have been working on. Moon, *et al.* [52] reported that by measuring the oil conductivity with a carbon nano tube (CNT) sensor (Figure 1.8), lubrication oil oxidation rate can be monitored. They correlated the CNT conductivity data with TAN of the test oil and the results shows that CNT sensor is effective regarding to the oil oxidation deterioration. Since many sensors with chemical based techniques has relatively short life span problems and not capable on online diagnostics. This CNT sensor reduced the maintenance cost and provided an instant data collection solution. Basu *et al*.[7] and Lee *et al*. [39] both found that conductivity changes due to chemical and physical changes in the additives commonly used in commercial lubricant. However, their methods required prior knowledge of the oil formulation and they only tested on gasoline engines, also no thermal effects were made. While conductivity sensors are capable of online diagnostic and the result is well correlated with oxidation rate of the oil degradation, more hardware are needed to cover other oil basic degradation features.

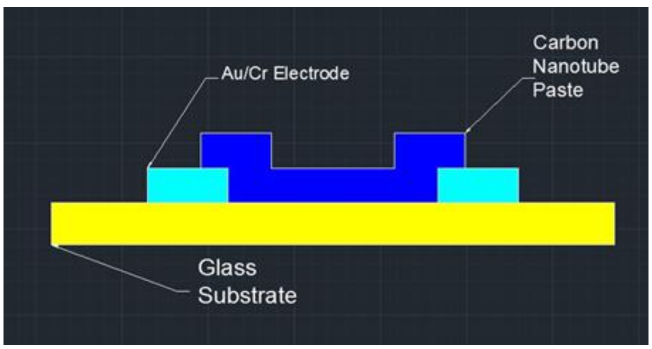


Figure 1.8 CNT oil sensor

Hedges *et al*. [25] developed Polymeric Bead Matrix (PBM) technology for on-board condition based monitoring of fluid-lubricated aircraft components (Figure 1.9). This technique utilized the electrical properties of an insoluble polymeric bead matric to measure oil degradation. Charged ion groups were covalently bound to the matrix. By measuring the impact of solvating effect on the electrical characteristic (conductivity and polarity) of the matrix, lubrication oil deterioration monitoring was achieved. This sensing technique can monitor water and particle contamination along with oxidation. However, the sensor does need to be replaced along with the replacement of the oil.


Figure 1.9 CNT oil sensor

Magnetic Susceptibility

Monitoring the magnetic properties changes when oil degrades was the earliest developed system for lubrication oil diagnostic. Halderman [22] used a magnetic plug placing in the flow of oil. The plug has to be removed and ferromagnetic fragments were collected. The fragments were then inspected for condition analysis. Ferromagnetic fragments analysis usually calls for complicated micro scopes and is time consuming. Turner and Austin [71] used a magnetic susceptibility balance trying to investigate links between magnetic properties of lubrication oil and its usage, measured by viscosity variation. Figure 1.10 shows a typical commercial magnetic balance.


Figure 1.10 Commercial magnetic balance (Sherwood Scientific. Ltd)

The result shows that the magnetic characteristics of lubricating oil do change as the oil degrades, but the measurement were poorly correlated with viscosity and do not seem to offer much promise as the basis of an oil monitoring system. Even though magnetic susceptibility balance and magnetic plug provides the simplest solution for oil deterioration sensors, they have poor correlation with viscosity, not sensitive or calls for complicated further data processing.

Currently, most magnetic based oil condition monitoring techniques are used for oil bourn metallic particle detection like ferrous particle which is one of the most common results of component wear. Typical systems includes Patrol-DM™ wear debris monitor developed by Poseidon Systems, LLC as shown in Figure 1.11 and On-Line Metallic Wear Debris Sensor along with On-Line Ferrous Wear Debris Sensor developed by Kittiwake Developments Ltd as shown in Figure 1.12 and Figure 1.13 respectively. These systems are sensitive with metallic particle contamination. However, particle contamination is only one of the 3 basic degradation features of the lubricant.


Figure 1.11 Patrol-DM™ wear debris monitor (Poseidon Systems, LLC)

Figure 1.12 On-line metallic wear debris sensor (Kittiwake Developments Ltd)

Figure 1.13 On-line ferrous wear debris sensor (Kittiwake Developments Ltd)

Electrochemical impedance spectroscopy (EIS) is another electrical technique that can provide valuable insights into the condition of lubricating oils and their additive packages as stated by Byington *et al.* [12][13]. This sensor has been proved to detect chemical and mechanical property variation of lubrication oil including TAN/TBN, soot content, viscosity and degree of nitration. Byington *et al* [12][13] correlated EIS sensor output with different performance parameters, then by means of symbolic regression, several data driven models were developed to describe the lubricant deterioration behavior. At last, Sequential Mont Carlo (SMC) technique was used as a remaining useful life prediction tool for oil prognostics.

Typical commercially available EIS sensor is SmartMon-Oil™ developed by Poseidon Systems, LLC as shown in Figure 1.14. They developed a technique called “Broadband AC Electrochemical Impedance Spectroscopy”. By means of injecting complex voltage signal into the fluid at one electrode, and received by another electrode, the impedances are measured at different frequencies. The measured impedances are then correlated to the chemical and physical properties of the oils. This EIS sensor is capable of measuring water and soot contamination level as well as general oil quality.


Figure 1.14 SmartMon-Oil™ (Poseidon Systems, LLC)

Micro Acoustic Viscosity

Viscosity variation beyond or below operating limits is commonly considered that lubrication oil is degrading. Because all the basic oil degradation features can be detected by a viscometer including oxidation, water/particle contamination and fuel dilution. Also, the mileage of an engine or operating duration of a gearbox cannot be considered equal to lubricant deterioration reference (operating conditions, individual operating habits, ambient condition and fuel quality). Viscosity is usually considered lubricant degradation comparison standard for its independence on various operating conditions. Agoston *et al.* [1] used a micro acoustic sensor to measure the viscosity electrically for automotive applications. This sensor, whose structure is shown in Figure 1.15, is small and has a long life span and can be deployed in aggressive industrial environments. The indirect data provided by the engine management and its relation to the oil wear will depend on the actual engine platform used whereas the data provided by the sensors are directly linked to the oil condition and are thus platform-independent. The micro acoustic viscometer can measure all the basic oil degradation features online with space efficient design. However, lack of practical tests from industry and problems with oil contain viscosity modifiers may limit its application is the industry.

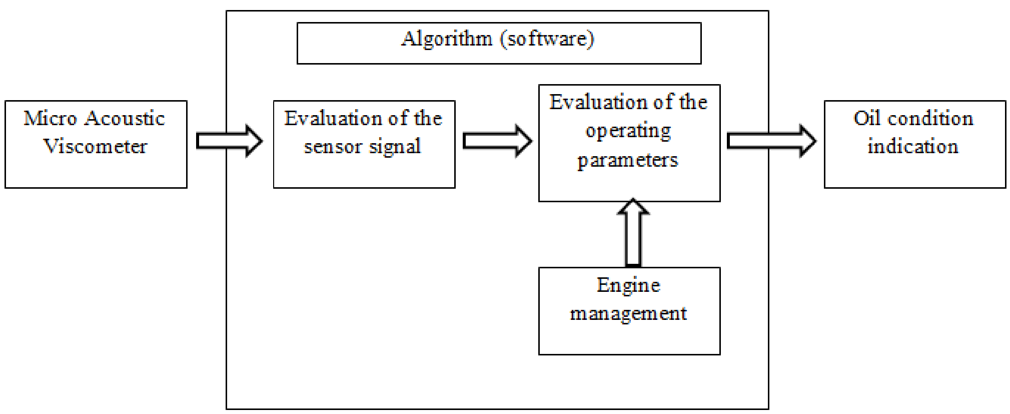


Figure 1.15 Structure of a sensor assisted algorithm for a lubrication monitoring system

### 1.2.3. Physical Techniques

<u>Kinematic (Electromagnetic) Viscosity</u>

As it is mentioned in the micro acoustic viscosity sub section, all the basic oil degradation features have influence on the viscosity. Kinematic viscosity can be acquired by a traditional kinematic viscometer which is also called electromagnetic viscometer as shown in Figure 1.16.

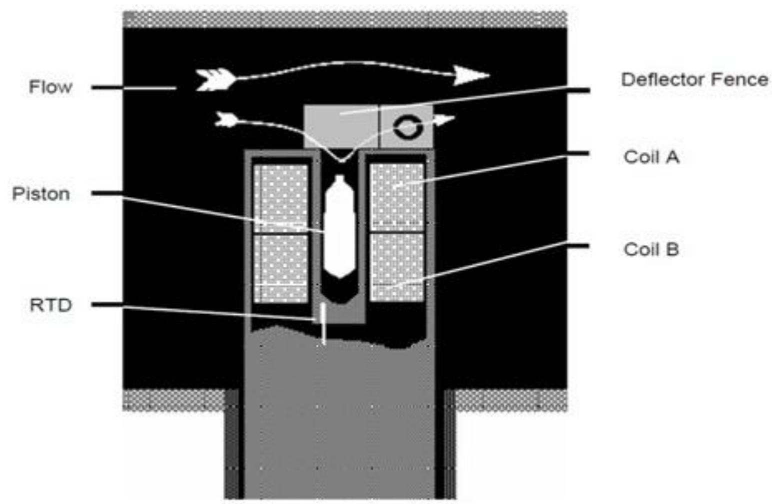


Figure 1.16 Typical kinematic viscometer structure (Cambridge Viscosity. Ltd)

This kind of viscometer usually involves a piston that dipped into the test lubricant and the coils inside the sensor body magnetically force the piston back and forth a predetermined distance. By alternatively powering the coils with a constant force, the piston’s round trip travel time is measured. An increase in viscosity is sensed as a slowed piston travel time. The time required for the piston to complete a two way cycle is an accurate measure of viscosity. The deflecting fence acts to continuously deflect fresh sample into the measurement chamber. Since measurement of the piston motion is in two directions, variations due to gravity or flow forces are annulled. Also, because the piston has very little mass, magnetic forces greatly exceed any disturbances due to vibration. The investigation of Schmitigal and Moyer [65] on diesel engines proved that the kinematic viscometer is capable of lubricant soot particle, water contamination and oxidation deterioration detection. The kinematic viscometers are capable of monitoring all the oil basic degradation features online with low data processing complexity and maintenance cost. However, the commercially available kinematic viscometers have a relatively high manufacture cost.

Ultra Sound

Sound and vibration are used for many health monitoring applications. In the case of oil condition monitoring, early research using ultrasound was published in 1980s [10] [71]. BHRA [10] developed a system with a sensor and receiver. They are placed on opposite sides of an oil flow. The receiver is oriented so that it will only detect ultrasound scattered by oil-borne solid particles in clean hydraulic fluid. This technique is capable of online health monitoring. However, no record using this technique to monitor heavy lubrication oil like engine or transmission oil has been reported.

Thermo Conductivity

Another physical approach of lubricant deterioration detection is thermal conductivity. Kuntner *et al.* [38] reported that water contamination and degradation processes in mineral oil leads to an increased thermal conductivity, indicating that the potential of thermal conductivity sensors in the field of oil condition monitoring. A special designed hot film micro sensor, as shown in Figure 1.17, using a resistive thin-film molybdenum structure on a glass substrate was fabricated with the technique of transient hot-wire method.

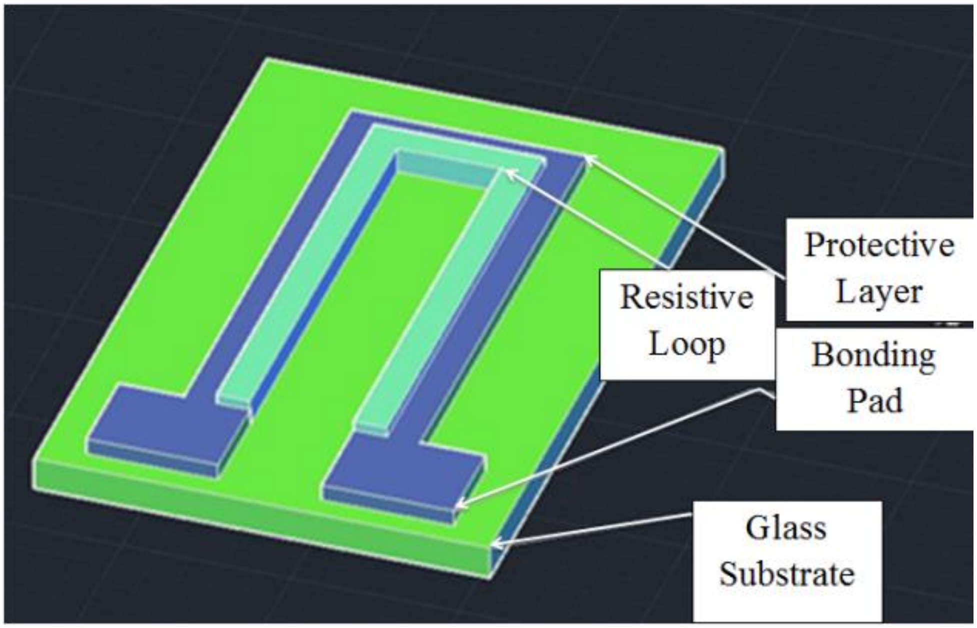


Figure 1.17 Miniaturized thermal conductivity sensor

The authors considered a hot film micro-sensor, which is operated using an adapted transient method. Considering the small dimensions of the sensor compared to the used sample volumes (15ml) of the investigated liquids, the corresponding temperature field at some distance from the sensor can be approximate calculated by solving the heat diffusion equation for a thermal point source switched on at *t = 0*, as:

$$\varsigma(r,t) = \frac{\emptyset}{4\pi\lambda r} erfc\,(\frac{r}{\sqrt{4at}}) \tag{1.6}$$

where Ø is the heating power, $\lambda$ the thermal conductivity, *a* the thermal diffusivity, and *r* the radial distance from the point source. Note that for small *r*, this approximation becomes inaccurate and even yields a non-physical singularity for *r = 0*. The diffusivity is related to the heat capacity $C_p$ and can be computed as:

$$a = \frac{\lambda}{\rho Cp} \tag{1.7}$$

where $\rho$ is the mass density. For $t \rightarrow \infty$, the complementary error function *erfc* in Equation (1.6) approaches unity such that in the steady state, the temperature distribution depends only on the thermal conductivity and the heating power shown as:

$$\varsigma(r)=\frac{\emptyset}{4\pi\lambda r} \text{ when } t \rightarrow \infty \tag{1.8}$$

It was also proved that this kind of sensor is capable of real time health monitoring and may have potential in oil oxidation degradation monitoring. The robustness and sensitivity balance of the sensor structure may need more tests in order to improve its durability and effectiveness in aggressive industrial environment.

Ferrography

As mentioned in the magnetic susceptibility subsection ferromagnetic fragments are collected and send to a laboratory for further ferrography analysis. Ferrography is a typical traditional oil diagnostic technique for analyzing particles present in lubricants [63]. It uses microscopic examination and was developed in the 1970s for predictive maintenance, initially analyzing ferrous particles in lubricating oils. Levi and Eliaz [40] conducted ferrography, atomic emission spectroscopy, scanning electron microscopy and quantitative image analysis for the purpose of detecting a variety of wear particles in open-loop oil. The technique is field tested with a Wankel engine. However, this technique is not capable of online health monitoring, requires high level of data processing and costly test equipment.

### 1.2.4. Chemical Techniques

pH Measurement

Lubrication oils contain long-chain oxidizable hydrocarbons. In an operating engine, these hydrocarbons are exposed to high temperatures, which make them more vulnerable to be attacked from free radicals, reported by Turner and Austin [71]. Mann [48] mentioned that the effects of oxidation due to chemical reaction as well as the by-products of combustion generate relatively high acidic compounds inside an engine. These compounds cause corrosion of internal engine components, deposits, and changes in oil viscosity, varnish, sludge and other insoluble oxidation products that can cause a performance and durability degradation of the engine over a period of time. Wang *et al.* [74] [75] [76] [77] designed a microprocessor-controlled total acid number sensor. Their sensing technique calls for a high degree of signal processing filtering in order to obtain useful data. Others tried pH-based measurement of different lubrication oil condition. However the test result seems unreliable and has repeatability problems questioned by Turner and Austin [71].

Thin-film Contaminant Monitor

The lubrication oil performance stay stable if the oil temperature is maintained within the manufacture recommended range. In case it is not operating in the required condition, the oil deterioration starts and it reflects the degradation of lubricating oil. As a general thumb rule, a 10℃ rise in temperature doubles the oxidation rate and so is formation of oxidation products. Initially these oxidation particles are soft and gummy products. When these particles come in contact with high-temperature zones these lead to formation of hard and abrasive particles. These on contact with the components cause generation of wear particles causing further reduced system performance as reported by Sharma and Gandhi [66]. The thin-film contaminant monitor approach used a thin metallic film which forms part of an electric circuit to monitor the particle contamination in lubrication oil flow as stated by Halderman [22]. The film is exposed to the oil flow and continuous eroded by oil-borne solid particles as oil degrades. As a result, the resistance rises. This technique is dependent on the particle size and concentration which needs frequent maintenance. Overall, thin film contaminator is good for online diagnostics but only capable of particle contamination monitoring and the measurement may not be well correlated with viscosity.

### 1.2.5. Optical Techniques

Optical Transparency or Reflectometry

With the goal of achieving online oil deterioration analysis, optical oil condition monitoring techniques was born. This technique usually correlates oil optical transparency or reflection rate with oil general degradation basic features. Tomita [70] built a lubrication deterioration sensor based on optical reflectometry in laboratory condition. However, the device is not yet field tested in harsh industrial environments. Zhang [82] also designed an optical sensor and tested on an internal combustion engine. Kumar and Mukherjee [37] fabricated an optical sensor with light dependent resistor (LDR) to record the oil transparency and then convert it to resistance. The sensing system is shown in Figure 1.18.

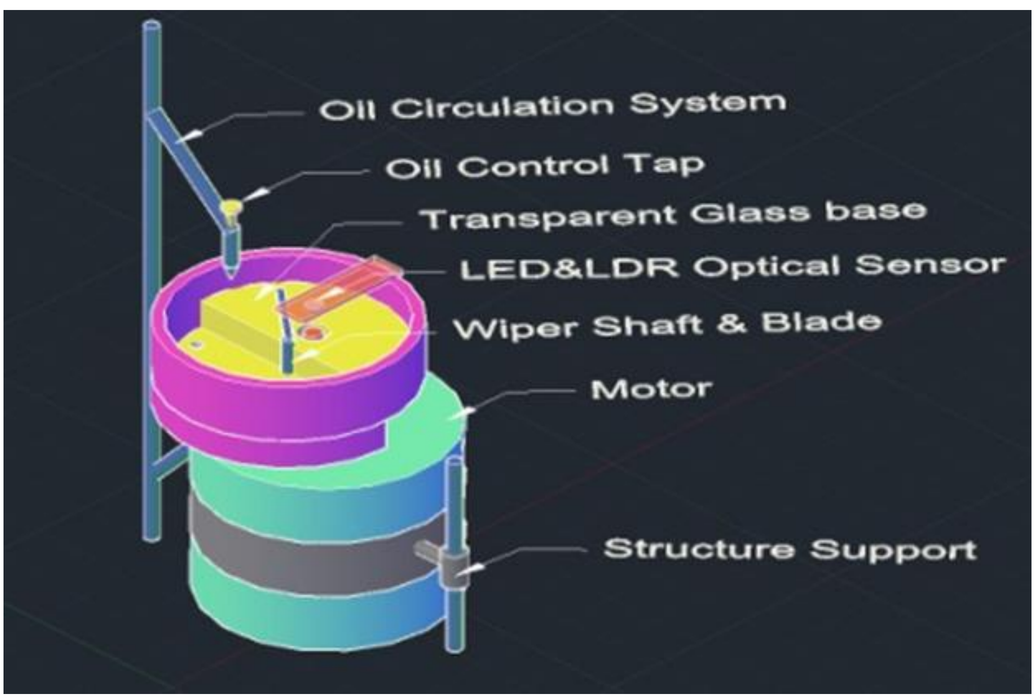


Figure 1.18 Optical transparency sensor

The sensor was tested on a six cylinder gasoline engine. The authors correlated the resistance data with working hours, viscosity and oxidation (scaled by pH measurement) and prove the effectiveness of the designed sensor. According to the paper, this optical sensor has full basic degradation feature coverage and online diagnostic and prognostic capability. However, this sensor do has a complicated structure which may cause reliability issues. Also, some paper reported that optical changes do not correlate well with oil degradation process.

IR Absorption

When oil deteriorates, nitrate compound is generated. This compound absorbs infrared (IR) radiation with a wave length of 6.13 μm. This effect was used in a sensor that measured the IR absorption along a fix path length and attempted to correlate the measurement with oil condition reported by Agoston *et al.* [3] [4] and Turner and Austin [71]. Even though it is capable of online oil degradation monitoring, this sensing system may need some future improvement to overcome repeatability problems and reduce the manufacturing cost.

### 1.2.6. Performance Evaluation of Lubrication Oil Monitoring Systems and Techniques

Defined Evaluation Properties

*Data Acquisition Instantaneity:* Lubrication oil condition monitoring techniques are evolving from off-line sampling to online instant diagnostic data acquisition. In the past, off-line monitoring is the only solution available. Lubricant samples were collected from machineries and sent to laboratories or companies specialize in oil condition monitoring. A report with raw data was then prepared. The data was then analyzed and several necessary action options were provided thereafter. This process normally takes more than 24 hours and is time and cost consuming as reported by Kumar and Mukherjee [37]. When lubrication oil analysis is done somewhere else and results turns up sometime later, it is hard to relate the data with the machine's health status at the time of sampling. The burden of collecting representative samples virtually relegates oil analysis to a secondary status in a condition monitoring program. Also, actual condition of the oil cannot be determined as the samples are collected when the machine is not in the running condition. With more and more attention drew into oil condition monitoring field, on-line, onboard diagnostic techniques started to merge which significantly reduced the oil deterioration data acquisition delay. Therefore, whether the oil condition monitoring technique is capable of instant data acquisition is considered a key evaluation property.

*Prognostic Capability:* Among all the lubrication oil health monitoring techniques and solutions, many of them was developed with the purpose of extend the life of the lubricant. This purpose cannot be achieved without both real time condition monitoring and remaining useful life prediction. In industrial applications, one needs advance notice or early warning of oil replacement. Otherwise sudden diagnose of failure which needs immediate action will have influence on the production rate because the equipment needs to be shut down in order to prevent unnecessary wear or damage. Also, in large applications like wind turbines, knowing the exact time of lubricant change can optimize the maintenance schedule therefore reduce the cost. Hence, the capability of lubrication oil prognostics is another crucial evaluation property that needs to be taking into account.

*Basic Degradation Feature Coverage:* As mentioned above, the basic lubrication degradation features are oxidation degradation, particle (soot) contamination and water contamination. Some oil health monitoring techniques covers one or more of these features. In practical applications, for the diagnostic system robustness and effectiveness concern, all the basic deterioration features have to be considered. Focusing on one specific feature will not provide a sufficient or objective result regarding to the status of oil degradation or health condition. The more features a technique covers, the more objective the results will be. Basic degradation feature coverage is an important property that has to be evaluated during different approach comparison.

*Data Processing Complexity:* Some of the diagnostic approaches require certain level of data processing. The complexity of the data analyzing have direct impact on processing time and data acquisition delay. Moreover, for on-board instant oil condition monitoring complicated data analyzing algorithm may requires extra processing device which will add certain manufacturing cost. Also, developing sensing technique with complicated algorithm for mobile engineering systems will continuously occupy CPU resources of onboard computer which may slow the system down and cause data jam. When it comes to practical industrial applications, simple and effective are always the basic design principles. Therefore, the data processing complexity should always be considered and evaluated.

*Sensitivity:* The sensor's reaction amplitude upon basic degradation features' variation is defined as sensitivity of the technique. In order to achieve real-time lubrication oil health monitoring, the sensing systems have to exhibit a quick reaction time regarding to the degradation and amplitude that can be scaled by a device that come with the system. Low sensitivity will result in either an unnecessary need for demanding measurement equipment or a delay between the output and the real degradation status of the lubrication oil. For every sensing technique, sensitivity is always an evaluation property that cannot be ignored.

*Field Tested:* The ultimate way to evaluate the effectiveness and robustness of a sensing technique's is to perform field tests in actual industry environment. An oil condition monitoring solution that is not capable of industrial deployment is not reliable. Given the aggressive operating condition the lubrication oil condition monitoring sensors will be in, one must present high tolerance of dust, high temperature, sudden temperature change and many other ambient conditions. A solution that only works in the laboratory has no real world contributions and ought to be improved.

*Manufacture Cost:* Manufacture cost is another property that has to be evaluated. The cost of a lubrication oil sensing technique depends on several factors. Sensor fabrication cost takes a large proportion of the total cost. A complicated sensor or sensing technique need to be well designed and precise manufactured. This issue may affect the deployment in civilian applications like automotive and limit the wide spread of the technology. The development of data processing algorithm will also increase the cost because it takes time and investment. Moreover, certain sensing techniques focus on only one application, if another application come up, new sensors or algorithms have to be developed. This is also considered not cost efficient.

*Maintenance Cost:* The life time of the designed oil deterioration sensor determines the sensing system maintenance cost. As addressed in the former sections, lubrication oil condition monitoring sensors should exhibit a long life time in aggressive operating conditions. The sensors should be able to perform continuous condition monitoring without frequent maintenance. The pH measurement and chemical corrosion monitoring techniques need frequent replacement of critical components which will increases the maintenance cost. Sensor component change needs to be performed while the machine is not in the running condition which may also reduce the production rate. The evaluation of oil condition monitoring solutions will not do if this unavoidable issue is not considered.

Performance Evaluation and Comparison

In this sub-section, the characteristic of each lubrication oil health monitoring solution or sensing technique is evaluated and compared in Table 1.2 with the seven properties defined in the previous section. Three evaluation properties, data processing complexity, manufacture cost and maintenance cost is scaled as low, medium and high. All the techniques are classified and profiled into its evaluation categories

Table 1.2 Performance evaluation and comparison of lubrication oil health condition monitoring systems and techniques

<table>
<tr><th colspan="2">Oil Monitoring Techniques Classification</th><th>Specific Monitoring Technique</th><th>Data Acquisition Instantaneity</th><th>Prognostic Capability</th><th>Basic Degradation Feature Coverage</th><th>Sensitivity</th><th>Data Processing Complexity</th><th>Field Tested</th><th>Manufacture Cost</th><th>Maintenance Cost</th></tr>
<tr><td rowspan="8">Electrical (Magnetic) Techniques</td><td rowspan="8">Dielectric Constant</td><td>Grid capacitance sensor</td><td>Online</td><td rowspan="5">No</td><td rowspan="4">Oil oxidation, wear particle concentration, water contamination</td><td rowspan="8">High</td><td>Low</td><td>No</td><td>Low</td><td>Low</td></tr>
<tr><td>Inter-leveled disk capacitor</td><td>Online</td><td>Low</td><td>No</td><td>Low</td><td>Low</td></tr>
<tr><td>Capacitive IDT (Inter-Digit Type) sensor</td><td>Online</td><td>Low</td><td>Tested</td><td>High</td><td>Low</td></tr>
<tr><td>CSI oil view model 5500</td><td>Online</td><td>Low</td><td>Tested</td><td>High</td><td>Low</td></tr>
<tr><td>Permittivity sensor</td><td>Online</td><td>Water contamination</td><td>Low</td><td>No</td><td>Low</td><td>Low</td></tr>
<tr><td>Dielectric spectroscopy analyzer for Petroleum (DSAP)</td><td>Online</td><td rowspan="2">Yes</td><td>Oxidation and particle contamination</td><td>Medium</td><td>No</td><td>Medium</td><td>Low</td></tr>
<tr><td>Tan Delta dielectric sensing</td><td>Online</td><td>Water Contamination, Oxidation</td><td>Low</td><td>Yes</td><td>Medium</td><td>Medium</td></tr>
<tr><td>thin film capacitance sensors</td><td>Online</td><td>No</td><td>Water Contamination</td><td>Low</td><td>Yes</td><td>Medium</td><td>Medium</td></tr>
</table>

Table 1.2 Performance evaluation and comparison of lubrication oil health condition monitoring systems and techniques (continued)

| Oil Monitoring Techniques Classification | | Specific Monitoring Technique | Data Acquisition Instantaneity | Prognostic Capability | Basic Degradation Feature Coverage | Sensitivity | Data Processing Complexity | Field Tested | Manufacture Cost | Maintenance Cost |
|---|---|---|---|---|---|---|---|---|---|---|
| Electrical (Magnetic) Techniques | Conductivity | Multiwall carbon nano tube conductivity sensor | Online | No | Oxidation and wear particle contamination | High | Low | No | High | High |
| | | Conductivity sensor | Online | | Particle contamination | Medium | Low | No | Medium | Medium |
| | | Diesel oil condition and level sensor | Online | | Particle contamination | High | Low | Tested | Medium | Medium |
| | | Polymeric Bead Matrix (PBM) | Online | | Particle and water contamination and Oxidation | High | Medium | Yes | Medium | High |
| | Magnetic Susceptibility | Magnetic susceptibility balance | Offline | | None | Low | Low | No | Low | Low |
| | | Magnetic Plug | Offline | | Particle contamination | Low | Low | No | Low | Low |
| | | magnetometry | Online | | Particle contamination | High | Medium | Yes | Medium | Medium |
| | Micro Acoustic Viscosity | Micro acoustic viscometer | Online | | Oil oxidation, wear particle concentration, water contamination | High | Low | No | Medium | Low |
| | Electro-chemical Impedance Spectroscopy (EIS) | Broadband AC Electrochemical Impedance Spectroscopy | Online | Yes | Oil oxidation, wear particle concentration, water contamination | High | Low | Yes | Medium | Low |

Table 1.2 Performance evaluation and comparison of lubrication oil health condition monitoring systems and techniques (continued)

<table>
<tr><th colspan="2">Oil Monitoring Techniques Classification</th><th>Specific Monitoring Technique</th><th>Data Acquisition Instantaneity</th><th>Prognostic Capability</th><th>Basic Degradation Feature Coverage</th><th>Sensitivity</th><th>Data Processing Complexity</th><th>Field Tested</th><th>Manufacture Cost</th><th>Maintenance Cost</th></tr>
<tr><td rowspan="4">Physical Techniques</td><td>Kinematic Viscosity</td><td>Kinematic viscometer</td><td>Online</td><td rowspan="4">No</td><td>Oil oxidation, wear particle concentration, water contamination</td><td>High</td><td>Low</td><td>Tested</td><td>Medium</td><td>Medium</td></tr>
<tr><td>Ultra sound</td><td>Ultra sound sensor and receiver</td><td>Online</td><td>Particle contamination</td><td>Medium</td><td>Medium</td><td>No</td><td>Medium</td><td>Medium</td></tr>
<tr><td>Thermal conductivity</td><td>Thermal conductivity sensor</td><td>Online</td><td>Water contamination and oxidation</td><td>High</td><td>Medium</td><td>No</td><td>Medium</td><td>Low</td></tr>
<tr><td>Ferrography</td><td>Micro scopes</td><td>Offline</td><td>Particle contamination and oil oxidation</td><td>High</td><td>High</td><td>Tested</td><td>High</td><td>High</td></tr>
<tr><td rowspan="2">Chemical Techniques</td><td>pH measurement</td><td>Micro processor controlled TAN sensor</td><td>Offline</td><td rowspan="2">No</td><td>Oil oxidation</td><td rowspan="2">Medium</td><td>High</td><td>No</td><td>High</td><td>High</td></tr>
<tr><td>Thin film contaminant monitor</td><td>Thin metallic film connected to a electric circuit</td><td>Online</td><td>Particle contamination</td><td>Low</td><td>No</td><td>Medium</td><td>High</td></tr>
<tr><td rowspan="4">Optical Techniques</td><td rowspan="3">Optical transparency or reflectometry</td><td>Optical color sensor</td><td>Online</td><td>Yes</td><td rowspan="4">Particle contamination and oil oxidation</td><td>High</td><td>Low</td><td>Tested</td><td>High</td><td>Medium</td></tr>
<tr><td>Optical reflectometry sensor</td><td>Online</td><td>No</td><td>High</td><td>Low</td><td>No</td><td>High</td><td>Medium</td></tr>
<tr><td>Optical sensor for internal combustion engines</td><td>Online</td><td>No</td><td>High</td><td>Low</td><td>Tested</td><td>High</td><td>Medium</td></tr>
<tr><td>IR absorption</td><td>A sensor measures IR absorption along a fixed path length</td><td>Offline</td><td>No</td><td>Medium</td><td>Low</td><td>No</td><td>High</td><td>High</td></tr>
</table>

From the summarized information in Table 1.2, one can conclude that viscosity and capacitance sensor have the best lubrication oil basic degradation feature coverage and the lowest maintenance cost. Moreover, kinematic viscosity and dielectric constant are two performance parameters that are able to perform lubrication oil deterioration online monitoring with the lowest data processing complexity. However, most techniques do not offer integrated lubrication oil remaining useful life prediction solution. Some reported papers used analytical or statistical method to perform lubrication oil prognostic or evaluate basic degradation features' impact on oil protective property degradation. Sharma and Gandhi [66] developed a parameter profile approach with multiple performance parameters data. The data were collected and tested on an internal combustion engine with a promising result. In general, if combined with proper data analysis techniques, online oil degradation monitoring with capacitance and viscosity sensors has great potential and will probably be the future of online onboard lubricant deterioration monitoring, diagnostic and prognostic.

## 1.3. Research Objective

The research objective of this thesis is to develop a feasible online lubrication oil condition monitoring and remaining useful life prediction solution based on commercially available sensors and particle filtering algorithm. In order to achieve online remaining useful life prediction, lubrication oil degradation physics models were developed and integrated into the particle filtering algorithm. To achieve the goal of this research, the following steps were conducted.

1) Comprehensive investigation of current state of the art lubrication oil condition monitoring techniques.
2) Based on the investigation result, select the feasible performance parameters and commercially available sensors for online oil condition monitoring and RUL prediction.

3) Develop lubrication oil degradation physics models based on the selected performance parameters for different basic degradation features.
4) Validate the developed oil degradation physics models with commercially available sensors.
5) Integrate the developed physics models into special designed particle filtering algorithm for lubrication oil remaining useful life prediction.
6) Validate the effectiveness of the remaining useful life prediction algorithm by integrating the developed physics model and particle filtering techniques into an industrial scenario simulation model.

The above mentioned research steps are key components of the advancement of the condition based maintenance technology, which ultimately will significantly reduce the maintenance cost of large assets like wind turbines. Combined with vibration analysis and current analysis, online lubrication oil analysis can be easily integrated into the current condition based maintenance system to provide reliable condition indication of the lubricant and the mechanical system which will optimize the maintenance schedule, reduce unscheduled maintenance therefore reduce the maintenance cost.

### 1.4. Dissertation Overview

The background, motivation and research objectives of this dissertation are presented in Chapter 1. The comprehensive investigation and review of current state of the art lubrication oil condition monitoring solutions are also reviewed in Chapter 1. Chapter 2 focuses on the lubrication oil degradation physics model development and validation. Viscosity and dielectric constant are selected as performance parameters to model the degradation of lubrication oil. Then in Chapter 3, the particle filtering technique is explained in two sections, state estimation and RUL prediction. In Chapter 4, the developed physics models and particle filtering algorithm are integrated into an industrial scenario simulation model to validate the effectiveness of the developed lubrication oil condition monitoring and remaining useful life prediction solution. Chapter 5 summarizes the accomplishments of this dissertation and presents the topics for future research.

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# CHAPTER 2

# PHYSICS MODEL DEVELOPMENT AND VALIDATION FOR LUBRICATION OIL DEGRADATION

## 2.1. Introduction

In this chapter, based on the result of the comprehensive investigation on current lubrication oil condition monitoring techniques from literature review section, viscosity and dielectric constant were selected as the performance parameters to provide feasible solution to perform online oil condition analysis. Lubrication oil physics models that describe oil deterioration due to water and particle contamination in terms of viscosity and dielectric constant were developed and validated. The goal of the physics model derivation is to find a mathematical relationship between lubrication oil degradation and contamination level of different basic degradation features.

There are two ways of modeling condition degradation of machineries, data driven modeling and physics based modeling. When it comes to lubrication oil degradation modeling, limited literature has been reported. Most of the modeling techniques used to model oil degradation was data driven modeling. Under various temperatures, the sensor output and oil condition are correlated with field and/or lab based data to form a correlation model. For example, Byington [11] [12] correlated viscosity, Nitration, soot contamination and oxidation with electrochemical impedance spectroscopy (EIS) output. The EIS sensors were installed on diesel truck fleets. The lubrication oil was sampled and sent to an offsite lab for analysis. The oil degradation models were constructed using symbolic regression based on the report from the lab and the EIS sensor output. This was a very typical method for data driven modeling. Data driven modeling has many advantages, among which system dynamic information independent is the most important attractive feature. That is to say, one don’t necessarily have to understand the physics of the systems for model construction .Compared with data driven modeling, physics based modeling has many advantages including short training time and case independent. As one can understand, when trying to perform data driven modeling, great amount of data is needed to construct an accurate model. The time required to collect these data are so called training time. For physics based model, the training time can be eliminated to a maximum extend. Therefore, physics based models are quick to implement. Another issue for data driven modeling is that it is case dependent. For lubrication oil analysis, it means the developed model can only be used on the specific oil and sensor combination. If either the sensor type or the oil type changed, the data driven model has to be reconstructed which again will require a long training time. This remains an issue and concern for industrial applications. However, physics based models do not share this shortcoming. They can be adapted into any specific systems of the same type with little initial adjustment. In case of lubrication oil degradation physics models, given any healthy base oil information, the developed models can be immediately implemented. Healthy oil information refers to the relationship between dielectric constant (or viscosity) and the specific kind of healthy oil across certain range of operating temperature. This information can be obtained by heating healthy oil inside a temperature controlled chamber and record the dielectric and viscosity property of the oil. With the utilization of the derived physics model, given any water/particle contamination level at any temperature, one could simulate the viscosity and the dielectric sensor output of the degraded oil mixture with maximum accuracy.

This chapter is arranged as following. Section 2.2 presents the process of lubrication oil degradation model development which is divided into 4 subsections, viscosity model for water contamination, dielectric constant model for water contamination, viscosity model for particle contamination, dielectric constant for particle contamination, respectively. Section 2.3 presents the validation process of the developed physics models which includes experimental setup, model validation for water contaminated lubrication oil, and model validation for particle contaminated oil, respectively. Finally, Section 2.4 summarized Chapter 2.

## 2.2. Lubrication Oil Degradation Physics Model Development

### 2.2.1. Viscosity Model for Water Contamination

Not only does water have a direct harmful effect on machine components, but it also plays a direct role in the aging rate of lubricating oils. The presence of water in lubricating oil can cause the progress of oxidation to increase tenfold, resulting in premature aging of the oil, particularly in the presence of catalytic metals such as copper, lead and tin. In addition, certain types of synthetic oils such as phosphate esters and dibasic esters are known to react with water, resulting in the destruction of the base stock and the formation of acids [34]. Therefore, water contamination is a key basic degradation feature to monitor for lubrication oil condition based maintenance.

In industrial practice, to determine the viscosity of a mixture, one can simply using American Society for Testing and Materials (ASTM) viscosity paper with linear abscissa representing percentage quantities of each of the fluids. This paper offers simplified solutions for volume fraction based viscosity calculation for mixtures from two liquids. Others approach for mixture viscosity calculation includes Refuta's Equation. However, Refuta's Equation is a mass fraction based viscosity calculation which may not be ideal for industrial standard of oil water contamination. The industrial standard to describe water contamination is parts per million or ppm which is a volume fraction based unit. For example, 1000 parts per million means volume fraction of 0.1%.

The viscosity of a fluid is a measure of its resistance to gradual deformation by shear stress or tensile stress. For liquids, it corresponds to the informal notion of "thickness". For example, honey has a higher viscosity than water [43]. Viscosity is due to friction between neighboring parcels of the fluid that are moving at different velocities. When fluid is forced through a tube, the fluid generally moves faster near the axis and very slowly near the walls, therefore some stress (such as a pressure difference between the two ends of the tube) is needed to overcome the friction between layers and keep the fluid moving. For the same velocity pattern, the stress required is proportional to the fluid's viscosity. A liquid's viscosity depends on the size and shape of its particles and the attractions between the particles. There are two kinds of viscosity expressions. They are dynamic viscosity and kinematic viscosity. Kinematic viscosity is dynamic viscosity divided by the fluid density. The viscosity mentioned in this dissertation is kinematic viscosity which unit is Cst.

Define:

$T$ = temperature, in Celsius

$V_{oil,T}$ = viscosity of the healthy oil at temperature $T$, in Cst

$V_{water,T}$ = viscosity of the water at temperature $T$, in Cst

$P$ = water volume percentage

According to Stachowiak and Batchelor [42], water and oil mixture viscosity at a certain temperature $V_{M,T}$ can be computed as:

$$V_{M,T} = \left(V_{oil,T} - V_{water,T}\right) \times (1 - P) + V_{water,T} \tag{2.1}$$

where:

$$V_{water,T} = -0.451 \times \ln T + 2.3591 \tag{2.2}$$

Note that in Equation (2.1), $V_{oil,T}$ is defined as the healthy lubrication oil information and is extracted from our initial test while $V_{water,T}$ is defined as the water physical attribute which can be considered known factors. Based on Equation (2.1), we can compute the degree of oil degradation as the result of water contamination in terms of viscosity as: $DD_{viscosity} = \frac{V_{M,T}}{V_{oil,T}}$.

Equation (2.1) represents the kinematic viscosity of the degraded oil as a function of temperature and water contamination level.

### 2.2.2. Dielectric Constant Model for Water Contamination

Maxwell Garnett dielectric formula is the most widely used mixing rules to calculate the average dielectric constant of the mixture consist of multiple components. The original Maxwell-Garnett equation [14] reads:

$$\left(\frac{\varepsilon_{eff}-\varepsilon_m}{\varepsilon_{eff}+2\times\varepsilon_m}\right)=\delta_i\times\left(\frac{\varepsilon_i-\varepsilon_m}{\varepsilon_i+2\times\varepsilon_m}\right) \tag{2.3}$$

Where:

$\varepsilon_{eff}$ is the effective dielectric constant of the medium

$\varepsilon_i$ is the one of the inclusion

$\varepsilon_m$ is the one of the matrix

$\delta_i$ is the volume fraction of the inclusions

In general terms, the Maxwell Garnett EMA is expected to be valid at low volume fractions $\delta_i$ since it is assumed that the domains are spatially separated. The simplified equation was developed by Sihvola in [41] and was applied to lubrication oil situation by Jakoby and Vellekoop [27].

Define:

$\varepsilon_{oil,T}$ = dielectric constant of healthy oil at temperature $T$

$\varepsilon_{water,T}$ = dielectric constant of water at temperature $T$

According to Jakoby and Vellekoop [27], the dielectric constant of water and oil mixture at a certain temperature $\varepsilon_{M,T}$ can be computed as:

$$\varepsilon_{M,T}=\varepsilon_{oil,T}\times\left(1+3\times P\times\frac{\varepsilon_{water,T}-\varepsilon_{oil,T}}{\varepsilon_{water,T}+2\times\varepsilon_{oil,T}-P\times(\varepsilon_{water,T}-\varepsilon_{oil,T})}\right) \tag{2.4}$$

where:

$$\varepsilon_{water,T}=80-0.4\times((T+273)-293) \tag{2.5}$$

Note that in Equation (2.4), $\varepsilon_{oil,T}$ is defined as the healthy lubrication oil information and is extracted from our initial test while $\varepsilon_{water,T}$ is defined as the water physical attribute which can be considered known factors. Based on Equation (2.4), we can compute the degree of oil degradation as the result of water contamination in terms of dielectric constant as: $DD_{dielectric\ constant}=\frac{\varepsilon_{M,T}}{\varepsilon_{oil,T}}$.

Equation (2.4) represents the dielectric constant of the degraded oil as a function of temperature and water contamination level.

The simulation application of the lubrication oil deterioration model due to water contamination in terms of viscosity and dielectric constant can be summarized in Figure 2.1. The simulation input is the temperature and water contamination ratio. The simulation output is the degraded oil kinematic viscosity and dielectric constant. Using the simulation application, one could generate a series of viscosity and dielectric constant values accordingly to reflect the true status of the lubrication oil

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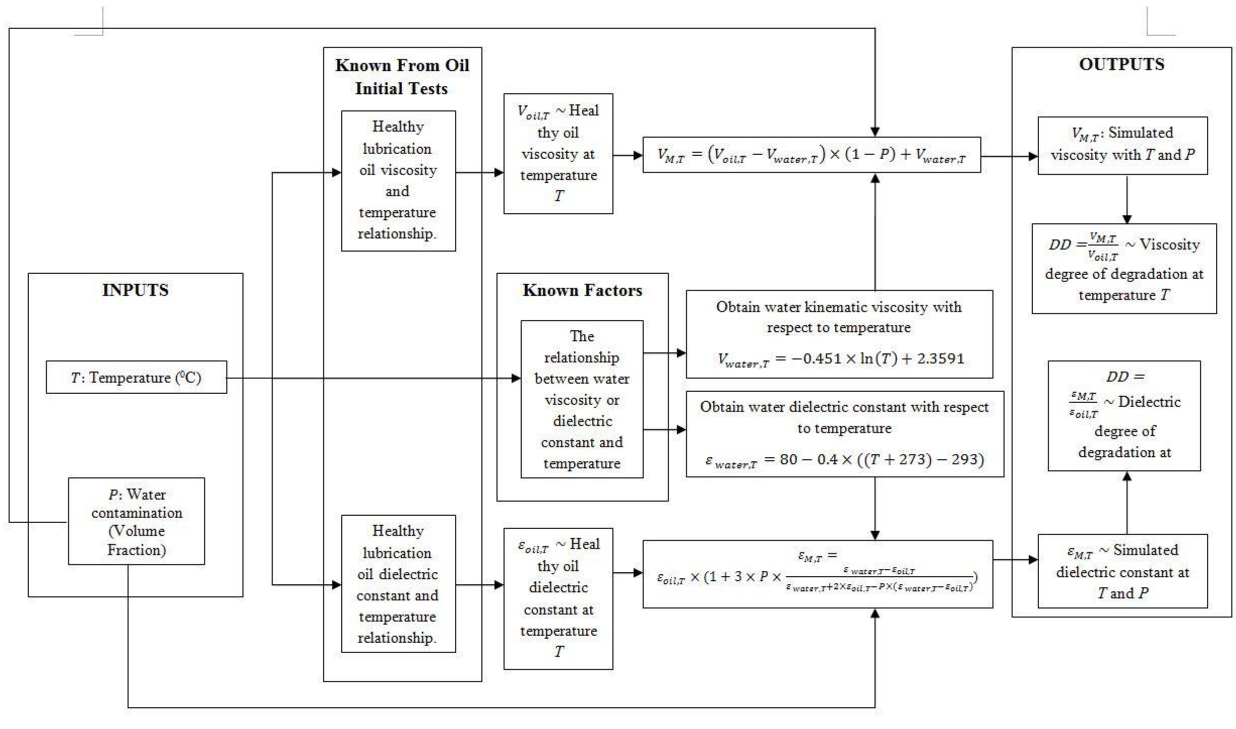


Figure 2.1 Lubrication oil water contamination simulation model for viscosity and dielectric constant

### 2.2.3. Viscosity Models for Particle Contamination

Particle contamination is one of the three most common encountered basic lubrication oil degradation features including water contamination, oil oxidation and particle contamination as stated in [48]. It is well-known that particle contaminants have a great impact on oil physical, electrical and magnetic properties which may leads to excessive mechanical wear and failure. Since over 80% of the machine wear is induced by particle contamination as stated in [33]. Lubrication oil particle contamination plays a significant role in machine failure prevention.

Lubrication oil particle contamination can be classified into two categories: iron and soot. For iron contamination, the source of contamination normally is the metal debris coming out of machine components because of frequent friction and wear. The main chemical component of the metal debris is ferrous which creates impact on oil electric and magnetic properties. These conductive metal particles lead to oil deterioration by means of increasing the permittivity of the lubrication oil, weaken the oil insulation characteristics and also induce oxidation.

For soot contaminations, the source of contamination mainly comes from oil borne insoluble particle resulting from oxidation and dust from outside the mechanical system. Soot particles mainly consist of silicon dioxide which has influence on lubricant physical property. High concentration of soot particles increase lubricant viscosity and may lead to engine cold start oil starvation, sever mechanical components wear and failure.

In this dissertation, physics models were derived in order to establish the mathematical relationship between lubrication oil degradation and particle contamination level. Experiments awerere performed to validate the developed model by comparing viscosity and dielectric constant sensors output of different particle concentration levels with those simulated by the lubricant deterioration physics models. These models were further applied to particle filter as the observation functions. And the particle contamination level template is generalized and used to form the state transition function.

Einstein (1906) in [18] [19] developed an equation to calculate the viscosity of solid particle and liquid mixture, assuming the mixture retains fluidity. The viscosity of the mixture can be described as relative to the viscosity of the liquid phase. In the case of extremely low concentration of fine particles the relative viscosity (dimensionless) can be expressed as a function of volume fraction $\emptyset$ of solid particles as follow.

$$\mu_r = \frac{\mu_S}{\mu_L} = 1 + 2.5 \times \emptyset \tag{2.6}$$

Where, in the case of lubrication oil particle contamination

$\mu_r$: The relative viscosity (dimensionless).

$\mu_S$: The dynamic viscosity of the mixture (degraded oil mixture).

$\mu_L$: The dynamic viscosity of the oil.

$\emptyset$: The volume fraction of the particles.

Later, in [23], Guth and Simha modified and improved Einstein's equation, as Equation (2.6), by taking into account the interaction between the solid particles. The equation they proposed can handle higher particle concentration and is shown below.

$$\mu_r = \frac{\mu_S}{\mu_L} = 1 + 2.5 \times \emptyset + 14.1 \times \emptyset^2 \tag{2.7}$$

Therefore, from Equation (2.7), the dynamic viscosity of the oil and particle mixture ($\mu_S$) can be expressed as:

$$\mu_S = (1 + 2.5 \times \emptyset + 14.1 \times \emptyset^2) \times \mu_L \tag{2.8}$$

With reference to the former developed physics model for lubrication oil water contamination and the experimental setup for the particle contamination tests, the following notations are defined.

*T*: a given temperature.

$V_{oil,T}$: the viscosity of the healthy oil at temperature *T*.

$V_{M,T}$: the viscosity of the oil and particle mixture which is the degraded oil viscosity at temperature *T*.

$M_S$: the mass or mass flow of solids in the oil sample.

$M_L$: the mass or mass flow of liquid in the oil sample.

$SG_L$: the specific gravity of the oil sample.

$SG_S$: the specific gravity of the contamination particle.

*P*: the contamination percentage used while conducting the experiments which unit is mg/L.

Substitute the above defined notation into Equation (2.8), one can have the equation for particle contamination physics model as shown in Equation (2.9)

$$V_{M,T} = (1 + 2.5 \times \emptyset + 14.1 \times \emptyset^2) \times V_{oil,T} \tag{2.9}$$

The volume fraction of the contaminant can be calculated by Equation (2.10) as stated in [46], as follow:

$$\emptyset = \frac{M_S \times SG_L}{M_S \times SG_L + M_L \times SG_S} \tag{2.10}$$

Note that in Equation (2.9), $V_{oil,T}$ is defined as the healthy lubrication oil information and can be extracted from initial tests. Based on Equation (2.9), one can compute the degree of oil degradation as the result of particle contamination in terms of viscosity as: $DD_{viscosity} = \frac{V_{M,T}}{V_{oil,T}}$.

Equation (4) represents the kinematic viscosity of the degraded oil as a function of temperature $T$ and particle contamination volume fraction $\emptyset$.

### 2.2.4. Dielectric Constant Models for Particle Contamination

Theoretical mixing rules for spherical inclusions in a host medium have been established by Maxwell Garnett [20]. Compared with other effective medium theories used for modeling electromagnetic properties of composites, Maxwell Garnet model is simple and convenient for modeling due to its linearity. The simplified equation was developed by Sihvola in [41]. The simplified result, applied to the case of particle contamination in lubrication oil can be expressed as:

$$\varepsilon_{M,T} = \varepsilon_{oil,T} \times \left(1 + 3 \times \emptyset \times \frac{\varepsilon_{particle,T} - \varepsilon_{oil,T}}{\varepsilon_{particle,T} + 2 \times \varepsilon_{oil,T} - \emptyset \times (\varepsilon_{particle,T} - \varepsilon_{oil,T})}\right) \tag{2.11}$$

where

$\varepsilon_{M,T}$: The dielectric constant of the mixture which is the degraded oil viscosity.

$\varepsilon_{oil,T}$: The dielectric constant of healthy oil at temperature $T$

$\varepsilon_{particle,T}$: The dielectric constant of the particle at temperature $T$

In the case of iron contamination, according to material in [13] by Carey (1998), the dielectric constant of conductive metals are considered infinity at all temperatures. As mentioned in section 2.2.3, the chemical component of iron contaminant is mainly Ferrous which is a typical conductive metal. Hence, for iron contamination, the $\varepsilon_{particle,T}$ in (2.11) is set to be infinity. After substitution, one can derive the following equation.

$$\varepsilon_{M,T} = \varepsilon_{oil,T} \times \left(1 + \frac{3\emptyset}{1-\emptyset}\right) \tag{2.12}$$

Equation (2.12) represents the dielectric constant of the degraded oil because of iron contamination as a function of temperature *T* and particle contamination volume fraction $\emptyset$.

In the case of soot contamination, reported by Gray *et al* in [21], the main chemical component is silicon dioxide. The dielectric constant of silicon dioxide is 3.9 regardless of the temperature variation. Therefore, for soot contamination, the $\varepsilon_{particle,T}$ in Equation (2.11) is set to be 3.9. After substitution, one can derive the following equation.

$$\varepsilon_{M,T} = \varepsilon_{oil,T} \times \left(\frac{(2-2\emptyset)\times\varepsilon_{oil,T}+7.8\times\emptyset+3.9}{(2+\emptyset)\times\varepsilon_{oil,T}-3.9\times\emptyset+3.9}\right) \tag{2.13}$$

Equation (2.13) represents the dielectric constant of the degraded oil because of soot contamination as a function of temperature *T* and particle contamination volume fraction $\emptyset$.

Note that in Equation (2.12) and (2.13), $\varepsilon_{oil,T}$ is defined as the healthy lubrication oil information and is extracted from the initial test. Based on Equation (2.12) and (2.13), one can compute the degree of oil degradation as the result of particle contamination in terms of dielectric constant as: $DD_{dielectric\ cosntant} = \frac{\varepsilon_{M,T}}{\varepsilon_{oil,T}}$.

The simulation application of the lubrication oil deterioration model due to particle contamination in terms of viscosity and dielectric constant can be summarized in Figure 2.2. The simulation input is the temperature and particle contamination volume fraction. The simulation output is the degraded oil kinematic viscosity and dielectric constant. Using the simulation application, one could generate a series of viscosity and dielectric constant values accordingly to reflect the true status of the lubrication oil.

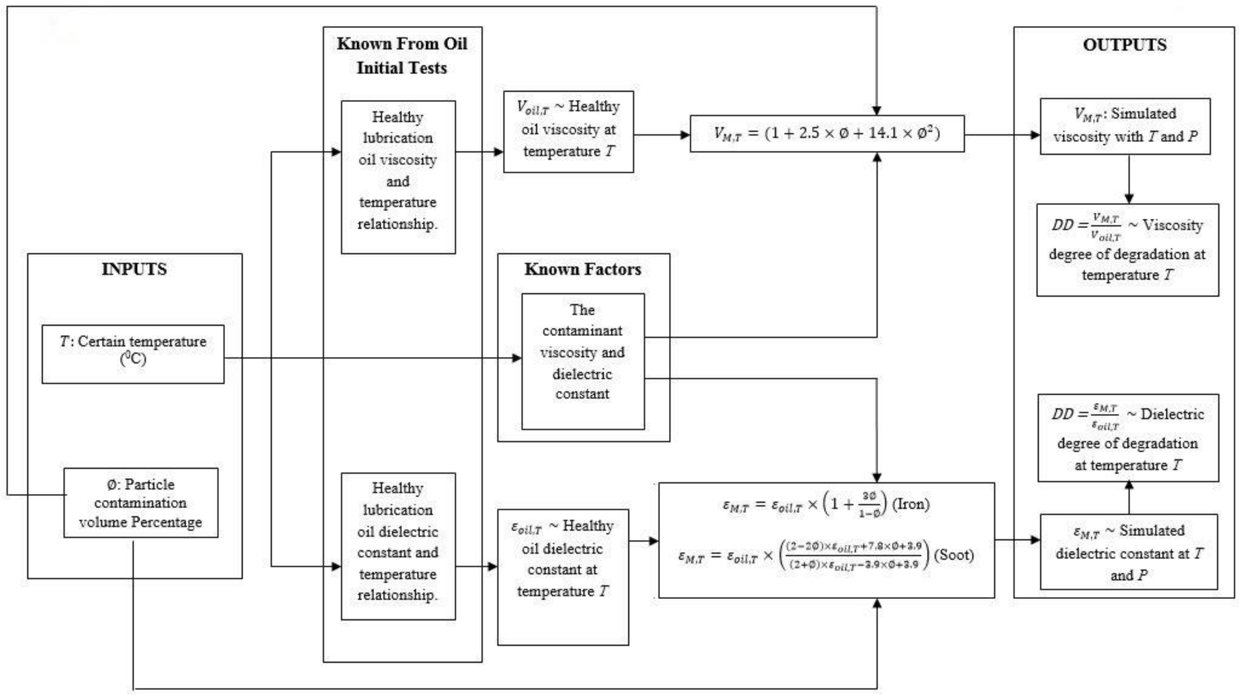


Figure 2.2 Lubrication oil particle contamination simulation model for viscosity and dielectric constant

## 2.3. Lubrication Oil Degradation Physics Model Validation

### 2.3.1. Experimental Setup

In this section, the experiment setup using both capacitance and viscosity sensors are presented. In order to obtain the viscosity and the dielectric constant data, VISCOpro2000 from Cambridge Viscosity Inc. and Oil quality sensor from GILL Sensor were used. For the kinematic viscometer, the sensor output data with a RS232 port and was connected to Window PC through a RS232 and USB converter. The software interface on the PC was HyperTerminal that comes with Microsoft Windows XP. The viscometer involves a piston that dipped into the test lubricant and the coils inside the sensor body magnetically force the piston back and forth a predetermined distance. By alternatively powering the coils with a constant force, the round trip travel time of piston is measured. An increase in viscosity is sensed as a slowed piston travel time. The time required for the piston to complete a two way cycle is an accurate measure of viscosity. The practical unit of viscosity is centipoises (Cp), which is identical to the MKS unit mPa s (The viscosity of water is approximately 1 Cp).  The viscosity sensor and its data acquisition system are shown in Figure 2.3. As we programmed according to the user manual that comes with the sensor. The sensor will send out analogue output including absolute viscosity, temperature compensated viscosity and the according temperature along with the date and time.

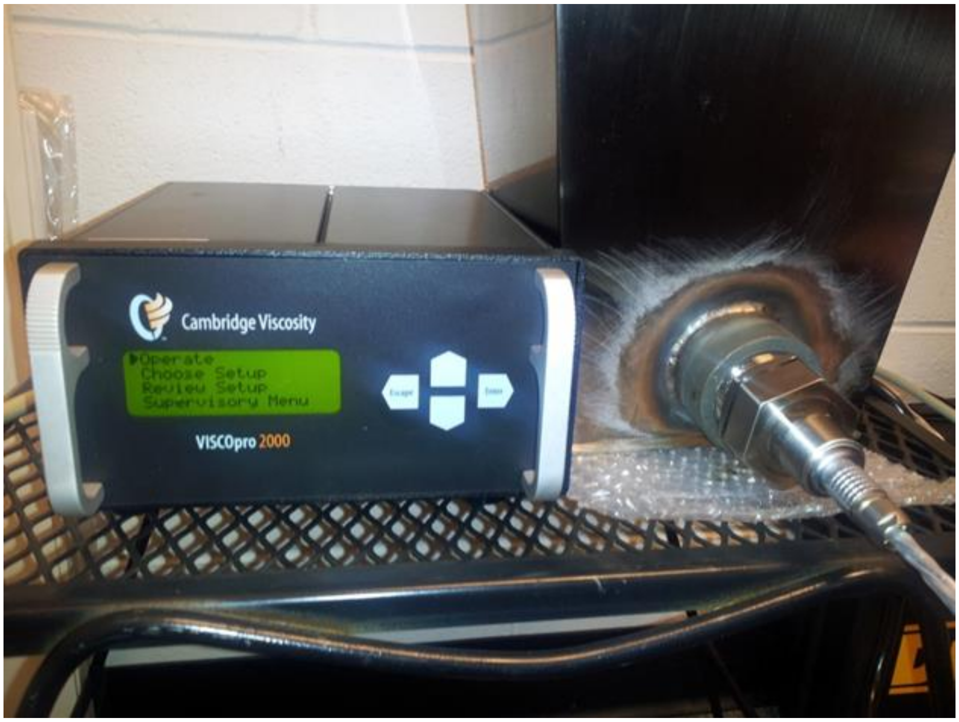


Figure 2.3 Viscometer and its data acquisition system

The dielectric constant sensor from Gill Sensor Inc. measures the capacitance of the test liquid then calculate the dielectric constant by the equation D=Coil/Cair, which is the capacitance of the test liquid divided by the capacitance of air, then output a voltage accordingly.  The output analog signal was captured by LabJack U12 which was the data acquisition unit for the sensor and the voltage signal was recorded with Logger and Scope, software that comes with the U12. The dielectric constant sensor and its data acquisition system along with the entire experiment setup are shown in Figure 2.4 and 2.5.

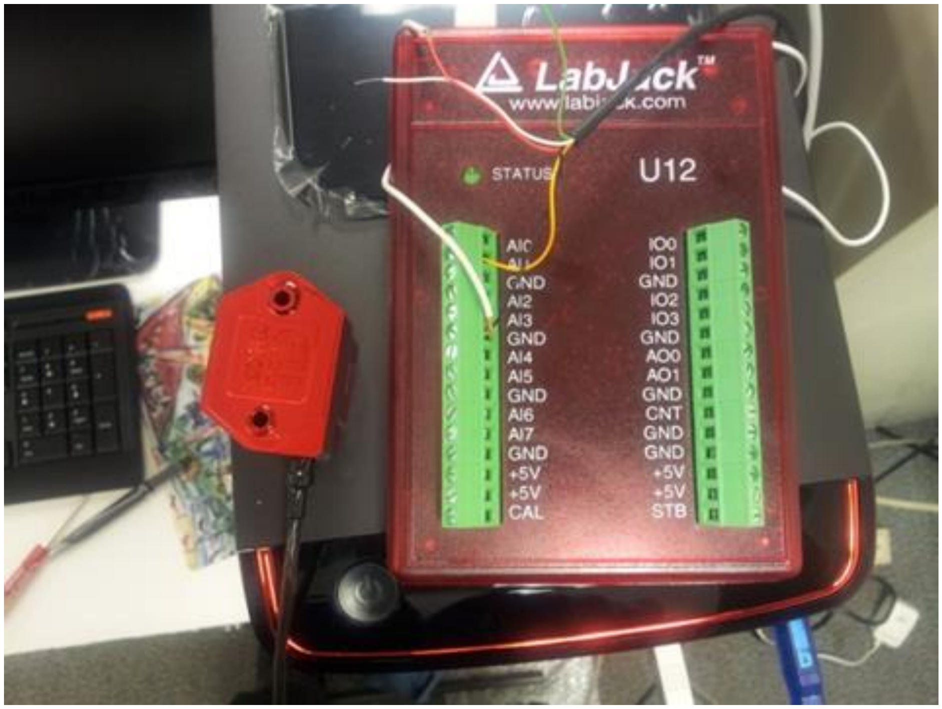


Figure 2.4 Dielectric constant sensor and the LabJack U12 data acquisition system

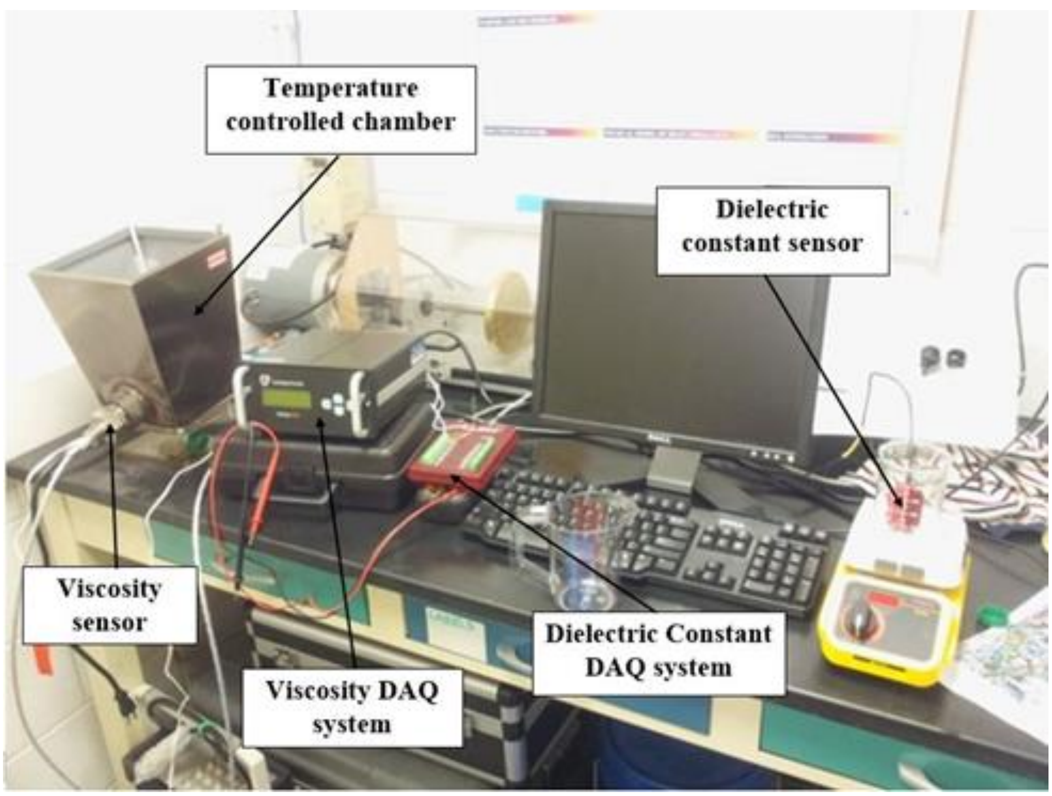


Figure 2.5 Experimental setup

Also needed for the tests were temperature control units. For the dielectric constant test, we used a temperature controlled hotplate from Thermo Scientific. It was a ceramic hotplate with temperature control and digital indication of temperature on the contact surface. However, since the viscometer had to be installed with sensor side facing up, we installed the sensor on a steel container and heated the oil inside with a liquid heater. In both situations, the test oils were preserved in a temperature controlled container and heated from around 25 to approximately 60 degrees Celsius. Instant temperatures were recorded along with the according viscosity and dielectric constant.

Several measuring cups for lubrication oil samples were used for the particle contamination tests. The volume of oil sample for each separated test is 1200mL. The weight of the particles was measured by a milligram scale from American Weigh GPR-20 Gemini-PRO Digital Milligram Scale. Particle powders are purchased from SIGMA-ALDRICH. The size of the silicon dioxide powders is less than 230 mesh and the size of the iron particles is -325 mesh as shown in Figure 2.6 and 2.7.

Also needed for the tests were temperature measurement and control units. For the dielectric constant test, EI1034 Temperature Probe from LabJack was used and the probe was attached to the same DAQ as dielectric sensor in order to synchronize the data. Viscosity sensor has an integrated temperature sensor for data synchronization. Both sensors were installed in the same container along with the temperature probe mounted close to the dielectric sensor. The test lubrication oil samples are preserved in the container and heated by an electrical liquid heater from around 25 to approximately 70 degrees Celsius. Instant temperatures are recorded along with the according viscosity and dielectric constant.


Figure 2.6 Iron powder from SIGMA-ALDRICH

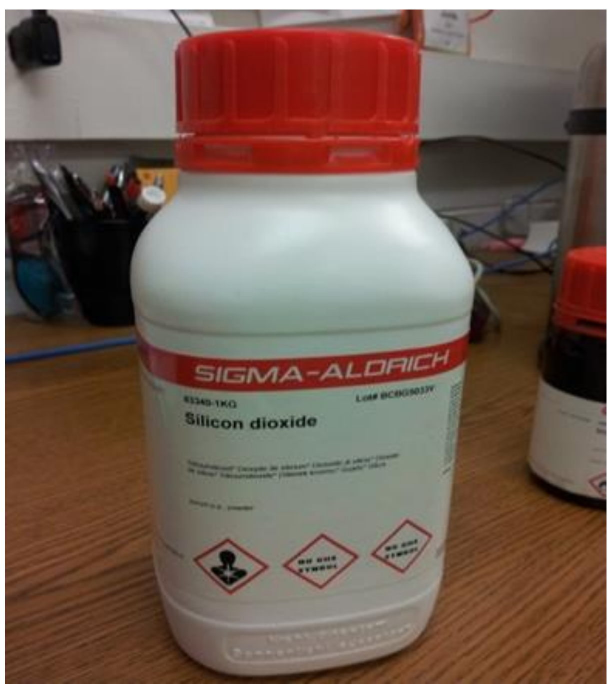


Figure 2.7 Silicon dioxide powder from SIGMA-ALDRICH

### 2.3.2. Model Validation for Water Contaminated Lubrication Oil

In order to validate the physics models, viscometer and dielectric constant sensor readings under different water contamination levels with varying temperatures were compared with those computed from the physics models under the same conditions.

During the experiment, Castrol SAE 15W-20 lubrication oil was selected to perform the physics model validation. The healthy SAE 15W-20 lubrication oil kinematic viscosity in relation with temperature was obtained from the experimental tests as following:

$$V_{oil,T} = 57470.5189 \times T^{-1.935} \tag{2.14}$$

Also, the healthy SAE 15W-20 lubrication oil dielectric constant in relationship with temperature was obtained from the experimental tests as following:

$$\varepsilon_{oil,T} = 4.90028 \times T^{-0.121} \tag{2.15}$$

Figure 2.8, 2.9, 2.10, and 2.11 show the plots of the kinematic viscosity obtained from the experiments and the physics models at water contamination level of 0.5%, 1%, 2%, and 3%, respectively. 40 data points were used to validate the viscosity physics model. Judging from the kinematic viscosity curves, the experiment result validated the simulation result. For a fixed water contamination level, as temperature increases the viscosity drops, the measured viscosity variation follows the pattern of the simulated kinematic viscosity curves.

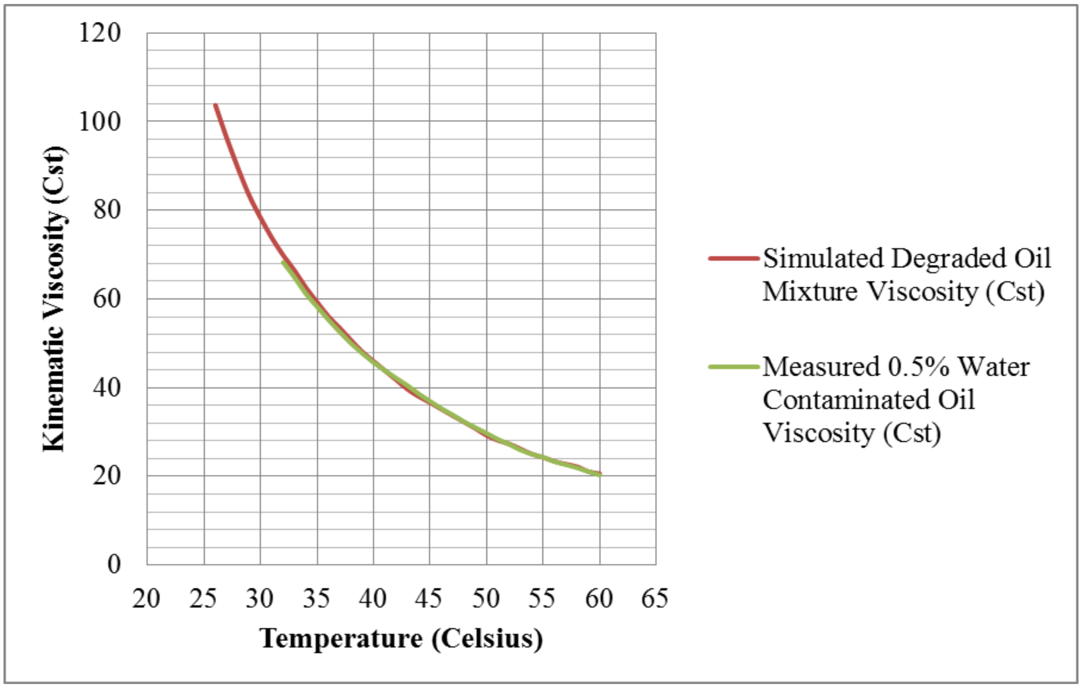


Figure 2.8 Kinematic viscosity comparison between simulated 0.5% water contaminated oil and measured 0.5% water contaminated oil

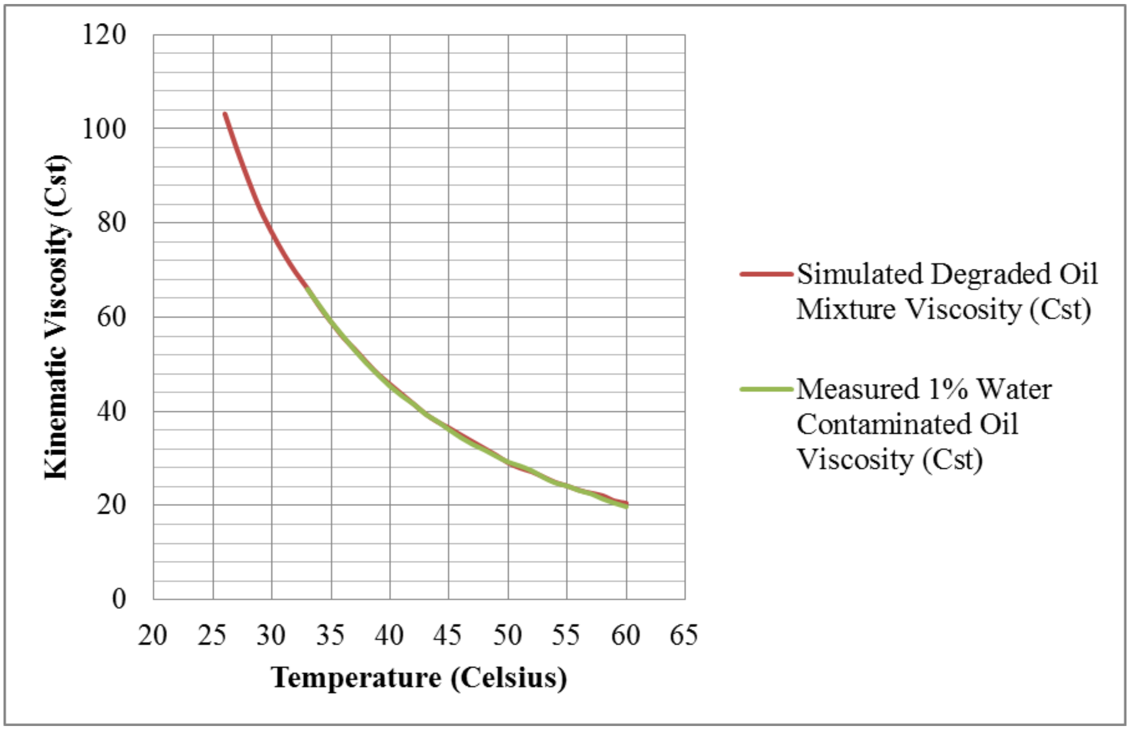


Figure 2.9 Kinematic viscosity comparison between simulated 1% water contaminated oil and measured 1% water contaminated oil

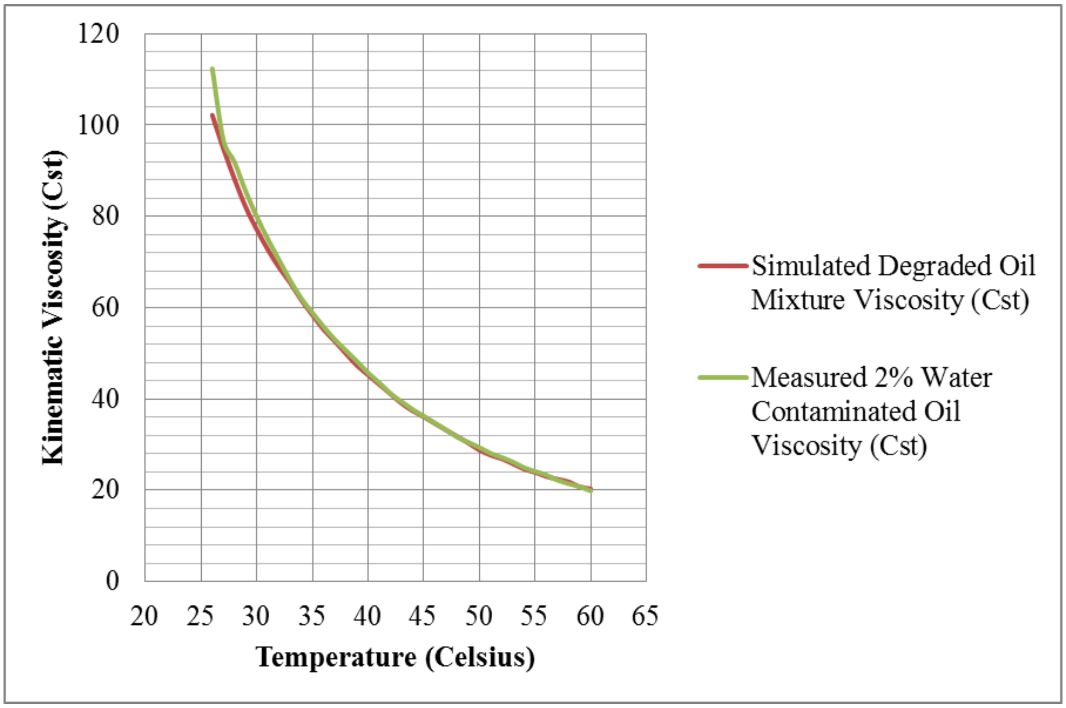


Figure 2.10 Kinematic viscosity comparison between simulated 2% water contaminated oil and measured 2% water contaminated oil.

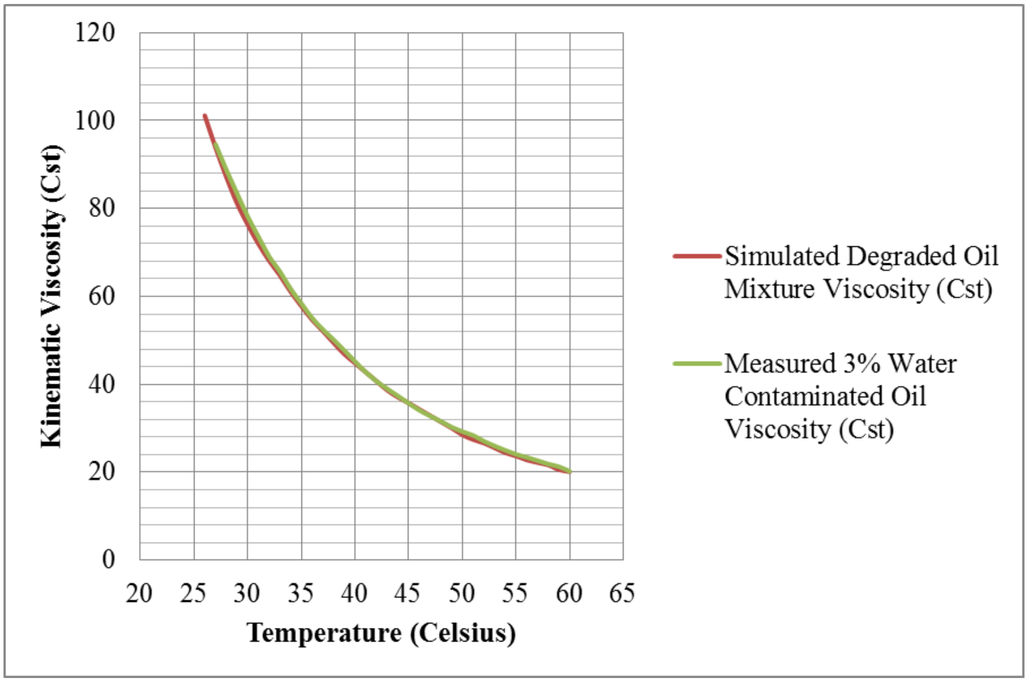


Figure 2.11 Kinematic viscosity comparison between simulated 3% water contaminated oil and measured 3% water contaminated oil

Figure 2.12 shows the plots of the dielectric constant obtained from the experiments and the physics models at water contamination level of 0.5%. 40 data points were used to validate the dielectric constant physics model. Similar to the case of kinematic viscosity, the experiment result validated the simulation result. For a fixed water contamination level, as temperature increases the dielectric constant increases, the dielectric constant variation follows the pattern of the simulated dielectric constant curves. The dielectric constant physics model has been validated by Jakoby and Vellekoop [27] for lubrication oil applications.

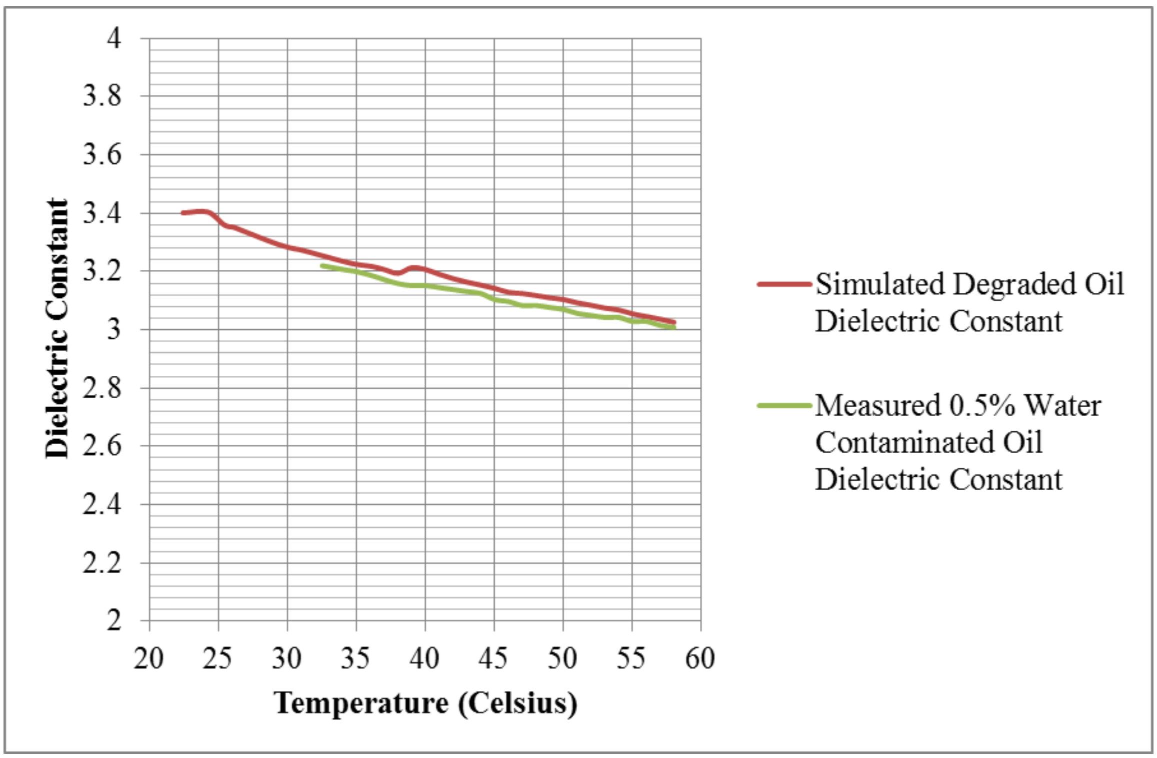


Figure 2.12 Dielectric constant comparison between simulated 0.5% water contaminated oil and measured 0.5% water contamination oil

### 2.3.3. Model Validation for Particle Contaminated Lubrication Oil

In order to validate the derived physics models, viscometer and dielectric constant sensor readings under different particle contamination levels were compared with those computed from the physics models under the same conditions.

Castrol SAE 15W-20 lubrication oil was again selected to perform the physics model validation. The healthy SAE 15W-20 lubrication oil absolute viscosity and temperature relationship ($V_{oil,T}$) was obtained from initial experimental tests along with the healthy SAE 15W-20 lubrication oil dielectric constant and temperature relationship ($\varepsilon_{oil,T}$) as shown in Equation (2.14) and (2.15).

Viscosity Model Validation for Iron Contamination

For iron contamination viscosity model, Figure 2.13 shows the plots of the absolute viscosity obtained from the experiments and the physics models at iron contamination level of 50mg/L, 100mg/L, 150mg/L and 200mg/L respectively. Judging from the absolute viscosity trend line, the experiment result validated the simulation result from the physics models. For a fixed temperature of 65 degree Celsius, as the iron particle contamination level increases the viscosity increases along with it. The experiment measured viscosity variation follows the pattern of the simulated absolute viscosity curves.

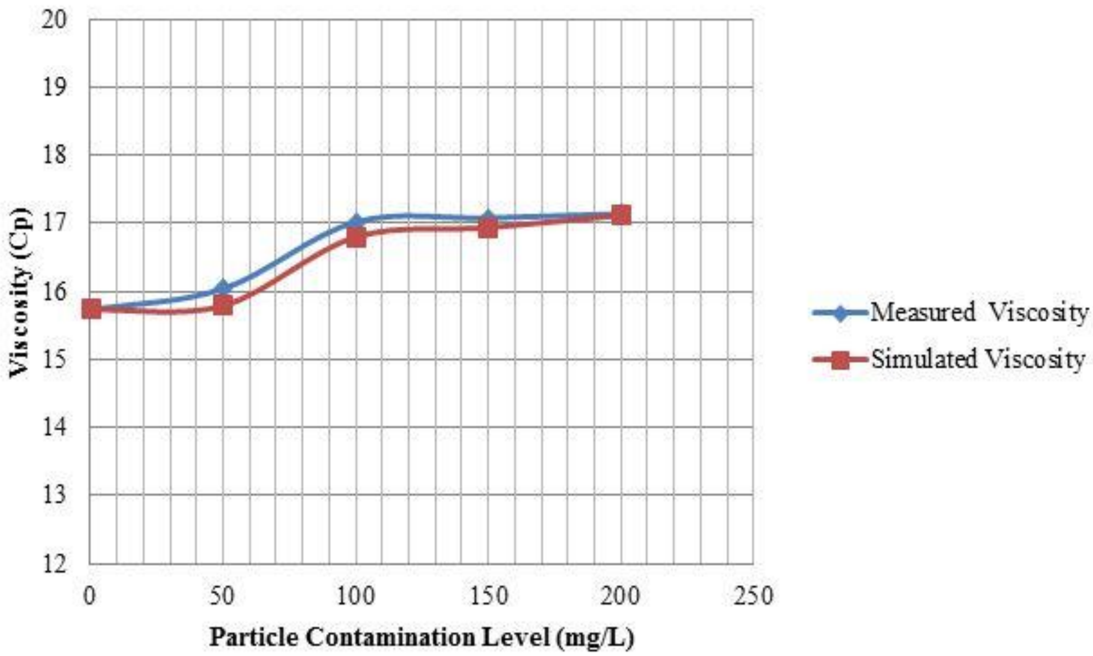


Figure 2.13 Viscosity comparison between sensor measured absolute viscosity and simulated viscosity at 65℃ (particle contamination, iron contamination)

Viscosity Model Validation for Soot Contamination

Again, for soot contamination viscosity model, Figure 2.14 presents the plots of the absolute viscosity obtained from the experiments and the physics models at soot contamination level of 50mg/L, 100mg/L, 150mg/L and 200mg/L respectively. By comparing the absolute viscosity variation against increasing particle contamination level, the experiment result validated the simulation result from the physics model. For a fixed temperature of 65 degree Celsius, as soot particle contamination level increases the viscosity increases accordingly. The measured viscosity variation follows the pattern of the simulated kinematic viscosity curves.

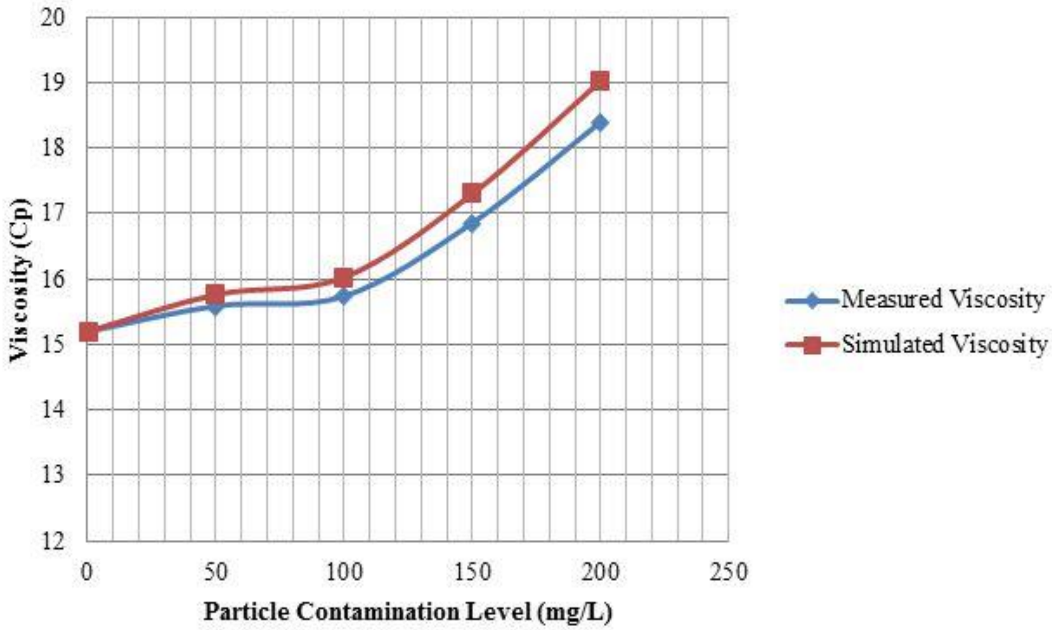


Figure 2.14 Viscosity comparison between sensor measured absolute viscosity and simulated viscosity at 65℃ (particle contamination, soot contamination)

Dielectric Constant Model for Iron Contamination

For iron contamination dielectric model, Figure 2.15 shows the plots of the dielectric constant obtained from the experiments and the physics models at iron contamination level of 50mg/L, 100mg/L, 150mg/L and 200 mg/L respectively. Similar to the case of absolute viscosity, the experiment result validated the simulation result. For a fixed temperature of 65 degree Celsius, as particle contamination level increases the dielectric constant increases along with it. The dielectric constant variation follows the pattern of the simulated dielectric constant curves.

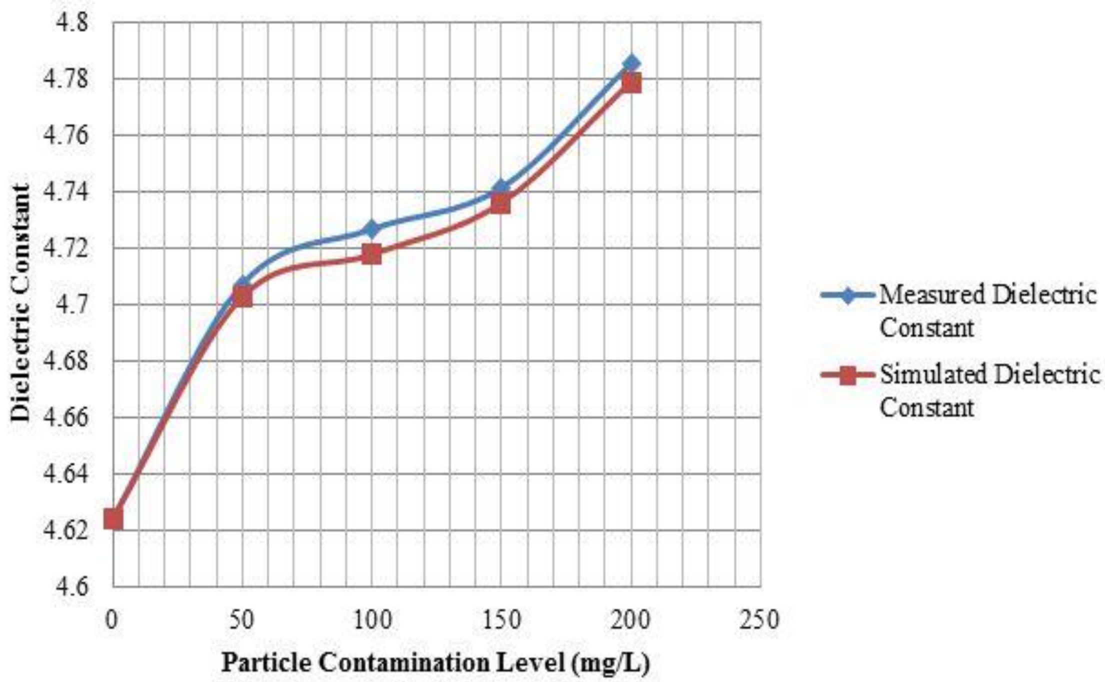


Figure 2.15 Dielectric constant comparison between sensor measured dielectric constant and simulated dielectric constant at 65℃ (particle contamination, iron contamination)

Dielectric Constant Model for Soot Contamination

For soot contamination dielectric model, Figure 2.16 shows the plots of the dielectric constant obtained from the experiments and the physics models at soot contamination level of 50mg/L, 100mg/L, 150mg/L and 200mg/L respectively. Similar to the case of absolute viscosity, the experiment result validated the simulation result. For a fixed temperature of 65 degree Celsius, as particle contamination level increases the dielectric constant increases accordingly. The dielectric constant variation follows the pattern of the simulated dielectric constant curves.

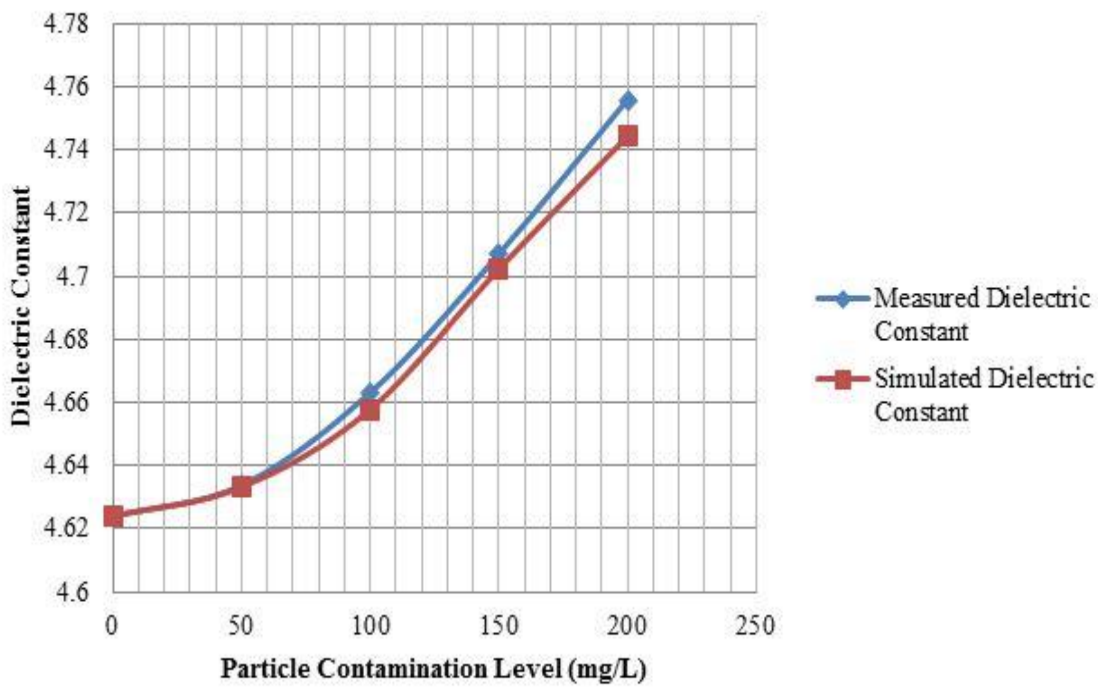


Figure 2.16 Dielectric constant comparison between sensor measured dielectric constant and simulated dielectric constant at 65℃ (particle contamination, soot contamination)

## 2.4. Summary and Discussions

In this chapter, based on the result of the comprehensive investigation on current lubrication oil condition monitoring techniques from literature review section, viscosity and dielectric constant were selected as the performance parameters to provide feasible solution to perform online oil condition analysis. Lubrication oil physics models that describe oil deterioration due to water and particle contamination in terms of viscosity and dielectric constant were developed and validated. Due to the complexity and lack of proper test kit to quantify the oxidation process, oxidation as one of the basics degradation features were not modeled and validated. However, certain solution has been looked into and will be implemented in the future. The result of the validation simulation experiments showed that the developed models are effective to describe the oil deterioration process caused by water or particle contamination. Compared with soot contamination, iron contamination which is a part of the particle contamination can indicate both lubrication oil condition and machine components health condition. Some condition monitoring techniques analyze the metallic components that are dissolved in the lubrication and trace back to certain group or specific component of the mechanical system. Therefore, iron contamination is relativity more attractive to scientists and researchers. The goal of the physics model derivation is to find a mathematical relationship between lubrication oil degradation and contamination level of different basic degradation features. Also, in order to perform remaining useful life prediction, system dynamic models are required. With the successful development and validation of the lubrication oil degradation physics models, one can select the appropriate RUL prediction algorithm. Most common statistical methods to perform state estimation are Kalman filter and Particle filtering. Depends on the model dynamics, if it is a linear system with Gaussian noise, one can select Kalman Filter. If it is linear systems with non-Gaussian noise, one can use Extended or Unscented Kalman Filter. When dealing with nonlinear system with non-Gaussian noise, particle filtering technique is ideal because nonlinear Kalman filter is linearization based technique. If the system nonlinearity grows, any of linearization (either local or statistical linearization) methods breaks down. In the RUL stage, particle filtering can handle statistical data unlike many parameter estimation techniques. In the next chapter, detail discussion of particle filtering techniques and how it is applied to our case which is lubrication oil RUL prediction is illustrated.

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# CHAPTER 3

# PARTICLE FILTERING TECHNIQUE FOR LUBRICATION OIL REMAINING USEFUL LIFE PREDICTION

## 3.1. Introduction

Most common statistical methods to perform state estimation are Kalman filter and Particle filtering (or sequential Monte Carlo method). Ever since its inception, Kalman filter (KF) [24] has been the most widely used estimation strategy due to its elegant recursive form, computational efficiency and ease of implementation. Therefore, even though KF only tracks the first two moments of the state (mean and covariance), it is extremely powerful. However, KF is only optimal if the following assumptions hold [40].

1) The dynamic system model is a linear function of the state and process noise.
2) The measurement model is also linear function of the state and measurement noise.
3) The process noise and the measurement noise are mutually independent and zero-mean Wiener process with known covariance.
4) The posterior density is Gaussian.

Unfortunately, most real life situations do not uphold all of the above assumptions. As a result, a nonlinear version of KF was required. The local linearized version of KF, known as the Extended Kalman Filter (EKF) [22] was proposed. In the EKF, the nonlinear system is replaced with a first order perturbation model obtained via Taylor Series expansion about a reference trajectory. While EKF extends the applicability of the Kalman filter to nonlinear dynamic systems and measurement models, it performs poorly when the higher order terms start to dominate (e.g. when perturbation grows in magnitude over time due to nonlinear effects). To overcome this weakness, higher-order EKF [29] algorithms using the second or even higher order terms in the Taylor series expansion were introduced. However, the fundamental problem remains the same, i.e. divergence due to nonlinear effects can only be delayed but not avoided. Overall, the class of EKF algorithms has the following general shortcomings.

1) Linearization or high order system approximations are prone to divergence dependent on degree of system nonlinearity.
2) Linearized transformation sometimes cannot be obtained through Jacobian matrix, e.g. if the system contains a discontinuity, the Jacobian does not exist.
3) Computing the Jacobian matrix can be tedious, often involving excessive and complex algebraic manipulations. Also, the computation process is prone to human error.
4) In the higher-order EKF algorithms, these problems can become more serious.

Recently, Julier and Uhlmann proposed another filtering strategy based on the so called unscented transformation (UT) sampling and the Kalman filter framework. This filter is known as the unscented Kalman filter (UKF) [23]. As opposed to EKF, which performs local linearization, the UKF is based on the principle of statistical linearization. By virtue of statistical linearization, the first two moments of the system derived from the sample points match exactly with the first two moments of the actual system. To perform the unscented transformation, a minimal set of sample points (called sigma points) are deterministically selected around the currently known mean of the state. The sigma points are then propagated through the nonlinear system dynamics (i.e. without analytic local linearization). As a consequence, the UKF algorithm is applicable to systems with discontinuities. However, if nonlinear effects are strong, the UKF strategy may not be adequate to describe state uncertainty.

The other popular filtering strategy is the sequential Monte Carlo (SMC) method (also known as particle filter (PF)) [1] [10] [25] [34]. The basic idea behind the SMC is to characterize state uncertainty in terms of a finite number of particles. As opposed to the UKF, the SMC methods can capture higher order statistical information of the system state (e.g. the mean, variance, skewness, kurtosis etc.), by analysis of the particle statistics.

Even though the first versions of the SMC methods can be found in papers dating back to the 1950s [16], they could not become popular immediately due to the following drawbacks:

1) The SMC methods generally require high computing power, which have only recently became readily available.
2) The early SMC methods were based on the sequential importance sampling (SIS) technique, which suffers from a serious problem called "sample degeneracy (a.k.a. particle depletion)".

In 1993, Gordon, Salmond and Smith proposed the sequential importance resampling (SIR) [13] algorithm to overcome sample degeneracy. Since introduction of the SIR filter, research in the SMC methods has grown vigorously and resulted significant theoretical progress. In addition, thanks to the recent computer revolution, the SMC methods became increasingly amenable to the online demands of the filtering problem. After the SIR filter was introduced many other resampling ideas were proposed and implemented to improve the SIR filter. For example, multinomial resampling [13], residual resampling [28], strarified resampling [25], and systematic resampling [25] algorithms have been proposed by many authors. Following several years of implementation, the general consensus appears to be that owing to its simple implementation, low computation complexity and low sample variance, the systematic resampling algorithm is the most widely used resampling technique.

As comparison made above, depends on the nature of systems dynamics and noise source, if it is linear systems with Gaussian noise, one can select Kalman Filter. If it is non-linear systems with Gaussian noise, one can use Extended or unscented Kalman Filter. When dealing with non-linear system with non-Gaussian noise, particle filtering technique is ideal.

Using particle filter for RUL prediction is a recent development in combining both physics based and data driven approaches for prognostics as state by He *et al*. [17]. Applications of particle filters to prognostics have been reported in the literature, for example, remaining useful life predication of a mechanical component subject to fatigue crack growth reported by Zio and Peloni [41], online failure prognosis of UH-60 planetary carrier plate subject to axial crack growth [31], degradation prediction of a thermal processing unit in semiconductor manufacturing [6], and prediction of lithium-ion battery capacity depletion as stated by Saha *et al*. [35]. The reported application results have shown that particle filters represent a potentially powerful prognostics tool due to its capability in handling nonlinear dynamic systems and non-Gaussian noises using efficient sequential importance sampling to approximate the future state probability distributions. Particle filters were developed as an effective online state estimation tool reported by Doucet [11] and Arulampalam et al. [1].

In this dissertation, an integrated approach using particle filters for lubrication oil RUL prediction is presented. In this dissertation, a particle filtering algorithm is utilized as RUL prediction tool. For oil condition monitoring, an effective and accurate state estimation tool will be beneficial to reduce machine downtime. An on-line RUL estimator includes two stages: state estimation and RUL prediction. First, in the state estimation stage, even though there are many state estimation techniques, Kalman filter and particle filter are the most utilized ones. However, Kalman filter requires many assumptions such as: 1) zero-mean Gaussian process noise, 2) zero-mean Gaussian observation noise, 3) Gaussian posterior probability density function (pdf), etc. Because nonlinear Kalman filter is linearization based technique, if the system nonlinearity grows, any of linearization (either local or statistical linearization) methods breaks down as stated by Merwe *et al.* [30]. Second, in RUL estimation stage, particle filtering can handle statistic prediction data unlike the other methods (parameter estimation). As a result, particle filtering algorithm provides feasible solutions for a wide range of RUL predication applications. A particle filtering algorithm integrated with physics based oil degradation models will provide a basis to develop practically feasible tools for accurate RUL prediction of lubrication oil.

### 3.2. Particle Filtering for State Estimation

Applying particle filters to state estimation will be discussed first in this section. Particle filters are used to estimate the state of a dynamic system using state and observation parameters. The state transition function represents the degradation in time of the lubrication oil. The observation or measurement represents the relationship between the degradation state of the lubrication oil and the health monitoring sensor outputs.

To apply particle filtering method, state estimation problem should be formulated first as stated by Yoon [40]. The problem of state estimation (a.k.a. filtering) is to estimate the dynamic state in terms of the posterior probability density function (pdf), based on all available information, including the sequence of measurements up to the current time step $k$. Let us introduce $x_k \in \mathbb{R}^{nx} and\ z_k \in \mathbb{R}^{nz}$ which represent system state vector and observation (or measurement) vector at the current time k respectively, where $nx$ and $nz$ are the dimension of the corresponding state vector and observation vector; $\mathbb{R}$ is a set of real numbers; $k \in \mathbb{N}$ is the time index; and $\mathbb{N}$ is the set of natural numbers. Consider the following discrete-time hidden Markov model (a.k.a state transition and observation model):

$$\boldsymbol{X_k}|(\boldsymbol{X_{k-1}} = x_{k-1}) \triangleq p(x_k|x_{k-1}) \tag{3.1}$$

$$\boldsymbol{Z_k}|(\boldsymbol{X_k} = x_k) \triangleq p(z_k|x_k) \tag{3.2}$$

where $\boldsymbol{X_k} = \{x_0, x_1, \dots, x_k\}$ is the sequence of the system state up to time $k \in \mathbb{N}$, and $\boldsymbol{Z_k} = \{z_0, z_1, \dots, z_k\}$ is the sequence of observation that is available up to current time k. Note that the above notation $\boldsymbol{X_k}$ is sometimes represented as $x_{0:k}$. Also, the state transition and the state observation models can be rewritten in functional form as follows:

$$x_k = f_{k-1}(x_{k-1}, v_{k-1}) \tag{3.3}$$

$$z_k = h_k(x_k, w_k) \tag{3.4}$$

where $v_k \in \mathbb{R}^{\mathrm{nv}}$ and $w_k \in \mathbb{R}^{\mathrm{nw}}$ denote the process noise and measurement noise at time k respectively; $v_k$ and $w_k$ are white noise; the initial state distribution $p(x_0) \triangleq p(x_0|z_0)$ is assumed known. Note that the state transition function is a mathematical representation of the lubrication oil degradation in time. Also, the observation model represents the health monitoring sensor outputs indicating the degradation state of the lubrication oil.

Then, the marginal pdf of the state can be recursively obtained in two steps: prediction and update. In the prediction step, suppose the state estimate at the time $\mathrm{k}-1$ $p(x_{k-1}|\boldsymbol{Z_{k-1}})$ is known. Then the prediction (or prior) pdf of the state is obtained involving the system model via the *Chapman-Kolmogorov* equation as:

$$p(x_k|\boldsymbol{Z_{k-1}}) = \int p(x_k|x_{k-1})p(x_{k-1}|\boldsymbol{Z_{k-1}})dx_{k-1} \tag{3.5}$$

In the update step, the new measurement $z_k$ becomes available and the posterior pdf can be obtained via the *Bayes* rule as follows:

$$p(x_k|Z_k) = \frac{p(z_k|x_k)p(x_k|\boldsymbol{Z_{k-1}})}{p(z_k|\boldsymbol{Z_{k-1}})} \tag{3.6}$$

where the normalizing constant is:

$$\mathrm{p(z_k|\mathbf{Z_{k-1}})} = \int p(x_k|\boldsymbol{Z_{k-1}})\, p(z_k|x_k)dx_k \tag{3.7}$$

The above obtained recursive propagation of the posterior pdf is a conceptual solution; it cannot analytically determined.

In any state estimation problem, based on the desired accuracy and processing time, a wide variety of tracking algorithms can be utilized. Especially, particle filter (a kind of suboptimal filter) increases accuracy while minimizing assumptions on the dynamic and measurement models. Due to its general disposition, particle filter became widely used in various filed. In the particle filter process, the marginal posterior density at time *k* can be approximated as follows:

$$p(x_k|\boldsymbol{Z_k}) \approx \sum_{i=1}^{N} w_k^i \delta(x_k - x_k^i) \tag{3.8}$$

where $\{\mathrm{x}_\mathrm{k}^i, w_k^i\}_{i=1}^N$ represents the random measure of the posterior pdf $p(x_k|Z_k)$ ; $\{x_k^i, i = 1, \ldots, N\}$ is a set of support points with associated weights $\{w_k^i, i = 1, \ldots, N\}$; $\delta(\cdot)$ is a Dirac delta function; and sum of weights $\sum_i w_k^i = 1$. Since we are not able to directly sample from the posterior $p(x_k|\boldsymbol{Z_k})$ itself, associated weights $w_k^i$ are computed by introducing importance density $q(x_k|\boldsymbol{Z_k})$ which is chosen easily sample from (normally transitional prior is used):

$$w_k^i \propto \frac{p(x_k^i|\boldsymbol{Z_k})}{q(x_k^i|\boldsymbol{Z_k})} \tag{3.9}$$

Thus, the desired posterior and weight update can be factorized in recursive forms as:

$$p(x_k|\boldsymbol{Z_k}) \propto p(z_k|x_k)p(x_k|x_{k-1})p(x_{k-1}|\boldsymbol{Z_{k-1}}) \tag{3.10}$$

$$\mathrm{w}_\mathrm{k}^i = w_{k-1}^i \frac{p\left(z_k\middle|x_k^i\right)p(x_k^i|x_{k-1}^i)}{q(x_k^i|x_{k-1}^i,z_k)} \tag{3.11}$$

Note that, after the weights are obtained via Equation (3.11), weight normalization is required ($\sum_i w_k^i \neq 1$) to satisfy the nature of probability density function ($\sum_i w_k^i = 1$) as follows:

$$\mathrm{w}_\mathrm{k}^i = \frac{w_k^i}{\sum_j w_k^j} \tag{3.12}$$

It can be shown that $\lim_{\mathrm{N}\to\infty}\{\mathrm{x}_\mathrm{k}^\mathrm{i}, w_k^i\}_{i=1}^\mathrm{N} = p(x_k|Z_k)$ .

## 3.3. Particle Filter for RUL Prediction

In order to apply particle filter to estimate the remaining useful life (RUL), an *l*-step ahead estimator is required. An *l*-step ahead estimator will provide a long term prediction of the state pdf $p(x_{k+l}|\boldsymbol{Z_k}), for\ l = 1, \dots, T-k$, where $T$ is the time horizon of interest (i.e. time of failure). In making an *l*-step ahead prediction, it is necessary to assume that no information is available for estimating the likelihood of the state following the future *l*-step path $\boldsymbol{X}_{k+1:k+l}$ , that is, future measurements $z_{k+l}, for\ l = 1, \dots, T-k$ cannot be used for updating the prediction. In other word, the desired state pdf of particular future time $p(x_{k+l}|\boldsymbol{Z_k})$ can be factorized with the current posterior pdf $p(x_k|\boldsymbol{Z_k})$ to desired $p(x_{k+l}|\boldsymbol{Z_k})$ and the state transition function $p(x_k|x_{k-1})$ as $\prod_{j=k+1}^{k+l} p(x_j|x_{j-1})$. By combining Equation (3.1) and (3.4), an unbiased *l*-step ahead estimator can be obtained as stated by Zio and Peloni [41], as well as Orchard and Vachtsevanos [31].

$$p(x_{k+l}|\boldsymbol{Z_k}) = \int \dots \int \prod_{j=k+1}^{k+l} p\left(x_j\middle|x_{j-1}\right) p(x_k|\boldsymbol{Z_k}) \prod_{j=k}^{k+l-1} dx_j \tag{3.13}$$

Despite the fact that an unbiased estimator provides the minimum variance estimation, solving equation (3.7) can be either difficult or computationally expensive. Thus, a sampling based approximation procedure of the *l*-step-ahead estimator is provided by Zio and Peloni [41].

Assume that the state $x_{t=k}$ represents the particle contamination level at the current time $k$, the particle contamination level increases by time and RUL is the object's remaining usable time before it fails (or needs maintenances). If an $l$-step-ahead state from the time $k$ (i.e. $x_{t=k+l}$) goes across a pre-specified critical value $\lambda$ (i.e. $x_{t=k+l} \geq \lambda$), the object's RUL at the time $k$ can be computed as $\mathrm{RUL_k} = (k+l) - k = l$. At each time step before its failure (i.e. $t \leq k+l$), the state $x_{t \leq k+l}$ would be projected up to the future time of failure $\mathrm{t} = k + l$. In this manner, estimating $\mathrm{RUL} \leq l$ is equivalent to estimating $x_{k+l} \geq \lambda$, rewriting as:

$$\hat{p}(RUL \leq l|\boldsymbol{Z_k}) = \hat{p}(\boldsymbol{X_{k+l}} \geq \lambda|\boldsymbol{Z_k}) \tag{3.14}$$

When RUL (*l*-step-ahead prediction) is implemented using particle filter as stated by He, *et al*. [17] corresponding weights are computed by introducing an estimated measurement $\widehat{z_{k+n}}$ according to Equation (3.4) (i.e. measurement model) as:

$$\widehat{\boldsymbol{z_{k+n}}} \sim h_{k+n}(\widehat{\mathrm{x}_{k+n}}) \tag{3.15}$$

where *n* is a future time step $0 < n \leq l$. Then, the updating process is accomplished by Equation (3.6) and (3.7). While RUL is computed, no measurement errors for the estimated measurements $\widehat{z_{k+n}}$ are considered. Note that the actual system has not been altered. Zero measurement errors are only applied in order to predict *l*-step-ahead state $\hat{p}(\boldsymbol{X_{k+l}} \geq \lambda|\boldsymbol{Z_k})$ because the future observation values are never accessible. In this thesis, an integrated prognostic technique using the *l*-step-ahead RUL estimating particle filter is exploited.

### 3.4. Implementation of Particle Filtering

In order to implement particle filtering, state transition function and observation function is required. In the case of lubrication oil remaining useful life prediction, the state of interest is the contamination level of water or particle. The observation function is the developed physics model. Since for each state of interest, two observation functions regarding to two sensors output exists. The two sensor outputs are kinematic viscosity and dielectric constant. In order to combine the two sensors into a particle filter based RUL prediction, a multivariable Gaussian distribution is used:

$$f_y(y_1, \dots, y_k) = \frac{1}{(2\pi)^{\frac{k}{2}}|\Sigma|^{\frac{1}{2}}} \exp(-\frac{1}{2}(y-\mu)^T \Sigma^{-1}(y-\mu)) \quad (3.16)$$

where $\Sigma$ is the covariance matrix of observations, $|\Sigma|$ is the determinant of $\Sigma$. Note that $y_k$ in Equation (30) represents the sensor output data $Z_k$.

By applying the probability density function, each particle will be assigned a weight according to its observation and updated similarly.

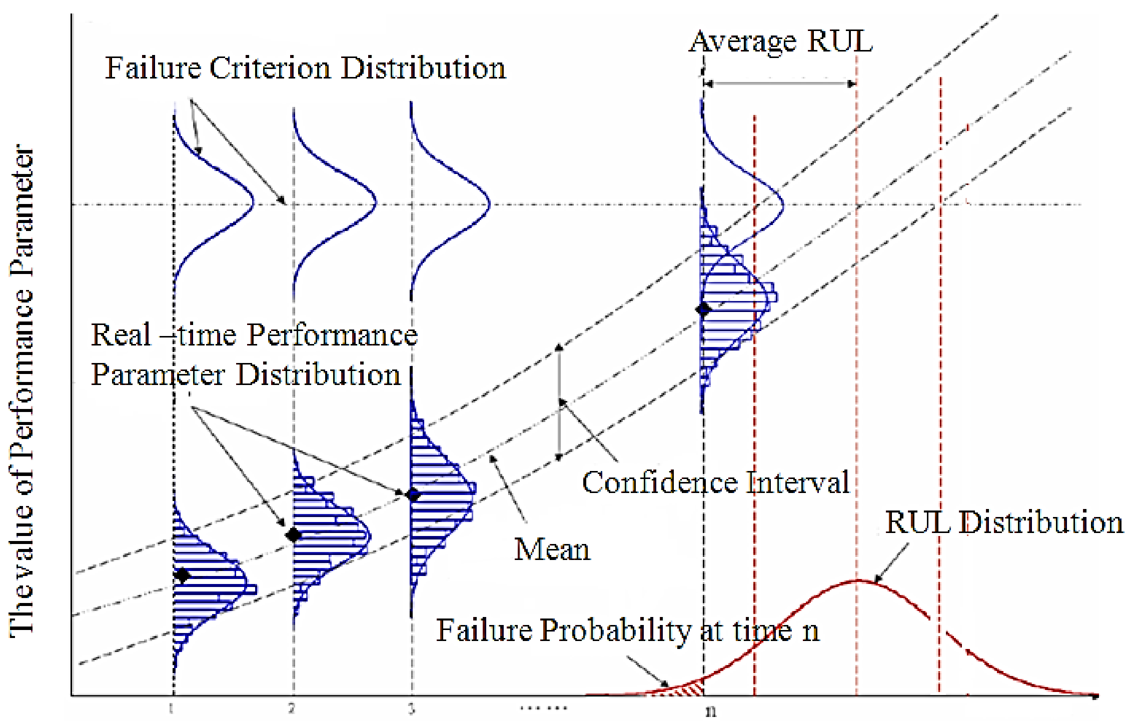


Figure 3.1 Conceptual illustrations of particle filtering techniques

As shown above, Figure 3.1 showed a conceptual illustration of particle filtering techniques. The x axis represents the time step. For example, if the sample rate is 1 point every 20 minutes, the time steps represents the 1$^{st}$ 20 minutes, 2$^{nd}$ 20 minutes and 3$^{rd}$ 20 minutes and so on. The y axis represents the state of interest, in our case for example, water contamination level. The upper dash line represents the point of breakage or the failure threshold, for example, 1000 ppm water contamination. The normal distributions around the upper dash line are failure criterion distribution. The distributions in the lower part are the real-time performance parameter distributions which consist of a selection of particles. The "particle" is defined as random measurement of the system. The black dots and dash line in the middle are prediction mean value by particle filtering while the side dash lines are the 90% confidence interval of every parameter distribution. We can see there are three intersection points of the failure criterion mean value and the state parameter predictions. If we map these three points to the time axis, we can get the RUL distribution like the bottom part shows. At each time step, state estimation and RUL prediction are performed. State estimation or so called filtering is by estimating the best state of the system (of interest) with two major information sources, systems dynamics and observation model. The initial state is also required. At the RUL prediction stage, the particle filtering algorithm propagates particles in particle filter up to the point of breakage or failure threshold. The propagation time estimation is recorded. Some of the particle may hit the failure threshold early and some may hit it late. As time goes by, the prediction result gets more and more accurate. The reason behind that is, as time progresses, the algorithm is performing less and less steps ahead prediction and more and more observation are flown into the system.

### 3.5. Discussions

In this chapter, the explanation of the particle filtering algorithm is presented along with the implementation of the algorithm in the lubrication oil remaining useful life prediction case. The background of particle filtering was presented as well as a comparison with other state estimation technique including Kalman Filter. There are many cases that particle filtering technique was implemented in the industry including bearing or gear crack growth prediction, battery depletion prediction. In this dissertation, particle filtering technique was utilized to predict the RUL of lubrication oil. The contamination level of water and particle are treated as system state of interest. The physics models developed in Chapter 2 are treated as the observation. Since two sensors are installed to monitor 1 state, multivariate Gaussian distribution was applied to distribution the weight of the particle. The detail implementation of particle filtering in the case of lubrication oil RUL prediction was discussed at the end of the chapter.

In the next chapter, the developed lubrication degradation model and particle filtering technique for remaining useful life prediction of lubrication oil are simulated under industrial conditions to validate the effectiveness and robustness of the developed solution for oil condition monitoring and RUL prediction.

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# CHAPTER 4

# SIMULATION CASE STUDIES

## 4.1. Introduction

In this chapter, in order to validate and demonstrate the effectiveness of the particle filter technique based lubrication oil RUL prediction approach, a simulation case study was conducted. With the help of the developed physics models, practical industrial scenario simulation framework was constructed for either water contaminated or particle contaminated lubrication oil. The framework simulates a wind turbine under extreme weather conditions on daily bases. Normally, the operating temperature inside the oil circulation systems is rather stable at around 50 to55℃. However, this case study simulated the temperature variation inside the turbine oil circulation system to be relatively unstable against the ambient temperature in order to test the effectiveness and the robustness of the RUL predicting algorithm. A temperature compensation algorithm was integrated into the simulation model to overcome this problem. With the integration of temperature compensation module, the RUL prediction 95% confidence interval region had been greatly narrowed. Therefore the prediction accuracy was improved and false alarm rate was much reduced. As comparison, single observation RUL prediction result based on either dielectric constant or viscosity data was compared with dual observation RUL prediction result based on both sensor observations. Also, comparison between different particle population RUL result and their impact on algorithm processing time is conducted. Hence, based on the need of the maintenance, wind farm operators can decide and balance how many sensors are needed, how large the predicting population should be, what is the accuracy required, and how soon can they acquire one prediction. The developed lubrication oil condition monitoring and remaining useful techniques can provide feasible solution for practical implementation on current condition based maintenance systems. The physics model can be integrated into the firmware of the oil quality sensors to provide condition monitoring for any kind of lubricant with minimum training time. The general processing flowchart of the case study simulation model is shown in Figure 4.1.

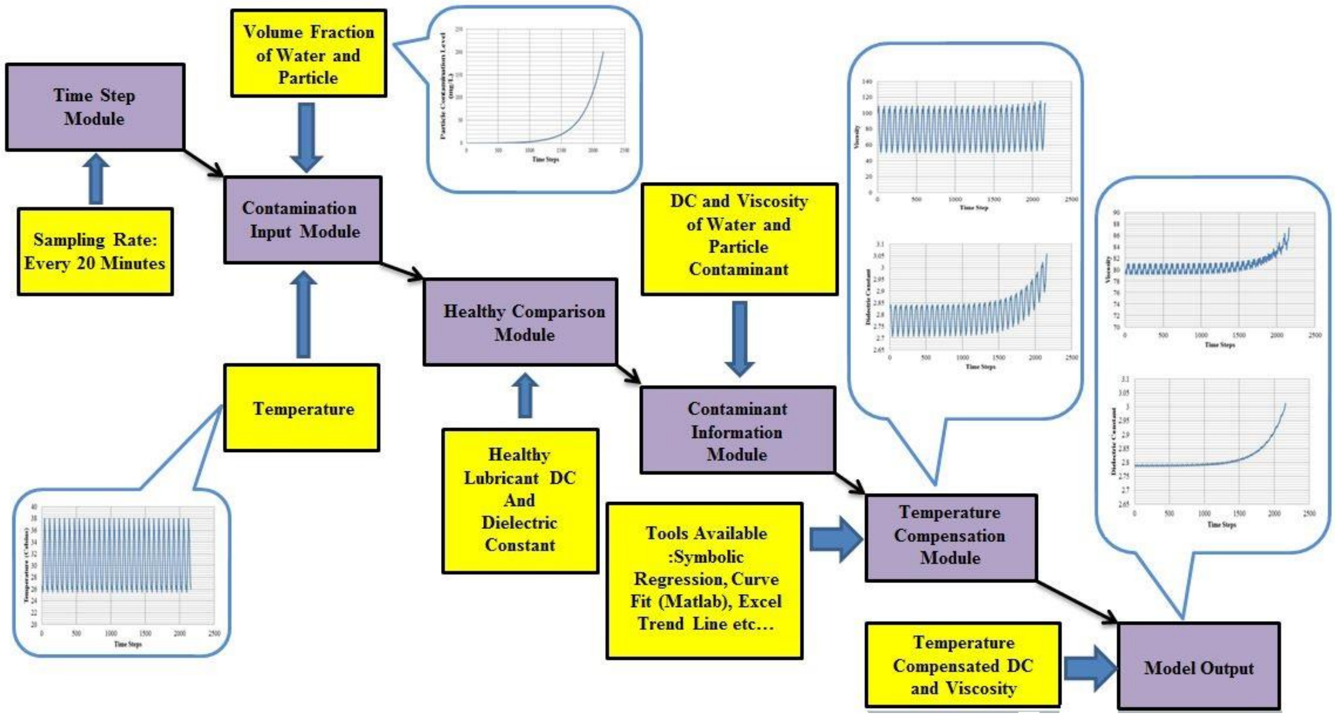


Figure 4.1 General simulation case study flowcharts.

### 4.2. Water Contamination Simulation Case Study

#### 4.2.1. Simulation Model Construction

In this simulation case study, a scenario of lubrication oil deterioration due to water contamination was simulated with the physics models presented in Sections 2.2.1 and 2.2.2. In this scenario, a temperature template was used to simulate a daily temperature variation of the wind turbine as shown in Figure 4.2. The other aspects of the simulation were defined as follows:

1) The deterioration state of the lubrication oil was defined as the water contamination level *P*.
2) The viscometer and dielectric constant sensor outputs were defined as observation data.
3) The lubrication oil deterioration process was simulated for 30 days (720 hours).

4) At the end of the simulation, the water contamination level *P* reached at 5%.

5) The sampling time interval was set to be every hour.

6) The failure threshold was set as 3% which was defined as the industry water contamination level limit.

7) At approximately the 525th hour, the water contamination level reached 3%.

Figure 4.3 shows the water contamination propagation over 720 hours during the simulation with the given temperature.

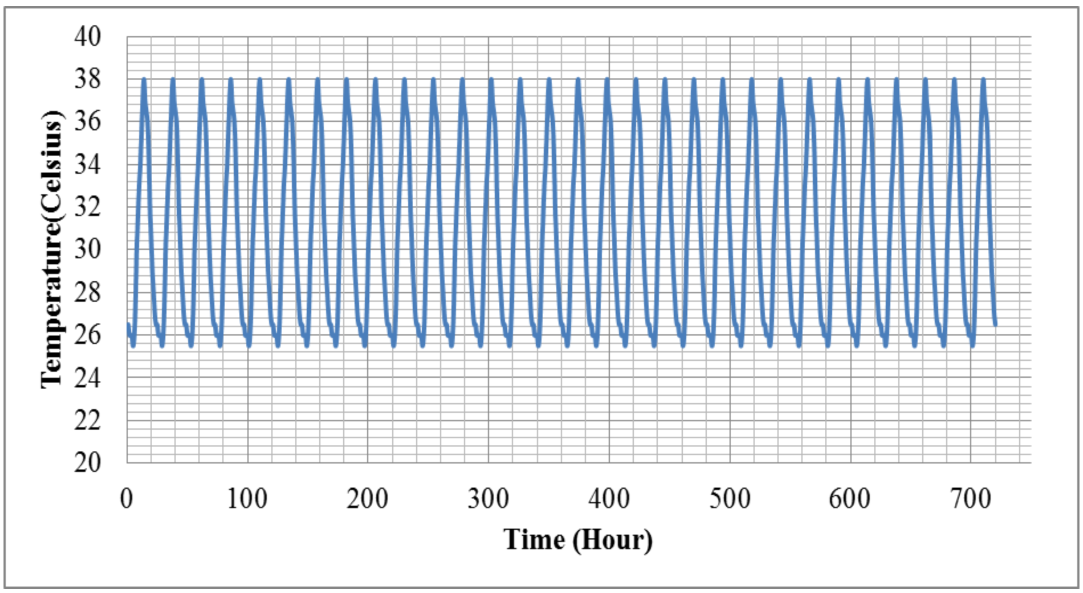


Figure 4.2 Temperature variation template

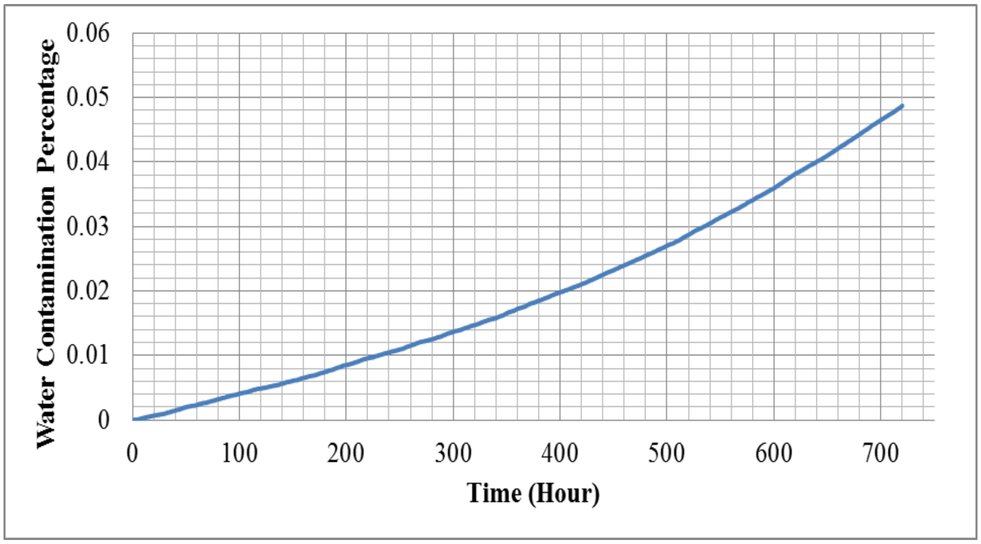


Figure 4.3 Water contamination propagation template

### 4.2.2. Particle Filtering Implementation for RUL Prediction

To implement a particle filter for the RUL prediction of the lubrication oil in the simulation case study, the state transition function was defined as Equation (4.1). It is generated as progression of the state of interest which in our case is the water contamination.

$$X_{k+1} = 1.0017 \times X_k + Random(0,1) \times 0.00007 \tag{4.1}$$

Two observation functions could be established using kinematic viscosity and dielectric constant physics models as Equation (4.2) and (4.3).

Note that Equation (4.2) is the observation function expressed in terms of kinematic viscosity and Equation (4.3) the observation function expressed in terms of dielectric constant.

Generalized observation function could be established by combining kinematic viscosity and dielectric constant as Equation (4.4).

$$Z_k = \left(5740.5189 \times T_k^{-1.935} + 0.451 \times \ln T_k - 2.3591\right) \times (1 - X_k) - 0.451 \times \ln T_k + 2.3591 \tag{4.2}$$

$$Z_k = 4.90028 \times T_k^{-0.121} \times (1 + 3 \times X_k \times \frac{-0.4 \times T_k + 88 - 4.90028 \times T_k^{-0.121}}{-0.4 \times T_k + 88 + 9.80056 \times T_k^{-0.121} - X_k \times (-0.4 \times T_k - 4.90028 \times T_k^{-0.121})}) \quad \ldots (4.3)$$

$$Z_k = \begin{bmatrix} Viscosity_k \\ DC_k \end{bmatrix} = \begin{bmatrix} h_1(X_k, T_k) \\ h_2(X_k, T_k) \end{bmatrix} = \begin{bmatrix} h_1(X_k, T_k) \\ h_2(X_k, T_k) \end{bmatrix} =$$

$$\begin{bmatrix} \left(57470.5189 \times T_k^{-1.935} + 0.451 \times \ln \mathrm{T_k} - 2.3591\right) \times (1 - X_k) - 0.451 \times \ln \mathrm{T_k} + 2.3591 \\ 4.90028 \times T_k^{-0.121} \times (1 + 3 \times X_k \times \frac{-0.4 \times T_k + 88 - 4.90028 \times T_k^{-0.121}}{-0.4 \times T_k + 88 + 9.80056 \times T_k^{-0.121} - X_k \times (-0.4 \times T_k - 4.90028 \times T^{-0.121})}) \end{bmatrix} \quad (4.4)$$

In the implementation of the particle filter, number of particles was fixed as 50 and the prediction started at time point 425th hour during the simulation with *l* being 100 time steps. The reason for selecting 50 particle populations is to balance accuracy and processing time. The particle population impact will be discussed in the Section 4.2.3.

In order to reduce observation data fluctuation and RUL prediction variation, a temperature compensation module was integrated into the physics models. With a reference to 30 degree Celsius, which was the median temperature of the operating condition over a 24 hours cycle, the observation data was adjusted according to viscosity or dielectric constant functions with respect to the temperature. For example, at a certain temperature, the temperature compensated viscosity was the true value of the viscosity plus the theoretical viscosity difference between 30 ℃ and current temperature. The compensated value can be obtained from the following equations:

$$\varepsilon_{compensate,T} = \varepsilon_T + (\varepsilon_{30}{}' + \varepsilon_T{}')$$

$$= \varepsilon_T + \left(\varepsilon_{30}{}' - (0.0001529 \times T^2 - 0.02241 \times T + 3.901)\right); \quad (4.5)$$

$$\varepsilon_T{}' = 0.0001529 \times T^2 - 0.02241 \times T + 3.901; \quad (4.6)$$

$$V_{compensate,T} = V_T + (V_{30}{}' + V_T{}')$$

$$= V_T + \left(V_{30}{}' - (0.21565 \times T^2 - 18.225 \times T + 431.5)\right); \quad (4.7)$$

$$V_T{}' = 0.21565 \times T^2 - 18.225 \times T + 431.5; \quad (4.8)$$

Figure 4.4 and Figure 4.5 present the observation variation before the temperature compensation.

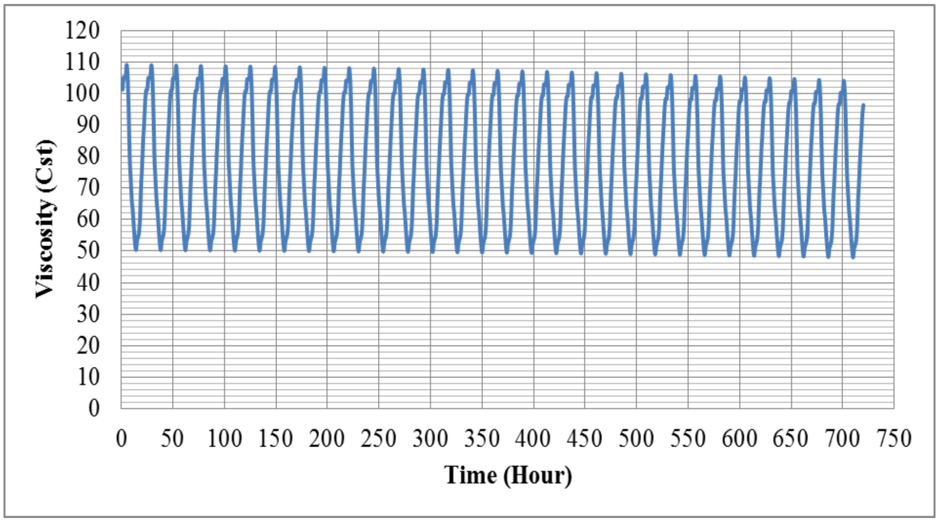


Figure 4.4 Observation data (kinematic **VISCOSITY**) fluctuation before temperature compensation

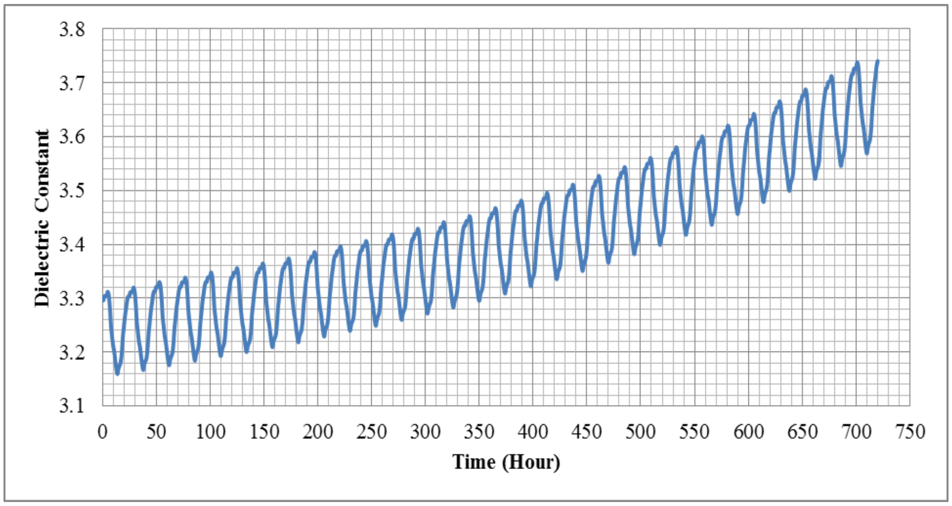


Figure 4.5 Observation data (dielectric constant) fluctuation before temperature compensation

Figure 4.6 and Figure 4.7 present the observation data variation after the temperature compensation.

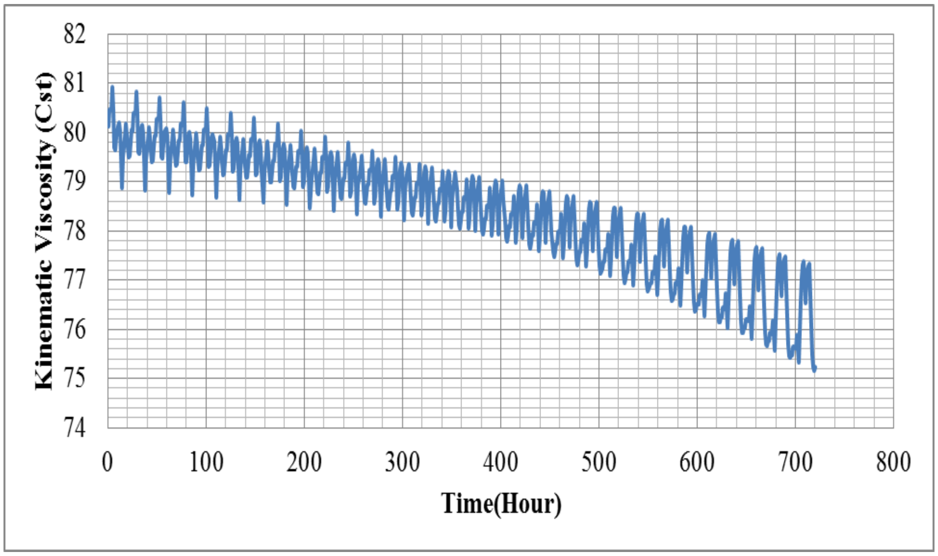


Figure 4.6 Observation data (kinematic viscosity) fluctuation after temperature compensation

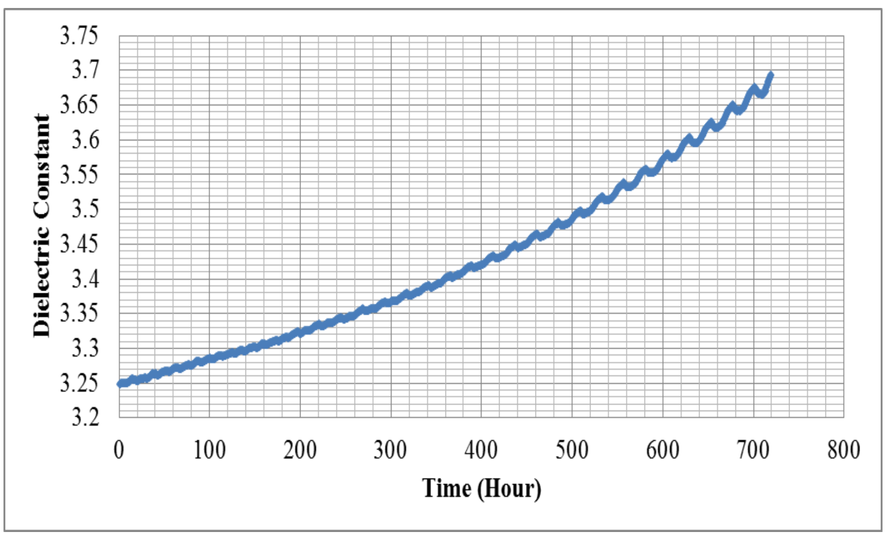


Figure 4.7 Observation data (dielectric constant) fluctuation after temperature compensation

In comparison of Figure 4.4 with Figure 4.6, and Figure 4.5 with Figure 4.7, it is obvious that the observation data fluctuation is greatly reduced after the temperature compensation and the data are ready for RUL prediction. Figure 4.8 summarizes the implementation of particle filter technique for lubrication oil RUL prediction.

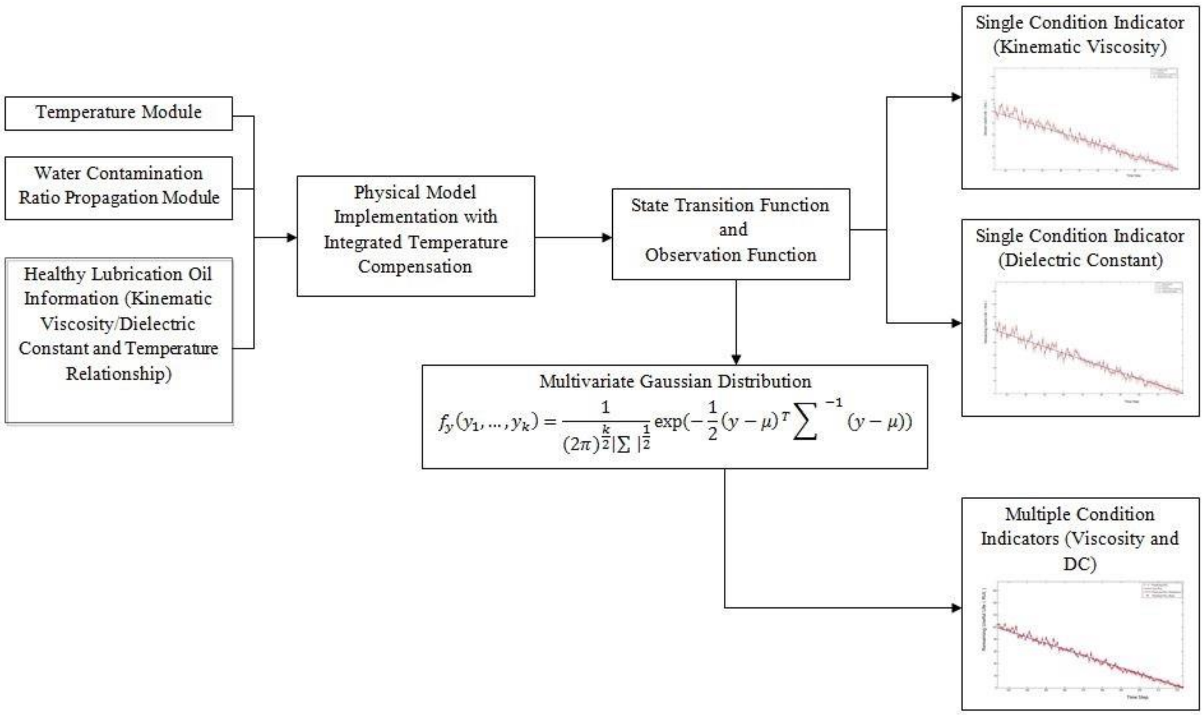


Figure 4.8 Particle filtering technique implementation.

### 4.2.3. RUL Prediction Results Using One Sensor Observation

Using the particle filter technique, RUL of the lubrication oil was predicted with either the viscosity or dielectric constant sensor observation. The prediction results are provided in Figure 18 and Figure 19, respectively. The *x* axis represents the true simulation time step. The *y* axis represents the time steps until failure. The blue line is the true remaining useful life and the red dots are our prediction mean while the vertical red bars are the 90% confidence intervals. From Figure 4.9 and Figure 4.10, one can see that with a certain degree of fluctuation at the beginning, the prediction becomes more and more accurate towards the end for both predictions. For a comparison purpose, the RUL prediction results with 200 particles are provided in Figure 4.11. As one can observe, using the same dielectric constant sensor observation under the same condition, a larger particle population provide better accuracy. However, larger particle population requires more processing times. The relationship between particle population and processing times is shown in Table 4.1.

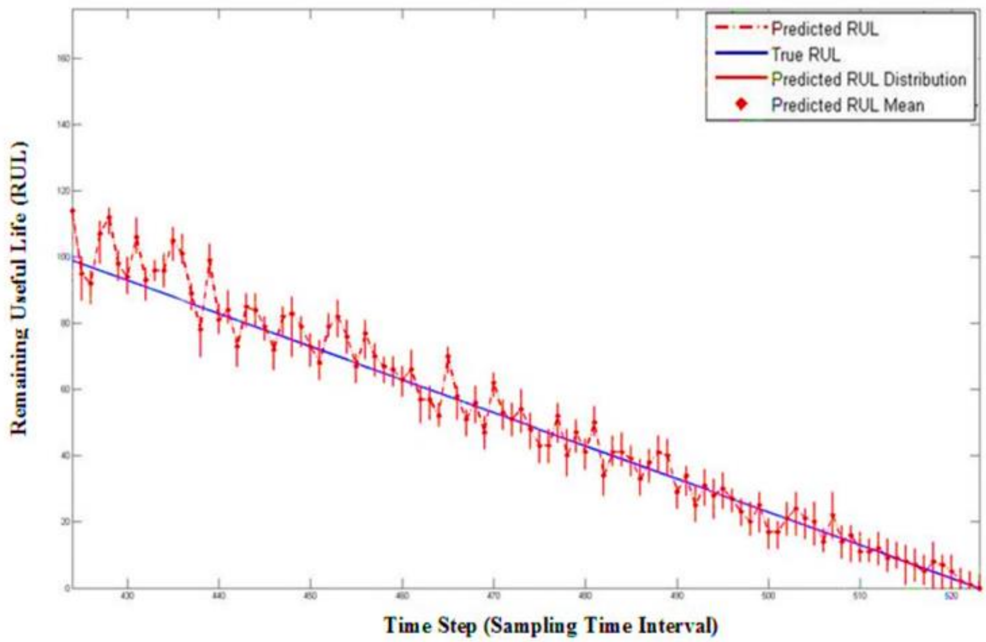


Figure 4.9 RUL prediction with only kinematic viscosity observation data (particle population=50)

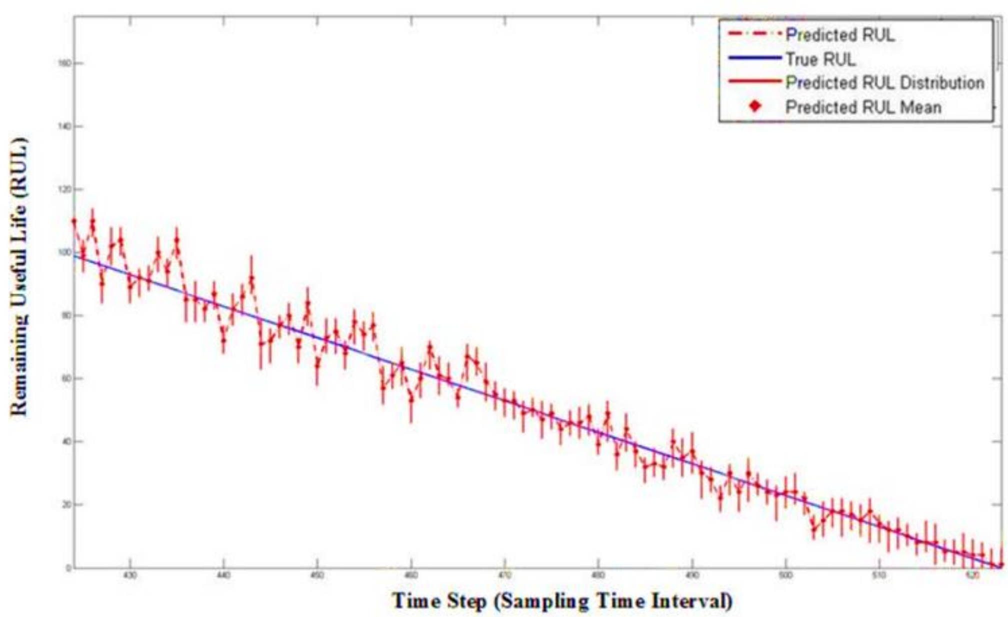


Figure 4.10 RUL prediction with only dielectric constant observation data (particle population=50)

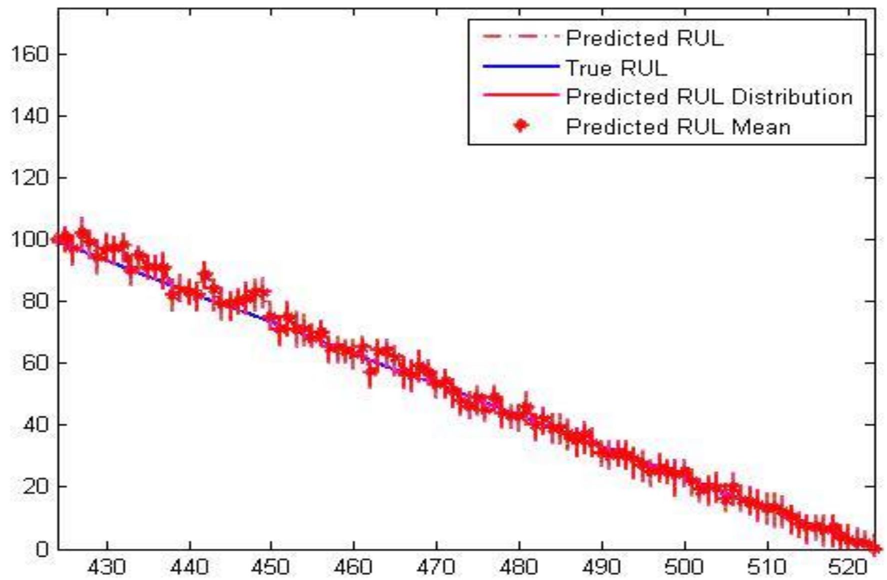


Figure 4.11 RUL prediction with only dielectric constant observation data (particle population=200)

Table 4.1 Particle population and prediction time relationship with only dielectric constant observation data

| Particle Population (N) | Prediction Time |
|---|---|
| 50 | 3 minutes 49 seconds |
| 75 | 4 minutes 40 seconds |
| 100 | 5 minutes 47 seconds |
| 150 | 7 minutes 59 seconds |
| 200 | 10 minutes 16 seconds |

#### 4.2.4. RUL Prediction Result Using Multiple Sensor Observation

The RUL prediction results presented in previous section were obtained using only one sensor. In order to combine the two sensors into a particle filter based RUL prediction, a multivariable Gaussian distribution is used:

$$f_y(y_1, \dots, y_k) = \frac{1}{(2\pi)^{\frac{k}{2}}|\Sigma|^{\frac{1}{2}}} \exp(-\frac{1}{2}(y-\mu)^T\Sigma^{-1}(y-\mu)) \tag{4.9}$$

where $\Sigma$ is the covariance matrix of observations, $|\Sigma|$ is the determinant of $\Sigma$. Note that $y_k$ in Equation (4.9) represents the sensor output data $Z_k$.

By applying the probability density function, each particle will be assigned a weight according to its observation and updated similarly. The RUL prediction results of combining two sensors are provided in Figure 4.12. As one can see from Figure 4.9, Figure 4.10, and Figure 4.12, in comparison with the RUL prediction results using only one sensor, the RUL prediction variation in combining two sensors has been reduced from the beginning until the end. Moreover, the accuracy of the prediction has also been improved significantly. The shortcoming of utilizing particle filtering algorithm is that it is considered a computational expensive algorithm. However, using particle filtering algorithm in combination with viscosity and dielectric constant based physics models would provide a feasible and effective solution for RUL predication of lubrication oil.

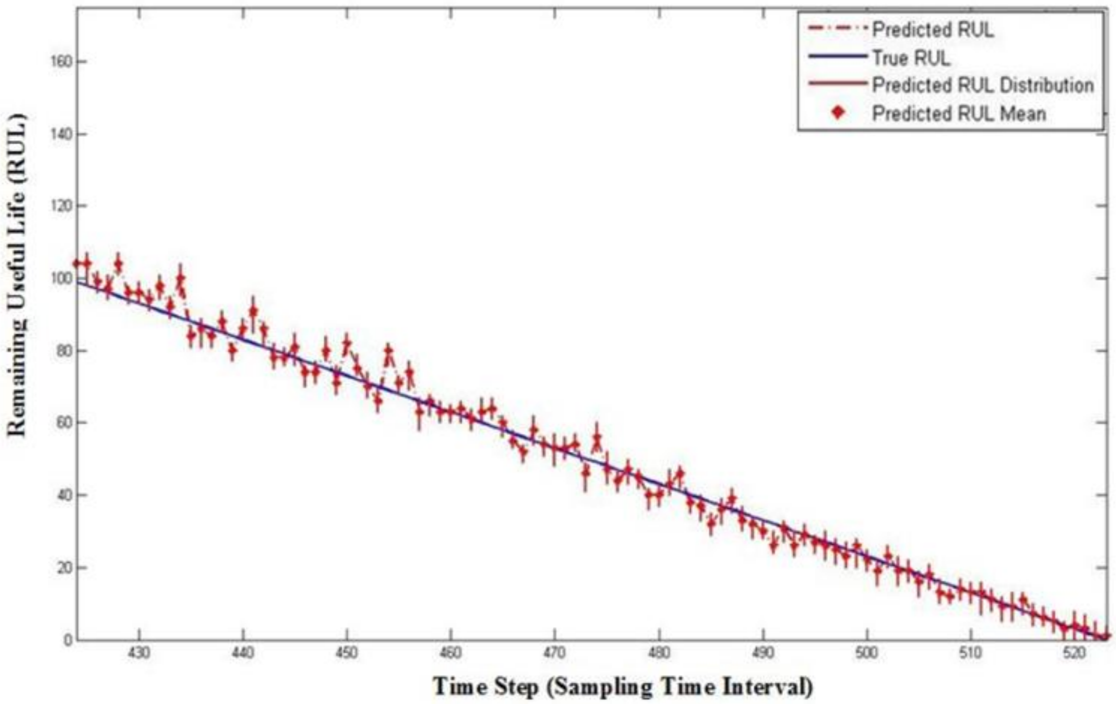


Figure 4.12 RUL prediction with both kinematic viscosity and dielectric constant observation data (particle population=50)

### 4.3. Particle Commination Simulation Case Study

#### 4.3.1. Simulation Model Construction

In order to implement particle filter technique, a field scenario needs to be simulated with the developed physics models. A temperature template was used to simulate a daily temperature variation of the wind turbine (Figure 4.13). The simulation was designed as following:

1) The particle contamination propagation was assigned as the state.
2) The viscometer and dielectric constant sensor output were assigned as observations.
3) Iron contamination is selected as the specific particle contamination case.
4) The simulation model was run for a month (30 days, 720 hours).

5) By the end of the month, the particle contamination (state) reached at 200mg/L.

6) The sampling time interval was set to every 20 minutes (total 2160 time steps).

7) The failure threshold is set as 150 mg/L which is the industry particle contamination acceptable limit.

8) At approximately the 2077th time step, the particle contamination ratio reached 150mg/L.

9) The particle population was set variously from 50 to 10000.

10) The *l*–step-ahead prediction started approximately 150 time step before the particle contamination ($x_k$) crosses the failure threshold.

11) RUL would be displayed for the last 100 time steps only.

Figure 4.14 shows the true trajectory of the particle contamination ($x_k$). Under specific circumstances (i.e. a fixed temperature), the state change is observed for 720 hours.

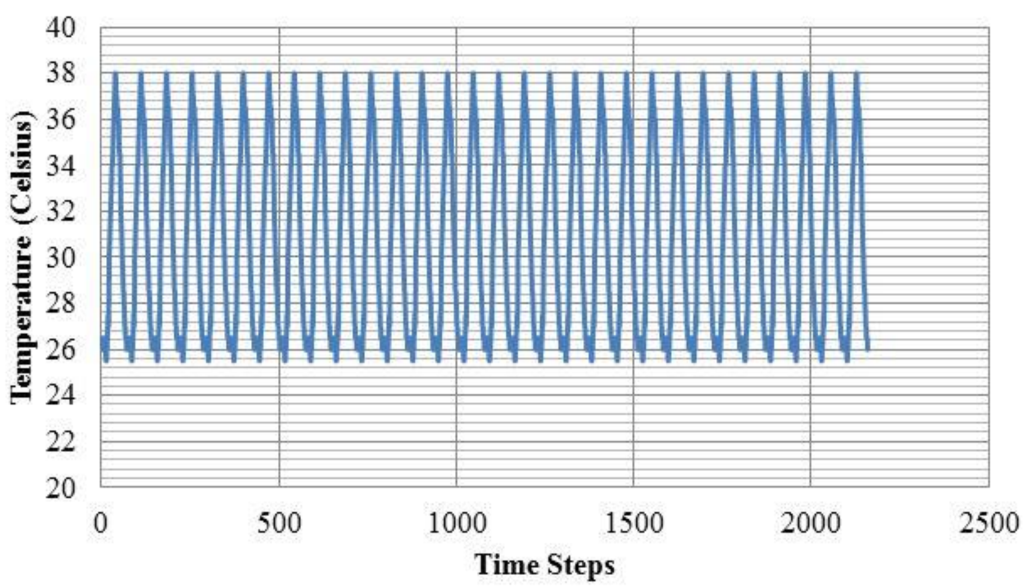


Figure 4.13 Temperature variation template

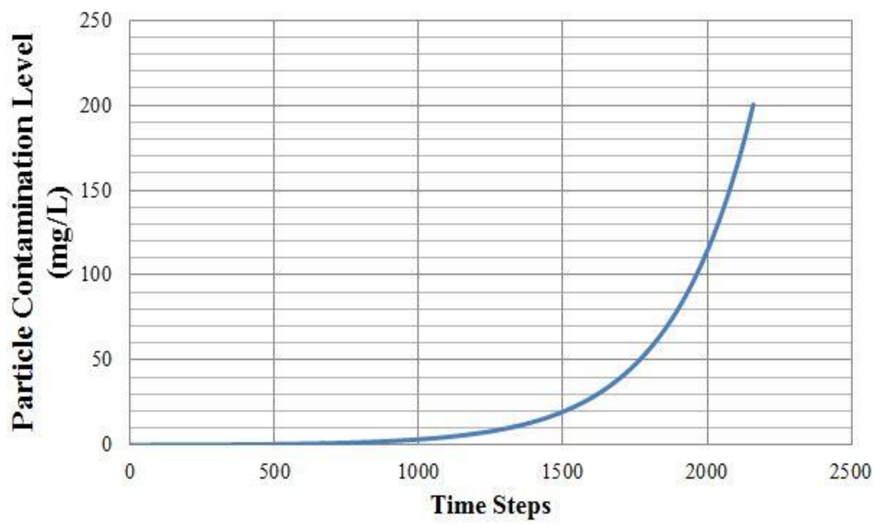


Figure 4.14 Particle contamination propagation template

### 4.3.2. Particle Filtering Implementation for RUL Prediction

In order to meet the requirement addressed above, the state transition function was constructed as:

$$x_{k+1} = 1.00352 \cdot x_k + v_k \tag{4.10}$$

where the process noise covariance is given as $v_k \sim \mathcal{N}(0.0007^2)$. After combining the equations in the physics simulation models, the observation models for kinematic viscosity and dielectric constant can be expressed in mathematical forms as following:

$$z_k^{viscosity} = 57470.5189 \cdot (1 + 2.5\, x_k + 14.1\, {x_k}^2) \cdot {T_k}^{-1.935} + w_k^{viscosity} \tag{4.11}$$

$$z_k^{DC} = 4.20444 \cdot \left(1 + \frac{3x_k}{1 - x_k}\right) \cdot {T_k}^{-0.121} + w_k^{DC} \tag{4.12}$$

Also, the vector form (2nd dimensional) of the observation model can be written as:

$$\boldsymbol{z_k} = \begin{bmatrix} z_k^{viscosity} \\ z_k^{DC} \end{bmatrix} = \begin{bmatrix} 57470.5189 \cdot (1 + 2.5\, x_k + 14.1\, {x_k}^2) \cdot {T_k}^{-1.935} \\ 4.20444 \cdot \left(1 + \frac{3x_k}{1 - x_k}\right) \cdot {T_k}^{-0.121} \end{bmatrix} + \boldsymbol{w_k} \tag{4.13}$$

And the observation noise covariance term was factorized as:

$$\boldsymbol{w_k} = \begin{bmatrix} w_k^{viscosity} \\ w_k^{DC} \end{bmatrix} \tag{4.14}$$

where each observation noise covariance terms were computed based on the compensated observation data sets and derived as $w_k^{viscosity} \sim \mathcal{N}(0, 0.1^2)$ and $w_k^{DC} \sim \mathcal{N}(0, 3.3571e-6^2)$.

Also, with the purpose of reducing observation data fluctuation and improving RUL prediction stability, a temperature compensate module had to be integrated into the physics model. With reference to 30 degree Celsius, which was the median temperature of the operating condition in 24 hours cycle, the observation data was adjusted according to viscosity or dielectric constant functions with respect to temperature. The true viscosity or dielectric constant can be calculated by the physics models as the simulation output. For example, at a certain temperature, the temperature compensated viscosity is the true value of the viscosity plus the theoretical viscosity difference between 30℃ and current temperature.

The theoretical viscosity was obtained by correlating the true viscosity or dielectric constant output with the according temperature in the simulation model. This correlation procedure utilized the symbolic regression analysis tool which is free and available to developers through Eureqa, software developed by researchers at Cornell University. The symbolic regression algorithm was used to construct general and potential complex relationships, in this case between the true dielectric constant (or viscosity) and temperature. The algorithm relies on genetic programming to search for the best functional/algebraic map between groups of parameters. The symbolic regression algorithm is a generalization to the standard regression problem formulation in that is requires very few assumptions regarding the underlying regression model and the output of the algorithm is a closed form that can easily be implemented on an embedded platform [8]. The symbolic regression technique is very efficient and accuracy to handle complex relationship between parameters with limited system dynamic information. Also, the application of the algorithm effectively automates the process of feature adding or subtracting (or any other manipulation) when compared with the application of linear regression. When it comes to embedded system deployment, the symbolic regression has significant advantages over traditional linear regression.

The temperature compensation calculation can be obtained from the following equations:

$$\varepsilon_{compensate,T} = \varepsilon_T + (\varepsilon'_{30} + \varepsilon'_T)$$

$$= \varepsilon_T + (\varepsilon'_{30} - (0.000055 \times T^2 - 0.01434 \times T + 3.26354)) \quad (4.15)$$

$$\varepsilon_T{}' \quad = \quad 0.000055 \cdot T^2 - 0.01434 \cdot T + 3.26354 \quad (4.16)$$

$$V_{compensate,T} = V_T + (V'_{30} + V'_T)$$

$$= V_T + \left(V_{30}{}' - (0.2178 \times T^2 - 18.5452 \times T + 442.978)\right) \quad (4.17)$$

$$V_T{}' \quad = \quad 0.2178 \times T^2 - 18.5452 \times T + 442.978 \quad (4.18)$$

where

$\varepsilon_T$: the true dielectric constant under temperature $T$

$\varepsilon'_T$: the theoretical dielectric constant under temperature $T$

$V_T$: the true viscosity under temperature $T$

$V'_T$: the theoretical viscosity under temperature $T$

The two following figures (Figure 4.15 and Figure 4.16) present the observation variation before the temperature compensation:

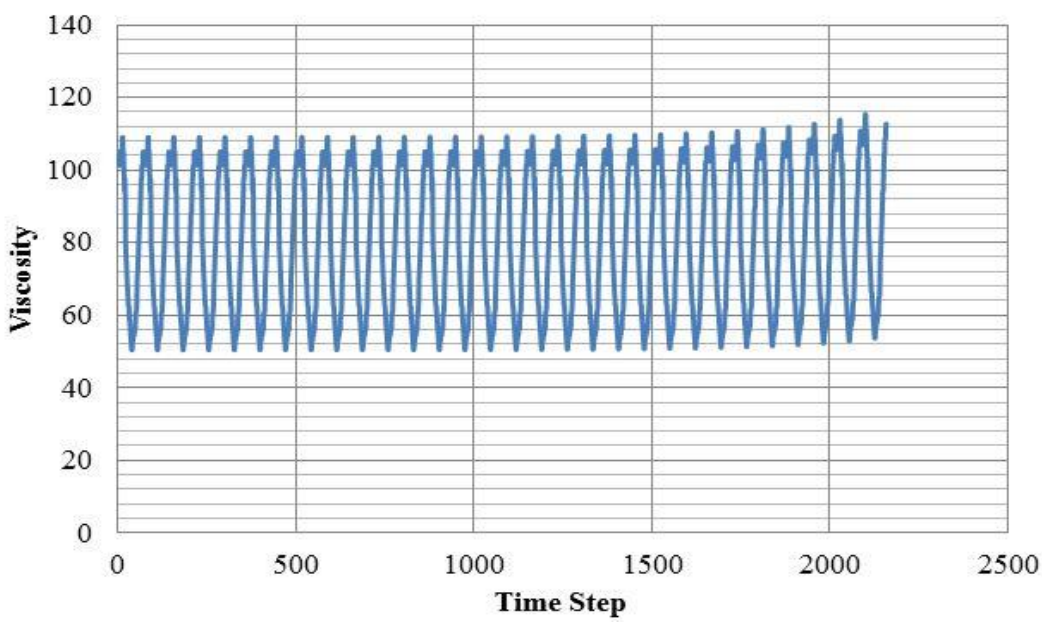


Figure 4.15 Observation data (kinematic viscosity) fluctuation before temperature compensation

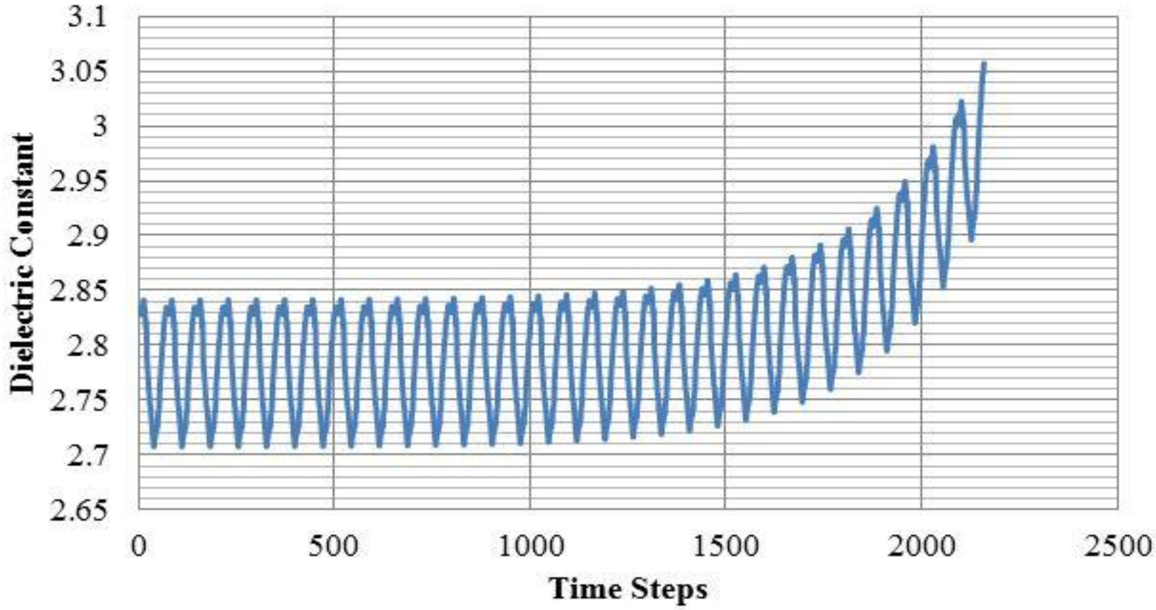


Figure 4.16 Observation data (dielectric constant) fluctuation before temperature compensation

And the two following figures (Figure 4.17 and Figure 4.18) present the observation data variation after the temperature compensation.

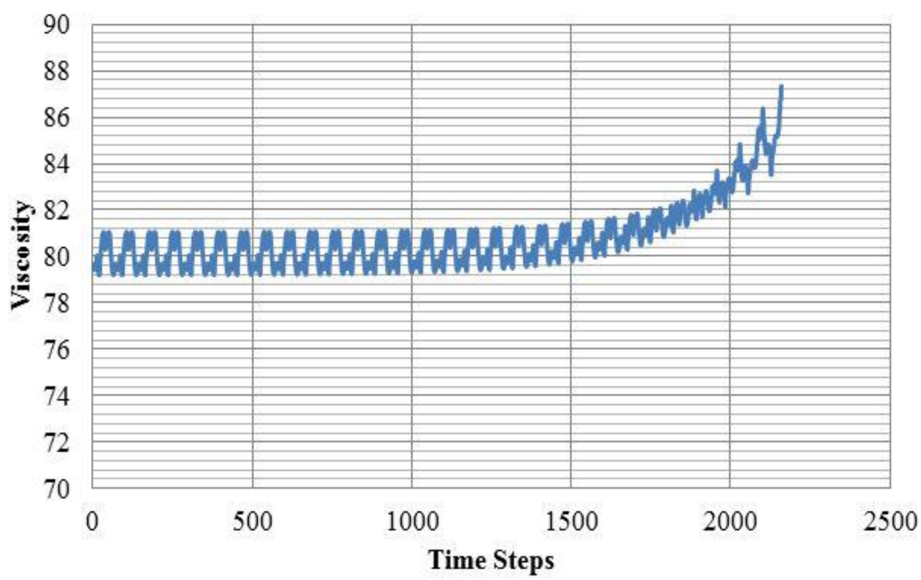

Figure 4.17 Observation data (kinematic viscosity) fluctuation after temperature compensation

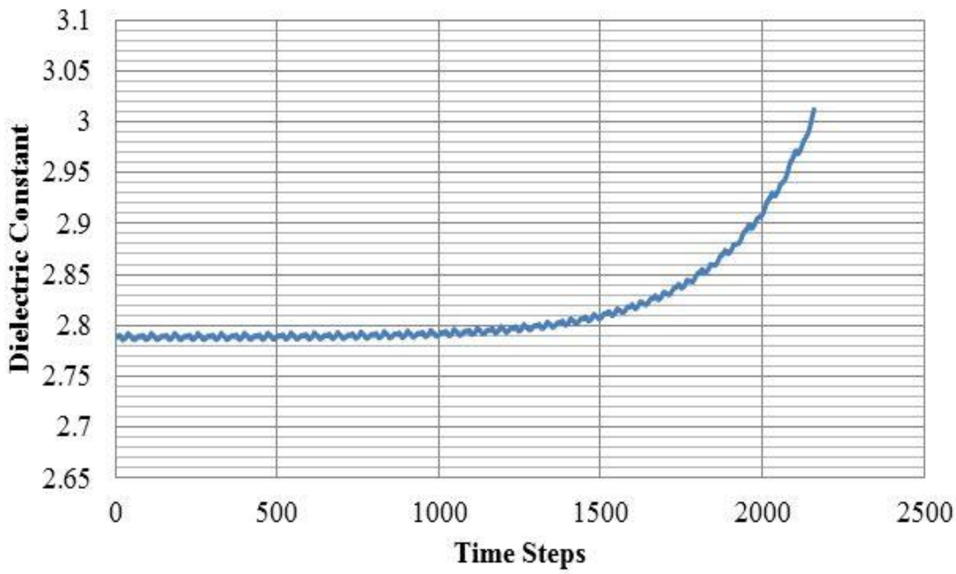


Figure 4.18 Observation data (dielectric constant) fluctuation after temperature compensation

It is quite obvious that the observation data fluctuation was greatly reduced after the temperature compensation. Now the model is ready for RUL prediction.

### 4.3.3. RUL Prediction Result Comparison

In this subsection, remaining useful life (RUL) was numerically computed by changing observations data (viscosity, dielectric constant or both). As described in Chapter 2, Section 2.2 Lubrication Oil Degradation Physics Model Development, two independent observation models were developed, viscosity and dielectric constant, which depict the particle contamination level of lubrication oil. In order to utilize the both observation models in $2^{nd}$ dimensional form, the multivariate Gaussian probability density function were utilized. The probability density function has the following form:

$$\boldsymbol{f_Y}(\boldsymbol{y}) = \frac{1}{(2\pi)^{\frac{k}{2}}\det(\boldsymbol{\Sigma})^{\frac{1}{2}}}\exp(-\frac{1}{2}(\boldsymbol{y}-\boldsymbol{\mu y})^{\boldsymbol{T}}\boldsymbol{\Sigma^{-1}}(\boldsymbol{y}-\boldsymbol{\mu y})) \tag{4.19}$$

Equation (4.19) was used to compute the likelihood in the updating stage. Note that $\Sigma$ is the covariance matrix of observations noise; $\mu$ is the mean; $y$ is a random vector; $k$ is the dimension of the random vector; and $\det(\Sigma)$ is the determinant of $\Sigma$. In this experiment, 50, 100, 1000 and 10000 particle populations were tested. Thus, comparative results along with combinatorial analysis of the observation models and the number of particles are presented.

In the Figure 4.19, RUL prediction for the DC is presented. When *N*=50 particles (top-left) were used, prediction result was burst widely and seems not reliable. But as the particle population *N* increased to *N*=100 and *N*=1000 (top-right and bottom-left), the particle bursting become smaller and smaller. As a result, one can observe that prediction accuracy becomes more reliable if *N*=10000 particles are propagated. From here on, the estimated RUL result of the viscosity and the dual observation cases with *N*=10000 particles are considered in this dissertation.

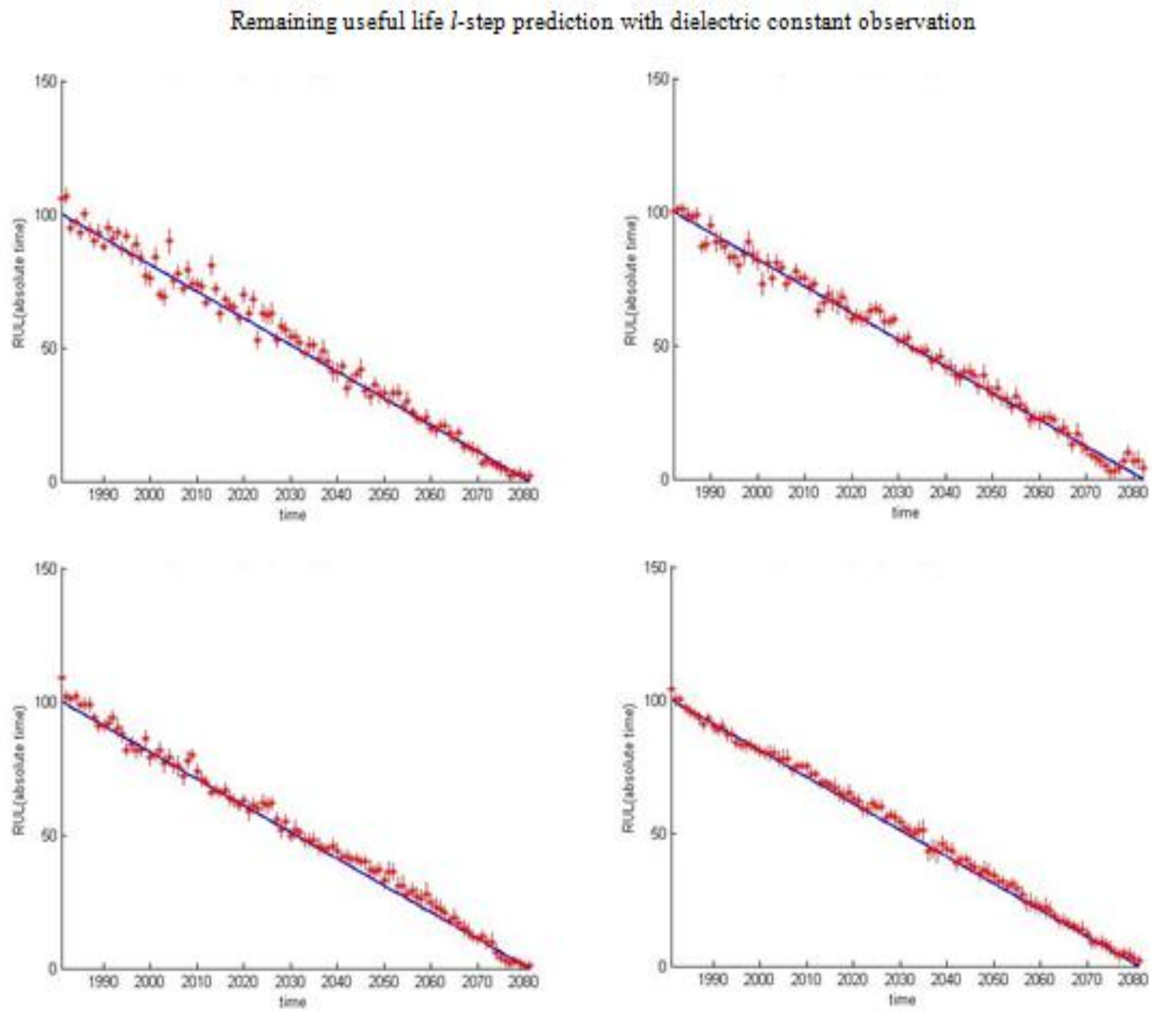


Figure 4.19 Remaining useful life (RUL) *l*-step prediction with dielectric constant (DC) only observation and varying particle population *N*=50(top-left), *N*=100(top-right), *N*=1000(bottom-left) and *N*=10000(bottom-right)

In the Figure 4.20, RUL *l*-step prediction result of the viscosity only (left) and dual observation (right) cases are presented. Note that particle population was set to *N*=10000 for better reliability results. From the left side, one can easily confirm that the DC only case outperforms the viscosity only case. Also, it is obvious that dual observation case displays slightly better prediction performance.

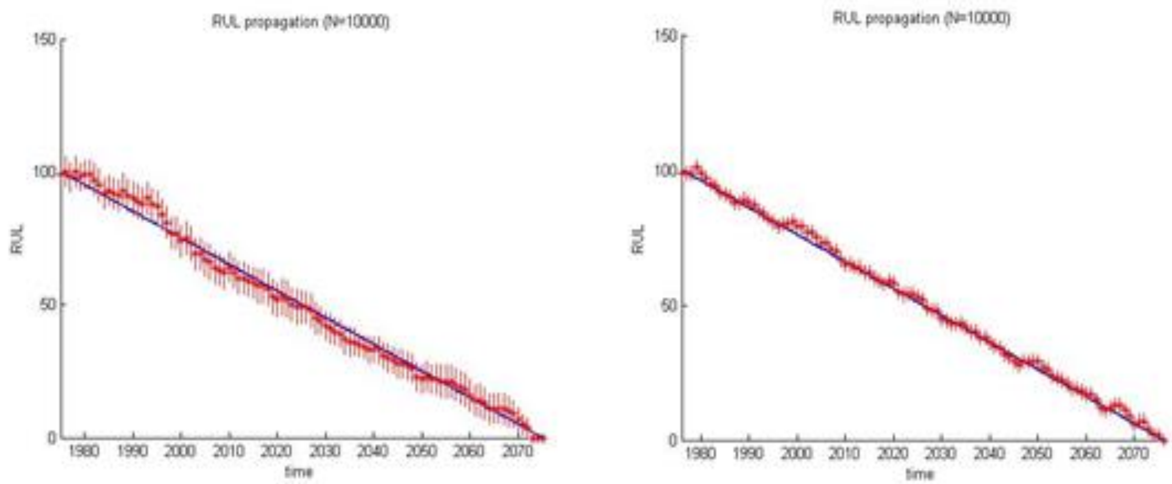


Figure 4.20 Remaining useful life (RUL) *l*-step prediction with the viscosity observation (left) and RUL with dual observation (right) with $N$=10000 particles

In the Figure 4.21, compare the RUL distribution of $N$=50 and $N$=10000. When $N$=50 particles were used. RUL distribution shows more chaotic and likely not following any distribution form. However, when N=10000 particles were propagated with dual observation, RUL distribution displays almost perfect Gaussian (normal) distribution.

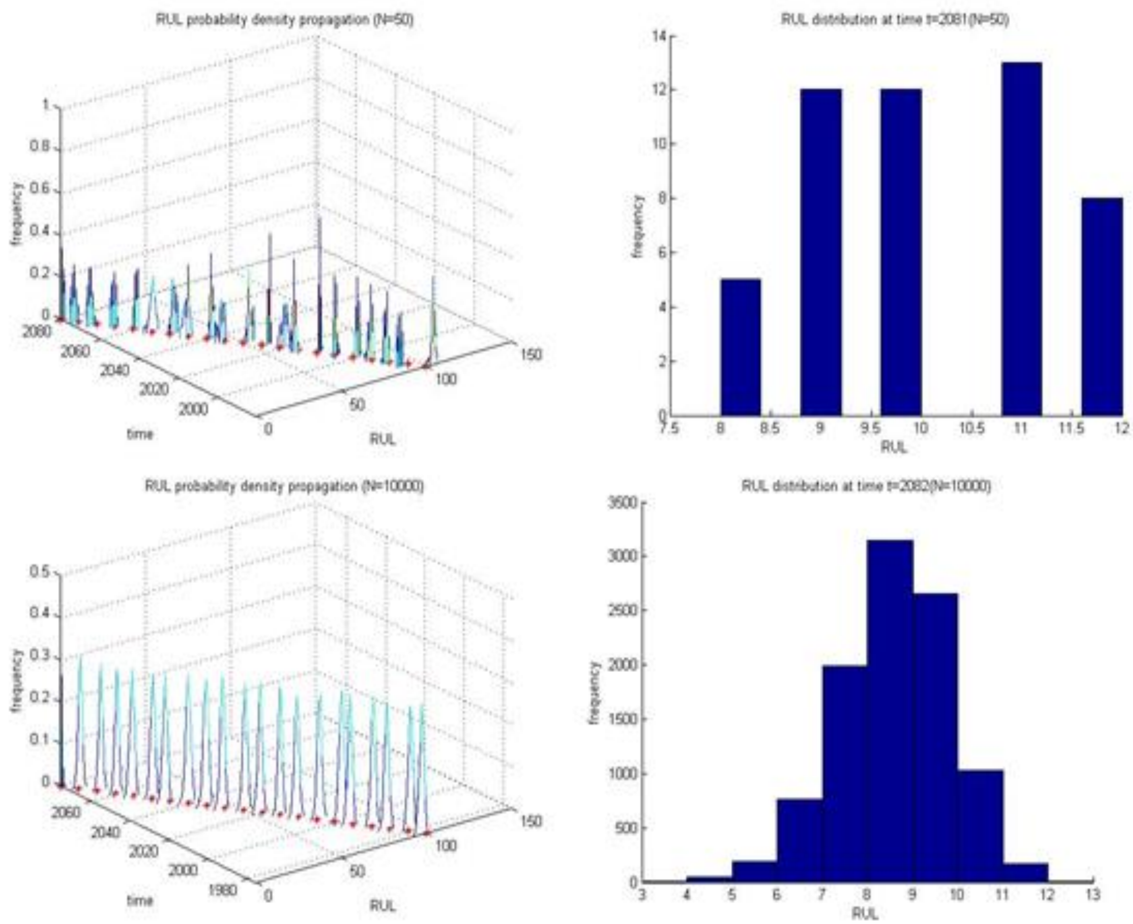


Figure 4.21 RUL propagation with dielectric constant (DC) observation and *N*=50 (top-left), RUL distribution at time step k=2081(top-right), RUL Propagation with dual observation and *N*=10000(bottom-left) and RUL distribution at time step k=2082 (bottom-left)

In the Table 4.2, root mean square error (RMSE) and standard deviation (σ) of the RUL prediction are provided. One can confirm that the accuracy of the RUL prediction increases as the number of particle (N) increases. But notable point is that the highest accuracy was obtained when single DC observation was used. On the other hand, the highest reliability was obtained when dual observation were used (higher reliability was also predictable from the Figure 4.20). Combining DC and viscosity observation compromised the accuracy because viscosity observation was highly fluctuating (compare the Figure 4.17 and 4.18). But it raises the reliability because more information was available.

Table 4.2 RMSE of RUL prediction by varying observations and particle populations

| **Particle population($N$)** | **Single observation** | | | | **Dual observation** | |
|---|---|---|---|---|---|---|
| | **Viscosity** | | **Dielectric constant** | | | |
| | RMSE | σ | RMSE | σ | RMSE | σ |
| **50** | 100.36 | 27.66 | 3.55 | 0.59 | 3.33 | 0.29 |
| **100** | 75.17 | 21.39 | 2.61 | 0.31 | 2.72 | 0.20 |
| **1000** | 63.36 | 37.65 | 2.08 | 0.30 | 2.38 | 0.12 |
| **10000** | 56.17 | 21.36 | 2.06 | 0.23 | 2.28 | 0.08 |

In the Table 4.3, one can also recognize that more processing time is required as more particles are used. Especially in dual observation case, approximately 15~20% more processing time was consumed due to dimensional increment.

Table 4.3 Processing time of varying observations and particle populations

| **Particle population($N$)** | **Single observation** | | **Dual observation** |
|---|---|---|---|
| | **Viscosity** | **Dielectric constant** | |
| **50** | 20.26 (sec) | 20.53 (sec) | 22.76 (sec) |
| **100** | 31.54 (sec) | 30.95 (sec) | 34.54 (sec) |
| **1000** | 257.83 (sec) ≈ 4.30 (min) | 255.64 (sec) ≈ 4.26 (min) | 309.60 (sec) ≈ 5.16 (min) |
| **10000** | ≈ 15.24 (min) | ≈ 15.61 (min) | ≈ 18.65 (min) |

## 4.4. Discussions

In this chapter, the physics models developed in Chapter 2 and the particle filtering techniques presented in Chapter 3 were utilized and integrated into several simulation case studies to validate the proposed online lubrication oil condition monitoring and remaining useful life prediction algorithm. The simulation case study only discussed the water or particle contaminated lubricant. In the future, if lubrication oil oxidation degradation can be successfully modeled either by physics based method or data driven modeling method, it would be interesting to test the models in simulation case studies designed in this chapter. At the moment, some ideas were proposed to quantify the oxidation experimental simulation test. Stable radical are needed and total acid number or total base number test kits are needed.

The simulation case study result showed that the developed lubrication oil RUL prediction tool was effective and can be integrated into the current industry condition based maintenance expert systems like Supervisory Control and Data Acquisition (SCADA) system. Also, the RUL prediction results of the simulation case study showed that when only one sensor was utilized (single observation), the RUL prediction with particle filtering had a slight fluctuation around the true RUL at the beginning of the prediction process. When both viscosity and dielectric sensors were used, the prediction fluctuation at the beginning was reduced and the RUL prediction accuracy was greatly improved throughout the entire prediction process. Also, larger particle population increased prediction accuracy. However, as particle population increased, the computational time for RUL prediction increased along with it. Therefore, for condition monitoring and RUL prediction to provide feasible solution for maintenance management, one have to balance between, number of observations, particle populations, RUL prediction processing time, prediction accuracy and so forth. Instead of providing only prediction result, the developed oil RUL prediction algorithm is very flexible and can adaptively meet the need of different practitioners and industries.

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# CHAPTER 5

# SUMMARY AND PERSPECTIVES

## 5.1 Summary

In this dissertation, lubrication oil degradation basic degradation features have been investigated. Lubrication oil degradation is classified into three categories: particle contamination, water contamination and oxidation which are defined as three basic degradation features. A comprehensive review of current state of the art lubrication oil condition monitoring techniques and solution has been conducted. Viscosity and dielectric constant are selected as the performance parameters to model the degradation of lubricant based on the result of the literature review. Physics models have been developed to quantify the relationship between lubricant degradation level and the performance parameters. Commercially available viscosity and dielectric sensors have been acquired and installed in a temperature controlled chamber to validate the developed performance parameter based lubrication oil deterioration physics models. Water and particle contamination are the most common oil deterioration features. Therefore, it is essential to keep monitoring the water and particle content of the lubricant. Particle filtering techniques are introduced and adapted to predict the remaining useful life of lubrication oil based on the developed physics models. In the particle filtering algorithm, state transition function was constructed to estimate the fault progression. Observation function was assembled based on the output of the sensors (physics model based on state transition function) which are viscosity and dielectric constant, respectively.

The developed prognostic methodology has been implemented into two case studies to test the effectiveness and the robustness of the developed RUL prediction algorithm. The first study is an industrial scenario simulation with progressing water contamination. The second case study is an industrial simulation with progressing iron contamination. Temperature compensation module has been integrated to smooth the prediction result. The impact of the number of observations (number of sensors implemented), particle populations have been investigated and compared.

The contributions of the research described in this dissertation are summarized as follows:

1) A comprehensive investigation and evaluation on current state of the art oil condition monitoring techniques and solutions have been conducted. The results of the investigation have showed that viscosity and dielectric constant sensors are capable of performing online oil condition analysis. This investigation is the first publication that systematically summarized and evaluated current oil condition monitoring solutions in the industry and academia, commercially available and under development.

2) Physics based models for lubrication oil performance degradation evaluation have been developed. The two most common basic degradation features: water contamination and particle contamination have been both successfully modeled and validated. Commercial available dielectric constant sensor and viscometer have been acquired and utilized in lab based simulation tests to validate the developed physics models. Most oil degradation models reported are data driven, this research is the first one that developed physics based models to describe the degradation of the lubricant and also the first one to use physics based model to perform lubrication oil remaining useful life prediction.

3) With the help of particle filtering technique, the remaining useful life prediction of lubrication oil has been successfully performed. The developed physics models have been integrated into the particle filtering framework as observation functions. The state transition function can be correlated based on previous experience and data of the system dynamics. Also within the particle filtering algorithm, an *l*-step ahead state parameter prediction and RUL estimator have been developed to enable this technique to perform *l*-step ahead prediction while most of other papers published just show one-step prediction. Therefore the developed RUL prediction technique is capable of providing practical and feasible solution to the current condition based maintenance systems. This is the first time particle filtering technique was successfully implemented to predict the remaining useful life of the lubrication oil.

4) The developed lubrication oil condition monitoring and RUL prediction technique has been validated using two simulation case studies, water contamination case study and particle contamination case study. Within the industrial simulation model, a temperature compensation module has been integrated into the physics model and RUL prediction algorithm. This module enhances the lubrication oil condition monitoring and RUL prediction algorithm so the developed technique can handle highly fluctuating operating temperature conditions with reliable and consistent RUL prediction result.

## 5.2 Topics for Future Research

After the successful development and validation of the physics models for water and particle contamination, there are still many topics that need to be covered in the future. Since only two of the three basic degradation features are covered. Lubrication oxidation degradation remains to be unsolved. The reason is that the lubrication oxidation is a very complicated process and is very hard to quantify. Therefore lab based oxidation simulation experiment is hard to perform. However, based on our preliminary research, some feasible ideas have been proposed. Based on recent literature and product simulation tests from other companies, the author suggests using a stable free radical named DPPH. The most common performance parameter to describe the oxidation degradation of lubrication oil are total acid number (TAN) and total base number (TBN). It is very likely that oxidation process will have a data driven model as system dynamic model. In order to be able to validate the oxidation model, one needs to design experiments and be able to quantify the relationship between DPPH concentration level and the TAN level. However, the relationship between the level of DPPH and TAN calls for further investigation. Therefore, a much longer time period is required for the research. Oil samples that have TAN labeled on them will definitely help. Additional time is needed to investigate the relationship between TAN and the amount of DPPH. In order to evaluate the level of oxidation simulated by DPPH, TAN test kit is needed for comparison. Total Acid Number test kit can be purchased from Kittiwake. The order information is

FG-K24743-KW, ECON TAN drop test kit. The product catalog is available online. This kit can perform the test 25 times. Two or more of these kits may be needed for future tests. DPPH can be purchased from Sigma Aldrich for $273.00 (5g). Currently, the amount needed for the oxidation test is uncertain. There is always a possibility that more DPPH may be needed in the future. Because the DPPH has human health impact categorized as Health Hazard GHS08, laboratory protection equipment is also needed including rubber gloves, cloth towels, goggles and respirators with spare filters.

Once the lubrication oil oxidation model is developed and validate, there are still many things in the future that needs to be considered. Under practical industrial operating condition, there is usually more than one kind of basic degradation feature exists in the circulation system. Also, oxidation, water contamination, particle contamination are not mutually exclusive. Water contamination causes oxidation. Oxidation normally leads to water contamination and particle contamination. Most of the mechanical systems do offer high levels of filtering to get rid of the contaminated particle as much as they could. However, most oil circulation systems, except from at the point of the oil breather, are designed to be perfectly sealed from the ambient environment. Hence, once water gets into the circulation system, it is very hard to get out. In the future, one needs to develop physics or data driven models for coexisting basic degradation features. Due to the complex nature of the coexisting contamination degradation, it seems more likely that data driven model is the way to go. Once the model that can hand multiple contamination coexisting oil degradation, one can always try to use particle filtering technique to predict the remaining useful life of the lubricant.

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