

Providing Embedded, In-situ Oil Quality Monitoring for Improved Maintenance and On-Board Diagnostics in Trucking and Automotive Applications

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ABSTRACT

This paper presents the development of a fluid quality sensor to provide a real-time, on-board oil quality assessment capability for commercial, military, and off-highway vehicle applications. The sensor provides for improved vehicle health state awareness and enables a condition-based approach to lubricant maintenance. The technology is based on a broadband approach to electrochemical impedance spectroscopy (EIS) and is applicable to all high impedance fluids. The EIS results are fused with the measurements from a capacitive relative humidity sensing element and are normalized with respect to temperature as measured by an embedded thermistor. The authors' experiences in developing, packaging, and testing this technology are chronicled.

INTRODUCTION

Lubricants are the life-blood of modern machinery, serving to remove heat, prevent wear, and provide corrosion resistance. Automotive lubricants are no exception, and proper maintenance of these lubricants is vital to engine, transmission, and gearbox health. For these reasons, standard practice is either to maintain on a conservatively set schedule, or to move towards condition based monitoring by employing traditional lubricant condition monitoring using periodic sampling and laboratory analysis.

In terms of the sampling approach, it has some key disadvantages. This includes being time consuming, labor intensive, costly, and error prone. Sampling location; container cross-contamination; and test methodology, accuracy, and repeatability can all contribute as sources of error. Laboratory analysis reports require significant expertise to interpret, making the transition from 'data' to actionable 'knowledge'

difficult. Perhaps most importantly, off-line oil analysis also suffers from potentially lengthy turn-around times to wait for results. This opens a window for equipment damage during the "unmonitored" lag period.

A technology which can monitor the condition of vital automotive lubricants in an on-line, continuous manner in order to eliminate assumptions inherent in schedule-based maintenance practices, and to overcome the difficulties associated with traditional sampling and laboratory analysis methods, is therefore necessary. Significant long term cost savings from reoccurring maintenance expenses, productivity down-time, requiring 'spares', and avoidance of losses due to previously unforeseen catastrophic failure can be realized. A continuous stream of system and component health information means equipment can be serviced when it is truly needed, maintenance can be planned in advance based on this health, and emerging equipment problems can be caught and dealt with before they become costly.

Modern lubricants have been designed to accomplish a wide variety of critical tasks. Complex additive packages are employed to protect metal surfaces, extend the range of lubricant applicability, and extend lubricant life. If any one portion of this chemical system ceases to function properly, the lubricant must be serviced. Sensing oil quality online is then complicated by the multitude of potential failure modes. Unfortunately, these modes are not all observable through the monitoring of a single bulk fluid parameter (e.g. viscosity) [1]. This means it is not acceptable to rely on a sensing method which only captures a single fluid failure mode for an oil quality evaluation.

Technical difficulties associated with an online oil quality sensing technology include requiring operation over a wide temperature range and under severe vibration,

operating in the presence of extreme contamination (i.e. from water, fuel, acids, sludge and varnish), and continued operation over the life of the vehicle [1]. To be valuable, the technology must generate actionable knowledge which is useful to operators, maintainers, and life-cycle managers. “Actionable” information includes lubricant remaining useful life (RUL) estimates, as well as fluid failure mode identification and quantification (i.e. depletion of additive package, oxidation, contamination by water, fuel, glycol, soot, etc). Of course, all this must be accomplished in a cost-effective manner.

SENSING ARCHITECTURE

As is depicted in Figure 1, three sensing elements are employed to assess oil quality. A set of conductive electrodes are used to perform the EIS measurement, a capacitive relative humidity element is used to help resolve failure mode ambiguity groups, and a thermistor is used to normalize EIS and RH results with respect to temperature. In order to operate in different lubricants which could exhibit impedances that differ by several orders of magnitude, a software reconfigurable gain selection and signal conditioning module was designed into the device’s electronics. The embedded system is facilitated by a microcontroller that performs data acquisition, analysis, and communication functions.

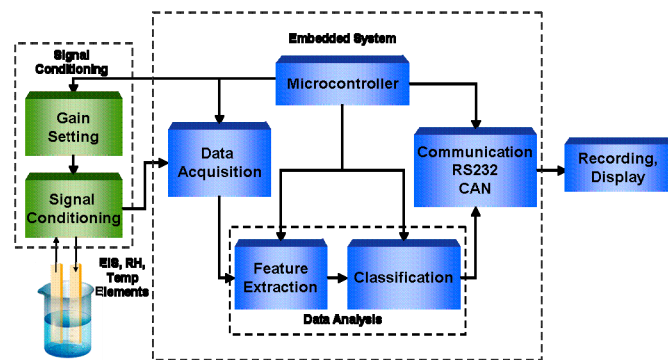


Figure 1: Oil Sensor System Architecture

ELECTROCHEMICAL IMPEDANCE SPECTROSCOPY (EIS) MEASUREMENT TECHNIQUE

The measurement backbone of the oil quality sensing technology is a novel approach to electrochemical impedance spectroscopy. Electrochemical impedance spectroscopy (EIS) is a well-known technique for characterizing corrosion, thin films, curing processes, batteries, etc. For example, Kozlowski et al [2] explored techniques for using impedance spectroscopy to model electrochemical cells for predicting state of charge and state of health in batteries. In the case of lubricant quality sensing, the principal idea is that changes in fluid health due to additive package depletion, oxidation, contamination, etc, manifest themselves in the electrochemical properties of the fluid. EIS provides a means to quantify these electrochemical properties, which can be subsequently mapped to fluid quality, failure mode, etc via statistical classifiers.

In EIS measurement, an AC signal is injected into the system of interest. The electrical signal is measured

after it has passed through the system. The excitation and response signals are then compared [3]. In traditional laboratory applications of this technique the system of interest is interrogated using a succession of single tones over an extended period of time (e.g. 50 minutes) to generate a full-spectrum impedance response of the fluid [4]. The possibility of large errors that would come from environmental or engine operational changes during this timeframe precludes its use in an online monitoring system. So as to not lose the valuable information included in the broadband impedance response of the fluid, Impact developed a method for EIS interrogation using a single broadband AC signal that includes a wide range of frequency content.

Frequencies selected for inclusion in the signal are logarithmically spaced and, depending on the class of fluid, vary between DC and 10kHz. Equation 1 is used to generate this series of frequency values for a given decade D.

$$f_D(n) = 10^{\left(D + \frac{n}{N-1}\right)} \text{ for } n = 0, 1, 2, \dots, N-1 \quad (1)$$

where N is the number of frequencies desired and D is the decade the frequencies should span. High frequency interrogation signals result in stronger response signals due to the capacitive nature of the measurement. For this reason, the interrogation is accomplished decade by decade (i.e. 1Hz to 10Hz with D=0, 10Hz to 100Hz with D=1, etc.) and is reassembled in post processing. The measured response signal is dynamically scaled to take advantage of the full range and bit resolution of the embedded analog to digital converters. Equation 2 defines the generation of the interrogation waveform itself, $W_D(t)$.

$$W_D(t) = A \cdot \sum_{n=0}^{N-1} \sin\left(2\pi \cdot 10^{\left(D + \frac{n}{N-1}\right)} \cdot t\right) \quad (2)$$

Here A is a scalar set to obtain the desired voltage magnitude, D defines the decade desired, and N is the desired number of log spaced tones. This results in an interrogation waveform for a given decade similar to that depicted in Figure 2.

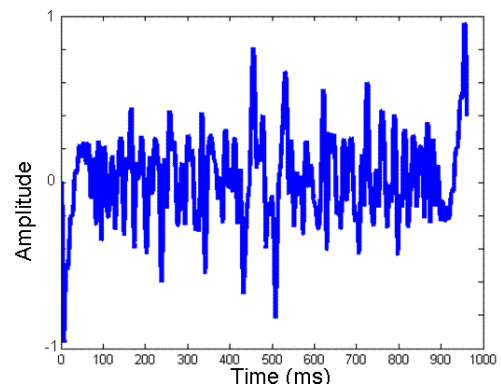


Figure 2: Interrogation Signal

Since current is difficult to measure given the high impedance of the fluids of interest, a circuit configuration was developed that allows for measurement of impedance with low-powered (5mW) signals. A simplified view of this circuit is depicted in Figure 3.

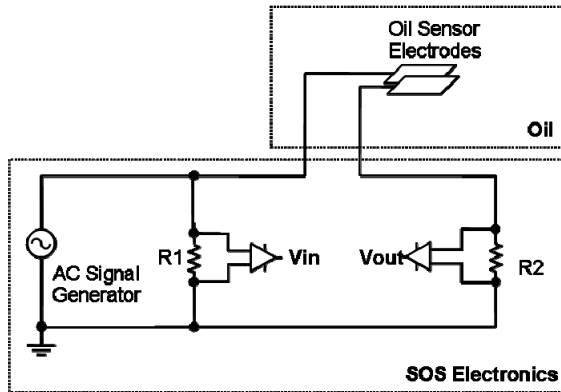


Figure 3: EIS Measurement Circuit

V_{in} and V_{out} are measured across the reference resistors R_1 and R_2 , and the measured waveforms are stored in memory. Windowing algorithms and Fast Fourier transforms are applied to the interrogation and response signals. Peaks that correspond to frequencies in the interrogation signal are autonomously located and magnitude and phase information is extracted. These magnitude and phase data are calculated using Equation 3, where R is equal to the value of R_2 in Figure 3.

$$Z_{OIL}(\omega) = \frac{V_{IN}(\omega t) - V_{OUT}(\omega t - \phi)}{V_{OUT}(\omega t - \phi)} \cdot R - Z_{SENSOR} \quad (3)$$

A common way to represent this impedance data is a Nyquist plot like that depicted in Figure 4 (multiple Nyquist “curves” are plotted). The impedance data is converted from polar to rectangular coordinates through the employment of Euler’s relation. These X and Y values on a Nyquist plot represent the real and imaginary components of the oil’s impedance respectively. These plots provide a means to assess magnitude and phase data simultaneously.

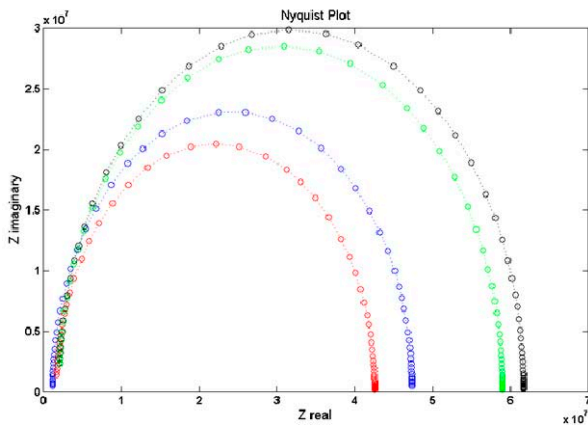


Figure 4: Representative Nyquist Curves

DATA FUSION AND CLASSIFICATION

The impedance data captured by the EIS measurement was fit to an electrochemical model of the fluid under test using a linear least squares regression.

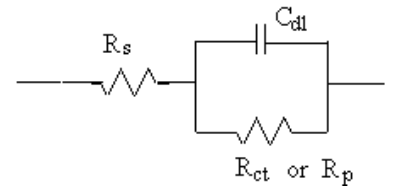


Figure 5: Randles Cell

The Randles Cell, as pictured in Figure 5, is a simple and common electrochemical cell model. It consists of a bulk solution resistance R_s , a double layer capacitance C_{dl} , and a charge transfer / polarization resistance R_{ct} or R_p [5]. Fitting the measured impedance data to an electrochemical model like the Randles Cell connects the fluid quality assessment to actual physical processes in effect in the oil. As the fluid degrades or becomes contaminated these physical process are affected, and the values of the elements in the electrochemical model will change accordingly.

The calculated values of the elements in the electrochemical model, along with temperature and the relative humidity measurement were used as inputs to a three tiered classifier (Figure 6) which mapped these values to fluid quality. This method required the generation of a set of ground truth data which linked electrochemical features to fluid failure modes, contaminants, and quantities. The classifier was used to compare a new observation of electrochemical data to previously observed values in this ground truth dataset. The classifier then calculated an estimate of fluid quality based on the ground truth dataset’s corresponding fluid quality feature vectors. This dataset was constructed in the laboratory using a series of designed experiments which will be discussed in later sections of this paper.

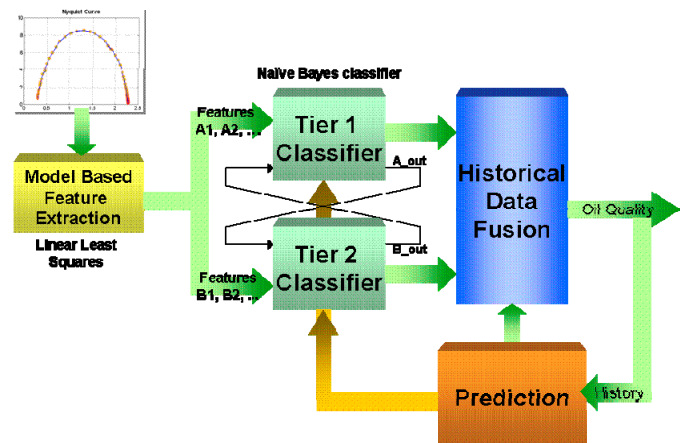


Figure 6: Classifier Architecture

Both real time data and historical sensor outputs were used to reinforce classification. A cross coupled architecture linked the first and second tier classifiers, forcing them to find a mutually acceptable classification; this served to increase stability and accuracy while keeping overall system complexity low. A Bayesian