Impact of Safety Efforts

Intervention Effectiveness Research: Phase 1

Developing a Mathematical Relationship Between Interventions & Incident Rates for the Design of a Loss Prevention System

By JOEL M. HAIGHT, ROBERT E. THOMAS, LEO A. SMITH, ROBERT L. BULFIN JR. and BILL L. HOPKINS

oss prevention and safety programs are often implemented without a quantified design. This two-phase study was designed to determine whether such a program could be quantified, then optimized through a design that minimizes the incident rate and the human resources needed to implement the program's interventions. A model was developed for this purpose. Phase 1 of this study analyzed an oil production operation. Four categories of interventions were studied 1) behavior modification, incentives and awareness; 2) training; 3) job/procedural design; and 4) equipment.

The percentage of available time spent implementing each intervention was the independent variable (known as the intervention application rate) and the incident rate was the dependent variable. Findings show a mathematical relationship between interventions and incident rates. The resulting best-fit function is an intuitively expected, exponential function showing a decreasing incident rate with an increasing intervention application rate. This model can be used to analyze the function for a minimized incident rate (Phase 2, to be published in the June 2001 issue of PS), which aids in designing an optimized loss prevention or safety program.

INTRODUCTION & PROBLEM DESCRIPTION

The current research was established to determine whether a loss prevention system could be quantified, designed and, therefore, optimized as any engineering-based system. This required that a statistically significant mathematical relationship be shown between the intervention activity implemented to reduce the incident rate (independent variable) and the incident rate itself (dependent variable). Many studies evaluate the effectiveness of an individual intervention activity, including Fellner and Sulzer-Azaroff; McKelvey, et al; and Kalsher, et al. Building on these studies, the current research was designed to evaluate a complete loss prevention system while exploring main effects from a comprehensive set of interventions, as well as interactive effects between interventions. This study integrated all components of a defined loss prevention system or safety program in order to establish a mathematical relationship that would allow for the design and optimization of a complete safety program.

EXPERIMENTAL METHOD & DESIGN

The empirical observation study was undertaken at an oil production and processing operation in Central Asia. The joint venture company operates using a Western-style safety program that can be found in the U.S., Canada or Western Europe. The organization operated its oil production fields with 130 employees, who collectively worked an average of 5,500 hours per week. For 26 weeks, employees tracked and reported the amount of time spent implementing four categories of safety-related interventions and the resulting weekly incident rate (both traditional and total incident rates). "Traditional incident rates" included spills, fires, injuries and toxic releases, while "total incident rates" included traditional incidents as well as unplanned process upsets or shutdowns, and equipment damage. Reported data were used for the research, and the researchers did not intervene in program implementation.

Four categories of interventions were established as the independent variables, while the loss-producing incident rate was established as the dependent variable. The independent variables were quantified each week by using the amount of man-hours applied by the work group of 130 employees to these defined intervention activities, then multiplying this number by 100 and dividing it by the actual number of hours worked collectively for that week.

These computations resulted in the percentage of available man-hours that were applied to implementing the safety-related interventions. This became the "intervention application rate."

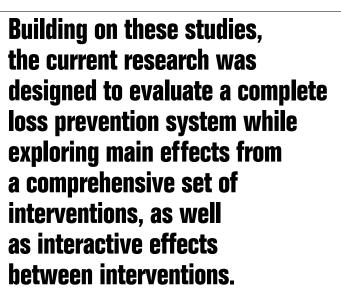
The dependent variable was developed by recording the number of incidents that occurred during each week, multiplying it by 200,000 hours (the approximate hours worked in a year by 100 workers) and dividing it by the number of hours worked by the 130 employees, yielding the "incident rate." This was done for both the traditional incidents and the total incidents.

The intervention application rate was organized into four categories. Interventions were categorized to allow a complete evaluation of all integrated components of the loss prevention system. Figure 1 provides a graphic representation of the resultant experimental model.

For each of 26 weeks, the reported intervention application rate and incident rate were recorded. Supervisors collected and recorded the number of hours applied to each intervention by their group. Prior to data collection, supervisors were given a one-hour introductory training session on how and what data to collect. They were provided with data sheets listing all intervention activity from their program that was relevant to the study. Data sheets were translated into Russian to accommodate the predominant language of supervisors. Figure 2 presents a representation of the sheets used to collect and tabulate these data.

A total of eight work groups were included in the study. They were organized as shown (not numbered from one through eight) for operational purposes, not for the study. Both Group 2s were organizationally equivalent, as were all Group 3s. During the 10th week of the study, one Group 3 was divided into two separate groups. The number of workers and supervisors remained the same, except that there was a fourth Group 3 for which data were collected for weeks 10 to 26. These data were input on a separate spreadsheet each week until 26 weeks of data were recorded.

Throughout the study, the structure of the loss prevention program remained constant and all personnel includ-



ing management remained intact. The data collection for Phase 1 took place from February 1998 into July 1998. It should be noted that Supervisors 2 and 3 oversaw more than one work group.

ANALYSIS & RESULTS

The combined 26 weeks of intervention application rate and incident rate data were recorded in another spreadsheet. The four factors (main effects) and the two incident rates were recorded. Also recorded were the cross multiplication products of the main effects to account for interactive effects

INPUT OUTPUT (Independent Variable) (Dependent Variable) Incident Rate Intervention Application Rate Factor A Behavior-based activities, motivation, awareness, incentives, etc., interventions Factor B Safety and skill enhancement training interventions Loss Incident Rate or Prevention Incidents/200,000 System Factor C Job design interventions Factor D Equipment interventions (e.g., inspections, preventive maintenance, etc.)

FIGURE 1 Representation of the Loss Prevention System Model

FIGURE 2 Example Data Collection & Tabulation Sheet

	Week -	From	1-Feb-98	Date to:	7-Feb-98	1			
Data Input Representative	1	2	2	3	3	3	4	5	Totals
	1	2	4	5	5	5	т	5	10013
Factor A - Behavior, Awareness, Motivation	1								147.8
1. Implementing Behavior Modification	0	0	0	6	3	3	0	0	12
2. Training Behavioral Observers		0	0	0	0	0	0	0	0
3. Developing/Implementing Action Plans	0	0	0	30	7	0 7	0	0	44
4. Managing Behavior Data	0	0	0	0	0	0	0	0	0
5. Implementing Awards, Incentives etc.	1	0	0	0	0	0	0	0	1
Program	1	Ũ	Ŭ	Ŭ	U U	Ŭ	Ŭ	Ŭ	1
6. Providing Safety-Related Feedback to	0	0	0	0	0	0	2	2	4
Employees									
7. Developing Slogans, Posters, etc. Programs	0	0	0	0	0	0	0	1	1
3. Implementing Safety Committees	0	0	0	0	0	0	32.5	3	35.5
9. Safety-Related Communications	3	0	0	0	0	2	0	0	5
10. Safety Meetings	0	0	0	10	30	3.3	2	0	45.3
Factor B - Skill Development and Training						l	l		82
1. Safety Training	0	0	0	0	0	3	0	42	45
2. Skill and Craft Training	0	0	0	28	0	6	0	0	34
3. Drills (emergency, safety, etc.)	3	0	0	0	0	0	0	0	3
(1				-	1	ľ	ľ.
Factor C - Job Design									4
		0	0	0	0	0	1	0	1
2. Contractor Safety Performance Evaluations	0	0	0	0	0	0	0	2	3
3. Job Procedure Development/Implementation		0	0	0	0	0	0	0	0
4. Procedure Compliance Assurance		0	0	0	0	0	0	0	0
5. Task Analysis and Redesign	0	0	0	0	0	0	0	0	0
	0	Ŭ	Ŭ	0	Ū	Ŭ		Č	°
Factor D – Equipment-Related Work									21.5
1. Equipment/Facilities Inspections	0	0	0	5.5	12	4	0	0	21.5
2. Hazard Analysis	0	0	0	0	0	0	0	0	0
3. Housekeeping Inspections and Follow Up	0	0	0	0	0	0	0	0	0
4. Managing Change/PSM	0	0	0	0	0	0	0	0	0
5. Alarm and Instrument Testing	0	0	0	0	0	0	0	0	0
. Maint and instrument resultg	0	0	0	0	0	0	0	0	0
Totals For Each Column	8	0	0	79.5	52	28.3	37.5	50	255.3
	0	0		159.8			37.5	50	
Fotals For Each Representative Number	0	°		155.0			57.5	50	
Fotal Hours for Department: (month=23,927)								hrs/	5981.62
For distance in the state of the	1							wk	2
Traditional Incidents									2
Total Incidents Rate (per 200,000 hours)									66.871
lotal Incidents									2
CALCULATION OF % OF TOTAL MHRS EMPLOYED									
				Ì		1	İ	1	1
Factor A - Behavior, Awareness, Motivation	2.471%					I	l	1	1
Factor B - Skill Development and Training	1.371%	<u> </u>	1	1			<u> </u>	<u> </u>	
Factor C - Job Design	0.067%				-				
Factor D - Equipment-Related Work	0.359%		<u> </u>	<u> </u>	<u> </u>				
			<u> </u>	<u> </u>					
Total The numbers across the tov (1-5) revresent th	4.268%								

between factors. To integrate all interactive effects from the two-, three- and four-factor interactions, 15 independent variables resulted. Figure 3 shows a representation of the totaling spreadsheet.

Regression analysis methods are used to analyze data from experiments with observations of uncontrolled occurrences (Montgomery and Runger). Although this loss prevention system was partially controlled by management practices in general, the empirical observation study was not designed to control any of the results. Therefore, it met the criteria for applying regression analysis techniques. Several linear and non-linear regressions were performed on the data.

To determine a best-fit function for these data, 64 separate regression analyses were carried out using Excel's "Logest" function for the non-linear fits on the traditional and total incident rates. The "Linest" function was used to explore both incident rates for a linear fit. These functions employ the least squares method of regression used to assess the adequacy of the fit.

An assumption in industry is that the effect from a safety or loss prevention intervention is neither instantaneous, nor permanent. So, a means to evaluate how long the effect of an intervention lasts was needed. Using weekly data points to calculate two-, three-, four-, five- and sixweek moving averages (forward projection) for the incident rates, one can determine whether any effect from week one carries over to week two, three, four, etc., by assessing the quality of the regression fit.

An additional analysis was carried out in this same manner, but instead of using the moving average technique, a

The numbers across the top (1-5) represent the individual supervisors that recorded data for their work groups.

Week	Factor A	Factor B	Factor C	Factor D	AxB	Nxn	AxBxC	nxnxn	AxBxCxD	Traditional Incident Rate	Total Incident Rate
1	X_{a1}	X_{b1}	X _{c1}	X _{d1}	X_{ab1}		X_{abc1}		•	\boldsymbol{Y}_{tr1}	Y_{t1}
2								•			
n	X _{an}	X_{bn}	X _{cn}	X _{dn}	X_{abn}		X _{abcn}			Y _{trn}	Y_{tn}

FIGURE 3 Representation of Data Collection & Totaling Spreadsheet

forward-applied exponential smoothing technique was used in an attempt to bolster or support the moving average findings.

In this case, the exponential smoothing equation (adapted from Elsayed and Boucher) used was:

 $X_{t} = \alpha X_{t} + \alpha (1 - \alpha)^{*} X_{t+1} + \alpha (1 - \alpha)^{2*} X_{t+2} + \alpha (1 - \alpha)^{1 + 2*} X_{1} + (1 - \alpha)^{1} * X_{0}$ The variables are defined as follows: α=smoothing constant, X=weekly data point - output variable - incident rates and t=time period (e.g., week 1). The same equation was used, but it was applied to forward periods as opposed to historic reference periods. The logic is the same as with the moving average concept: Each intervention application will have an immediate and a carryover effect, and these two methods (moving average and exponential smoothing) help explore the extent and length of the effect of that intervention.

The function used for analysis pro-

vided standard error values for each of the 15 regressor variables and constant "b." The analysis yielded the coefficient of determination (R²), which is a measure of how well the function or model predicts the difference between an estimated incident rate (yest) and the observed incident rate (y). The R^2

values range from 0 to 1 with 1 representing perfect correlation. Hence, an R^2 of 1 would mean 100 percent of observed variation in the variables would be attributable to the model.

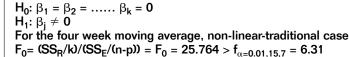
The analysis also yielded the standard error for the (v) estimate and an F statistic (F_0) (the measure of statistical significance of the relationship) to determine whether the observed relationship between the independent and the dependent variables occurred by chance. The degrees of freedom and regression and error sums of squares were also determined to allow for the calculation of the Mean Square Error (MS_F) . The MS_{E} , R^2 , and $F_0/F_{\alpha, v1, v2}$ are used to assess the goodness of fit of the function to the data and are the criteria for choosing the correct regression to produce the function (the target mathematical relationship) to be optimized in future research.

Direct & Moving Average Results

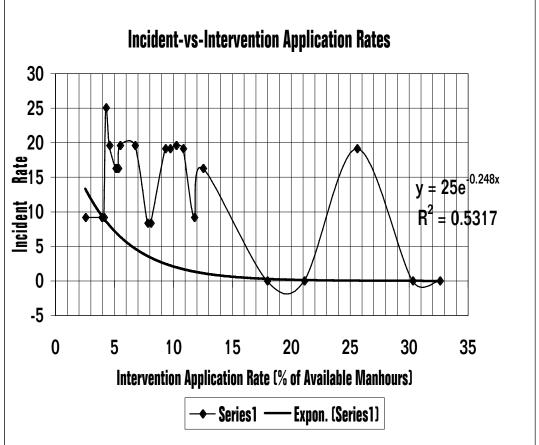
An assumption in industry is that the effect from a safety or loss prevention intervention is neither instantaneous, nor permanent. So, a means to evaluate how long the effect of an intervention lasts was needed.

FIGURE 4

Hypothesis Testing Results for the Four-Week, Non-Linear Traditional Regression Case







The direct and moving The R²=0.5317 is for the total input curve only. The strongest fit model incorporating all 15 factors shows average results are shown in $R^2=0.982209$ (four-week moving average traditional model).

FIGURE 6 Mathematical Model Representing the Relationship Between the Incident Rate & All 15 Regressor Variables

$$\label{eq:LnY=Xabcd} \begin{split} & LnY=X_{abcd}*Inm_{abcd}+X_{bcd}*Inm_{bcd}+X_{acd}*Inm_{acd}+X_{abd}*Inm_{abd}+X_{abc}*Inmabc+Xcd*Inmc \\ & d+X_{bd}*Inm_{bd}+X_{bc}*Inm_{bc}+X_{ad}*Inm_{ad}+X_{ac}*Inm_{ac}+X_{ab}*Inm_{ab}+X_{d}*Inm_{d}+X_{c}*Inm_{c}+X_{b}*In \\ & m_{b}+X_{a}*Inm_{a}+b \end{split}$$

 $\begin{array}{l} LnY=X_{abcd}^{*}(ln0.00188)+X_{bcd}^{*}(ln3.826E+16)+X_{acd}^{*}ln(2014.943)+X_{abd}^{*}ln(6.966)+X_{abc}^{*}(ln(4.2998E+12)+Xcd^{*}ln(1.85E-13)+X_{bd}^{*}ln(.001597)+X_{bc}^{*}ln(7.01E-65)+X_{ad}^{*}ln(0.15024)+X_{ac}^{*}ln(5.82E-11)+X_{ab}^{*}ln(.000517)+X_{d}^{*}ln(404.4604)+X_{c}^{*}ln(1.063E+45)+X_{b}^{*}ln(449.5E+7)+X_{a}^{*}ln(526.9246)+1.03E-7. \end{array}$

Y is the incident rate, X_i is the individual intervention values for each of the 15 factors, and m_i is the slope at each represented point on the curve. The function shown here contains actual m values.

Table 1, while the exponential smoothing results are shown in Table 2.

In an effort to determine whether a linear transformation would affect the results, a base-10 logarithmic transformation was used. The data were log-transformed and the same multivariate linear and non-linear regression analyses were performed on the transformed data as on the non-transformed data, including the moving average based analyses. However, none of these results were statistically significant and, as such, are not shown.

DISCUSSION OF RESULTS

Analysis shows that the best fit occurs when regressing the four-week moving average model and traditional incident rate. The resulting function is exponential, with an R²=0.982209, F₀=25.764 vs. $F_{\alpha=.01,15,7}$ =6.31, and an MS_E=0.78069. A strong fit also occurs in a) the non-linear four-week exponential smoothing model for the traditional incident rate, and b) the non-linear five-week moving average and exponential, traditional incident rate cases. Other statistically significant fits were found, but none are as strong as the four- and five-week moving average and exponential smoothing average and exponential five-week moving average and exponential smoothing cases.

The hypothesis test for significance of the regression further helps to strengthen the case for choosing the four-week, non-linear traditional case as the best-fit function. The calculation used is shown in Figure 4. This test was used to further strengthen the assessment that a relationship exists between the incident rate (dependent variable) and the intervention application rates. A rejection of H₀ (null hypothesis) implies that at least one of the variables contributes significantly to the model, according to Montgomery and Runger. Given the results in Figure 4, H₀ is rejected and it is concluded that the regressors contribute significantly to the model.

Figure 5 graphically shows the total intervention application rate curve. As demonstrated, the exponential trend line is fit to the *total* intervention application rate, and it generates an R^2 value of 0.5317 even without all the interactive effects shown. As was noted above, with all interactive effects and variables included, the R^2 is 0.98209.

Figure 6 shows the resulting function for the four-week case linear transformed function.

CONCLUSIONS & SUMMARY

Interventions are implemented as part of loss prevention or safety programs because they are expected to reduce the incident rate. Intuitively, one would expect that the more intervention activity applied to the safety program, the lower the incident rate would be. One might also expect that at some point, an effect would be present, but the incident rate reduction or (improvement in performance) would be diminishing or "leveling off" as more intervention activity is applied.

This research strongly indicates that at the α =0.01 level, the incident

rate is sensitive to the intervention application rate for traditional incidents. The results suggest that a strong, statistically significant relationship between the interventions and the incident rate exists.

The resulting function for the four-week case appears to show an exponential relationship. For the particular organization studied, it appears possible to predict an incident rate for a given percentage of available man-hours applied to the organization's safety program. When properly derived, the function appears to allow for the prediction of (y) values or incident rates.

The question of how long the effect of a particular intervention lasts appears to have been answered for the organization studied (four weeks). Whether or not these findings can be extrapolated to other organizations is a topic for further research. Interestingly, in this case, the interventions did not appear to have a strong effect on "total incidents." (These are the unplanned process upsets and shutdowns and/or equipment damage cases.) Possibly, it can be surmised that many of the mature and developed loss prevention interventions in practice have developed over time with the intent of only preventing traditional incidents.

Many modern industrial organizations tend to refer to all incidents as the same, regardless of their consequences. In this light, an incident is an incident, and is considered to be the same in all respects regardless of the consequences (e.g., production down-time vs. an injury). Relative to the effect of the interventions in this study, that may not be the case. This is left for further and future research.

FUTURE RESEARCH

This development of a mathematical relationship between incident rate and intervention application rate allows for development of an objective function for a linear/nonlinear mathematical programming problem. One can research theoretical incident rates by testing multiple combinations of the four factors and their eleven interactive effect variables. This is the subject of Phase 2 of this study, which will be published in the June 2001 issue of *Professional Safety*. This study evaluated the effect of changing the quantity of the safety-related interventions. It did not evaluate the effect of changing the quality of those interventions. This is also left for future research.

Incident Rate Breakdown	Degrees of Freedom (df)	Regression Sum of Squares (SS _R)	Error Sum of Squares (SS _t)	Mean Square Error (MS _E)	Fo	F α _{=.01}	F α _{=.25}	Coefficient of Determination (R²)
No Moving Average	10	328.9453	224.119517	22.4119	.978476	4.56	1.53	.594767
Two-week	9	497.2739	148.9041	16.5449	2.003735	4.96	1.57	.769562
Three-week	8	475.3722	75.80674	9.475843	3.34445	5.52	1.62	.862464
Four-week	7	301.7044	5.464811	.78069	25.764**	6.31	1.68	.982209
Five-week	6	161.4328	6.098805	1.01647	10.58783**	7.56	1.76	.963596
Six-week	5	84.00627	4.926801	.98536	5.683625	9.72	1.89	.944601

TABLE 1 Statistical Analysis Results of Non-Linear Traditional Incident Rate Model—Moving Averages

**=significant at α =.01

TABLE 2 Statistical Analysis Results of Non-Linear Traditional Incident Rate Model—Exponential Smoothing

Incident Rate Breakdown	Degrees of Freedom (df)	Regression Sum of Squares (SS _R)	Error Sum of Squares (SS _r)	Mean Square Error (MS _e)	Fo	F α _{=.01}	F α _{=.25}	Coefficient of Determination (R²)
Two-week smoothing	9	496.6689	149.9723	16.66358	1.987042	4.96	1.57	.768075
Three-week smoothing	8	476.4263	74.932	9.3665	3.390994	5.52	1.62	.864096
Four-week smoothing	7	301.5879	6.649	.949857	21.16714**	6.31	1.68	.978429
Five-week smoothing	6	164.4553	5.38636	.89773	12.21272**	7.56	1.76	.968286
Six-week smoothing	5	87.74735	4.077917	.81558	7.17256	9.72	1.89	.95559

**=significant at α =.01

LIMITATIONS

An adequate number of error degrees of freedom existed for this study. However, the study could have been strengthened with more data. But, since it takes considerable time to collect the data, extending the study to collect more data would introduce the risk of having the safety program change in the middle of the study.

The results of this model are not transferable to other organizations since it is based on the specific performance and data of the organization being studied. Other organizations will have different interventions, qualities of interventions and management philosophies. The model works but, to apply it, an organization would need to accumulate its own data. Eventually, it is expected that the model can be applied to enough organizations and that the database will grow sufficiently to allow for more generalization and transferability of results.

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