

Impact of Safety Efforts

Intervention Effectiveness Research: Phase 2

Design, Optimization & Verification of the Loss Prevention System & Analysis Models

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

In Phase 2 of this empirical observation study, an attempt is made to determine whether a designed loss prevention program can be optimized to minimize the loss-producing incident rate. In Phase 1, a statistically significant mathematical relationship was proposed between the incident rate and interventions implemented to reduce that rate. In this phase, the primary objective is to use the Phase 1 mathematical function to formulate a mathematical model that calculates a minimized incident rate.

Evaluating 81 application rate level combinations of four intervention categories and subjecting them to management constraints accomplished this. The resulting model provides insight into the design of a loss prevention program that will prescribe the appropriate amount of human resource time that should be assigned to specific safety-related intervention activity.

The secondary objective of Phase 2 is to use actual verification data in conjunction with Phase 1 data to test the adequacy and accuracy of the optimization model. Findings indicate that the model predicts with reasonable accuracy, intuitively expected results. The verification data show that the model's "optimum" intervention application rate was within the actual observed lower incident rate range.

In engineering, systems are designed to meet defined objectives. In industrial engineering, these systems involve humans. One industrial engineering system often implemented without being quantifiably designed is the loss prevention system, often called a safety program. Application of the model developed in this two-phase study is expected to produce the "better mix" of safety program activities that Rinefort (1997) calls for. This study was undertaken at an oil production and processing operation in Central Asia. This company operated its oil production fields with 130 employees, who collectively worked about 5,500 hours per week.

In Phase 1 of this study (see *PS*, May 2001, pp. 38-44), a strong, statistically significant mathematical relationship (function or equation) between implemented safety-related interventions and the incident rates they were intended to reduce was developed to facilitate the design of a safety program. The objective in Phase 2 is to optimize this mathematical function as the objective function in an analysis based on operations research. The intent is to determine whether a theoretical minimum incident rate can be achieved by evaluating the objective function using 81 different combinations of the four categories of intervention activities defined in Phase 1 as the input/independent variables. These four intervention categories were:

- 1) behavior modification, awareness, incentive interventions;
- 2) training interventions;
- 3) job design and procedure interventions;
- 4) equipment interventions.

The model was subject to a management constraint of, at most, 20 percent of available manpower applied to the safety program, and a process constraint that required the incident rate (y) to be greater than or equal to zero. The model mathematically generates incident rates from which minimum values can be observed and chosen. The approach assumes that the incident rate can be reduced while minimizing the commitment of available human resources devoted to the safety program. It also expected that the loss prevention "recipe" can be designed with a reasonable amount of confidence to reduce loss-producing incidents.

FIGURE 1 Mathematical Model That Represents the Relationship Between the Incident Rate & All 15 Regressor Variables

Minimize:

$$\ln Y = X_{abcd} * \ln m_{abcd} + X_{bcd} * \ln m_{bcd} + X_{acd} * \ln m_{acd} + X_{abd} * \ln m_{abd} + X_{abc} * \ln m_{abc} + X_{cd} * \ln m_{cd} + X_{bd} * \ln m_{bd} + X_{bc} * \ln m_{bc} + X_{ad} * \ln m_{ad} + X_{ac} * \ln m_{ac} + X_{ab} * \ln m_{ab} + X_d * \ln m_d + X_c * \ln m_c + X_b * \ln m_b + X_a * \ln m_a + b$$

S.T. $X_A + X_B + X_C + X_D \leq 20\%$
 $Y \Rightarrow 0$

Shown with the m values included, the complete objective function is as follows:

$$\ln Y = X_{abcd} * \ln(0.00188) + X_{bcd} * \ln(3.826E+16) + X_{acd} * \ln(2014.943) + X_{abd} * \ln(6.966) + X_{abc} * \ln(4.2998E+12) + X_{cd} * \ln(1.85E-13) + X_{bd} * \ln(0.001597) + X_{bc} * \ln(7.01E-65) + X_{ad} * \ln(0.150024) + X_{ac} * \ln(5.82E-11) + X_{ab} * \ln(0.000517) + X_d * \ln(404.4604) + X_c * \ln(1.063E+45) + X_b * \ln(449.5E+7) + X_a * \ln(526.9246) + 1.03E-7.$$

This function becomes the objective function for the mathematical model. Y is the incident rate, and X_a, X_{ab}, X_{abc}, etc., are the individual intervention values for each of the 15 factors, including cross-multiplied interactive effects; m_i is the regression coefficient and S.T. is "such that."

EXPERIMENTAL METHOD

This phase involved experimental and theoretical application of data to the mathematical model developed in the first phase. This was accomplished using the mathematical relationship and function from the four-week moving average model, for traditional incident rates developed in Phase 1, as the objective function. The oil operation’s superintendent established a constraint requiring a total intervention application rate of less than or equal to 20 percent of available manhours. The process induced a constraint on the model requiring the incident rate (y) to be greater than or equal to 0 (i.e., having no incidents produces an incident rate of 0; it cannot be any less). Figure 1 shows the objective function that resulted.

Intervention combinations were developed using 26 weeks of original data from Phase 1. The (max/min) range of intervention application rate values for each intervention category (the input variable) was divided into three equal segments to represent three levels of each factor (intervention activity categories). The median value in each range (one-third) was chosen to represent that level for each factor, generating three levels for each of the four factors. This was then used in a design similar to what would be a three-level, four-factor experimental design (34). The result was 81 fac-

tor-level combinations for the reported intervention application rate, and these combinations were used to evaluate the model (see Table 1).

With this model, it is possible to generate an unlimited amount of intervention combinations for consideration; however, as the number of levels increases, the number of combinations also increases exponentially. For example, an increase of one level to a 44 design would result in 256 combinations to consider. Figure 2 lists some of the resulting combinations.

Once the four factors were established for the main effects, the cross-product multiplication results were generated to account for the interactive effects of the independent variables (Figure 3).

Each of the 81 combinations of the 15 input variables was then plugged into the objective function. The objective function yielded 81 different possible incident rates (y). The resulting (y) value was then converted to a natural log. This was done to account for a linear transformation of the original exponential function that resulted when the mathematical relationship between the intervention application rate and the incident rate was first established.

The model was set up as an Excel equation, and all results yielding an intervention application rate greater than

TABLE 1 Representation of Minimization Model Results Showing the Five Lowest Incident Rates or “Y” Values

Level Representation of Intervention Activity	A%	B%	C%	D%	Y	Ln Y Incident Rate	Total (sum) ABCD%
A1B1C1D1	2.754	0.602	0.128	5.2705	157.6332	5.0603	8.7545
A1B1C2D1	2.754	0.602	0.3445	5.2705	194.138	5.2685	8.971
A1B1C3D1	2.754	0.602	0.5609	5.2705	230.626	5.4408	9.1874
A1B2C3D1	2.754	1.828	0.5609	5.2705	1681.975	7.4277	10.4124
A1B2C2D1	2.754	1.827	0.3445	5.2705	1703.500	7.4404	10.196

One industrial engineering system often implemented without being quantifiably designed is the loss prevention system, often called a safety program. Application of the model developed in this two-phase study is expected to produce a “better mix” of safety program activities.

20 percent and a (y) less than 0 were discounted as being outside the constraints. Results were sorted in ascending order to move the minimum “y” values to the top of the list for consideration. Finally, Phase 1 and the 11-week verification data were compared to the theoretically minimized incident rates to determine whether the model could be given credence.

ANALYSIS & RESULTS

The 81 intervention combinations were systematically evaluated in the objective function using the Excel program routine designed for the study. Initial (y) values or incident rates were then converted to natural log values to fit the transformed linear model (Figure 1). The highest 20 combinations (or the 20 lowest “(ln y)”) values were selected for comparison to Phase 1 and verification data. The total intervention application rate for the four main effects in these 20 results ranged from approximately eight to 17 percent of total available manhours. Table 1 shows the five best-yet-still-feasible results (i.e., those yielding the lowest incident rate with reasonably low or “optimized” intervention application rates) from the model.

Tables 2 and 3 show results of an evaluation of several factor-level combinations and resulting incident rates from Phase 1 and verification data. From Phase 1 data only, it is evident that when the total intervention application rate is

in the 5.01 to 10 percent range, the mean traditional and total incident rates are significantly lower than when the intervention application rate is in the 0 to 5 percent range and the 10.01 percent and above ranges. The same phenomenon is evident when the 11-week verification data are incorporated into the database. This is consistent with the findings of the theoretical model, which showed the lowest incident rates (lowest five results) to be in the 8 to 10 percent range.

DISCUSSION OF RESULTS

The theoretical minimum incident rate is achieved when the total intervention application rate falls in the range of 8 to 17 percent (results of the 20 lowest incident rates generated by the operations research model). The three lowest results, as seen in Table 1, indicate a design using levels 1) A1B1C1D1; 2) A1B1C2D1; and 3) A1B1C3D1, with a total input of 8 to 9 percent. This can be illustrated by applying an example. If design number one (A1B1C1D1) were selected, the intervention application rate ranges for each factor-level combination would be:

Factor A (level 1): 2.754 to 4.151 percent

Factor B (level 1): 0.602 to 1.224 percent

Factor C (level 1): 0.128 to 0.669 percent

Factor D (level 1): 5.271 to 10.187 percent

This design would generate a total intervention applica-

FIGURE 2
An Abbreviated Representation of the Factor Level Combinations of the Four Factors Run in the Optimization Model

Factor Level Combinations
A1B1C1D1
A1B1C1D2
A1B1C1D3
A1B1C2D1
A1B1C2D2
A1B1C2D3
.
.
.
.
A3B3C3D3

TABLE 2 Mean Incident Rates for Ranges of Intervention Application Rates from Phase 1 Data, for Comparison to Model-Generated Incident Rates

Total ABCD%	Mean % (Intervention Application Rate)	Standard Deviation %	Mean Traditional Incident Rate	Mean Total Incident Rate
0-5%	3.807	0.723	30.332	98.446
5.01-10%	7.110	1.785	9.854	69.985
10.01-15%	11.326	1.004	19.152	104.833
15.01-25%	21.530	3.83	0.0	77.559
25.01-36%	33.186	3.247	0.0	65.603

These rates are based on phase 1 data.

FIGURE 3 Representation of the Cross-Product Multiplication Performed to Account for Interactive Effects from the Factors

A	B	C	D	AB	AC	AD	BC	BD	CD	ABC	ABD	ACD	BCD	ABCD
---	---	---	---	----	----	----	----	----	----	-----	-----	-----	-----	------

TABLE 3 Mean Incident Rates for Ranges of Intervention Application Rates from Phase 1 and Verification Data, for Comparison to Model-Generated Incident Rates

Total ABCD%	Mean % (Intervention Application Rate)	Standard Deviation %	Mean Traditional Incident Rate	Mean Total Incident Rate
0-5%	3.807	0.723	30.332	98.446
5.01-10%	7.050	1.652	17.436	92.382
10.01-15%	11.341	0.787	31.893	101.762
15.01-25%	21.530	3.83	0.0	77.559
25.01-36%	33.186	3.247	0.0	65.603

These rates are based on phase 1 and verification data.

Although direct extrapolation of these specific results to other organizations is not recommended, the model can be used in any organization generating its own data for study.

tion rate at the low end of 8.755 percent (by adding the above-listed minimum values in the above-listed ranges for each level) and at the high end of 16.231 percent (by adding the above-listed maximum values in the above-listed ranges for each level). This result is within the range obtained by using the 20 lowest incident rates produced by the model (8 to 17 percent).

Data from Phase 1 indicate that the minimum traditional incident rates are achieved with intervention application rates in the 5.01 to 10 percent range (Table 2). If the 11-week verification data are included, minimum traditional incident rates are achieved with intervention application rates in the same range (Table 3).

It appears that total incident rates may also follow this same convex pattern, with the minimum being achieved in the 5.01 to 10 percent range. However, the means are not sufficiently different from each other to make a "minimum result" claim, as with the traditional incident rates. In each case, lower incident rates are achieved at intervention application

rates greater than 20 percent, but they do not meet the constraint criteria.

CONCLUSION & SUMMARY

Results of the study provide a valuable potential approach to help engineers design future safety programs. The model appears to provide intuitively expected and verifiable results that facilitate design and optimization of a loss prevention program. The design minimizes the incident rate while facilitating selection of intervention application rates that are well under the 20-percent constraint.

The Phase 1 mathematical relationship between the independent and dependent variables is statistically significant and strong. Employing this relationship, the Phase 2 optimization model produces a minimized incident rate. The model appears to be valid for the facility studied. However, it could obviously be refined through further testing against more-extensive field data. Although direct extrapolation of these specific results to other organizations is not recommended, the model can be used in any organization generating its own data for study.

FUTURE RESEARCH

This study lends itself to further research. Other types of operations should be studied and other loss prevention systems with different interventions investigated. Larger databases applied to the models would lend more confidence to the results as well.

Furthermore, the quality of the interventions was not studied. Intervention quality is an important aspect of any loss prevention program, and that aspect should be incorporated into future research. In this case, quality of the interventions was not changed throughout the study. ■

REFERENCES

Crites, T.R. "Reconsidering the Costs and Benefits of a Formal Safety Program." *Professional Safety*. Dec. 1995: 28-32.

Diehl, A.E. and M.A. Ayoub. "Cost, Effectiveness and Allocation of Resources." *Occupational Safety and Health Standards*. (1973): 49-64.

Donaldson, G.A. "Safety Spending: Usually Begrudged, Often Misallocated, Highway at the Crossroads." *Proceedings of the American Society of Civil Engineers*. Reston, VA: ASCE, 1988. 140-150.

Fox, D.K., B.L. Hopkins and W.K. Anger. "The Long-Term Effects of a Token Economy on Safety Performance in Open Pit Mining." *Journal of Applied Behavior Analysis*. 20(1987): 215-224.

Haure, E. "An Application of the Likelihood/Bayes Approach to the Estimation of Safety Countermeasure Effectiveness." *Accident Analysis and Prevention*. 15(1983): 287-298.

Hermann, J.A. "Effects of a Safety Program on the Accident Frequency and Severity Rate of Automobile Workers." Unpublished Dissertation. Lawrence, KS: University of Kansas, 1979.

Montgomery, D.C. and G.C. Runger. "Multiple Linear Regression." In *Applied Statistics and Probability for Engineers*. New York: John Wiley and Sons Inc., 1994.

Montgomery, D.C. "Regression Analysis." *Design and Analysis of Experiments*. New York: John Wiley and Sons Inc., 1991.

Oi, W.Y. "On the Economics of Industrial Safety." *Law and Contemporary Problems*. (1974): 92-104.

Rinefort, F.C. "Directions in Safety: The Economics." *Professional Safety*. 37(1992): 42-45.

Rinefort, F.C. "A New Outlook at Occupational Safety." *Professional Safety*. 22(1977): 36-48.

Smith, R.S. "The Feasibility of an 'Injury Tax' Approach to Occupational Safety." *Law and Contemporary Problems*. (1978): 92-104.

Tarrant, W.E. "The Evaluation of Safety Program Effectiveness." *Selected Readings in Safety*. Atlanta: International Safety Academy, 1979.

ACKNOWLEDGMENTS

The authors wish to thank Dave Jensen for allowing the study to be performed in his department and for his support throughout the data collection process. The authors also thank Kenzhetai Tlgenov and Bauyrzhan Abdigali for their diligence in helping to collect data reports each week.

AUTHOR INFORMATION

Joel M. Haight, Ph.D., P.E., CSP, CIH, is an assistant professor in the Dept. of Energy and Geo-Environmental Engineering within Penn State University's Industrial Health and Safety Program. He has a Ph.D. and Master's of Industrial and System Engineering, both from Auburn University. Prior to joining the faculty at Penn State, Haight worked as a safety engineer for Chevron Corp. for 18 years. A professional member of ASSE, Haight is also a member of the American Industrial Hygiene Assn. and the Human Factors and Ergonomics Society.

Robert E. Thomas, Ph.D., P.E., CPE, is an associate professor of Industrial and Systems Engineering at Auburn University. Thomas has industrial engineering degrees (through the Ph.D.) from Georgia Institute of Technology and Texas A&M University. Prior to joining the faculty at Auburn in 1989, Thomas retired from the U.S. Army, for which he served a tour of duty in Vietnam. He is a member of the Human Factors and Ergonomics Society.

Leo A. Smith, Ph.D., P.E., CSP, is a professor emeritus of Industrial and Systems Engineering at Auburn University, where he has been a faculty member since 1969. Smith earned a Master's in Industrial Engineering from Georgia Institute of Technology, and a Ph.D. in Industrial Engineering from Purdue University. He has served three separate terms on the AIHA Ergonomics Committee.

Robert L. Bulfin Jr., Ph.D., is professor of both industrial and systems engineering and technology management at Auburn University. Bulfin holds degrees in Industrial Engineering and Operations Research from Georgia Institute of Technology. He is co-author of the textbook, *Production: Planning, Control and Integration*.

Bill L. Hopkins, Ph.D., is a professor of psychology at Auburn University. He obtained a bachelor's degree from Emory University and a Ph.D. from Indiana University. He has taught at various universities in Washington, Florida, Michigan, Illinois and Kansas, and has been a professor in industrial/organizational psychology at Auburn since 1988.

**ASSE TECHNICAL FORUM
READER FEEDBACK**

Did you find this Technical Forum article interesting and useful? Circle the corresponding number on the reader service card.

YES	44
SOMEWHAT	45
NO	46

Share your insight about the world of safety

Why should you write an article for *Professional Safety*?

- Share knowledge in order to expand the safety profession's body of knowledge
- Offer different perspectives and introduce new ways of thinking about the practice of safety.
- Receive professional recognition, enhance career advancement and enjoy personal satisfaction.
- Advance the journal's standard of excellence—as well as ASSE's standing as the leading SHE resource.

Visit www.asse.org

to download a copy of the journal's Manuscript Guidelines brochure, which details submission requirements, offers writing tips and outlines the review process.