A framework for assessing the safety performance of industrial projects using safety-related measures

by

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Abstract

Although previous research has emphasized the use of safety-related measures to assess and control safety performance, many construction companies continue to rely on reactive indicators for safety control. The reluctance of industry to use safety-related measures for the proactive evaluation of safety performance is a consequence of the unique characteristics of construction projects, which renders the identification and evaluation of safety-related measures difficult in practice. From a theoretical perspective, models developed to proactively assess the safety performance have difficult considering (1) the specific characteristics of an organization due to the limited amount of data points provided and (2) the dynamic nature of construction sites, which can affect measure performance.

The objective of this research was to develop a framework that could proactively assess safety performance using safety-related measures. A framework, which combines Case-Based Reasoning (CBR) with simulation modelling, was proposed for this purpose. CBR was chosen as an assessment method for its ability to assess safety output under conditions of limited data, while simulation was considered for its ability to reliably reproduce project behavior.

Prior to framework implementation, challenges for understanding current Safety Managements System (SMS) practices and identifying safety-related measures were researched. Then, a risk-rating approach designed to investigate the complex relationship between SMS factors and accident precursors from a holistic perspective was developed. This approach allows for not only the identification of high-priority SMS factors and accident precursors but also for the evaluation

of associations between them, and a many-to-many relationship was found to exist between these groups. A case-study was then conducted to analyze and review the effective use of departmental data to control and assess safety performance. Several safety-related measures collected by several departments were found to be useful for proactively controlling safety performance. Altogether, the findings presented here strongly support the use of a holistic approach for the evaluation and control of safety performance

The framework was developed and applied in an industrial construction organization. A total of 27 safety-related measures were identified from data collected from departmental databases, documents, and interviews. After reducing the dimensionality of the database through the application of statistical tests and Correlation Feature Based Selection Algorithm, the final approach considered nine measures. From a practical perspective, the model was found to reliably predict trends in safety performance, and can be used to predict how specific decisions made in practice can affect safety performance.

This research has resulted in (1) the development of a CBR approach that can be used to assess the safety performance of construction projects characterized by few data points (i.e., few incidents) while allowing for the consideration of an organization's unique conditions and (2) the integration of CBR with a simulation model, which allows managers to more easily predict how decisions, both individually and in combination, influence overall safety performance. Furthermore, the results of this research support the use of (3) a holistic approach for the establishment and evaluation of proactive SMS mitigation strategies and (4) the collection and consideration of various departmental data to more reliably evaluate proactive safety performance.

Preface

This thesis is an original work by Estacio Pereira. The thesis follows a paper-based format. Various chapters, or portions thereof, are in submission, revision, or have been published in peer-reviewed journals.

Chapter 2 of this thesis has been accepted for publication as E. Pereira, S. Ahn, S. Han, S. AbouRizk. "Identification and Association of High-Priority Safety Management System Factors and Accident Precursors for Proactive Safety Assessment and Control" *Journal of Management in Civil Engineering* on June 2017 and has been reprinted with permission of the American Society of Civil Engineers. E. Pereira was responsible for questionnaire design, data collection and analysis, and manuscript composition. S. Ahn and S. Han assisted with questionnaire design and edits to the manuscript. S. AbouRizk was the supervisory authority and was involved with concept formation and manuscript composition.

Chapter 3 of this thesis has been published as E. Pereira, S. Han, S. AbouRizk, and U. Hermann, "Empirical Testing for Use of Safety Related Measures at the Organizational Level to Assess and Control the On-Site Risk Level" *Journal of Construction Engineering and Management*, vol. 143, issue 6, 10.1061/(ASCE)CO.1943-7862.0001303, 05017004 and has been reprinted with permission of the American Society of Civil Engineers. E. Pereira was responsible for data collection and analysis as well as manuscript composition. S. Han assisted with manuscript edits. U. Hermann provided access to data and was involved with concept formation. S. AbouRizk was the supervisory authority and was involved with concept formation and manuscript composition.

The research project, of which this thesis is a part, received research ethics approval from the University of Alberta Human Research Ethics Board, Project Name "Assessing and predicting ongoing risks on construction projects using safety-related measures", No. 00070884, March 2, 2017, and Project Name "Using leading indicators to assess the safety risk level on construction projects, No 00056161, November 11, 2015.

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Last but not least, I would like to praise and glory the Lord for this opportunity. It has been a wild journey my Friend.

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Chapter 1: Introduction

1.1 Problem Statement

The construction industry is characterized by the high risk associated with its projects. According to Raheem and Hinze (2014), the construction sector in industrialized countries is responsible for 20-40% of fatal accidents, although it employs around 10% of the workforce. According to Association of Workers' Compensation Boards of Canada (2012), accident rates in the construction industry are 30% greater than any other industry. The consequences of accidents negatively impact the construction sector by increasing direct and indirect project costs (Ikpe et al. 2012), inducing schedule delays (Han et al. 2014), and by adversely affecting workers' families, companies' reputations, and society at-large (García-Herrero et al. 2012).

According to the Health and Safety Executive (1999), an *"accident is any unplanned event that results in injury, damage, or loss"*. In an effort to mitigate risks and avoid the occurrence of accidents, Safety Management Systems (SMS) have been implemented within construction companies to identify, mitigate, control, and evaluate safety performance prior to incident occurrence (Hinze 1997). According to Wachter and Yorio (2014), SMS "consist of programs, process, policies, and procedures for which there is a formal function overseeing their development, implementation, and ongoing administration." ANSI/AIHA (2012) characterizes SMS as a set of inter-related and interacting components that are strategically designed to establish and achieve project safety goals and, consequently, avoid the occurrence of accident precursors.

However, the use of SMS in practice is associated with certain deficiencies. For instance, safety performance is usually measured using reactive indicators. These indicators, such as Total Recordable Incident Rate (TRIR), loss-time rate, and fatality rate (Guo et al. 2016), calculate safety performance as a ratio of the number of accidents to working hours. Although simple to understand, these measures are limited by their inability to identify flaws prior to incident occurrence, which can jeopardize proactive action and may emphasize achievement of safety targets over risk prevention. However, as highlighted by Salas and Hallowell (2013), companies often use reactive indicators due to the difficulties associated with reliably identifying proactive safety measures. In addition, SMS focus primarily on the implementation and control of traditional safety programs, such as safety training, hazard analysis, employee involvement in safety practices, and equipment inspections (OHSA, 2010; CCOHS 2007).

Although traditional safety programs have been shown to mitigate risks (Hallowell et al 2013), this approach is incapable of identifying and evaluating external measures, such as building design, project performance, and market availability of skilled workers (Han et al. 2014; Mitropoulos et al. 2005; Hinze 1997), that are not traditionally controlled by safety departments. SMS factors and accident precursors, however, are characterized by a complex, many-to-many causal relationship (Saleh et al. 2014). In this context, there is a need to enhance the scope of SMS beyond the safety department, as a poor understanding of this relationship renders the identification and selection of safety-related measures difficult in practice. Moreover, it is necessary to establish safety-related measures that can assess the performance of these SMS factors and, consequently, avoid the occurrence of accident precursors. Figure 1.1 demonstrates the relationship between these three concepts.

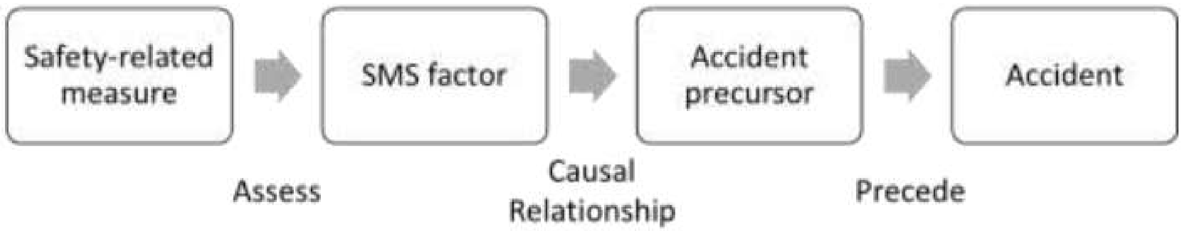

Figure 1.1 Relationship between safety-related measures, SMS factors, and accident precursors

Several theoretical models for proactively assessing safety output, which combine safety-related measures and various evaluation methods, have been proposed. Despite their ability to determine the level of influence of safety-related measures on safety performance (Esmaeili et al. 2015; Lingard et al. 2017; Salas and Hallowell 2016), these methods are limited by their inability to consider characteristics unique to specific companies. Method(s) usually employed by these models [such as Artificial Neural Network (Goh and Chua 2013; Patel and Jha 2014) and Linear Regressions (Esmaeili et al. 2015; Lingard et al. 2017; Salas and Hallowell 2016)] require a minimum ratio between the quantity of safety-related measures and the number of data points Kim et al. (2004). However, since the occurrence of accidents on construction sites is relatively infrequent (Hopkins 2009), and as many safety-related measures can influence the safety performance (Jablonowski 2011), the number of data points available in one organization may not be sufficient to appropriately apply these methods.

To increase the number of data points, these models usually consider accidents from more than one organization. This often restricts the use of measures to those collected and assessed by safety departments, due to the difficulties in assessing measures beyond the safety department in the accident investigations, thereby limiting the ability of the model to examine safety performance from a holistic perspective. Furthermore, since measure availability and influence differ between companies due to variability in safety culture, organizational characteristics, and project types, the relevancy of the measures and, therefore, outputs, may be limited.

Current assessment models are also limited by their inability to evaluate how managerial decisions can affect the presence or occurrence of safety-related measures. Construction projects are dynamic processes that may change considerably during project delivery, particularly as managerial decisions are made. Current models cannot reproduce the performance of construction projects or associated safety-related measures and are, therefore, unable to predict how managerial decisions will affect the performance of safety-related measures overtime.

Several practical and theoretical limitations may jeopardize the ability of current proactive measurement approaches to reliably evaluate safety output for individual companies. An approach that is capable of both holistically and dynamically assessing safety performance while considering the unique characteristics of an organization will be required to overcome these limitations.

1.2 Research Objectives

This research aims to develop a framework for evaluating the safety performance of industrial construction projects using safety-related measures. This framework is designed to assist managers with, and reduce the effort required to, examine SMS from a holistic perspective while, at the same time, examining the effect of managerial decisions on dynamic safety performance.

The followings objectives have been identified as a mean of achieving this aim:

- To understand the association between SMS factors and accident precursors from a holistic perspective.
- To collect and analyze the safety-related measures available in an organization and to review and assess the appropriateness of these measures for the assessment and control of safety performance.
- To propose a method for the evaluation of safety performance, using safety-related measures, in conditions characterized by limited data quantity and high meausre variability.
- To combine Case-Based Reasoning (CBR) with simulation modeling to proactively assess safety performance of construction projects.

1.3 Scope of Research

- This thesis is limited to industrial construction projects. Although safety-related measures not considered in Chapter 4 may also affect safety performance, this research has not considered these measures due to the absence of data regarding these measures at the test organizations.
- Safety performance was evaluated at a organizational level

- While results may be used to inform researchers and practitioners in other regions, survey participants (Chapter 2) are from Alberta, thereby limiting the conclusion of Chapter 2 to this area.

1.4 Research Methodology

The research was conducted in four phases to achieve the stated aim. In the first phase, a literature review was conducted to identify accident precursors and SMS factors. Items for each group were also identified from accident investigation reports from construction companies. Subject matter experts were also asked to provide their opinions on the item list to reduce list redundancy. Based on the final set of items, a questionnaire was developed to evaluate the likelihood and influence of each measure. The purpose of the questionnaire was to identify critical SMS factors and accident precursors as well as the association(s) between them. A questionnaire method was chosen due to the ease and timeliness in which data could be collected.

In the second phase, a literature review was conducted to identify safety-related measures that could be used to evaluate safety performance. Based on this information, data were collected through a case study, and a Multi-Linear Regression (MLR) model was used to identify the empirical association between safety-related measures and safety performance. MLR was selected for its ability to estimate mathematical relationships between variables and for the ease in which models can be interpreted when linearity between dependent and independent variables can be assumed (Zayed and Halpin 2005).

In the third phase of this research, interviews were conducted with safety and project managers at a construction organization to identify safety-related measures. The variables identified by the subject matter experts were collected from databases, documents, and a questionnaire. Following data collection, proactive evaluation of the safety performance was performed using a CBR method. According to Kim, An and Kang (2004), advantages for using CBR are (1) the clarity of the explanation between the relationship of input and output variables, (2) the simplicity in which the model can be updated with new data, and (3) the absence of a minimum requirement ratio between input and output data.

In the fourth phase, a simulation model, capable of reproducing the performance of a construction project, was developed to assist managers with the decision-making processes associated with the proactive control of safety performance. Simulation was selected as a suitable approach due its ability to capture dynamic and complex interactions between various measures and to model construction processes while considering the uncertainty inherent in construction. In this research, Simphony (Hajjar & AbouRizk 1996) was used as a simulation tool since it is programmable, can be customized for further developments, and has been successfully used in previous studies to reproduce the performance of construction projects (Razavialavi, 2016; Alvanchi et al. 2012).

1.5 Framework Overview

Chapters 4 and 5 propose a framework for evaluating safety performance using safety-related measures (Figure 1.2). The final framework is composed of three components. In the data identification component, measures that may influence safety performance must first be identified. This can be accomplished through brainstorming sessions between project and safety managers. Recently published studies (Hallowell et al., 2013; Han et al., 2014; Esmaeili, Hallowell and Rajagopalan, 2015; Salas and Hallowell, 2016) may guide the discussion and identification of measures. Following this, data should be collected and stored in the Onsite Risk Level Database. Notably, measures can be quantitative or qualitative.

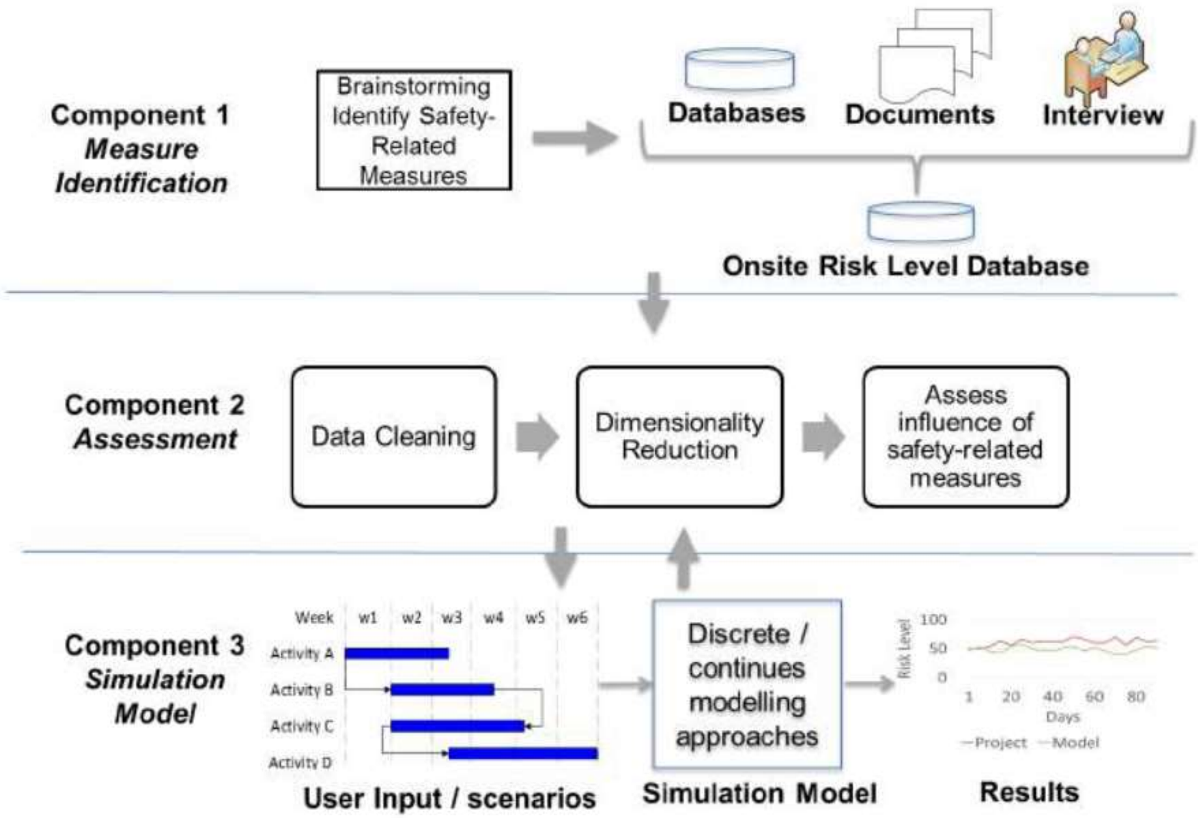

Figure 1.2 Thesis framework

The second component is the assessment. In this component, the influence of each safety-related measure is identified and safety performance is assessed. Prior to the determination of measure influence, it is necessary to (1) clean and (2) reduce the number of random variables in the onsite risk level database. A Pearson correlation test and Correlation Feature Base Selection were used to reduce the dimensionality of the dataset. To assess the influence of safety-related measures on safety performance, a CBR/GA method was suggested due to its ability to generate knowledge based on previous experiences using a limited number of data points.

In the third component, a simulation model is developed to mimic the behaviour of safety-related measures and, using the method defined in Component 2, predict safety performance. Advantages to using simulation models to reproduce the behaviour of safety-related measures are their ability to (1) correctly model complex activities and their interactions with the resources required to perform them; (2) model environmental parameters (such as temperature) from historical data; and (3) include onsite worker availability when calculating productivity rates. A combined discrete/continuous simulation model is suggested to mimic project behaviour. The discrete portion of the model is responsible for controlling the flow of entities (workers) and its attributes. In the continuous component of the model, time interval is set at one day, where the state variable is working hours per day. The continuous component of the model is responsible for regulating the time advance of the entire model. The safety-related measures are updated based on the dT defined by the user. The final goal of the simulation model is to predict the effect of managerial decisions on safety performance.

1.6 Thesis Organization

The purpose of Chapters 2 and 3 is to further understand the current practices of SMS in construction companies, how managers perceive the influence and likelihood of factors present on construction sites, and how these factors affect safety performance. Based on the foundation provided in these two chapters, an approach to proactively assess safety performance is proposed and developed in Chapters 4 and 5. The chapters in this thesis are organized as follows:

Chapter 2 focuses on identifying, from the perceptions of project and safety managers in Alberta, Canada, critical SMS factors and accident precursors as well as the association between these two groups. A framework using a questionnaire-based methodology was developed. This framework is capable of exploring the many-to-many relationships between these two groups, thereby assisting companies with the development of strategies aimed at controlling the occurrence of accident precursors. Results of this study have reinforced the importance of applying a holistic approach when evaluating safety performance.

Chapter 3 provides insights on several measures identified in literature to proactively assess safety performance. Difficulties in utilizing these measures in practice, such as the lack of data integration between departments and the cost of data collection, are discussed. A case study analyzes the use of safety-related measures at an organizational-level to assess safety performance. Finally, this chapter discusses the relationship between safety-related measures and safety performance as well as the benefits for using data from multiple organizational departments to mitigate risks.

Based on the understanding acquired from Chapters 2 and 3 (suggesting the use of a holistic approach to avoid the occurrence of accident precursors), Chapter 4 discusses the limitations of current theoretical assessment models to evaluate safety output. A framework, capable of overcoming these limitations, to evaluate the safety performance of construction projects using safety-related measures and CBR is proposed. Notably, this approach considers data from databases, documents, and information from several departments. Furthermore, a case study is presented to demonstrate the effectiveness and advantages of using the proposed framework to evaluate safety performance in practice.

Chapter 5 focuses on how CBR can be combined with simulation modeling to assist managers with decision-making processes. A case study is presented to demonstrate how this hybrid simulation approach can be used to evaluate safety performance at a project-level. Scenarios were tested to demonstrate framework performance.

Chapter 6 summarizes the conclusions of this thesis and its academic and industrial contributions. Recommendations for future studies are also described here.

Chapter 2: Identification and Association of High-Priority Safety Management System Factors and Accident Precursors for Proactive Safety Assessment and Control

2.1 Introduction

While the implementation of safety management practices over the last several decades has resulted in a reduction in fatal and non-fatal worksite injuries, current construction safety management practices have been criticized for their reactive nature, often applying corrective actions after, rather than prior to, incident occurrence (Robson et al. 2007; Wu et al. 2010b). With the aim of pre-emptively reducing worksite accidents, researchers have attempted to identify SMS factors that elicit the development of conditions or events, termed accident precursors, that precede accident occurrence (Wu et al. 2010b).

While methods allowing construction worksite managers to prioritize critical SMS factors have been developed, these methods are unable to determine associations of the identified SMS factors with the development of high-priority accident precursors. Given that flaws in the SMS factors are a step in an injury event (Bentley 2009) and that accident precursors typically precede accident occurrence (Kyriakidis et al. 2012), identification of associations between SMS factors and accident precursors can provide construction managers with valuable insight into their current SMS. Specifically, this may provide practitioners with an overview of which SMS factors require additional attention or control if a particular accident precursor is observed and may also assist practitioners in predicting which accident precursors are likely to arise if a particular set of SMS factors are present. A method capable of determining which SMS factors are associated with the occurrence of high-priority accident precursors is crucial for developing a safety management system that can mitigate high-risk conditions or environments before they develop into accidents and for ensuring that safety management resources are prioritized and allocated appropriately.

This study proposes and demonstrates the effectiveness of a risk rating-based approach for assessing and prioritizing current safety management system (SMS) factors and accident precursors based on industrial practitioners' experiential knowledge. In addition to its prioritization capabilities, the proposed approach is also capable of examining associations between high-priority SMS factors and accident precursors and provides a feasible method for identifying relationships between SMS factors and accident precursors. To demonstrate its practical functionality, the proposed method was applied at 15 distinct construction companies in Alberta, Canada.

2.2 State of Art

ANSI (2012) defines a SMS as a set of interrelated, interacting factors that are strategically designed to establish and achieve project safety goals. A SMS involves the systemic planning and management of various safety elements (Haas and Yorio 2016; Robson et al. 2007) including safety standards, safety policies, safety programs, safety evaluation, incident reporting, and incident investigation (Choudhry et al. 2008; Hinze et al. 2013a). The performance of a SMS is influenced by a large number of internal and external SMS factors that may be associated with the development of accident precursors, which are defined as "an event or condition that increases the probability of an accident which may result in the injury or death" (Kyriakidis et al. 2012 p. 1537).

Previous studies have provided insight into various SMS factors, revealing that deficient SMS may result in worksite incidents. For example, Cheng et al. (2012) have stated that written safety policies, accident investigation and reporting, and safety records (a formal record of safety information for communication and sharing between safety parties) are the most effective means of maintaining worksite safety. On the other hand, Sun et al. (2008) reported that emergency response planning and contractors' commitment to safety had a high impact on safety performance during construction projects that were planned for the 2008 Beijing Olympic Games. Furthermore, Costella et al. (2009) and Subramanyan et al. (2012) demonstrated that safety values shared by all management levels and safety commitment by all worksite personnel considerably improved safety performance. Several external SMS factors, which are factors that are not typically related to safety departments, such as building designs, schedules, and market availability of skilled workers, have also been identified (Han et al. 2014; Mitropoulos et al. 2005; Hinze 1997). When applied to daily practice, however, the ability to determine which particular SMS factors would be most critical in given conditions throughout the life cycle of a project and across variable working environments remains challenging for practitioners.

SMS factors themselves do not result in immediate threats to safety. However, due to their ability to elicit accident precursor occurrence, they are considered to be an early step in an injury event (Bentley 2009). Researchers have associated SMS factors with the occurrence of accidents precursors. Han et al. (2014) have indicated that project delays increase frequency of unsafe worker behavior. Jiang et al. (2015) have demonstrated that ineffective safety programs and insufficient resources for safety measures can increase the occurrence of unsafe behavior. Jiang et al. (2015) also found that harsh environments can increase the number of worksite hazards.

In contrast to SMS factors, accident precursors are considered to be both causal and indicatory in nature (Kyriakidis et al. 2012; Saleh et al. 2014). According to Wu et al (2010), incident precursors are the condition, events, and sequences that preceded and lead up to accidents. Similarly, Suraji et al (2001) explained this concept as an undesired event, which was an unwanted incident immediately preceding and leading to an accident that have, or could have, injured construction personnel or the general public or damaged property or the environment.

In this regard, relationships between SMS factors and accident precursors, if identified, can be used to guide and adapt current safety management practices by providing insight into which SMS factors should be further observed, controlled, or mitigated when particular accident precursors are observed onsite. Identification of these relationship is difficult in practice due to the complexity of the associations between these two groups (Saleh et al. 2014), as shown in Figure 2.1. SMS factors may exist in a simple one-to-one relationship with an accident precursor, the presence of several SMS factors may be required to elicit one accident precursor, or a single SMS factors may be involved in the development of several accident precursors. This complex causal influence, therefore, requires research to examine the impact of safety SMS factors on accident precursors from a holistic perspective.

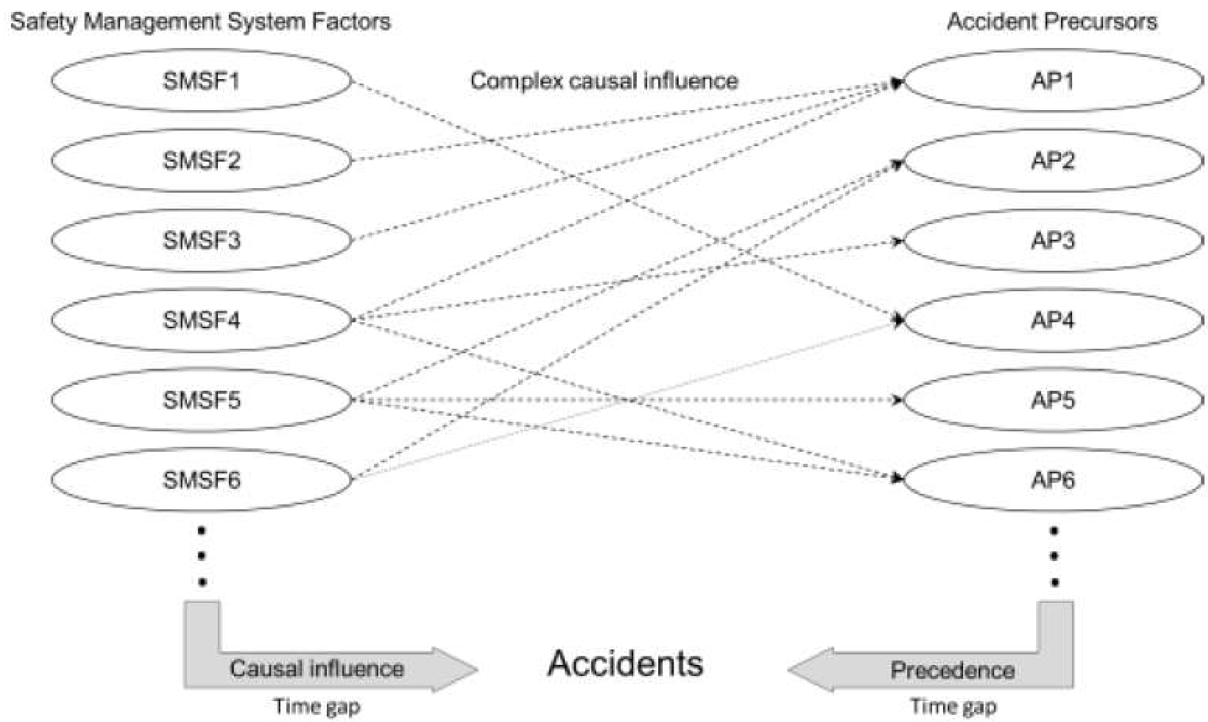

Figure 2.1. A relational model of safety system factors, accident precursors, and accidents

While previous studies have examined SMS factor and accident precursor relationships, these studies have evaluated the priority of SMS factors with respect to only one accident precursor (Fang et al. 2015; Jiang et al. 2015; Patel and Jha 2016; Zhang et al. 2016). In this context, previous studies overlook the impact of SMS factors on accident precursors as part of a holistic system. In addition, other studies (Ahmed et al. 2000; Guo and Yiu 2016; Leung et al. 2014; Patel and Jha 2014; Zhang et al. 2016) have primarily focused on SMS factors associated with safety programs and commitment to worksite site safety and have not considered the impact of external SMS factors on the development of accident precursors. A method capable of examining the association of a comprehensive set of internal and external SMS factors with multiple accident precursors has yet to be developed.

2.3 Methodology

To determine the importance of SMS factors (input variables) and accident precursors (output variables) and to understand the complexity between the two, a survey-based, risk-rating questionnaire was designed to assess the perceptions of construction practitioners.

2.3.1 Constructs

A total of 96 SMS factors or accident precursors were identified following the review of safety management literature and the examination of three accident investigation reports provided by private construction companies. To increase participant compliance, redundant variables were removed to reduce questionnaire length. The finalized list of variables was examined by five safety researchers from Universities in Canada and the United States and by three senior industrial practitioners (average experience > 25 years). Based on the feedback received from these individuals, a total of 28 SMS factors and 24 accident precursors were selected for inclusion in the questionnaire. The description, sources, and classification of these variables are summarized in Tables 2.1 and 2.2. SMS factors (Table 2.1) were categorized into four groups: safety programs (Hinze et al. 2013a), commitment to safety (Choudhry et al. 2008), resources (both budgets and personnel; Fang et al. 2004; Zou and Zhang 2009), and external factors (Mitropoulos et al. 2005). Accident precursors (Table 2.2) were categorized into four groups according to Wu et al. (2010b)'s classification of accident precursors: worker behavior-, teamwork-, workplace-, and materials and equipment-related.

2.3.2 Data Collection and Analysis Method

SMS factors and accident precursors were prioritized using a risk-rating method that was based on (1) *likelihood*, defined as the probability of factor or precursor occurrence, and (2) *impact*, defined as the magnitude of potential consequences of the factor or precursor (i.e., the perceived influence of the factor or precursor on eliciting a worksite accident). The use of a likelihood- and impact-based rating identifies critical factors across two different dimensions and enables quantitative risk analysis by measuring distinct perception (Sun et al 2008).

The likelihood and impact of each SMS factor and accident precursor is evaluated by domain experts using a 5-point Likert scale. *Likelihood* of each item was rated as unlikely (1) to very likely (5) and *impact* as not influential (1) to extremely influential (5). A questionnaire was developed as an instrument to collect likelihood and impact data for each of the SMS factors and accident precursors indicated in Tables 2.1 and 2.2 Prior to its finalization, the questionnaire was tested by seven participants, all of whom had at least five years of experience in the construction industry or in construction research. The final questionnaire is available on Appendix A.

Table 2.1 List of SMS factors included in this research

Group	Factor	Description	Sources
Safety Programs	Safety policy	Safety policy defines responsibilities for employees, third party companies, or individuals. In addition, safety policy outlines the general framework for enforcement of health, safety, and environment rules.	Hislop 1999; Hinze 1997
	Safety training	Safety training implements health and safety procedures into specific job practices and increases workers' understanding of the hazards they may be exposed to; operating procedures and safeguards; and emergency procedures.	Hinze 1997; Al Haadir and Panuwatwanich 2011
	Safety committee	Safety committee reviews accident investigation reports, discusses site safety matters, and improves safety programs.	Hislop 1999; Hinze 1997
	Safety incentive program	Safety incentive programs reinforce workers' positive safety behavior. The incentives can be made at the individual- or group-level.	Hinze 1997; (CII 2012)
	Subcontractor assessment	In subcontractor assessment, subcontractors' safety measures are reviewed to ensure that they meet the safety requirements established by the general contractor.	Al Haadir and Panuwatwanich 2011
	Emergency planning	Emergency plans establish guidelines and procedures for dealing with emergencies, such as major injuries, fires, explosions, etc.	Hislop 1999; Hinze 1997
	Accident investigation	In accident investigations, accident data are analyzed to reveal trends and points of weakness in the safety program.	Hislop 1999; Hinze 1997
	Hazard assessment	Identify potential hazardous and mitigation strategies in activities associated with the construction process.	Hislop 1999; Hinze 1997
	Employee involvement program	Motivate workers to be involved in various safety and health activities, such as job hazard analyses, toolbox talks, and inspections.	Hislop 1999; Hinze 1997
	Inspection and auditing	Safety inspections and auditing identify uncontrolled hazardous	Hislop 1999;

Group	Factor	Description	Sources
		exposures to workers and/or violations of safety standards	Hinze 1997
	Pre-construction safety and constructability review	In pre-construction safety planning and constructability reviews, the implementation of safety requirements are discussed in an early stage of the construction phase.	Hislop 1999; Hinze 1997
	Substance abuse program	Substance abuse programs prevent the use of illegal drugs onsite and screen those who are affected by substance abuse at work.	CII 2012
	Safety meetings	In safety meetings, safety issues are updated among stakeholders. and solutions for identified problems are discussed.	Hallowell and Gambatese 2009
	Behavior-based safety program	Behavior-based safety programs attempt to reduce workers' risk-taking/unsafe behavior.	Hallowell and Gambatese 2009
Commitment to Safety	Owner's commitment to safety	Owner commitment to prioritizing the selection of safe contractors, addressing safety in design, and participating in safety management.	Sun et al. 2008
	Management team's commitment to safety	Management team commitment to investing in safety, defining safety management programs, and keeping pressures on workers low.	Hinze 1997
	Subcontractors' commitment to safety	When subcontractors are committed to safety, subcontractors would comply with the safety procedures specified by the general contractor.	Sun et al. 2008
	Management team's priority with safety over schedule	When a management team prioritizes safety over schedule, the management team does not compromise safety even when the schedule is lagging.	Han et al. 2014; Lee et al. 2012
	Management team's priority with safety over cost	When a management team prioritizes safety over schedule, the management team does not compromise safety even when the costs are overrun.	Lee et al. 2005
Resources	Safety budget	Sufficient safety budgets allow for the implementation of safety programs.	Zou and Zhang 2009;
	Safety personnel	Sufficient numbers of safety personnel allow the implementation of safety programs.	Suraji et al. 2001

Group	Factor	Description	Sources
	Foremen	Sufficient numbers of foremen allow orienting and discussing safety procedures with workers.	Han et al. 2014
External Factors	Change orders	Change orders can induce changes in work plans and sequences, demotivate workers, and obscure safety hazards.	Wanberg et al. 2013
	Design	Complex building design can affect safety by increasing hazards and workers' exposure to unfamiliar types of methods and materials.	Sun et al. 2008
	Reworks	Reworks can demotivate employees to follow safety rules and develop hazards that were not previously identified	Han et al. 2014
	Contract schedule	Tight contract schedules can cause schedule pressure on workers and result in disregard of safety recommendations.	Sun et al. 2008; CII 2012
	Available skilled workers	Low numbers of skilled workers in the local market can affect the general skill levels of workers onsite.	Zou and Zhang 2009
	Government regulations	Stringent government regulations can influence safety management practices by establishing strict safety standards and procedures	Zou and Zhang 2009

Table 2.2. List of accident precursors included in this research

Group	Accident precursor	Sources
Worker-related	Workers' failure to identify hazards	Rodrigues et al., 2015
	Workers' neglect of hazards	Rodrigues et al., 2015
	Workers under the influence of drugs or alcohol	Suraji et al. 2001
	Workers' low skill level	Suraji et al. 2001
	Workers under high levels of stress due to schedule pressure	Mitropoulos et al. 2005
	Workers' high level of fatigue	Zou and Zhang 2009
Teamwork-related	Inadequate communication/enforcement of safety rules within teams	Toole 2002
	Insufficient experience of safety management personnel	Sun et al. 2008
	Insufficient experience of foremen	Toole 2002
	Lack of attention to coworkers' safety	Zou and Zhang 2009
	Misunderstanding of safety requirements by workers or subcontractors	Brown et al. 2000
Workplace-related	Site congestion	Fortunato et al. (2012)
	Workers' exposure to extreme weather conditions	Lee et al. 2012
	Workers' unfamiliarity with work environment	Lee et al. 2012
	Poor housekeeping	Khanzode et al. 2012
	Low level of ergonomic consideration of workspace	Mitropoulos et al. 2009
	Lack of mitigation of hazardous site environments (e.g., noise)	Lee et al. 2012
	Inadequate safety guards or barriers	Reiman and Pietikäinen 2012
	Unclear emergency procedures	Sun et al. 2008
	Inadequate/inaccurate site information	Suraji et al. 2001
Materials and equipment-related	Inadequate use of tools	Toole 2002
	Inadequate use of personal protective equipment	Zou and Zhang 2009
	Inadequate use of heavy equipment	Suraji et al. 2001
	Workers' exposure to hazardous materials	Hallowell et al. 2013

22 SMS factors from the *Safety Programs*, *Commitment to Safety*, and *Resource* groups are described in the questionnaire as a desirable state. For example, the questionnaire item for the "safety committee" factor is "Safety practices and procedures are periodically reviewed and evaluated by the safety committee." If a respondent answers "very likely," it implies that the respondent's perception of "safety committee" is desirable. As for impact, if a respondent answers "little influential," it implies that the respondent perceives the actions of the safety committee as having little influence on accident occurrence—even if the respondent perceives the actions of safety committee as undesirable. In contrast, six SMS factors and 24 accident precursor items from the *External Factors* group are described as an undesirable state. The questionnaire item for "workers' exposure to hazardous materials" is "Workers are frequently exposed to hazardous material (e.g. explosive, toxic, flammable)." If a respondent answers "very likely," it implies that the respondent perceives that "workers' exposure to hazardous materials" occurs frequently. As for impact, if a respondent answers "little influential," it implies that the respondent perceives "workers' exposure to hazardous materials" as having little influence on accident occurrence—even if exposure occurs regularly. In the questionnaire, the SMS factors from the *External Factor*s group are presented in combination with accident precursors.

Once likelihood and impact are evaluated, likelihood scores for the SMS factors from the *Safety Programs*, *Commitment to Safety*, and *Resource* group are reversed to reflect a "high risk" scenario. Then, in accordance with ISO standards (IEC/ISO 31010, 2009), standardized scores are multiplied to generate a risk score for each factor or precursor. Notably, this method has been used in numerous social and economic studies (Ostrom and Wilhelmsen 2012) and has been adapted to assess factors influencing safety (Fang et al. 2004; Sun et al. 2008).

Likelihood and impact scores are combined to generate risk scores using the following equations:

$$F_j^i = \varphi_j^i \beta_j^i \tag{1}$$

$$I^i = \frac{\sum_{j=1}^{n} F_j^i}{n} \tag{2}$$

where n = number respondents; φ_j^i = likelihood score for the *i*th item assessed by the *j*th respondent; β_j^i = impact score for the *i*th item by the *j*th respondent; F_j^i = risk score for the *i*th item assessed by the *j*th respondent; and I_j^i = average risk score of the *i*th SMS factor or accident precursor (Sun et al. 2008).

2.3.3 Sample and Survey Procedure

The online link to the final questionnaire was distributed—through key industrial liaison personnel—to 15 construction companies in Alberta, Canada. Industrial liaison personnel distributed the online questionnaire link to experienced safety personnel or to construction managers in their organization via email. No information regarding their individual or organization identity was collected. Survey participation was anonymous, voluntary, and self-administered.

A sample size for the study that would result in meaningful findings was determined from the formula introduced by Cochran (1977) (Equation 3) for scaled variables:

$$n = \frac{t^2 x\, s^2}{d^2} \quad (3)$$

where *n* = sample size; *t* = value selected for significance; *s* = estimate of variance deviation for the scale used for data collection, which is calculated by dividing the inclusive range of the scale by the number of standard deviations that include almost all possible values in the range; and *d* = number of points on the primary scale multiplied by the acceptable margin of error.

The significance adopted in this research is 95% (therefore, t = 1.96) and the margin of error is 0.05%. Bartlett et al. (2001) have described how Equation 3 may be adapted for data collected using a Likert scale. Briefly, the estimated variance (s) can be measured by dividing the questionnaire scale (i.e. 5) by the standard variation (5), yielding a value of 1. Accordingly, the minimum sample size was calculated to be 62 participants.

$$n = \frac{1.96^2 x\ 1^2}{(5\ x\ 0.05)^2} = 62\ participants$$

A total of 102 responses were received, of which six were removed due to incompleteness; 96 responses were analyzed. The average construction industry experience of the respondents was 18.80 years (σ = 11.58 years) (Figure 2.2a). A majority of the respondents were currently employed on industrial construction projects (Figure 2.2b), and most of the respondents were managers (Figure 2.2c).

Figure 2.2 Respondent demographic information. (a) Experience; (b) type of industry; and (c) current occupation

2.4 Results

Internal consistency was tested to ensure that the survey questionnaire design produced consistent results. Critical SMS factors and accident precursors were identified and prioritized using the risk-rating method. Correlation analysis was then performed to examine associations between high-priority SMS factors and high-priority accident precursors both at a group- and individual-level.

2.4.1 Internal Consistency Test for Each Group of Variables

Cronbach's alpha (α) is used to assess internal consistency within a group of variables that are believed to measure a single, latent construct. Latent constructs are often used to conveniently summarize a number of variables (Bollen 2002). According to (Byrne 1998), a latent construct cannot be observed or measured directly and, therefore, should be inferred from other observable measures. Given the presence of latent variables in the current study, the use of the Cronbach's alpha test in this research is useful for testing the appropriateness of variable grouping. As there are two measures—likelihood and impact—for each variable, two Cronbach's alphas are calculated for each group of variables as shown in Table 2.3. According to Kline (2000), a grouping is deemed acceptable, poor, or unacceptable if Cronbach's alpha is greater than 0.7, between 0.7 and 0.5, or lower than 0.5, respectively. Here, most groupings were considered acceptable, both in terms of likelihood and impact, suggesting that the variables within these groups were under the influence of a single, latent construct. Exceptions to this were the *Resource* and *External Factors* groups, indicating these groups may be comprised of unrelated variables. Indeed, variables within the *Resource* or *External Factors* groups are unique in terms of likelihood or impact. For example, under the *External Factors* category, the likelihood that skilled workers are available in the market and the likelihood that tight contract schedules cause employee pressure are likely unrelated. Similarly, under the *Resource* category, onsite foremen availability and onsite safety personnel availability may not similarly impact accident occurrence: since foreman have a direct relationship with workers, they may have a greater influence than safety personnel with respect to incident prevention.

Table 2.3. Internal consistency scores for each group of variables.

Category	Group	Likelihood	Impact
SMS Factors	Safety Programs	0.887	0.860
	Commitment to Safety	0.846	0.851
	Resources	0.781	0.640
	External Factors	0.529	0.722
Accident Precursors	Worker-related	0.810	0.870
	Teamwork-related	0.806	0.877
	Workplace-related	0.794	0.893
	Materials and Equipment-related	0.814	0.859

2.4.2 Identification of High-Priority SMS factors

Table 2.4 summarizes the likelihood, impact, and risk scores of each SMS factor. The mean likelihood score for all SMS factors was 2.23 (σ = 0.72), the mean impact score was 3.83 (σ = 0.46), and the mean risk score was 8.39 (σ = 2.70). *External Factors* tended to have higher likelihood scores, whereas factors related to *Safety Programs*, *Safety Commitment*, or *Resource* tended to have higher impact scores. The three highest-rated SMS factors in terms of risk scores, in descending order, were: contract schedule, skilled worker availability, and change orders.

Notably, several factors from the *External Factors* group were determined to be 'high-risk' (i.e., perceived to have a high impact when they occur and were perceived to occur frequently). This is consistent with previous studies, which have emphasized both the direct and indirect adverse impact of contract schedule (Mohamed 2002), lack of available skilled workers (Rodrigues et al. 2015), and change orders (Wanberg et al. 2013) on safety performance.

Table 2.4. Likelihood, impact, and risk scores for SMS factors

Group	Components	Risk Score		Likelihood Score		Impact Score	
		R	μ	R	μ	R	μ
Safety Programs	Employee involvement program	9	8.17	18	1.95	4	4.26
	Subcontractor assessment	10	8.03	13	2.08	13	3.98
	Behavior-based safety program	12	8.01	20	1.93	7	4.19
	Safety incentive program	15	7.35	7	2.53	27	2.93
	Safety committee	14	7.51	10	2.18	23	3.56
	Pre-project safety plan	17	7.30	16	1.97	15	3.91
	Hazard assessment	18	7.14	23	1.66	2	4.42
	Substance abuse program	19	7.15	17	1.96	17	3.90
	Inspection and auditing	20	6.86	22	1.69	9	4.16
	Safety meetings	21	6.85	15	1.98	21	3.68
	Accident investigation	22	6.79	24	1.61	8	4.18
	Emergency planning	25	6.29	21	1.83	22	3.57
	Safety policy	27	5.86	28	1.44	6	4.23
	Safety training	28	5.73	26	1.49	11	4.07
	Group Average		7.07		1.88		3.93
Commitment to Safety	Subcontractors’ commitment to safety	5	10.20	6	2.58	14	3.96
	Management team’s priority with safety over cost	7	8.58	8	2.24	12	3.98
	Management team’s priority with safety over schedule	8	8.53	9	2.21	10	4.08
	Owner’s commitment to safety	23	6.45	25	1.55	3	4.28
	Management team’s commitment to safety	24	6.44	27	1.46	1	4.49
	Group Average		8.04		2.00		4.16
Resources	Foremen	11	8.02	19	1.94	5	4.23
	Safety budget	13	7.77	12	2.12	19	3.73
	Safety personnel	16	7.32	14	2.04	20	3.71
	Group Average		7.70		2.03		3.89
External Factors	Contract schedule	1	15.98	2	3.98	16	3.90
	Skilled worker availability	2	15.97	3	3.73	18	3.75
	Change orders	3	13.87	1	4.12	25	3.26
	Reworks	4	11.46	4	3.31	24	3.31
	Design	6	9.27	5	2.81	26	3.07
	Government regulations	26	6.08	11	2.14	28	2.51
	Group Average		12.10		3.35		3.30

R: Ranking position based on the item average

μ: Item average

Interestingly, SMS factors related with safety programs had lower risk scores than risk scores of SMS factors belonging to the *External Factors* group. Traditionally, safety management practices in industry have attempted to improve safety programs by reinforcing their commitment to current safety practices (Hallowell and Gambatese 2009). However, many researchers (Han et al. 2014; Mitropoulos et al 2005) have contended that external factors may impact safety and, therefore, a shift in the focus of current safety practices rather than a reinforcement of its practices may be more effective at improving safety performance. Indeed, while other SMS factors, such as ineffective accident investigation, may be expected to have a high impact on safety, they were rated as low- or medium-risk due to the rarity of their occurrence.

2.4.3 Identification of High-Priority Accident Precursors

Table 2.5 summarizes the likelihood, impact, and risk scores of each accident precursor. The mean likelihood score for all accident precursors was 2.82 ($\sigma = 0.46$), the mean impact score was 3.57 ($\sigma = 0.38$), and the mean risk score was 10.72 ($\sigma = 2.26$). The three highest-rated accident precursors in terms of likelihood were: site congestion, workers' exposure to extreme weather conditions, and workers' failure to identify hazards. The three highest-rated accident precursors in terms of impact were: workers' failure to identify hazards, workers' neglect of hazards, and insufficient experience of foremen. Finally, the three highest-rated accident precursors in terms of risk scores were: workers' failure to identify hazards, site congestion, workers' neglect of hazards.

The top three accident precursors have been identified as critical by other researchers. For instance, many researchers have identified that failure to recognize hazards and indifference to hazards (Han et al 2014; Jiang et al. 2015) can lead to accidents. Similarly, level of congestion was identified by (Irumba 2014) as a primary cause of accidents. According to (Elbeltagi et al. 2004), construction site congestion is associated with falls and struck-by accidents and, therefore, should be avoided.

Table 2.5. Likelihood, impact, and risk scores for accident precursors

Group	Precursors	Risk Score		Likelihood Score		Impact Score	
		R	μ	R	μ	R	μ
Worker-related	Workers' failure to identify hazards	1	15.39	3	3.56	1	4.23
	Workers' neglect of hazards	3	13.69	4	3.11	2	4.22
	Workers' low skill level	6	12.23	6	3.07	5	3.88
	Workers under high levels of stress due to schedule pressure	7	11.82	7	3.05	16	3.51
	Fatigue	11	10.77	12	2.85	13	3.56
	Workers under the influence of drugs or alcohol	20	8.63	23	2.14	6	3.85
	Group Average	-	12.09	-	2.96	-	3.88
Teamwork-related	Insufficient experience of foremen	4	12.85	5	3.10	4	3.96
	Inadequate communication/enforcement of safety rules within teams	5	12.56	11	2.95	3	4.03
	Lack of attention to coworkers' safety	15	10.44	17	2.57	7	3.84
	Insufficient experience of safety management personnel	16	10.42	9	2.97	19	3.36
	Misunderstanding of safety requirements by workers or subcontractors	19	9.01	20	2.42	17	3.47
	Group Average	-	11.06	-	2.80	-	3.73

Group	Precursors	Risk Score		Likelihood Score		Impact Score	
		R	μ	R	μ	R	μ
Workplace-related	Site congestion	2	14.84	1	3.88	8	3.79
	Workers' exposure to extreme weather conditions	9	11.73	2	3.67	21	3.15
	Workers' unfamiliarity with work environment	10	11.31	10	2.96	11	3.64
	Poor housekeeping	13	10.61	14	2.79	12	3.59
	Low level of ergonomic consideration of workspace	14	10.47	13	2.81	18	3.37
	Lack of mitigation of hazardous site environments (e.g., noise)	18	9.02	18	2.55	20	3.31
	Inadequate safety guards or barriers	22	7.13	24	1.87	14	3.55
	Unclear emergency procedures	23	6.98	21	2.32	22	2.95
	Inadequate/inaccurate site information	24	6.93	19	2.45	24	2.66
	Group Average	-	9.89	-	2.81	-	3.33
Materials and equipment-related	Inadequate use of tools	8	11.78	8	3.03	9	3.72
	Inadequate use of heavy equipment	12	10.62	16	2.65	10	3.66
	Inadequate use of personal protective equipment	17	10.31	15	2.70	15	3.52
	Workers' exposure to hazardous materials	21	7.73	22	2.26	23	2.94
	Group Average	-	10.11	-	2.66	-	3.46

R: Ranking position based on the average

μ: Item average

The results demonstrated that, of the top three accident precursors, two were related to the *Worker-Related* group. This result reinforces the findings of Rowlinson (2004) who estimated that 80% of accidents are influenced by worker behavior. These results suggest that, in spite of functional safety programs (Table 2.4), adequate observation and control of worker behavior remains limited in practice.

2.4.4 Correlation Between SMS Factors' Likelihood and Accidents Precursors' Likelihood.

Previous studies have indicated that many-to-many, complex causal relationships may exist between SMS factors and accident precursors (Figure 2.1; Saleh et al. 2014; Kyriakidis et al. 2012). To determine if the SMS factors identified were associated with the accident precursors, a Pearson's correlation test was performed to examine the relationship between the likelihood scores of high-priority SMS factors and accident precursors. According to Gravetter and Wallnau (2010), the Pearson's correlation test measures the degree and direction of the linear relationship between two variables. De Vaus (2002) interprets the correlation coefficient as follows: < 0.3 weak; 0.30 – 0.49 moderate; 0.50 – 0.69 substantial, and > 0.7 very strong. In addition to determining the strength of the relationship, the significance of the correlation should also be verified. Gravetter and Wallnau (2010) have indicated that a probability value of 0.05 (or less) indicates that the correlation observed is "very unlikely" to have occurred by chance.

Several moderate and weak correlations between the SMS Factors and accident precursors were identified (Table 2.6). A correlation classified as substantial between "Skilled worker availability" and "Worker's low skill level" was identified. Notably, almost all of the incident precursors had at least one moderate correlation with an SMS factor. The exception was the "Extreme weather condition" precursor, which is likely a consequence of workers not being required to work when temperatures fall below -30°C.

Table 2.6. Pearson's correlation between SMS factors' likelihood and accidents precursors' likelihood

Incident Precursors \ SMS Factors	Contract schedule	Skilled worker availability	Change orders	Reworks	Subcontractors' commitment to safety	Design	Management team's priority with safety over cost	Management team's priority with safety over schedule
Workers' failure to identify hazards	.306**	.234*	-	.267**	-	-	-	-
Site congestion	-	-	-	-	-	.208*	-	.242*
Workers' neglect of hazards	.315**	.247*	-	-	-	.267**	-	-
Insufficient experience of foremen	.247*	.330**	-	-	-	-	-	.274**
Inadequate communication/enforcement of safety rules within teams	.223*	-	-	.215*	.238*	.297**	-	.315**
Workers' low skill level	.326**	.571**	-	.296**	-	-	-	-
Workers under high levels of stress due to schedule pressure	.224*	-	-	-	-	.332**	.262*	.342**
Inadequate use of tools	.405**	.235*	-	.398**	-	.277*	-	.277**
Workers' exposure to extreme weather conditions	-	-	-	-	-	.208*	-	-
Fatigue	-	-	-	-	-	.287**	-	-
Workers' unfamiliarity with work environment	.318**	.364**	-	.296**	-	.380**	-	-

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

- Correlation not significant

Identification of these relationships (Table 2.6) should incite the participating companies to better define accident precursor avoidance strategies. For instance, if companies are concerned about the accident precursor "Workers failure to recognize factors," efforts should be concentrated on controlling associated SMS factors such as "contract schedules," "skilled worker availability," and "rework.' This may include managerial actions to increase hiring of skilled workers or inciting onsite safety management to focus on improving the skill level and familiarity with working environments of current employees. The results generated from the application of the proposed method can also be used by managers and practitioners to review and update current safety management practices to better represent organization culture. For example, results in Table 2.6 suggest that SMS should focus on implementing interdepartmental integration. This may include the promotion and development of holistic safety policies and the fostering of a organization-wide commitment to safety, which, ultimately, may improve decision-making processes and overall safety performance.

It should be noted that, while a substantial number of associations between SMS factors and accident precursors have been identified (Table 2.6), causality cannot be established from these results. Correlation results only demonstrate that two variables related; they provide limited insights into the causal relationship that may exist between variables. Although previous studies support the presence of causality, additional investigation and in-depth analyses are required to establish the cause and effect relationship between SMS factors and accident precursors. An example is the correlation between "complexity of design" (an SMS factor) and "workers' exposure to extreme weather conditions" (an accident precursor). An interpretation of this relationship may be that an increase in design complexity may adversely affect entire project duration (i.e., by causing delays) or the difficulty of construction operations (as reported by Weinstein et al. 2005). These phenomena may increase workers' operations under unfavorable weather conditions (e.g. to compensate for schedule delays). However, the relationship between "complexity of design" and "extreme weather conditions" should to confirmed by further investigation to establish causality.

2.4.5 Validation

Two techniques, namely comparison to other models and event validity, were used to validate the proposed methodology and to determine if the methodology was capable of producing reliable results. These validation techniques are described below:

Comparison to other models: As described by Sargent (2005), this validation technique compares the results generated by a proposed method with results obtained using alternate methods, where result consistency is indicative of model validity. To apply this validation technique, correlation results between the three highest-priority SMS factors and accident precursors were compared to previously reported results. The SMS factor "contract schedule" was found to correlate with "worker's failure to identify hazards," "worker's neglect of hazards," and "worker's low skill level" (Table 2.6). Consistent with this, Wilson Jr and Koehn (2000) found that tight contract schedules often reduce the amount of attention allocated to safety management in favor of attaining construction deadlines. Jiang et al. (2015) found that work pressures resulting from tight schedules can influence workers' safety behavior, safety knowledge, and perceived behavioral control.

In line with the correlations observed between “skilled worker availability” and “worker’s low skill level” (Table 2.6), previous findings have demonstrated that reduced availability of skilled workers can affect an employee’s skill, behaviors, and familiarity with the workplace. In 2013, Caputo et al. stated that skills are necessary to enable workers to successfully perform activities. Gibb et al. (2006) have contended that lack of skills can shape a worker’s actions, behavior, capabilities, and, consequently, influence accident occurrence.

Although “change order” was not related to any of the “critical incident” precursors, the results demonstrated that “change order” was correlated with “rework” ($r = 0.339$; $n=96$; $P<0.01$). Love and Edwards (2004) stated that rework may undermine effective supervision, while Wanberg et al. (2013) indicated that rework can alter work environments, thereby affecting a worker’s ability to recognize hazards. Wanberg et al. (2013) also indicated that rework tasks may demotivate workers to follow safety practices and, consequently, neglect hazards. These findings are consistent with the results in Table 2.6, which demonstrate a significant correlation between “change order,” “rework,” and the three highest-priority accident precursors.

Event validity: In this technique, conditions found to associate with event occurrences are compared to a real system to determine if they are similar (Sargent 2005). Here, a “real system” was extracted from two accident reports collected by the companies participating in this research. The accident reports are summarized as follows:

Accident Case #1: Worker was removing a pipe spool after a hydrotest. The filler was stuck to the flange face, and upon removal, the filler sliced through the worker's glove causing a laceration to his right hand. The investigation identified that the worker did not understand the safety requirements during the activity due to a deficiency in safety training.

Accident Case #2: Worker crushed right-hand middle finger between jack-stand base and tongue of portable welding machine. The accident precursors, as identified by the organization, were neglect of hazards and inadequate enforcement of rules. An in-depth investigation conducted demonstrated failure in the employee involvement program (supervisor and worker did not discuss the equipment issue properly).

Consistent with the findings of this study, that "safety training" was correlated with "safety requirements," which were not clearly communicated ($r = 0.208$; $n=96$; $P<0.05$), and that "employee involvement program" was correlated with "worker's neglect of hazards" ($r = 0.225$; $n=96$; $P<0.05$) and "inadequate communication," ($r = 0.278$; $n=96$; $P<0.01$), the cases described above provide anecdotal evidence directly associating accident precursors, such as "workers' ignorance of hazards" or "inadequate communication of safety requirements," with SMS factors, such as the "safety training" and "poor implementation of employee involvement programs."

Results of the proposed method were shown to be consistent with the findings of several previously reported safety management studies and from "real system" accident reports. The ability of the proposed model to reliably prioritize and associate SMS factors with accident precursors has been validated using two validation techniques.

2.5 Discussion

As a consequence of limited resources, practitioners must balance SMS efficiency with SMS efficacy. Although this can be accomplished by allocating resources towards the control of SMS factors and accident precursors that are most predictive of accident occurrence, identifying and prioritizing SMS factors and accident precursors remains challenging in practice. To overcome these difficulties, this study has developed and validated a method that (i) allows for the comprehensive and concurrent assessment of the importance of numerous SMS factors and accident precursors, (ii) facilitates the prioritization of SMS factors and accident precursors, and (iii) examines relationships between high-priority SMS factors and accident precursors. Results generated by this method can be used by practitioners to determine if prioritized SMS factors are, in fact, associated with accident precursor occurrence, thereby ensuring that resource allocation to these factors will result in meaningful improvements in practice.

By identifying high-impact SMS factors and accident precursors, results generated by the proposed method may provide practitioners with insight regarding flaws in their ongoing SMS. Identification and prioritization of these factors and conditions can motivate practitioners to modify current SMS and safety practices to better control safety performance. For example, since the “lack of skilled workers in the market” was identified as a critical SMS factor, companies may implement competency tests to evaluate a worker’s skills prior to engaging in an activity or project. To avoid the effect of “tight contract schedules” on accident precursor occurrence, companies may increase onsite safety personnel to better alleviate worker pressure or to assist with worker identification of hazards.

To examine the model's functionality, the proposed method was used to evaluate the importance of SMS factors and accident precursors at several construction companies in Alberta, Canada. The highest priority SMS factors and accident precursors identified were consistent with many high-priority factors previously identified in literature The proposed method was also validated using two validation techniques, which demonstrated that the proposed method is capable of generating results that are both consistent with previously reported findings and reflective of a real system.

Notably, four of the highest priority SMS factors were classified as external factors (i.e., factors that are not typically associated with safety management). Although the perceived impact of these factors was low, the perceived likelihood of these factors was high. These results demonstrate that there is a need to consider safety management practices beyond the traditional approach, as the implementation of traditional safety management programs may not be sufficient to improve onsite safety performance. Companies must be aware of other potential root causes of accident precursors and safety incidents. This is not to say that external SMS factors, such as contract schedule control, are more important than traditional SMS factors, such as safety training. Rather, these findings highlight the notion that certain external factors are perceived to pose a greater risk to safety within the current SMS due to increased event likelihood as a consequence of limited or absent control of external factors by current SMS.

Although previous studies have demonstrated the influence of external SMS factors on incident precursors (Mohamed 2002; Rodrigues et al., 2015; Wanberg et al. 2013), management of external factors remains poorly integrated with the achievement of safety goals. This is due, in part, to the difficulties associated with identifying and prioritizing external SMS factors. The proposed questionnaire can be used to address these challenges. The questionnaire can identify and assess accident risk of numerous external factors across several organization departments. By identifying high-priority external SMS factors using the method presented here, companies can adopt broad safety practices to proactively control safety performance, such as defining realistic contract schedules to decrease production pressure on workers, evaluating the workers' competency during the hiring process, conducting new hazard assessments when rework occurs, and implementing "safety through design."

It was also found that SMS factors that are typically related to safety programs were perceived as high-impact factors, yet their perceived likelihood was low. Based on their low likelihood scores, safety-associated SMS factors appear to be appropriately controlled by current SMS of the studied companies. This phenomenon may be a consequence of the demand for safety excellence by local governments and owners when contracting a construction organization in the local market. Notably, similar patterns may not be observed in other countries and regions whose contracting practices may differ (Zou and Zhang 2009). These results suggest that high-impact factors, such as safety programs, are well managed and controlled in the construction sector in Alberta.

Recently, a systems-based approach to safety, which incorporates safety management practices across various areas of an organization, has been widely advocated througout safety management literature (Jiang et al. 2015; Leveson 2004; CII 2002). In this approach, various safety management elements are systemically planned and managed throughout the lifecycle of a project (Choudhry et al. 2008; Hinze et al. 2013a), across multiple functional units of an organization, and in a technical, organizational, or regulatory manner (Saleh et al. 2014). Many researchers have emphasized the importance of a holistic SMS approach for developing effective safety management practices (Hinze 1997; Leveson 2004; Wahlström and Rollenhagen 2014) and to improve safety performance (Haas and Yorio 2016). In consideration of this, a key feature of the proposed method is its comprehensive assessment of several SMS factors and accident precursors across various organization departments and areas. For instance, the likelihood of SMS factors related to safety management programs was perceived, overall, as low despite the continued presence of high-impact accident precursor occurrence onsite (Table 2.5), suggesting that conventional safety management programs and practices are not addressing all causes of onsite accidents. Companies, therefore, should be motivated to be aware of and begin to investigate other potential root causes using reliable, easy-to-use methods such as the one presented here.

While the current study supports the use of the proposed method to prioritize management of certain high-risk SMS factors and accident precursors in ongoing safety systems, the findings of this study should be interpreted in consideration of the following limitations. First, although the survey instrument was developed through rigorous development and testing procedures, a portion of the factor-selection process was dependent on the subjective opinions of subject matter experts; the examination of additional research cases is required to generalize method application to other sectors, industries, or regions. Second, although the list of variables in this research was identified following an extensive literature review and several expert interviews, additional SMS factors and accident precursors that were not identified may be affecting organization safety performance. Third, as previously mentioned, in-depth exploration of the complex relationships between SMS factors and accident precursors is limited by the methods employed in this paper. Fourth, as the respondents were employed in various types of construction projects, further research is required to identify factor and precursor risk within specific industries.

2.6 Conclusion

For achieving proactive safety management in construction, SMS factors and accident precursors that influence accident occurrence must be identified, prioritized, monitored, and controlled prior to worksite accident or injury. The reliable identification of high-priority SMS factors and accident precursors will allow construction companies to appropriately allocate and make efficient use of safety management resources and to effectively enhance safety management systems and approaches. Here, a survey-based, risk-rating method was proposed as an effective approach for identifying high-priority SMS factors and accident precursors. In this method, likelihood and impact scores of several SMS factors or accident precursors are collected from construction practitioners via surveys. These scores are then combined to generate risk scores, which are used to identify SMS factors and/or accident precursors that are most predictive of accident occurrence.

This method was used to identify and prioritize SMS factors and accident precursors and to provide insight into likelihood patterns and impact scores for SMS factors and accident precursors on construction sites in Alberta, Canada. The results demonstrated that “contract schedule,” “skilled worker availability,” and “change orders” were the highest-priority SMS factors in the region. As these SMS factors are considered external factors, these results suggest that external factors are not well-controlled by current safety management practices in this construction sector. Results also found the highest-priority accident precursors to be “workers’ failure to identify hazards,” “congestion,” and “workers’ neglect of hazards.” Of the top three accident precursors, two were related to worker behavior suggesting that current SMS practices are not adequately controlling worker behavior. Association results also supported previous findings of many-to-many relationship between high-priority SMS factors and accident precursors.

The expected contributions of this research are twofold. First, this research enhances the understanding of the complex relationships existing between SMS factors, accident precursors, and accidents by identifying and prioritizing high-risk SMS factors and accident precursors that are most relevant to construction companies in Alberta. Notably, the questionnaire included SMS factors that are not commonly considered in practice or in safety management literature. As discussed previously, due to its comprehensive approach, this questionnaire can effectively identify gaps in SMS across many departments and areas and, therefore, can be used to assess the impact of multiple risk factors on precursor occurrence throughout the lifecycle of ongoing projects.

Second, the proposed association approach can indicate which SMS factors should be addressed based on accident precursors observed, or which accident precursors are most likely to occur based on the presence of critical SMS factors. These research findings will assist companies to improve SMS and practices by guiding which SMS factors and accident precursors should be prioritized with respect to resources and attention based on the specific conditions observed onsite. The associations identified in this research can also be used to investigate cause-and-effect relationships between SMS factors and accident precursors.

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Chapter 3: Empirical Testing for Use of Safety-Related Measures at Organizational Level to Assess and Control Onsite Risk Level

3.1 Introduction

Construction laborers are frequently exposed to hazardous environments such as work at height, proximity to heavy equipment, or use of toxic and electrical materials. As a result, the construction industry is regarded as one of the most dangerous job sectors in many countries. For example, the construction industry in Canada had the highest number of fatalities and the third highest loss-time injuries in 2013 (AWCBC 2014). Safety incidents on the construction job site psychologically influence the worker and his/her family, coworkers, and society (Ikpe et al. 2012); and negatively affect project schedule (Han et al. 2014), cost, and quality (Wanberg et al. 2013). The role of management in incident prevention is therefore to diagnose and mitigate symptoms of managerial failure early on by setting appropriate safety goals and identifying means to achieve these targets (Petersen 1978).

Risk assessment, referred to as "a way of managing hazards of an organization" (Harms-Ringdahl 2004), is considered the core approach to safety management (Fung et al. 2012). Thus it is critical for an organization to manage safety risks, and to define and maintain certain measures to be within an acceptable level of safety throughout the life cycle of activity, process, or project (Antonsen et al. 2012). The use of safety-related measures at an organizational level[1] to control safety performance has been suggested and emphasized (Hinze 1997) since doing so provides a proactive approach to avoiding incidents (García-Herrero et al. 2012). However, the adoption of organizational safety-related measures is still a challenge due to the unknown influence of these measures on safety performance (Hallowell et al. 2013), the time-consuming process of data collection (Huang and Hinze 2003), and the dynamic behavior of construction sites (Han et al. 2014). Moreover, since safety performance is affected by numerous factors related to the different parties involved in a project—for example, owner commitment (Huang and Hinze 2006), project planning (Mitropoulos et al 2005), supply chain (Hallowell et al. 2013), subcontractors (Rowlinson 2004), design (Huang and Hinze 2003), and worker characteristics (Hinze 1997)—, it is difficult to establish which and how many measures should be used to evaluate ongoing safety performance on a given site.

Previous studies in construction have identified several safety-related measures at an organizational level to control factors related to incidents. These measures are commonly related to the organizational safety culture, site safety climate, worker's competency, worker behavior, and hazard management (Zhou et al. 2015). For example, Rowlinson (2004) and Hinze et al. (2013) impart the importance of establishing measures to control subcontractors' commitment to safety through the pre-project safety plan and contract type. Although these studies provide insight into effective policies and procedures that can be implemented to enhance safety

[1] Organizational level, in this research, refers to safety-related measures controlled by departments of an organization at a project level

management, it is still difficult to collect data from construction projects and identify the influence patterns of safety-related measures to control the safety performance. Moreover, in practice, difficulties in measuring safety-related factors arise from the complexity of an organization's structure—especially when relevant safety data are not adequately shared between various functional units (e.g., human resources, scheduling, and finance). This lack of integration may occur because the relationship between safety measures and outcomes (e.g., incidents) are not fully identified from a data perspective; there may be a lack of understanding between the functional units of an organization as to which data are available in practice, whose job it is to collect such data, and how such data can be analyzed and used for safety management. For instance, an organization investigated in the preliminary study stated that there is a need for evidence that the use of safety-related measures available on departmental databases may be used to improve safety performance. Based on this evidence, companies may re-design their databases to 1) support data sharing between departments to allow the control of safety-related measures and 2) improve decision-making processes to decrease onsite risk.

This paper aims to review and evaluate adoption of safety-related measures at an organizational level to assess and control onsite risk level (ORL). Through a cross-sectional case study, measures are selected and collected from databases of several departments—namely, human resources, safety, and payroll. Furthermore, a regression analysis is performed to model statistical relationships between organizational data and measured ORLs. The results of this analysis are compared with a new construction project to test the validity of the measures when the data are used for the purpose of management in practice. The rest of the paper is organized as follows: First, a background research about organizational measures for safety management is presented. Research methods section proposes a statistical framework to quantify the impact of the measures on the ORL and determine the acceptable ranges of the measures to be maintained. A case study is conducted to evaluate the proposed method and the analysis of results and discussion section examines the research results and study limitations, and in conclusion section the findings of this paper are summarized.

3.2 State of Art - Challenges in Defining Safety Measures

Antonsen et al. (2012) emphasize that safety performance may be improved by the standardization of working methods, separation of planning from execution, and implementation of a safety management system. When safety management programs are established and operated on a job site, defining appropriate measures associated with the safety practice is also critical to monitoring and controlling the ongoing project safety performance (Wachter and Yorio 2014). However, the safety performance measures commonly used in practice, such as total recordable incident rate (TRIR) and experience modification rate (EMR), are reactive. According to Hinze et al. (2013b), reactive indicators measure the safety performance after an incident has already occurred as a result of flaws in the safety system rather than functioning as precursor measures that can be used for the prevention of an incident in the first place. In addition, reactive measures do not necessarily indicate the risk level on construction sites (Mohamed 2002); according to Laitinen et al. (1999), sites with zero incidents can have even higher risk levels than sites with a few incidents. Accordingly, many research efforts (Guo and Yiu 2015; Hallowell et al. 2013; Hinze et al. 2013; Lee et al. 2012) have recently been made to define proactive strategies with which to control the risk level within a daily practice rather than reactively learning from previous incidents to avoid the recurrence of similar incidents.

Safety risk can be monitored and controlled by collecting and analyzing relevant data that represent a degree of risk involved in construction activities (Jannadi and Almishari 2003). Recent studies reveal that risk can be proactively identified and mitigated by understanding how various factors lead to safety incidents; such factors include schedule delay (Han et al. 2014), rework (Mitropoulos et al. 2005), and safety policies (Jiang et al. 2015). On this basis, numerous measures to control safety risks have been proposed, as shown in Table 3.1.

Although the adoption of all these measures (Table 3.1) on a job site can be unworkable and non-economical from a practical aspect (Wachter and Yorio 2014), previous studies have focused more on identifying safety performance measures than assessing the use of such measures in practice. Measures have generally been identified through questionnaire (Guo and Yiu 2015; Hallowell et al. 2013; Lee et al. 2012) or the use of accident causation models (Mitropoulos et al. 2005; Han et al. 2014; Jiang et al. 2015). Survey questionnaires reveal respondents' perceptions of the influence of measures on risk level, while accident causation models provide insight into the mechanisms by which various safety factors lead to an incident. Although findings from previous studies, summarized in Table 3.1, suggest various safety-related measures that may proactively control safety performance, the need to investigate which types of data can be collected in practice, as well as how these measures influence a safety system as a whole, still exists. The notion of this relationship, as exemplified through a case study, may be instrumental to the application and benchmarking of these findings, as the data analysis collected here can provide considerable insight on the maintenance and control of project risk level from a practical perspective.

Table 3.1: Summary of safety measures in previous studies

Studies	Number of measures proposed	Measure examples	Validation method
Guo and Yiu (2015)	32	Safety rules are in place; working hours per day; adequate safety resources are provided on site; frequency with which senior managers provide feedback on safety performance	Expert interview
Hallowell et al. (2013)	10	Near miss reporting; worker observation process; stop work authority	Expert interview
Toellner (2001)	6	Effective score of barricade performance; number of closed down areas; housekeeping quality	Visual assessment
Rajendran (2013)	3	Pre-task planning review; worker safe observation behaviour; site safety audits	Data from residential projects
Hinze et al. (2013)	2	Percent of worker observations that were safe; number of positive reinforcements provided per 200,000 h.	14 projects
Lee et al. (2012)	43	Workers' age; temperature; quantity training per month	Expert interview
NOSHC (1999)	26	Budget for safety programs; sub-contractors contract include safety practices; number of sub-standard conditions identified and corrected	Expert interview
AOHS (2015)	55	Hazard identification; hazard control; training competency	Expert interview
COAA (2011)	300	Behavioral based observation in place; employees perception surveys; active management safety participation	Expert interview
Brown et al. (2000)	61	Perceived safety climate; perceived pressure for shortcuts; perceived safety climate	Workers' opinions

Existing literature also incompletely discusses sources from which safety-related measures may be collected within an organization. In general, the health and safety department is mainly responsible for collecting and storing safety-related data (Hallowell 2012; Hinze et al. 2013). As the amount of data collected from construction projects is experiencing explosive growth, valuable information can also be obtained from other departments (Soibelman and Kim 2002). Consequently, further research needs to demonstrate that in addition to data collected from job sites, measures collected at the organizational level can also be used to evaluate safety performance and establish safety policies in order to engage the entire organization in safety risk control.

3.3 Research Methods

This case study leverages cross-sectional data analysis to verify the influence of safety-related measures on the ORL on construction sites. Specifically, a multiple linear regression (MLR) model is built using the safety-related data sets to 1) test correlation between variables, 2) understand trends in data, and 3) evaluate the trustworthiness of results (Montgomery et al. 2007). Further information on the safety-related measures considered in this research is detailed in Data Collection Section.

3.3.1 MLR Model Description

Regression analysis is one of the most powerful and popular techniques that allows for estimating the mathematical relationships among variables and easily interpreting model results when linearity between dependent and independent variables can be assumed (Zayed and Halpin

2005). In an MLR model, the dependent variable is related to two or more independent or regressor variables. The model is represented by Equation 1:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \epsilon \qquad \text{Equation 1}$$

In Equation 1, $\beta_0, \beta_1 \ldots. \beta_n$ are regression coefficients, $x_1, x_2, \ldots, x_n$ are independent variables, ϵ is the random error term, and Y is the dependent variable. In this case, a stepwise variable selection was adopted to identify the critical independent variables (i.e., safety-related measures in this paper), which can potentially be used as the best predictor variables (Norusis 2005). In general, the stepping method criteria selected a p-value = 0.05 to enter a measure into the regression equation and a p-value = 0.10 to remove it. The best model is the model with highest coefficient of determination (adjusted R^2, or Adj. R^2), which indicates how data fit in the MLR model.

In this paper, the dependent variable in the MLR model is based on the quantity of construction site incidents counted during a specific time interval. The number of incidents considered in this research includes any instances of fatality, first aid, medical aid, lost time, and modified work injury, and is used to calculate the total incident rate (TIR) (Equation 2), where 200,000 represents the quantity of working hours in one year per 100 full-time employees working for 40 hour per week and 50 weeks per year on a given project. Then, the ORL is calculated, based on the maximum TIR for all projects analyzed (Equation 3), and is rounded to the nearest whole number from 1 to 10. Furthermore, TIR outliers are identified and assigned with ORL = 10 to minimize the impact of extreme values on the regression model. According to Lee et al. (2012), integer numbers (such as the Likert scale) are commonly used to assess risk within the construction industry and have also been adopted by the organization in the present case study. Notably, this approach intends to measure the ORL on a construction site rather than to quantify incident severity. According to Khanzode et al. (2012), it is problematic to predict consequences when risk attributes determining consequence severity have not fully been investigated.

$$\mathrm{TIR_n} = \frac{\sum \mathrm{Incidents}}{\mathrm{total\ working\ hours}} * 200{,}000 \quad \text{Equation 2}$$

$$\mathrm{ORL_n} = \frac{\mathrm{TIR_n}}{\mathrm{TIR_{max}}} * 10 \quad \text{Equation 3}$$

It is important to check violations of regression assumptions in the modeling process. Following Gravetter and Wallnau (2010), the following four assumptions are tested in this paper:

(1) Autocorrelation: Autocorrelation is a characteristic of the data collected in which the correlation between the values of the same variables is based on related objects. In this research, autocorrelation is verified using a Durbin-Watson test. If autocorrelation (ρ) < 0.3, than it is possible to reject the hypothesis of autocorrelation.

(2) Lack of multicollinearity: Multicollinearity occurs when two or more variables are highly correlated. In this research, multicollinearity is assessed through a variance inflation factor (VIF) test. If VIF < 10, multicollinearity can be rejected.

(3) Normality of residuals: In an MLR model, it is assumed that the standardized residuals follow a standard normal distribution. A Shapiro-Wilk test is used to check this assumption. If a *p*-value > 0.05, then the normality of the residuals cannot be rejected (Montgomery et al. 2007).

(4) Homoscedasticity: Homoscedasticity is the constancy of the residual variance. When the residual variance is not constant over all the observations, the residual is said to be heteroscedastic. A Breusch-Pegan test is used to test for heteroscedasticity. If the test result is higher than 0.05, heteroscedasticity can be rejected.

3.3.2 MLR Model Evaluation

Once the assumptions of the MLR model are verified, the mean absolute percentage errors (MAPEs) can be computed to evaluate the model performance (Equation 4). In this case, a 10k cross-validation procedure was adopted to measure the accuracy of the model. In this procedure, the entire data were divided into 10 data sets where nine were used to train an MLR model, and one was used for the validation. The MAPE was calculated to measure the difference between values predicted by the MLR model and the values observed. In addition, a completely new data set (i.e., data from a new project) was used to test the reliability of the model by eliminating any potential inter-correlation among data points.

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{P_v - A_v}{A_v}\right| \qquad \text{Equation 4}$$

Where: n is the number of observations, P_v is the predicted ORL, and A_v is the actual ORL.

The prediction errors were further analyzed using inequality statistics tests to investigate error sources. In these tests, error components (e.g., $U^M + U^S + U^C = 1$) are decomposed into the variables U^M, U^S, and U^C that represent bias proportion, variance proportion, and covariance proportion, respectively (Sterman 1984); herein, U^M, U^S, and U^C are fractions of the mean squared error (MSE) (Equation 5). U^M measures the extent to which the average values of the predicted and actual value deviate from each other (Equation 6). U^S indicates the ability of the model to replicate the degree of variability in the variable of interest (Equation 7). U^C represents the remaining error after deviations from actual values have been accounted for (Equation 8). The ideal distribution of inequality over the three proportions is U^M and $U^S = 0$ and $U^C = 1$.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(P_i - A_i)^2 \qquad \text{Equation 5}$$

$$U^M = \frac{(\bar{P} - \bar{A})^2}{\mathrm{MSE}} \qquad \text{Equation 6}$$

$$U^S = \frac{(S_P - S_A)^2}{\mathrm{MSE}} \qquad \text{Equation 7}$$

$$U^C = \frac{2(1-r)S_P S_A}{\mathrm{MSE}} \qquad \text{Equation 8}$$

Where: n is the number of observations; P_i is the predicted value I; A_i is the actual value I; $\bar{P}, \bar{A}$ are the means of P and A; S_P, S_a are standard deviations of P and A; r is the correlation coefficient between P and A.

3.3.4 Comparison between High and Low ORLs Group

To understand how the safety-related measures can be controlled to avoid peaks of ORL, the recommended boundaries of safety-related measures analysed in this case study were determined by comparing the performances of two groups with high and low ORLs. For this task, the data sets are divided into two groups (i.e., ORL $\leq$ 5 and ORL $>$ 5) and analyzed using a non-parametric test, namely a Mann-Whitney U test. This test is used to compare differences between two independent groups when the dependent variable is either ordinal or cardinal, but not normally distributed. It tests the null hypothesis that two samples come from the same population against an alternative hypothesis that a specific population has higher values than the other (Gravetter and Wallnau 2010).

3.4 Data Collection

The MRL model was built and tested through a case study in which cross-sectional data of safety-related measures were collected from construction projects located in Canada. In particular, in this research the data stored in the human resource, payroll, and safety departments in the given case study organization was analyzed to verify the claims of previous studies of the use safety-related measures to manage the ORL. Based on the availability of data in these departments' databases, a focus group consisting of safety managers in the organization identified seven safety-related measures for which relationships with the ORL may be tested (Table 3.2). Since high and low temperatures may increase the risk of accidents (Lee et al 2012), the safety-related "temperature" measure calculates the absolute value of the deviation from the ideal temperature. Since there is no available data that indicate ideal temperatures for the areas where the projects were performed, here, the ideal temperature is set at 18ºC. The ideal temperature is based on findings by Lee et al. (2012), who determined that accident risk is lowest when temperatures range between 16-20ºC.

Table 3.2: Description of safety-related measures

Measure	Metric	Source Department
BBO card rate	$\text{BBO rate} = \frac{\text{BBO filled}}{\text{working hours}} * 200{,}000$	HSE
Near miss rate	$\text{Near miss rate} = \frac{\text{quantity near miss}}{\text{working hours}} * 200{,}000$	HSE
New workers rate	$\text{New workers (\%)} = \frac{\text{new workers}}{\text{Total workers}} * 100$	Finance
Temperature	$\text{Temperature} = \left\lvert \frac{\sum_{i=1}^{n} \text{temperature}}{\text{total calendar hour}} - \begin{matrix}\text{desirable} \\ \text{temperature}\end{matrix} \right\rvert$	Environment Canada
Workers' age	$\text{Workers' age} = \frac{\sum_{1=1}^{n} \text{workers' age}}{\text{total workers}}$	Human Resources
Crew size	$\text{Crew size} = \frac{\text{total workers}}{\text{total foreman}}$	Finance
Working days	$\text{Working hours} = \frac{\sum_{i=1}^{n} \text{workers higher 21 days}}{\text{Total workers}}$	Finance

n – observation

The safety-related measures were collected from four different industrial construction projects—described in Table 3.3—in the same organization. Each measure was collected on a calendar monthly basis. Three projects were utilized as a training set (A, B, and C, n = 84) and one project (D) was used to validate the model (n = 17). Analysis of each project excluded the first six months of the execution phase due to the low number of workers on the job site at that time. Temperatures were collected from the Environment Canada database (Environment Canada 2015). The safety-related measures identified in this study are described below:

Table 3.3: Project description

Project	Description	Duration (month)	Data collection Start	End	Total	Work hours (million)	Location
A	Utility plant for heavy oil extraction facility	30	1/2013	12/2014	24	2.246	Alberta, Canada
B	Construction of new steam-assisted gravity drainage facility	33	10/2012	12/2014	27	3.647	Alberta, Canada
C	Expansion of existing potash mine and mill	39	6/2012	7/2015	33	2.370	Saskatchewan, Canada
D	Mechanical tank and pipe rack installation	23	2/2013	3/2015	17	1.126	Alberta, Canada
Total					101	9.389	

Behavior-based observation (BBO) rate. In the BBO program, workers fill out a card to evaluate co-workers' safety behavior. After identifying risky behaviors in their peers, workers give constructive one-on-one feedback to their peers to reinforce safe work conditions and discourage risky behaviors. According to Vaughen et al. (2010), implementing BBO makes workers more likely to avoid risky behaviors.

Near miss rate. Investigating near misses can contribute to safety performance improvement since it can reveal trends in safety deficiencies (Hallowell et al. 2013). In the organization investigated in this case study, workers report to supervisors whenever a near miss happens. This behavior may indicate worker participation in safety management. Furthermore, a high number of near misses might suggest a higher probability of incidents on a construction site.

New workers rate. Workers lacking experience may have difficulty recognizing onsite hazards (Jiang et al. 2015) and consequently may be at greater risk for incidents. The new workers rate can also be affected by turnover rate. Higher turnover rates can additionally affect worker safety behavior since in such environments, workers are more prone to taking shortcuts (Emberland and Rundmo 2010).

Temperature. Temperature can also contribute to risky behaviors on construction sites (Lee et al. 2012). Poor environmental conditions (e.g., extreme temperatures) can increase workers' physical and mental fatigue, decreasing their attention to the task at hand (Leung et al. 2012).

Workers' age. Each worker age group has a different influence on risk assessment on construction sites (Lee et al. 2012). For example, Feola et al. (2012) report that older workers tend to use less personal protective equipment (PPE).

Ratio of workers to supervisors (crew size). Supervisors have an important role in maintaining safety conditions on the work site since they are responsible for planning out activities, and rearranging activities when required equipment are not available or when worker absence occurs. Leung et al. (2014) state that increasing the presence of supervisors leads to an increase in positive perception of safety.

Working days. Expressed as a ratio of total workers working more than 21 days in a month to the total number of workers, working days can also indicate safety on a project site. Prolonged working hours can produce fatigue due to a decrease in workers' muscular strength and mental stress (Alvanchi et al. 2012). Fatigue can lead workers to take shortcuts (Jiang et al. 2015).

The data of each safety-related measure and from incident records were extracted from the departments' database through SQL (Structured Query Language). As an example, the raw data obtained from the payroll department database is presented in Figure 3.1a. Data was collected for each safety-related measure individually from the three departments. Following collection, data from different departments were matched. A query containing the values of all safety-related measures was re-organized by project and month and was used for data analysis (Figure 3.1b).

Payroll

WorkerCode	JobTyp	JobTypDescription1	SumOfHour	WorkDate	Project
3076	1903	PIPEFITTER-J/M	10	08/05/2013	D
3076	1903	PIPEFITTER-J/M	10	09/05/2013	D
3076	1903	PIPEFITTER-J/M	10	10/05/2013	D
3076	1903	PIPEFITTER-J/M	10	11/05/2013	D
3076	1903	PIPEFITTER-J/M	10	12/05/2013	D
3076	1903	PIPEFITTER-J/M	10	13/05/2013	D
3076	1903	PIPEFITTER-J/M	10	14/05/2013	D
3076	1903	PIPEFITTER-J/M	10	15/05/2013	D
3076	1903	PIPEFITTER-J/M	10	16/05/2013	D
3076	1903	PIPEFITTER-J/M	10	17/05/2013	D
3076	1903	PIPEFITTER-J/M	10	18/05/2013	D
3076	1903	PIPEFITTER-J/M	10	19/05/2013	D
3076	1903	PIPEFITTER-J/M	10	20/05/2013	D
3076	1903	PIPEFITTER-J/M	7	21/05/2013	D
3076	1903	PIPEFITTER-J/M	10	29/05/2013	D
3076	1903	PIPEFITTER-J/M	10	30/05/2013	D
3076	1903	PIPEFITTER-J/M	10	31/05/2013	D

(a)

ProjectInformation

Project	Year	Mont	WorkingDays	WorkersAge	CrewSize	Temperature
D	2013	8	142.39	44.02	7.37	17.61
D	2013	9	145.85	44.09	7.56	13.31
D	2013	10	159.15	43.9	7.76	3.48
D	2013	11	156.07	43.88	8.68	-9.55
D	2013	12	91.86	43.68	7.47	-22.95
D	2014	1	131.64	44.43	6.6	-16.32
D	2014	2	140.91	44.59	8.01	-19.03
D	2014	3	147.84	44.4	9.01	-11.11
D	2014	4	164.15	44.9	8.7	0.94
D	2014	5	177.71	45.24	8.32	8.34
D	2014	6	171.6	45.83	7.09	15.4
D	2014	7	176.08	45.99	6.03	19.05
D	2014	8	157.58	45.98	6.21	17.13
D	2014	9	157.78	46.4	6.35	9.05
D	2014	10	161.89	46.65	6.22	4.63
D	2014	11	173.97	47.2	6.31	-11.72
D	2014	12	34.18	46.57	6.62	-13.15

(b)

Figure 3.1. (a) Raw data provided by the payroll department; (b) example of data extracted for project D.

3.5 Analysis of results and discussion

The data collected was analyzed to assess the ORL through an MLR model and to define values for controlling safety-related measures through a Mann-Whitney U test. For this purpose, TIR was first computed and checked to identify outliers. Consequently, three outliers were identified based on the middle 50% of the scores in a boxplot. The ORL was then rounded to the nearest whole number from 1 to 10. Months with a TIR = 0 had their ORL assigned as 1, and those with a TIR > the value boundary had their ORL assigned as 10. This classification was applied to make it perceptually easy to assess and compare the estimated ORLs in the field.

Table 3.4 summarizes the safety-related measures collected on a monthly basis from the four projects. A high variance in the BBO rate (σ = 1497.94) can be observed, implying that the organization may not set and control a target value for the BBO rate efficiently, while the high variance on near miss rate (σ = 10.65) indicates that there are certain higher-hazard time periods during project execution. The average temperature in the project locations is low (μ = 0.99 ºC). The working days (σ = 11.01) and new workers (σ = 10.76) measures have high variation, demonstrating that project progress and working environments dynamically change over time. On the other hand, crew size (σ = 1.67) presented low variance compared to all other measures, indicating that the organization may maintain the ratio of workers per supervisor on a job site. The workers' age measure has low variance (σ = 2.50), showing that at the time of data collection, most workers on the project were 44 years old on average.

Table 3.4: Descriptive statistics of collected safety-related measures

Variable	Unit	Mean	Standard deviation	Upper level	Lower level
BBO rate	$\frac{\text{BBO}}{\text{working hours}} * 200{,}000$	2824.69	1497.94	7014.47	145.49
Near miss rate	$\frac{\text{near miss}}{\text{working hours}} * 200{,}000$	9.70	10.65	51.61	0
New workers rate	%	12.68	11.70	67.59	0
Temperature	ºC	17.20	12.68	40.99	0.08
Workers' age	Years	44.60	2.50	49.29	40.39
Crew size	Worker/superviosr	7.51	1.14	10.27	5.45
Working days	% workers > 21 days	19.90	11.01	42.13	0.00

A stepwise MLR, with significance lower than 0.05, was conducted to identify the influence of safety-related measures on the ORL and five models were identified (1 to 5) (Table 3.5). The measure with the most influence on the ORL is the BBO rate (negatively correlated with ORL) in Model 1, followed by the new workers measure (positively correlated with ORL), workers' age measure (positively correlated with ORL), near miss rate (positively correlated with ORL), and temperature (positively correlated with ORL) in models 2 through 5, respectively. Model 6 and 7 were additionally conducted to observe the significance of missing variables and the relationship between the measures and the ORL. While crew size is positively correlated with ORL, the significance of safety-related measures is higher than 0.05 (Model 6). Model 7 indicates that the working days measure is, unexpectedly, negatively correlated with the ORL, although the significance was greater than 0.05. This behavior may be a consequence of the holiday season in December and January. Therefore, these measures were not considered in the analyses. For each of the models, significance is less than 0.05 (ANOVA), indicating that the regression equation accounts for a significant portion of the variance for the ORL. Eventually, between model 1 to 5, Model 5 was considered the best model, as its measures had a higher adjusted R^2 (0.488) and the significance of safety-related measures were less than 0.05. According to Gravetter and Wallnau (2010), there is no definitive criterion at which the value of adjusted R^2 is acceptable; the required level of adjusted R^2 depends on the data available during model development and the purpose of the MLR model. In addition, lower values of adjusted R^2 can still reveal trends and relationships between measures (Montgomery et al. 2007). In the present study, the results of the error analysis demonstrated that the MLR model was able to identify the relationship between several safety-related measures and ORL, using the data stored in the three departments. Although crew size was not statistically significant in MLR Model 6 (Table 3.5), this finding may be due to the lack of data available. Therefore, further analysis is required before crew size can be used to assess safety performance.

Table 3.5: Results of statistical analysis (extracted from SPSS)

Model	**Dependent variable(s)**	**B**	**Sig[1]**	**R**	***R^2***	**Adj. *R^2***	**ANOVA F**	**ANOVA Sig[2]**
1	Constant	6.222	0.000	0.502	0.252	0.243	27.633	0.000
	BBO rate	-0.001	0.000					
2	Constant	5.372	0.000	0.594	0.353	0.337	22.070	0.000
	BBO rate	-0.001	0.000					
	New workers rate	0.071	0.001					
3	Constant	-5.577	0.176	0.638	0.407	0.385	18.296	0.000
	BBO rate	-0.001	0.000					
	New workers rate	0.060	0.003					
	Workers' age	0.250	0.008					
4	Constant	-8.300	0.040	0.688	0.473	0.446	17.726	0.000
	BBO rate	-0.001	0.000					
	New workers rate	0.044	0.027					
	Workers' age	0.285	0.002					
	Near miss rate	0.074	0.002					
5	Constant	-8.900	0.022	0.720	0.519	0.488	16.839	0.000
	BBO rate	-0.001	0.000					
	New workers rate	0.048	0.012					
	Workers' age	0.275	0.002					
	Near miss rate	0.081	0.001					
	Temperature	0.046	0.008					
6	Constant	-14.10	0.005	0.733	0.537	0.501	14.889	0.000
	BBO rate	-0.001	0.000					
	New workers rate	0.038	0.055					
	Workers' age	0.326	0.000					
	Near miss rate	0.070	0.003					
	Temperature	0.047	0.005					
	Crew size	0.387	0.088					

Model	Dependent variable(s)	B	Sig[1]	R	R^2	Adj. R^2	ANOVA	
							F	Sig[2]
7	Constant	-10.50	0.048	0.744	0.554	0.513	13.482	0.000
	BBO rate	-0.001	0.000					
	New workers rate	0.039	0.047					
	Workers' age	0.275	0.004					
	Near miss rate	0.067	0.005					
	Temperature	0.275	0.182					
	Crew size	0.380	0.091					
	21 days working	-0.040	0.094					

Where: *B* = standardized coefficient; Sig[1] = significance of independent variables; R = correlation coefficient; F = F-ratio ANOVA test; and Sig[2] = ANOVA test significance

3.5.1Model Assumptions Test

The principal assumptions mentioned in Section 3 were tested to justify the use of the MLR model; the results are summarized as follows:

Autocorrelation: The Durbin-Watson test result was inconclusive. However, as $\rho = 0.238$, it was possible to conclude that the model is not auto-correlated.

Normality: The Shapiro-Wilk test result (p = 0.673) suggests that normality of the residuals cannot be rejected.

Heteroscedasticity: The heteroscedasticity test result (p = 0.808) suggests that the model can reject heteroscedasticity.

Multicollinearity: As VIF = 1.386, multicollinearity can be rejected.

The results of these tests reveal that Model 5 did not violate any assumptions of MLR analysis, so it is appropriate to use in analyzing the data collected in this study.

3.5.2 Model Performance Evaluation

A 10-fold cross validation was conducted to assess the performance of the selected MLR model (i.e., Model 5). Equation 9 was used to calculate model output and model performance was evaluated using Equation 4. According to Gravetter and Wallnau (2010), MAPE results can be evaluated using the following criteria: $< 10\%$ for highly accurate forecasting; 10–20% for good forecasting; 20–50% for reasonable forecasting; and $> 50\%$ for inaccurate forecasting. Here, the MAPE average was found to be equal to 39.09%, which is considered a reasonable forecast. Furthermore, the model accuracy in predicting the ORL was tested using a new data set (Project D), which resulted in a MAPE of 36.69%. Therefore, MAPE results indicate that this model can provide reasonable forecasting for entirely new data sets. Furthermore, inequality statistics were computed to understand the sources of errors. The results—UM = 0.099, US = 0.371, and UC = 0.529—demonstrated that the error in the model is highly related to the variability and remaining errors of deviation. The relatively low UM and US reveals that the difference between the predicted value and actual data is low. The higher UC indicates that, although the model can forecast the trend of the ORL, there is a random component that was not identified by Model 5. The random variable shows that further research is necessary to identify other safety-related measures in the organization's database to improve the model's prediction capability.

$$\mathrm{ORL} = (-0.001 * \mathrm{SRM}_1) + (0.048 * \mathrm{SRM}_2) + (0.275 * \mathrm{SRM}_3) + (0.081 * \mathrm{SRM}_4) + (0.045 * \mathrm{SRM}_5) - 8.900 \quad \text{Equation 9}$$

Where SRM_1 = BBO rate; SRM_2 = new workers rate; SRM_3 = workers' age; SRM_4 = near miss rate; SRM_5 = temperature.

In addition, the performance of Model 5 was compared with individual performance of safety-related measures (Table 3.6). The only model producing a MAPE results with a reasonable forecast when individual measures were compared was Model 5. The MLR regression model, which is built from the cross-sectional data collected in the case study, reveals that better ORL control is provided using data sources obtained from a variety of departments in a construction organization versus those collected from individual safety-related measures.

Table 3.6: Performance evaluation of individual measures and Model 5.

	Workers Age	Temperature	Near Miss Rate	BBO Rate	New workers	Model 5
Adj R^2	0.036	0.021	0.234	0.243	0.080	0.488
MAPE (%)	68.90	131.58	106.44	83.61	125.07	36.69

3.5.3 Difference between Means in Group Comparison

The data from projects A, B, C, and D were divided into two groups—Group 1, for which ORL ≤ 5 (n = 6378) and Group 2, for which ORL > 5 (n = 231)—to determine if a significant difference exists between them (Table 3.7). It was observed that the near miss rate (ρ <0.05) and new workers rate (ρ <0.05) in Group 1 were significantly higher than in Group 2, while the BBO rate (ρ <0.05) in Group 1 was significantly lower than in Group 2. In addition, if considering only one tail in the test, temperature in Group 1 is significantly lower than in Group 2 (ρ <0.05). The absence of significance for the workers' age measure was likely a consequence of the low standard deviation of this measure. These results can be used by the organization to establish appropriate goals focused on maintaining risk levels within safe boundaries, such as those indicated in Group 2. For example, in this case study, acceptable ranges of ORL were achieved when the BBO rate on average was higher than 3750, near miss rate lower than 6.48, new workers per month less than 11.18%, with temperatures not deviating more than 15.57ºC from the desirable temperature (18ºC±15.57). In addition, the results also demonstrated the importance of interdepartmental collaboration to control measures such as new workers rate and planning schedule to avoid outdoor work during extremely low temperatures.

Table 3.7: Results of Mann-Whitney U Test

Safety-related measure	**Group**	**Mann-Whitney U**	**Z**	**Asymp. Sig. (2-tailed)**	**Median**
Age	1	822	-0.607	0.544	44.87
	2				45.39
Temperature	1	622	-2.227	0.026	15.57
	2				22.76
BBO rate	1	344	-4.478	0.000	3750.70
	2				1871.61
Near miss rate	1	310.5	-4.756	0.000	6.48
	2				16.77
New workers rate	1	558	-2.746	0.006	11.18
	2				19.17

3.5.4 Theoretical and Practical Implications

An in-depth understanding of the causal mechanism through which the safety-related measures lead to the occurrence of incidents allows for the development of further strategies for safety enhancement. In this sense, relevant theories and studies were reviewed as follow:

BBO rate. Hallowell et al. (2013) suggest that BBO card rate can be used as a proactive safety measure since it can demonstrate the organization's commitment to safety. According to Jiang et al. (2015) a BBO card program can affect a worker's individual conditions such as safety awareness, safety knowledge, attitude, and perceived behavioral control; they also emphasize that the BBO card can be used to avoid inappropriate worker behavior, thereby controlling hazardous exposures. These findings corroborate the results identified in this research indicating that BBO rate can be used to control and predict the ORL.

New workers rate. New workers may not have enough experience to identify hazards on the site (Jiang et al., 2015), so they may increase the ORL. In addition, new workers can also influence the site environment. For instance, project delay, schedule pressure, or inappropriate planning may lead organizations to hire a considerable number of new workers, causing site congestion and consequently increasing workers' exposure to struck-by or struck against incidents (Fortunato et al. 2012). Therefore, new workers can affect both site conditions and worker behavior, and the measure should be controlled by the organization to decrease ORL.

Workers' age. The age of workers can influence their decision to comply with safety practices and regulations. Workers with high experience may think that safety practices are not important and consequently may not follow safety practices recommended by their companies (Gherardi and Nicolini 2002). Such inappropriate “macho” (Mullen 2004) behaviour can influence younger workers to likewise deviate from safety practices. Although controlling onsite workers’ age is difficult, organizations can carefully establish policies for workers with more experience by emphasizing the importance of complying the safety recommendations.

Near miss rate. According to Wu et al. (2010), analysis of near misses has great supplementary potential to identify incident precursor factors since 90.9% of all incidents produces no injuries. Near miss investigation can help identify each incident’s root causes, and improve workers’ intention to work safely through communicating the results (Hallowell et al. 2013). A high near miss rate can suggest to workers that management is not concerned with identifying and controlling the near miss root causes, which may consequently incentivize unsafe behaviors such as not following safety procedures and taking shortcuts.

Temperature. Extreme temperature on construction sites can fatigue workers by contributing to mental and physical stress conditions (Mitropoulos et al. 2009). According to Arslan et al. (2014), prolonged exposure to cold temperature can cause workers to experience hypothermia, frostbite, and trench foot. To avoid the cold weather, workers may take shortcuts, ignoring safety procedures (Leung et al. 2012). The unsafe behavior of a worker may increase the ORL and consequently cause incidents. In addition, low temperatures may cause slipperiness due to icing surfaces, which can physically increase the ORL.

Previous studies support that these safety-related measures directly or indirectly influence workers’ behavior, which is associated with about 80% of incidents on construction job sites

(Lingard and Rowlinson 2005). To this end, controlling the safety-related measures identified in this research can contribute to controlling workers' safe behavior, improving their intention to work safely, and increasing their ability to identify hazards.

3.5.5 Limitations and Future Research

In the case study, the working days measure was not significant in the three projects. However, fatigue can play an important role in workers' perception of safe work and their intention to perform it (Shapira et al. 2012). Therefore, further investigation is needed to identify measures related to worker fatigue. In addition, the datasets were collected from four projects in the case study; three were used to build the regression model, while one was used for validation purposes. Due to the small size of samples used in this study, however, further research is necessary to generalize the findings of this case study. Another potential issue may arise from the limited number of safety-related measures studied in this paper. These measures were chosen mainly to (1) scrutinize the data available in the organization's database, as recommended by safety experts, rather on a job site and (2) minimize the impact of known safety measures (e.g., working hours, training hours) on the regression analysis. However, the use of only seven safety-related factors may contribute to the relatively low adjusted R^2, since other measures directly related to safety were not considered even though they may better fit the data into the MLR model. Thus, the MLR model identified (Equation 9) needs to be further adjusted for the use in practice since the influence of the safety-related measures can be affected by other variables such as the project type and safety culture.

3.6 Conclusion

This paper demonstrated that the use of data-based safety-related measures suggested by existing literature can assist companies in assessing and controlling the ORL. Safety-related measures collected by different departments (i.e., BBO rate; near miss rate; temperature; crew size; working hours; workers' age; and new workers rate) were tested using a MLR model and verified for their usage in assessing, controlling and predicting the ORL. The model results showed that five of the seven variables significantly impact the ORL. In addition, the holistic view achieved by using numerous measures can result in a better assessment of the ORL than is possible to achieve through individual measures. The causal relationship between the measures and the incident occurrence was verified through literature review, and it was observed that they are most related to workers' safe behavior—although site conditions can also be influenced by the new workers rate (congestion) and temperature (slippery surface) measures. In summary, organizations can use safety-related measures to develop models to control the ORL and to identify and implement safety strategies to avoid ORL peak. The findings potentially support the proposal that safety-related measures collected at an organizational level can help the organization to 1) save the safety department additional time and resources required for data collection by sharing existing data in an organization and 2) control the measures by establishing acceptable boundaries based on historical data. In addition, organizations should emphasize an integrated cross-department safety approach to achieve safety performance excellence.

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Chapter 4: Assessing the safety performance of construction projects using Case-Based Reasoning

4.1 Introduction

Safety Management Systems (SMS), which are designed and implemented to improve safety performance, have resulted in reduced accident rates. However, to ensure that current SMS remain functional, it is important to periodically evaluate the performance of a company's SMS to detect and mitigate any flaws in the system's procedures or policies that may develop over time. Currently, safety performance of construction companies is often evaluated using reactive measures (Hinze et al. 2013), such as the Total Recordable Incident Rate (TRIR) or the Days Away Restrictions and Transfers (DART) rates, which are assessed by retrospectively examining safety performance based on the number of recordable accidents that have occurred (per working hour). Consequently, these measures are not effective at evaluating current risk-levels of a worksite and provide little insight into practices that can be implemented to avoid future accidents (Grabowski et al. 2007). Furthermore, as suggested by Mengolini and Debarberis (2008), reactive measures may convey the unintended message that actual safety prevention is less important than safety performance goals, which may incite laborers to avoid reporting incidents to create an artificial improvement in safety performance.

To overcome these difficulties, previous studies have proposed the use of proactive measures or indicators to evaluate safety performance. These measures arise from the identification of relationships between accident rates and certain safety-related measures (Esmaeili et al. 2015;

Lingard et al. 2017; Salas and Hallowell 2016). By identifying this relationship, managers can take proactive actions to improve safety-related measures prior to incident development and, in turn, avoid accidents. Current methods for proactively assessing SMS performance, however, require a minimum ratio of the number of safety-related measures being assessed to the number of incidents that have occurred (Kim et al. 2004).

As a large number of safety-related measures have been reported to affect safety performance (Jablonowski 2011), and since the occurrence of recorded accidents on construction sites are comparatively low (Hopkins 2009), the number of data points available in one company may not be sufficient to appropriately apply these methods and may incite companies to avoid using a comprehensive list of safety-related measures to achieve the minimum ratio required. While organizations may opt to use an abridged list of safety-related measures that has been established using data from other organizations, the type and form of safety-related measures most critical to a project or company vary considerably based on project type, organizational policies, and cultural background, and previously developed lists may not produce reliable results when applied to other contexts. A method capable of evaluating current and predicting future safety performance from a comprehensive set of safety-related measures in conditions with small sample sizes, however, has yet to be developed.

This study has developed an approach, based on Case-Based Reasoning (CBR) and genetic algorithms (GA), to more accurately assess and predict safety performance in conditions where incident occurrence is low and the quantity of safety-related measures is high. A case study was used to demonstrate method application in a practical setting. The method was shown to be adaptable, to produce reliable results, and to be updatable in real-time. In addition to providing a reliable evaluation of current SMS performance, results generated using the proposed method can also be used to more objectively predict how decisions taken in various areas of an organization can affect overall safety performance.

4.2 State of the Art

4.2.1 Methods for Evaluating Safety Performance

Safety performance can be monitored and controlled by collecting and analyzing relevant measures that influence the occurrence of an accident (Jannadi and Almishari 2003). Since they can monitor the level of safety in a system (Hale 2009), can describe conditions that precede an incident, have a predictive value, and can indicate interventions to improve safety performance (Hinze et al. 2013), safety-related measures are particularly well-suited for this purpose. Many safety-related measures, such as the behavior-observation rate (Hallowell et al. 2013), work stop-authority, and working hours per day (Guo and Yiu 2016), have been proposed in safety management literature.

Models using safety-related measures to assess safety performance have also been developed. However, these models are limited by their use of methods, such as Artificial Neural Networks (Goh and Chua 2013; Patel and Jha 2014) and linear models (Esmaeili et al. 2015; Lingard et al. 2017; Salas and Hallowell 2016), which require a minimum ratio of the quantity of safety-related measures to available data points (Kim et al. 2004). To address the need for a large sample size, these models are typically designed to collect data from mulitple companies and to only consider safety-related measures most commonly identified during the incident investigation. In essence, these models are designed to consider a particular set of safety-related measures that are applied across all companies without adjustment. Although these approaches can be used to evaluate SMS performance, they are limited by their propensity to (1) consider that specific measures are available in all companies—not accounting for its individual characteristics, (2) assume that measures equally influence accident occurrence, and (3) only consider safety-department associated measures.

These limitations can impair the method's effectiveness in practice. The uniqueness of the construction projects, dynamic project conditions (Sousa et al. 2015), and organizational safety culture that characterize each company cause variations in the types of measures that are collected by organizations in practice. In this context, measures such as a behavior observation program—suggested by Hallowell et al. (2013)—may not be available in every organization since the program (behavior observation) may not be implemented. In addition, while certain factors may be similar across organizations, the magnitude of the measure's influence on safety performance may differ. For instance, while Wachter and Yorio (2014) suggested the use of the safety-related measure "amount of working hours per worker" to proactively control safety risk, Pereira et al. (2017) empirically determined that this measure was insignificant in a particular organization where a case study was conducted. Finally, records collected during incident investigations usually contain data related to safety programs and lack data involving other project components. However, safety is a part of a system (Jiang et al. 2015; Saleh et al. 2013) that is affected by various components of a construction project, such as project schedule (Jiang et al. 2015), quality (Wanberg et al. 2013), and cost, which must be considered to generate a comprehensive evaluation of a SMS.

4.2.2 Case-Based Reasoning and Genetic Algorithm

The construction industry gathers various types of data that it collects from several departmental sources. This data may contain relevant historical experience that can provide companies with useful information for assessing and estimating safety performance outcomes. As the amount of data points available to assess the safety performance is limited and the influence of each measure on the safety perfromance is different, this research proposes a method using CBR and GA to address these issues, respectively.

CBR has been applied in construction research to solve problems related to cost estimation (Choi et al. 2014; Kim and Shim 2014) and safety hazards identification (Goh and Chua 2010). It is a problem-solving methodology from the cognitive science field, which imitates the human action of reasoning by recalling previous experiences (Lopez 2013). When a user inputs a new case, CBR generates a solution by comparing the new case with similar cases in the database. CBR is capable of identifying associations between inputs and outputs using a limited quantity of data (Lopez 2013) and is, therefore, able to extract solutions from small databases while considering several measures. In this context, CBR can be used to evaluate safety performance by identifying similarities between cases from previous experiences (containing multiple safety-related measures) with a new case. CBR can be combined with GA, which can determine the weight (i.e., influence) of the attribute (i.e., safety-related measures) and, in turn, minimize prediction error (Kim and Kim 2010).

4.3 Method Development

A method capable of identifying relationships between safety-related measures and safety performance outcomes from a limited amount of data in consideration of an organization's individual culture and characteristics is proposed. Measures are first identified through several round of interviews with project and safety managers. Then, critical measures are selected and the level of influence of each measure is determined using GA. Finally, CBR is used to assess ongoing safety perfromance. The procedures used to develop the proposed method are illustrated in Figure 1 and are detailed in the following section. The method was validated using Correlation and Mean Absolute Percent Error (MAPE).

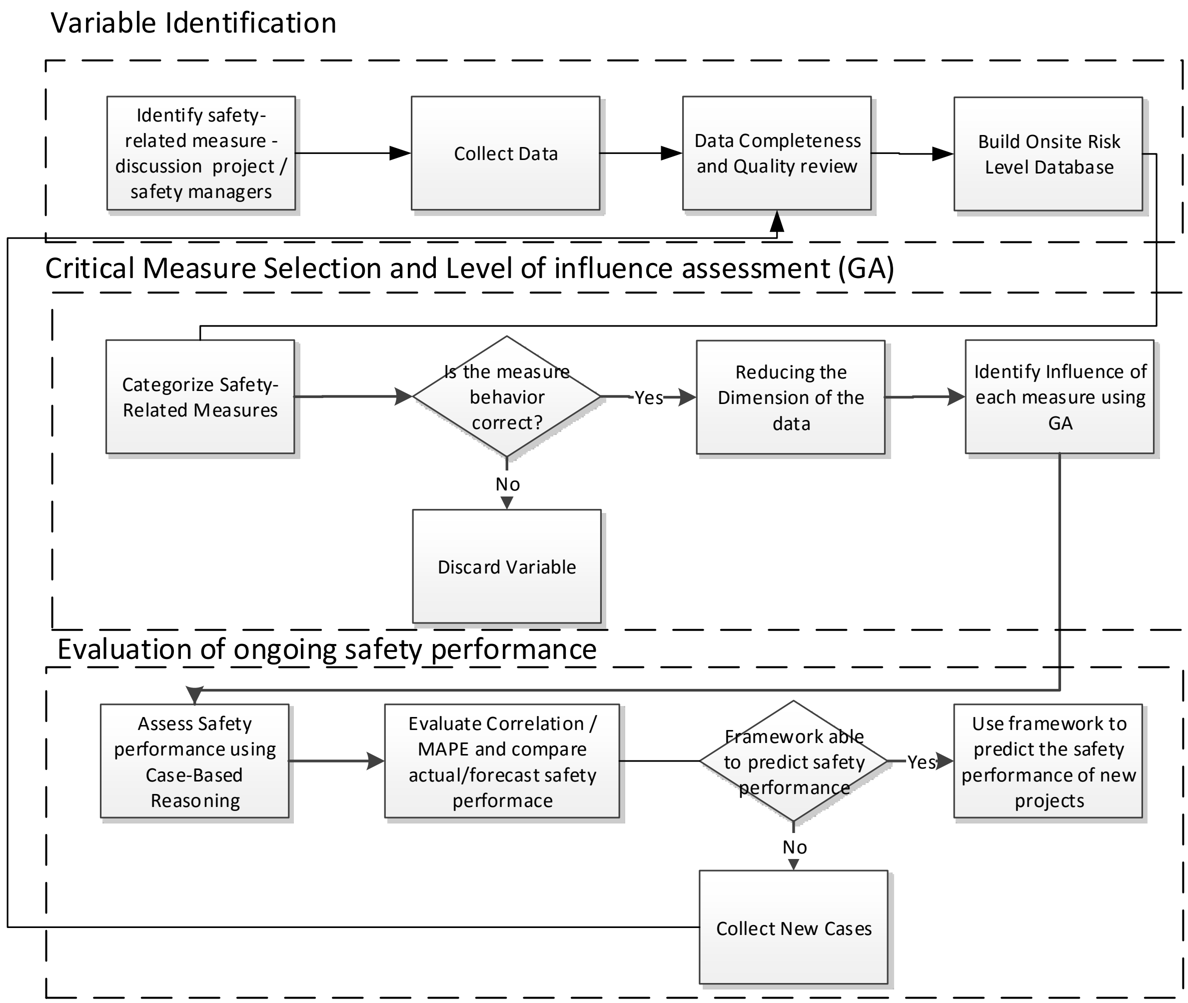

Figure 4.1: Method procedures for assess the safety performance

4.3.1 Safety-Related Measures Identification

Safety-related measures that influence safety performance can be identified through discussions between project and safety managers. Safety management literature should also be consulted to ensure the generation of a comprehensive list of measures. Researchers have associated safety-related measures with safety program efficiency (Rajendran 2013), worker behavior, (Leung et al. 2012), coworker behavior, supervisory encouragement (Brown et al. 2000), and inherent technical aspects of engineering systems (Han et al. 2014).

Since the proactive control of safety performance can be related to (1) quantity of accidents (Salas and Hallowell, 2015) or (2) onsite risk (Lee et al 2012), two outputs related to safety performance were considered in this research: the total incident rate (TIR) and the safety risk (SR). TIR includes fatalities, major first aid, medical aid, and lost time incidents (Equation 1). In addition to including the aforementioned incidents, the SR also consider the perceived severity of each type of incident as suggested by Hallowell and Gambatese (2009) and as indicated in Table 4.1 (Equation 2).

$$TIR_n = \frac{Incidents_n}{total\ working\ hours_n} * 200000 \qquad (Equation\ 1)$$

where TIR_n= total incident rate during time interval *n*; $Incidents_n$= total of incidents during time interval *n*; $total\ working\ hours_n$ = quantity of working hours during time interval *n*; with 200,000 representing the quantity of working hours in one year per 100 full-time employees working for 40 hours per week and 50 weeks per year.

Table 4. 1: Severity scale (Hallowell and Gambatese 2009)

Subjective Severity	Relative Impact Score (RIS)
Temporary discomfort	2
Persistent discomfort	4
Temporary pain	8
Persistent pain	16
Minor first aid	32
Major first aid	64
Medical case	128
Lost work-time	256
Permanent disablement	1,024
Fatality	26,214

$$SR_n = \frac{\sum \#Incidents\ type_n * RIS}{total\ working\ hours_n} * 200000 \qquad (Equation\ 2)$$

where SR_n = safety risk in time interval *n*; $\#incident\ type_n$= quantity of each incident type; $total\ working\ hours_n$ = quantity of working hours in time interval *n*; and RIS = subjective severity defined by the relative impact score for each type of incident (Table 2).

Integer numbers (such as the Likert scale) are commonly used in practice to assess risk due to the familiarity of these rating systems to project/safety managers within the construction industry (Lee et al 2012). TIR/SR are discretized using the equal frequency binning method. In this method, a fixed number of intervals are defined (e.g. 5) and, following the examination of the histogram of each attribute, n-1 cuts are determined so that approximately the same number of objects fall into each of the n intervals. After discretizing the safety outputs, measures are cleaned, queried, and integrated into a centralized database. The database is formatted as a table, where each column contains safety-related measures and outputs used to assess safety performance and each line contains a new instance.

4.3.2 Safety-Related Measures Selection

Since most algorithms that reduce dataset dimensionality evaluate variables in one format (Hall 1999), the continuous measures were discretized using the equal frequency binning method combined with a GA. This combination identifies optimum breakpoints within the safety-related measures and the safety performance outputs according to the significance concept introduced by Pawlak (1998). Specifically, if the safety output (D) depends entirely on a safety-related measure (C), denoted as $C \Rightarrow D$, all values of the safety output are uniquely determined by one measure. To generalize this concept, Pawlak (1998) introduced the idea of partial dependency attributes (γ), which states that "some values of D are determined by values of C. If D depends totally on C, γ = 1, otherwise, it depends partially on C (0 ≤ γ ≤ 1)" (Equation 3).

$$\gamma = \sum_{X \in U/D} \frac{|C_*(D)|}{U} \quad (Equation\ 3)$$

where $C_*(D)$ = safety outputs (D) that can be identified according to the safety-related measures (C) and U/D = the set of all elements used in this research categorized in D.

To identify the optimum breakpoints, each input attribute (i.e., safety related measures) is ranked from the lowest to the highest value with its corresponding discrete value (1 to 5) and decision attribute (TIR/SR). The objective function aims to maximize the dependency between the input/decision attribute (Equation 4.2). Figure 4.2 demonstrates how the GA affects the interval range of each attribute. Notably, if the safety-related measure behavior is expected to be negatively correlated with TIR/SR, the scale (1-5) should be reversed.

$$\max[(\gamma)] \quad (Equation\ 4)$$

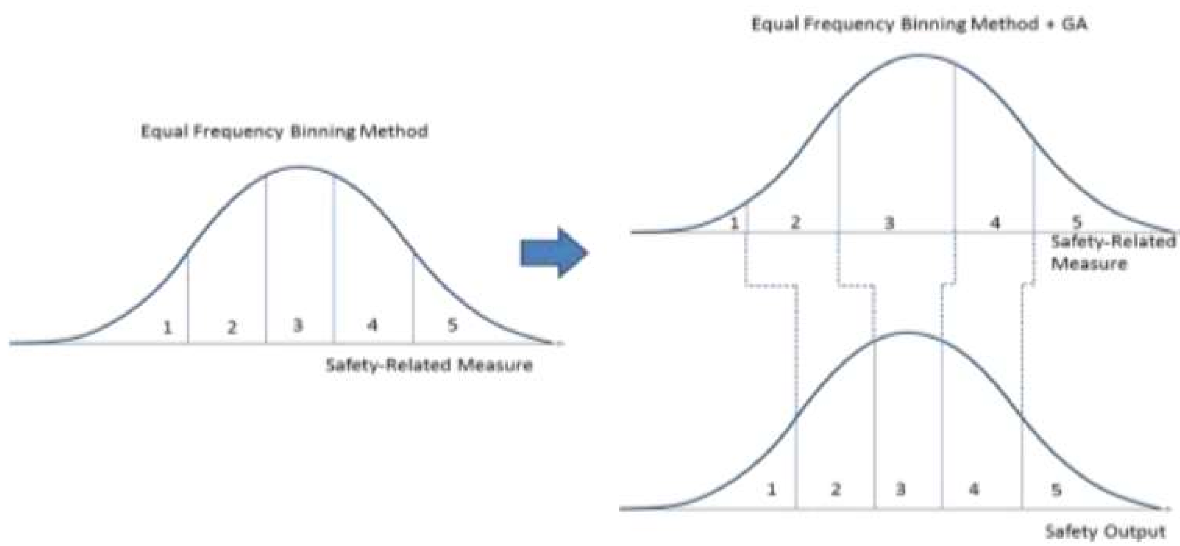

Figure 4.2. Safety-Related Measure Discretization Combining Equal Frequency Binning and GA

After identifying the optimum breakpoint, a Pearson correlation test is performed between each measure and each safety output (Equation 5). If the correlation direction is different from established theories (e.g. crew size has a negative correlation with TIR/SR), the measure is discarded to avoid any bias in practice. For instance, in some companies, months with a lower crew size have more accidents due to poor performance of other measures; therefore, the pattern observed with this measure may not be accurate.

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2]\,[n\sum y^2 - (y)^2\,]}} \; (Equation\;5)$$

where r = correlation coefficient; x = safety related measure value; and y = corresponding safety performance.

From the remaining safety-related measures, a correlation-based feature selection (CFS) is performed to reduce the dimension of the dataset while retaining the maximum possible variance. The CFS algorithm is a filter selection method that evaluates the relevance of attributes for explaining the variance of an output variable (Hall 1999). It was chosen for its ability to accommodate a large dimension of safety-related measures and a small number of instances while preserving the original representation of the attributes (Guyon et al. 2003). CFS ranks the safety-related measures based on a heuristic evaluation function (Equation 6): the numerator in Equation 2 provides an indicator of the capacity of the measure to predict safety output, while the dominator indicates how much redundancy exists among the measures (Hall 1999).

$$M_s = \frac{k\bar{r}_{cf}}{\sqrt{k + k(k-1)\bar{r}_{ff}}} \qquad (Equation\;6)$$

where M_s = heuristic merit for the safety-related measures subset S containing k measures; $\bar{r}_{cf}$ = average safety-related measures for the safety output correlation ($f \in S$); and $\bar{r}_{ff}$ = average measure-to-measure correlation (Hall 1999).

4.3.3 Safety Assessment Model Using CBR and GA

CBR offers various advantages that can address several challenges associated with this study:

- Results are easily and rapidly obtained from a CBR model. This allows the simultaneous comparison of various safety performance scenarios, which can facilitate effective decision-making during the conceptual planning phase and throughout the execution phase of a project.
- Although the number of cases influences the accuracy of the CBR model (Doğan et al. 2008)), there is no minimum quantity of data points required to establish an association between safety-related measures and TIR/SR.
- The model is easily updated with new data (Kim et al. 2004), which ensures that the model remains relevant and reflective of the real system.

CBR is based on four main processes: retrieve, reuse, revise, and retain (Lopez 2013). When a user inputs a new case to estimate safety performance, the model first *retrieves* comparable cases from the case-base by calculating the similarity point, which represents the degree of similarity between the input and retrieved cases for a particular safety-related measure (Choi et al. 2014).

Once the final dataset of measures are selected, the CBR and GA algorithms are employed to determine the impact (i.e., weight) of each measure on safety output and to assess safety performance. Here, the similarity between safety-related measures was determined as recommended by Choi et al. (2014) (Equation 7). The model calculates the similarity score (sim) of each case with the new input case using the nearest neighbor matching (NNM) technique, and *reuses* the case safety output to assess the TIR/SR (Equation 8). The result is then *revised* by selecting the top five cases which presented highest $score_n$ to assess the TIR or SR (Equation 9). Finally, the model *retains* the new case for future use.

$$sim(x_a^I, x_a^R) = \begin{cases} 0, & d\,(x_a^I,\, x_a^R) > 0.3 \\ 60, & d\,(x_a^I,\, x_a^R) \leq 0.3 \\ 80, & d\,(x_a^I,\, x_a^R) \leq 0.2 \\ 100, & d\,(x_a^I,\, x_a^R) \leq 0.1 \end{cases} \quad Equation\ 7$$

where x_a^I, x_a^R = the safety-related measure a for input case I and retrieved case R and the difference rate $d(x_a^I,\, x_a^R) = \mid (x_a^R - x_a^I)/\, x_a^I \mid$

$$score_n = \frac{\sum_{a=1}^{m}[sim(\, x_a^I,\, x_a^R) \times w_a]}{\sum_{a=1}^{m} w_a} \; Equation\ 8.$$

where m = number of attributes and w_a= weight of attribute a.

$$SR\ or\ TRI = \sum_{i=1}^{5}\left((SR\ or\ TIR)_i * \frac{score_i}{\sum score}\right) \; (Equaion\ 9)$$

where safety performance = predicted safety performance of the input case (final result of the CBR model); SP_i = safety performance of the top-scored $case_i$; $score_i$ = similarity score of the ith top-score case; and $\sum score$ = sum of top five scores.

A GA is used to define the weight of each safety-related measure (w_a) to maximize the correlation provided by the CBR (Kim and Kim 2010; Kim and Shim 2014). The objective function of the GA is to maximize the correlation between the actual and predicted TIR/SR

(Equation 10). For the genetic algorithm computation, the database is split into learning cases (≈25%) and base cases (≈75%).

$$Max\ r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2]\,[n\sum y^2 - (y)^2\,]}}\ (Equation\ 10)$$

where $Max\ r$ = maximum correlation between actual and predicted TIR/SR; x = actual safety performance; y = predicted safety performance; and n = number of learning cases.

Once the weights of the attributes are verified, the performance method can be evaluated by computing the correlation (r) and MAPE (Equation 5 and 11). A 10k cross-validation procedure is recommended to evaluate the accuracy of the proposed method. In this procedure, a database is divided into ten data sets, with nine used as learning cases and one used as a test case. The correlation and MAPE are then calculated to determine the difference between the values predicted by the CBR model and the values observed. A completely new data set (i.e., data from a new project) could also be used to test the reliability of the model, thereby eliminating any potential inter-correlation amongst data points.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{P_v - A_v}{A_v}\right|\ Equation\ 11$$

where *n* = number of new cases; P_v = predicted TIR/SR; and A_v = actual TIR/SR.

4.4 Method Application

The proposed method was applied at an industrial construction company in Edmonton, Canada. Safety-related measures were collected from four different industrial construction projects undertaken by the case company, totaling more than 22 million hours. Three projects were utilized as a training set (A, B, and C; n = 93) and one project (D; n = 18) was used to validate the model. The first six months of the execution phase of each project were excluded due to the low number of onsite workers during this period. Data was then collected on a monthly basis.

From interviews with project and safety managers, 27 safety-related measures were identified (Table 4.2). Data were collected from department databases and project documents. In addition, measures such as congestion level and scope changes were collected through interviews with project managers based on questions developed by the Construction Industry Institute (Construction Industry Institute 2006). Data for temperature measures were calculated as the absolute value of the deviation from the ideal temperature. Temperatures were collected from the Environment Canada database (Environment Canada 2015). The ideal temperature was defined here as 18ºC as recommended by Lee et al. (2012) who determined that accident risk is lowest when temperatures range between 16-20ºC. Absolute deviations were then calculated. The unemployment rate was collected from the Alberta and Saskatchewan Unemployment Rate Database (Alberta, 2017; Saskatchewan 2017).

Table 4.2: Safety-related measures selection

Safety-related measure	Source	Type	Unit	TIR		SR	
				Corr	CFS	Corr	CFS
Crew size	Payroll	Cont.	Workers / foreman	✓	✓	✓	✓
Hours worked per worker	Payroll	Cont.	Hours worked / worker				
Worker experience on project	Payroll	Cont.	Days	✓		✓	
Foreman experience on project	Payroll	Cont.	Days	✓		✓	
BBO rate	HSE	Cont.	# BBO filled / working hour	✓	✓	✓	✓
Inspection rate	HSE	Cont.	# Inspection / working hour	✓		✓	
Near miss rate	HSE	Cont.	Near misses/working hour	✓	✓	✓	✓
Total PSI audited rate	HSE	Cont.	#PSI audited/working hour				
Ramp up / ramp down	Payroll	Cont.	# $workers_n$ / # $workers_{n-1}$	✓		✓	✓
Operators	Payroll	Cont.	# operators / total workers	✓	✓	✓	✓
Temperature	Canada environm.	Cont.	ºC	✓	✓	✓	✓
Wind speed average	Canada environm.	Cont.	km/h	✓			
Scaffolding rate	Payroll	Cont.	Scaffolding hours/working hour	✓		✓	
New workers rate	Payroll	Cont.	New workers / total workers	✓		✓	
Workers age	Human resource	Cont.	% workers younger than 30 and older than 50 years old	✓	✓	✓	✓
Foreman age	Human resource	Cont.	% foreman younger than 30 and older than 50 years old				
Unemployment Rate	Economics Canada	Cont.	% unemployment rate				
Delay S curve	Scheduling	Cont.	actual hours / planned hours	✓	✓	✓	✓
Quality subcontractors	Procurement	Disc.	Likert scale (1-5)*	✓		✓	
Scope change	Quality	Disc.	Likert scale (1-5)*				
Rework level	Quality	Disc.	Likert scale (1-5)*	✓		✓	

Safety-related measure	Source	Type	Unit	TIR		SR	
				Corr	CFS	Corr	CFS
Cost overrun	Estimating	Disc.	Likert scale (1-5)*				
Congestion level	Project control	Disc.	Likert scale (1-5)*				
Project elevation	Project control	Disc.	Likert scale (1-5)*	✓	✓	✓	✓
Design	Project control	Disc.	Likert scale (1-5)*	✓		✓	
Schedule pressure	Scheduling	Disc.	Likert scale (1-5)*	✓		✓	

Where: Cont is continuous measure; Disc is discrete measure

** Questionnaire available in the Appendix E*

Each continuous safety-related measure was discretized, and the correlation between the measure and the TIR/SR was verified. The measures “hours worked per worker,” “foreman age,” “unemployment rate,” “scope change,” “cost overrun,” and “congestion level” did not result in an expected correlation and, therefore, were not considered in the dimensionality reduction. Several factors may underlie these observations: holiday season in December and January decreased working hours per worker, foreman age may not have been related to foreman competency, unemployment rate may not have been related to the availability of skilled workers in the market, and safety training may have been standardized within the company resulting in low measure variance. Notably, although “scope changes,” “congestion,” and “cost overrun” have been recognized as factors that can influence the safety performance, (Albert et al. 2015; Han et al. 2014), the questionnaire was not designed to assess the magnitude of their influence. It is recommended that different measures should be established by this company to evaluate—and, in turn—control the effect of these variables on safety performance.

Ultimately, a total of 21 measures were considered in the CFS reduction technique. Using the Waikato Environment of Knowledge Analysis (WEKA) to perform the reduction technique, eight measures were selected: “crew size,” “Behavior-based Observation (BBO) rate,” “near miss rate,” “operators,” “temperature,” “workers’ age,” “delay S curve,” and “project elevation.” The “ramp-up/ramp-down” measure was considered only in the SR model.

Following the dimension reduction, the weight of each measure was identified using Evolver (Table 4.3). “Operators,” “crew size,” and “near miss rate” were determined to have the greatest weight with respect to SR, while “operators,” “project elevation,” and “workers’ age” had the greatest weight with respect to TIR.

Table 4.3: Optimal weights of safety-related measures

Safety-Related Measure	TIR(%)	SR(%)
Crew size	9.84	16.15
BBO rate	5.44	8.69
Near miss rate	5.04	14.92
Ramp up/Ramp down	-	10.83
Operators	24.04	17.31
Temperature	5.78	7.88
Workers age	10.04	8.12
Delay S curve	6.22	8.25
Project elevation	33.60	7.85
Total	100.00	100.00

As previously described, two tests were performed to validate the proposed method: correlation and MAPE (Table 4.4). In social or behavioral sciences, a correlation coefficient value of 0.30–0.49 is typically interpreted as moderate to substantial evidence of an association and 0.50–0.69 is interpreted as substantial to very strong (de Vaus 2002). According to Salas and Hallowell (2016), if the analysis provided a strong relationship for the model, it can be used for predictive purposes. The correlation identified in Table 4.4 is considered very strong. MAPE results can be evaluated using the following criteria: < 10% for highly accurate forecasting; 10–20% for good forecasting; 20–50% for reasonable forecasting; and > 50% for inaccurate forecasting (Gravetter and Wallnau 2010). Here, MAPE average was found to be 32%, which is considered a reasonable forecast. The model accuracy for predicting TIR/SR was tested using a new data set (Project D), which resulted in a MAPE value of approximately 21.5% and a correlation of approximately 0.66. The correlation and MAPE results indicate that the proposed method can provide an acceptable forecast for new projects.

Table 4.4: MAPE and correlation results:

Output	10k fold correlation	MAPE	New project correlation	MAPE
TIR	0.6822	34.14%	0.6450	22.18%
SR	0.7129	30.92%	0.6786	21.04%

The correlation result from the CBR and GA was also compared with other methods to evaluate the performance of the proposed approach (Table 4.5). The correlation result obtained by the CBR and GA is at least 8% greater than others methods, suggesting that this approach can be used to evaluate the safety performance. In addition, since the prediction accuracy of the CBR model is governed by the quantity of cases in the case base, this method is expected to improve with each addition of cases to the case base over time.

Table 4.5 Comparison between CBR and other assessment techniques (10 k fold)

Test	TIR correlation	Improvement GA and CBR	SR correlation	Improvement GA and CBR
Gaussian Process	0.3141	126%	0.3407	109%
Multilayer perceptron	0.4450	53%	0.3381	111%
Simple linear regression	0.5636	21%	0.5709	25%
Additive regression	0.6343	8%	0.6582	8%
RapTree	0.4455	53%	0.5730	24%
CBR and GA	0.6822	-	0.7129	-

4.5 Discussion

Although studies have used safety-related measures to evaluate safety performance, their methods require a minimum ratio between safety-related measures and safety output to produce reliable results. Since accidents have a low probability of occurrence, the limited number of safety performance data points incites companies to use an abridged set of measures, which may jeopardize the model's results by not considering a full-spectrum of measures that accurately capture the unique characteristics of a company. To overcome these limitations, a CBR- and GA-based method, which is able to (1) reliably assess safety performance with a limited number of data points, (2) consider specific characteristics of each company, and (3) determine the influence of various measures on future safety performance, was proposed. The model was validate using MAPE and correlation methods and was shown to be capable of producing reliable results.

The method was applied in a practical context to evaluate its functionality. For this purpose, data from an industrial construction project were used. The model was shown to easily evaluate safety performance and to identify and select safety-related measures. The final model of the case study was composed of nine assessment measures: "crew size," "BBO rate," "near miss rate," "operators," "temperature," "workers' age," and "delay S curve." This result is consistent with measures previously identified in safety management literature. For instance, numerous researchers have emphasized both the indirect and indirect impact of the project delay (Han et al. 2014; Mitropoulos et al. 2005); environmental conditions and workers` age (Lee et al. 2012); near miss reporting and worker observation process (Hallowell et al. 2013); teamwork

(Mitropoulos and Memarian 2012); and congestion related to equipment (Fortunato et al. 2012) on safety performance. The results also demonstrated that safety-related measures were associated with “worker behavior,” “teamwork,” “equipment and material,” and “workplace” factors. As highlighted by Wu et al. (2010), these factors are associated with construction accident precursors, and their presence can indicate that certain hazards have not been effectively removed or mitigated.

Through the use of CBR, the proposed was shown to be capable of reliably evaluating safety performance in situations with a limited sample size. The ability to extract knowledge from a small sample size increases the model’s applicability, allowing it to evaluate safety performance of specific activities (such as welding and civil works) at a project level. In turn, the outputs presented by the model can then be used to assess effectiveness of current SMS. Application of this method during the planning phases of a new project could allow strengths and weakness of the current SMS to be identified, allowing practitioners to proactively improve safety performance. As the model is able to predict safety performance trends, it can also be used to proactively evaluate the SMS and guide companies at an organizational level, facilitating decision-making regarding changes to current policies and procedures to achieve the safety goal. Finally, since the model is able to identify measures with the greatest impact on performance, it can also be used by practitioners to identify potential deficiencies in their SMS.

The lack of a required ratio between attributes and output variables also provide the advantage of adaptability to the proposed model. The CBR-based model considers the key attributes of a problem and provides solution according to the organization’s culture and background (Lopez

2013). As demonstrated in previous studies, CBR is adaptable to the quantity of attributes and data types available in each specific domain (Choi et al. 2014; Kim and Kim 2010; Kim and Shim 2014). This adaptability allows the CBR to provide companies with personalized suggestions to improve safety performance. The feature also allows the CBR-based method to be easily updated. In contrast to other methods such as linear models, which must be re-performed to update the model with new data, CBR is continuously improved through the constant accumulation of new cases in its database.

Although the evidence presented in the current study support the use of the proposed method to identify and evaluate the safety performance of construction projects, the findings of this study should be interpreted in consideration of the following limitations. First, the safety-related measures were selected based on the data available by the company. Other variables related to work processes, such as union versus non-union workers, schedule over time, automation, and procurement, can (and should) be used to provide a comprehensive overview of potential safety management deficiencies onsite. In addition, although some measures were not identified as significant in the present research, this pattern should not be generalized for other companies due to unique organizational factors such as cultures, regional characteristics, or construction types. As previously recommended, safety-related measures should be purposefully selected for each assessment. Second, the causality effects of the identified measures were not examined due to the absence of randomized experiences. Further research is necessary to determine the cause and effect relationship between the measures identified. Finally, the predictive models are influenced by the data collected onsite. Since the data collection process is manually conducted and uploaded in databases, there is a natural limitation related to the accuracy of data entry.

The results and procedures adopt by the company shared in this paper revealed several themes of useful future study. First, since safety-related measures can be affected by the dynamic conditions of construction projects, the integration between CBR and simulation models (designed to replicate the performance of projects) may assist managers in comprehending how the interaction of various decisions affect overall safety performance. Second, an in-depth understanding of the cause and effect between the safety-related measures can enhance SMS strategies to mitigate the risks during project planning and execution phase. Third, since it is not available, the data related to the day the workers start to work in the construction industry, further research can evaluate how a worker's field experience, as opposed to a worker's age, affects safety risk.

4.6 Conclusion

Results generated by this assessment tool can be used to more accurately evaluate SMS performance, particularly in situations with small sample sizes. In addition, the model can also be used to assess how various scenarios can affect risk levels and can be used to test scenarios and assist managers with decision-making processes. By reliably evaluating and predicting SMS performance, managers can examine how various strategies can impact safety output. For safety management in construction to become proactive in nature, it is necessary to control safety-related measures prior to the occurrence of accidents. This research proposes a method that uses existing data from companies to assess the safety performance of construction sites by identifying and evaluating various safety-related measures. The CBR and GA method were found to be effective at producing reasonable results with a limited amount of data points. The proposed method was found to accurately identify the measures, determine their impact on safety performance, assess safety performance of construction projects, and visually demonstrate its performance. The framework was validated using correlation and MAPE.

The presented CBR/GA-based method is expected to assist companies with (1) identifying safety-related measures within the information available in a company and assessing each measure's influence on safety performance, (2) controlling safety performance using a proactive holistic approach, and (3) producing reliable, meaningful information that can be used to improve safety management practices and policies. Its functionality was demonstrated following its application in a case study of a company located in Edmonton, Canada. Here 27 measures were initially identified as possible potential measures of safety performance. Following method application, nine safety-associated measures were selected and considered in the final model. Measures associated with "resource allocation," "scheduling," "human resource," "cost control," and "environmental policies," were determined to have the greatest impact on safety outcome at this company. Based on the model results, companies can establish policies such as defining minimum penetration rate of Behavior-based observation rate and maximizing crew size. The framework also allows practitioners to verify how policy combinations influence overall safety performance.

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Chapter 5: Integrating Case-Based Reasoning and simulation modeling for testing strategies to control safety performance

5.1. Introduction

The construction industry is considered one of the most hazardous industries across numerous countries and regions throughout the world (International Labour Organization 2014). Since accidents influence project performance, efforts to reduce incident occurrence on construction projects are important not only for worker health but also to successfully achieve financial, schedule, and quality targets (Dadeviren and Yuksel 2008). In this context, evaluation of project safety performance is critical. Evaluation can assist in identifying possible flaws in an organization's Safety Management System (SMS), thereby improving proactive safety planning, and ultimately, in reducing incident occurrence. While the evaluation of safety performance is common in practice, it is done primarily using reactive indicators such as Total Recordable Incident Rate (TRIR) and Severity Rate (SR) (Salas and Hallowell 2016). Since these indicators are based on accident frequency, they cannot alert practitioners to deficiencies in SMS prior to accident occurrence. Use of these indicators renders the definition and development of proactive risk mitigation strategies difficult in practice and may even produce unreliable results, which can adversely affect safety performance.

Researchers have, therefore, concentrated their efforts on proactively assessing and controlling safety performance by focusing their attention on identifying safety-related measures that can be used to predict onsite safety risk. Multiple factors influence accident occurrence, and most models have been developed to evaluate the combined effect of several safety-related measures

(Esmaeili et al. 2015; Lee et al. 2012; Lee and Halpin 2003). However, to be useful in practice, models, in addition to being comprehensive, must also be capable of considering the dynamic behavior of construction projects. Dynamic conditions, such as workers and equipment availability, work team rotations, and environment conditions, often affect project schedule. In response, managers may be required to make decisions that result in project delivery deviating from original project plans. Notably, these decisions may have effects on the performance or occurrence of several safety-related measures and may substantially impact overall safety performance. The inability of current evaluation models to incorporate and respond to multiple, concurrent decisions makes it difficult to alter safety policies in response to changing project conditions.

A hybrid simulation/Case-Based Reasoning (CBR) approach that can assist managers with the proactive development of comprehensive safety management strategies while considering the impact of managerial decisions on safety performance overtime is proposed. Here, CBR is used to determine onsite safety risk from company-specific safety-related measures, and a combination of both continuous and discrete simulation modeling is used to reliably replicate the behavior of construction projects overtime. Together, this approach is capable determining how dynamic project conditions can affect safety performance and, therefore, can be used to inform and support decision-making processes and to facilitate the development of risk mitigation strategies throughout various stages of project delivery.

5.2 State of the Art

This research has defined safety-related measures in accordance with the definition proposed by Harms-Ringdahl (2009), which defines safety-related measures as “observable measures that provide insights into a concept – safety – that is difficult to measure directly” (p.482). According to Hallowell et al. (2013), safety-related measures are recommended for proactive control of the safety level in construction projects due to their well-established relationship with lagging indicators such as TRIR and SR. Notably, as a consequence of the unique conditions of construction projects, safety culture of each organization, and diversity of causes that can contribute to accident occurrence [(such as worker behavior (Li et al. 2015), site conditions (Lee et al. 2012), and managerial commitment to safety (Guo and Yiu 2016)], several researchers (Goh and Chua 2013; Lee et al. 2012; Patel and Jha 2014; Salas and Hallowell 2016; Esmaeili et al. 2015; Lingard et al. 2017) have recommended evaluation approaches that are capable of considering a combination of multiple safety-related measures.

Although comprehensive, these models are unable to consider the performance of safety-related measures overtime, making it difficult to estimate the impact of changing safety policies (e.g. penetration of behavior based observation rate) or resource allocation on safety performance. As highlighted by Han et al. (2014) and Cooke (2003), safety-related measures such as the quantity of safety training and number of workers often change throughout project delivery. To ensure that model outcomes are relevant and representative, models must be able to incorporate variations in measure performance that may occur overtime. Furthermore, current assessment models are also limited by their inability to examine how project performance itself can affect the performance of safety-related measures overtime. As demonstrated by Mitropoulos et al. (2005) and Jiang et al. (2015), strategies implemented to ensure that construction projects achieve planned schedules can affect the performance of safety-related measures. Therefore, it is also critical to consider how the performances of safety-related measures are altered within a dynamic environment.

Simulation models have been used to successfully replicate the performance of construction-associated measures and construction projects (Alvanchi et al. 2012, Lee et al. 2009; and Razavialavi and Abourizk 2015). Simulation modeling has also been used to identify periods of high risk level by overlapping risk associated with construction activity (Choe and Leite 2015; Wang et al. 2006; Zolfagharian et al. 2014). In these studies, activity risk is assessed using data from organizational databases (e.g. OSHA), which considerably limits the efficacy of these approaches. Changes to other safety-related measures that affect safety performance, but that are not included in such databases, are not considered in these models. These approaches also assume that measures influence are the same across the organizations, not considering that factors such as organization' safety culture and programs can vary and affect the safety performance (Haas and Yorio 2016).

There is a need, therefore, to integrate simulation models with an assessment method capable of effectively and appropriately evaluating safety performance. Methods such as Artificial Neural Network (Goh and Chua 2013; Patel and Jha 2014) and linear models (Esmaeili et al. 2015; Lingard et al. 2017; Salas and Hallowell 2016) have been used to assess the safety performance. However, as these methods requires a minimum ratio between quantity of safety-related measures and amount of data points and as many safety-related measures can be correlated with the safety performance (Jablonowski 2011), the amount of data points may not be enough to apply these methods. One such approach, proposed by Pereira et al (2017), ("Evaluating safety performance using CBR and Safety-Related Measures" submitted, University of Alberta, Edmonton, Canada), is the use of a CBR-based method. CBR is capable of evaluating safety performance when data points are limited and measure variability is high. Consequently, this approach is effective at considering multiple safety-related measures of an organization as well as their level of impact on safety performance, thereby representing an evaluation method that is capable of capturing the unique characteristic of an organization. Notably, this method can accommodate various types of data (such as numerical and nominal data) and can effectively overcome issues related to incomplete data and variable data structure (Arditi and Tokdemir 1999).

5.3 Methodology

This research proposes the use of an integrated Case-Based Reasoning (CBR) and simulation modeling approach to assess safety performance. Here, CBR is used to assess safety performance, while a simulation model is used to reproduce project conditions and to update the performance of safety-related measures overtime.

Simulation "is the science of developing and experimenting with computer-based representations of construction systems to understand their underlying behavior" (AbouRizk 2010). Simulation models the logic of activities required to perform a task, the resources necessary to complete this task (e.g. crews, equipment, and material), and the environmental conditions (e.g. weather temperature, wind speed, and ground conditions) that may affect project performance (AbouRizk, 2010). In essence, simulation allows for the concomitant analysis of several safety-associated measures and, therefore, can be used to determine how a combination of decisions can influence overall project cost, schedule, quality, and safety. Here, the simulation model is responsible for replicating project behavior and for updating the values of the safety-related measures. Two types of simulation are used in this conceptual approach, namely continuous and discrete-event simulation, to achieve this goal.

5.3.1 Continuous and discrete-event simulation modeling

Several authors (Lee et al. 2009; Puri and Martinez 2013; Razavialavi and Abourizk 2015) have contended that a combination of discrete-even and continuous simulation may enhance the understanding of complex interactions between various processes and resources. Given that safety is affected by a multitude of construction-associated factors, a continuous and discrete-event simulation approach was selected as a means of best representing the complexity associated with safety performance.

Continuous simulation (CS) is used to represent systems experience continuous change (Roth 1987). CS relies on the differential equation for determining the values of continuous variables (Equation 1)

$$\mathrm{S}(\mathrm{t}_2) = \mathrm{S}(\mathrm{t}_1) + \frac{\mathrm{Ds}}{\mathrm{Dt}}\,\mathrm{dt} \qquad \textit{Equation } 1$$

where $S(t_2)$ and $S(t_1)$ are the value of the continuous variable S at time t_2 and t_1, respectively ($t_2 = t_1 + dt$), and Ds/Dt is the rate of change of the continuous variable.

According to Reggelin and Tolujew (2011), CS is most suitable for modeling events at a strategic level with aggregate data when a low-level of detail and modeling effort, relative to that required for discrete-event simulation, is needed. Razavialavi and Abourizk (2015) have indicated that CS is mostly used to predict the long-term behavior of a project and to model managerial corrective actions. Accordingly, CS was chosen to simulate the project schedule to establish the relationship between the start and end times of a project's activities. Here, the work breakdown structure of a project is classified into disciplines that are defined depending on project type. The quantity of required worker hours in each discipline is defined by the project estimation department and is obtained from the planned scheduled. Actual project hours are tracked by the CS, and the rate of change is calculated using Equation 2. The time unit used by the simulation model is set as days.

$$\frac{Ds}{Dt} = worker * working\ hours * HE\ (Equation\ 2)$$

where $\frac{Ds}{Dt}$ is the change rate; *worker* is the quantity of workers available for the discipline; and *HE* is the Hours Effective factor determined by the project manager onsite.

In the current model, discrete-event simulation (DES) is used to determine project completion from the outputs provided by the CS component of the model. According to Alvanchi et al. (2011), DES is extremely useful for modeling the effects of operation-level variables in sequential systems. Here, the DES portion is used to (1) update safety-related measures that change monthly (e.g. crew size) or daily (e.g. Temperature) based on distributions defined by the user or from historical database information, (2) control time advancement of the model and finalize the simulation when project duration has elapsed, (3) calculate project safety performance, and (4) simulate specific tasks in which the use of resources, materials, or weather conditions significantly affect project schedule. Figure 5.1 schematically demonstrates the behavior of the simulation model. The project information is read from a spreadsheet by the simulation software, and data are stored in the system. When t = 0, monthly and daily attributes, and the rate of change for day 1, are calculated. Then, information is provided to the CS and DES models. Safety-related measures are updated for time intervals defined by the user. Project schedule is updated by the CS on a daily basis.

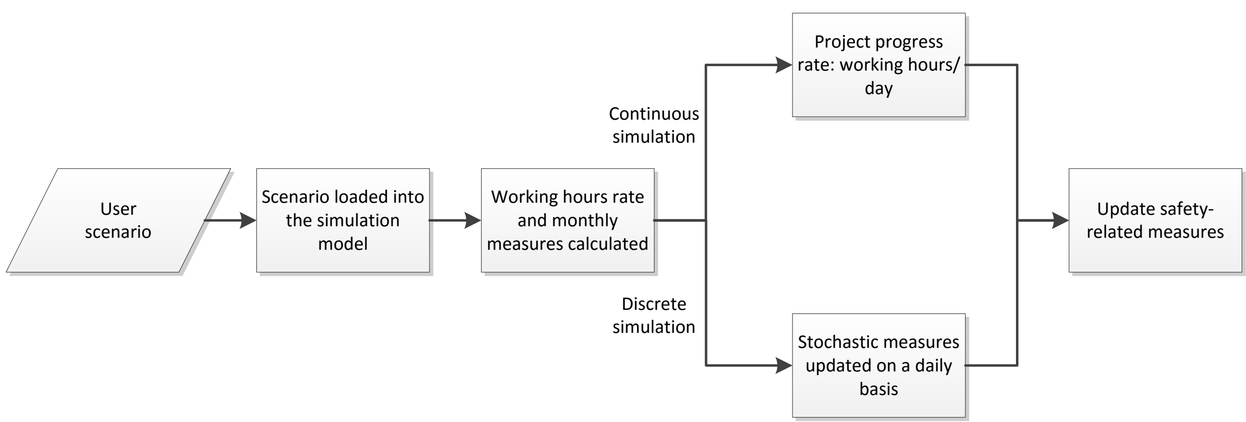


Figure 5.1. Integrated continuous and discrete-event simulation model

5.3.2 Case-Based Reasoning

CBR is an artificial intelligence-based method that utilizes a problem solving approach to imitate the human action of reasoning (Watson 1999). In this method, the solution is obtained from previous experiences that are accumulated by the system over time (Lopez 2013). CBR solves new problems by matching the characteristics of a new problem to those of the old cases that have been successfully solved (Richter and Weber 2013). CBR has been applied in the construction domain to estimate costs (Choi et al. 2014; Kim et al. 2004; Kim and Kim 2010; Kim and Shim 2014), identify hazard (Goh and Chua 2010), estimate resource allcoation (Du and Bormann 2014; García et al. 2015), assist in bid decision-making (Chua et al. 2001), assess performance of scheduling and planning (Dzeng and Tommelein 2004)), and evaluate contractor prequalifications (Ng 2001)). Application of a CBR-based approach to evaluate safety performance has been proposed by Pereira et al (2017), ("Evaluating safety performance using Case-Based Reasoning and safety-related measures," submitted, University of Alberta, Edmonton, Canada). In brief, safety-related measures are collected from various departments at an organization. Correlation Feauture Selection Based and Genetic Algorithm are used to select and determine the influence of safety-related measures on safety performance, respectively. Then, the measures selected by this approach are used as inputs for the simulation. Safety-related measures are updated on a monthly basis. The simulation model is responsible for accessing the database, which contains all the safety-related measures, and for plotting safety performance. CBR is integrated into the simulation to assess the safety performance (the CBR code is available on Appendix F). Similarity scores between the new case and previous cases contained in the historical database are verified by the CBR code using Equations 3 and 4 (Choi et al. (2014). Interactions between the CBR and simulation models are illustrated in Figure 5.2

$$sim(x_a^I, x_a^R) = \begin{cases} 0, & d\,(x_a^I,\ x_a^R) > 0.3 \\ 60, & d\,(x_a^I,\ x_a^R) \le 0.3 \\ 80, & d\,(x_a^I,\ x_a^R) \le 0.2 \\ 100, & d\,(x_a^I,\ x_a^R) \le 0.1 \end{cases} \quad Equation\ 3$$

where x_a^I, x_a^R represents the values for the input case I and the retrieved case R for the safety-related measure a, respectively, and the difference rate $d(x_a^I,\ x_a^R) = |(x_a^R - x_a^I)/\ x_a^I\ |$

$$score_n = \frac{\sum_{a=1}^{m}[sim(\ x_a^I,\ x_a^R) \times w_a]}{\sum_{a=1}^{m} w_a} \quad Equation\ 4.$$

where m represents the quantity of safety-related measure and $w_a$represents the weight of the safety-related measure a.

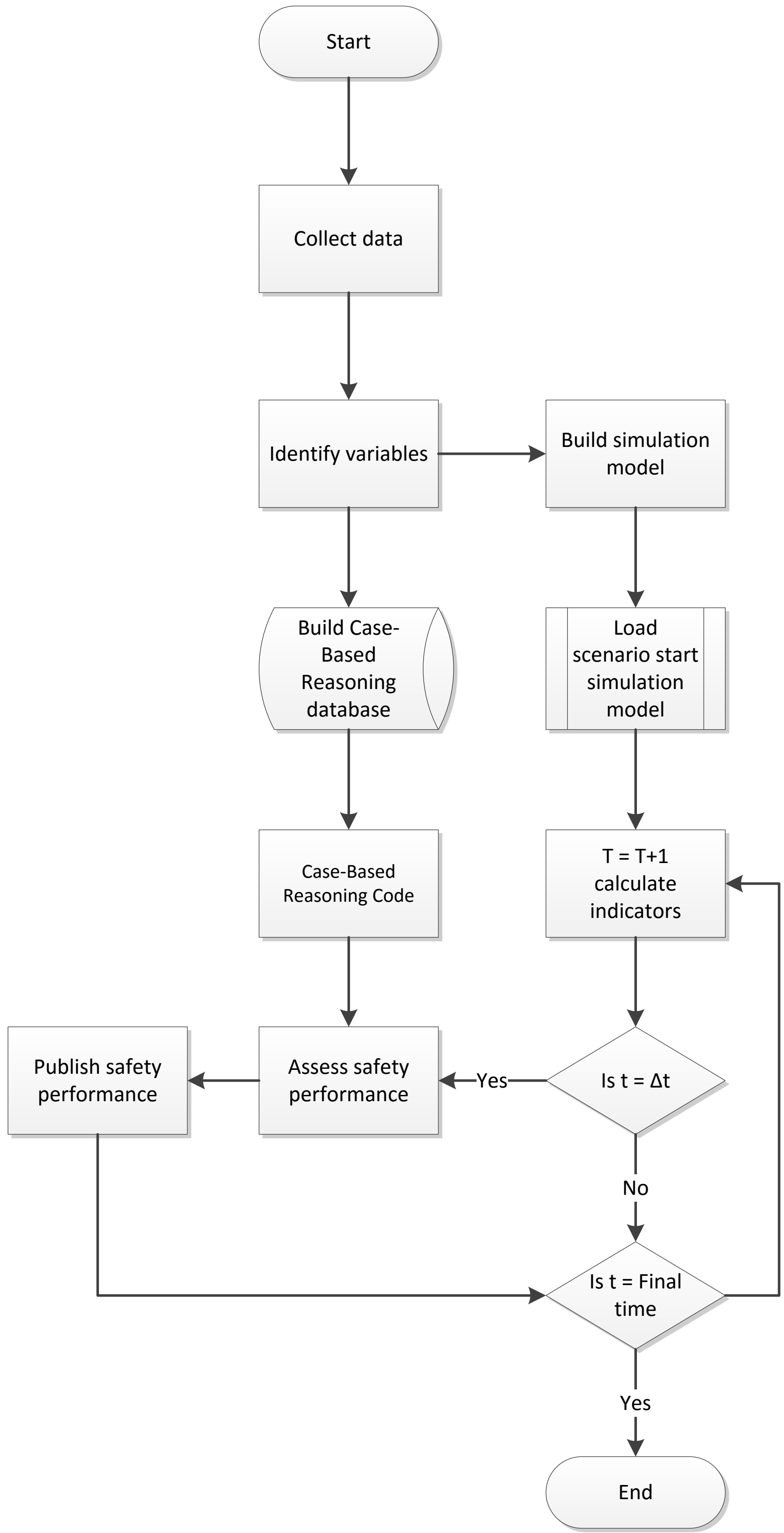


Figure 5.2. Interactions between the CBR and the simulation model components

5.4 Method Application

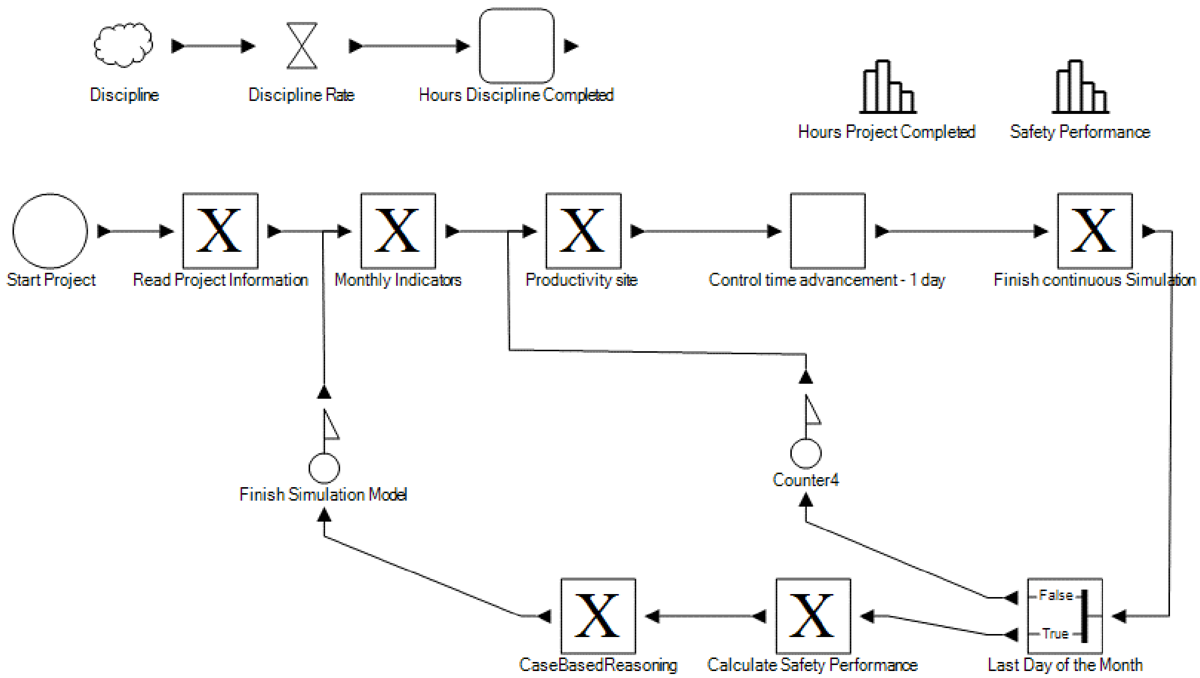
The model functionally and performance was tested through a case study. Three industrial construction projects totalizing 93 data points were used to build the assessment model. Two outputs were considered to evaluate the safety performance: Total Incident Record (TIR), which consider the amount of accidents divided by the amount of working hours, and the Severity Risk (SR), which multiplies incident types by perceived severities defined by Hallowell and Gambatese (2009). Both outputs were discretized (1 to 5) using the equal frequency binning method. Outliers were identified in the dataset and excluded from the analysis.

A total of 27 measures were identified and collected from departmental databases, spreadsheets (e.g. project performance), drawings, and interviews with project managers. Based on these data, nine variables related to SR and eight related to TIR were selected. Results of this work are summarized in Table 5.1 and are detailed in Pereira et al (2017), ("Assessing the safety performance of construction projects using Case-Based Reasoning," submitted, University of Alberta, Edmonton, Canada). The final product of the CBR approach is a model that is capable of proactively assessing safety performance.

Table 5.1. Determined weights of each variable

Variable	TIR(%)	SR(%)	Unit	Maximum	Minimum	Average
Crew Size	9.84	16.15	Workers / foreman	10.8	4.07	7.35
Behavior Based Observation (BBO) Rate	5.44	8.69	# BBO filled / working hour *200,000	6226.98	41.33	2026.67
Near Miss	5.04	14.92	Near misses/working hour *200,000	51.96	0.66	10.00
Ramp Up/ Ramp Down	-	10.83	# $workers_n$ / # $workers_{n-1}$	105.42	-43.58	8.40
Operators	24.04	17.31	# operators / total workers	10.91	0.66	3.83
Temperature	5.78	7.88	ºC	40.99	0.07	16.53
Workers Age	10.04	8.12	% workers younger than 30 and older than 50 years old	59.24	44.95	51.49
Delay S curve	6.22	8.25	actual hours / planned hours	1.16	0.24	0.73
Project Elevation	33.60	7.85	Likert Scale	4	1	2.5

A simulation model, based on the measures indicated in Table 5.1, was built using Simphony (Abourizk and Hajjar 1998). Figure 5.3 demonstrates model implementation. Following initiation of the simulation (Figure 5.3a), scenario information is loaded from an excel spreadsheet (Figure 5.3b) into the simulation system. From this information, monthly indicators are sampled based on distributions defined by the user. In this case study, the safety-related measures “near misses,” “crew sizes,” “ramp up and ramp down,” “project elevation,” “workers’ age,” and “behavior-based observation rate,” are sampled on the first day of each month. Notably, users can also define specifics tasks that can impact discipline and/or project schedule.



	A	B	C	D	E	F	G	H	I	J	K	L	M
1		Jan	Feb	March	April	May	June	July	Aug	Sep	Oct	Nov	Dec
2	Discipline A	1000	2000	3000	4000	5000	6000	7000	8000	9000	10000	11000	12000
3	Discipline B	1000	2000	3000	4000	5000	6000	7000	8000	9000	10000	11000	12000
4	Discipline C	1000	2000	3000	4000	5000	6000	7000	8000	9000	10000	11000	12000
5	Discipline D	1000	2000	3000	4000	5000	6000	7000	8000	9000	10000	11000	12000
6	Discipline E	1000	2000	3000	4000	5000	6000	7000	8000	9000	10000	11000	12000
7	Discipline F	1000	2000	3000	4000	5000	6000	7000	8000	9000	10000	11000	12000
8	Discipline G	1000	2000	3000	4000	5000	6000	7000	8000	9000	10000	11000	12000
9	Total Hours	30000	40000	50000	60000	70000	80000	90000	95000	105000	110000	120000	125000
10	% Operators	4	4	4	4	4	4	4	4	4	4	4	4
11	Project Elevation	1	1	1	1	1	1	1	1	2	2	2	2
12	Quantity of Workers	160	200	250	330	380	396	400	449	567	560	580	600
13	Workers Age Ditribution	48	50	59									
14	Productivity Factor	0.75	0.8	1									
15	Hours Worked per day	10											
16	BBO Rate	500	1500	2000									
17	Near Misses	5	7	9									
18	Crew size	6	8	10									

Figure 5.3. (a) Simulation model implemented in Simphony **(b)** Excel spreadsheet used to load scenarios.

Once monthly indicators are defined, the simulation model calculates the Effective Working Hours (EWH)[2] (Equation 5), and the daily working hours for each discipline is calculated by multiplying the quantity of workers by the Effective Working Hour factor (EWFH) defined by the user in the excel spreadsheet. This information is used by the continuous component of the model to replicate the schedule performance of each discipline (Figure 3). The discrete component of the model is used to establish daily temperatures and to advance simulation time.

$$EWH = EWFH * Quantity\ of\ Workers * working\ hours\ per\ day\ (Equation\ 5)$$

After all daily information is computed, the model determines if it is the last day of the month. If it is not the end of the month, daily information (e.g., temperature, daily productivity and daily discipline production) is updated, and the simulation proceeds forward by one day. If it is the last day of the month, information for each safety-related measure is reported. Then, the CBR algorithm (Appendix H) identifies which of the cases in the database are most similar to the reported values and uses the associated historical data to calculate safety performance (Equation 1 and 2). Results are then displayed in a graphical format. The model continues to operate until the project is complete.

An industrial project (Project D) located in Edmonton, Canada, was used to assess the functionality and validity of the proposed approach. Data from 12 months of the project execution phase were collected (Table 5.2). Project D was comprised of six disciplines, namely

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[2] $EWFH$ ranges from 0 to 1.

ironworkers, operators, welders, civil workers, electricians, and millwrights; the total working hours planned for this period was 975,000. Based on project information, five scenarios were established to examine the effect of various risk mitigation strategies on TIR and SR. For testing purposes, activities were set to occur concurrently with no start/end relationship, specific activities that could substantially affect project schedule were not defined, and the start date of the project was set as September 1. Characteristics of each scenario are detailed as follows:

Scenario 1: Quantity of workers remains as defined by Project D. The performance of safety-related measures, such as “BBO rate,” “crew size,” “near miss,” and “workers’ age,” is improved.

Scenario 2: Quantity of workers remains as defined by Project D. Performance of safety-related measures, such as “BBO rate,” “crew size,” “near miss,” and “workers’ age,” is reduced.

Scenario 3: Quantity of workers is increased during the first six months of project execution. Additionally, performance of safety-related measures, such as “BBO rate,” “crew size,” “near miss,” and “workers’ age,” is reduced.

Scenario 4: Quantity of workers is drastically increased during the final six months of project execution. Performance of safety-related measures, such as “BBO rate,” “crew size,” “near miss,” and “workers’ age,” is reduced.

Scenario 5: Quantity of workers is drastically increased during the final six months of project execution. Performance of safety-related measures, such as “BBO rate,” “crew size,” “near miss,” and “workers’ age,” is improved.

Table 5.2. Actual information for Project D

Safety-Related Measures	Month 1	2	3	4	5	6	7	8	9	10	11	12
Total Working Hours	29310	40548	54391	68323	88836	49594	69407	89741	113549	123145	133484	142972
Crew Size	6.38	7.50	7.48	7.83	8.65	7.30	7.53	8.05	8.93	8.85	8.66	8.91
Elevation	1	1	1	1	1	1	1	1	2	2	2	2
BBO Rate	3132	3167	4071	4104	5169	5404	5541	7424	5450	5265	4781	5084
Near Miss	0.01	4.93	3.68	5.85	4.50	8.07	8.64	2.23	7.05	3.25	10.49	8.39
Delay S Curve	0.49	0.51	0.58	0.68	0.78	0.80	0.91	0.88	0.90	0.91	0.93	0.97
Workers Age	50.23	50.88	51.07	51.30	49.56	49.16	48.26	49.84	47.69	46.54	50.20	48.77
Temperature	1.03	0.39	4.63	14.52	27.59	40.99	34.32	37.01	29.11	17.06	9.76	2.60
Operators	3.37	3.77	3.89	3.26	3.60	4.43	4.27	3.65	2.94	2.27	1.81	1.60

Definitions, values, and distributions used for each scenario are indicated in Figure 5.4 Triangular distributions were used in the present case study to facilitate range definition of safety-related measures such as crew size and BBO rate. Notably, the simulation model supports the use of other distribution types, including beta, normal, and exponential distributions. Project elevation was kept consistent for all scenarios.

	Quantity of Workers					Operators				
Month	1	2	3	4	5	1	2	3	4	5
1	160	160	420	200	200	3	3	6	1	1
2	200	200	500	200	200	3	3	6	1	1
3	250	250	600	220	220	3	3	6	1	1
4	330	330	650	240	240	3	3	6	1	1
5	380	380	500	300	300	3	3	6	1	1
6	396	396	500	380	380	3	3	6	1	1
7	400	400	450	450	450	3	3	3	6	6
8	449	449	400	550	550	3	3	3	6	6
9	567	567	300	600	600	3	3	3	6	6
10	560	560	250	700	700	3	3	3	6	6
11	580	580	200	750	750	3	3	3	6	6
12	600	600	200	900	900	3	3	3	6	6

*Project elevation was kept constant for all scenarios

Scenario	Workers Age	Productivity	BBO Rate	Near Miss Rate	Crew Size
1	(42,45,46)	(0.8, 0.9, 1)	(5500, 6000, 7000)	(1, 2.5, 3)	(4, 5, 6)
2	(48, 50, 59)	(0.75, 0.8, 1)	(500, 1500, 2000)	(5, 7, 9)	(6, 8, 10)
3	(48, 50, 59)	(0.75, 0.8, 1)	(500, 1500, 2000)	(5, 7, 9)	(6, 8, 10)
4	(48, 50, 59)	(0.6, 0.75, 0.9)	(500, 1500, 2000)	(5, 7, 9)	(6, 8, 10)
5	(42, 44, 48)	(0.6, 0.75, 0.9)	(6000, 6500, 7000)	(1, 3, 4)	(4, 5, 6)

Figure 5.4. Scenarios used to visualize model behavior

5.4.1 Method Results

The maximum and average TIR and SR values from 50 simulation runs are depicted in Figure 5.5.

Safety Risk

Scenarios	Safety Level	Months												Actual hours
		1	2	3	4	5	6	7	8	9	10	11	12	
1	Average	1	2	2	2	2	2	2	1	2	2	2	2	978057
	Maximum	2	3	3	3	3	2	2	2	2	2	2	2	
2	Average	3	3	3	3	3	3	3	3	3	3	3	3	923461
	Maximum	4	3	3	3	4	3	4	3	3	3	3	3	
3	Average	4	4	4	4	4	4	3	2	2	2	2	2	939249
	Maximum	4	5	4	4	4	4	3	3	3	3	2	3	
4	Average	2	2	3	3	3	2	3	3	3	3	3	3	918650
	Maximum	3	3	3	4	3	3	4	4	4	4	4	4	
5	Average	1	2	1	1	2	2	2	2	2	3	2	2	918650
	Maximum	2	2	2	2	3	2	3	3	4	4	3	3	

Total Incident Rate

Scenarios	Output	Months												Actual hours
		1	2	3	4	5	6	7	8	9	10	11	12	
1	Average	1	2	2	2	1	2	2	1	2	2	2	2	978057
	Maximum	2	2	2	2	2	3	2	2	2	2	2	2	
2	Average	3	2	2	3	3	3	3	3	2	3	2	2	923461
	Maximum	4	3	4	4	4	4	4	4	3	4	4	4	
3	Average	4	4	4	4	4	3	2	3	2	2	2	2	939249
	Maximum	5	5	5	4	4	5	3	3	3	3	3	3	
4	Average	3	3	3	3	2	2	3	3	4	4	4	3	918650
	Maximum	4	4	3	4	3	3	4	4	4	4	4	4	
5	Average	2	2	2	2	2	2	2	3	2	3	2	2	918650
	Maximum	2	2	2	3	3	2	4	3	3	3	3	3	

Figure 5.5. Simulation results of various project scenarios

The model was able to predict the influence of several company policies on the safety performance, such as quantity of crew size, behavior based observation card filled per workers, and resource allocation. These policies are defined by a variety of departments, which prompted the recommendation that a holistic, interdepartmental approach should be considered during the development and deployment of risk mitigation procedures and strategies.

Results also demonstrated that, while increasing the performance of safety-related measures can, on average, reduce TIR and SR, peaks of risks (values greater than 3) can still occur (Scenarios 2 and 4). Findings such as these can motivate organizations to increase the stringency of safety mitigation strategies during these riskier periods. Furthermore, the results demonstrated that even decreasing the performance of safety-related measures with a high influence on SR and TIR (e.g. Operators in Scenario 5) it is possible to define strategies to keep the safety performance in a level lower or equal to average.

Although the quantity of workers and EWHF changed in the scenarios, it is possible to observe that the maximum delay is about 60,000 hours (Scenario 4 and 5) (≈ 6%). Therefore, based on the project characteristics, the five scenarios were able to accomplish the project planning schedule. The results also suggest that different production scenarios require different strategies to control the safety performance. For instance, although scenarios 1 and 5 presents low TIR and SR on average, the crew size distribution is more restrictive in scenario 5 due to the higher percentage of Operators and New Workers Rate in the last six months of project.

The results also reinforce that a systematic approach should be considered to improve safety performance, since individual actions have limited influence on the safety performance. In addition, Figure 6 suggests possible strategies to improve the safety performance such as limit the crew size, increase the BBO Rate, decrease the near miss rate, control the amount of young and experienced workers on the site, and limit the new workers rate.

5.4.2 Method Verification and Validation

The proposed approach was verified and validated using several validation techniques.

Trace validation

Trace validation aims to verify the accuracy of a model's logic. Here, project behavior is recorded in a trace window (Figure 5.6). The information such as daily productivity calculation and the sample from each distribution was traced and verified to be equal to results calculated by hand calculation. In addition, TIR and SR values calculated by the system were consisted with those obtained using alternate calculation methods.

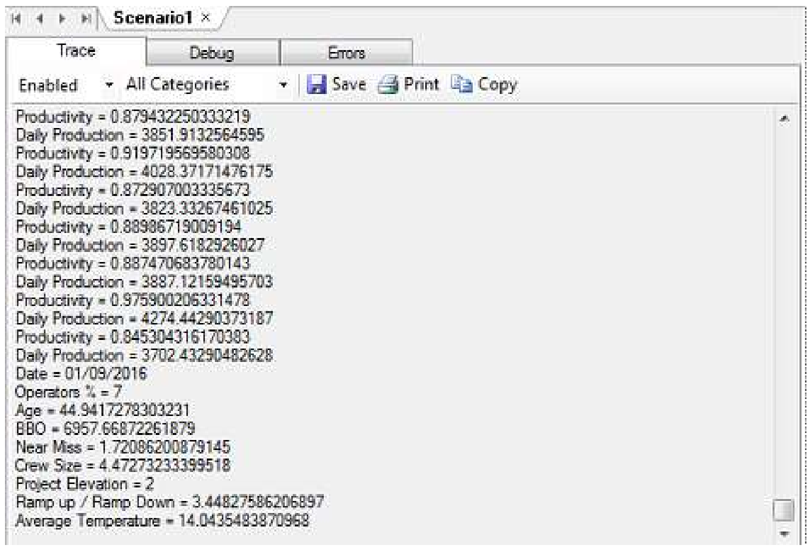

Figure 5.6. Trace window from simulation tool

Sensitivity analysis

This test determines if the model is sensitive to input variability. In essence, input conditions are modified and resultant outputs are compared to those expected in a real system (Razavialavi and Abourizk 2016). Scenario 1 was used to conduct the sensitivity analysis, where one safety-related measure was altered at a time. Figure 5.7 illustrates how changing crew size input from the 15th, 50th, and 85th percentile was predicted to affect TIR and SR. Here, safety outputs were found to improve with increasing crew size. Module results were consistent with expected outcomes, further confirming the model's validity.

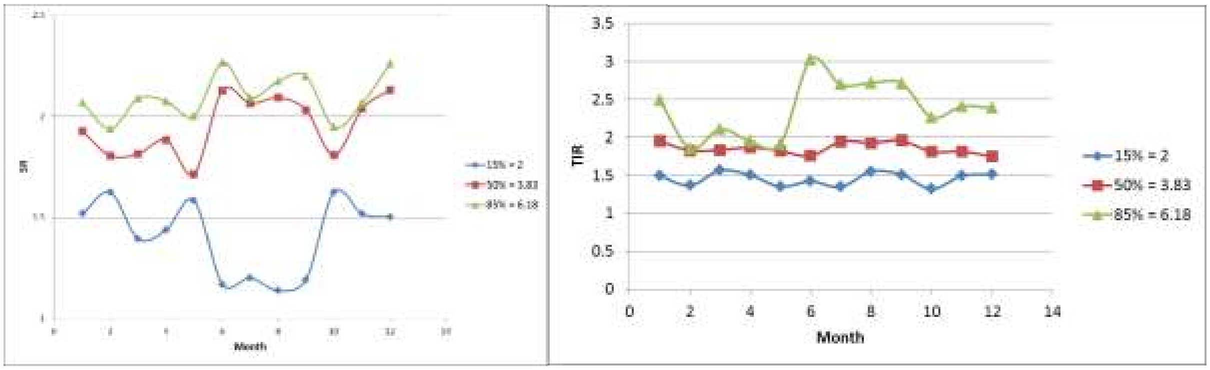

Figure 5.7. Sensitivity Analysis

Historical data validation

Model were tested using MAPE and Spearmann correlation (Equation 6 and 7) to assess safety performance. Correlations for Project D were determined to be 0.6450 (TIR) and 0.6786 (SR), which are considered, according to de Vaus (2002), as substantial to very strong evidence of forecasting ability. The MAPE for Project D was 22.18% (TIR) and 21.04% (SR), which indicates a reasonable forecasting ability (Gravetter and Wallnau 2010).Altogether, these results demonstrate that the CBR component of the method was capable of generating reliable forecasts.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{P_v - A_v}{A_v}\right| \; Equation\ 6$$

where: n is the number of new cases; P_v representes the predicted TIR/SR; and A_v is the actual TIR/SR.

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2]\,[n\sum y^2 - (y)^2\,]}}\ (Equation\ 5)$$

where r = correlation coefficient; x = predicted safety performance; and y = actual safety performance.

5.4 Discussion

The dynamic conditions of construction projects require managers to make frequent decisions to ensure that projects continue to achieve planned schedule, cost, quality, and safety targets in spite of changing circumstances. However, it is difficult, in practice, to identify how multiple decisions, taken often simultaneously, can affect overall project performance. This research proposes a conceptual approach combining CBR and simulation modeling that is capable of reliably evaluating the impact of multiple decisions on safety performance over time. Specifically, the proposed model (1) considers the dynamic behavior of construction projects to assist managers in understanding how decisions can affect safety performance, (2) allows managers to proactively test the effect of scenarios and risk mitigation strategies on safety performance, and (3) assists managers in determining the impact of various interdepartmental policies on safety performance.

The proposed model was applied in a practical setting at an industrial construction organization. A CBR database, containing information from three projects (93 cases), was used to assess the safety performance of an industrial construction project in Edmonton, Canada. The model was able to predict safety performance trends under several, pre-defined scenarios. Results of the proposed model are expected to assist practitioners at this organization in defining, developing, and deploying risk mitigation strategies in a proactive manner. The simulation model can also be used to compare expected project durations, identify gaps in safety practices, and determine how such deficiencies affect safety performance.

Safety-related measures used in this research are consistent with those identified in and used by many cases described in literature. Numerous researchers have emphasized both the indirect and indirect impact of the project delay (Han et al. 2014; Mitropoulos et al. 2005); environmental conditions, workers' age (Lee et al. 2012); near miss reporting, worker observation process (Hallowell et al. 2013); teamwork (Mitropoulos and Memarian 2012), and congestion (Fortunato et al. 2012) on safety performance. Furthermore, the several types and sources of safety-related measures identified here support the use of a systems approach for safety performance control. In this approach, various safety management elements are planned and managed throughout the lifecycle of a project, in multiple functional units of an organization, and by technical, organizational, or regulatory manner (Saleh et al. 2014). In this scenario, organizations should emphasize an integrated safety approach between all parts of the project to achieve safety performance excellence (Guo et al. 2016; Han et al. 2014; Lee et al. 2012; Wu et al. 2010a).

The findings of this study should be applied in consideration of the following limitations. First, the simulation model was built based on the measures identified in the case study. Other variables, such as quantity of inspections, and project cost not included in this model, may be affecting safety performance at other organizations. For this purpose, the simulation model should be modified to reflect specific organizational conditions and characteristics.

Generalization of this research results, therefore, should be done with caution. Second, the industrial project used to validate the model was comprised of a multitude of activities, which limits the use of DES to reproduce project behavior and, ultimately, limits the model's ability to assess the safety performance. Application of the proposed approach to projects characterized by a lower quantity of activities, such as earthmoving or tunneling operations, will allow for increased model detail and, consequently, will allow for the examination of more elaborate test scenarios.

Several themes of future work for enhancing the proactive assessment of safety performance can be performed based on the results of the conceptual model. First, since using data from different sources was found to provide a better evaluation of safety performance, a distributed simulation model could facilitate the definition of safety policies for each department. Second, a data adaptor can be developed to automatically gather data from various departments within the organization to build the CBR database. This data adaptor should be able to read and extract information from project designs, spreadsheets, and word documents.

5.5 Conclusion

The dynamic conditions and the complex relationship between various areas of a construction project limits the ability of practitioners to develop strategies to proactively control safety performance. This research proposes a conceptual approach, which combines CBR and simulation modeling, to evaluate scenarios and proactively mitigate risks. In the proposed approach, the simulation model simulates project behavior by using CS and DES, while safety assessment is performed using CBR. To validate the project approach, a case study was conducted in a construction organization and five scenarios were tested to identify the influence of various strategies on safety performance. Results demonstrated that various strategies can be defined by managers to proactively control safety performance. These strategies will depend on project requirements and the level of risk accepted. The results also demonstrated that, even in projects where there is increased pressure on workers to achieve the project schedule (e.g. high new workers rate), it is possible to control safety performance by improving other safety-related measures. These results also support the notion that safety is a part of a system and emphasizes the importance of implementing a holistic approach for controlling safety performance.

The conceptual approach developed in this research contributes to the body of knowledge. In particular, (1) by combining simulation modeling with CBR, the proposed approach can assist practitioners in predicting how concomitant decision affect the project and, therefore, improve proactive mitigation of project risk and (2) the proposed approach allows companies to customize this model to their own needs and to the data available at their organization. Notably, this research may also contribute to improved practice by increasing the commitment of managers from different sectors with the Safety Management System and to better identify and implement safety policies.

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Chapter 6: Conclusions, Limitations, and Future Work

6.1 Research Conclusions

Construction companies often use reactive indicators to evaluate safety performance, which can jeopardize the ability of SMS to proactively control incident occurrence. A holistic approach, which considers multiple factors beyond those conventionally associated with safety departments, may facilitate and improve the outcome of decision-making processes aimed at improving safety output. This thesis proposed a framework to assess safety performance using such safety-related measures. CBR and simulation modeling were combined: CBR was used to assess safety output, using safety-related measures, in consideration of specific organizational characteristics, and a simulation model was used to predict the impact of decisions on project and safety-related measure performance. Results of the current research demonstrate that the proposed model can be used to evaluate SMS and to proactively define risk mitigation strategies.

Chapter two proposed a framework capable of identifying critical SMS factors and accident precursors as well as the association(s) between these two groups, thereby allowing companies to more appropriately allocate and make efficient use of safety management resources. Application of the model demonstrated that critical accident factors were primarily from the environment group (e.g. “contract schedule,” “lack of skilled worker availability in the market,” and “change orders”). Results also found the highest-priority accident precursors to be “workers’ failure to identify hazards,” “congestion,” and “workers’ neglect of hazards.” Of the top three accident precursors identified, two were related to worker behavior suggesting that current SMS practices are not adequately controlling this safety-related measure. The results also demonstrate that most accident precursors have more than one SMS factor associated with it, suggesting that improvements to SMS should consider many-to-many relationship(s) that may exist between SMS factors and accident precursors.

Results of the case study conducted in Chapter three suggest that safety-related measures that are not traditionally associated with safety departments can—and should—be used to evaluate safety performance. Multi-linear regression model results demonstrated that measures such as “temperature,” “workers’ rate, and “workers’ age” can affect the occurrence of accidents. Furthermore, results from the mean comparison reinforced the notion that policies should also consider the level of measure influence.

Chapters 4 and 5 proposed a framework to evaluate safety performance using safety-related measures. CBR was suggested due to its ability to generate knowledge based on previous experiences using a limited number of data points, thereby allowing this method to consider the unique characteristics of each organization. The framework can also identify many safety-related measures. The simulation model was applied to predict the effect of managerial decisions on safety performance, and a case study from an organization was conducted to evaluate the framework. Twenty-seven measures were identified, and nine were selected by the final model. Findings indicated that resource allocation, scheduling, human resources, cost control, and environmental policies all affected safety outcomes at the case organization. The proposed simulation model was found to (1) facilitate examination of the impact of various decisions defined by managers on overall safety output and (2) assist managers in predicting safety performance overtime (each month) and deploying corrective actions prior to incident occurrence.

A case study from an organization was conducted to evaluate the framework. Twenty-seven measures were identified, and nine were selected by the final model. Findings indicated that resource allocation, scheduling, human resources, cost control, and environmental policies all affected safety outcomes at the case organization. The proposed simulation model was found to (1) facilitate examination of the impact of various decisions defined by managers on overall safety output and (2) assist managers in predicting safety performance overtime (each month) and deploying corrective actions prior to incident occurrence.

6.2 Academic Contributions

This research study has resulted in the development of several academic contributions:

- Department data others than safety department can—and should—be used to develop proactive strategies to control safety performance, including the implementation of policies designed to improve the performance of safety-related measures.
- The questionnaire developed in Chapter 2 has expanded the understanding and facilitated the exploration of the nature of the relationships between SMS factors and accident precursors. In addition to considering factors that are not commonly controlled by the safety department, the questionnaire facilitates the identification of critical SMS factors for various accident precursors. The comprehensive approach can be used to identify gaps in SMS across multiple areas in an organization.

- Association results described in Chapter 3 can serve as a foundation for future studies attempting to identify and understand causal relationships between these two groups.
- The CBR method proposed is a reliable alternative for assessing safety performance of construction projects or organizations with few data points.
- The integration between simulation modeling and CBR substantially facilitates the ability to predict how decisions, both individually and in combination, affect safety performance. Furthermore, by considering the dynamic conditions of construction projects, the integration between these methods provides a better approach to evaluate safety performance dynamically.
- The use of a holistic approach during the development, evaluation, and deployment of proactive mitigation strategies is supported by the findings of the present research, which also reinforces the notion that isolated actions may not result in significant improvements in safety performance.

6.3 Industrial Contributions

Industrial contributions have arisen out of collaborative research efforts with partners organizations and include the following:

- A holistic approach for controlling safety performance, such as enhancing interdepartmental data sharing, is recommended to improve safety performance in the construction industry and to reduce the time and resources required by safety departments for data collection.

- The proposed association approach between SMS factors and accident precursors can assist managers in identifying which SMS factors should be addressed based on accident precursors observed or to predict which accident precursors are most likely to occur based on the presence of critical SMS factors. This is expected to not only improve safety performance but to also result in the more efficient allocation of available resources.
- Through the development of a reliable, easy-to-use method for comprehensively evaluating safety performance, application of this research can be used to increase the deployment of effective policies and to increase interdepartmental focus on safety.
- The approach can also assist managers with the identification and evaluation of safety-related measures from existing departmental data.
- The simulation approach can assist managers with the proactive examination of various project delivery scenarios, thereby allowing managers to establish mitigation strategies prior to incident occurence.
- Safety-related measures identified, as suggested by previous studies listed in Chapter 4, can be used by other organizations from different sectors to proactively control safety performance. However, the use of the same CBR/GA model should be made with caution due to the different characteristics of each organization.

6.4 Limitations of the Proposed Approach

Although the results presented in previous chapters support the use of the approaches developed, the findings should be interpreted in consideration of certain limitations.

The SMS factors and accident precursors selected in Chapter 3 were dependent on the subjective opinions of subject matter experts. Alternative SMS factors and accident precursors should be examined prior to the application of the questionnaire to other industries or regions. In addition, further research is required to establish cause-and-effect relationships between SMS factors and accident precursors

Safety-related measures identified in Chapters 2 and 4 were limited by the data available within the case organization. Other variables related to work process and contract type should be further investigated to identify their influence on safety outputs. Furthermore, measures identified as not significant in this research should not be disregarded by other organizations due to the unique conditions of each organization.

The simulation model developed in Chapter 5 considered the safety-related measures identified in previous chapters. Therefore, generalization of this model to other companies should be considered with caution, particularly as the level of measure influence on safety output may vary considerably between organizations.

6.5 Envisioned Future Research

This thesis revealed several themes of useful future study. For instance, the implementation of a data adaptor component can assist companies with the identification and automatic extraction of safety performance evaluation data. As departmental data are often stored in a disconnected databases. Database integration may enhance the proposed framework by increasing the quantity of available measures.

From a simulation perspective, distributed simulation may be used to improve reproducibility of project several agents (e.g. different departments). High-Level Architecture supports the building of complex virtual environments using distributed computer simulation systems to create a collaborative research project. In this scenario, each department is responsible for developing their own simulation model, and the High-Level Architecture is responsible for connecting and sharing the information between these models.

The data collection process may also be improved. For example, data collection for Behavior-Based Observation Cards and site inspections are often collected manually and are later digitized and loaded into databases. This is a time-consuming, error-prone process that could be improved with automation. Companies could develop software applications that could load this information into databases automatically. Another potential area for improvement is the adjustment of the CBR-Simulation approach to allow for the identification of safety-related measures from photos and videos.

The simulation CBR approach can be further expanded to integrate project schedule, quality, and cost performance. This approach would assist companies in evaluating how project performance is affected overall, and could enhance companies' abilities to more effectively allocate resources to areas that would benefit most.

Lastly, the simulation CBR approach should be expanded to allow for its application at additional levels, such as at the activity-level and process-level. As the approach proposed can evaluate performance using a limited quantity of data, managers can expand the scope of this thesis by identifying how safety-related measures affect various levels of a project.

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Appendix A: Questionnaire to evaluate SMS Factors and Accident Precursors

UNIVERSITY OF ALBERTA

Department of Civil and Environmental Engineering
Hole School of Construction and Engineering

This survey is conducted by the University of Alberta in order to identify the impact of safety factors with relation to safety programs on construction sites.

The survey should take around 10-15 minutes to complete.

Completing and submitting this survey implies giving consent to participate in this study as per the conditions outlined in the accompanying information/consent letter.

Thank you for your participation.

In section 1, you are given statements about managerial efforts for enhancing safety on job sites. For each statement, please select an option that best fits your perception of its ***LIKELIHOOD*** (i.e., how likely you will see that achieved in a project) and your perception of the ***INFLUENCE ON INCIDENT PREVENTION*** (i.e. *if that happened* how influential it would be on incident prevention).

		Likelihood						**Influence on Incident Prevention**				
#	**Phenomena Affecting Safety**	**Unlikely**	**Somewhat Unlikely**	**Neutral**	**Somewhat Likely**	**Very Likely**		**Not Influential**	**Little Influential**	**Somewhat Influential**	**Largely Influential**	**Extremely Influential**
1	**Safety responsibility** and **goals** are clearly defined among project team members.											
2	**Safety training** increases worker safety knowledge											
3	Safety Practices and procedures are periodically reviewed or evaluated by the **safety committee**											
4	Workers are given **incentives** to work safely											
5	**Subcontractors** are adequately assessed and managed for safety											
6	**Worker participation** in safety programs is high											
7	**Emergency response** plan is clear communicated											
8	**Incident investigations** are properly performed, stored or analyzed to prevent future incidents											
9	**Potential hazards** are effectively identified and mitigated											
10	**Tools/Equipment and site conditions** are											

#	Phenomena Affecting Safety	Likelihood						Influence on Incident Prevention				
		Unlikely	Somewhat Unlikely	Neutral	Somewhat Likely	Very Likely		Not Influential	Little Influential	Somewhat Influential	Largely Influential	Extremely Influential
	regularly inspected											
11	**Project safety plan / kickoff meeting** (considering design, schedule, constructability etc.) is properly reviewed before the project starts											
12	The supervision, monitoring , and control of **workers' drug and alcohol consumption is effective**											
13	**Safety meetings** are effective to reinforce safety practices											
14	**Worker safety behavior** is observed and evaluated routinely											
15	The **owner/client** considers safety as a core value of the company											
16	**Management team** considers safety as a core value											
17	Management team considers safety ahead of **cost**											
18	Management team considers safety ahead of **schedule**											
19	**Subcontractor** considers safety ahead of other business priorities											
20	**Budget** assigned to safety management is sufficient to carry out the program											
21	**The number of safety personal** is sufficient to											

#	Phenomena Affecting Safety	Likelihood						Influence on Incident Prevention				
		Unlikely	Somewhat Unlikely	Neutral	Somewhat Likely	Very Likely		Not Influential	Little Influential	Somewhat Influential	Largely Influential	Extremely Influential
	implement safety practices											
22	**The number of foremen** is sufficient to implement safety practices											

In section 2, you are given statements about safety-related phenomena that you might observe on job sites. For each statement, please select an option that best fits your perception of the **LIKELIHOOD** (i.e., how likely you will observe the phenomenon in your project) and your perception of the **INFLUENCE ON INCIDENT OCCURRENCE** (i.e. *if that happened* how influential it would be on incident occurrence).

		Likelihood						**Influence on Incident Occurrence**				
#	**Phenomena Affecting Safety**	Unlikely	Somewhat Unlikely	Neutral	Somewhat Likely	Very Likely		Not Influential	Little Influential	Somewhat Influential	Largely Influential	Extremely Influential
23	There are a large number of **change orders** on the project											
24	The **design** involves new technologies and materials that the management team is not familiar with											
25	There are a large amount of **reworks**											
26	**Contract schedule** is too tight											
27	There is a shortage of **skilled workers** in the market											
28	Companies are more concerned about **WCB cost (**worker rehabilitation cost assessment) than safety of personnel											
29	Workers are frequently exposed to **hazardous material** (e.g. explosive, toxin, flammable)											
30	**Tools** are not properly used											
31	Workers do not use the **personal protective equipment (PPE)** properly											
32	**Heavy equipment** is not properly used											
33	Safety personnel have **insufficient experience** in implementing safety practices											
34	Workers' **skill** levels are low											

		Likelihood						Influence on Incident Occurrence				
#	Phenomena Affecting Safety	Unlikely	Somewhat Unlikely	Neutral	Somewhat Likely	Very Likely		Not Influential	Little Influential	Somewhat Influential	Largely Influential	Extremely Influential
35	Workers are **unfamiliar** with the **work environment**											
36	**Foremen** have **insufficient experience** to implement safety practices											
37	Workers **fail to identify** an unsafe condition											
38	**Workers continue their work** even when they identify an unsafe condition or behavior											
39	Workers are under the influence of **drugs or alcohol** while at work											
40	Workers do not pay attention to **coworkers' safety**											
41	Foremen do not **communicate and enforce safety rules**											
42	Ergonomic issues (e.g. worker posture, weight of objects) are not considered in construction activities											
43	**Safety requirements** in the project are not clearly communicated/understood by workers and subcontractors											
44	**Housekeeping** is poor											
45	Construction site is **congested**											
46	**Site information** (e.g. soil tests and survey reports) is inadequate or inaccurate											
47	Workers are exposed to **extreme weather conditions** (e.g. temperature less than -30 °C)											

#	Phenomena Affecting Safety	Likelihood						Influence on Incident Occurrence				
		Unlikely	Somewhat Unlikely	Neutral	Somewhat Likely	Very Likely		Not Influential	Little Influential	Somewhat Influential	Largely Influential	Extremely Influential
48	The **safety guards or barriers** (e.g. fall protection system) are inadequate											
49	Workers are under a high level of **fatigue**											
50	**Hazardous site environments** (e.g. noise, luminosity, space, ground, etc.) are not effectively mitigated											
51	Workers are not clear about **emergency procedures**											
52	Workers are under high stress due to **schedule pressure**											

Please tell us about your experience and current position.

1. Which is the province/state that you are currently working? ☐ Alberta ☐ Saskatchewan ☐ British Columbia ☐ Manitoba ☐ Others
2. Current Position : ☐ HSE Manager ☐ Project Manager ☐ Project Control ☐ H&S Staff ☐ Technical/Administrative Staff ☐ Foreman

   ☐ Field Worker ☐ Others Specify ______________________

3. Experience in construction: _____ years

4. Experience in the field: ________ years

5. Industry type: ☐ Heavy Construction ☐ Industrial ☐ Buildings ☐ Others Specify_________

Thank you very much for participating in our survey!