7th CSCE/ASCE/CRC International Construction Speciality Conference
7e SCGC/ASCE/CRC International Conférence Spécialisée sur la Construction

Laval (Greater Montreal), Canada
June 12–15, 2019/ *Juin 12–15, 2019*

LEADING INDICATORS FOR SAFETY MANAGEMENT: UNDERSTANDING THE IMPACT OF PROJECT PERFORMANCE DATA ON SAFETY PERFORMANCE

Emad Mohamed[1], Parinaz Jafari[1], Shih-Chung Kang[1], Estacio Pereira[1], and Simaan AbouRizk[1,2]
[1]Department of Civil and Environmental Engineering, University of Alberta, Edmonton, AB, Canada
[2]abourizk@ualberta.ca

Abstract: The construction industry continues to experience an elevated number of accidents and fatalities, rendering safety a major concern for many construction companies. To develop more effective, proactive strategies capable of reducing future accidents, safety performance must be monitored and assessed prior to incident occurrence. Safety leading indicators can be used to proactively assess safety performance, provide insights into the effectiveness of an organization's safety practices, and offer guidance on how to improve. Although useful, an agreed-upon set of leading indicators for proactively assessing safety performance has yet to be established in the literature. This research aims to investigate and test the feasibility of using project-related data together with safety-related data to more accurately assess proactive safety performance in industrial construction projects. Data utilized in this study were obtained from a large contractor in North America, pulled from eight industrial construction projects over a period of two years. Databases from different departments are matched and integrated into a single dataset. Correlation and feature selection techniques were used to identify the variables with the greatest impact on safety performance. Results of this study indicate that project performance data were associated with safety performance, demonstrating that project data, in addition to traditional safety leading indicators, can be used to build a safety management system to more effectively monitor safety in a project. Additionally, this study has shed light on the project performance metrics that could be collected by safety leaders to better predict safety performance on construction sites.

1 INTRODUCTION

Effective management of safety, health, and the environment are essential to the success of any construction company. Indeed, safety performance is one of the main measures of the success in a project (Mohammadi, Tavakolan, and Khosravi 2018). The construction industry is dynamic in nature; safety-management techniques, therefore, must regularly be altered to satisfy industry requirements (Akroush and El-adaway 2017). Safety indicators play an important role in providing information on organizational safety performance, and recognizing these safety indicators is a motivating factor for stakeholders to increase organizational potential for safety (Reiman and Pietikäinen 2012).

Traditionally, safety performance has been measured by lagging indicators, or 'after the loss' measurements such as accident rates, which can only be measured after the occurrence of an accident (Grabowski et al. 2007, Akroush and El-adaway 2017, Hinze, et al. 2013). Used primarily by insurance companies, owners, and companies to compare performances or to examine performance trends over cost-time, lagging indicators can be used neither to predict the safety performance of a construction company nor to predict the current level of risk of a particular construction project (Hinze et al., 2013). Indeed, monitoring classic measures such as total recordable injury rate (TRIR) and the experience modification rate (EMR) has not, as of yet, reduced injury rates to achieve optimal improvement in safety performance. This is primarily because it is both difficult and unlikely to identify deficiencies and flaws prior to incident occurrence using lagging indicators (Hinze et al. 2012). Although there is prevalent use of lagging indicators, their effectiveness in anticipating safety performance and proactively reducing occurrence of accidents is under scrutiny (Akroush and El-adaway 2017). Many safety professionals and researchers agree that lagging indicators may not provide the necessary insights for taking corrective action to avoid future accidents (Grabowski et al. 2007, Hinze et al. 2013, Kjellén 2009).

The construction industry is moving away from lagging indicators and toward leading safety indicators as an alternative method of measuring safety performance (Akroush and El-adaway 2017). Due to their ability to facilitate preventative decision making, leading indicators have become the preferred method for assessing construction safety (Versteeg 2018). Leading indicators in current use are based on case studies, content analysis of completed projects, and safety experts' knowledge (Guo and Yiu 2016), with many leading safety indicators reported in literature focusing only on safety-related data. However, multiple researchers have demonstrated the potential associations between quality (Wanberg et al. 2013) and schedule (Han et al. 2014) performance and safety. Despite collecting rich stores of performance data from different departments (such as cost, quality, and schedule) construction companies do not fully utilize this existing information to develop safety leading indicators in practice.

The objective of this paper is to investigate and test the feasibility of using existing, yet under-utilized, project-related data together with safety-related data to more accurately assess proactive safety performance in industrial construction projects. First detailing the development process of finding leading indicators, the study investigates whether or not integrated project-performance data can be used within quantitative development methodologies to identify safety useful leading indicators.

2 LITERATURE REVIEW

To take corrective actions, safety indicators must be both detectable before an event and be linked in a causal pathway leading to the event (Hale 2009). A leading indicator is a measure of attitudes, behaviours, practices, or conditions that influence construction safety performance (Hinze et al. 2012, Guo and Yiu 2016). In addition to informing practitioners of the current safety performance, threshold values for leading indicators (below which corrective actions should be taken) can be established to guide risk mitigation practices to reinstate above-level performance (Akroush and El-adaway 2017). The careful selection, measurement of, and response to leading indicators of safety performance in the construction industry all have helped to improve construction-site safety and organization (Ng et al. 2012, Hinze et al. 2012).

Leading indicators can be classified as passive or active (Hinze et al. 2012). Passive indicators are a set of strategies and actions that are set up prior to the beginning of the project and cannot be adjusted once the project has started (Hinze et al. 2012, Akroush and El-adaway 2017). In contrast, active indicators can be measured and adjusted dynamically during the construction phase, allowing for the real-time implementation of risk mitigation practices (Akroush and El-adaway 2017, Hinze et al. 2012).

2.1 Development of safety leading indicators in construction

Multiple researchers have defined many base-criteria for selecting leading indicators in construction. Criteria established by Hale (2009) include validity, reliability, sensitivity, representativeness, openness to bias, and cost-effectiveness. Guo and Yiu (2016) categorized essential attributes of safety leading indicators into two dimensions: a scientific dimension and a managerial dimension. From the scientific perspective, indicators should have strong scientific and conceptual bases, be developed from safety models, reflect causes of accidents, be sensitive to changes in safety conditions, and allow for early warning. From the managerial perspective, indicators should be compatible with practical safety management, drive appropriate behaviour, be easily observable, and be cost-effective in terms of collection. Akroush and El-adaway (2017) added to this list by identifying four additional criteria that selected leading indicators should satisfy: indicators should be complete, consistent, and reliable in covering critical assumptions of safety; they should be unbiased, and not susceptible to or influenced by manipulation; they must be easily measured and quantifiable on a numerical scale; and finally, they should significantly correlate to a reduction in number of incidents.

Qualitative and quantitative methods have been used to develop safety leading indicators in the construction industry. Qualitative models, aimed at identifying leading indicators and then assessing both their effectiveness and their correlation to safety performance (Akroush and El-adaway 2017), include (1) questionnaires, interviews, accident investigations and focus groups; (2) safety audits built by the organization to monitor and measure safety performance factors; (3) perception surveys asking employees, supervisors, and top management about their perceptions regarding the corporate and safety climate in the organization; (4) behavioural observation to identify unsafe behaviours and promote safer attitudes through necessary training; (5) case studies and brainstorming sessions by research teams and experts in the field, and data extraction from industry databases; and (6) the Delphi method: a structured communication technique involving a panel of experts giving initial estimates, and revising those estimates after in-depth discussion. A number of passive and leading indicators have been identified using qualitative methods (Hallowell et al. 2013, Hinze et al. 2012, Akroush and El-adaway 2017).

Qualitative methods are questioned by some researchers (Guo and Yiu 2016, Guo et al. 2017) owing to the fact that the indicators are not selected based on a conceptual framework that provides theoretical guidance on developing leading indicators. Furthermore, (Hinze et al. 2013) pointed out that safety practitioners face challenges in developing indicators that fit well into existing safety programs. A few construction companies have successfully implemented the monitoring of safety leading indicators; however, there is little published information concerning successfully applied, specific leading indicators (Hinze et al. 2013).

Limitations associated with qualitative methods, such as subjective nature, have prompted researchers to develop quantitative methods for the identification of leading indicators. Guo and Yiu (2016) developed a conceptual framework for developing leading indicators in construction where they clarified the concept of a leading indicator; a model was then used to conceptualize the safety conditions. Despite being an important first step, their approach lacked quantitative validation, as their only means of validation was expert judgment. Guo et al. (2017) proposed a pressure-state-practice model as a theoretical basis for developing leading indicators in construction. Their model represented the safety level of a construction project as a dynamic phenomenon characterized by interrelationships between safety state, safety practice, and pressures. Similar to the early neural network model proposed by Goh and Chua (2013), the model only considered safety aspects of the project. Later, Poh, Ubeynarayana, and Goh (2018) proposed a machine-learning approach for developing leading indicators that incorporated other aspects of projects, including project delay and percentage completion. In spite of the model's novelty, data regarding quality and cost performance were not examined, and the procedures other contractors should use to collect and combine such data to apply the methodology were not clarified.

3 RESEARCH METHODOLOGY

The research methodology for investigating the association and impact of project performance data on safety performance is described. This methodology presents a general framework that can be applied by any construction company. Collection, processing, and preparation of input data, as well as data analysis and investigation, are described in Figure 1.

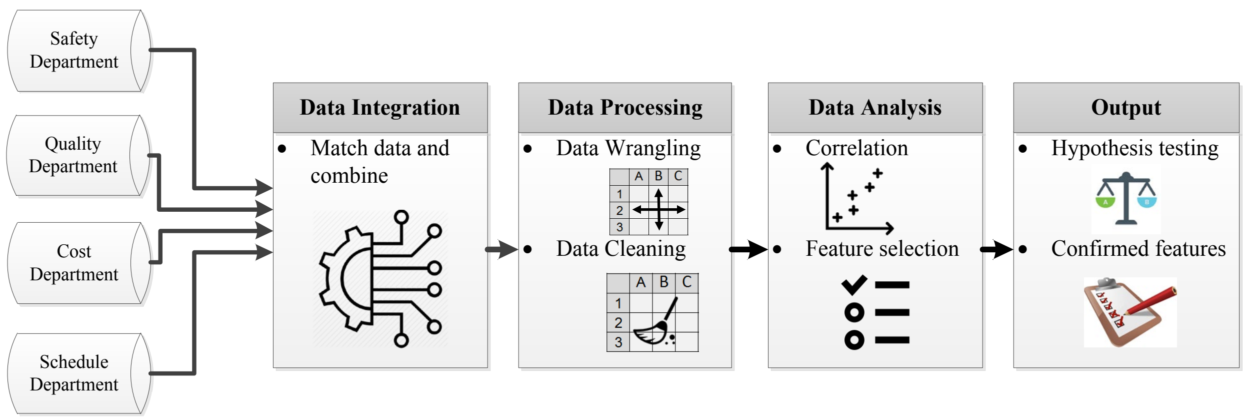

Figure 1: Research methodology

3.1 Data Collection and Understanding

In industrial construction projects, project performance data (including safety, quality, schedule, and costs) are collected separately by each designated department. Data are collected periodically (usually every two weeks) according to the specific conditions of each project. Each department collects only related data. For example, the cost department tracks the financial records and indicators of cost performance, such as the cost performance index and money spent in each reporting period. The scheduling department records the schedule performance index and assesses whether or not the project has progressed as planned. The quality department tracks of the number of change orders. The safety department keeps track of the number of working-hours spent in each reporting period and tracks whether or not incidents have occurred.

3.2 Data Preparation and Processing

In order to process the data, it must first be integrated into one centralized dataset. A common challenge with centralizing the data is the differences in reporting periods used by the various departments within an organization; in these instances, recording dates may be used to match and combine project data. Once centralized, the dataset is cleaned to identify missing data and remove outliers.

3.3 Data Analysis and Investigation

The final step is to test the hypothesis that project performance data can be used to develop safety leading indicators. This step is conducted by correlation testing and the Boruta feature selection function in *R* (R Team 2013) to determine if variables are feasible (i.e., important) or not.

4 CASE STUDY

The dataset used in this research was collected from a large construction company in Alberta, Canada. The company engages in many types of projects such as building, industrial, and infrastructure projects. Data spanned eight industrial projects over a period of two consecutive years, from 2016 to 2017. Project-performance-related data within the dataset consists of cost, schedule, quality, and safety performance data collected from different departments.

4.1 Data Collection and Understanding

Table 1 describes the collected features from each department and defines each attribute.

Table 1: Description of the collected variables in each department

No.	Variable/feature	Description	Department
1	Project ID	Unique identifier for the project	All
2	Contract type	The specific type of contract used for the project	All
3	Report date	The date at which the variables are measured	All
4	Contract change order (**CCO**)	A change in the work or change in the contract sum or the contract time at report time	Cost
5	Outstanding CCO	A change in the work or change in the contract sum or the contract time at report time that will change original contract	Cost
6	CCO submitted to date	The cumulative amount of CCO at report time	Cost
7	RFI	The total number of **R**equests **F**or **I**nformation at report time	Quality
8	RFI submitted to date	The cumulative amount of RFI at report time	Quality
9	Open RFI	The number of unresolved RFI at report time	Quality
10	Original budget	The planned/ estimated cost of the project	Cost
11	Re-baseline budget	The modified budget of the project at the report time	Cost
12	Approved changes	The cost of the changes in the project at the report time	Cost
13	Revised contract value	The sum of re-baseline budget and approved changes	Cost
14	Pending changes	The cost of the changes in the project at the report time waiting for approval	Cost
15	Forecast at completion (**FAC**)	Forecasted value of the project at completion time	Cost
16	Earned value	The budgeted cost of work performed	Cost
17	Incurred value	The money spent for the work accomplished	Cost
18	Outstanding change %	The percentage of change in the original budget at report time	Cost
19	Field Surveillance Report (**FSR**)	A proactive quality surveillance technique	Cost
20	FSR submitted to date	The cumulative amount of FSR at report time	Cost

21	Open FSR	The number of unresolved FSR at report time	Cost
22	Work order **CPI**	The ratio of the earned value to the incurred/actual value at report time (**C**ost **P**erformance **I**ndex)	Cost
23	Work order % complete	The progress of the project at report time as percentage	Schedule
24	Non-conformance report (**NCR**)	The number of reports showing the quality deviation at report time	Quality
25	Open NCR	The number of reports showing the quality deviation which are not resolved	Quality
26	Work order HPI	Evaluation of the accomplishment of the schedule and budget of the activities executed at report time(**H**uman **P**erformance **I**ndex)	Cost & Schedule
27	Work order SPI	The ratio of the earned value to the planned value at report time (**S**chedule **P**erformance **I**ndex)	Schedule
28	(0-1) years' experience direct hours	The total numbers of hours spent on the project up to the report time by workers that have experience less than one year	Safety
29	(1-2) years' experience direct hours	The total numbers of hours spent on the project up to the report time by workers that have experience greater than one year and less than two years	Safety
30	(2-3) years' experience direct hours	The total numbers of hours spent on the project up to the report time by workers that have experience greater than two years and less than three years	Safety
31	(3-4) years' experience direct hours	The total numbers of hours spent on the project up to the report time by workers that have experience greater than three years and less than four years	Safety
32	+4 years' experience direct hours	The total numbers of hours spent on the project up to the report time by workers that have experience greater than four years	Safety
33	Foreman hours	The total numbers of hours spent on the project up to the report time by foreman	Safety
34	Shift hours	The total number of hours spent on the project by all workers at the report time	Safety
35	Exposure hours	The cumulative amount of shift hours	Safety
36	Incident	The variable that shows if an incident happened on the project at report time	Safety

4.2 Data Preparation and Processing

Raw data was processed, cleaned, and transformed into a proper format before analysis. Because data may have been collected in an ad hoc manner, including empty fields in records or mistakes in data entry, data preparation was given the utmost care (Soibelman and Kim 2002). Data were integrated into one dataset; both project ID and report dates were then used to match different records from various datasets. The collected variables were investigated, and features/variables that were not useful for the purpose of this work were removed. For example, in the provided dataset the variables “Contract Type” and “Project ID,” which are the same type for all the 8 projects (and, therefore, for all the records in the dataset) were removed. Due to the similarity in meaning between the three budget variables (Original Budget, Re-Baseline Budget, Revised Contract Value), only “Re-baseline Budget” was kept. Additionally all “To Date” variables were removed, as they could be easily calculated from the corresponding non-cumulative variable (e.g., CCO Submitted and CCO Submitted to Date).

Another common issue in all datasets, and in the case study dataset particularly, is missing values. Missing values were removed or substituted by values that allowed them to be used in further analysis while, at the same time, not adversely affecting dataset behaviour (Witten et al. 2016). In this particular dataset, 50% of the total records for “0-1,” “1-2,” “2-3,” and “3-4 Years’ Experience Direct Hours” were missing; therefore, these columns were removed due to the limited number of data points. After filtering the variables (from Table 1), 23 features remained.

4.3 Correlation

To investigate the degree of association, the Pearson correlation coefficient between all attributes was calculated. The results of correlation analysis are summarized in Table 2. The attributes with the highest positive and negative correlation with “Accident” were “Foreman Hours” (r = 0.50) and “Work Order HPI” (r = -0.28), respectively. Evans (1996) suggested that a value of r between 0 and 0.19 represents a very weak correlation; 0.20 and 0.39 represents a weak correlation, and 0.40 and 0.59 represents a moderate correlation. Here, “Foreman Hours,” “Shift Hours,” “+4 Years’ Experience Direct Hours,” “RFI,” “Open FFI,” and “Contract Change Order (CCO),” were determined to be moderately correlated with “Accident.” In contrast, “Work Order HPI,” “Forecast at Completion (FAC),” and “Re-baseline Budget,” were weakly correlation with “Accident.” Remaining attributes were very weakly correlated with “Accident.” The feature selection process was also performed to provide further insight into the feasibility of the features.

Table 2: Correlation matrix

	ReBaseBudget	ApprChanges	PendChanges	FAC	Earned	Incurred	Outstanding.Changes.of.Original.Budget	WOComplete	WOHPI	WOSPI	WOCPI	FM.Hours	Shift.Hours	X4.yrs.Exp	RFI	Open.RFI	FSR	Open.FSR	NCR	Open.NCR	CCO	Outstanding.CCO	ACCIDENT
ReBaseBudget	1																						
ApprChanges	0.63	1																					
PendChanges	0.16	0.16	1																				
FAC	1	0.69	0.18	1																			
Earned	0.79	0.73	0.08	0.82	1																		
Incurred	0.78	0.72	0.09	0.82	1	1																	
Outstanding.Changes.of.Original.Budget	-0.3	-0.23	0.55	-0.3	-0.23	-0.22	1																
WOComplete	-0.11	0.21	-0	-0.07	0.34	0.34	0.16	1															
WOHPI	-0.46	-0.35	-0.4	-0.47	-0.38	-0.39	-0.2	-0.1	1														
WOSPI	-0.57	-0.19	-0.1	-0.54	-0.06	-0.05	0.24	0.65	0.16	1													
WOCPI	-0.09	-0.09	-0.3	-0.11	-0.11	-0.13	-0.5	-0.2	0.58	0.08	1												
FM.Hours	0.74	0.42	0.23	0.75	0.73	0.74	-0.2	0.1	-0.53	-0.19	-0.1	1											
Shift.Hours	0.67	0.41	0.25	0.69	0.76	0.77	-0.1	0.21	-0.49	-0.1	-0.2	0.94	1										
X4.yrs.Exp	0.38	0.2	0.32	0.39	0.43	0.44	0.04	0.18	-0.55	-0.03	-0.3	0.72	0.76	1									
RFI	0.56	0.34	0.19	0.57	0.58	0.58	-0.2	-0.1	-0.29	-0.14	0.15	0.72	0.72	0.43	1								
Open.RFI	0.7	0.31	0.03	0.69	0.6	0.6	-0.3	-0.1	-0.29	-0.36	-0	0.74	0.72	0.4	0.73	1							
FSR	0.52	0.43	-0	0.53	0.66	0.65	-0.1	0.19	-0.26	-0.02	-0.1	0.56	0.59	0.35	0.42	0.48	1						
Open.FSR	0.67	0.48	0.06	0.68	0.86	0.87	-0.2	0.27	-0.32	-0.02	-0.1	0.75	0.78	0.43	0.64	0.66	0.73	1					
NCR	0.34	0.28	-0.1	0.35	0.45	0.45	-0.2	0.21	-0.2	0.02	-0.1	0.5	0.53	0.37	0.26	0.32	0.57	0.53	1				
Open.NCR	0.52	0.47	0.09	0.55	0.78	0.79	-0.2	0.42	-0.26	0.11	-0.1	0.66	0.73	0.41	0.52	0.48	0.51	0.85	0.64	1			
CCO	0.58	0.5	0.09	0.6	0.59	0.58	-0.1	0.05	-0.35	-0.2	-0.1	0.56	0.54	0.27	0.44	0.44	0.41	0.49	0.28	0.43	1		
Outstanding.CCO	-0.11	-0.08	0.23	-0.1	-0.07	-0.07	0.69	0.19	-0.26	0.16	-0.4	-0.2	-0.18	-0.1	-0.2	-0.21	-0.1	-0.1	-0.1	-0.1	0.13	1	
ACCIDENT	**0.39**	**0.03**	**0.06**	**0.37**	**0.29**	**0.28**	-0.1	-0.1	-0.28	-0.18	**0.01**	**0.5**	**0.48**	**0.41**	**0.47**	**0.48**	**0.22**	**0.26**	**0.15**	**0.12**	**0.43**	-0.08	1

4.4 Feature Selection

Feature subset selection is another important data preparation and testing step for checking and selecting the most important predictive features (Poh et al. 2018). This technique aims to reduce the number of features based on their importance and impact as irrelevant features in the dataset can negatively impact the accuracy of the prediction model and cause unnecessary computational complexity. The feature subset selection algorithm performs a subset search using the induction algorithm as part of the evaluation function (Soibelman and Kim 2002).

As opposed to previous feature selection techniques, which are limited by assumptions of normality, the Boruta feature selection function in *R* (R Team 2013) runs a random forest classifier on the dataset and ranks the features in a step-wise manner. Boruta was applied to the 23 features remaining after the data cleaning and preparation step. The results of the feature selection method are summarized in Figure 2. Box plots are used to show the distribution of a feature's importance over a Boruta run, and colors are used to indicate importance outputs, where green indicates an important feature, red indicates a feature that is not important, and yellow indicates a tentative feature. A total of 10 features (indicated in green) were identified as important, from which the "Shift Hours" feature was determined to be the most important among the features analyzed. The correlation results are in agreement with the feature selection results where the nine variables determined to be moderately or weakly correlated were classified as the most important in the feature selection process. Only one variable with a very weak correlation ("Approved Changes") was considered important in the feature selection. This research study is focused on proving that combined project performance metrics can be utilized as inputs for machine learning algorithms when evaluating project safety performance. More details on applying machine learning algorithms using selected features was provided by Jafari et al (2019) where the authors extended their work by investigating different models and measuring their performance.

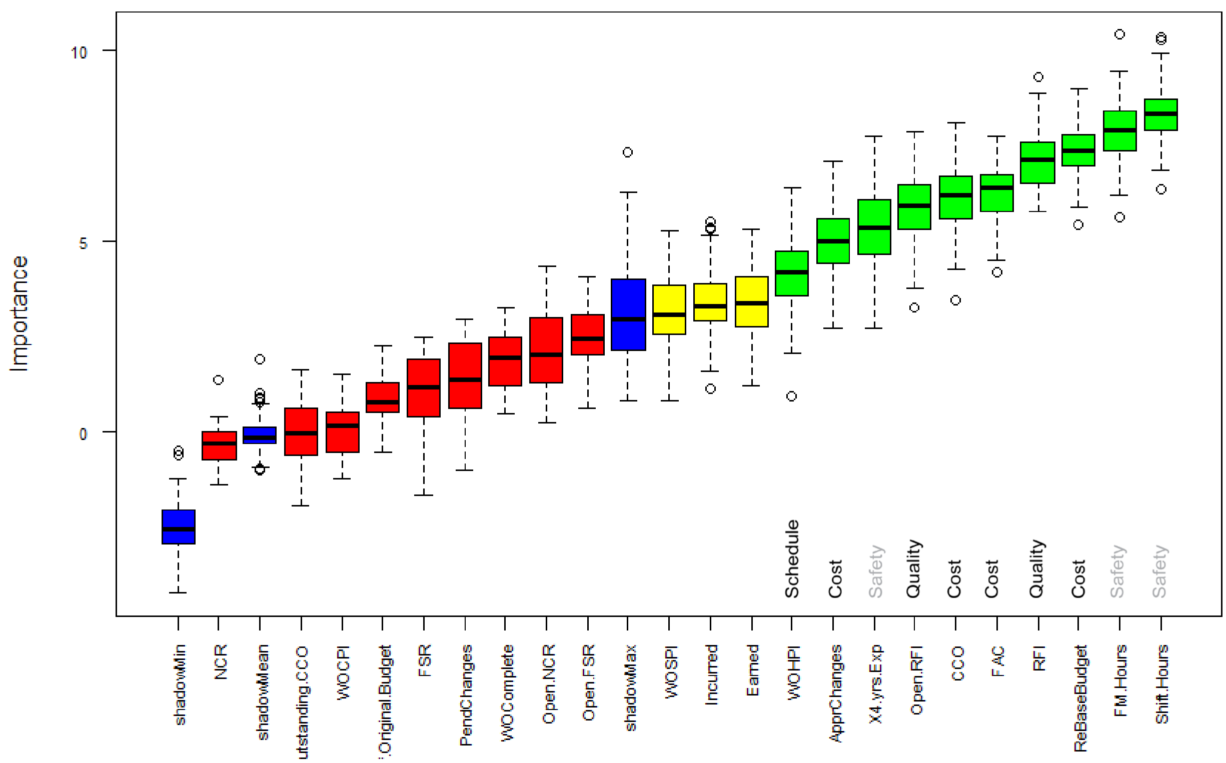

Figure 2: Boruta feature selection results

5 CONCLUSIONS

In current practice, construction companies collect rich stores of data related to various aspects of project performance such as quality, safety, cost, and schedule. Yet, it is uncommon for these data to be used to predict safety performance and accident occurrence. This research study has demonstrated that existing project performance data can be used as safety leading indicators and to build machine-learning algorithms for predicting safety performance; of the ten variables identified as important by the Boruta feature selection, seven were from non-safety-associated departments. Notably, while schedule and quality performance variables were associated with accident occurrence, variables conventionally associated with cost performance represented 40% of the most important variables identified using the Boruta feature selection.

Although currently limited, an increasing number of studies are suggesting that project performance data can be used to develop safety leading indicators. This study has expanded upon previous work and applied a Boruta feature selection procedure to demonstrate not only that project performance variables are important for predicting accident occurrence but that they are feasible for use to build machine-learning algorithms for predicting safety risk. As these data are already being collected by various departments for alternative purposes, using these existing data can reduce the time, efforts, and resources required to monitor and track safety leading indicators.

While the specific variables identified as important in the current study (foreman hours, shift hours, years' experience direct hours, re-baseline budget, forecasts at completion (FAC), contract change orders (CCO), approved changes, and work order HPIs, requests for information (RFI), and open RFI) may motivate practitioners to monitor these metrics in practice, it is important to note that, as a result of differences in safety cultures, types of activities, and scope of projects, these variables may not be associated with accident occurrence in all construction organizations. Additionally, the data set used in the current study was limited by its small size and by the large number (up to 50%) of missing data points. Future research is recommended to address these limitations.

ACKNOWLEDGEMENTS

This research was made possible by the financial support of a Collaborative Research and Development Grant (CRDPJ 492657) from the Natural Sciences and Engineering Research Council of Canada. The authors would also like to thank Elisia Snyder for her assistance with manuscript editing.

REFERENCES

Akroush, N.S. and El-Adaway, I.H., 2017. Utilizing construction leading safety indicators: Case study of tennessee. *Journal of Management in Engineering*, **33**(5): 06017002.

Evans, J.D., 1996. *Straightforward statistics for the behavioral sciences*. Thomson Brooks/Cole Publishing Co.

Goh, Y.M. and Chua, D., 2013. Neural network analysis of construction safety management systems: a case study in Singapore. *Construction Management and Economics*, **31**(5): 460-470.

Grabowski, M., Ayyalasomayajula, P., Merrick, J., Harrald, J.R. and Roberts, K., 2007. Leading indicators of safety in virtual organizations. *Safety Science*, **45**(10):1013-1043.

Guo, B.H. and Yiu, T.W., 2015. Developing leading indicators to monitor the safety conditions of construction projects. *Journal of Management in Engineering*, **32**(1): 04015016.

Guo, B.H., Yiu, T.W., González, V.A. and Goh, Y.M., 2016. Using a pressure-state-practice model to develop safety leading indicators for construction projects. *Journal of Construction Engineering and Management*, **143**(2): 04016092.

Hale, A., 2009. Why safety performance indicators?. *Safety Science*, **4**(47): 479-480.

Han, S., Saba, F., Lee, S., Mohamed, Y. and Peña-Mora, F., 2014. Toward an understanding of the impact of production pressure on safety performance in construction operations. Accident analysis & prevention, **68**: 106-116.

Hinze, J., Hallowell, M.R., Gibbons, B., Green, L., Trickel, S. and Wulf, D., 2012. Measuring safety performance with active safety leading indicators. Construction Industry Institute, CII Research Summary.

Hinze, J., Thurman, S. and Wehle, A., 2013. Leading indicators of construction safety performance. Safety science, **51**(1): 23-28.

Jafari, P., Mohamed, E., Pereira, E., Kang, S. and AbouRizk, S., 2019. Leading safety indicators: application of machine learning for safety performance measurement. *In Proceedings for the 36th international symposium on Automation and Robotics in Construction*, ISARC, Banff, AB, Canada [Accepted].

Kjellén, U., 2009. The safety measurement problem revisited. *Safety Science*, **4**(47): 486-489.

Mohammadi, A., Tavakolan, M. and Khosravi, Y., 2018. Factors influencing safety performance on construction projects: A review. *Safety science*, **109**: 382-397.

Ng, K., Laurlund, A., Howell, G. and Lancos, G., 2012. lean safety: using leading indicators of safety Incidents to improve construction safety. In *Proceedings for the 20th Annual Conference of the International Group for Lean Construction: are We Near a Tipping Point* , San Diego, CA, USA, p. 173.

Poh, C.Q., Ubeynarayana, C.U. and Goh, Y.M., 2018. Safety leading indicators for construction sites: A machine learning approach. *Automation in Construction*, **93**: 375-386.

Reiman, T. and Pietikäinen, E., 2012. Leading indicators of system safety–monitoring and driving the organizational safety potential. *Safety science*, **50**(10): 1993-2000.

Soibelman, L. and Kim, H., 2002. Data preparation process for construction knowledge generation through knowledge discovery in databases. *Journal of Computing in Civil Engineering*, **16**(1): 39-48.

Team, R.C., 2013. R: A language and environment for statistical computing.

Versteeg, K., 2018. *Utilizing Construction Safety Leading and Lagging Indicators to Measure Project Safety Performance: a case study* (Master's thesis, University of Waterloo).

Wanberg, J., Harper, C., Hallowell, M.R. and Rajendran, S., 2013. Relationship between construction safety and quality performance. *Journal of Construction Engineering and Management*, **139**(10): 04013003.

Witten, I.H., Frank, E., Hall, M.A. and Pal, C.J., 2016. *Data Mining: Practical machine learning tools and techniques*. Morgan Kaufmann.