EXPERT SYSTEMS, A DECADE OF USE
FOR
USED-OIL DATA INTERPRETATION

Larry A. Toms

Larry A Toms Technical Services
5018 High Pointe Drive
Pensacola, FL 32505-1825,
TEL: (904) 494-1310

ABSTRACT

Pressed by the need to improve oil analysis performance, some equipment operators have increased sampling frequency (shortened intervals) in order to increase the probability of early fault detection. As a consequence, laboratory labor costs increased considerably--quadrupled in some cases. Over the past 10 years, expert systems have been increasingly used to compensate for the increased processing time by automatically interpreting sample data in near real time, improving evaluation reliability and minimizing the associated labor costs.

A properly designed expert system can quickly review all recorded equipment and sample data, while keeping the analysis time and costs within acceptable levels. These systems greatly increase data interpretation consistency, and can generate significant returns-on-investment. This paper presents an overview of several of these systems and the general principles utilized in their development.

KEY WORDS: Expert system; fault detection; fault library; knowledge based systems; oil condition monitoring; railway systems; statistical process control; used-oil analysis

INTRODUCTION

Used-oil analysis, pioneered by American railways and the Department of Defense, has led to significant reductions in unexpected equipment failure and has increased equipment reliability and safety of operation[1]. The traditional used-oil analysis process is based on frequent periodic samples, simple-to-use test methods and trained oil analysts to evaluate findings and advise maintenance personnel of a required action. The high sampling frequency required for reliable monitoring of diesel powered (< 250 hours) and gas turbine powered (< 25 hours) equipment requires substantial labor (and costs) for testing and data interpretation. The greater the sample frequency or the number of tests performed on each sample, the greater the costs involved. In addition, reliable interpretation of machinery and fluid condition requires assessment of many other types of data including, oil related failure mechanisms, their symptoms, effects and costs; machine configuration changes and utilization; scheduled and completed maintenance; etc. Requiring a review of all possible data for every sample is very labor intensive and costly. As a consequence,

Proc: Technology Showcase: Integrated Monitoring, Diagnostics and Failure Prevention, p 65-72, Mobile AL, 1996

the scope of an oil analysis program is often limited to fit the available resources. The usual result is longer sample intervals, less analysis reliability, fewer quantifiable benefits and less confidence in the program.

Pressed by the need to improve locomotive reliability after the recession of 1981/82, the Canadian Pacific Railway (CP) conducted an evaluation of locomotive engine failure modes, their effects and costs[(2)]. One of the outcomes of this evaluation was the conclusion that the used-oil analysis program did not always indicate the occurrence of an oil related engine failure mode prior to failure. In fact, agreement between laboratory recommendations and subsequent inspection or failure reports indicated the laboratory reliability to be about 65%. At the time, CP, as with most railways, obtained engine oil samples during Federal Government mandated inspections at either 46 or 92 day intervals. These intervals were very convenient but failed to respect failure mode duration or timing. Oil analysis at such long sample intervals identified some faults before failure, although sometimes, engine failure was the first sign of trouble. Engine reliability was not considered a serious problem as sophisticated preventive maintenance (PM) procedures kept failure rate down. However, with large fleets of 1000 plus locomotives, even a “low number” can be significant. The 40 or so engine failures per year experienced by CP amounted to several million dollars in loss and it was thought that something could be done to recover these expenditures. It was also thought that more effective monitoring would lead to longer PM intervals with a considerable reduction in maintenance costs.

The failure modes analysis conducted at CP during the mid 1980’s indicated that oil contamination and metallic wear faults were the most prevalent problems and would provide the highest return on investment for an oil analysis program. The symptoms of these faults include coolant contamination, fuel dilution, metallic wear, incorrect oil addition and bad sample recognition. While other oil related faults are possible, they were statistically non-prevalent in the CP locomotive fleet. Analysis of failure mode progression intervals suggested that the sample interval required a significant reduction if the important failure modes were to be monitored reliably. To maximize the probability of early fault detection, CP shortened the sample interval to about 200 to 250 hours of engine operation or about every 7 to 10 running days. This however, resulted in a three-to-four fold increase in the sample collection rate--and a commensurate increase in laboratory labor and consumables’ costs. Offsetting this increase was very desirable and expert systems were investigated as a possible solution.

DEVELOPMENT CONSIDERATIONS

The real world of used-oil analysis presents many obstacles to the expert system developer. Consider the following problems, which had to be overcome during the development of the CP expert system:

1. When the CP system development started in 1984, very little documentation or published work on "used oil" analysis was available. Consequently, the company had to document and validate all of the factors and relationships involved in the used-oil analysis process. Since there were multiple “expert” opinions and very little science, this was a very frustrating process. Taking samples, applying some ASTM tests and reporting the data does not make a condition-monitoring program. One must have a plan, tailored to some objective such as failure prevention, or maintenance costs reduction..

2. As with most traditional practitioners of used-oil analysis, CP compared individual oil measurements to a set of empirical limits and recommended an inspection in the event of a limit exceedence. Little was known about the statistical behavior of sample data, the relationships among data parameters, the relationships between data and fault mechanisms, or the impact of operational policies on data variability. Limits were arbitrarily determined by an “expert” by somewhat mysterious procedures. In summary, the data evaluation procedure depended on the intuitive response of a highly trained person. The procedure was not completely clear and could not provide a reliable expert system. The entire data interpretation process had to be re-thought and developed into a general-purpose paradigm which could be encoded into the available expert system software.

3. Used-oil sample data is subject to frequent change from both reported and unreported events. When a technician encounters a fluctuating data pattern, a variety of intellectual processes can be utilized for interpretation and problem resolution. This is time consuming and very costly, but generally works. However, an expert system does not readily adapt to fluctuating data and should only be used where data variability can be controlled, or the interpretative knowledge can be provided. Fortunately, analysis of several years of test and maintenance history indicated that oil data variability can be brought under control by strict adherence to corporate standard operating, maintenance, sampling and testing procedures. Any remaining sample data variability is usually compensated by an adaptive trending algorithm--part of the expert system implementation.

4. In addition to evaluating sample data, reliable used-oil analysis recommendations require access to, and the evaluation of, a myriad of operational factors including equipment configuration change, maintenance and usage. However, a knowledge base that includes all of these factors, for each different equipment model, function and operational circumstance, will be enormous, difficult to develop and even more difficult to validate and maintain.

A PRACTICAL EXPERT SYSTEM

Consequently, CP decided on a general purpose, statistically based data analysis paradigm, which would be compact, efficient and easy to maintain. The development and validation of this procedure required many months of effort, and the analysis of many thousands of used-oil samples. The new software integrated spectrographic, water contamination and oil viscosity analyses with an expert system for data interpretation. The expert system evaluated all relevant test and maintenance data and significantly improved the performance and consistency of interpretation while eliminating the labor involved. In early 1987, a statistical study of 20,000 samples taken from 1200 locomotives over a 3-month period verified the premise that simple analytical tests performed at a high frequency provided reliable indicators of engine and lubricant condition. The study placed the effectiveness of the CP expert system at 98.6%, with no engines missed[(2)]. By comparison, the oil analysis data interpretation effectiveness before 1986 averaged less than 65%. By the beginning of 1988 oil-related engine failure occurrences at CP were nearly eliminated. In addition, the company moved to a reliability centered maintenance (RCM) program, which significantly extended component life utilization. The move would not have been possible without the availability of up-to-date accurate equipment condition data. Today the shortened interval, consistent analysis and quick turnaround time permits problem engines to be inspected and repaired early, generating substantial savings in materials and labor.

The fact that the original CP expert system is still in operation, and without modification since 1989, attests to its success. In fact, many other equipment operators, including Canadian National Railways, Chinese National Railway, CSX Transportation, Royal Canadian Navy[3] and Royal Navy have implemented oil analysis expert systems based on the general principles first used at CP Rail. While the performance statistics of the military applications are unknown, it should be noted that Canadian National and CSX Transportation also recorded marked improvements in locomotive failure rates and oil utilization after their oil analysis expert systems were commissioned. In each case, a reduction in engine failures of 40% or greater was reported at the end of the first year of operation. These benefits were a direct result of consistent, early problem indication, and improved maintenance scheduling.

GENERAL DATA INTERPRETATION PRINCIPLES

Before an equipment monitoring process can be automated by an expert system, it is necessary to completely understand the equipment system in terms of how it behaves; its inputs and outputs; it's performance, reliability and cost factors, etc. It is also necessary to reduce this information into a set of general principles which can be easily encoded into an expert system knowledge base(4,5). If this is not done, the knowledge base grows at an exponential rate as individual machine related rules and relationships are added. Such a knowledge base is very complex and difficult to validate or maintain. Fortunately, statistical process control (SPC) procedures provide a convenient, compact and general-purpose paradigm for an expert oil analysis system. In a SPC based paradigm, the machinery train or equipment fleet is viewed as a "closed loop" system as shown in Figure 1 below.

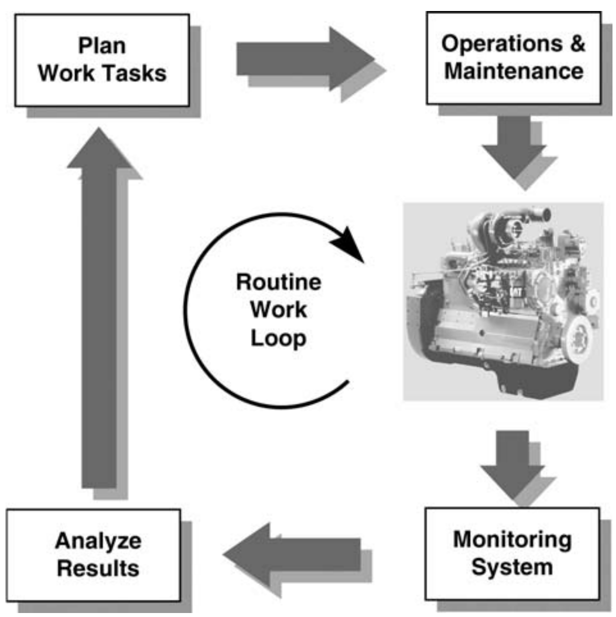

Figure 1: SPC Work Loop (Sequence of events)

In a closed loop system, frequent oil samples provide condition-indicating data (feedback); sample analysis determines the individual component condition and standard responses to direct machine rehabilitation (control). Abnormal sample data identifies failing components; once identified, they are removed, repaired or replaced and cease to become contributors of abnormal data; oil consumption, make-up addition and oil change function to restore sample data to normal levels. Thus, the system attains a dynamic equilibrium and under normal circumstances, a relatively normal frequency distribution.

When the machinery system is maintained by consistent procedures, sample data also tends to be consistent, changing only as a function of equipment usage, a fault occurrence or a maintenance action. Since condition-data variability due to usage and consistent maintenance is predicable, and usage and maintenance data is recorded, condition-data variability due to a developing fault is easily identified. In fact, data deviations caused by some maintenance procedures can be monitored by the occurrence of a particular pattern or trend and provide an additional source of useful information to the maintenance manager. In addition, historical condition-data from a normally operating equipment system can be utilized to calculate statistical alarm limits for each fault signature monitored. Thus, an SPC based condition monitoring system is simple, general purpose, machine independent, easy to automate with an expert system, and easy to maintain once deployed. However, condition-data will only exhibit a “normal” distribution if proper, consistent operating practices are implemented. Any improper practice such as incorrect sampling, improper maintenance, excessive oil change, permitting deep sumps to run low, etc. will profoundly affect system equilibrium and data distribution, with a commensurate effect on the reliability of sample data interpretation and alarm limit calculations.

STATE OF THE ART

Oil data interpretation can be performed by a simple set of data driven procedures using a divide and conquer procedure. The evaluation problem is divided into four main procedures, each with it’s associated databases and rules as shown in Figure 2:

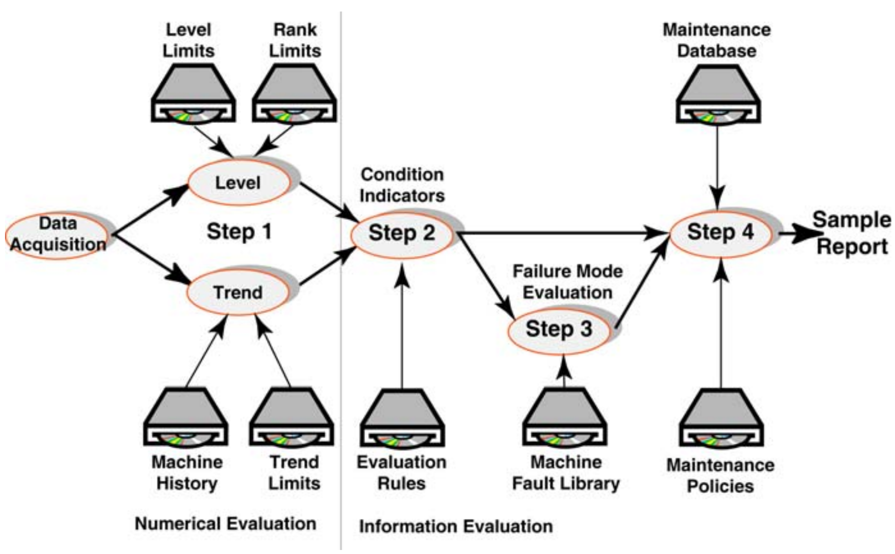

Figure 2: Data analysis process

Evaluation procedure 1 prepares raw data and converts it into symbolic text or status values that carry the meaning imparted by the data. This process uses current sample, historical and statistical data to completely define a parameter's meaning in simple language terms. In this process, each input parameter is considered an object defined by a series of attributes. The symbolic value of each attribute is indicated by plain language, domain related terms. For example:

Input Parameter: Percent Water

Descriptive Attributes:	Level	(Normal, Marginal, Reportable)
	Trend:	(Decreasing, Stable, Increasing, Etc.)
	Rank:	(Hi-Reader, Nominal, Low-Reader)

For simplicity, all input data is defined by the same attributes and each attribute's value is established by statistically based limits. Attribute text phrases are chosen to impart real meaning in human terms.

Evaluation Procedure 2 combines parameter attributes to generate an overall Condition Indicator Status. The status of the condition indicator is related to the maintenance response required by corporate policy should the indicated abnormal status of the parameter be true. For Example:

Condition Indicator: Percent Water

Descriptive Attributes: Normal, Alert, Urgent, Hazard, Danger

Normal	No Action Required, Continue Routine Sampling
Alert	Shorten Sample Interval
Urgent	Maintenance Recommended, Deferral Permitted
Hazard	Maintenance Required, No Deferral Permitted
Danger	Shut Machine Down, Immediate Maintenance Required

Since a condition indicator can sometimes indicate an abnormal state for other reasons such as false positives, bad samples, multiple occurring fault signatures, improper maintenance, unreported maintenance or the lack of maintenance, other evaluation steps are necessary to ensure an accurate response to any indicated abnormal status, and eliminate any potential false positive.

Evaluation Procedure 3 compares all abnormal condition indicator statuses to a library of fault signatures to arrive at a diagnosis. A positive diagnosis increases the certainty that an abnormal data indication is justifiably abnormal and rates a maintenance response. The fault signature library contains signatures for all known faults, bad sample indications, false positive indications, inappropriate trend indications or any known symptom which could impact the accuracy or reliability of an intended maintenance response.

Evaluation Procedure 4 combines diagnosis and condition indicator status levels and generates an overall risk of failure indication. This module searches the user's maintenance database, scheduled maintenance to-do lists for factors, which would alter a maintenance recommendation based solely on condition data. For example, it would be more desirable to inspect or repair a fault at a PM interval and knowledge of the next PM may prevent a request for shutdown and repair of a machine. Similarly, knowledge of recent component and lubricant maintenance would refine the response generated by a purely condition based recommendation. Once the maintenance data is known, the a set of corporate business rules determines the appropriate maintenance response which is printed on the output report.

An expert system based on an SPC based paradigm, such as the one shown in Figure 2 above, can evaluate sample data, rapidly and consistently, and return reliable recommendations for all samples where there is a high certainty of outcome. Favorably, this is over 98% of all samples. In the few cases where there is incomplete data or unusual external factors limiting the certainty of interpretation, the expert system can request re-tests, additional tests, additional samples, or assistance.

The expert systems used by Canadian Pacific, Canadian National and CSX Transportation are excellent examples of the level of reliability that can be achieved using a statistically based data interpretation paradigm. For example the CN and CSX systems operate completely unattended, transmitting recommendations directly to the railways' maintenance shops. The CSX system processes over 700 samples per day and supports the integrity of a fleet of 3000 locomotives providing maximum reliability at a substantial saving in laboratory labor. This level of success can be easily achieved if the following development considerations are followed:

1. Perform a failure modes, effects and criticality analysis for each machine type to determine the failure modes which are most damaging to reliable equipment operations, which are economical to monitor, their respective fault mode symptoms (fault signatures) and the appropriate sampling interval.

2. Select the required analytical tests to be performed on each sample from an evaluation of failure mode symptoms. Only tests which economically provide failure symptom data need to be considered. Use the failure-modes analysis as the primary guidance in the selection of tests. Be wary of traditional testing conventions, many traditional tests were developed for new-oil performance testing, not used-oil condition monitoring. Data parameters that do not relate to fault indicators or bad sample/test indicators only consume resources with little probability of generating a return.

3. Develop a structured set of alarm responses in accordance with maintenance and operational policy. These responses dictate the maintenance measures to be taken when a particular alarm level is encountered.

4. Utilize SPC procedures to calculate an appropriate alarm limit corresponding to each alarm status response. Magnitude, trend and other statistical evaluations may be combined to achieve the desired evaluation matrix.

5. Develop and validate a structured set of condition indicator/failure mode relationships. These diagnostic indicators are encoded into the expert system knowledge base (fault library) to provide the basis for fault diagnosis or verification.

Lastly, integrate the evaluation steps into a logical paradigm such as indicated in Figure 2 above. Divide the data evaluation problem into simple discrete steps, in which simple plain language analysis rules can be used to solve each step. This design provides high run-time performance and is easy to modify and maintain over the long term.

Note: system maintenance and validation procedures are often performed by field grade personnel. It will be very helpful to have the expert system knowledge base and any mathematical formulae encoded in plain domain related language for easy reading and understanding.

CONCLUSION

The development and operation of the oil analysis expert systems over the past 10 years demonstrates that expert system technology is mature and can be used effectively for used-oil analysis automation. The systems implemented at major North American railways also indicate the level of sophistication that can be achieved with low cost expert system technology[(4,5)]. The major lesson learned from the development of these systems is that the key to the successful development of a used-oil analysis expert system requires the establishment of:

1. Simple and reliable 'condition indicators' of equipment failure mechanisms based on oil wear metal and contamination data,

2. Statistically based limits for the magnitude and trend of each condition indicator,

3. Validated fault signatures indicating the relationships between condition indicator variations (or combinations) and specific component failure mechanisms, and;

4. Application of consistent operational and maintenance practices to ensure high data integrity.

REFERENCES

(1) Toms, L., Machinery Oil Analysis - Methods, Automation and Benefits, Chapter 1, Sections 1.4 and 1.5, pages 6 to 8, Pensacola, Fl, 1995.

(2) Toms, L., “Lube Oil Analysis, A Knowledge Engineering Perspective” presented at ‘Update 88’ Conference of the National Association of Corrosion Engineers (NACE), Toronto, Ontario, 1988.

(3) Sams, D., “ The Oil and Coolant Condition Analysis Program (OCCAP)”, proceedings of the 1992 Joint Oil Analysis Program International Condition Monitoring Conference, Pensacola, Fl.

(4) Toms, L. and D.E. Muir, “Expert Systems for Engine Condition Data Reduction and Interpretation”, proceedings of the Third Symposium on Expert Systems at Royal Military Collage, Kingston, Ontario, 1991.

(5) Toms L., “Laboratory Automation and Expert Systems”, proceedings of the 1992 Joint Oil Analysis Program International Condition Monitoring Conference, Pensacola, Fl.