Responsible Design and Delivery of the Constructed Project
Edited by Abdul-Malak, M., Khoury, H., Singh, A., and Yazdani, S.

ISBN: 978-0-9960437-5-5

SIMULATION-BASED ANALYTICS: ADVANCING DECISION SUPPORT IN CONSTRUCTION

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Construction projects are predominantly managed with a heavy reliance on the knowledge and experience of construction professionals and supporting enterprise resource planning systems. The construction sector continues to struggle with the management, analysis, and transformation of data into useful information for improved decision-making. While development of data-driven decision support systems for construction would improve the accuracy and relevancy of decision-making processes, several challenges currently limiting the incorporation of dynamic project data into prediction models must first be addressed. An envisioned solution for advancing data-driven decision making in construction using a simulation-based analytics framework capable of overcoming such limitations is presented and discussed. Concept feasibility is demonstrated through the successful completion of a prototype for quality-associated decision support that has been developed using the proposed conceptual framework.

Keywords: Data-driven decision-making, Predictive analytics, Quality management, Construction management.

1 DECISION SUPPORT IN CONSTRUCTION

Competitiveness of the construction sector depends on numerous improvements across multiple areas of project delivery as documented by many researchers and industrial organizations (Construction Industry Institute 2008, Construction Owners Association of Alberta 2015, Hanna 2016). Yet in spite of these advances, the construction industry remains challenged by a slow adoption of innovation and technological developments, high capital costs, decreased labor productivity, and reduced operational efficiency. While the construction industry has adopted a variety of information technology solutions (e.g. commercial enterprise resource planning systems, scheduling and contract management software, or in-house computer systems) for improved decision support, these systems lack the quantitative predictive capabilities required to produce desired results (Oracle 2010, Pritchard *et al.* 2012). Accordingly, construction management continues to rely heavily on the subjective knowledge and experience of construction professionals whose ability to capture intricate details of various processes, resources, and uncertainties associated with project execution are often limited (Manyika *et al*. 2011).

2 DATA-DRIVEN DECISION SUPPORT SYSTEMS: THE IDEAL

To remain competitive, the construction industry must take advantage of newly emerging technologies and tools to facilitate improvements in production efficiency, product quality, and safety management practices. A new generation of decision support systems capable of (1) providing interpretable, up-to-date project information, (2) generating reliable project predictions throughout both the project planning and execution phases of construction, and (3) allowing for analysis and investigation of various potential project scenarios would represent a notable advancement in how construction is managed in practice. Despite the desire for such tools, however, analytical systems capable of comprehensively and automatically generating reliable decision support outputs from existing project data have yet to be successfully implemented in construction practice.

3 ENVISIONED SOLUTION: SIMULATION-BASED ANALYTICS

Achievement of the ideal will require the development and implementation of systems that can integrate a variety of datasets and incorporate associated project uncertainty to dynamically reflect actual project conditions in an automated manner. Simulation modeling has emerged as a technological means of addressing the dynamicity and uncertainty associated with construction operations for improved system predictability (AbouRizk 2010) and represents a technique capable of providing the functionalities required to create this ideal system.

However, as with many decision support systems (Darema 2004), a lack of (1) appropriate approaches at the application level for enabling dynamic feedback and measurement coupling, (2) techniques for interfacing applications with measurement devices and instruments, (3) application algorithms adaptable to dynamic data inputs, (4) methods for handling uncertainty in input data, and (5) computer programs capable of supporting such environments have considerably limited the integration of real construction project data into simulation models, in turn, limiting the predictive capabilities of current systems. Indeed, models stemming from this work have remained limited to specific construction applications (e.g., module yard schedule, crane selection and allocation). The inability of simulation methods to achieve full, effective integration into organizational decision-making (Akhavian and Behzadan 2015) is due, primarily, to the inability of current process interaction-based simulation modeling methods to automatically recalibrate themselves as new project data are collected, greatly limiting their applicability during project delivery. Successful implementation of a simulation-based analytics solution will require:

- Advances in dynamic, data-driven simulation applications for decision support in construction engineering and management
- Investigation of methods for integrating (1) data that are currently collected, (2) simulation-derived data to supplement existing data when required, (3) measurement processes that are steered, as required, to enhance decision-support when possible, and (4) decision support applications
- Examination of structured methods for integrating analytics into organizational decision-making to improve effectiveness
- Transitioning the role of simulation beyond traditional analysis into an essential component of decision support

4 SIMULATION-BASED ANALYTICS FOR CONSTRUCTION

We have explored and built upon recent advances in data analytics applications (Barton and Court 2012), dynamic data-driven application systems (Darema 2004), and simulation-based analytics (Dube *et al.* 2014) to develop a conceptual, simulation-based analytics framework for construction (SAC) that we believe possesses the attributes and characteristics required to support data-driven decision-making in construction. The conceptual SAC framework, illustrated in Figure 1, is comprised of *data adapters*, which are involved in data transformation and preparation, and *analysis modules*, which are composed of a suite of algorithms that interact with *simulation components* to facilitate production of required *decision support metrics*. Rationale and functionalities of each component are detailed as follows.

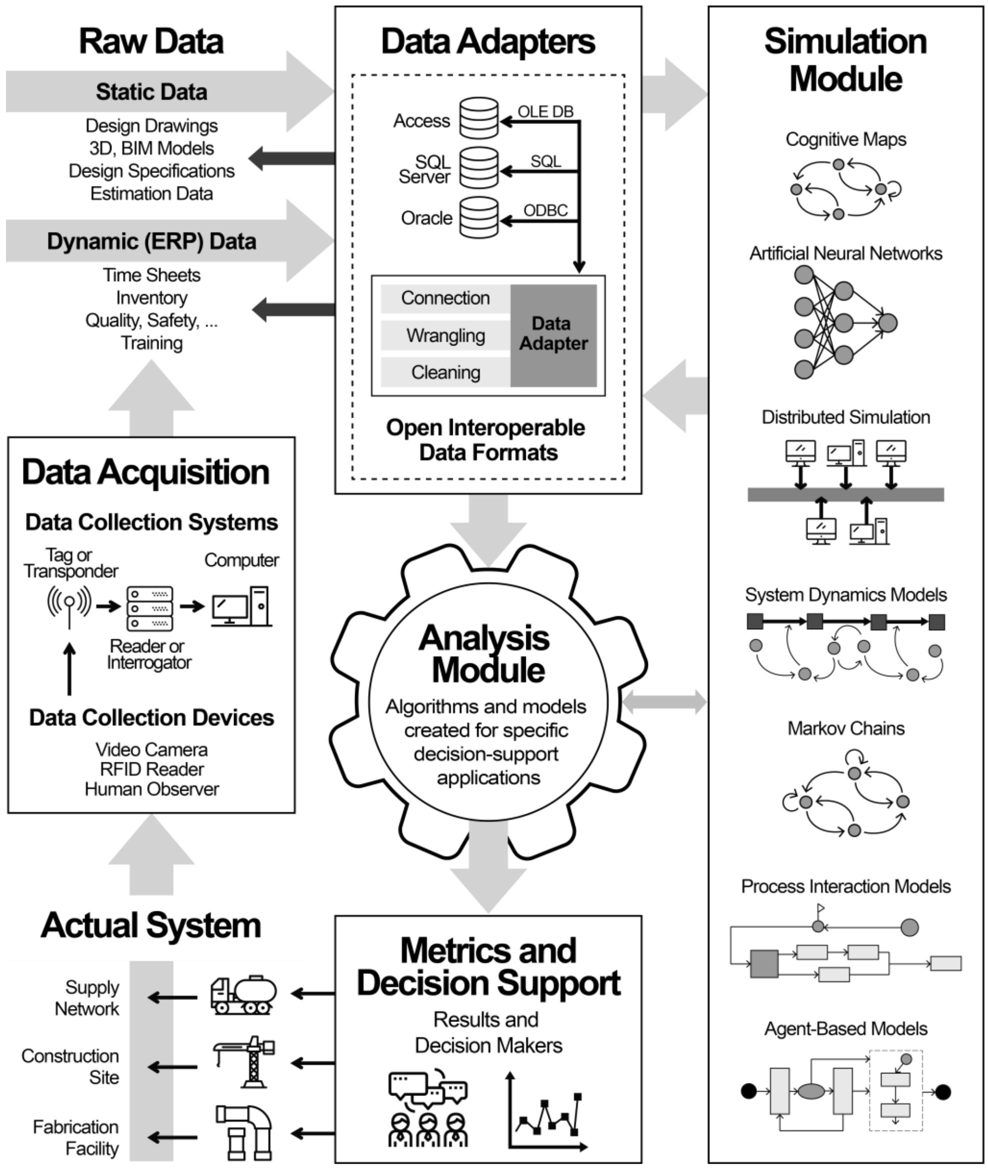

Figure 1. Proposed simulation-based analytics for construction framework.

4.1 SAC Framework Components

Construction companies handle vast amounts of raw data, which can be classified into two main types, namely dynamic data stored in data management systems (e.g., time sheets, safety incidences, quantities) and static data passed on from engineering (e.g., 2D, 3D, and BIM models). Raw data are generally not effective for decision support, as they are not always reliable, aggregated at the required level, or transformed into useful information. The *data adapter* portion of the framework is required to transform raw data into useful information. Data adapters apply a variety of analytical methods (e.g., data mining) to identify anomalies and missing data as well as simulation models to populate and validate data.

While the data adapter is responsible for collecting, organizing, and cleaning raw data, transformed data are not often stored in an easily interpretable format. As such, the conceptual SAC framework contains an *analysis module*, which is comprised of a suite of algorithms that facilitate production of required metrics for decision support. The primary function of this module is to drive the simulation process, invoking the appropriate analytic (e.g., descriptive analytic from a database query or predictive analytic derived from a data-driven simulation) and cycling through the process until decisions are made. The simulation component module includes (1) process interaction models, which simulate production processes, supply market, logistical issues, external factors (e.g., weather and economic conditions) and (2) factor models, which estimate the states of various measures, such as facility productivity based on values of identified influencing factors. Factor models, which can take the form of artificial neural networks, structural equations models, cognitive maps, and tree models, follow a three-stage process of factor identification, Principal Component Analysis, and factor analysis or model training.

At the core of the proposed framework is a dynamic data-driven application system (DDDAS) concept (Darema 2004). This concept refers to a paradigm that strives to seamlessly couple simulation and measurement (i.e., data collection) disciplines, enabling the dynamic addition of new data into simulation models. The addition of new data (e.g., archival data, real-time generated data, or sensor-detected measurements from actual systems) triggers an automated, internal calibration of the original model, increasing the representativeness and, in turn, the reliability of system predictions. DDDAS concepts have been successfully applied to model a variety of systems, including smart cities (Fujimoto *et al.* 2016), expressway traffic (Sunderrajan *et al*. 2016), dynamic manufacturing (Kück *et al.* 2016), and for crisis management analysis (Badr *et al.* 2015). Recent works in the construction domain include the development of a tunneling application, where data are collected in real-time and applied to simulation models to enhance predictions (Bi *et al*. 2015), and a framework for model-driven acquisition and analytics of visual data using unmanned aerial vehicles for construction progress monitoring (Lin *et al*. 2015).

4.2 Simulation Methods and Techniques to Facilitate Deployment of the Framework

The virtual environment is responsible for enabling dynamic data-driven simulation and for supporting the integration of various forms of simulation. It can be built using extensions of COSYE (AbouRizk and Hague 2009), Simphony (AbouRizk *et al.* 2016), and/or a variety of other information technology and modeling tools as required. Key elements of the virtual environment are detailed as follows.

4.2.1 *Data preparation algorithms*

Data adaptors are built to transform, clean, and prepare data for use in the analytics. Prepared data are warehoused using data incubators similar to those described by Fan et al. (2008) and Hammad (2009). Warehouse models consist of an object-oriented, integrated, non-volatile, and time-variant collection of data capable of supporting management decisions (Inmon 2005) and of providing a variety of decision support capabilities that cannot be attained using relational databases. Such capabilities include (1) validation, transformation, and scrubbing of data to ensure quality prior to storage, (2) collection and integration of data from various sources, and (3) use of multi-dimensional data models to organize data by subject allowing decision-makers to perform data analysis from various perspectives at various levels of detail. Concurrently, online analytical processing of data warehouses facilitates user-directed information retrieval and interactive analysis through visual operations of drill-down, roll-up, slicing and dicing, and pivoting.

Notably, data adapters should be designed specifically for particular datasets. For example, data adapters for unconventional data, such as images, differ from those designed to extract and transform data retrieved from enterprise resource planning systems, as image data must be inferred from geometric entities as opposed to being selected from an information system's database. Data adapters, therefore, may be designed to extract geometric model information from 3D models (Han *et al*. 2017) or to contain a variety of computer vision algorithms capable of reconstructing as-built 3D point cloud models from photographs (Martens 2017). The overall objective of this step is the development of intelligent data adapters that can identify a variety of information for planning various construction activities and processes.

4.2.2 *Simulation modeling infrastructure*

To function successfully, the framework must combine and integrate various subsystems that execute in a harmonious manner. This will require advancing construction simulation methods to facilitate real-time communication, enable dynamic data-driven simulation approaches, and accommodate hybrid simulations (e.g., system dynamics, agent-based modeling, discrete-event simulation, construction/time-stepped simulation, and fuzzy cognitive maps).

Simulation models often use statistical distributions or Markov chains to represent uncertainties that exist in the systems they are analyzing. Although useful for assessing static data, the ability to recalibrate these models following the incorporation of new data remains challenging. Bayes' theorem, which describes a method for updating probabilities when provided with new evidence, can be used for updating statistical distributions. The use of Bayes' theorem reported in literature, however, remains limited to normal distribution updating (Lynch 2007, Chung *et al.* 2004) due to the low dimensionality associated with normal distribution parameters and to the computational challenges associated with evaluating Bayes' mathematical formulation for updating probabilistic models. Various numerical techniques, including appropriate conjugate selection (Gelman *et al.* 2013) and numeric integration, will allow updating capabilities to be extended to other distribution types commonly used in construction simulation. Markov chain updating will be achieved using a variety of approaches, including application of Bayes' theorem variants and techniques such the Baum-Welch (Rabiner 1989), Ensemble Learning (MacKay 1997), and Viterbi (Rabiner 1989) algorithms.

5 SIMULATION-BASED ANALYTICS FOR CONSTRUCTION

Feasibility of the conceptual framework is being examined through the completion of specialized decision support prototypes, including an earned value management prototype, which captures project schedule while considering the historical performance of individual activities, and a safety management prototype, which allows users to test and predict the impact of various safety management strategies on safety performance.

Concept feasibility has been demonstrated through the successful completion of a prototype for quality-associated decision support developed using SAC concepts. This prototype uses quality management, engineering design, and cost management data to determine operator quality performance, product complexity, and quality performance for project quality forecasting and quality-induced rework cost management. The specialized framework underlying the prototype contains several SAC framework components, namely a data adapter, data analysis module, simulation module, and decision support module, which have been customized to facilitate system application for quality-associated decision support. R (R Core Team 2017) programming software for statistical computing and graphics was utilized to drive framework components.

5.1 Data Sources and Data Adapter

Data sources available for analysis include dynamic quality management data (e.g., quality inspection results, rework time, and operator information) and static engineering design data (e.g., product design attributes, such as pipe material, thickness, and diameter). A data adapter specific to this dataset was built to transform raw data, through data connection (i.e., integration of multiple sources of data), wrangling (i.e., conversion of data into a tabular format), and cleaning (i.e., noise reduction and omission of missing values) into a compatible and interpretable dataset. Example of data adapter inputs and outputs are detailed in Figure 2.

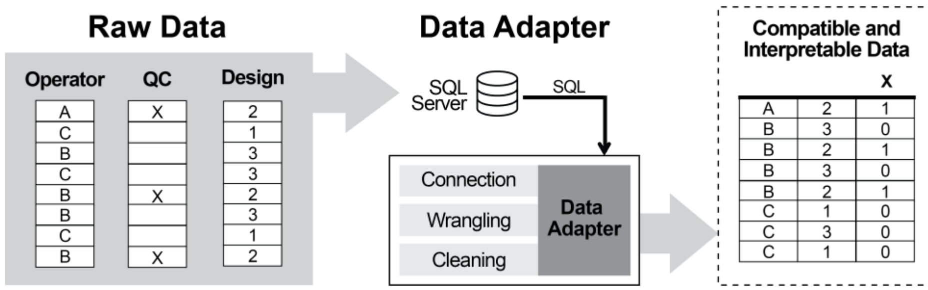

Figure 2. Example of real-time updating mechanism of quality performance.

5.2 Analysis Module

The analysis module functions to convert transformed data into useful decision support information or into a format that is suitable for simulation input. In this specialized framework, the analysis module is responsible for determining quality performance (i.e., failure rates) of individual operators and of particular product designs.

5.3 Simulation Module and Decision-Support Outputs

The simulation module generates data for desired prediction metrics for a given decision support application using transformed data from the data adapter and/or analysis module. The specialized framework uses a variety of simulation or simulation-associated components. Specifically, a Metropolis-Hasting Algorithm component is used to convert binary quality data (i.e., failure rates) into distributions for simulation purposes. A Monte Carlo simulation module (Ji and AbouRizk 2016) and an absorbing Markov chain (Ji and AbouRizk 2018b) are used to incorporate uncertainty and to model the rework process for forecasting purposes, respectively. Specific functionalities of the simulation module are described as follows.

5.3.1 *Bayesian-based quality performance modeling*

To estimate product quality performance, a Bayesian-based solution was developed to drive a distribution for incorporating uncertainty (Ji and AbouRizk 2017). In addition to providing more accurate, reliable, and interpretable estimation of product quality performance, the proposed solution addresses some of aforementioned challenges associated with simulation model updating. Application of these methods allows the simulation models to realign with dynamic, real-time data generated by the actual system. As demonstrated in Figure 3 the quality performance distribution can be updated using real-time quality inspection data.

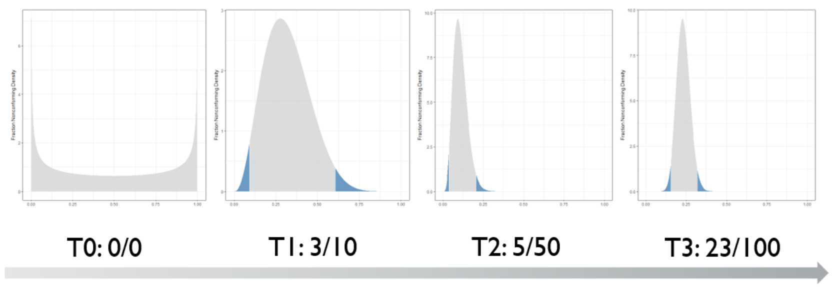

Figure 3. Example of real-time updating mechanism of quality performance.

The components comprising the specialized simulation-based analytics environment allows simulation models to be adjusted by real-time data and measurements. The approach also develops descriptive and predictive analytical metrics, namely operator quality performance measurements and project quality performance forecasts, for supporting and improving decision-making processes (Ji and AbouRizk 2018a). For instance, by using historical product quality performance data as inputs, quality performance for a new project can be simulated to achieve a quality performance distribution at a project-level, supporting decision making in consideration of particular risk attitudes (Figure 4).

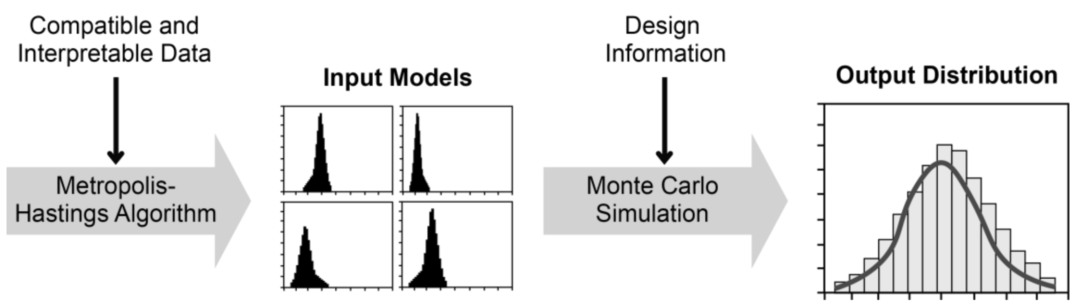

Figure 4. Workflow of the simulation model for project quality performance measurement.

5.3.2 *Product complexity clustering*

To further extend the functionality of the proposed system, a hybrid data mining approach for quantitatively analyzing product complexity from product quality performance data (i.e., failure rate) was developed (Ji *et al.* 2018). The proposed model is comprised of three steps, which (1) measure product complexity by introducing a Bayesian-based nonconforming quality performance indicator, (2) score each type of product complexity by developing a Hellinger distance-based distribution similarity measurement, and (3) cluster products into homogeneous complexity groups by using the agglomerative hierarchical clustering technique. Practitioners can implement this approach to enhance their product complexity management practices from the perspectives of (1) strategic bidding, (2) complexity-driven production planning, and (3) customized training. As demonstrated in Figure 5, practitioners can directly obtain product design information, complexity score, total business percentage, and its corresponding complexity level from the outputs.

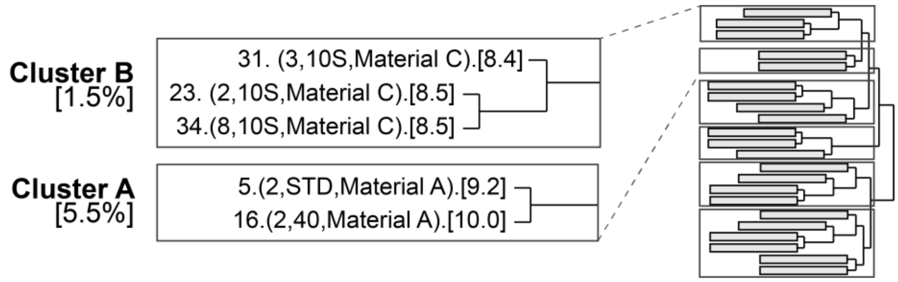

Figure 5. Example of outcomes of product complexity analysis.

5.3.3 *Rework cost estimation and control*

A novel functionality for supporting quality-induced rework cost estimation and control for construction product prefabrication was also developed using absorbing Markov chains (Ji and AbouRizk 2018b). Two types of decision support metrics are established to support decision-making processes, namely (1) rework cost estimation during the project planning phase and (2) rework cost control during the project execution phase. As shown in Figure 6, a distribution of rework cost estimation is simulated in project planning phase and is utilized to construct a control chart for monitoring purposes. At each time point, the simulated rework cost is updated by incorporating real-time quality and rework cost information. Abnormal patterns can be detected for practitioners to analyze root causes and improve their operation processes.

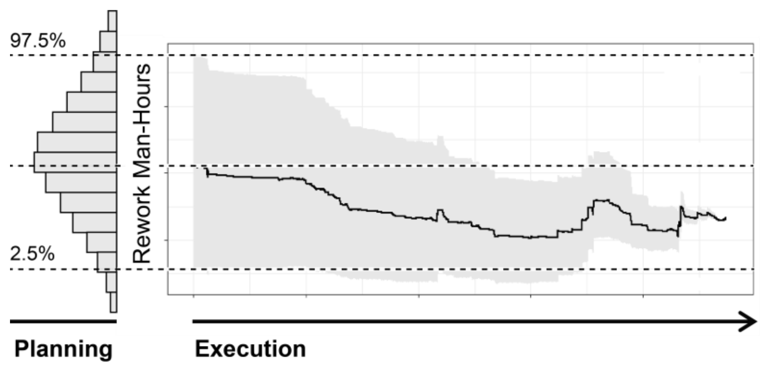

Figure 6. Decision support metrics for quality-induced rework cost estimation and control.

6 CONCLUSIONS

The use of predictive analytics and other advanced data analytics methods capable of extracting value from existing data is becoming increasingly common and employed across all types of industries and sectors (Manyika *et al*. 2011). While the construction industry is advancing the way they collect and store data, methods capable of transforming raw data into valuable and interpretable information for decision-support remains limited (Dean 2014). The simulation-based analytics framework for construction proposed here represents a new approach for decision support that takes advantage of emerging concepts and technologies in data analytics and computing sciences.

While demonstration projects and prototypes developed using a simulation-based analytics approach demonstrate the feasibility of the proposed framework, transformation and refinement of demonstration projects into automated, fully-functional decision support systems will require additional research and development in the areas of distributed simulation, information integration, and dynamic data updating. For such systems to become implemented and universally-accessible in industry, research efforts must also focus on creating systems that are easy-to-use and relevant to decision makers. Collaborations with industry will be essential for integrating analytics into organizational effectiveness and for enhancing sector efficiency and competitiveness.

Acknowledgments

This research is funded by a Collaborative Research and Development Grant (CRDPJ 492657) from the Natural Sciences and Engineering Council of Canada. Section 5 of this paper is adapted from Dr. Wenying Ji's doctoral thesis (Ji 2017). Simaan AbouRizk would like to thank Graham Industrial Services LP, JV Driver Projects Inc., Ledcor Constructors Inc., and PCL Constructors Inc. for their continued support of this project and Dr. Catherine Pretzlaw for her assistance with manuscript composition.

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