

# Trailing Safety Indicators

## Enhancing Their Value Through Statistics

By Jan K. Wachter

**T**railing or lagging safety indicators are after-the-fact indicators which measure events or consequences that have occurred. These events or consequences are often associated with unwanted events, such as injuries, illnesses, workers' compensation costs, hospital visits, notices of violation, regulatory fines and litigation costs. By measuring performance results over past time periods, such indicators are also reactive, since they are essentially reacting to previous conditions and circumstances. These indicators are also termed incident-based indicators, since organizations typically react to the occurrence of these specific unwanted incidents (e.g., fatalities, lost workday cases).

OSHA-based measures are one type of trailing indicator. These measures are the most common type of safety and health performance metrics being collected and used by organizations. In particular, the recordable incident rate (also known as the total recordable case rate or TRC rate) is the most prevalently used OSHA-based measure (Coffey, 2009). The TRC rate is a mathematical calculation that describes the number of OSHA recordable incidents which a company experiences per 200,000

hours worked (e.g., 100 full-time employees) in any given period. Another common OSHA-based trailing indicator is the days away, restrictions or transfers (DART) case rate, which describes the number of recordable injuries and illnesses per 200,000 hours worked (e.g., 100 full-time employees) that results in days away from work, restricted work activity, and/or job transfer that a company has experienced in a given time period.

### What's Wrong With Using Trailing Indicators?

Trailing indicators measure essentially the consequences of not having effective safety and health programs in place (Coffey, 2009). They provide little information on the effectiveness of current activities, since it may take time for those efforts to affect trailing indicators. Thus, trailing indicators have little predictive power in showing where organizations may be headed in terms of safety and health performance. Moreover, when organizations review trailing indicators infrequently (e.g., annually), opportunities for nearer-term corrective and preventive actions, and interventions may be unnecessarily delayed (Wachter & Bird, 2011).

The problem with trailing indicators is that they do not necessarily act as forcing functions for implementing actions which could improve safety and health performance in the future. In addition, individual workers may not be as empowered to take control of their safety and health responsibilities and to contribute to improving the organization's safety and health culture if trailing indicators are exclusively being used to assess safety and health performance at the corporate level. This is because these measures tend to be high-level organizational metrics beyond the control of employees.

Another problem involves rewarding or recognizing organizational, group and individual performance based on trailing indicators. Employees may feel fear and pressure to not report accidents, injuries, near misses or other incidents so as to keep the safety record intact to receive rewards/recognition and/or avoid punishment. Failure to report incidents and near misses defeats the

### IN BRIEF

- SH&E professionals use trailing safety indicators to assess safety performance, including their inclusion in balanced scorecard approaches. Applying appropriate statistical protocols can enhance the value and utility of these indicators.
- SH&E professionals should be able to display trailing safety indicator information, such as total recordable case rates using rolling averages, and to statistically analyze and interpret trailing safety indicator data using control charts. In particular, by using control charts, SH&E professionals can address the organizational and statistical significance of changing trailing safety indicator information.
- SH&E professionals also can use these tools to correlate leading safety indicator measurements with trailing safety indicator results to determine the effect of leading safety indicators on injury reduction.

Jan K. Wachter, Sc.D., M.B.A., CSP, CIH, is an associate professor in the Safety Sciences Department at Indiana University of Pennsylvania. He holds a B.S. in Biology, an M.S. in Environmental Health, and an M.B.A. and a doctorate in Hygiene from University of Pittsburgh. Prior to joining academia, he was employed by *Fortune* 100 companies and the U.S. Department of Energy as an environmental health and safety administrator and researcher. Wachter is a professional member of ASSE's Western Pennsylvania Chapter.

purpose of implementing performance indicator programs, whose goal is to generate as much information as possible on trends so that steps can be taken to control future problems through preventive actions. In short, if misuse of trailing indicator information and programs prevents workers from providing accurate incident feedback, then managers have little information on which to base future safety and health directives and initiatives.

In recent years, organizations have gravitated toward using proactive leading indicators to measure safety and health performance. The intent of leading indicators is to actively drive safety and health performance, not to passively react to it. Leading indicators typically measure actions, behaviors and processes (the things people actually do for safety) that will make injuries and illnesses less likely to occur (Blair & O'Toole, 2010). Success in implementing these activities, initiatives and programs will theoretically improve and drive safety performance (Wachter & Bird, 2011).

### What's Good About Using Trailing Indicators?

Trailing indicators have a positive side: They are concrete, understood and easily measured. They are absolutely results-oriented, the proverbial "proof in the pudding." They provide the most relevant and critical information required to objectively judge an organization's overall safety and health performance. Trailing indicators also provide an overall estimate of the progress toward achieving noble (but most times unachievable) end goals, such as a state of zero harm, as represented by a TRC rate of zero.

From a pragmatic perspective, for organizations under OSHA jurisdiction, information used to formulate these indicators must be provided to OSHA anyway. Thus, there is an impetus to continue to use these indicators since the information is already being collected and have been over time. This enables organizations to compare their recent performance with many years of past performance, within a particular business sector and against best-in-class performers.

Many organizations use a combination of trailing and leading indicators, referred to as a *balanced scorecard*, a term historically applied to quality assessments. A balanced scorecard seeks to balance indicators used to measure organizational results (trailing indicators) against the drivers of that performance (leading indicators) (Kausek, 2007). It makes practical sense to use a combination of indicators that point to where the organization both has been and is going.

Perhaps the best reason for continued use of trailing indicators in this balanced scorecard approach is that these indicators measure safety and health results which become the baseline against which future organizational performance (e.g., using leading indicators as forcing functions) will be assessed. The bottom line is this: How can organizations measure the success of actions being implemented through its leading safety indicator program if not through trailing safety indicators?

### Applying Mathematics & Statistics to Increase the Value of Trailing Safety Indicators

Despite commentary highlighting their shortcomings, one can cite important reasons to use trailing safety indicators. More value and utility can be associated with trailing indicators if appropriate statistics are applied to better understand the information collected and to resolve some of their perceived deficiencies. The expertise level in statistics required to analyze most trailing indicator information is not advanced. It can be achieved by taking a college-level introductory statistics course or by having a good command of general mathematical operations. (For specific texts related to the statistical analysis of trailing safety indicator data, see the sidebar on p. 53.)

SH&E professionals should already know about various applications for trailing measures, such as trend analysis, control charts and evaluating the effectiveness of safety initiatives (Blair & O'Toole, 2010). However, based on anecdotal information received by this author from young professionals (e.g., those with less than 5 years' experience after university graduation), problems exist when dealing statistically with these trailing indicators; this can lead to information either not being gathered or not being used maximally or correctly. This article acts as a refresher and a springboard for applying statistics to increase the use of and respect for trailing safety indicators.

One problem with using trailing indicators is the seesaw effect with data over time as well as the low number of events being measured. Another issue is determining whether an increase or decrease in the indicator information warrants organizational commendation or condemnation. A third issue is how to appropriately link leading indicator results with trailing indicator results.

Often, management may not fully understand the dynamic variability within these types of trailing measures. As a result, it may overreact to a single point of information. For example, if trailing indicators for the last quarter suggest better safety performance, management is optimistic and hosts a celebratory lunch. If metrics suggest worsening safety and health performance compared to the previous quarter, pessimism and accusations abound.

The latter situation may prompt a knee-jerk response from management requesting drastic and unwarranted corrective actions to be implemented based on the latest single set of metrics, when these metrics represent only the natural variability in the data itself. This is not to say that major decreases in safety performance assessed through trailing indicators should not be addressed immediately (e.g., a TRC rate increasing from 1 to 5); however, when these measures increase or decrease on a quarterly basis by what is perceived organizationally to be a small amount (e.g., 20%) (Wachter & Bird, 2011), one could apply statistical protocols consistently to determine whether this increase or decrease is significant to the organization.

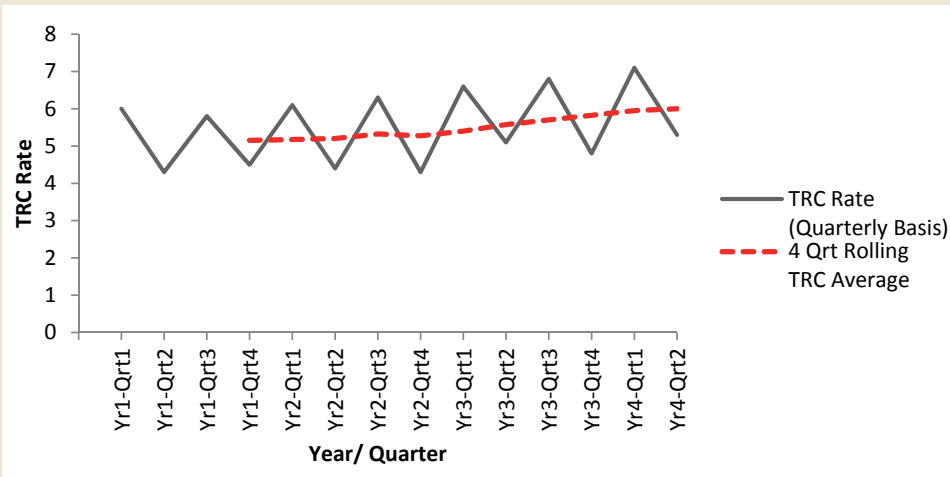
What an organization perceives to be a "small" amount is discretionary based on its level of risk



More value and utility can be associated with trailing indicators if appropriate statistics are applied to better understand the information collected and to resolve some of their perceived deficiencies.

**Figure 1**

## Quarterly & Rolling Average TRC Data



Energy (2009), use a four-quarter rolling average approach to display trailing safety indicator information. The organization itself must determine how many data sets (e.g., quarters) it will use to generate the individual rolling averages. However, if an organization uses an excessively large number of data sets to do so, it runs the risk of visually dampening out all data variability so that when the rolling average data are plotted through time, the data will appear to be a straight line with little slope.

As an example of using rolling averages, Figure 1 provides

a plot of trailing indicator data (from a metal fabrication facility in southwestern Pennsylvania). The data fluctuate when viewed on an instantaneous quarter-by-quarter basis. However, by calculating a four-quarter moving average of the quarterly data, it is easier to visually discern an upward trend in the data. The trend observed indicates that safety and health performance in this facility may be degrading over the course of 4 years.

Thus, rolling average charts can be used to discern visually the longer-term trends in data (e.g., TRC rates) that could be obscured by near-term data variability. However, these rolling average charts do not incorporate statistical analysis to determine whether these trends are significant. To determine whether there is statistical significance in the data they are visually observing and trending, SH&E professionals could learn how to construct and apply control charts to the information being collected.

### Understanding Control Charts

Questions that often arise in interpreting trailing indicator information are, When should an organization become concerned when faced with increasing (negative) trailing indicator results? What constitutes a significant increase in these results? Also, how does one deal with analyzing events that occur infrequently so that any increase or decrease in their numbers appear significant? Equally important, how does an organization know that it has significantly improved its safety performance based on trailing indicator information?

One way to track improvements is through the application of control charts, and in particular, the u-chart. Control charts are a powerful tool for analyzing variation and degree of control in most processes, including manufacturing, administrative (Wortman, 1995) and safety-related management systems. Statistical processes used to construct control charts in the quality arena can be applied with some adjustments to safety performance results.

Control charts are line graphs that display the dynamic picture of process and system behavior. The practical purpose of control charts is to graphi-

**Table 1**

## Attribute Control Chart Types

Type of chart	Records	Unit size
p-chart	Fraction or percent defective	Varies
np-chart	Number of defectives	Constant
c-chart	Number of defects	Constant
u-chart	Number of defects per unit	Varies

Note. To use these charts, the average number of defects or defectives in a sample group should be equal to or greater than 4 or 5. Adapted from CQE Primer, 4th ed., by B. Wortman, 1995, West Terre Haute, IN: Quality Council of Indiana.

averseness. However, if an SH&E manager's trailing indicator information (e.g., TRC rates) is based on analyzing large numbers of hours worked (e.g., millions of hours worked), a perceived small increase or decrease in a TRC rate could actually be significant based on the statistical power of having a large sample size ( $n$ ). The application of the central limit theorem predicts that as  $n$  increases, the degree of deviation from the mean that would indicate a significant change decreases. Thus, it makes good sense to apply statistical protocols to determine the significance of changing trailing indicator data regardless of the perceived degree of these changes.

### Using Rolling Averages

One of the easiest and most common ways to deal with the seesaw effect of trailing indicator information is to use rolling (or moving) averages. Rolling averages deal with natural data variability of trailing indicators by "dampening" out these variations. By looking at the average of four or more sequential quarters of metrics data, for instance, then progressively moving this rolling average through time on a quarterly basis (e.g., replacing the previous 1st quarter data set with the most current quarter data set), one can dampen out the seesaw effect of the data and begin to look visually at trends that the metrics may reveal.

Many organizations, such as U.S. Department of

**Table 2**

## Characteristics, Definitions & Formulas for Constructing u-Charts

<p><u>Characteristics:</u> Sample size varies; Poisson distribution assumed</p>
<p><u>Definitions:</u></p> $\bar{u} = \frac{\sum c}{\sum n} = \frac{\text{total number of defects in all samples}}{\text{total number of units in all samples}} = \text{average defects per unit}$ $\bar{n} = \frac{\sum n}{k} = \text{average sample size (e.g., in a lot analyzed), where } k = \text{number of sample sets}$
<p><u>Formulas (for 3s charts):</u></p> $UCL_u = \bar{u} + 3 \frac{\sqrt{\bar{u}}}{\sqrt{n}} \quad LCL_u = \bar{u} - 3 \frac{\sqrt{\bar{u}}}{\sqrt{n}} \quad \text{Note: } \frac{\sqrt{\bar{u}}}{\sqrt{n}} \text{ is equivalent to 1 standard deviation}$ <p>where <math>UCL_u</math> = upper control limit and <math>LCL_u</math> = lower control limit.</p> <p><u>Note:</u></p> <ul style="list-style-type: none"> <li>• When the “n” (the sample size) in <i>unequal</i> among the sample sets being analyzed, an individual UCL and LCL is calculated for <u>each</u> particular sample set using that “n” associated with that particular sample set.</li> <li>• When the “n” is <i>equal</i> among the sample sets, then that “n” is used in the above equations. Only one UCL and LCL are calculated when constructing the process chart.</li> <li>• When the “n” is <i>approximately equal</i> among the sample sets (e.g., sample sizes do not vary by more than ~15%), then the average “n” (<math>\bar{n}</math>) is used in the above equations and only one UCL and LCL are calculated when constructing the process chart.</li> </ul>

*Note.* Adapted from Manual on Presentation of Data and Control Chart Analysis, 6th ed., by American Society for Testing and Materials, 1995, Baltimore, MD: Author; and CQE Primer, 4th ed., by B. Wortman, 1995, West Terre Haute, IN: Quality Council of Indiana.



Initially, it may appear intimidating to construct a control chart. However, the mathematical skills and operations required to construct a control chart are not at an advanced level.

cally and visually identify outliers and trends in data. These outliers and trends indicate areas that may need to be addressed, potentially resulting in management intervention. These line graphs also feature a line indicating the process mean and two lines indicating upper and lower control limits (UCLs and LCLs, respectively).

The two types of control charts are variable and attribute. Attribute control charts plot “either-or” process categories or characteristics, such as being injured or not injured, being ill or not ill, passing or failing a safety test, being in compliance or out of compliance, having or not having hazardous characteristics. Only one variable is plotted on an attribute control chart (Janicak, 2007). The general rule is that at least 100 data points (Wortman, 1995), such as 25 sets of data each comprised of four data points (NIST/SEMATECH, 2010), are required to construct a control chart. Table 1 lists the four types of attribute charts.

Initially, it may appear intimidating to construct a control chart. However, the mathematical skills and operations required to construct a control chart are not at an advanced level. Typically, in developing control charts, the safety manager must be able to 1) sum a list of numbers; 2) determine the mean for a list of numbers; 3) take the square

root of certain sets of summed numbers; and 4) input these values into equations that will be used to determine control limits. The calculation formulas of these control limits depend on the type of control chart being constructed (Janicak, 2007). See the sidebar (p. 53) for basic mathematical operations required to generate most control charts.

In these charts, the particular control limits that instruct an organization on its process stability and variability are chosen by management, but calculated using process data. For manufacturing operations, the UCL is often set at three standard deviations or sigma (3 sigma) above the process mean and LCL is set at 3 sigma below the process mean. In control charts analyzing normally distributed data, approximately 68%, 95% and 99.7% of the data will fall within  $\pm 1$  sigma,  $\pm 2$  sigma and  $\pm 3$  sigma of the process mean, respectively. Thus, if the process is considered a  $\pm 3$  sigma manufacturing process, 99.7% of the averages should fall inside the boundaries of the UCL and LCL (Wachter & Bird, 2011; Wortman, 1995).

A process under statistical control is characterized by points that do not exceed UCL or LCL of the process. When a process is in control, it is predictable; conversely, when a process is out of control, it is no longer predictable (Wortman, 1995).

**Table 3**

## Data & Calculations for Constructing a u-Chart for the Trailing Indicator: Number of OHU Visits per FTE

Month k=12	Number of FTEs (n)	Number of Visits to OHU (c)	Number of OHU Visits per FTE	UCL	LCL
January	160	16	0.10	0.25	0.06
February	167	18	0.11	0.24	0.06
March	171	16	0.09	0.24	0.06
April	165	17	0.10	0.24	0.06
May	301	50	0.17	0.22	0.09
June	420	68	0.16	0.21	0.10
July	441	77	0.17	0.21	0.10
August	510	95	0.19	0.20	0.10
September	440	84	0.19	0.21	0.10
October	180	23	0.13	0.24	0.07
November	150	17	0.11	0.25	0.06
December	130	14	0.11	0.26	0.05
Totals:	Σn = 3,235	Σc = 495			

**CALCULATIONS:**

$$\bar{u} = \frac{\sum c}{\sum n} = \frac{495}{3,235} = 0.153 \text{ OHU visits per FTE (process average)}$$

**THREE SIGMA CONFIDENCE LEVELS [EXAMPLE CALCULATIONS PRESENTED FOR TWO DATA SETS ABOVE (see shaded entries)]:**

**JANUARY DATA SET (n = 160)**

$$UCL_{\mu} = \bar{u} + 3 \frac{\sqrt{\bar{u}}}{\sqrt{n}} = 0.153 + 3 \left( \frac{\sqrt{0.153}}{\sqrt{160}} \right) \quad UCL_{\mu} = 0.153 + 3 \left( \frac{0.391}{12.6} \right) = 0.153 + 0.093$$

**UCL<sub>μ</sub> = 0.25 OHU visits per FTE**

$$LCL_{\mu} = \bar{u} - 3 \frac{\sqrt{\bar{u}}}{\sqrt{n}} = 0.153 - 3 \left( \frac{\sqrt{0.153}}{\sqrt{160}} \right)$$

$$LCL_{\mu} = 0.153 - 3 \left( \frac{0.391}{12.6} \right) = 0.153 - 0.093$$

**LCL<sub>μ</sub> = 0.06 OHU visits per FTE**

**JUNE DATA SET (n = 420)**

$$UCL_{\mu} = \bar{u} + 3 \frac{\sqrt{\bar{u}}}{\sqrt{n}} = 0.153 + 3 \left( \frac{\sqrt{0.153}}{\sqrt{420}} \right)$$

$$UCL_{\mu} = 0.153 + 3 \left( \frac{0.391}{20.5} \right) = 0.153 + 0.057$$

**UCL<sub>μ</sub> = 0.21 OHU visits per FTE**

$$LCL_{\mu} = \bar{u} - 3 \frac{\sqrt{\bar{u}}}{\sqrt{n}} = 0.153 - 3 \left( \frac{\sqrt{0.153}}{\sqrt{420}} \right)$$

$$LCL_{\mu} = 0.153 - 3 \left( \frac{0.391}{20.5} \right) = 0.153 - 0.057$$

**LCL<sub>μ</sub> = 0.10 OHU visits per FTE**

Various criteria have been established that define a control chart as being “out of control” and for causing management concern and resulting action. The criteria include (Duncan, 1974):

- one or more points outside the ± 3 sigma limits on a control chart;

- one or more points in the vicinity of the ± 3 sigma control limit, which suggests the need to immediately take more data to determine whether the process is going out of control beyond the ± 3 sigma limits;

- a run of 2 or more points outside of the 2 sigma limit;

- a run of 4 or 5 points outside of the 1 sigma limit;

- a run of 7 or more points (a run up or a run down, especially if the run is above or below the central line on the control chart);

- cycles or other patterns in the data.

The calculation of process mean and control limits can be applied to trailing safety indicator information, such as TRC and DART rates, with some adjustments. However, it is noted upfront that LCLs for trailing indicator injury data often are calculated to be less than zero; under these situations, the LCLs are assumed to be zero when constructing these charts.

**Using u-Charts to Interpret Trailing Indicator Information**

In terms of interpreting and practically using trailing safety indicator information, the u-chart is the most applicable control chart, since the sample size (e.g., number of employees or hours worked) is allowed to vary when constructing such a chart. This chart is most appropriate to measuring infrequent events (as described by a Poisson distribution), such as the average number of injuries in the workplace. In addition, the typical characteristic being plotted in a u-chart, the number of defects per measured unit, is much like a classic OSHA trailing indicator (number of injuries per 200,000

hours worked). OSHA measures such as TRC and DART rates can be broadly interpreted as being the average number of defects (e.g., injuries) per unit (e.g., hours worked).

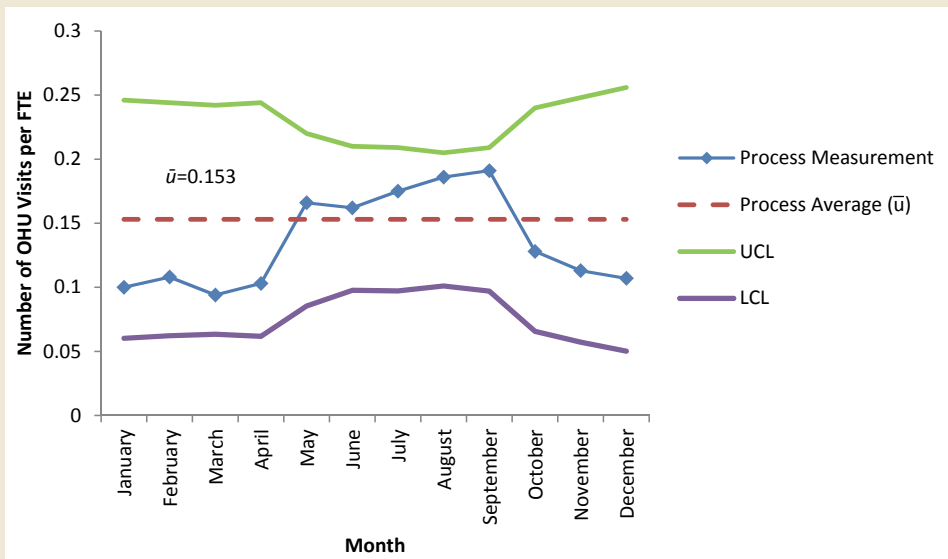
Thus, in the safety area, a u-chart can be used to track the number of total recordable injuries, total lost workday injuries, or injuries resulting in restricted work or job transfer, all of which reflect “defects.” The number of injuries is counted in a fixed time interval (e.g., monthly, quarterly, annually), but the sample size contributing to the injury measurement varies (e.g., hours worked, number of employees), since the number of people employed by companies and their hours of work almost always change during the course of the year (Wachter & Bird, 2011).

The characteristics, definitions and formulas for calculating u-chart parameters are shown in Table 2 (p. 51). An example of how to calculate a u-chart and its parameters based on trailing indicator safety information follows. Let’s assume that the SH&E manager is tracking the monthly number of visits to the facility’s occupational health unit (OHU) due to occupational injuries (including minor cuts and other lesser injuries) or illnesses. He wonders whether he needs to worry about the fluctuations in the number of visits each month.

However, the manager also knows that the facility’s worker population greatly fluctuates, especially during the summer, due to seasonal work. So, the safety manager calculates the number of full-time equivalent workers (FTEs) on the monthly basis and begins to track the number of OHU visits per FTE. The manager collects the data and makes the calculations (Table 3) necessary to construct the u-chart (3 sigma confidence limits; varying sample sizes).

**Figure 2**

## u-Chart Showing Number of OHU Visits per FTE



*Note.* u-Chart (3 sigma confidence limits; variable sample size) showing number of occupational health unit (OHU) visits per FTE.

## Math Functions Used to Construct Control Charts

When constructing control charts, the process mean (derived from process data) is calculated and plotted along with the upper and lower control limits (UCL and LCL), along with the collected process data that were used to calculate the process mean. Depending on the specific control chart being constructed, the formulas for calculating the process mean and the UCL and LCL will differ slightly. Typically, the following mathematical operations need to be conducted when developing control charts:

- Calculation of a sum of numbers ( $\Sigma$ ).
- Calculation of the arithmetic mean ( $\bar{x}$ ) for a set of numbers; these types of calculations are used to determine the process mean and an average sample size (for use in calculating the UCL and LCL).
- Calculation of the square root ( $\sqrt{\quad}$ ) for a number; the square roots of the process mean and average sample size are often needed to calculate the UCL and LCL.
- The use of the above calculated numbers (e.g., process mean and average sample size) in two equations

(one for determining UCL, the other for LCL), which are specific to the control chart being constructed.

- And then plotting the collected process data, the calculated process mean, the UCL, and the LCL versus time in order to construct the control chart.

For SH&E managers interested in developing more expertise analyzing trailing indicator information, including the statistical methods discussed in this article, the following three books are recommended:

- Janicak, C.A. (2007). *Applied statistics in occupational safety and health* (2nd ed.). Lanham, MD: Government Institutes, Scarecrow Press Inc.
- Janicak, C.A. (2011). *Safety metrics: Tools and techniques for measuring safety performance* (2nd ed.). Lanham, MD: Government Institutes, Scarecrow Press Inc.
- Wachter, J. & Bird, A. (2011). *Applied quantitative methods for occupational safety and health*. San Diego, CA: University Readers.

**Table 4**

## Data & Calculations for Constructing a u-Chart for the Trailing Indicator: Number of Injuries per Hour Worked

Time Period, k=12	Hours Worked (n)	Number of Injuries (c)	Number of Injuries ( $\times 10^{-5}$ ) per Hour Worked	Corresponding OSHA TRC Rate [(No. of Injuries $\times 10^{-5}$ per Hour Worked) $\times 200,000$ hrs]
Year 1, Quarter 1	98,776	7	7.1	14.2
Year 1, Quarter 2	103,456	8	7.7	15.5
Year 1, Quarter 3	99,006	7	7.1	14.1
Year 1, Quarter 4	100,882	9	8.9	17.8
Year 2, Quarter 1	100,872	10	9.9	19.8
Year 2, Quarter 2	99,980	10	10	20.0
Year 2, Quarter 3	101,427	8	7.9	15.8
Year 2, Quarter 4	101,332	9	8.9	17.8
Year 3, Quarter 1	100,876	7	6.9	13.9
Year 3, Quarter 2	101,298	9	8.9	17.8
Year 3, Quarter 3	99,972	10	10	20.0
Year 3, Quarter 4	101,980	9	8.8	17.7
Totals:	$\Sigma n = 1,209,857$	$\Sigma c = 103$		

**CALCULATIONS:**

$$\bar{u} = \frac{\sum c}{\sum n} = \frac{103}{1,209,857} = 0.000085 \text{ (or } 8.5 \times 10^{-5} \text{) injuries per hr worked (average)}$$

$$\bar{n} = \frac{\sum n}{k} = \frac{1,209,857}{12} = 100,821 \text{ hours worked each quarter (average)}$$

**THREE SIGMA CONFIDENCE LEVELS:**

$$UCL_{\mu} = \bar{\mu} + 3\frac{\sqrt{\bar{\mu}}}{\sqrt{\bar{n}}} = 0.000085 + 3\left(\frac{\sqrt{0.000085}}{\sqrt{100,821}}\right) = 0.000085 + 3\left(\frac{0.0092}{317.5}\right) = 0.000085 + 0.000087$$

**$UCL_{\mu} = 0.000172 = 17.2 \times 10^{-5}$  injuries per hr worked**

$$LCL_{\mu} = \bar{\mu} - 3\frac{\sqrt{\bar{\mu}}}{\sqrt{\bar{n}}} = 0.000085 - 3\left(\frac{\sqrt{0.000085}}{\sqrt{100,821}}\right) = 0.000085 - 3\left(\frac{0.0092}{317.5}\right) = 0.000085 - 0.000087$$

**$LCL_{\mu} = -0.21 \times 10^{-5}$  injuries per hr worked = 0 (since calculated  $LCL_{\mu}$  is less than zero)**

**ONE SIGMA CONFIDENCE LEVELS:**

$$UCL_{\mu} = \bar{\mu} + \frac{\sqrt{\bar{\mu}}}{\sqrt{\bar{n}}} = 0.000085 + \left(\frac{\sqrt{0.000085}}{\sqrt{100,821}}\right) = 0.000085 + \left(\frac{0.0092}{317.5}\right) = 0.000085 + 0.000029$$

**$UCL_{\mu} = 0.000114 = 11.4 \times 10^{-5}$  injuries per hr worked**

$$LCL_{\mu} = \bar{\mu} - \frac{\sqrt{\bar{\mu}}}{\sqrt{\bar{n}}} = 0.000085 - \left(\frac{\sqrt{0.000085}}{\sqrt{100,821}}\right) = 0.000085 - \left(\frac{0.0092}{317.5}\right) = 0.000085 - 0.000029$$

**$LCL_{\mu} = 0.000056 = 5.6 \times 10^{-5}$  injuries per hr worked**

Note. Years 1 through 3 data.

As shown in Figure 2 (p. 53), the process average ( $\bar{u}$ ) is 0.153 OHU visits per FTE. The UCL ranges from 0.20 to 0.26 and the LCL ranges from 0.05 to 0.10. The measurements obtained for the trailing indicator (number of OHU visits per FTE) indicate process control (related to OHU visits) since all measurements are between UCL and LCL, although the September measure is approaching the UCL. If this September measurement would have exceeded UCL, it would have indicated that, based on  $\pm 3$  sigma confidence limits, a significant change occurred in the number of OHU visits per FTE during September.

None of the other criteria that define a 3 sigma control chart being “out of control” was achieved. Also, note that during late spring through early fall months (May through September), when the number of workers is much higher, the range of acceptable trailing indicator values between the UCL and LCL narrows. This is because as sample size increases (a higher  $n$ ), there is a higher degree of confidence in the data analysis results, which is reflected in a reduced range of “acceptable” measurement values.

In many safety and health situations, sample size (e.g., hours worked; FTEs present) varies, but not significantly (e.g., less than 15% variation in sample sizes). In these cases, an average sample size can be calculated and applied to the group of samples. A single (uniform) UCL and LCL is then calculated and plotted (rather than a range). An example follows. One also can extrapolate from this averaging convention that u-charts also can be used to plot and analyze TRC and DART rate data, where the injury and illness case numbers have been normalized to an average, constant sample size of 200,000 hours worked.

An SH&E manager working in a high-hazard industry that historically has had el-

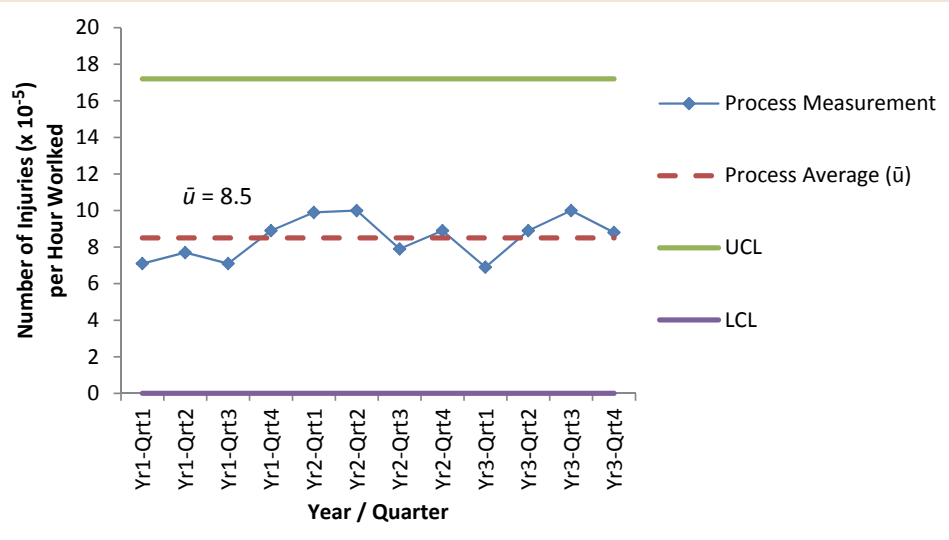
evated TRC rates, collects the number of injuries at the worksite every 3 months over a 3-year period (Table 4). S/he also collects the total number of hours worked per quarter. The manager wants to construct a u-chart of total number of OSHA recordable injuries per hours worked during a 3-month period to see what constitutes a status quo control injury mean and range at the workplace (and to determine whether the organization is consistently within this range of performance, even if this range of performance is considered to be high by industry standards). The data in Table 4 have been used to calculate the parameters needed to generate the u-chart presented in Figure 3.

As shown in Figure 3, the safety system under investigation is considered to be “in control” (e.g., the system is not changing) as determined by the constructed chart based on the calculated process mean ( $\bar{u} = 8.5 \times 10^{-5}$  injuries/hr worked) and its 3 sigma control limits (UCL =  $17.2 \times 10^{-5}$  injuries/hr worked; LCL = 0 injuries/hr worked). All data fall between the upper and lower control limits. The process mean corresponds to an OSHA TRC rate of 17: ( $8.5 \times 10^{-5}$  injuries/hr worked)  $\times$  200,000 hr worked; the UCL corresponds roughly to an OSHA TRC rate of 34: ( $17.2 \times 10^{-5}$  injuries/hr worked)  $\times$  200,000 hr worked, and the LCL corresponds to an OSHA TRC rate of zero.

Thus, in terms of practically applying the 3 sigma control limits typically associated with manufacturing operations to analyzing injury information using a u-chart in this example, it appears that almost the entire experience-based universe of TRC rate values for industry would be contained within these control limits. In this case, little practical information is being provided to managers for signaling when interventions may be needed (e.g., performance is near UCL) or that

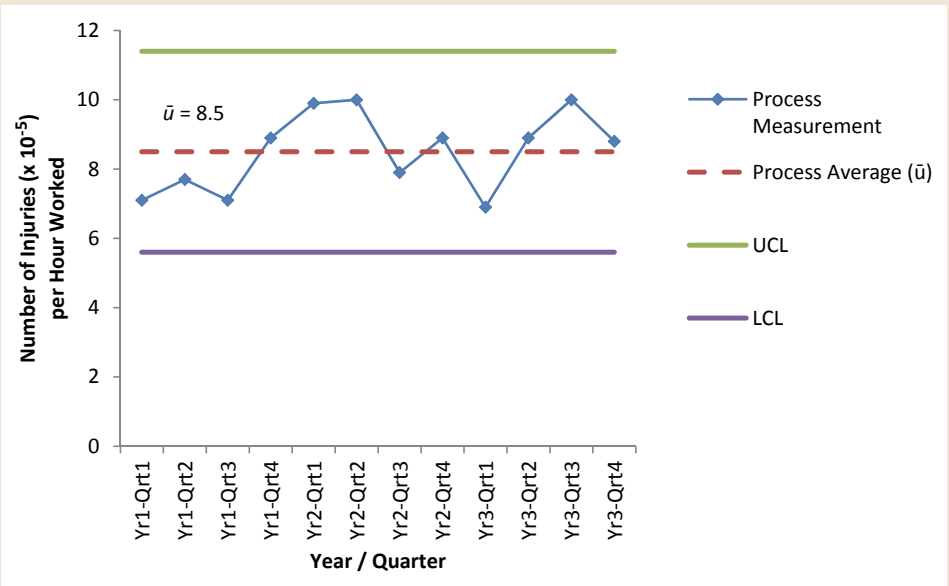
they are significantly improving (e.g., performance is near LCL).

**Figure 3**  
**u-Chart Showing Number of Injuries per Hour Worked**



*Note.* u-Chart (3 sigma confidence limits; approximately the same sample size; years 1 through 3 data used in calculations) showing number of injuries ( $\times 10^{-5}$ ) per hour worked.

**Figure 4**  
**u-Chart Showing Number of Injuries per Hour Worked**



*Note.* u-Chart (1 sigma confidence limits; approximately the same sample size; years 1 through 3 data used in calculations) showing number of injuries ( $\times 10^{-5}$ ) per hour worked.



Thus, from a risk management perspective, it is more practical in this case for management to adopt a more narrow range of acceptable trailing indicator information for determining whether the safety management systems are "in control." Management has the prerogative to set the control limits based on its degree of risk averseness and its desire for continual improvement.

For instance, if management adopts a 1 sigma control limit approach, statistics would theoretically indicate that most safety indicator data for the system being investigated (68% chance) should be contained within the control limits, but this still allows a 32% chance for data to be outside the

control limits, signaling to management that interventions or improvements may be required or that safety performance is indeed improving. This seems to be a reasonable approach in many situations, balancing the need for identifying change with the need not to be reactive to smaller changes in trailing indicator information.

However, a drawback to using 1 sigma confidence limits is that the safety manager may be reacting to outlier data which occurred due only to chance and not due to any true phenomenon. This is why looking at trailing indicator measures over a period of time and observing other characteristics of control charts indicating out-of-control situations (e.g., run of data points in a certain direction) are important.

A u-chart based on using 1 sigma limits (Figure 4, p. 55) indicates a much tighter fit of the trailing indicator information between the control limits. Again, this system appears to be in control (e.g., status quo is being maintained) from a safety perspective based on the assumptions being made. The system is neither improving nor degrading.

In terms of using this approach over a time course, additional data (e.g., Year 4 data) would be collected (see Table 5 for additional shaded Year 4 data), then charted using the parameters previously calculated. As shown in Figure 5, some additional Year 4 data in this example are below LCL, indicating that the safety management system is out of control, but in a good way. Safety performance as measured through injury data is improving based on this analysis and management's assumptions used in constructing this chart. In addition, the run of six points in a downward direction supports this conclusion.

Control chart parameters are then periodically updated (e.g., annually). Compatible with a rolling average approach, Year 1 data used to construct the chart are removed and replaced with the more recent annual data (Year 4) to recalculate the process mean ( $\bar{u}$ ), UCL and LCL for the u-chart. Injury data are then replotted on an updated control chart. Based on the data contained in Table 5 (using Years 2, 3 and 4 data), the  $\bar{u}$  was recalculated to be  $7.5 \times 10^{-5}$

**Table 5**

## Data & Calculations for Constructing a u-Chart for the Trailing Indicator: Number of Injuries per Hour Worked

Time Period, k=12	Hours Worked (n)	Number of Injuries (c)	Number of Injuries ( $\times 10^{-5}$ ) per Hour Worked
Year 2, Quarter 1	100,872	10	9.9
Year 2, Quarter 2	99,980	10	10
Year 2, Quarter 3	101,427	8	7.9
Year 2, Quarter 4	101,332	9	8.9
Year 3, Quarter 1	100,876	7	6.9
Year 3, Quarter 2	101,298	9	8.9
Year 3, Quarter 3	99,972	10	10
Year 3, Quarter 4	101,980	9	8.8
Year 4, Quarter 1	114,286	8	7.0
Year 4, Quarter 2	111,111	6	5.4
Year 4, Quarter 3	121,951	5	4.1
Year 4, Quarter 4	105,263	4	3.8
Totals:	$\Sigma n = 1,260,348$	$\Sigma c = 95$	

### Calculations:

$$\bar{u} = \frac{\sum c}{\sum n} = \frac{95}{1,260,348} = 0.000075 \text{ (or } 7.5 \times 10^{-5} \text{) injuries per hr worked (average)}$$

$$\bar{n} = \frac{\sum n}{k} = \frac{1,260,348}{12} = 105,029 \text{ hours worked each quarter (average)}$$

### ONE SIGMA CONFIDENCE LEVELS:

$$UCL_{\mu} = \bar{u} + \frac{\sqrt{\bar{u}}}{\sqrt{\bar{n}}} = 0.000075 + \left( \frac{\sqrt{0.000075}}{\sqrt{105,029}} \right) = 0.000075 + \left( \frac{0.0087}{324.1} \right) = 0.000075 + 0.000027$$

$$UCL_{\mu} = 0.000102 = 10.2 \times 10^{-5} \text{ injuries per hr worked}$$

$$LCL_{\mu} = \bar{u} - \frac{\sqrt{\bar{u}}}{\sqrt{\bar{n}}} = 0.000075 - \left( \frac{\sqrt{0.000075}}{\sqrt{105,029}} \right) = 0.000075 - \left( \frac{0.0087}{324.1} \right) = 0.000075 - 0.000027$$

$$LCL_{\mu} = 0.000048 = 4.8 \times 10^{-5} \text{ injuries per hr worked}$$

Note. Years 2 through 4 data.

injuries/hr and the UCL (1 sigma) and the LCL (1 sigma) were recalculated to be  $10.2 \times 10^{-5}$  and  $4.8 \times 10^{-5}$  injuries/hr worked, respectively (Figure 6).

Figure 6 indicates again that the safety system is out of control (improving) based on Year 4 data. However, the mean ( $\bar{u}$ ) of the trailing indicator on the control chart has been reduced from  $8.5 \times 10^{-5}$  to  $7.5 \times 10^{-5}$  injuries/hr (an improvement); based on data collected, the 1 sigma control range (UCL-LCL) has been slightly reduced from  $5.8 \times 10^{-5}$  injuries/hr ( $11.4 \times 10^{-5} - 5.6 \times 10^{-5}$ ) to  $5.4 \times 10^{-5}$  injuries/hr ( $10.2 \times 10^{-5} - 4.8 \times 10^{-5}$ ), indicating a more limited control limit range (tighter control). This revised control chart would then be used to plot Year 5 data that would be collected.

There is flexibility when using this u-chart approach in that management can establish its own acceptable sigma control limits to impose on its safety management system based on its degree of risk tolerance or desire for system improvement. In short, management determines what level of sigma control limits is acceptable and significant. Once these limits are determined for generating these charts, management must apply it consistently and not arbitrarily or capriciously for determining whether the system is in control (status quo), improving or degrading (the latter requiring intervention).

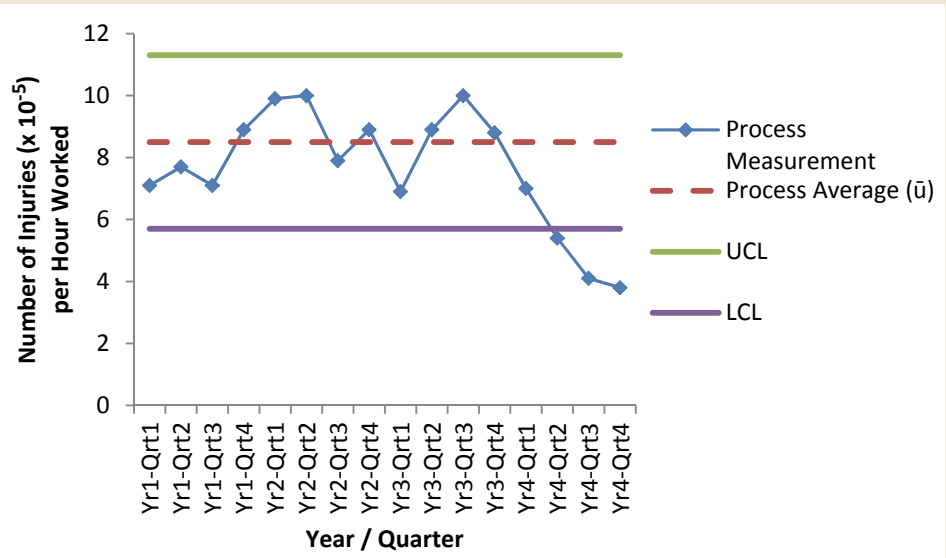
#### Using Correlation & Regression Analyses for Trailing & Leading Indicators

A balanced scorecard contains trailing and leading indicators. If the list of leading indicators chosen truly drives root actions to address root causes of previously identified incidents, then one should be able in many circumstances to correlate the information obtained from leading indicator metrics (independent variable,  $x$ ) with the results from trailing indicators (dependent variable,  $y$ ). In this way, managers can be better assured that organizational resources

are being appropriately placed in those leading actions or activities that will drive down injuries and illnesses (Wachter & Bird, 2011).

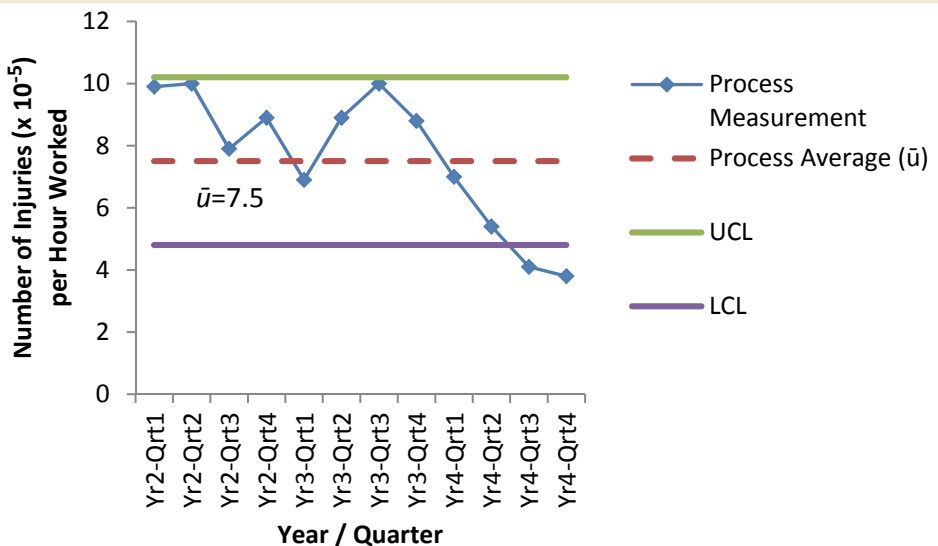
By attempting to correlate trailing and leading

**Figure 5**  
**u-Chart Showing Number of Injuries per Hour Worked**



*Note.* u-Chart (1 sigma confidence limits; approximately the same sample size; years 1 through 3 data used in calculations + Year 4 data charted) showing number of injuries ( $\times 10^{-5}$ ) per hour worked.

**Figure 6**  
**Revised u-Chart Showing Number of Injuries per Hour Worked**



*Note.* Revised u-chart (1 sigma confidence limits; approximately the same sample size; years 2 through 4 data used in calculations) showing number of injuries ( $\times 10^{-5}$ ) per hour worked.

**Table 6**

## Leading & Trailing Indicator Data Collected & Analyzed Over 3-Year Period

Year / Quarter (n = 12)	Leading Indicator: Percent of new / revised job tasks covered by hazard assessment (independent variable $x_i$ )	$(x_i - \bar{x})^2$	$x^2$	Trailing Indicator: Number of total recordable cases (TRCs) associated with new / revised job tasks (dependent variable $y_i$ )	$(y_i - \bar{y})^2$	$y^2$	$(x)(y)$
Y1, 1 <sup>st</sup> Q	4	2,938	16	11	10.2	121	44
Y1, 2 <sup>nd</sup> Q	10	2,323	100	11	10.2	121	110
Y1, 3 <sup>rd</sup> Q	22	1,310	484	10	4.8	100	220
Y1, 4 <sup>th</sup> Q	33	635	1,089	10	4.8	100	330
Y2, 1 <sup>st</sup> Q	45	174	2,025	9	1.4	81	405
Y2, 2 <sup>nd</sup> Q	60	3	3,600	8	0.04	64	480
Y2, 3 <sup>rd</sup> Q	72	190	5,184	8	0.04	64	576
Y2, 4 <sup>th</sup> Q	80	475	6,400	7	0.6	49	560
Y3, 1 <sup>st</sup> Q	88	888	7,744	6	3.2	36	528
Y3, 2 <sup>nd</sup> Q	90	1,011	8,100	5	7.8	25	450
Y3, 3 <sup>rd</sup> Q	94	1,281	8,836	4	14.4	16	376
Y3, 4 <sup>th</sup> Q	100	1,747	10,000	4	14.4	16	400
$\sum x_i$ or $\sum y_i$	698			93			
<b>AVERAGE*</b>	<b>58.2 (<math>\bar{x}</math>)</b>			<b>7.8 (<math>\bar{y}</math>)</b>			
$\sum(x_i - \bar{x})^2$ or $\sum(y_i - \bar{y})^2$		<b>12,975</b>			<b>71.9</b>		
<b>STANDARD DEVIATION**</b>	<b>34.3 (SD<math>x</math>)</b>			<b>2.6 (SD<math>y</math>)</b>			
Values used in Pearson Correlation Coefficient $r$ calculation (see text)							
$\sum x =$	<b>698</b>						
$\sum x^2 =$			<b>53,578</b>				
$\sum y =$				<b>93</b>			
$\sum y^2 =$						<b>793</b>	
$\sum xy =$							<b>4,479</b>

\*The averages (or means) for the list of  $x$  and  $y$  values were calculated using the following formulae:

$$\bar{x} \text{ (average)} = \frac{1}{n} \sum x_i \quad \bar{x} \text{ (average)} = \frac{1}{12} (698) = 58.2$$

$$\bar{y} \text{ (average)} = \frac{1}{n} \sum y_i \quad \bar{y} \text{ (average)} = \frac{1}{12} (93) = 7.8$$

\*\*The standard deviations (SD) for the list of  $x$  and  $y$  values were calculated using the following formulae:

$$SD_x = \sqrt{\frac{\sum(x_i - \bar{x})^2}{n-1}} = \sqrt{\frac{12,975}{11}} = \sqrt{1,179.5} = 34.3$$

$$SD_y = \sqrt{\frac{\sum(y_i - \bar{y})^2}{n-1}} = \sqrt{\frac{71.9}{11}} = \sqrt{6.54} = 2.6$$

The mean and standard deviation can also be calculated easily by inputting the list of  $x$  and  $y$  values into a spreadsheet that can calculate means and standard deviations.

**Note.** Leading indicator (% new/revised job tasks covered by hazard reviews) and trailing indicator (number of TRCs associated with new/revised jobs) data collected and analyzed over 3-year period.

indicator information to better understand the strength of their associations, the value of and respect for collecting trailing indicator information consequently increases. However, it should be noted that discerning correlations and associations are not necessarily distinguishing cause-and-effect relationships, since cause-and-effect relationships are typically only determined through experimentation.

As an example, assume that most of an organization's total recordable cases in the last year are related to lack of hazard control. Incident investigation reports point to lack of upfront hazard analyses for new or revised job tasks as the cause. Without these upfront evaluations, hazards occur undiagnosed and unabated until incidents eventually result. Thus, the organization decides to adopt a new leading performance indicator by tracking the percent of new or revised job tasks covered by hazard evaluations. This measure would then lead the organization to taking root actions by actually performing these hazard evaluations and taking appropriate action as necessary, thereby theoretically reducing the future incidence of injuries.

The safety manager collects data shown in Table 6

over a 3-year period (12 quarters). These data have been plotted in a scatter chart in Figure 7. As seen in this chart, a negative correlation appears to exist between the leading indicator ( $x$  variable) and the trailing indicator ( $y$  variable), which makes intuitive sense. Increasing performance of the leading “good” indicator is associated with decreasing performance of the “bad” trailing indicator.

Several statistical protocols can be used to analyze this associative information. A primary statistical protocol available for use is called a bivariate correlation where a dependent ( $y$ ) variable (e.g., trailing indicator measurement) is correlated with an independent ( $x$ ) variable (e.g., factor or contributing/root cause from an incident investigation that is reflected in the choice of a leading indicator). In conducting a bivariate correlation, a correlation coefficient ( $r$ ) is calculated to measure association strength. These correlation coefficients range from  $-1.00$  to  $+1.00$ , with  $-1.00$  being indicative of a perfect inverse (or negative) correlation;  $+1.00$  being indicative of a perfect positive correlation; and  $0.00$  being indicative of an absence of any correlation.

For the data set in Table 6, the Pearson Correlation Coefficient  $r$  was calculated to be  $-0.96$ , using the formula below (Janicak, 2007; see calculations in Table 6).

$$r = \frac{\sum xy - \frac{(\sum x \sum y)}{n}}{\sqrt{\left[ \sum x^2 - \frac{(\sum x)^2}{n} \right] \left[ \sum y^2 - \frac{(\sum y)^2}{n} \right]}}$$

$$r = \frac{\sum 4,479 - \frac{(698 \sum 93)}{12}}{\sqrt{\left[ \sum 53,578 - \frac{(\sum 698)^2}{12} \right] \left[ \sum 793 - \frac{(\sum 93)^2}{12} \right]}}$$

$$r = \frac{4,479 - \frac{64,914}{12}}{\sqrt{\left[ 53,578 - \frac{487,204}{12} \right] \left[ 793 - \frac{8,649}{12} \right]}} = \frac{4,479 - 5,410}{\sqrt{[53,578 - 40,600][793 - 721]}}$$

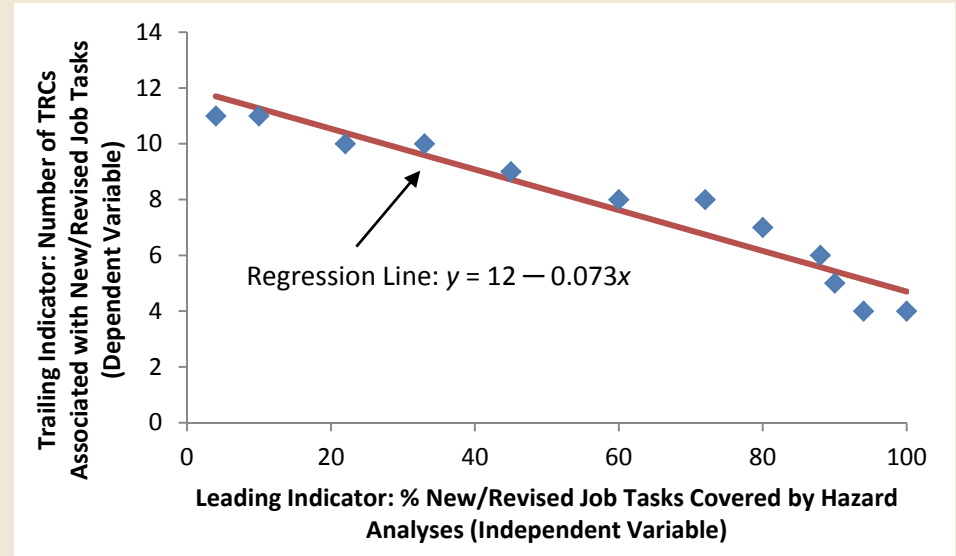
$$r = \frac{-931}{\sqrt{[12,978][72]}} = \frac{-931}{\sqrt{[934,416]}} = \frac{-931}{967}$$

$$r = -0.96$$

Another measure of correlation is the coefficient  $r^2$ , known as the coefficient of determination. By squaring the correlation coefficient  $r$ , the amount of variability in the dependent variable ( $y$ ) that can be

**Figure 7**

## Scatter Chart Showing Association Between Leading & Trailing Indicators



*Note.* Revised u-chart (1 sigma confidence limits; approximately the same sample size; years 2 through 4 data used in calculations) showing number of injuries ( $\times 10^5$ ) per hour worked.

directly attributed to the independent variable ( $x$ ) can be determined. In this example, 92%  $[(-0.96)^2 \times 100]$  of the variation of the trailing indicator data can be explained by the variation in the leading indicator data.

But this near perfect association/correlation occurs infrequently since many causes typically contribute to incidents. The safety manager also must consider when trying to associate leading and trailing indicators that there is probably a temporal (time) association between these indicators that may not be synchronous. In other words, it may take some time for the benefits associated with implementing actions associated with leading indicators to pay off, as evidenced in changing trailing indicator results. This association is seldom instantaneous, and may take weeks, months or years to see the connection.

For instance, if the safety manager conducts hazard evaluations for all new/revised job tasks, it may take some time to realize the outgrowths of these endeavors. After hazard evaluations are conducted, workplace redesign or hazard abatements may be needed. Thus, the manager may need to “dephase” the leading indicator results from trailing indicator results by the amount of time s/he believes it will take to see results from the leading indicator actions being taken. Therefore, the organization may need to be patient in observing an association between the positive effects of its leading indicators on performance results (trailing indicators).

In this example, a strong negative correlation ( $-0.96$ ) exists between the leading indicator and the trailing indicator. In such a case, the SH&E



Trailing safety indicators will ultimately be used to judge the effectiveness of leading indicators and overall organizational safety performance.

manager may elect to perform a regression analysis to generate the best linear equation to predict how a trailing indicator (dependent variable) will be affected (on average) by the leading indicator (independent variable). Knowing the Pearson Correlation Coefficient  $r$  and the standard deviation of data within the two data sets ( $x$  and  $y$  variables) (see Table 6 for how  $SD$ s were determined), a safety manager can calculate the equation of the regression line:  $y = a + bx$ , where  $b$  is the slope of the line and  $a$  is the  $y$  intercept. The slope of the line  $b$  can be calculated using the formula below (Cohen & Cohen, 1983):

$$b = r \left( \frac{SD_y}{SD_x} \right)$$

where  $r$  = Pearson correlation coefficient and  $SD_y$  is the standard deviation of the  $y$  data set and  $SD_x$  is the standard deviation of the  $x$  data set (Table 6).

The  $y$  intercept,  $a$ , is then calculated by inputting the calculated slope,  $b$ , into the following equation:  $a = \bar{y} - b\bar{x}$ , where  $\bar{y}$  is the average value of the  $y$  data and  $\bar{x}$  is the average value of the  $x$  data (Table 6). Using the data in the example, the following parameters in the linear equation can be calculated:

$$b = r (SD_y)/(SD_x) = -0.96 (2.6)/(34.3) = -0.073$$

$$a = \bar{y} - b\bar{x} = 7.8 - (-0.073) (58.2) = 12$$

Thus, the linear equation ( $y = a + bx$ ) for the regression line becomes:  $y = 12 - 0.073x$ . A plot of this regression line is shown in Figure 7 (p. 59).

The safety and health manager can then apply this equation to predict how future results (trailing indicator measurements) would be affected by leading indicator performance. For example, the safety manager may want to know the predicted results if only 70% of new or revised job tasks are covered by hazard assessments in the future. Substituting "70" for  $x$  in the equation (or by visually looking at the results in Figure 6), the manager would estimate that 6.9 injuries would still result.

In addition, the equation predicts that no TRCs would result if ~164% of the job tasks would be covered by hazard assessments (substituting 0 for  $y$  in the above linear equation and solving for  $x$ ). This is a rather absurd conclusion, which highlights some of the imprecision and uncertainties in developing and applying the best linear equation to predict the effect of leading indicator performance on trailing indicator performance even when the correlation between the two variables appears to be highly significant (Wachter & Bird, 2011). However, the equation generally predicts that by performing hazard evaluations for all new/revised tasks, most, although not all, of the historic injuries associated with new/revised task activities may be eliminated.

### Conclusion

Although many criticize trailing safety indicators for their lagging and nonpredictive characteristics, and many organizations have replaced them with leading safety indicators due to their proactive,

predictive and forcing nature, SH&E professionals must continue to use trailing safety indicators to objectively assess safety performance. These indicators will ultimately be used to judge the effectiveness of leading indicators and overall organizational safety performance.

The value of measuring trailing safety indicators can be enhanced by applying appropriate statistical protocols. These include the use of rolling averages, the construction of u-control charts, and the application of correlation statistics for discerning associations between leading indicator results and trailing indicator results. **PS**

### References

- American Society for Testing and Materials.** (ASTM). (1995). *Manual on presentation of data and control chart analysis* (6th ed.). Baltimore, MD: Author.
- Blair, E. & O'Toole, M.** (2010, Aug.). Leading measures: Enhancing safety climate and driving safety performance. *Professional Safety*, 55(8), 29-34.
- Coffey, W.** (2009). Developing metric systems for sustained improvements. Professional Development Course at the American Industrial Hygiene Conference and Exposition, Toronto, Ontario.
- Cohen, J. & Cohen, P.** (1983). *Applied multiple regression/correlation analysis for the social sciences*. Hillsdale, NJ: Erlbaum.
- Duncan, A.** (1974). *Quality control and industrial statistics*. Homewood, IL: Richard D. Irwin.
- Janicak, C.A.** (2007). *Applied statistics in occupational safety and health* (2nd ed.). Lanham, MD: Government Institutes.
- Janicak, C.A.** (2011). *Safety metrics: Tools and techniques for measuring safety performance* (2nd ed.). Lanham, MD: Government Institutes, Scarecrow Press Inc.
- Kausek, J.** (2007). *OHSAS 18001: Designing and implementing an effective health and safety management system*. Lanham, MD: Government Institutes, Scarecrow Press Inc.
- NIST/SEMATECH.** (2010). e-Handbook of statistical methods. Washington, DC: Author. Retrieved from [www.itl.nist.gov/div898/handbook](http://www.itl.nist.gov/div898/handbook).
- U.S. Department of Energy.** (2009). Corporate safety analysis performance. Washington, DC: Author, Office of Corporate Safety Analysis. Retrieved from [www.hss.doe.gov/sesa/analysis/performance\\_statistics/pdfs/Occ\\_Safety\\_All\\_DOE\\_FY2009\\_Q4.pdf](http://www.hss.doe.gov/sesa/analysis/performance_statistics/pdfs/Occ_Safety_All_DOE_FY2009_Q4.pdf).
- Wachter, J. & Bird, A.** (2011). *Applied quantitative methods for occupational safety and health*. San Diego, CA: University Readers.
- Wortman, B.** (1995). *CQE primer* (4th ed.). West Terre Haute, IN: Quality Council of Indiana.



Watch Professor Wachter's YouTube video on employee engagement research and the role of data in safety management at [www.asse.org/psextra](http://www.asse.org/psextra).