

# Plant Services

PREDICTIVE MAINTENANCE / LUBRICATION

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## Be Proactive with OIL SAMPLE DATA

### Use statistical evaluation to check alarm limits for machine lubricants

#### Properly used statistical

techniques are powerful tools for validating and improving the alarm limits applied during evaluation of oil samples taken from operating machinery periodically. Limitations in the application of statistical process control (SPC) might make it advantageous to use the cumulative distribution technique described in ASTM D7720 from the American Society for Testing and Materials ([www.astm.org](http://www.astm.org)). An actual case where a serious fault was detected, trended, and corrected reveals the extent to which cumulative distribution can be effective.

For evaluating alarm limits for lubricating oils in steam turbines

TABLE 1. TURBINE OIL DATA

Parameter	Count	Average	Median	Distribution
% Dielectric Change	2,319	0.8	0.4	Causal
Viscosity @ 40 °C	2,304	31.5	31.8	Normal
Ferrous Index	2,304	43.1	0.0	Causal
PPM Water	2,304	125	23	Causal
ISO >4	2,300	15	15	Discrete
ISO >6	2,300	14	14	Discrete
ISO >14	2,300	11	11	Discrete

TABLE 2. PULVERIZER OIL DATA

Parameter	Count	Average	Median	Distribution
% Dielectric Change	1,754	0.4	0.0	Causal
Viscosity @ 40 °C	1,754	201	199	Normal
Ferrous Index	1,745	14.3	1.6	Causal
PPM Water	1,745	10	0	Causal

and coal pulverizers, statistical techniques, including SPC and cumulative distribution, are defined in ASTM D7720, “Standard Guide for Statistically Evaluating Measure and Alarm Limits When Using Oil Analysis to Monitor Equipment and Oil for Fitness and Contamination.”

Data gleaned from more than 1,700 coal-pulverizer oil samples and more than 2,300 steam-turbine oil samples were collected and analyzed between 2002 and 2012 by Joey Frank and Stan Sparkman of the Tennessee Valley Authority (TVA) Gallatin Steam Plant. The maintenance and reliability department at the Gallatin Steam Plant clearly handles lubricating oil data in a consistent and proactive manner to implement predictive maintenance strategies, avoid unexpected shutdowns, and extend equipment longevity.

**STATISTICAL ALARMS**

Two primary kinds of statistical evaluations for alarm limits are described in ASTM D7720. One is for normal data, and the other is for causal data. In normally distributed populations, data plotted from low to high create a bell curve where the average value is almost the same as the median value, or middle, with similar tails on left and right. Causal data distributions typically are skewed so that the average value is much higher than the median value. Something obviously causes a portion of the measurements to increase in the latter case, making SPC unsuitable for evaluating alarm limits.

According to D7720, SPC only can be used when data is in “control,” in which case the data must be normally distributed. On the other hand, the alternate statistical technique, cumulative distribution, can be used with causal data, which is skewed, typically from moderate to extremely high values. Actually, much of the data produced through machinery monitoring are causal. For example,

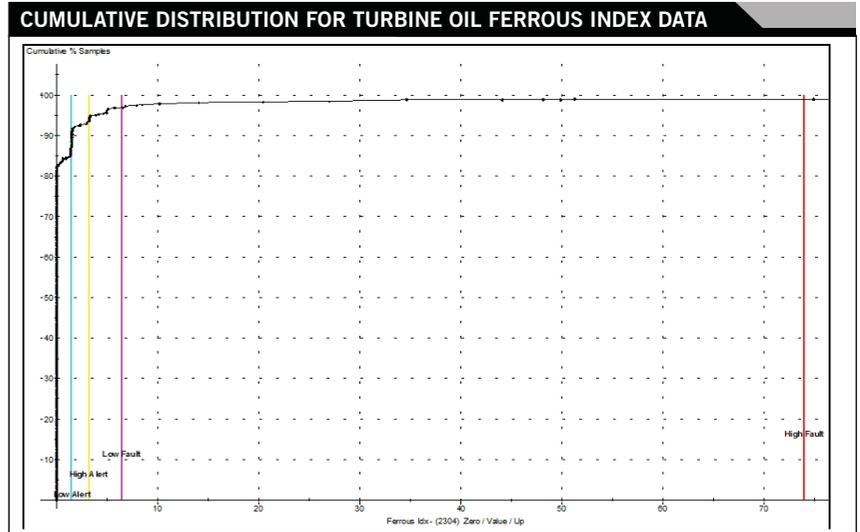


Figure 1. Eighty percent of the turbine oil samples show a ferrous index of zero with the numbers escalating from that point.

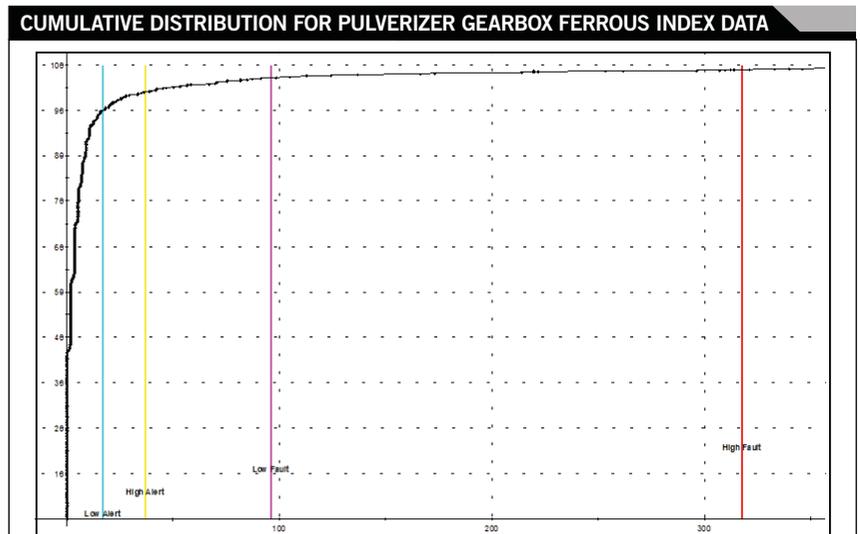


Figure 2. Thirty-five percent of the pulverizer gearbox oil samples show a ferrous index of zero with the numbers escalating from that point.

when measuring the amount of water or iron particles in oil, the intent is to identify and correct root causes, not control. The cumulative distribution technique is well suited to such cases.

To best demonstrate the principle of cumulative distribution, data from more than 1,500 measurements have been employed (Tables 1 and 2). However, modest amounts of data can be used just as effectively. ASTM D7720 states the following about data population size:

- 6.1.1.1 For SPC techniques using a normal distribution, caution should be used for data sets with fewer than 30 members. Tentative limits can be set from as little as 10 samples, although the quality of the limits will improve with larger populations. Larger populations (for example, in the hundreds) can provide best alarm limits. However, the data needs to be representative of the equipment population.
- 6.1.1.2 For cumulative distribution

techniques, regardless of the form of distribution, caution should be used for data sets with fewer than 100 members. Tentative limits can be set from as little as 50 samples, although the quality of the limits will improve with larger populations. Larger populations (for example, 1,000 plus) can provide best alarm limits. However the data needs to be representative of the equipment population.

The two populations of data used for

this demonstration were accumulated at the Gallatin Steam Plant as alarm limit sets within Emerson’s AMS Suite: Machinery Health Manager. The turbine oil population includes roughly 2,300 different in-service sample sets, whereas about 1,700 different oil-sample sets were collected from coal pulverizer gearboxes. Statistics were generated automatically using the Export Statistics feature within the OilView tab.

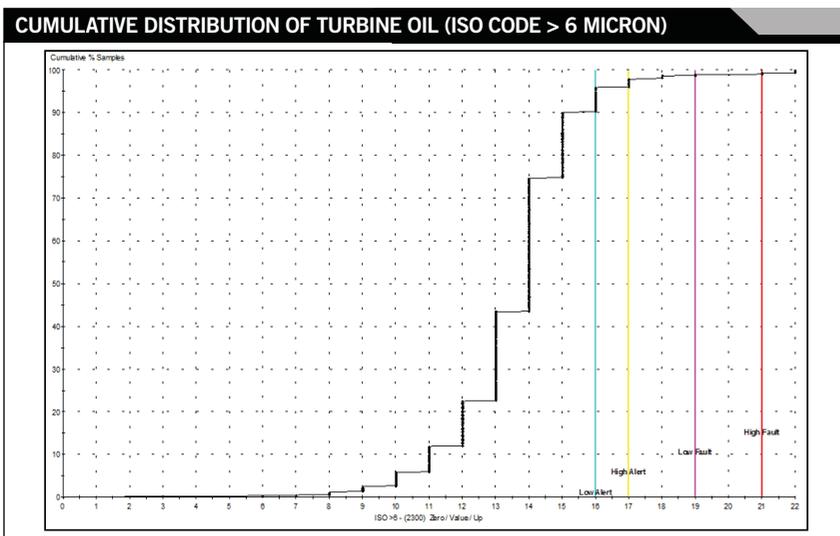
Tables 1 and 2 present the count or

number of measurand values, along with average and median values for each set of measurements. For several measurement parameters, the average value is substantially higher than the median value. This is generally true for zero-based measurements such as percent dielectric, often called “chemical index”; ferrous index; and PPM water. These are causal measurements, meaning they can reveal the cause of an evolving issue, such as lubricant degradation, freshly generated machine wear, or water contamination, respectively. Note that a median value of 0.0 indicates that at least 50% of all measurements are zero — not unusual for measurements that are specifically targeting potentially abnormal conditions. Since these measurements are all causal, they’re suitable for evaluation using cumulative distribution, but aren’t suitable for evaluation using SPC.

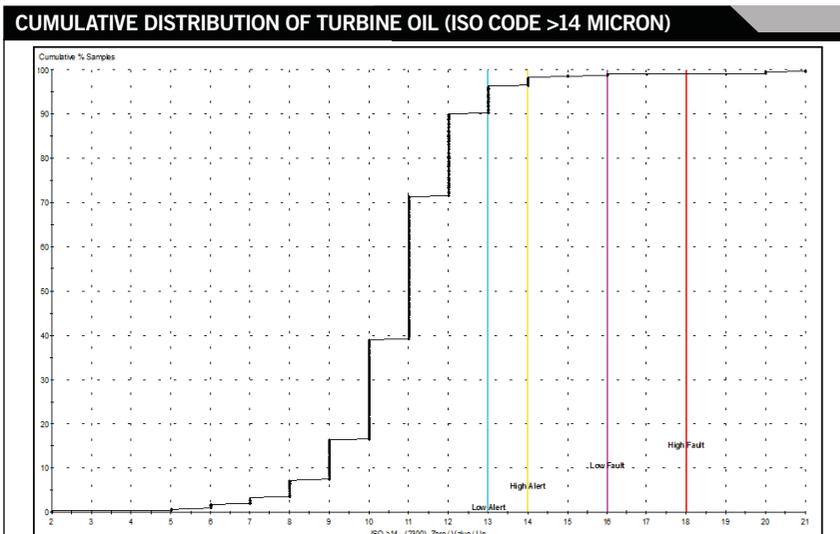
On the other hand, the statistics for viscosity at 40 °C that have approximately the average and median values are essentially the same. This is a good indication that viscosity measurements are in control with a well-behaved, bell-shaped parametric distribution. These measurements are suitable for evaluation using either SPC or cumulative distribution techniques as described in ASTM D7720.

**PLOTS OF CUMULATIVE DISTRIBUTIONS**

Figures 1 and 2 compare cumulative distribution plots for the ferrous-index data presented in Tables 1 and 2 obtained from the samples of in-service turbine oils and coal pulverizer gearbox oils. The ferrous index is a measure of freshly generated iron-wear debris, which typically is caused by abrasion, adhesion, or fatigue wear mechanisms. You will see that 80% of the turbine oil samples and 35% of the pulverizer gearbox oil samples show a ferrous index of zero, with the numbers escalating from that point. For turbine oils, the 90th percentile



**Figure 3.** For ISO >6 measured on turbine oils, the 90th percentile corresponds to 16, the 95th percentile to 17, the 97th percentile to 19, and the 99th percentile to 21.



**Figure 4.** For ISO >14 measured on turbine oils, the 90th percentile corresponds to 13, the 95th percentile to 14, the 97th percentile to 16, and the 99th percentile to 18.

**TABLE 3. PULVERIZER GEARBOX WEAR DATA**

Sample Date	Ferrous Index
November 2010	0.0
January 2011	4.8
April 2012	7.0
July 2012	8.8
October 2012	124.0

corresponds to a ferrous index of 2, the 95th percentile is 3, 97th percentile is 6 and the 99th percentile is 73. For pulverizer oils, the 90th percentile corresponds to ferrous index of 20, the 95th percentile to 45, 97th percentile to 95, and the 99th percentile to 320. Depending on the application, such threshold percentiles can be used to evaluate alarm-limit settings corresponding directly to low alert, high alert, low fault, and high fault.

Figures 3 and 4 show cumulative distribution data for particle count of ISO 11171 code values measured on approximately 2,300 in-service turbine oil samples. ISO code values are reported only in integers where each step between one integer and the next represents roughly a doubling of measured particle counts per milliliter. Therefore, the plot shows

steps in what is called a discrete cumulative distribution. For ISO >6 measured on turbine oils, the 90th percentile corresponds to 16, the 95th percentile to 17, the 97th percentile to 19, and the 99th percentile to 21. For ISO >14 measured on turbine oils, the 90th percentile corresponds to 13, the 95th percentile to 14, the 97th percentile to 16, and the 99th percentile to 18.

**PREVENTING FAILURE**

In a recent case, statistical analysis of oil samples saved a pulverizer gearbox from catastrophic failure. All measurements of oil chemistry and lubrication-system contamination (dielectric 2.21, water 0.0021%, viscosity 171 cSt) were satisfactory. However, the wear-indication data climbed sharply between July 2012 and October 2012, as shown in Table 3. The ferrous index measures 5 micron and larger iron alloy particulate matter in oil samples per ASTM D7416.

This pulverizer gearbox was approaching high fault condition with serious wear indicated by the high ferrous index. Subsequent microscopic wear debris analysis revealed brass particles, and analysis of vibration

data confirmed that a bearing failure was in progress. This information led to a decision to replace the bearing immediately. The pulverizer had to be taken out of service for 10 hours, but a costly outage of about two weeks was avoided. If the bearing problem hadn't been corrected, catastrophic damage to the pulverizer could have occurred.

In this case, SPC limits based on multiples of standard deviation (standard deviation = 63) would be grossly overstated because the data population is not parametric. The ferrous-index data population is better suited to use of cumulative distribution probability density calculations.

In one actual case, a serious bearing fault was detected, trended, and corrected, and the corresponding measurement data were compared favorably with the cumulative distribution information. ©

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