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Standard Guide for Practical Lubricant Condition Data Trend Analysis[1]

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INTRODUCTION

This standard provides specific guidelines for trend analysis, as they are applied to condition monitoring of machinery. The main purpose of trend analysis is to learn how rapidly the machine and fluid are deteriorating. A significant change in trend is indicative of a developing failure. Intervention in the early stages of deterioration is much more cost effective than failure of the machine.

Maximum reliability of in-service machine components and fluids requires a program of condition monitoring to provide timely indications of performance and remaining usable life. To achieve these goals, a condition monitoring program should monitor the rate of progression of the failure by including sufficient tests to determine the rate of degradation, increase of contaminants, and quantity and identity of metal debris from corrosion or wear.

The condition monitoring process determines the presence of oil-related failure modes, allowing remedial maintenance to take place before failure and subsequently expensive equipment damage occurs. In order to diagnose and predict machinery and fluid condition, the rate of change of machine condition must be trended. Equipment maintainers expect conditionmonitoring information to clearly and consistently indicate machinery condition, that is, the rate-of-change of component damage over time and the risk of failure.

Trending utilizes a comparison of a condition parameter with time. For example, plots of a condition-related parameter as a function of time is used to determine when the parameter is likely to exceed a given limit. Forecasting the expected breakdown of a machine well in advance enables the operator to minimize the machine's downtime

1. Scope*

1.1 This guide covers practical techniques for condition data trend analysis.

1.2 The techniques may be utilized for all instrumentation that provides numerical test results. This guide is written specifically for data obtained from lubricant samples. Other data obtained and associated with the machine may also be used in determining the machine condition.

1.3 *This standard does not purport to address all of the safety concerns, if any, associated with its use. It is the responsibility of the user of this standard to establish appropriate safety and health practices and determine the applicability of regulatory limitations prior to use.*

2. Referenced Documents

2.1 *ASTM Standards:*[2]

D4057 Practice for Manual Sampling of Petroleum and Petroleum Products

D4177 Practice for Automatic Sampling of Petroleum and Petroleum Products

D7720 Guide for Statistically Evaluating Measurand Alarm Limits when Using Oil Analysis to Monitor Equipment and Oil for Fitness and Contamination

D7874 Guide for Applying Failure Mode and Effect Analysis (FMEA) to In-Service Lubricant Testing

E2587 Practice for Use of Control Charts in Statistical Process Control

3. Terminology

3.1 *Definitions of Terms Specific to This Standard:*

[1] This guide is under the jurisdiction of ASTM Committee D02 on Petroleum Products, Liquid Fuels, and Lubricants and is the direct responsibility of Subcommittee D02.96.04 on Guidelines for In-Services Lubricants Analysis.

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[2] For referenced ASTM standards, visit the ASTM website, www.astm.org, or contact ASTM Customer Service at service@astm.org. For *Annual Book of ASTM Standards* volume information, refer to the standard's Document Summary page on the ASTM website.

***A Summary of Changes section appears at the end of this standard**

3.1.1 *alarm, n*—a means of alerting the operator that a particular condition exists.

3.1.2 *alarm limit, n*—set-point threshold used to determine the status of the magnitude or trend of parametric condition data.

3.1.2.1 *Discussion*—In OEM provided alarm limits individual measurements are interpreted singly. Most fluid and machine failure modes do not give rise to symptoms identifiable by a single measurement parameter. Early positive identification of a fault generally requires the combination of multiple condition measurements into a unique fault signature. See Guide D7874.

3.1.2.2 *Discussion*—Establishing proper alarm limits can be a valuable asset for interpretation of test results to reflect the equipment's operation. The level and trend alarms can assist the equipment maintainer with reliability control and improvement. With the trending approach established, the machine operator's next objective is to establish guidelines for limits or extremes to which the results may progress to before requiring maintenance actions to be taken. The calculation of alarm limits should initially be developed based on the ideal conditions and limitations from a sample population of condition data, although in reality, ideal conditions are not often met.

3.1.3 *condition indicator, n*—a condition indicator is a variable that is statistically associated with an equipment or lubricant failure modes whose value can be established by inclusion of one or more measurements. Development of a condition indicator involves considerable analysis of equipment test, maintenance and failure histories. Most condition monitoring and analysis systems are centered on the gathering, storage and display of raw test data and trends. Data interpretation generally involves the evaluation of limit exceedence and trend plots.

3.1.3.1 *Discussion*—A condition indicator should be unambiguous in its indication of a problem. The minimum requirement is that a combination of condition measurements and equipment usage provides a reliable indication of a specific machine or lubricant problem without ambiguity. A condition indicator should be statistically well behaved. It should stay within defined bounds given by the variability of machine-to-machine performance and instrument reproducibility. It should also be sufficiently sensitive to trigger an early alarm and it should be monotonic in its variation. Reliable warning and alarm limits should be established and maintained.

3.1.4 *condition tests, n*—the requirement for an effective condition monitoring program is utilizing tests that indicate failure modes and in sufficient time to prevent them.

3.1.4.1 *Discussion*—Although the concept of measuring parameters to determine running condition of a system seems simple, a great many additional variables must be considered to ensure reliable condition prediction. These include, but are not limited to, machine type, machine configuration, operational considerations, oil type, oil quantity, consumption rate, maintenance history, etc.

3.1.5 *dead oil sampling, n*—oil sample taken that is not representative of the circulating or system oil due to one of several reasons, including the fluid in the system is static, the sample is taken from a non-flowing zone, and the sample point or tube within the oil was not flushed to remove the stagnant oil in the tube.

3.1.5.1 *Discussion*—Without a proper oil sample, oil analysis techniques are not useful. The most fundamental issue for any oil analysis program is sample quality. Oil samples must be taken using the appropriate procedure for the machinery in question. The sample must be taken from the most effective location on the machine, whether it is via an on-line sensor or a bottled sample.

3.1.5.2 *Discussion*—Maintenance, operational events, and sampling location are major factors affecting sample representation and, thus, the test results. Sampling without regard to location or maintenance and operational activities causes a high level of data variability. High data variability results in poor data interpretation and loss of program benefits.

3.1.6 *lubricant condition monitoring, n*—field of technical activity in which selected physical parameters associated with an operating machine are periodically or continuously sensed, measured, and recorded for the interim purpose of reducing, analyzing, comparing, and displaying the data and information so obtained and for the ultimate purpose of using interim results to support decisions related to the operation and maintenance of the machine.

3.1.7 *machinery health, n*—qualitative expression of the operational status of a machine subcomponent, component, or entire machine, used to communicate maintenance and operational recommendations or requirements in order to continue operation, schedule maintenance, or take immediate maintenance action.

3.1.8 *optimum sample interval, n*—optimum (standard) sample interval is derived from failure profile data. It is a fraction of the time between initiation of a critical failure mode and equipment failure. In general, sample intervals should be short enough to provide at least two samples prior to failure. The interval is established for the shortest critical failure mode.

3.1.8.1 *Discussion*—Sampling, maintenance, and oil additions may not be performed at the precisely specified intervals. The irregular intervals common to most equipment operations have a profound effect on measurement data. In particular, the concentration of wear metals, contaminants and additives is affected greatly by oil additions and machine usage. Consequently, both the level and rate-of-change of these parameters must be considered for proper condition assessment. It is critical to establish an optimum sample interval. The optimum sample interval for a machine can be defined as an interval short enough to provide at least two samples during the period between the start of an abnormal condition and the initiation of a critical failure mode. In practice, an engineer should determine or at least verify all sample intervals by analyses of the equipment and historical data.

3.1.9 *prognostics, n*—forecast of the condition or remaining usable life of a machine, fluid, or component part.

3.1.10 *remaining usable life, n*—subjective estimate based upon observations or average estimates of similar items, components, or systems, or a combination thereof, of the number of remaining time that an item, component, or system is estimated to be able to function in accordance with its intended purpose before replacement.

3.1.11 *sample population, n*—group of samples organized for statistical analysis.

3.1.12 *statistical analysis, n*—a structured trending and evaluation procedure in which statistics relate individual test results to specific equipment failure mode and statistics is used to define the interpretation criteria and alarm limits.

3.1.13 *statistical process control (SPC), n*—set of techniques for improving the quality of process output by reducing variability through the use of one or more mechanisms, control charts, for example. A corrective action strategy is used to bring the process back into a state of statistical control (Practice E2587).

3.1.14 *trend analysis, n*—monitoring of the level and rate of change over operating time of measured parameters.

3.2 *Symbols:*

Avg = average
C = current sample
H = usage metric (for example, hours)
OI = time on-oil interval
P = previous sample
PP = predicted prior sample
SSI = standard sample interval
T = trend

4. Summary of Guide

4.1 This guide provides practical methods for the trend analysis of condition data in the dynamic machinery operating environment. Various trending techniques and formulae are presented with their associated benefits and limitations.

5. Significance and Use

5.1 This guide is intended to provide machinery maintenance and monitoring personnel with a guideline for performing trend analysis to aid in the interpretation of machinery condition data.

6. Interferences

6.1 Sampling, maintenance, filter, and oil changes are rarely performed at precise intervals. These irregular, opportunistic intervals have a profound effect on measurement data and interfere with trending techniques.

6.2 *Machinery Operation*—Operational intensity can impact how quickly a component wears and how rapidly a fault progresses (**1**).[3] A relevant indicator of machine usage must be included in any calculations. The selected usage indicator must reflect actual machine usage, that is, life consumed (for example, stop/start cycles, megawatt hours, hours of use, or fuel consumption).

6.3 *Maintenance Events*—Component, filter, and oil changes impact the monitoring of machine performance, wear debris, contamination ingress and fluid condition. Maintenance events should always occur *after* a sample is taken (or condition test is performed). All maintenance events should be documented and taken into account during condition data interpretation. In all cases, maintenance events, if not reported, will reduce trending reliability.

6.4 *Sampling Procedures*—Improper or poor sampling techniques can profoundly impact condition test data (see Practices D4057 and D4177). Taking a good oil sample is a critical part of data trending. The following should be considered for a proper sampling procedure:

6.4.1 *Sample Quality:*

6.4.1.1 The most fundamental issue for any oil analysis program is sample representativeness. While poor analytical practices or insufficient data integrity checks generate data that cannot be reliably interpreted, improper sampling practices generate inaccurate data which is often meaningless with respect to condition monitoring or fault diagnosis.

6.4.1.2 Sample bottles can have a considerable influence on test results, particularly on oil cleanliness results. In practice, only sample bottles qualified for cleanliness should be used. When samples are to be taken from ultra clean machinery such as industrial hydraulic systems, the sample bottle must be rated as ultra clean. Exposing the new bottle or cap to the atmosphere negates any cleanliness certification.

6.4.1.3 The primary objective of the oil sampling process is to acquire a representative sample, for example, one whose properties, contaminants, and wear metals accurately reflect the condition of oil and machine. Theoretically, a representative sample means the concentration and size distribution of particulates and chemical species in the sample bottle correlate with those in the oil reservoir. Data variability may result from sampling procedures, sampling locations, improper maintenance activities, operational events (for example, exposure to high stress or temperature variation), analytical testing, data entry, and presence of one or more conflicting failure modes.

6.4.2 A significant difference in the test data could trigger a false trend alarm. Examples of poor sampling techniques are:

6.4.2.1 Stagnant sampling,

6.4.2.2 Sampling after component change out,

6.4.2.3 Sampling after oil, or filter changes, or both,

6.4.2.4 Irregular sample intervals, and

6.4.2.5 Sampling intermittent or standby equipment without circulating the oil and bringing the equipment to operating temperatures.

6.5 *Laboratory and Testing Practices*—The tools used to perform the condition monitoring tests impact the data.

6.5.1 Analytical instrument differences impact data reliability. Trending should only be performed on results from the same make and model of test instrument. For example, trending atomic emission inductively coupled plasma (ICP) results should be from ICPs with the same sample introduction configuration, same plasma energy, and preferably, the same manufacturer and model of the ICP instrument. Differences between testing laboratories always show the largest bias. The trend data should be generated by the same laboratory whenever possible. If a new laboratory is going to be used,

[3] The boldface numbers in parentheses refer to a list of references at the end of this standard.

overlapping test data should be performed. When multiple laboratories are utilized, a correlation between them should be established.

6.5.2 Analytical instruments with poor measurement repeatability and reproducibility will result in correspondingly poor trending. Testing repeatability should also be included with the trending studies.

6.5.3 Inappropriate analysis techniques can hide or distort interpretational conclusions. The condition-monitoring tool chosen must provide evidence of the critical failure modes under review.

6.6 *Machinery Wear Process*—Wear metal concentrations in oil are subject to variability (**2**).

6.6.1 Filters remove the majority of debris particles greater than filter pore size. Thus an oil sample only captures new wear and small, suspended, old wear.

6.6.2 Wear particle release is event driven; increased load or speed can result in increased wear.

6.6.3 The rate of wear debris release is not linear with time. For many fault mechanisms, wear occurs in bursts.

6.6.4 Wear metal analysis methods can have particle size limitations that should be included in the evaluations. For example, ICP metal analyses are limited to those particles below nominally 8 microns.

6.7 *Reservoir/Sump Volumes*—Fluid and wear condition parameters are concentration measurements and are affected by reservoir/sump size. Varying the oil volumes in a reservoir can impact the trending analysis. For example, infrequent top ups allows the oil volume to decrease and thus concentrate the wear debris and contaminants. Alternatively, large volumes of make-up oil dilute the concentrations. Small, routine oil top-ups reduce this interference. The fluid make-up rate should be considered as apart of the evaluation practice.

6.8 When trending for a specific piece of equipment, one should look at the difference between the current sample and an average of a group of previous samples from that piece of equipment or a group of samples from as many similar units as possible. Basing a trend on just two data points can leave significant room for error and misjudgment.

6.9 When samples cannot be taken in exact intervals, techniques should be applied that overcome these irregular intervals.

6.10 Effective data trending requires that the above interferences are taken into account. The effect of operation and maintenance activities must be tuned out for the most effective trending.

6.11 The data history under trend analysis must be from the machine component, and all samples must be contiguous.

7. Procedure

7.1 *Preparing Condition Data for Analysis*—The first step in preparing condition data is to ensure all measurement data, for example iron (Fe) from AES, is generated from the same analytical instrument. Due to the proprietary techniques used by instrument manufacturers, few instruments provide the same results from the same sample unless the instrument is the same make and model and has the same calibration. When multiple instruments or laboratories are utilized, the instruments must be controlled in a data correlated program. A lack of these conditions will contribute to increased variance and less accurate trending.

7.2 *Trending Test Data:*

7.2.1 *Traditional Techniques*—There are numerous techniques to calculate trends from the very simple to the more complex. There are advantages and disadvantages to each method.

7.2.1.1 *Difference (Delta) Trend*—The difference trend between sequential samples is the current sample value minus the previous sample value.

$$T = C - P \tag{1}$$

The difference trend is easy to calculate, however it does not account for machine usage and is ineffective in determining the rate of wear or oil deterioration. This is the traditional “eyeball” method where gross changes, such as doubling since the last sample, are noted. This formula does not factor in the equipment duty cycle and is a poor indicator of machinery or fluid condition.

7.2.1.2 *Percent Change Trend*—The percent change trend is the current sample minus the previous sample, divided by the current sample value, times 100.

$$T = (C - P)/C \times 100 \tag{2}$$

The percent change since the last sample can be a better indication of trend but still does not account for equipment usage or duty cycle. In addition, this calculation provides ambiguous numbers for fractional data. For example, an increase from 0.1 to 1 is the same percent change as from 10 to 100. Percent change is only effective for large trend changes (for example trending intervals that yield C or P of 100) and only when the equipment is used continuously and rigorously sampled at a standard interval.

7.2.1.3 *Rise-Over-Run Trend*—The rise-over-run trend is the current sample minus the previous sample, divided by the usage metric, times the standard sample interval. The usage metric and the standard sample interval metric must be the same units of measure, for example, hours.

$$T = [(C - P)/H] \times SSI \tag{3}$$

The rise-over-run trend calculation, which factors in equipment usage, is shown in Fig. 1. The scheduled sample interval for this equipment is 150 hours. In this example, the trend could be for any contaminant, for instance, the removal of lead from the Babbitt overlay of a bearing. The plot also indicates the “Alert” and “Reportable” alarm limits. Rise over run trend can be effective for continuous duty and intermittent duty machinery. However, condition samples must be taken at or near the optimum interval. The optimum (standard) sample interval is derived from failure profile data. It is a fraction of the time between initiation of a critical failure mode and equipment failure. In general, sample intervals should be short enough to provide at least two samples prior to failure. The interval can be established for the shortest critical failure mode. Samples taken at very short or very long intervals relative to

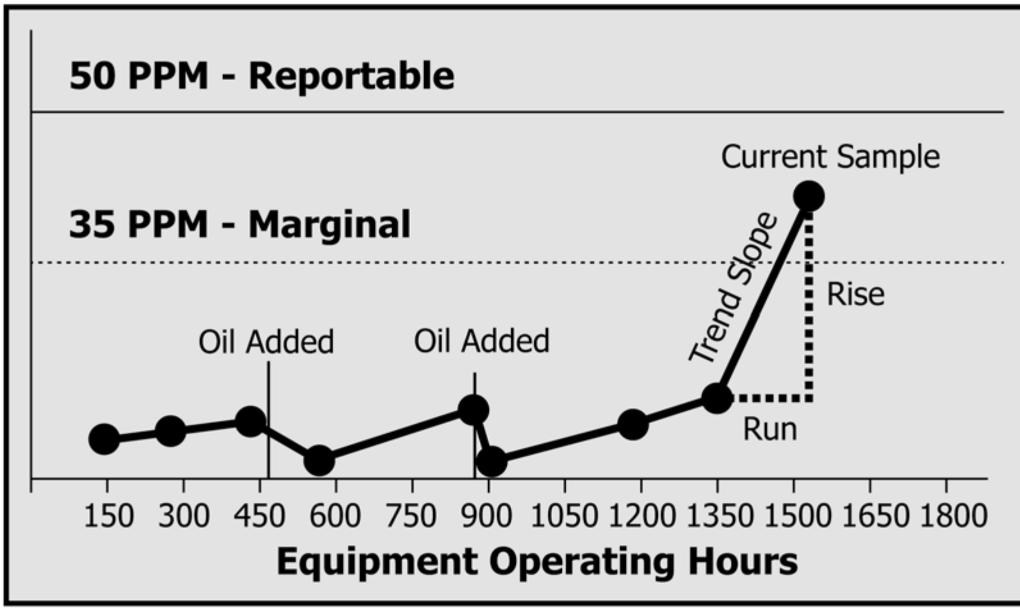

FIG. 1 Trend Plot Demonstrating Rise–Over–Run

the standard interval generate ambiguous results due to the multiplication factor in the formula.

7.2.1.4 *Cumulative Trend*—The cumulative trend is the sum of previous and current sample.

$$T = \sum_{n} C \tag{4}$$

The cumulative trend plot provides a quick indication as to whether data points in a series are maintaining a linear trend slope or are beginning to deviate due to an anomaly. The cumulative trend plot is most effective when equipment is used continuously. It works well for real-time data where there is a high sample rate such as online sensors. Fig. 2 shows a cumulative trend plot of real-time sensor data. In this example, high wear metal particle count instigated the removal of a wind turbine gear box for inspection. The plot in Fig. 2 shows the ferrous debris released from the bearing and gear over the period from November of 2001 until late June of 2003. The fault was initiated in October 2002. The onset of service wear is clearly observed beginning of March 2003 and reached a critical value by the end of May 2003. The early warning from

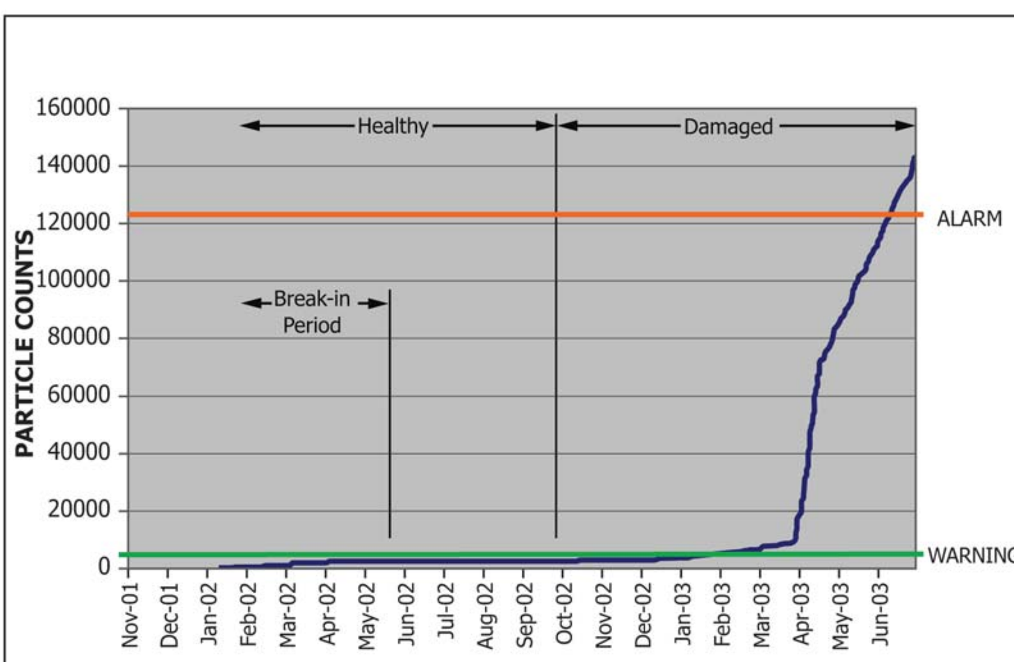

FIG. 2 Cumulative Trend Plot of Real-Time Sensor Data

the on-line debris sensor system provided a reasonable interval during which repair crew could plan and execute the repair mission.

7.2.2 *Adaptive Trending*—In practice, there is considerable difference between the standard sample interval and the actual sample interval. Because of intermittent equipment usage, or irregular sampling and maintenance, or a combination thereof, the trending techniques listed in 7.2.1 are incomplete for sampled condition monitoring. It is not practical to expect all equipment to have equal duty cycles, be sampled at specific and uniform intervals, or to be maintained at regular intervals. Maintenance and sampling operations are generally opportunistic in order to meet production goals. The solution is provided by a dynamically initiated or adaptive trend calculation that can compensate for varying sample intervals and reasonable makeup oil additions. When the sample interval is between 0.5 times and 1.5 times the standard interval, a conventional rise-over-run trend formula provides reliable trend data. When the actual sample interval is shorter than half the standard interval or longer than 1.5 times the standard interval, the rise-over-run formula no longer provides satisfactory results. In these cases, a predicted last sample value can be determined from a linear regression that predicts the last sample value based on the standard interval.

7.2.3 *Adaptive Trending Rules*—The following rules can be used to select the most appropriate formula based on sample interval and oil change information.

7.2.3.1 For routine samples taken at 0.5 to 1.5 times the standard sample interval and the oil has not been changed since the previous sample, it is recommended to use the rise-over-run equation in 7.2.1.3.

7.2.3.2 If the sample interval is smaller than 0.5 times the standard interval and there are sufficient samples, it is recommended to use a linear regression (see Note 1) to predict the prior sample value (*PP*), one standard interval prior to the current sample (*C*). One can calculate the test data trend for the current sample (*C*) using a rise-over-run equation, utilizing the standard sample interval (*SSI*).

$$T = \frac{C - PP}{SSI} \times SSI \tag{5}$$

NOTE 1—A linear regression over ten previous samples is suggested.

7.2.3.3 If the sample interval is greater than 1.5 times the standard interval and there are sufficient samples, it is recommended to use a linear regression to predict the prior sample value (*PP*), one standard interval prior to the current sample (*C*). One can calculate the test data trend for the current sample (*C*) using a rise-over-run equation with the standard interval (*SSI*). See Fig. 3.

7.2.3.4 If the sample is the first after an oil change or if there are insufficient samples since the last oil change to perform a linear regression calculation, it is recommended to calculate the trend for the current sample (*C*) using a rise-over-run equation and the time-on-oil interval (*OI*) and the standard sample interval (*SSI*). When there is no prior sample, it is recommended to use the average data of all samples taken immediately after an oil change for that equipment type.

$$T = \frac{C - Avg}{OI} \times 100 \tag{6}$$

7.2.3.5 Alternatively, if an oil change occurs immediately before the current sample is drawn, thus destroying the history of an abnormal trend, it is recommended to trend data before the oil change to estimate or predict a usable trend. It should be noted that destroyed trend data can never be fully recovered.

7.3 *Interpretation of Data:*

7.3.1 *Predictive Forecasting*—The second part of any trending operation is to understand or predict how the behavior of the fluid or machine will progress into the future. It is possible to estimate how long the fluid or machine is "predicted" to last, based on how it has behaved in the past. The formulas for a prediction model can be developed based on studying the

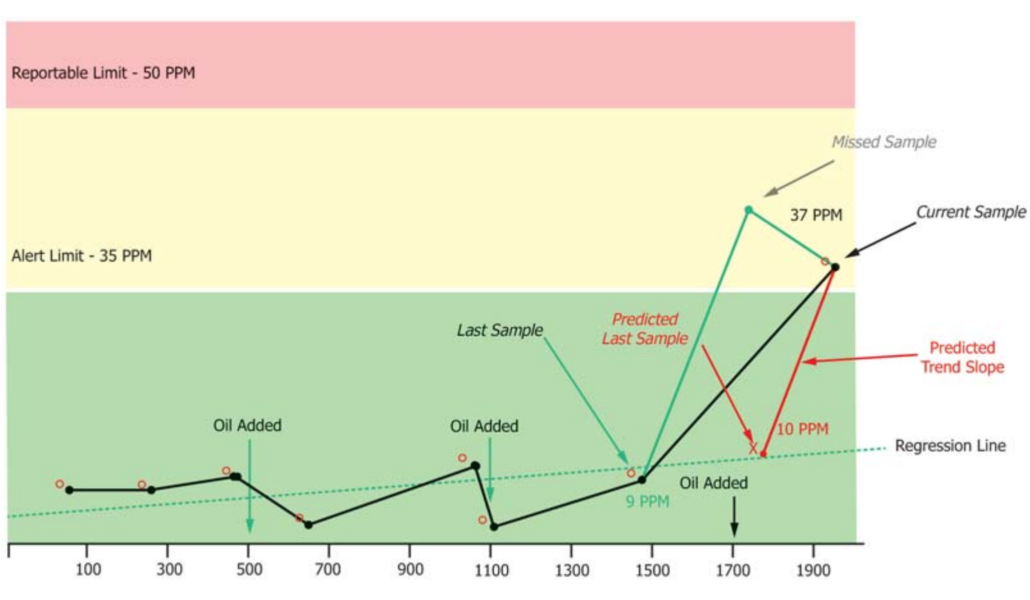

FIG. 3 Adaptive Trend Plot when Sample Interval is Greater than 1.5 Times the Standard Interval

single variables or polynomials representing the data acquired. The prediction is a regression equation that connects past data with the future. Regression analysis allows one to develop these model equations and the coefficients equation that can be used to predict the future. There are many mathematical models that can be used to develop these predicting equations. The extrapolation of a trend plot or least-square calculated line yields an extension of the data. Fig. 3 shows an example of linear regression line in adaptive trending. The regression equations take into consideration all data within a range of measurements yielding an averaging to the data from beginning to end. However for trend analysis, the last several results prior to fault is important to determine where to take the trend. A reliable predictive forecast may be obtained by a recursive mathematical approach similar to Kalman equations (**3, 4**) or by efficient organization of a mathematical model such as that used in the Group Method of Data Handling (GMDH) (**5**). These techniques employ matrix or polynomial mathematics to develop processing equations that are based on previously determined results for the equipment being studied.

7.3.2 *Limit Setting Procedures*—With the trending approach established, the equipment maintainer's next objective is to establish guidelines for limits or extremes to which the results may progress to before requiring maintenance actions to be taken. The calculation of alarm limits should initially be developed based on the ideal conditions and limitations from a sample population data.

7.3.2.1 The scientific basis of this method has been developed from large equipment fleets and can be applied to smaller fleets with longer history or with expert knowledge of monitoring. Extension of these alarms outside the ideal conditions can only be achieved after extensive and proper evaluation of data and the equipment's operation is achieved. The application of statistical analysis on the condition data for calculating the practical alarms is a recommended practice.

7.3.2.2 The alarm limits that indicate physical characteristics, for example state of equipment fluids and components, are often established by the original equipment manufacturer (OEM) guidelines. Consistency in interpretation may be obtained through utilization of the same interpretation technique for each numerical (parameter) measurement.

7.3.2.3 Structured trending and evaluation procedure utilizes statistics to relate individual test result to specific equipment failure modes. In addition, the statistics may also be used to define the interpretation criteria and alarm limits. Operations and maintenance activities influence monitoring of data in predictable ways. Thus, any change in monitored data not attributed to an operation or maintenance action can be considered abnormal and trigger an appropriate inspection and/or maintenance action. Any maintenance performed to correct an abnormality generates a compensatory change in the monitoring data and the system returns to its state of equilibrium.

7.3.2.4 The general assumptions to follow in setting these limits and alarms are:

(1) The equipment process is a closed loop system whereby test measurements are only affected by operations, maintenance or the onset of a failure mode.

(2) The equipment fleet is a well-maintained population of like machines.

(3) The equipment in the sample population operate in the same environment, under the same duty cycle and load conditions and have the same mechanical specifications, for example, oil capacity.

(4) A nominal sample interval has been established that accounts for the critical failure modes with at least two samples between failure mode initiation and its terminal phase.

(5) The sample population should cover at least one overhaul interval or in the case of a large fleet, all operational phases from new to overhaul.

(6) Each established failure mode indicator is unambiguous in its prediction and free from interference.

(7) The sample population includes a complete range of failure indication levels from problem initiation through component failure for each critical failure mode.

(8) Nominal condition data are expected to fall within two standard deviations of the mean or represent about 94 % of all samples taken.

(9) Abnormal condition data are expected to fall outside two standard deviations of the mean and represent about 6 % of all samples taken.

7.3.2.5 Procedures to calculate practical alarm limits are discussed in the Guide D7720. Determining the alarm limits includes setting initial limits, defining the population, defining the distribution ranges, and validating the alarms.

7.3.2.6 Limits calculation reliability depends on the following:

(1) Sample population size.

(2) Control of all factors that vary sample data:

(a) Scheduling of testing and maintenance—Long sample intervals will reduce data points.

(b) Oil makeup quantities and timing—Infrequent large additions will disrupt limits and trends.

(c) Oil and filter changes—Too many oil changes will lower limit values; too few oil changes will raise limit values.

(d) Component change out.

7.3.3 *Statistical Data Analysis*—The statistical analysis method encompasses a structured trending and evaluation procedure in which statistics relate individual test results to specific equipment failure modes. In addition, statistics is used to define the interpretation criteria and the alarm limits. The key to using statistics in this way is controlling those factors that cause sample data to vary for any reason other than the presence of a failure mode. Equipment usage, remaining component life, repair history, oil and filter changes should be monitored to isolate and control any maintenance practices that contribute to data variability. When the machinery system is under control, the entire data evaluation process can be divided into four simple procedures, each with the associated databases and evaluation rules. Keeping data variability under control allows interpretation with simple statistical rules and mathematical algorithms common to statistical process control (Practice E2587, Guide D7720):

7.3.3.1 *Step 1*—Convert test data to level and trend alarm through statistically based limit.

7.3.3.2 *Step 2*—Combine level and trend alarms to generate a uniform condition indicator status.

7.3.3.3 *Step 3*—Convert condition indicator status patterns into problem indications.

7.3.3.4 *Step 4*—Estimate overall equipment condition status utilizing worst case problem diagnosis.

7.3.3.5 *Step 5*—Generate a recommendation in compliance with operator maintenance policy.

7.3.3.6 Any change in monitored data not attributed to an operation or maintenance action should be considered abnormal and trigger an appropriate inspection and/or maintenance action. Any maintenance performed to correct an abnormality generates a compensatory change in the data monitored and the system returns to its state of equilibrium.

7.3.4 *Defining the Population*—Define the equipment that will be using the failure mode established. Candidates must be segregated by mechanical and operational characteristics including make, model, duty-cycle, and sump capacity. Remove any sample with differing characteristics such as component metallurgy, fuel consumption, etc. from the candidate histories and pull together the relevant condition data. For best performance select all available samples.

7.3.5 *Determining the Distribution Ranges*—Since all limits are based on a statistical calculation from the mean values, the mean and standard deviation for each indicator (measurement) should be calculated. From the average and standard deviation data for each test parameter, calculate a series of tentative limits based on the established formula.

7.3.6 *Validation of the Limits*—Limits should be established based on Guide D7720 and validated by reexamining the historical data. The validation process should consider the following.

7.3.6.1 100 % correlation between the new limit performance and previous limits or recommendations is not realistic.

7.3.6.2 Sample recommendations are based on data interpretation that includes much more than limits.

7.3.6.3 The purpose of this step is to find gross discrepancies. The validation evaluation should show a minimum of false positives and each one should be readily explainable.

7.3.6.4 Too many false positive alarms indicates that the limits are set too low.

7.3.6.5 False positives can also result when:

(1) The critical failure mode was not adequately represented in the population.

(2) The sample interval is too long.

7.3.6.6 Failure of equipment in the absence of alarm indicates limits are set too high.

7.3.6.7 Failure of equipment in the absence of an alarm may indicate improper measurement tool:

(1) This is also a problem if the limits were calculated from a population where the critical failure modes were over represented in comparison to the normal samples.

7.3.6.8 In case of statistical limits, level alarm limits establish the presence of an abnormal event. Trend alarm limits establish the degree of appropriate risk based on the rate of change as determined by adaptive formulae. Statistics from multiple machines can be used to calculate realistic limits.

7.4 *Estimating Remaining Usable Life*—Establishing the proper trending and limit alarm levels can be a valuable asset for interpretation of test results, and it should clearly reflects the equipment's operational condition. Proper implementation and setting of the limits should allow adequate notification of failure progression. When properly designed, these tools assist with equipment reliability control, improve equipment control and improve the bottom line productivity. These results should reflect the fluid and/or the equipment remaining life.

8. Keywords

8.1 condition monitoring; diagnostics; prognostics; remaining usable life; trend analysis

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SUMMARY OF CHANGES

Subcommittee D02.96 has identified the location of selected changes to this standard since the last issue (D7669 – 11) that may impact the use of this standard. (Approved April 1, 2015.)

(1) Revisions made throughout to account for all steps of trend analysis.