A Bayesian Network-based Decision Framework for Selecting Project Delivery Methods in Highway Construction

By

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ABSTRACT

Transportation agencies currently have several options in delivering their highway construction projects. Selecting an appropriate project delivery method (PDM) is a complex decision-making process. Researchers and transportation industry practitioners have been striving to discover the knowledge and methodologies to enhance the project delivery decision. However, through conducting an extensive literature review of existing methodologies, it is found that quantitative approaches, implementing probabilistic comparisons, to project delivery decisions are not fully addressed or understood. To fill this gap, this research aims at developing a decision framework by implementing Bayesian Network (BN), an advanced statistical tool, for selecting an appropriate PDM in highway construction industry. The BN-based decision framework incorporates the decision driving factors such as project attributes, risk profiles, project complexity, cost, and time. In developing the BN-based decision framework, this dissertation employed several research methodologies and techniques, including content analysis, questionnaire, case studies, cluster analysis, ANOVA, correlation and reliability analysis, and cross-validation techniques.

The dissertation follows a four-journal paper format. The first paper explores the impact of project size on highway design-bid-build (D-B-B) and design-build (D-B) projects. The second paper identifies and evaluates the risks involved in highway project delivery methods: D-B-B, D-B, and construction manager/general contractor (CM/GC). Building upon the findings and results from the first two papers, the third paper determines the probabilistic dependence between the decision factors and develops a theoretical decision framework using BNs for selecting an appropriate PDM. The fourth paper focuses on demonstrating the practical application of the proposed BN-based decision framework using case studies. In addition, the final paper presents a k-fold (cross-validation) technique to test and verify the accuracy of the proposed BN-based decision framework. This dissertation contributes to the theoretical body of knowledge by introducing a new quantitative approach using BNs for PDM selection. The findings from this study indicate that implementing BNs facilitate the owner/decision maker in better understanding of probabilistic comparison and selection of an appropriate PDM for highway construction projects. State transportation agency officials can utilize these findings as a supplemental tool for their project delivery decisions.

To my loving Grandma

Smt. Jalamma Pendyala

Family and Friends

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INTRODUCTION

Delivering and managing highway construction projects is a challenging task. One of the critical success factors in successfully delivering a highway project involves selecting an appropriate project delivery method (PDM). A PDM is the systematic approach of assigning the contractual responsibilities for designing and construction (AGC, 2011). The fundamental PDMs are design-bid-build (D-B-B), design-build (D-B) and construction manager/general contractor (CM/GC). There exist both opportunities and risks involved during the selection process of a PDM. Research has shown that no single method is right for every project (CMAA, 2012). However, it is recommendable to select a PDM in early phases of the project development process. Due to lack of detailed information on the project outcomes, with a high level of uncertainty, a project delivery decision-making process is complex. The selection process of a PDM may influences project performance. The project performance can be measured by several metrics such as cost growth, schedule growth, and construction intensity. Among other factors (e.g., the level of complexity, budget, and duration and other project characteristics), project risk profile plays a crucial role in the PDM selection process. Although state transportation agencies have been analyzing cost and schedule aspects of their highway projects, limited research has addressed of the interrelationship among project performance metrics, project characteristics and project risk profile with regard to the PDM selection process. This dissertation employed advanced statistical analysis, correlation and reliability analyses, factor analysis, and Bayesian Networks (BN) to develop a BN-based decision framework for selecting project delivery methods in highway construction. The key deliverables of this dissertation include the following:

1. Conducting an empirical comparison of project performance including cost and schedule growth associated with different PDM.
2. Comprehensive documentation of project risk profile that influences the decision making of delivery methods (D-B-B, D-B and CM/GC).

3. Developing a BN-based decision framework for selecting an appropriate project delivery method based on project cost, duration, project complexity, and project risk profiles. Case studies were conducted to verify the accuracy of the proposed model and demonstrate the testing and validation process.

DISSERTATION FLOW

The research problems, questions, methods, and results presented in this dissertation include a four-paper format. While the papers are independent, each paper builds directly upon the findings from the previous paper. As the papers are interrelated, some degree of overlapping exists between the papers (for example: research motivation, data collection, and methodology). This dissertation also presents a summary of contributions to both theoretical body of knowledge (academic) and practical application into the highway construction industry. A summary of theoretical and practical contributions of the research to date and suggestions for future research were presented. References used in each of the four papers were combined into the integrated references. Inclusive appendices were attached at the ending portion of the dissertation to facilitate the reader for quick reference.

The following section details the research motivation and sets the context for selecting project delivery decision as a research topic, detailing the background, identifying gaps in existing literature related to the research domain. In addition to the current status of the problem and research questions, the following section also presents the prospective contributions and expected research outcomes in building a BN based decision framework for selecting an appropriate PDM.

BACKGROUND AND RESERCH OVERVIEW

Background

State departments of transportation (DOTs) across the nation have been striving to adopt innovative procedures for selecting project delivery methods, procurement type, and payment provisions. The National Cooperative Highway Research Program (NCHRP) Report 658 indicated that "the need for delivering a highway project with in stipulated time frame, budget constraints are becoming increasingly risky and challenging." It is recommendable to make a delivery decision at early stages of project development process. Table 1 summarizes the existing project delivery selection methodologies.

Table 1. Existing Project Delivery Selection Methodologies

Researcher	Proposed Methodology
Paek and Lee (1992)	Fuzzy case based procurement selection
Gordon (1994)	Award method
Love et al. (1998)	Multi attribute utility analysis method
Konchar and Sanvido (1998)	Multivariate regression analysis
Gransberg (1999)	Statistical analysis
Kumaraswamy and Dissanayaka (2001)	Knowledge based decision support system
Chan et al. (2001)	Multi attribute selection model
Cheung et al. (2001)	Objective-subjective procurement selection method
Ribeiro (2001)	Case-based reasoning (CBR)
Ng et al. (2002)	Fuzzy membership function
Al Khalil et al. (2002)	Analytic Hierarchical Process (AHP)
Luu et al. (2003)	Case-based procurement advisory system (CPAS)
Luu et al. (2003)	Fuzzy case based procurement selection
Ling and Liu (2004)	Artificial neural network (ANN) technique
Ling et al. (2004)	Multivariate linear regression models
Mahdi and Alreshaid (2005)	Analytic Hierarchical Process (AHP)
Luu et al. (2005)	Case-based reasoning (CBR)
Oyetunji and Anderson (2006)	Multi criteria decision analysis method
Zhao and Liu (2006)	Non-structural fuzzy decision method (NSFDM)
Mafakheri et al. (2007)	AHP coupled with rough approximation concepts
Chan (2007)	Fuzzy procurement selection model (FPSM)
Ojiako et al. (2008)	Data envelopment analysis (DEA)

Zhuo et al. (2008)	Multi-Attribute fuzzy evaluation
Mostafavi and Karamouz (2010)	Fuzzy multi attribute decision making (FMADM)
Chen et al. (2011)	DEA-bound variable (BND) model
Moon et al. (2011)	Logistic regression analysis
Love et al. (2012)	Participatory action based approach
Tran (2013)	Risk based model

Gordon (1994) was one of the first researchers to propose a flowchart approach to select project delivery methods. Some researchers have explored a single project delivery method to highlight the benefits or challenges of these methods associated with project performance. Yates (1995) and Songer and Molenaar (1996), each focused on D-B. Their research on advantages and disadvantages of the D-B method, definitions of a successful D-B project and, strategies required to achieve a successful D-B project was informative to owners and practitioners. Beard et al. (2001) and Gransberg et al. (2006) produced books dedicated solely to the D-B method which also highlighted benefits of the method through careful examination and case studies. The work of Migliaccio et al. (2009) focused on the nuances of D-B two phase procurement by a case study of two significant projects, and this established an understanding of D-B procurement for highway projects. However, Migliaccio et al. (2009) noted that collection of significant data on procurement schedule durations and project characteristics was warranted to assess better which factors affect the duration of D-B procurement and also to be able to identify variations of the two-phase selection approach.

Though Lam et al. (2008) solely focused on the D-B method, their work introduced innovative statistical techniques, such as factor analysis, to analyze qualitative data from survey respondents and produced a defining index for D-B project success. Besides examining a singular project delivery method, Miller et al. (2000) were proponents of the concept of simultaneously using multiple project delivery methods. Not to be mistaken for implying the simultaneous use of multiple delivery methods on a single project, Miller et al. (2000) proposed that it would be advantageous for the public sector to be legally permitted to choose any of the available project delivery methods rather than limiting options to a single method, say D-B-B.

In advancing project delivery method selection, other researchers have underscored the value of experiential knowledge and proceeded to develop collections of such knowledge for applying lessons learned in past project delivery method selection to new projects. Kumaraswamy and Dissanayaka (2001), for example, established a knowledge-based advisory system to aid owners in making the project delivery method selection that would influence cost and schedule objectives for vertical building projects. This benefitted the project delivery method selection by highlighting important procurement and non-procurement variables that affect project performance. Kumaraswamy and Dissanayaka (2001) were prudent to highlight the limitations of their qualitative approach and make recommendations that a wider and more detailed study be designed to collect a project-based data-set, to extend findings into other construction project categories and to be able to categorize projects into more homogeneous groupings. Luu et al. (2003; 2006) emphasized a case-based approach founded on collected experiential knowledge. Luu et al. (2003; 2006) produced a computerized database that could be used as a decision tool for owners to access collected experiential knowledge and to compare the retrieved information with current project scenarios.

Further, the project delivery methods selection process was attained by the use of hierarchical analytical process (AHP) in work done by Al Khalil (2002) and by Alhazmi and McCaffer (2000). They essentially produced multi-criteria, multi-screening systems for project delivery method selection such as Alhazmi and McCaffer's (2000) project procurement system selection model (PPSSM). A potential flaw of approaching project delivery method selection in this manner is that explanations of the parameters or criteria used throughout the AHP can be vague and can easily be misconstrued by owners attempting to use this approach in practice. Ng et al. (2002) and Chan (2007) both established fuzzy logic selection models for construction projects. Those researchers were inspired to address what they felt was a deficiency of standard definitions of the parameters involved in project delivery method selection. Hence, they proposed models to overcome the need to establish universal definitions of project delivery attributes. Oyetunji and Anderson (2006) pointed out that, "Structured, quantitative decision analysis processes have several benefits over the simplistic and informal processes that typically characterize subjective evaluations." Over time many researchers made attempts to derive quantitative approaches from investigating project delivery methods. Consequentially, multi-attribute utility/value theories are developed in which the encompassing decision-making process was broken down into smaller components which could then be ranked and scored for comparison. Often, relative utility values of the components or attributes of project delivery would be determined on a numerical scale by survey respondents who had significant industry experience. Researchers whose work fell within this approach (Skitmore and Marsden, 1988; Love et al., 1998; Molenaar and Songer, 1998; Mahdi and Alreshaid, 2005; Oyetunji and Anderson, 2006) began to implement statistical techniques along with their conceived quantitative values to obtain an evaluation of project delivery method alternatives. However, the root of their quantitative values are based on subjective responses from industry practitioners and the results were still devoid of any relation to empirical project performance.

Even some of the recently developed project delivery selection methods (Tran, 2013;

Molenaar et al., 2014; Harper, 2014) contain subjective elements in the process of project delivery method selection and, some are designed for specific projects or circumstances. Tran (2013) developed a risk based model for selecting PDMs in highway constructions projects which is innovatively connected with probabilistic risk analysis. The model involves a complex statistical and computational approach that compares relative cost distributions for D-B, D-B-B and CM/GC. In addition, a sensitivity analysis was demonstrated to determine which risk factor is impacting the cost for each of the three delivery methods. A major limitation hindering widespread industry use is that the model can only be used for projects costing over $100M and it cannot be used without probabilistic risk-based cost estimating which remains a difficult concept in the construction industry to some extent. Tran et al. (2014) developed a project delivery selection matrix that can be used to validate the project delivery method decision. The process incorporates workshops with the agency personnel directly involved in project delivery and encourages discussion during the evaluation of project attributes, goals, and constraints as they are compared and rated, by a non-numerical system, among different delivery methods. The result is the selection of what the participants deem to be the optimal delivery method by this risk-based and objective selection approach to choose from the D-B-B, D-B, and CM/GC methods. *The proposed methods and significant results in this Ph.D. dissertation will allow the departure from work done by previous researchers who have made attempts to model project performance and project delivery selection*.

Research Setting

For optimizing the project performance, this research study has emphasized on project delivery decision which should be determined during initial phases of the project development process. Through an extensive literature review, it was observed that only a limited research employed probabilistic approaches for selecting PDMs in the highway construction industry. Not many selection frameworks/methodologies have exclusively addressed the integration of risk profiling, project attributes, cost and duration, complexity in determining the delivery decision. Failing to consider these elements would result in the underestimation of risks and consequences for project outcomes.

The use of D-B delivery began only in the 1990s and CM/GC after 2005 (FHWA, 2015). At the end of 2014, the number of states, or rather Departments of Transportation (DOTs), using the CM/GC method was at 17 and D-B use was at 35. Documented benefits of the two alternative contracting methods include saving cost, improving constructability, enhancing innovation, reducing risk, shortening construction schedules and the potential to lower operational cost and project life-cycle costs (Songer and Molenaar, 1996; FHWA, 2015; Touran et al., 2011). Growing demands of highway construction industry to accomplish a project within budget and schedule constraints leads to DOTs to enhance delivery method, procurement, payment and risk management. There is the need to explore and improve the skillful understanding of experts and concerned authorities regarding the risk factors and their impact on project outcomes. With empirical project data provided by state DOTs, there is an opportunity to apply statistical modeling techniques to explore these factors. Ultimately, there may be an opportunity to discover which factors, individually or in combination, lead to the highest likelihood of project success, as measured by various performance metrics. Conversely, there is an opportunity to discover which factors result in poor project performance or which delivery methods are not appropriate for particular projects.

Agencies frequently select project delivery methods subjectively. They rely on past experiences, case studies, comparisons of projects or even, trial and error. Each of those qualitative selection methodologies have the potential to introduce biases that could adversely affect the project performance. By using empirical project data and statistical modeling, agencies will have a more objective means for selecting an appropriate delivery decision. These decisions will be based on known highway construction project characteristics that can significantly influence the project performance. Motivated by the possibility of cost and time savings, numerous attempts have been made towards improving the selection process of an appropriate PDM. At the outset, the majority of procedures could collectively be considered as qualitative approaches. Many researchers have built upon the work of those qualitative procedures in developing the innovative ways of selecting a PDM. However, elements of those methods remain more on the subjective basis.

Research Questions and Point of Departure

As mentioned previously, the selection of the appropriate PDM is critical for project success, in most cases, the selection is made during the initial phases of project development process. This research seeks to enhance the decision-making process by developing statistically valid predictive models. Also, this adds value with a better understanding of the variables that impact the project success. The proposed work attempts to answer the following overarching research question:

> ***How do the risks, project attributes, project complexity, cost, and time factors be used to develop decision framework of the probabilistically suitable project delivery method in highway construction?***

To answer this overarching research question, various attributes that may influence project performance (e.g., the delivery method, project characteristics and risks) will be modeled.

The research study explores how these attributes affect project performance on their own and collectively. The overarching research question will be addressed through the following sub-questions.

1. *How do the projects perform regarding cost and schedule growth associated with each delivery method (e.g., D-B-B vs. D-B)?*
2. *How can we incorporate critical risk factors into the decision framework that can choose the best among the D-B-B, D-B, and CM/GC?*
3. *How can we apply BNs for developing a decision framework? What are the benefits of applying BNs for selecting the most suitable PDM and also considering critical risk factors in the decision framework?*
    - *How do the owners/agencies benefitted by implementing the proposed decision framework into practice for the project delivery method selection process?*
    - *What new information would be gained by applying BNs to decision making/ selection process for the risk-based project delivery method?*
    - *How does a Bayesian-based network decision framework contribute to this research area*?

The research approach section provides the research questions, detailing the data collection and data characteristics and briefly illustrating the proposed research's contributions. The accomplishment of a construction highway project depends on many influencing factors like cost over runs, schedule delays, market conditions, man power availability, environmental conditions, etc. However, all factors can be seen broadly regarding three basic parameters: cost, time and quality. Table 2 summarizes the primary research objectives, questions, outcomes and contributions associated with the three main research questions.

Table 2. Research questions, objectives and outcomes

Paper	Conceptual Idea	Research Questions	Outcome and contributions
1	How does the project performance metrics affect by project size and delivery method?	How does the project performance metrics of D-B-B and D-B associated with project size?	• Analyzed the projects based on delivery method and project size • Comparison based on cost growth and schedule growth as measuring metric.
2	What are the critical risk factors that influence the selection of delivery method?	How do the risk factors impact decision delivery?	• Identified critical risk factors for D-B-B, D-B/LB, D-B/BV and CM/GC • Determined the causes and factors that influence delivery decision
3	Implementing Bayesian Networks for selecting project method: theoretical application	How to select the project delivery method based on project attributes, Risk profile, and characteristics?	• Developed Bayesian Network based model as decision framework (theoretical) • Comparable probabilistic results before making delivery decision
4	Implementing Bayesian Networks to selecting project method: practical application?	How to implement decision framework and interpret the model results based on comparison of probabilistic inferences?	• Demonstration of Bayesian Network model (practical application) • Illustrative example with three nodal network • Three case studies • Model Tested and validated

The findings of this research offers several benefits and facilitate the decision makers and concerned authorities at managerial levels in selecting an appropriate PDM in highway construction. First, comparison of project performance metrics between D-B-B and D-B based on project size serve guidance for examining highway projects with varied budget ranges. Second, understanding risk profiling of different project characteristics and PDM can be helpful in the cyclic process of risk analysis and management. Third, the results from the initial phase of research served as input for developing theoretical framework to determine probabilistic interrelationships between the decision factors to selecting project delivery method using BNs. Finally, the computational model was developed as a continuing work to theoretical framework. Using computational models, for D-B-B, D-B, and CM/GC experimental case studies were conducted to demonstrate the practical application of the decision framework. The cross-validation of K-folds technique and sensitivity analysis were used to verify the accuracy and precision standards of the developed decision framework.

REFERENCES

Associated General Contractors (2004). Project delivery systems for construction, Associated General Contractors of America, Arlington, VA.

Al Khalil, M. I. (2002). “Selecting the appropriate project delivery method using AHP.” International Journal of Project Management, 20(6), 469-474.

Alhazmi, T., and McCaffer, R. (2000). “Project procurement system selection model.” Journal of Construction Engineering and Management, 126(3), 176–184.

Beard, J. L., Loulakis, M. C., Wundram, E. C. (2001). Design-Build: Planning Through Development, McGraw-Hill, New York, NY.

Chan, C. T. W. (2007). “Fuzzy procurement selection model for construction projects.” Construction Management and Economics, 25(6), 311-618.

Chen, Q., Jin, Z., Xia, B., Wu, P., and Skitmore, M. (2016). “Time and cost performance of design-build projects.” Journal of Construction Engineering and Management, 142(2)

Gordon, C. M. (1994). “Choosing appropriate construction contracting method.” Journal of construction engineering and management, 120(1), 196–210.

Gransberg, D., and Shane, J. (2010). “NCHRP Synthesis of Highway Practice 402: Construction Manager-at-Risk Project Delivery for Highway Programs.” Transportation Research Board of the National Academies, Washington, DC.

Gransberg, D. D., Koch, J. A., and Molenaar, K. R. (2006). Preparing for Design-Build Projects: A Primer for Owners, Engineers, and Contractors. American Society of Civil Engineers.

Konchar, M., and Sanvido, V. (1998). “Comparison of US project delivery systems.” Journal of Construction Engineering and Management, 124(6), 435-444.

Kumaraswamy, M. and Dissanayaka, S. (2001). “Developing a decision support system for building project procurement.” Building and Environment, 36(3), 337-349.

Love, P. E .D. Edwards, D. J., Irani, Z., and Sharif, A. (2012). Participatory action research approach to public sector procurement selection. ASCE Journal of Construction Engineering and Management, Vol.138, No.3, 2012, pp. 311–22

Love, P. E. ., Skitmore, M., and Earl, G. (1998). “Selecting a suitable procurement method for a building project.” Construction Management & Economics, 16(2), 221–233.

Luu, D. T., Ng, S. T., and Chen, S. E. (2003). “Parameters governing the selection of procurement system–an empirical survey.” Engineering, Construction and Architectural Management, 10(3), 209–218.

Luu, D. T., Ng, S. T., Chen, S. E. and Jefferies, M. (2006). “A Strategy for evaluating a fuzzy case based construction procurement selection system.” Advances in Engineering Software, 37, 159-171.

Mahdi, I. M., and Alreshaid, K. (2005). “Decision support system for selecting the proper project delivery method using analytical hierarchy process (AHP).” International Journal of Project Management, 23(7), 564–572.

Migliaccio, G., Gibson, G., O’Connor, J., and others. (2009). “Procurement of Design-Build Services: Two-Phase Selection for Highway Projects.” Journal of Management in Engineering, 25, 29.

Miller, J. B., Garvin, M. J., Ibbs, C. W., and Mahoney, S. E. (2000). “Toward a new paradigm: Simultaneous use of multiple project delivery methods.” Journal of Management in Engineering, 16(3), 58–67.

Molenaar, K. R., Songer, A. D., and Barash, M. (1999). “Public-sector design/build evolution and performance.” *Journal of Management in Engineering*, 15(2), 54-62.

Ng, S. T., Luu, D. T., Chen, S. E. and Lam K. C. (2002). “Fuzzy membership functions of procurement selection criteria.” Construction Management and Economics, 20, 285–296

Oyetunji, A. A., and Anderson, S. D. (2006). “Relative effectiveness of project delivery and contract strategies.” Journal of Construction Engineering and Management, 132(1), 3–13.

Skitmore, R. M. and Marsden, D. E. (1988). “Which procurement system? Towards a universal procurement selection technique.” Construction Management and Economics, 6, 71-89.

Songer, A. D., and Molenaar, K. R. (1997). “Project characteristics for successful public-sector Design-Build.” *Journal of Construction Engineering and Management*, 123(1), 34–40.

Touran, A., Gransberg, D. D., Molenaar, K. R., and Ghavamifar, K. (2011). “Selection of project delivery method in transit: drivers and objectives.” Journal of Management in Engineering, 27(1), 21–27.

Tran, D.Q., Harper, C.M., Molenaar, K.R., Haddad, N.B., and Scholfield, M.M. (2013). “Project Delivery Selection Matrix for Highway Design and Construction.” *In Transportation esearch Record: Journal of the Transportation Research Board, No. 2347, National Academies*, Washington, D.C., 3–10.

Yates, J. (1995). “Use of design/build in E/C industry.” Journal of Management in Engineering, 11(6), 33–38.

CHAPTER 2

EXPLORING THE IMPACT OF PROJECT SIZE ON HIGHWAY DESIGN-BID-BUILD AND DESIGN-BUILD PROJECT PERFORMANCE

ABSTRACT

The highway industry is increasingly using design-build (D-B) project delivery because of its documented benefits. Many studies have shown the superior performance of D-B projects when compared to traditional design-bid-build (D-B-B) projects. However, only limited studies compared project performance between D-B and D-B-B by project size. This study analyzed cost and schedule growth of 69 D-B-B and 69 D-B highway projects collected from six state Departments of Transportation (DOTs): Florida, Indiana, North Carolina, Ohio, Oregon, and Utah. These projects were classified into three groups in million (M) dollars, including \$10M to \$30M; \$30M to \$50M; and \$50M to \$70M. A two-way Analysis of Variance (ANOVA) was conducted to determine the impact of project delivery method, project size, and their interaction on the project cost and schedule performance metrics. The two-way ANOVA results indicated that project delivery method size had a statistically significant impact on cost performance. In terms of both the cost and schedule performance, D-B had lesser average cost growth and average schedule growth when compared to D-B-B, across the three levels of project size, but the results were not statistically significant. Additionally, the interaction effect of project size and delivery methods was found not statistically significant for both the cost and schedule performance. This study contributes to construction engineering and management body of knowledge by providing empirical comparisons between D-B-B and D-B performance based on project size. The study explored on what project delivery method and project size provide superior performance in terms of cost and schedule growth. The findings from this study also empower the state transportation agency officials to select an appropriate delivery method for their highway construction projects based on project size.

KEYWORDS

Project delivery methods, Cost Performance, Schedule Performance, Highways, Two-way ANOVA.

INTRODUCTION

A project delivery method is a comprehensive process of assigning the contractual responsibilities for designing and constructing a project (AGC 2004; Tran and Molenaar 2014). State departments of transportation (DOTs) across the nation use several methods for delivering their highway construction projects. In addition to the traditional design-bid-build (D-B-B) approach, alternative delivery methods including design-build (D-B) and construction manager/general contractor (CM/GC) are increasingly adopted nationwide. The scope of this study focused on comparing project performance between D-B-B and D-B projects.

Although most state DOTs have used D-B, it is still a relatively new approach to some DOTs. The highway industry first investigated D-B in 1988 when the Transportation Research Board (TRB) focused on improving alternative delivery methods. In the initial stages, Federal Highway Administration (FHWA) regulations did not allow the use of D-B on federally funded highway projects. In 1994, the FHWA authorized D-B under its Special Experimental Projects (SEP) No. 14 program that highlighted benefits of D-B regarding cost and schedule. Subsequently, the 1998 Transportation Equity Act for the 21st Century (TEA-21) allowed the use of D-B on select federally funded projects and required the FHWA to develop regulations for D-B project delivery use (TEA-21, Public Law, Title1, Subtitle C, Sec. 107). In 2002, the FHWA published its D-B contracting final rule, and the D-B project delivery method escalated from research status to mainstream use on federally funded projects (FHWA 2002). Since then D-B has increasingly been used in the highway industry. According to the Design-Build Institute of America (DBIA)'s report, only four state DOTs do not have specific authorization to use D-B for transportation projects as of 2017 (DBIA 2017).

D-B fundamentally differs with traditional D-B-B by the type of contractual relationships between the main players involved in a project. Conceptually, D-B has potential time savings because construction can begin before design plans are complete. In D-B, the design engineer and construction contractor have flexibility for innovations and opportunities to optimize workforce, equipment, and scheduling (Florida DOT 2004). The fundamental differences between D-B-B and D-B often result in diverted cost and schedule performance. A number of studies have compared cost and schedule performance between D-B and D-B-B projects. For the cost performance, previous studies (e.g., FHWA 2006; Kochar and Sanvido 1998; Hale et al. 2009; Shrestha et al. 2011; Goftar et al. 2014; Shrestha and Fernane 2016) showed that D-B outperforms D-B-B by an average percentage difference ranging from 5% to 10%. For the schedule performance, previous studies (FHWA 2006; Kochar and Sanvido 1998; Shrestha et al. 2011; Minchin et al. 2013; Shrestha and Fernane 2016) showed that D-B outperforms D-B-B by an average percentage difference ranging from 4% to 16%. It is noted that most of these findings were based on the expert's judgments (i.e., opinion-based data) or small project sample size. As a result, there are some inconsistent findings related to D-B-B and D-B performance in the existing literature.

A comprehensive literature review found that only limited studies have investigated the impact of project size on the cost and schedule performance between D-B-B and D-B projects. To fulfill this knowledge gap, the primary objective of this study is to empirically explore the impact of cost and schedule performance of a comparable set of D-B and D-B-B highway projects. From a comprehensive data set of 15,786 D-B-B and 596 D-B highway projects collected from six DOTs: Florida, Indiana, North Carolina, Ohio, Oregon, and Utah. Based on the contract award amount, data distribution is either skewed or sparingly observed for the projects that are lesser than $10 million and that are greater than $70 million. To explore the impact of project size without biased comparison, these projects were removed from the analysis. The remaining projects were classified into three equally ranging project size bins: $10 million to $30 million, $30 million to $50 million, and $50 million to $70 million. From the three project size bins, disparities exist between D-B-B and D-B sample sizes. To compare equal project sample size for D-B-B and D-B, the purposive random sampling technique was used. The purposive random sampling technique selects a diverse range of projects belonging to a specific pool. It allows the analysis to evaluate a comparable set of projects. By applying purposive random sampling technique, this paper compares the project performance of a comparable set of 69 D-B and 69 D-B-B highway projects.

LITERATURE REVIEW

Several studies compared the cost and schedule performance of D-B-B and D-B projects and examined various types of construction projects, including general buildings (CII 1997; Konchar and Savindo 1998; Songer and Molenaar 1997); apartment buildings (Park et al. 2015); military buildings (Hale et al. 2009); university buildings (Shrestha and Fernane 2016); industrial projects (Konchar and Savindo 1998; Songer and Molenaar 1997; CII 2002); mechanical projects (Riley et al. 2005), and highway projects. Readers can find a comparison of non-highway D-B-B and D-B project performance in previous studies such as Shrestha and Fernane (2016) and Goftar et al.

(2014). This section only focuses on discussing the cost and schedule performance metrics between D-B-B and D-B highway projects.

Ellis et al. (1991) evaluated 11 D-B projects in the Florida DOT Pilot D-B program and found that D-B produced approximately 11% cost savings and 36% faster delivery than D-B-B. With the updated database, Ellis et al. (2007) analyzed 66 D-B projects, 144 Incentive/Disincentive (I/D) projects, and 1,847 D-B-B projects. The result of that study showed that on average the cost growth of D-B-B projects was higher than D-B projects (9.4% vs. 4.5%). The cost growth for I/D projects was 12.5%. For the schedule metric, it was found that on average the schedule growth of D-B-B projects was higher than both D-B (16.5% vs. 7.1%) and I/D projects (16.5% vs. -0.3%). It should be noted that those studies did not report statistical significance.

Molenaar et al. (1999) conducted a survey of public-sector owners involved in the construction of the heavy highway, building, industrial, and environmental projects using the D-B method. The study found that a majority of these D-B projects were completed within budget and schedule. Ernzen and Schexnayder (2000) compared two similar highway projects delivered by D-B-B and D-B. By analyzing 10 construction activities from these projects, they found that the D-B projects outperformed the D-B-B projects in terms of total cost (10% less than the budget for the D-B project while 5% greater than the budget for the D-B-B project).

Warne (2005) investigated 21 D-B projects and 39 D-B-B projects with the cost ranging from $83 million to $1.3 billion across the United States. To compare D-B-B and D-B project performance, he gathered a significant amount of information about each of the 21 D-B highway projects by asking project managers hypothetical questions related to the project performance. Warne (2005) focused on four main indicators: schedule, cost, quality, and owner satisfaction. Based on the data collected from questionnaire and interviews, he found that the average cost growth for D-B projects was less than 4%. He also found that 76% of the D-B projects were completed ahead of schedule. When asking interviewees to estimate the project duration if it had been built by using D-B-B, Warne (2005) showed that 100% of the interviewees believed that the selected projects were built faster with D-B than D-B-B.

The FHWA conducted a Design-Build Effectiveness Study to benchmark D-B against D-B-B (FHWA 2006). The majority of this study was qualitative and based on survey questionnaires. Overall, participants in that study estimated that D-B delivery reduced the overall duration of their projects by 14%, reduced the total cost of their projects by 3% and maintained the same level of quality. The respondent also estimated that the average number of change orders for D-B projects was lower than D-B-B projects. The FHWA study also collected limited empirical data. It looked in detail at 11 pairs of comparable D-B and D-B-B projects. The comparison of these projects found -4.2% average schedule growth for D-B and 4.8% for D-B-B projects. It found 7.4% average cost growth for D-B and 3.6% for D-B-B projects

Shrestha et al. (2007) conducted a quantitative comparison of four D-B and 11 D-B-B projects. They found that the average cost growth for D-B projects was, albeit on a small number of projects, statistically significant lower average than that for the D-B-B project (-5.5% for D-B vs. 4.1% for D-B-B). The average of schedule growth for D-B projects was lower than that of D-B-B projects (7.6% for D-B vs. 12.9% for D-B-B). The average change order amount of D-B-B projects was lower than D-B projects (5.3% for D-B vs. 3.9% for D-B-B). However, there was no statistical significance with schedule growth and change order metrics. In a later study, Shrestha et al. (2011) analyzed six D-B and 16 D-B-B projects. They found that the average of total cost growth for D-B projects was 1.5% higher than that for the D-B-B project (7.8% for D-B vs. 6.3% for D-B-B). The average of schedule growth for D-B projects was 15.4% higher than that of D-B-B projects (20.5% for D-B vs. 5.1% for D-B-B).

Recently, Minchin et al. (2013) randomly selected 60 projects (30 for each method) from the Florida DOT database. After removing outliers, statistical analysis was performed on 21 D-B and 29 D-B-B projects. The results indicated that the D-B-B projects performed significantly better in terms of cost, but not in terms of duration. Specifically, Minchin found that the cost growth of D-B and D-B-B projects was 45.3% and 20.4%, respectively; the schedule growth of D-B and D-B-B projects was 20.2% and 23%, respectively. These results contradicted many previous studies in the literature. The authors' justification was that many highway projects in their study were completed about 15 years ago and at that time D-B was still developing while D-B-B had been used for a long time (Minchin et al. 2013). Table 1 summarizes the key findings of performance comparison between D-B-B and D-B delivery methods for highway projects.

Table 1. Summary of Highway D-B-B and D-B Project Performance Comparisons

Studies	Delivery Methods	Sample size	Major Findings and Statistical Results
COST GROWTH			
Warne (2005)	D-B vs. D-B-B	60	D-B outperformed D-B-B by 4%. No statistical results were reported.

FHWA (2006)	D-B vs. D-B-B	22	D-B-B outperformed D-B by 3.8%. No statistical results were reported.
Ellis et al. (2007)	D-B vs. D-B-B	1913	D-B-B outperformed D-B by 4.9%. No statistical results were reported.
Shrestha et al. (2007)	D-B vs. D-B-B	15	D-B outperformed D-B-B by 9.6%. F-test was used to compare means of two samples with p-value = 0.03. Note that F-test is often used to test variances of two samples.
Shrestha et al. (2011)	D-B vs. D-B-B	22	D-B-B outperformed D-B by 1.5%. ANOVA was used for analysis, but no significant results were found, p-value = 0.751.
Minchin et al. (2013)	D-B vs. D-B-B	50	D-B-B outperformed D-B by 24.9%. Nonparametric statistical tests were used but no significant results were found, p-value = 0.209.
TOTAL COST/UNIT COST			
Ellis et al. (1991)	D-B vs. D-B-B	11	D-B outperformed D-B-B by 11%. No statistical results were reported.
Ernzen and Schexnayder (2000)	D-B vs. D-B-B	2	D-B outperformed D-B-B by 15%. No statistical results were reported.
FHWA (2006)	D-B vs. D-B-B	22	D-B outperformed D-B-B by 3%. No statistical results were reported.
Molenaar (2003)	D-B vs. D-B-B	1	D-B-B outperformed D-B by 23%. No statistical results were reported.
Ernzen et al. (2003)	D-B vs. D-B-B	13	D-B outperformed D-B-B by 4%. No statistical results were reported.
SCHEDULE GROWTH			
FHWA (2006)	D-B vs. D-B-B	22	D-B outperformed D-B-B by 9%. No statistical results were reported.
Ellis et al. (2007)	D-B vs. D-B-B	1913	D-B outperformed D-B-B by 9.4%. No statistical results were reported.
Shrestha et al. (2007)	D-B vs. D-B-B	15	D-B outperformed D-B-B by 5.3%. F-test was used to compare means of two samples with p-value = 0.51. Note that F-test is often used to test variances of two samples.
Shrestha et al. (2011)	D-B vs. D-B-B	22	D-B-B outperformed D-B by 15.4 %. ANOVA was used for analysis, but no significant results were found, p-value = 0.17.
Minchin et al. (2013)	D-B vs. D-B-B	50	D-B outperformed D-B-B by 2.8%. Nonparametric statistical tests were used but no significant results were found, p-value = 0.229.
DELIVERY TIME			
Ellis et al. (1991)	D-B vs. D-B-B	11	D-B outperformed D-B-B by 36%. No statistical results were reported.
Warne (2005)	D-B vs. D-B-B	60	100% interviewees agreed that D-B was faster than D-B-B. No statistical results were reported.
FHWA (2006)	D-B vs. D-B-B	22	D-B outperformed D-B-B by 14%. No statistical results were reported.
Molenaar (2003)	D-B vs. D-B-B	1	D-B outperformed D-B-B by 16%. No statistical results were reported.
Ernzen et al. (2003)	D-B vs. D-B-B	13	D-B outperformed D-B-B by 22%. No statistical results were reported.

POINT OF DEPARTURE

A comprehensive literature review revealed that although many studies have attempted to compare cost and schedule performance of D-B-B and D-B projects, most of them were based on opinion-based data or small sample size. In fact, limited studies have empirically evaluated project performance of D-B versus D-B-B based on project size. To fulfill this gap, this study collected 15,786 D-B-B and 596 D-B highway projects from six state DOTs that have an extensive experience in D-B, including: Florida, Indiana, North Carolina, Ohio, Oregon, and Utah. The authors then randomly selected only a comparable set of 69 D-B-B and D-B projects for the analyses. These projects were classified into three categories based on a contract awarded amount: \$10M to \$30M; \$30M to \$50M; and \$50M to \$70M. To evaluate cost and schedule performance of D-B-B and D-B associated with these project sizes, a two-way Analysis of Variance (ANOVA) and its post hoc analysis were conducted.

PERFORMANCE METRICS

There are a number of performance metrics available to evaluate construction projects. This study employed the two main performance metrics: cost growth and schedule growth, to evaluate project performance between D-B-B and D-B. These metrics were measured using the Equations (1) and (2).

$$\text{Cost Growth} = \frac{\text{Final Cost} - \text{Contract Awarded Amount}}{\text{Contract Awarded Amount}} * 100\% \qquad (1)$$

$$\text{Schedule Growth} = \frac{\text{Actual Duration} - \text{Planned Duration}}{\text{Planned Duration}} * 100\% \qquad (2)$$

The cost growth metric is the percentage change in cost between the contract awarded amount and the final cost as shown in the Equation 1. During the project, change orders may increase the cost of the project causing a positive cost growth. A possibly overestimated or limiting work scope can reduce project cost and thus results in negative cost growth. For D-B-B, this value is for construction costs only. For D-B, this value is inclusive of construction and design costs by the design-builder. The final cost is the total cost of installation of all project components after changes and miscellaneous expenses accrued. The contract awarded amount is the price quoted by the bid winner and was not expected to include construction engineering inspection, right-of-way (ROW), or other costs unless part of the original bid.

The schedule growth metric indicates projects that are completed within the planned construction schedule (negative value) or beyond the planned construction schedule (positive value). It is the percentage change from the awarded contract duration of the project to the actual construction duration of the project as shown in the Equation 2. The awarded contract duration is estimated by the contractor or design-builder as necessary to execute and complete the physical building activities for the entire project. The duration is calculated by the difference between construction-started date and bid-contract-end date. The actual construction duration is measured as the period (in days) from the date that construction work started to the date of substantial completion of the work. For D-B-B, the schedule growth value involves activities during the construction phase. For D-B, this value is inclusive both of construction and design performed by the design-builder.

RESEARCH METHODS

The objective of this study is to discover the relationship between project sizes and project delivery methods in terms of cost and schedule performance. Specifically, this study aimed at answering the following research question: what project delivery method and project size provide superior performance in terms of cost and schedule growth in highways? To address this research question, three research hypotheses were developed and tested as follows:

- H1: Project delivery methods have a significant impact on cost and schedule performance metrics for highway projects. The null hypothesis that project delivery methods have no significant impact on performance metrics can be expressed mathematically in Equation (3).

$$\mu_{\text{DBB performance metrics}} = \mu_{\text{DB performance metrics}} \tag{3}$$

Where $\mu_{\text{DBB performance metrics}}$, $\mu_{\text{DB performance metrics}}$ are the mean performance metrics (e.g., cost growth and schedule growth) of D-B-B and D-B projects, respectively.

- H2: Project sizes have a significant impact on cost and schedule performance metrics for highway projects. The null hypothesis that project sizes have no significant impact on performance metrics can be expressed mathematically in Equation (4).

$$\mu_{\text{Performance metrics (1)}} = \mu_{\text{Performance metrics (2)}} = \mu_{\text{Performance metrics (3)}} \qquad (4)$$

Where $\mu_{\text{Performance metrics (1), (2), (3)}}$ are the mean performance metrics (e.g., cost growth and schedule growth) of the three different project sizes.

- H3: The interaction between project delivery methods and project sizes has a significant impact on cost and schedule performance metrics for highway projects. The null hypothesis that there is no interaction between project delivery methods and project sizes ($I_{\text{Project size (i) X (delivery method)}} = 0$) in terms of performance metrics can be expressed mathematically in Equation (5).

$$\mu_{DBB,1}-\mu_{DB,1} = \mu_{DBB,2}-\mu_{DB,2} = \mu_{DBB,3}-\mu_{DB,3} \qquad (5)$$

The first two hypotheses are referred to as main effects. The third hypothesis is referred to as the interact effect. To test these above research hypotheses, the two-way ANOVA test was conducted to determine the effects of project delivery methods and project size on the performance metrics (cost and schedule). Assuming the type I error (alpha) of 5%, for the null hypothesis to be false, the statistical significance (p-value) should be less than or equal to 0.05. For the third research hypothesis, rejecting the null hypothesis indicates the interaction between project delivery methods and project size exists for associated performance metrics. It is noted that a two-way ANOVA cannot be used to assess the main effects in the presence of a significant interaction. Instead, a one-way ANOVA analysis on the cell means or Post Hoc Tests should be used to avoid assessing the main effects across any interaction effect. The following sections discuss data collection, analysis, and results in detail.

DATA COLLECTION

To analyze and compare project performance between D-B-B and D-B highway projects, the authors requested data from six DOTs (Florida, Indiana, North Carolina, Ohio, Oregon, and Utah) that have most extensive experience in use of D-B delivery. In the request form, we asked for relevant information of highway projects completed from 2000 to 2014. The project under construction was not eligible for this study. The primary information in the request included: (1) project name or identification number; (2) project delivery method (D-B-B versus D-B); (3) project cost data; and (4) project schedule data. The project cost data has information related to engineers' estimate, contract awarded amount, final cost, construction engineering and inspection cost, and final design cost. The project schedule data has information related to date advertised, award date, construction start date (notice to proceed), bid contract end date, and final contract end date (substantial completion).

After multiple rounds of communication with six state DOTs' representatives, we initially received a comprehensive data set comprised of 16,382 highway projects. However, upon initial data collection, the fields relating to cost and schedule were somewhat inconsistent across the six state DOTs due to the attributes of each state DOT's contract record system. This inconsistency presented a significant obstacle to analyze and compare project performance. To overcome this challenge, the authors systematically analyzed and mined a comparable data field from each state's project database. The result of this process was verified by each state DOT's representative. Additionally, the authors conducted an on-line meeting with all six state DOT's representatives to solve inconsistent data issues and review the final database. As a result, some minor changes were made to obtain quality data across six state DOTs. For example, some state DOTs recorded the project completion date as a final contract end date while other DOTs recorded it as a substantial completion date. Through the discussions with six state DOT's representatives, it was determined that these dates had the same meaning. After the database was verified both individually and collectively, it was available for further analysis. The following sections discuss data screening and the purposive random sampling technique for analyzing the cost and schedule project performance between D-B-B and D-B.

ANALYSIS

This section presents four main steps in the data analysis process: (1) data screening, (2) purposive random sampling, (3) data treatment, and (4) two-way ANOVA analysis.

Data screening

The main objective of data screening is to capture a comparable set of D-B-B and D-B projects associated with each project size category. The authors employed a systematic approach to identifying and cleaning data errors, missing data, and outliers. Firstly, descriptive statistics (e.g., mean, minimum, and maximum) on the contract awarded amount were conducted to understand the overall data distribution and its characteristics. From the total of 16,382 projects across six state DOTs, it is noted that there was a wide range of contract award price. For 15,786 D-B-B projects, the contract awarded amount ranged from a minimum of $4,000 to a maximum of $219,996,000. Likewise, for 596 D-B projects, the contract awarded amount varied from a minimum of $24,477 to a maximum of $242,787,000.

Data screening identified a significant number of small projects, out of 16,382 projects collected, 205 D-B and 9,565 D-B-B projects had a contract price of less than $1 million. These projects often involved a portion of work that did not present the typical features of D-B-B and D-B project delivery. As a result, these projects were removed from the analyses. In addition, data distribution, based on contract award amount, is sparingly observed for projects less than $10 million and greater than $70 million. To eliminate unequal range of project size classification and better compare the performance of delivery methods, the authors took a conservative approach to removing all projects less than $10 million and greater than $70 million from the dataset. In the final step of data screening, all outliers based on contract award amount were removed to attain refined and comparable set of projects. This process resulted in a total of 698 projects, including 579 D-B-B and 119 D-B projects for further analysis. These projects were then divided into three categories by project size, with equal range, in terms of a million (M) dollars: $10M to $30M; $30M to $50M; and $50M to $70M. Table 2 summarizes the mean, minimum, and maximum values of contract awarded amounts of the three categories along with the sample size (n) associated with D-B-B and D-B projects.

Table 2. Classification of D-B-B and D-B projects

Delivery Method	Project Size	N	Mean	Min	Max
D-B-B	$10M - $30M	465	$16,471,620	$10,008,331	$29,959,073
	$30M - $50M	81	$38,261,434	$30,163,798	$49,523,514
	$50M- $70M	33	$58,508,256	$50,340,834	$68,535,720
D-B	$10M - $30M	69	$18,028,663	$10,073,110	$29,453,572
	$30M - $50M	27	$37,979,141	$30,523,000	$49,005,000
	$50M- $70M	23	$60,446,479	$51,292,885	$69,263,035

Data Treatment

Before performing the actual two-way ANOVA analysis, the authors conducted a series of statistical tests to identify outliers, based on performance metrics. Outliers are cases that have data values that are much larger or smaller than the data values for the majority of cases in the dataset (Navidi 2008). In the boxplot, any point that is more than 1.5 interquartile range above the third quartile, or more than 1.5 interquartile range below the first quartile is considered an outlier. Further, any point that is more than 3 interquartile range from the first or third quartile is considered an extreme outlier. It is important to note that outliers should always be scrutinized to determine whether the outliers should be removed.

The cost and schedule growth of each pair were calculated using Equations (1) and (2). For each project size category, box plots were generated to visualize and determine the outliers for the D-B-B and D-B projects. The results showed a number of outliers in the dataset. To obtain a set of D-B-B and D-B projects without outliers in both cost and schedule growth, the authors took a conservative approach to removing all outliers. This process is iterative until no outlier is observed. Table 3 summarizes the sample size (n) of D-B-B and D-B projects without outliers across three different project size categories.

Table 3. Sample size of D-B-B and D-B projects

Performance Metric	Project size	Sample size without Outliers		Sample size using purposive sampling	
		$n_{D\text{-}B\text{-}B}$	$n_{D\text{-}B}$	$n_{D\text{-}B\text{-}B}$	$n_{D\text{-}B}$
Cost Growth	\$10M - \$30M	425	59	23	23
	\$30M - \$50M	75	26	23	23
	\$50M- \$70M	25	**23**	23	23
Schedule	\$10M - \$30M	383	64	19	19

Growth	$30M - $50M	58	22	19	19
	$50M- $70M	25	**19**	19	19

Purposive Random Sampling

Table 3 shows that the number of D-B-B projects was substantially bigger than that of D-B projects. To obtain the reliable and comparable set of D-B-B and D-B projects associated with each project category, the authors utilized the purposive random sampling technique that is a built-in feature in the statistical package for social sciences (SPSS). Purposive sampling is a non-probability sampling method that is based on characteristics of a population and the objective of study (Black 2010). Researchers (e.g., Patton 1990, Kuzel 1999; Black 2010) found that the purposive sampling technique is appropriate when the study focuses on a particular subgroup (e.g., project size in this study) or when data required for the study (e.g., numbers of completed D-B projects) is limited. These findings confirmed that purposive sampling is a suitable technique to select comparable pairs of D-B-B and D-B projects for the analysis.

One can observe from Table 3 that the minimum sample size, based on cost growth metric, of all three project categories was D-B projects ranging $50M to $70M ($n_{D\text{-}B}$ = 23). This minimum sample size serves as a fundamental threshold to use the purposive random sampling technique. Specifically, three pairs of D-B-B and D-B projects associated with three project size categories ($10M to $30M; $30M to $50M; and $50M to $70M) with the sample size of 23 were generated using SPSS. For example, for the $50M to $70M project category, 23 D-B-B projects were randomly selected from the total of 25 projects. Similarly, for the $10M to $30M project category, 23 D-B-B and 23 D-B projects were randomly selected from the total of 425 D-B-B and 59 projects, respectively. Referring Table 3, purposive sampling resulted in an equal sample size of 23 based on cost growth and 19 based on schedule growth.

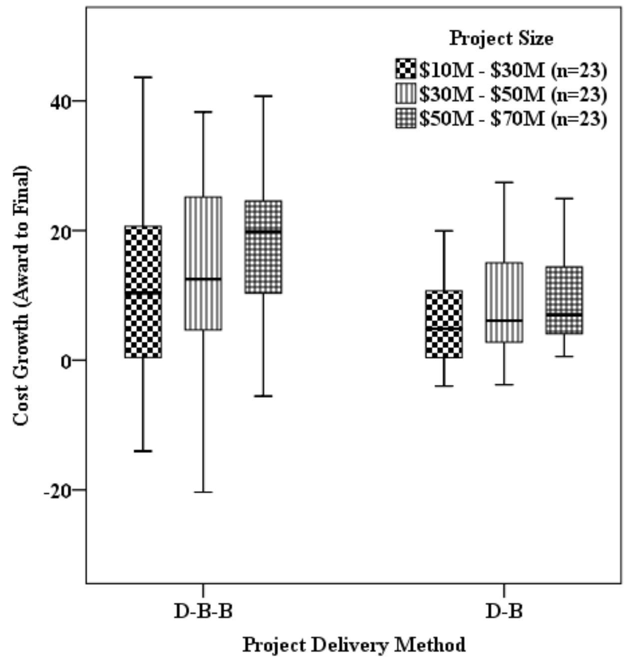

Figure 1. Box Plot for Cost Growth

Figures 1 and 2 display the box plots of cost growth and schedule growth for each project size, respectively.

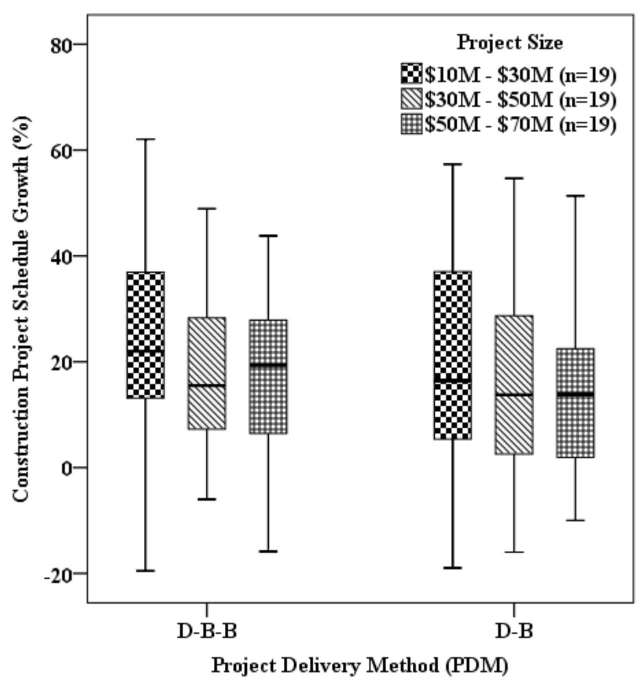

Figure 2. Box Plot for Schedule Growth

Two-way ANOVA Analysis

The main purpose of conducting a two-way ANOVA is to understand if there is an interaction between project size and project delivery methods on cost and schedule performance metrics. Essentially, interaction describes a situation in which the effect of one variable on a second variable is not uniform between levels. The underlying assumptions of the two-way ANOVA, are as follows:

1. The sample are independent and randomly selected;
2. The dependent variables should be in the interval or ratio scale (continuous data);
3. The independent variables should consist of two or more categorical levels;
4. The dependent variables should be approximately normally distributed for each combination of the two independent variables; and
5. The variances of each combination between the two independent variables should be equal;

The first assumption is typically referred to as the assumption of independence. The sample of D-B-B and D-B projects in this study satisfied this assumption because there were no relationships both within and between groups and levels. Additionally, the purposive random sampling technique was used to randomly select D-B-B and D-B projects for each level of project size. The second assumption requires that the dependent variable should be either the ratio or interval scale. In this study, two dependent variables (cost growth and schedule growth) were measured on the ratio scale. The third assumption requires that the independent variable should be measured on a categorical or discrete scale with at least two levels. In this study, both two independent variables (project delivery methods and project size) were on the categorical scale with two and three levels, respectively. The fourth assumption involves testing normal distribution of dependent variables for each combination of the two independent variables. Shapiro-Wilks test was performed between D-B-B and D-B for both cost growth and schedule growth, all p-values were larger than 0.05. Thus, the cost and schedule growth variables for each combination was normally distributed. The fifth assumption involves testing homogeneous variance of each combination between the two independent variables. Levene's test for equality of variance was performed. The result was statistically significant with p-value equal 0.00 less than 0.05. However, this assumption is not strictly required for a two-way ANOVA. Researchers concluded that ANOVA is robust to heterogeneity of variance if the sample sizes for each group are equal or approximately equal (Box 1953; Jaccard and Guilamo-Ramos 2002; Gastwirth et al. 2009; Moser 2016). In this study, the sample sizes of each combination between the two independent variables were equal after removing outliers. As a result, it is reasonable to conclude that the final assumption was satisfied for the two-way ANOVA.

Once all assumptions were successfully tested, the two-way ANOVA was performed to explore the relationship between project sizes and project delivery methods in terms of cost and schedule performance. The two-way ANOVA provides a means to assess the interaction effect of two independent variables (project sizes and delivery methods) before assessing their main effects on the dependent variables (project cost and schedule growth). If no interaction is present, each factor in the two-way ANOVA can be interpreted in isolation by using the principle that applies to the analysis of one-way ANOVA. If interaction is present, the impact of one factor depends on the levels of the other factor. Several approaches including a one-way ANOVA analysis on the cell means, Post Hoc Tests, Simple Effects Tests, or Planned Comparison can be used to avoid assessing the main effects across any interaction effect (Stevens 1999). The following sections discuss the results of both descriptive analysis and the two-way ANOVA in detail. The key difference between descriptive and inferential statistics (ANOVA) is that the descriptive statistics do not allow for making any conclusions beyond the data analyzed.

RESULTS

Descriptive Statistics Results

Table 4 summarizes the mean values (μ) of cost and schedule growth between D-B-B and D-B across three different project size categories ($10M to $30M; $30M to $50M; and $50M to $70M). For both the cost growth and schedule growth, D-B projects performed better than D-B-B projects for all the three project categories. Specifically, for project size $10M to $30M, the average cost growth of D-B projects was lower than that of D-B-B projects (2.85% versus 6.19%); and the average schedule growth of D-B projects was lower than that of D-B-B projects (19.63% versus 23.21%). For project size $30M to $50M, the average cost growth of D-B projects was lower than that of D-B-B projects (4.61% versus 5.97%); and the average schedule growth of D-B projects was lower than that of D-B-B projects (16.43% versus 19.26%). Lastly, for project size $50M to $70M, the average cost growth of D-B projects was lower than that of D-B-B projects (4.65% versus 8.97%); and the average schedule growth of D-B projects was lower than that of D-B-B projects (14.81% versus 17.93%).

Table 4. Summary of Cost Growth and Schedule Growth

Metric	Project Size	$n_{D\text{-}B\text{-}B}$	$n_{D\text{-}B}$	$\mu_{D\text{-}B\text{-}B}$	$\mu_{D\text{-}B}$
Cost Growth	$10M - $30M	23	23	6.19%	2.85%
	$30M - $50M	23	23	5.97%	4.61%
	$50M- $70M	23	23	8.97%	4.65%
Schedule Growth	$10M - $30M	19	19	23.21%	19.63%
	$30M - $50M	19	19	19.26%	16.43%
	$50M- $70M	19	19	17.93%	14.81%

It is important to note that the results presented in Table 4 were purely descriptive statistics. They were not inferential statistic results. Readers must be cautious about interpreting the results from Table 4 for a given pair of D-B-B and D-B projects.

Two-Way ANOVA Results

To draw statistical conclusions of D-B-B and D-B project performance associated with each project size category, the two-way ANOVA was conducted. Both cost and schedule growth performance metrics were included in the analysis.

Cost Growth

Table 5 shows a standard format of the two-way ANOVA's result for the cost growth metric with two main effects (delivery method and project size) and the interaction effect (delivery method x project size). Type III sum of squares is often used for unbalanced data and appropriate for testing a main effect after the other main effect and interaction (Keppel and Wickens 2004). One can observe from Table 5 that the interaction effect of delivery methods and project size was not significant at the alpha level of 0.05 (p-value = 0.47 > 0.05). Thus, it is reasonable to conclude that the mean differences of cost growth among D-B-B and D-B were constant across three levels or categories of project size. Without the interaction effect, the main effects (delivery methods and project size) can be analyzed and interpreted in isolation. It is noted that if the main effect is found significant, the post-hoc analysis should be performed. The purpose of conducting post-hoc analysis is to determine where the significant differences likely exist. If neither main effect is significant, it is reasonable to conclude that there is no evidence of any relationship between dependent variables and independent variables.

Table 5. Two-way ANOVA result for Cost Growth

	Type III	df	Mean	F	Sig.

Parameter	Sum of Squares		Square		
Delivery Method	312.06	1	312.06	9.08	0.03
Project Size	124.77	2	62.39	1.82	0.17
Delivery Method x Project Size	52.17	2	26.08	0.76	0.47
Residual Variation	4533.99	132	34.35		
Total	9257.10	138			

Table 5 indicates that the main effect, project delivery, was found significant at the alpha level of 0.05 (p-value = 0.03 < 0.05). This means that there is a statistically significant difference in terms of cost growth between D-B-B and D-B projects. From the Tukey post hoc analysis to further examine which delivery method performs better than the other (a pairwise comparison). The results indicate that the mean difference of cost growth between D-B and D-B-B projects was -3.01% (D-B has lesser average cost growth) and it was statistically significant (p-value = 0.00 < 0.05).

Similarly, Table 5 shows that the main effect, project size, was found not significant at the alpha level of 0.05 (p-value = 0.17 > 0.05). Based on the pairwise comparisons, project size $10M to $30M has mean differences of cost growth against $30M to $50M and $50M to $70M were -0.77% and -2.29% respectively. Similarly, for the project size $30M to $50M has the mean difference of cost growth against $50M to $70M was -1.52%. However, these differences were not significant at the alpha level of 0.05 (p-value > 0.05).

Schedule Growth

Table 6 displays a standard format of the two-way ANOVA's result for the schedule growth metric with two main effects (delivery method and project size) and the interaction effect (delivery method x project size). Table 6 indicates that the interaction effect of delivery methods and project size was not significant at the alpha level of 0.05 (p-value = 0.99 > 0.05). Thus, it is reasonable to conclude that the mean differences of schedule growth among D-B-B and D-B were constant across three levels or categories of project size.

Table 6. Two-way ANOVA result for Schedule Growth

Parameter	Type III Sum of Squares	df	Mean Square	F	Sig.
Delivery Method	287.34	1	287.34	0.88	0.35
Project Size	511.68	2	255.84	0.79	0.46
Delivery Method x Project Size	2.77	2	1.39	0.00	0.99
Residual Variation	35058.91	108	324.62		
Total	75069.48	114			

Table 6 indicates that the main effect, project delivery, was found not significant at the alpha level of 0.05 (p-value = 0.35 > 0.05). This means that there is not enough evidence from the samples of projects collected from this study to conclude that D-B statistically performs better than D-B-B in terms of schedule growth. The results indicate that the mean difference of cost growth between D-B and D-B-B projects was -3.17% (D-B has lesser average schedule growth) and it was not statistically significant (p-value = 0.35 >0.05).

Similarly, Table 6 shows that the main effect, project size, was found not significant at the alpha level of 0.05 (p-value = 0.47 > 0.05). Based on the pairwise comparisons, project size $10M to $30M has mean differences of schedule growth against $30M to $50M and $50M to $70M were 3.57% and 5.05% respectively. Similarly, for the project size $30M to $50M has the mean difference of schedule growth against $50M to $70M was 1.47%. However, these differences were not significant at the alpha level of 0.05 (p-value > 0.05).

DISCUSSION

The aim of this study was to explore the impact of project size on cost and schedule growth between D-B and D-B-B projects in the highway industry. Both descriptive statistics and inferential statistics (two-way ANOVA) analysis were conducted. For the schedule growth, the descriptive statistics results indicated that on average the schedule growth of D-B projects was lower than that of D-B-B projects regardless of project size (Table 4). However, the two-way ANOVA analysis results showed that there were no statistical significant differences in schedule growth between D-B and D-B-B projects. These findings were supported by several studies in the highway delivery literature. For example, FHWA (2006) compared 11 pairs of D-B-B and D-B highway projects and concluding that schedule growth of D-B projects was 9% less than D-B-B projects with regard to descriptive statistics result. The study did not conduct the inferential statistics. Shrestha et al. (2007) compared four D-B versus 11 D-B-B highway projects and concluded that the schedule growth of D-B was 5.3% less than D-B-B (7.6% for D-B versus 12.9% for D-B-B). The study also noted that the difference was not significant (p-value = 0.51). Recently, Minchin et al. (2013) conducted nonparametric statistics of 50 D-B and D-B-B highway projects. The study concluded that D-B outperformed D-B-B by 2.8% in schedule growth, but the result was not significant (p-value = 0.229). For the project size \$50M to \$70M, this study found that the schedule growth of D-B projects was 3.12% lower than that of D-B-B projects (Table 4). This finding was in contrast to the finding by Shrestha et al. (2011), which compared 16 D-B-B large (>\$50 M) highway projects in Texas with six D-B projects nationwide. Shrestha et al. (2011) showed that the schedule growth of D-B was 15.4% higher than D-B-B (20.5% versus 5.1%). One of the possible reasons for this contrast could be related to sampling errors.

For the cost growth, the descriptive statistics results indicated that D-B outperformed than

D-B-B for all the project size categories (Table 4). However, the two-way ANOVA analysis results showed that there were not statistically significant differences in cost growth between D-B and D-B-B projects at the alpha level of 0.05. There was enough evidence from the data collected for this study to conclude that D-B projects statistically had 3.01% less cost growth than D-B-B projects (p-value = 0.00 < 0.05). These results were in accordance with findings of some studies in the highway delivery literature. Warne (2005) concluded that D-B had 4% less in the cost growth in comparison with D-B-B. Shrestha et al. (2007) found that the cost growth of D-B projects was 9.6% significantly less than that of D-B-B projects (p-value = 0.03 < 0.05). For the projects over $50M to $70M, the descriptive statistics results (Table 4) showed that D-B outperformed D-B-B in terms of cost growth (4.65% versus 8.97%). This finding was also supported by the previous study on large highway projects. However, it was in contrast with the finding by Shrestha et al. (2011) which concluded that D-B-B had 1.5% less schedule growth than D-B for large highway projects (> $50M). It is noted that some other studies found that D-B-B had less cost growth than D-B (e.g., FHWA 2006; Ellis et al 2007). However, these studies did not take into account project size when comparing D-B-B and D-B performance. Additionally, these studies did not include inferential statistics to evaluate D-B-B and D-B performance. Researchers pointed out that one of the main reasons for lack of consensus in cost growth between D-B-B and D-B projects involved limited data, opinion-based data, or small and non-representative samples (Park and Kwak 2017). It is noted that this study did not use non-highway project delivery performance studies to benchmark the results.

The results from the two-way ANOVA also indicated that project size had no significant impact on both cost growth and schedule growth at the alpha level of 0.05 (p-value>0.05). In addition, there was not enough evidence from the data collected for this study to conclude that the interaction between project size and project delivery methods had a significant impact on cost and schedule growth in highways at the alpha level of 0.05 (p-value > 0.05). This finding is novel in that it provides empirical results to uncover the relationship between project sizes and project delivery methods in terms of cost and schedule performance. Public owners and highway agencies may not need to consider project size in the decision of selecting D-B over D-B-B. Rather, they may need to consider other factors such as project types, characteristics, complexity, and risk to obtain the most benefits from D-B in terms of cost and schedule performance.

CONCLUSION

The abundant literature has compared cost and schedule performance between D-B and D-B-B projects. This study added to the literature by presenting one of the first attempts to empirically explore the impact of project size on D-B and D-B performance in highways. This study employed the two-way ANOVA to analyze cost and schedule growth of 69 D-B-B and 69 D-B highway projects collected from six state DOTs. The results showed that there was no statistical interaction between project delivery methods (D-B and D-B-B) across the three levels of project size (10M to $30M, $30M to $50M, and $50M to $70M) in terms of cost growth and schedule growth. The two-way ANOVA results also showed that D-B had 3.01% less cost growth than D-B-B. This finding is consistent with the finding from Shrestha et al. (2007). Other findings of cost growth between D-B-B and D-B highway projects showed no statically significant difference. For the schedule growth, this study found that D-B performed better than D-B-B across all three levels of project size, but the results were not statistically significant at the alpha level of 0.05. This finding is consistent with all other previous studies' findings (FHWA 2006, Ellis et al. 2007; Shrestha et al.

2007; Shrestha et al. 2011, and Minchin et al. 2013).

The findings of this paper have substantial implications for researchers and practitioners to advance the understanding of project delivery method selection and performance. For researchers, this study is one of the first attempts that empirically investigate the impact of project size on cost and schedule performance metrics between D-B-B and D-B highway projects. The findings of this study contribute to the body of knowledge by showing that there was no statistical interaction between project size and project delivery methods with regard to project cost and schedule growth at the alpha level of 0.05. For practitioners, the findings from this study provide guidance on evaluating and benchmarking D-B over traditional D-B-B project performance. To select the most appropriate delivery method for a given project, the decision makers may need to focus on pertinent factors (e.g., project characteristics, complexity, and risk) instead of size of the project during the selection process.

There were several limitations in this study. First, the results of this study were based on analyzing data collected from six state DOTs. Although these six state DOTs have most extensive D-B data in the nation, it is expected that analyzing more data from other states will improve the validity of the findings. Second, this study focused on two main project performance metrics (cost and schedule growth), future research may need to consider other important metrics such as award growth, change orders, or construction intensity to better understand the benefits and challenges of D-B over D-B-B. Third, this study only collected and analyzed highway project data. Interpreting or generalizing the performance results requires examining external factors for different characteristics of highway construction. Future research may extend the findings from this study by analyzing the non-highway project data such as building and industrial projects. Finally, this study only focused on D-B and D-B-B delivery methods because of limited data available. It is suggested that other main delivery methods including construction manager/general contractor or public-private partnership should be included in future studies.

DATA AVAILABILITY STATEMENT

Data generated or analyzed during the study are available from the corresponding author by request.

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REFERENCES

Associated General Contractors. (2004). *Primer on project delivery*, Washington, D.C.

Black, K. (2010). *Business Statistics: Contemporary Decision Making*, 6th edition, John Wiley & Sons.

Box, G. E. P., (1953) "Non-normality and tests on variances." *Biometrika* 40 (3/4), 318–335.

Construction Industry Institute (CII). (1997). "Project delivery systems: CM at risk, design-build, and design-bid-build." The University of Texas at Austin. Austin, Texas.

Construction Industry Institute. (CII) (2002). "Measuring the Impacts of the Delivery System on

Project Performance-Design-Build and Design-Bid-Build. (NIST Publication No. BMM 2002-10).” The University of Texas at Austin. Austin, Texas.

Design-Build Institute of America (2017) “Design-Build Authorization for Transportation” http://www.dbia.org/advocacy/state/Documents/design_build_maps.pdf (accessed January 25, 2017)

Ellis, R. D., Pyeon, J., Herbsman, Z. J., Minchin, E. and Molenaar, K.R. (2007). “Evaluation of Alternative Contracting Techniques on FDOT Construction Projects.” Florida Department of Transportation.

Ellis, R.E., Herbsman, Z. J., and Kumar, A. (1991). “Evaluation of the FDOT Design/Build Program.” Final Report, Florida Department of Transportation, Tallahassee, Florida.

Ernzen, J., and Schexnayder, C. (2000). “One Company's Experience with Design/Build: Labor Cost Risk & Profit Potential.” *Journal of Construction Engineering and Management*, 126(1), 10-14.

FHWA (2002). *Design-Build Contracting: Final Rule*. Federal Register, 2002.

FHWA (2006). *Design-Build Effectiveness Study*. Final report to Congress as required by TEA-21, U.S. Department of Transportation, Federal Highway Administration.

Florida Department of Transportation. (2004). “Design Build Program Evaluation.” Project Management, Research & Development Office, FDOT, Tallahassee, Florida.

Gastwirth, J. L., Gel, Y. R., & Miao, W. (2009). “The impact of Levene's test of equality of variances on statistical theory and practice.” *Statistical Science*, 343-360.

Goftar, V. N., El Asmar, M., and Bingham, E. (2014). “A meta-analysis of literature comparing project performance between design-build (D-B) and design-bid-build (D-B-B) delivery systems.” In Construction in a Global Network. Atlanta: *Construction Research Congress*, 1389-1398.

Hale, D., Shrestha, P., Gibson, G., Jr., and Migliaccio, G. (2009). “Empirical Comparison of Design/Build and Design/Bid/Build Project Delivery Methods.” *Journal of Construction Engineering and Management*, 135(7), 579–587.

Jaccard, J., & Guilamo-Ramos, V. (2002). Analysis of variance frameworks in clinical child and adolescent psychology: Advanced issues and recommendations. *Journal of Clinical Child Psychology*, 31, 278 –294

Keppel, G., and Wickens, T. D. (2004). *Design and analysis: A researcher’s handbook*.

Konchar, M., and Sanvido, V. (1998). “Comparison of US project delivery systems.” *Journal of Construction Engineering and Management*, 124(6), 435-444.

Kuzel, AJ. (1999). “Sampling in qualitative inquiry.” In BF Crabtrree and WL Miller (Eds.) Doing Qualitative Research (second edition). Thousand Oaks, CA: *Sage Publications*, 33-45.

Minchin, R., Jr., Li, X., Issa, R., and Vargas, G (2013). “Comparison of Cost and Time Performance of Design-Build and Design-Bid-Build Delivery Systems in Florida.” *Journal of Construction Engineering and Management*, 139(10).1-5.

Molenaar, K. R., Songer, A. D., and Barash, M. (1999). “Public-sector design/build evolution and performance.” *Journal of Management in Engineering*, 15(2), 54-62.

Moser, B. K., and Stevens, G. R., (2016). “Homogeneity of Variance in the Two-Sample Means Test,” S.l.: *American Statistical Association*, Taylor & Francis, Ltd.

Navidi, W. C. (2008). *Statistics for engineers and scientists*. McGraw-Hill Higher Education.

Park, H. S., and Kwak, Y. H. (2017). "Design-Bid-Build (DBB) vs. Design-Build (DB) in the U.S. public transportation projects: The choice and consequences." *International Journal of Project Management*, 35(3), 280–295.

Patton, M.Q. (*1990*). *Qualitative evaluation and research methods* (2nd Ed.). Newbury Park, CA: Sage, 532.

Riley, D. R, Diller, B. E., and Kerr, D. (2005). "Effects of delivery systems on change order size and frequency in mechanical construction." *Journal of Construction Engineering and Management*, 131(9), 953–962.

Shrestha, P., Connor, J., and Gibson, G. J. (2011) "Performance Comparison of Large Design-Build and Design-Bid-Build Highway Projects." *Journal of Construction Engineering and Management*, 138(1), 1-13.

Shrestha, P., Fernane, J, (2016) "Performance of Design-Build and Design-Bid-Build Projects for Public Universities." *Journal of Construction Engineering and Management*, 0733-9364, 1-10.

Shrestha, P., Migliaccio, G., O'Connor, J., & Gibson Jr, G. (2007). "Benchmarking of large design-build highway projects: One-to-one comparison and comparison with design-bid-build projects." *Journal of the Transportation Research Board*, 17-25.

Songer, A. D., and Molenaar, K. R. (1997). "Project characteristics for successful public-sector Design-Build." *Journal of Construction Engineering and Management*, 123(1), 34–40.

Stevens, J. P. (1999) "*Intermediate Statistics: A Modern Approach* (2nd ed.). Mahwah, NJ: Lawrence Erlbaum Associates.

Tran, D., and Molenaar, K.R. (2014) "Exploring critical delivery selection risk factors for transportation design and construction projects." Engineering, Construction and Architectural Management, 21(6), 631-647.

Warne, T. R. (2005). "*Design-build contracting for highway projects: A performance assessment*." Tom Warne & Associates, LLC, 2005.

CHAPTER 3

EMPIRICAL IDENTIFICATION AND EVALUATION OF RISK IN HIGHWAY PROJECT DELIVERY METHODS

ABSTRACT

The highway industry currently uses three fundamental delivery methods, design-bid-build (D-B-B), design-build (D-B), and construction manager/general contractor (CM/GC), to deliver their transportation projects. Selecting an appropriate project delivery method is a complex decision and often fraught with risk and uncertainty. This paper presents the result of a two-tier approach to evaluating impacts of risks and uncertainties on project delivery selection in highways. Tier 1 involves identifying and verifying 31 risk factors related to project delivery based on experts with an average of 25 years of relevant experience. Tier 2 involves an empirical evaluation of project delivery risks through analyzing 274 completed highway projects (122 D-B-B, 118 D-B, and 34 CM/GC) collected from 26 transportation agencies. The risk score of each risk factor was determined. The Cronbach's alpha test and correlation analysis were conducted to verify internal consistency, interdependency, and reliability of delivery risk factors. The results showed the eight risk factors that substantially impact the project delivery decision are: (1) delays in completing in railroad agreements; (2) project complexity; (3) uncertainty in geotechnical investigation; (4) delays in a right-of-way (ROW) process; (5) unexpected utility encounter; (6) work zone traffic control; (7) challenges to obtain environmental documentation; and (8) delays in delivery schedule. This study discusses the pertinent findings and rationale behind these eight critical risk factors. Highway agencies and other practitioners can use these risk factors to make more effective and defensible decisions on which delivery method is the most suitable for their transportation projects.

Keywords: Delivery Methods, Risk Factors, Highways, Correlation; and Cronbach's alpha.

INTRODUCTION

Design-bid-build (D-B-B) has been used almost exclusively for past decades and is still a viable option today. Federal, state, and local agencies are familiar with the D-B-B procurement process and have a breath of expertise and staffing to execute D-B-B projects. However, many state departments of transportation (DOTs) have increasingly used alternative contracting methods including design-build (D-B) and construction manager/general contractor (CM/GC) to meet the demand for shortening project schedule within budget constraints. According to the report from the Design-Build Institute of America (DBIA) published in 2016, only four state DOTs, including North Dakota, Iowa, Wisconsin, and Oklahoma, do not have specific authorization to use D-B for transportation projects (DBIA 2016). Blanding and Lewis (2012) also pointed out that, more than 14 state DOTs have full authorization to use the CM/GC delivery method as of 2012. Figure 1 presents a timeline associated with D-B and CM/GC major milestones for federal aid projects.

FDOT D-B Program	**SEP-14**	**D-B Final Rule**	**EDC-1**	**MAP-21**	**EDC-2**
1987	**1990**	**2002**	**2011-2012**	**2012**	**2013-2014**

Figure 1: Major Milestone Timeline of D-B and CM/GC

The Florida DOT (FDOT) was one of the first DOTs in the nation to use D-B in their transportation projects. The FDOT started the first documented D-B contracting program in 1987, and its success helped to inspire other states to try this innovative contracting approach (Ellis et al. 1991). The FDOT has been a leader in D-B since the inception of their program. The Federal Highway Administration (FHWA) established Special Experimental Project Number 14 (SEP-14) – Innovative Contracting in 1990 to enable state transportation agencies to test and evaluate a variety of alternative contracting methods. The intent of SEP-14 was to evaluate non-traditional contracting practices and assess how those practices affect schedule and cost. In 2002, the FHWA published its Design-Build Contracting Final Rule, and the D-B project delivery method was moved from experimental status to mainstream use on federally funded projects (FHWA 2002).

The FHWA initiated the Every Day Counts (EDC) program in 2009 to accelerate technology and innovation deployment and to deliver timely transportation projects to the public. The EDC philosophy is that the sooner we can deliver projects, the sooner the public can enjoy their benefits. EDC- 1 advanced D-B and CM/GC project delivery methods to promote innovations during 2011 and 2012. In 2012, the passage of the Moving Ahead for Progress in the 21st Century Act (MAP-21) made a rapid change in the use of alternative contracting methods, including D-B and CM/GC (DBIA 2016). EDC-2 continued to advance D-B and CM/GC delivery method during 2013 and 2014. Both D-B and CM/GC are now becoming more predominant in highway design and construction.

The growing use of alternative delivery methods has led researchers and practitioners to seek an effective approach to choosing the most appropriate delivery method. The decision of selecting a project delivery method should be made in the scoping phase and certainly before the final design phase begins. However, the scoping stage lacks detailed site investigation or engineering design. Thus, the decision is complex due to risk and uncertainty.

LITERATURE REVIEW AND POINT OF DEPARTURE

Project delivery methods, by definition, allocate risk for design and construction. The risk allocation in D-B-B is understood by the transportation design and construction community. The transportation agency bears the majority of design risk, and the contractor bears the construction risk. Under D-B-B projects, the owner warrants the details of the design and is responsible for any errors or omissions in the drawings and specifications, and the contractor assumes the risk of completing construction in compliance with the contract documents. The contractor also assumes the risks related to scheduling, coordinating, and administering work conducted by subcontractors and suppliers (Tran and Molenaar 2014b).

One of the advantages of using D-B is to transfer two primary risks, design liability for errors and omissions in plans and disputes between designers/owners and contractors, to the design-builder (FHWA 2006). However, design liability and disputes are only two of many risks that DOTs must consider when deciding to use D-B. Research has shown that simply transferring other risks, whether intentionally or unintentionally, is not encouraged because it can result in higher initial prices or lower design-builder competition (Tran and Molenaar 2014a).

In CM/GC project delivery, construction managers are paid a fee for construction management services until a guaranteed maximum price (GMP) agreement for construction is reached, at which point the construction managers assume the risk for the final cost and time of construction. National Cooperative Highway Research Program (NCHRP) Project 15-46, "Design-Management Guide for Design-Build and Construction Manager/General Contractor Projects," found that one of the three biggest advantages of using CM/GC is "flexibility to allocate risk, and then to re-allocate risk and continue to re-allocate risk throughout the life of the project"(Minchin et al. 2014).

Increasing use of D-B and CM/GC sets a trend of identifying and quantifying the impact of risk factors on the delivery decision in highway construction. A number of studies have considered the risk as common influential factors in the project delivery selection framework. For example, the American Association of State Highway and Transportation Officials (AASHTO) Guide for DB procurement, published in 2008, includes risk allocation as one of the four-step approach to obtaining successful D-B projects (AASHTO 2008). Tran et al. (2013) developed a project delivery selection matrix based on risk and opportunity assessment and analysis of eight project delivery factors. Recently, researchers employ the cross-impact analysis technique to develop a risk-based model that integrates probabilistic risk-based cost estimating into the project delivery selection process (Tran and Molenaar 2015). Although the previous work has provided a systematic process to help highway agencies evaluate and select the most suitable delivery method, no studies have empirically documented the impact of risk on different project delivery methods.

Building upon the previous work, this study presents the result of a two-tier approach to evaluating the impact of risk on project delivery selection in highways. Tier 1 involves verifying 31 project delivery risk factors based on the national survey conducted by the authors in the previous study. Tier 2 involves empirical documentation of project delivery risks based on analyzing 274 completed highway projects (122 D-B-B, 118 D-B, and 34 CM/GC). Both correlation analysis and Cronbach's alpha test were conducted to examine the relationships among delivery risk factors and their internal consistency. The paper discusses the pertinent findings and rationale behind the critical project delivery risk factors in detail.

RESEARCH METHODOLOGY

The research methodology included four primary phases: (1) synthesizing existing documentation related to project delivery methods and risk analysis and management; (2) Tier 1: opinion-based data collection—using a survey questionnaire to collect information related to risk and uncertainty impact on each project delivery method; (3) Tier 2: empirical-based data collection—collecting a number of completed highway projects to identify and document the impact of risk on project outcomes; and (4) analysis and results. The following sections describe these phases in detail.

Synthesizing Literature Review

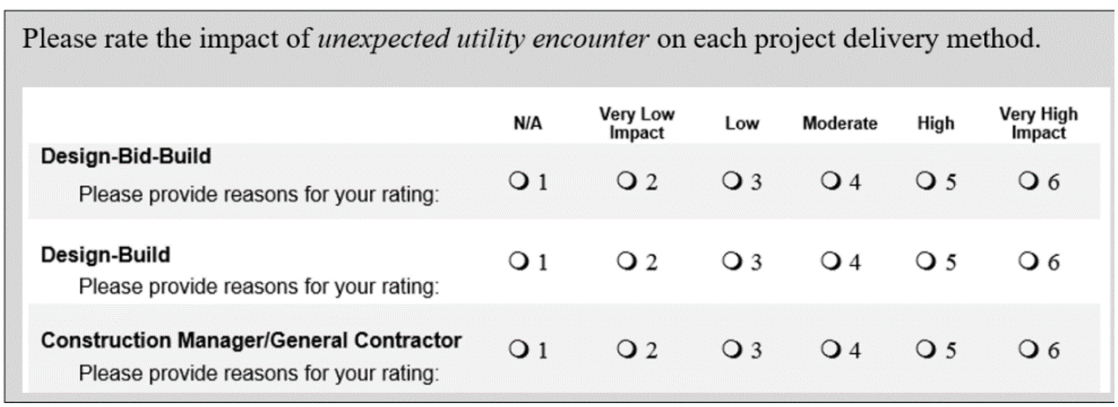
The authors conducted a comprehensive literature review of related project delivery methods including D-B-B, D-B, and CM/GC and risk assessment and management. The authors searched academic literature, industry publications, state DOT websites, and government reports to allocate relevant documents. The literature review was conducted by using Transportation Research Board (TRB) Information Systems, general internet search engines, academic databases, American Society of Civil Engineers (ASCE) civil engineering database, the Project Management Institute, the FHWA research library, and others.

The synthesizing literature review process resulted in a list of approximately 200 generic risk factors in highway design and construction projects. This comprehensive list was rigorously analyzed to combine overlapping risks. Risk factors that did not relate to project delivery decisions were removed. The authors took a conservative approach to combining and removing these risks to be certain that no relevant risks were excluded. As a result, a conservative list of 39 risk factors was considered for the next phase of this study

Tier 1: Opinion-based Data Collection

The authors employed a national survey questionnaire to determine the impact of each risk factor on the delivery method selection decision. The unit of analysis for this study was a transportation professional who had experience with risk assessment and project delivery methods. The survey questionnaire was distributed to the following organizations: TRB Construction Management Committee; TRB Project Delivery Committee; AASHTO Subcommittee on Construction; AASHTO Standing Committee on Planning; AASHTO Joint Technical Committee on Design-Build; and the DBIA Transportation Conference attendees.

The questionnaire requested information about the individual respondent's professional experience with risk and delivery methods in transportation projects. Respondents were asked to rate the impact of different risk factors on each project delivery method based on an ordinal scale (1 = Not Applicable (NA); 2 = Very Low Impact; 3 = Low Impact; 4 = Moderate Impact; 5 = High Impact; and 6 = Very High Impact). Figure 2 illustrates a sample of the survey questionnaire. It is noted that respondents were asked to provide the reason for their ratings associated with each project delivery method.


Please rate the impact of *unexpected utility encounter* on each project delivery method.

	N/A	Very Low Impact	Low	Moderate	High	Very High Impact
Design-Bid-Build Please provide reasons for your rating:	1	2	3	4	5	6
Design-Build Please provide reasons for your rating:	1	2	3	4	5	6
Construction Manager/General Contractor Please provide reasons for your rating:	1	2	3	4	5	6

Figure 2: Sample of questionnaire survey from Tier 1

A total of 152 valid responses out of 450 distributed questionnaires were received. The overall response rate was approximately 34%. These responses were grouped into three categories: owner agencies, design/engineering/consultant firms, and contractors/subcontractors. To obtain the reliable data, 15 respondents who had less than 10 years of relevant professional experience excluded from the analysis. The remaining 137 respondents had 25 years of professional experience on average. Out of these 137 responses, 71 respondents were from highway agencies representing all 50 state DOTs; 35 respondents were from design/engineering/consultant firms; and 32 respondents from contractors/subcontractors. The analysis result from this dataset revealed that eight risk factors were not relevant to project delivery selection (more than 90% of responses were NA). Thus, these eight factors were not considered further. The definition of these 31 risk and analysis results can be found in the previous study (Tran and Molenaar 2014b). The remaining 31 risk factors from the Tier 1 were used to further examine the impact of risk on project delivery selection in Tier 2.

Tier 2: Empirical-based Data Collection

Tier 2 involved a substantial effort of collecting a set of completed highway projects with the use of all three project delivery methods (D-B-B, D-B, and CM/GC). The D-B and the CM/GC projects were randomly selected from state DOTs which actively engaged in those delivery methods. The D-B-B projects were sampled to be similar in location, size, and time of award to the D-B and CM/GC projects. After approximately two years of the data collection process, the authors received totally 291 highway projects that were completed between 2004 and 2015. These projects were collected from state DOTs, FHWA, and Office of Federal Lands Highway. For each project, the authors developed a detailed questionnaire to collect pertinent information related to evaluating the influence of 31 risk factors on project outcomes. The authors sent the questionnaire to the agency's project representative by email and following up with phone correspondences as required for data verification. Based on the specific characteristics of each project, the project representative (e.g., project manager) were asked to rate the impact of risk on project cost and schedule performance prior to or at the time that the project delivery decision was made. Table 1 summarizes the risk rating system for Tier 2 project data questionnaire.

Table 1. Risk Rating Scale for Tier 2 Project Data Collection

Rating System	0 NA	1 Very Low	2 Low	3 Moderate	4 High	5 Very High
Cost Impact	NA	Insignificant C.I.	< 2% C.I.	2-5% C.I.	5-10% C.I.	> 10% C.I.
Schedule Impact	NA	Insignificant S.S.	< 2% S.S.	2-5% S.S.	5-10% S.S.	> 10% S.S.

Note: NA-Not Applicable; C.I.- Cost Increase; and S.S.- Schedule Slippage

The authors conducted a thorough screening of the risk data collected from 291 highway projects. We employed quality control techniques presented by Rahm and Do (2000) to ensure the quality of the collected data. The authors took a conservative approach to remove potential errors (i.e., no or illogical response data) in the dataset. For example, if a respondent provided a single rating value across all 31 risk factors (e.g., all high impacts or all scores of "4"), this project was classified as a high potential error and was omitted from the data set to avoid confounding further analyses. This process resulted in removing 17 projects. The remaining 274 projects, including 122 D-B-B, 118 D-B, and 34 CM/GC collected from 26 agencies were used in the next step of the analysis. Figure 3 illustrates the distribution of these 274 projects associated with each delivery method. The following sections discuss the analysis and results in detail.

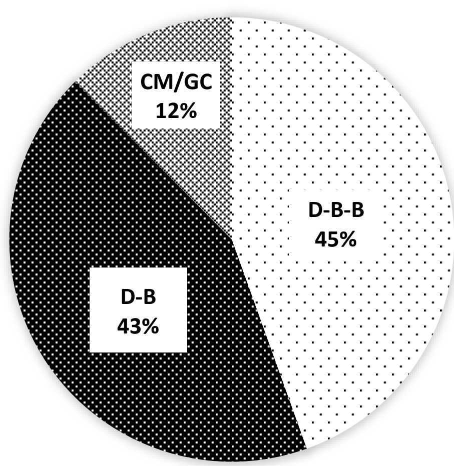


Figure 3: Distribution of Completed Highway Projects from Tier 2 (n = 274)

ANALYSIS AND RESULTS

It is noted that the ratings associated with cost and schedule impact across 31 risk factors are slightly different. To investigate the difference between cost and schedule impacts of 274 projects, the authors employed the Wilcoxon signed-rank test. The Wilcoxon signed-rank test is designed to provide more weight to a pair which shows a large difference than a pair which shows a small difference. The results from the Wilcoxon signed-rank test showed that there is no statistically significant different between cost and schedule impact of the risk rating. As a result, the authors combined these ratings together for further analysis. To determine the critical risk factors associated with each different delivery method, the authors calculated a risk score/criticality of 31 risk factors using Equation (1).

$$Criticality = \frac{\sum_{1}^{5}(n_i * r_i)}{\max(r_i) * \sum_{1}^{5} n_i} \qquad (1)$$

Where: r_i is the rating of each risk factor

n_i is the total number of responses associated with the rating r_i

The risk score varies from 0.0 to 1.0. If a risk factor has a score equal to zero, it is no impact on the project outcomes. If a risk factor has a score equal to one, it is the most critical to the project delivery selection process. The criticality of 31 risk factors was calculated for each project delivery method using Equation (1). The minimum risk score was 0.38, and the maximum score was 0.73. Based on risk score, ranks were determined under each delivery method. The top 10 risk factors under each delivery method were identified and verified through interdependent and reliability measurement as well as the result of content analysis from previous studies. Additionally, Cronbach's alpha indices of the top 10 risk factors for each delivery method was determined to measure internal consistency or scale reliability.

Table 2 summarizes the Cronbach's alpha test results of the top 10 delivery risks for D-B-B, D-B and CM/GC separately. The Cronbach's alpha values of D-B-B, D-B, and CM/GC were 0.83, 0.89, and 0.85, respectively. The alpha value of greater than 0.70 indicates the reliable rating scale (Kline 2000). The detailed discussion of correlation and Cronbach's alpha analyses was presented in next sections.

Table 2. Cronbach's Alpha Test Results

Delivery Method	Cronbach's Alpha (α)
D-B-B	0.83
D-B	0.89
CM/GC	0.85

Table 3 summarizes the top 10 risk factors for D-B-B project delivery based on the criticality of 122 D-B-B projects. Table 3 shows that delays in completing in railroad agreements (RR) was ranked first with the risk score equal to 0.54. Project complexity (PC) was ranked second with the risk score of 0.48. Unexpected utility encounter (UtEnc) was ranked third with the risk score of 0.44. From then, risk scores were consecutively decreased by 0.01 for each rank. Uncertainty in geotechnical investigation (Geotec), work zone traffic control (Traff), delays in right-of-way process (ROW), and delays in delivery schedule (Deliv) were ranked from fourth to seventh in the chronological order. Challenges to obtain environmental documentation (EnvDoc) was tied with construction sequencing/staging/phasing (Seq) with the risk score of 0.39. Lastly, scope definition (Scopd) was ranked 10th with the risk score equal to 0.38.

Table 3. The Top 10 Risk Factors for D-B-B (n =122)

Risk Factors	Risk Score	Rank
Delays in completing in railroad agreements (RR)	0.54	1
Project complexity (PC)	0.48	2
Unexpected utility encounter (UtEnc)	0.44	3
Uncertainty in geotechnical investigation (Geotec)	0.43	4
Work zone traffic control (Traff)	0.42	5
Delays in right-of-way process (ROW)	0.41	6

Delays in delivery schedule (Deliv)	0.40	7
Challenges to obtain environmental documentation (EnvDoc)	0.39	8
Construction sequencing/staging/phasing (Seq)	0.39	9
Scope Definition (Scopd)	0.38	10

Table 4 presents the correlation of D-B-B risk factors. Comparing the interdependencies among top 10 D-B-B risk factors, highest positive correlation coefficient of 0.611 was observed between work zone traffic control (Traff) and construction sequencing/staging/phasing (Seq). This indicates the risks associated with work zone traffic control is highly correlated with risks caused by construction sequencing/staging/phasing in D-B-B. The second highest correlation was observed between scope definition (Scopd) and project complexity (PC) with a correlation coefficient of 0.574. Scope definition risk (Scopd) is also highly correlated with delays in delivery schedule (Deliv) with the correlation coefficient of 0.569. It is noted that delays in completing in railroad agreements (RR) only had a considerable correlation with delays in right-of-way process (ROW) with a correlation coefficient of 0.411.

Table 4. Correlation of D-B-B Risk Factors (n=122)

	RR	PC	UtEnc	Geotec	Traff	ROW	Deliv	Seq	EnvDoc	Scopd
RR	1.0									
PC	-	1.0								
UtEnc	-	.502*	1.0							
Geotec	-	.403*	.493*	1.0						
Traff	-	.366*	-	-	1.0					
ROW	.411*	.335*	.30*	.335*	-	1.0				
Deliv	-	.487*	.403*	-	.354*	-	1.0			
Seq	-	.489*	.323*	.30*	.611*	-	.517*	1.0		
EnvDoc	-	.377*	.343*	-	-	.510*	.349*	-	1.0	
Scopd	-	.574*	.385*	-	.347*	-	.569*	.514*	-	1.0

Note: (-) denotes the correlation coefficient less than 0.30; *. Correlation is significant at the 0.01 level.

As mentioned previously, Table 2 shows the Cronbach's alpha value of 0.83 (>0.7) for the top 10 risk factors in D-B-B. This means that the top 10 D-B-B risk factors were constructed with a high level of internal consistency. Table 5 represents the individual contribution to the top 10 D-B-B risk factors. Delays in completing in railroad agreements (RR) secured the highest scale mean and variance of 14.56 and 63.87 respectively if deleted from the scale. Examining the last column in Table 5, one can observe that the Cronbach's alpha values ranged from 0.794 to 0.831 if one specific risk factor was removed from the analysis. This result confirmed that the top 10 risk factors for D-B-B were consistent and reliable. The Cronbach's alpha result provides the correlation between each item and a scale score excluding that item (corrected item-total correlation). Table 5 shows that all risk factors had corrected item-total correlation larger than 0.30. The risk related to project complexity (PC) had the highest correlation coefficient of 0.689 and the delays in completing in railroad agreements (RR) had the lowest correlation coefficient of 0.32. Finally, the squared multiple correlation column in Table 5 indicates the R-square value in multiple regression. For example, the construction sequencing/staging/phasing (Seq) risk had the highest R-square value of 0.54. This means that when considering the construction sequencing/staging/phasing (Seq) as a dependent variable and the rest of nine D-B-B risk factors as independent variables, the multiple regression model explained the variance of 54%. Similarly, delays in completing in railroad agreements (RR) had the least explained variance of 24.3%.

Table 5. Cronbach's Alpha Item-Total Analysis for D-B-B Risk Factors

Risk Factors	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
RR	14.56	63.873	.320	.243	.831
PC	13.03	54.751	.689	.503	.794
UtEnc	13.47	57.824	.556	.412	.809
Geotec	13.47	59.260	.451	.334	.821
Traff	13.25	61.503	.424	.394	.822
ROW	14.08	60.071	.467	.412	.818
Deliv	13.48	58.132	.595	.448	.805
Seq	13.48	59.089	.581	.540	.807

EnvDoc	13.46	59.960	.469	.341	.818
Scopd	13.47	58.081	.614	.484	.804

Table 6 summarizes the top 10 risk factors for D-B project delivery based on the criticality of 118 D-B projects. Table 6 shows that delays in completing in railroad agreements (RR) was ranked first with the risk score equal to 0.61. Uncertainty in geotechnical investigation (Geotec) was ranked second with the risk score of 0.54. Delays in right-of-way process (ROW) and unexpected utility encounter (UtEnc) were ranked third and fourth with risk scores of 0.50 and 0.48, respectively. Project complexity (PC) and delays in completing utility agreements (UtAgr) were tied with challenges to obtain environmental documentation (EnvDoc) with a risk score of 0.46. In the similar fashion, environmental impacts (EnvImp), design completion (DgnEnd), and Construction QA/QC process (QA/QC) were tied with a risk score of 0.45.

Table 6. The Top 10 Risk Factors for D-B (n =118)

Risk Factors	**Risk Score**	**Rank**
Delays in completing in railroad agreements (RR)	0.61	1
Uncertainty in geotechnical investigation (Geotec)	0.54	2
Delays in right-of-way process (ROW)	0.50	3
Unexpected utility encounter (UtEnc)	0.48	4
Project complexity (PC)	0.46	5
Delays in completing utility agreements (UtAgr)	0.46	6
Challenges to obtain environmental documentation (EnvDoc)	0.46	7
Environmental impacts (EnvImp)	0.45	8
Design completion (DgnEnd)	0.45	9
Construction QA/QC process (QC/QA)	0.45	10

Table 7 represents a correlation matrix of these top 10 D-B risk factors. One can observe from Table 7 that all risk factors were highly or moderately correlated with each other except delays in completing in railroad agreements (RR). Specifically, the highest positive correlation coefficient of 0.767 was identified between the unexpected utility encounter (UtEnc) and delays in completing utility agreements (UtAgr). The second highest correlation was observed between the design completion (DgnEnd) and construction QA/QC process (QA/QC) with the correlation coefficient of 0.723. Table 7 also shows that uncertainty in geotechnical investigation (Geotec) was highly correlated with both the challenges to obtain environmental documentation (EnvDoc) and environmental impacts (EnvImp), with the correlation coefficients of 0.668 and 0.659, respectively. Finally, delays in completing in railroad agreements (RR) only had a correlation with three risk factors, project complexity (PC), delays in right-of-way process (ROW), and delays in completing utility agreements (UtAgr), with the correlation coefficients slightly greater than 0.30.

Table 7. Correlation of D-B Risk Factors (n=118)

	RR	PC	UtEnc	Geotec	ROW	EnvDoc	EnvImp	DgnEnd	QA/QC	UtAgr
RR	1.00									
PC	.315*	1.00								
UtEnc	-	.445*	1.00							
Geotec	-	.613*	.325*	1.00						
ROW	.308*	.460*	.525*	.439*	1.00					
EnvDoc	-	.560*	.408*	.668*	.455*	1.00				
EnvImp	-	.626*	.414*	.659*	.591*	.813*	1.00			
DgnEnd	-	.547*	.413*	.522*	.336*	.450*	.453*	1.00		
QA/QC	-	.557*	.517*	.513*	.348*	.485*	.433*	.723*	1.00	
UtAgr	.311*	.442*	.767*	.408*	.640*	.424*	.470*	.469*	.507*	1.00

Note: (-) denotes the correlation coefficient less than 0.30; *. Correlation is significant at the 0.01 level.

The Cronbach's alpha of the top 10 D-B risk factors was 0.89 (Table 2), which indicates the high level of internal consistency. Table 8 represents the individual contribution to these top 10 D-B risk factors. Delays in completing in railroad agreements (RR) secured the highest scale mean and variance of 16.11 and 89.20 respectively if deleted from the scale. The last column in Table 8 indicates that the Cronbach's alpha value, if one specific risk factor was deleted, ranged from 0.874 to 0.901. This confirmed the consistent contribution of all top 10 risk factors to the D-B delivery method. Additionally, Table 8 shows that all risk factors had corrected item-total correlation larger than 0.6 except for delays in completing in railroad agreements (RR). The risk associated with environmental impacts (EnvImp) had the highest correlation coefficient of 0.730. Similar to the finding of the top 10 D-B-B delivery risk, the delays in completing in railroad agreements (RR) had the lowest correlation coefficient of 0.294. Finally, Table 8 shows that the risk associated with environmental impacts (EnvImp) had the highest R-square value of 0.754. This means that when considering the risk associated with environmental impacts (EnvImp) as a dependent variable and the rest of nine D-B risk factors as independent variables, the multiple regression model explained the variance of 75.4%. Similarly, delays in completing in railroad agreements (RR) had the least explained variance of 22.6%.

Table 8. Cronbach's Alpha Item-Total Analysis for D-B Risk Factors

Risk Factors	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
RR	16.11	89.203	.294	.226	.901
PC	14.50	78.718	.712	.564	.876
UtEnc	14.52	79.131	.634	.628	.881
Geotec	14.39	75.913	.669	.574	.879
ROW	15.24	77.063	.647	.547	.881
EnvDoc	14.57	77.902	.681	.717	.878
EnvImp	14.65	76.212	.730	.754	.874
DgnEnd	15.01	83.422	.632	.574	.883
QCQA	15.02	83.207	.666	.617	.881
UtAgr	14.99	76.388	.694	.686	.877

Table 9 summarizes the top 10 risk factors for CM/GC project delivery based on the criticality of 34 CM/GC projects. Table 9 shows that risk caused by project complexity (PC) was ranked first with the risk score equal to 0.73. The delays in right-of-way process (ROW) was ranked second with a risk score of 0.70. Different from D-B-B and D-B, the delays in completing in railroad agreements (RR) was ranked third with a risk score of 0.67. The uncertainty in geotechnical investigation (Geotec), construction sequencing/staging/phasing (Seq), and delays in procuring critical materials, labor, and specialized equipment (MatDel) were ranked fourth to sixth in the chronological order. The risk related to constructability in design (ConsDgn) and work zone traffic control (Traff) were tied with the risk score of 0.58. Finally, delays in delivery schedule (Deliv) and unexpected utility encounter (UtEnc) were ranked ninth and 10th with the risk score of 0.55 and 0.52, respectively.

Table 9. The Top 10 Risk Factors for CM/GC (n =34)

Risk Factors	Risk Score	Rank
Project complexity (PC)	0.73	1
Delays in right-of-way process (ROW)	0.70	2
Delays in completing in railroad agreements (RR)	0.67	3
Uncertainty in geotechnical investigation (Geotec)	0.65	4
Construction sequencing/staging/phasing (Seq)	0.63	5
Delays in procuring critical materials, labor, and equipment (MatDel)	0.61	6
Constructability in design (ConsDgn)	0.58	7
Work zone traffic control (Traff)	0.58	8
Delays in delivery schedule (Deliv)	0.55	9
Unexpected utility encounter (UtEnc)	0.52	10

Table 10 shows a correlation matrix of the top 10 CM/GC risk factors. Comparing the interdependencies among risk factors, the highest positive correlation coefficient of 0.759 was identified between delays in delivery schedule (Deliv) and project complexity (PC). The second highest correlation was observed between the uncertainty in geotechnical investigation (Geotec) and project complexity (PC) with the correlation coefficient of 0.741. Table 10 also displays that uncertainty in geotechnical investigation (Geotec) and project complexity (PC) had a substantial correlation with other risk factors (the correlation coefficient larger than 0.5). On the other hand, delays in completing in railroad agreements (RR) only had a correlation with two risk factors, unexpected utility encounter (UtEnc) and delays in right-of-way process (ROW), with the correlation coefficients of 0.538 and 0.378 respectively.

Table 10. Correlation of CM/GC Risk Factors (n=34)

	RR	PC	UtEnc	Geotec	Traff	ROW	Deliv	Seq	MatDel	ConsDgn
RR	1.00									
PC	-	1.00								
UtEnc	.538*	-	1.00							
Geotec	-	.741*	-	1.00						
Traff	-	.30	.598*	.351	1.00					
ROW	.378	.324	.472**	.518*	.363	1.00				
Deliv	-	.759*	-	.559*	.353**	.360**	1.00			
Seq	-	.599*	.379	.609*	.590*	.387**	.611*	1.00		
MatDel	-	.611*	-	.506*	-	-	.356**	.647*	1.00	
ConsDgn	-	.625*	-	.523*	-	-	.507*	.669*	.651*	1.00

Note: (-) denotes the correlation coefficient less than 0.30; **. Correlation is significant at the 0.05 level; *. Correlation is significant at the 0.01 level.

The Cronbach's alpha of the top 10 CM/GC risk factors was 0.85 (Table 2), which indicates the high level of internal consistency. Table 11 shows the individual contribution to these top 10 CM/GC risk factors. Similar to D-B-B and D-B, delays in completing in railroad agreements (RR) had the highest scale mean and variance of 25.18 and 106.63 respectively if deleted from the scale. Table 11 indicates that the Cronbach's alpha value if one specific risk factor was deleted ranged from 0.813 to 0.865. This confirmed the consistent contribution of all top 10 risk factors to the CM/GC delivery method. Table 11 also shows that only delays in completing in railroad agreements (RR) had corrected item-total correlation less than 0.3. The risk associated with construction sequencing/staging/phasing (Seq) had the highest correlation coefficient of 0.792. Table 11 shows that the risk associated with project complexity (PC) had the highest R-square value of 0.807. This means that when considering the risk associated with project complexity (PC) as a dependent variable and the rest of nine CM/GC risk factors as independent variables, the multiple regression model explained the variance of 80.7%. Similarly, delays in right-of-way process (ROW) had the least explained variance of 45.6%.

Table 11. Cronbach's Alpha Item-Total Analysis for CM/GC Risk Factors

Risk Factors	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
RR	25.18	106.635	.192	.494	.865
PC	22.53	94.317	.689	.807	.823
UtEnc	23.82	97.301	.462	.618	.842
Geotec	23.00	91.152	.733	.671	.818
Traff	23.50	94.500	.530	.566	.836
ROW	23.59	90.977	.544	.456	.836
Deliv	23.38	95.758	.587	.736	.831
Seq	23.00	90.182	.792	.780	.813
MatDel	23.29	97.184	.486	.676	.840
ConsDgn	23.24	97.398	.568	.635	.833

DISCUSSION

Table 12 summarizes the top 10 risk factors across all three delivery methods (D-B-B, D-B, and CM/GC). It is noted that these risk factors are distributed differently from each delivery method. For example, project complexity was first in CM/GC, ranked second in D-B-B but ranked fifth in D-B.

Table 12. Summary of Project Delivery Risk Factors in Highways

Rank	D-B-B	D-B	CM/GC
1	Delays in completing in railroad agreements	Delays in completing in railroad agreements	Project complexity
2	Project complexity	Uncertainty in geotechnical investigation	Delays in right-of-way (ROW) process
3	Unexpected utility encounter	Delays in right-of-way (ROW) process	Delays in completing in railroad agreements
4	Uncertainty in geotechnical investigation	Unexpected utility encounter	Uncertainty in geotechnical investigation
5	Work zone traffic control	Project complexity	Construction

			sequencing/staging/phasing
6	Delays in right-of-way (ROW) process	Delays in completing utility agreements	Delays in procuring critical materials, labor, and specialized equipment
7	Delays in delivery schedule	Challenges to obtain appropriate environmental documentation	Constructability in design
8	Challenges to obtain appropriate environmental documentation	Environmental impacts	Work zone traffic control
9	Construction sequencing/staging/phasing	Design Completion	Delays in delivery schedule
10	Scope Definition	Construction QC/QA process	Unexpected utility encounter

One can observe from Table 12 that eight risk factors that have a substantial impact on the project delivery selection process are: (1) delays in completing in railroad agreements; (2) project complexity; (3) uncertainty in geotechnical investigation; (4) delays in a ROW process; (5) unexpected utility encounter; (6) work zone traffic control; (7) challenges to obtain environmental documentation; and (8) delays in delivery schedule. The following section discusses these eight risk factors supported by the content analysis of qualitative data collected from Tier 1 and the relevant literature.

Delays in Completing in Railroad Agreement

This risk factor is the most critical across all project delivery methods. It was ranked first in D-B-Band D-B and second in CM/GC (Table 12). The previous studies indicate that the transportation agency will likely have more influence in obtaining the railroad agreements than contractors due to the fact that the local agencies and railroads have a traditional relationship with agency (AASHTO 2008). Under D-B-B projects, the owner is at risk for changes required after the bid. When asking for providing reasons to rank the impact of railroad risk on D-B-B from the Tier 1 data collection process, one experienced public owner stated that “railroads are a difficult/time-consuming entity to deal with and the railroad coordination should be fully completed prior to going to bid.” Because railroads operate on their own timetables, they are potential for huge impact/delay beyond the contractor’s control. One contractor pointed out “historically, railroad uncertainty involvement provides potential schedule-killers, with no recourse from the contractor”.

D-B allows for early coordination between project parties involved including designers, contractors, agency owners, and railroad companies. A D-B team can engage in the railroad agreement during plan development to minimize the uncertainty, but often assumes the liability and contingency on the final design. However, as mentioned previously, public owner agencies typically have a better working relationship with railroads than contractors. Under D-B, the design-builder has a contractual relationship with the agency, not these third parties. One experienced project manager explained the impact of railroad risk on D-B projects as follow: “railroads affects the overall completion time. Depends on who assumes this risk how it affects the outcome. Not normally under the total control of the design-builder.” Gransberg et al. (2006) also pointed out that managing railroad agreement risks in D-B projects requires that the agency invest a great amount of effort to clear the constraints imposed by railroad companies.

The levels of staff experience has a significant impact on railroad agreement risk under CM/GC projects. Research has shown that CM/GC allows a project to begin at risk because a project can start before the railroad agreements are cleared (Alder 2007). A word from the public owner “construction managers in CM/GC will identify risk [caused by railroad agreement] and bring it to the owner during plan development for resolution and redistributing project risks.”

While railroad impacts and processes can be resolved collaboratively by the agency, designer, and contractor under CM/GC, a lengthy resolution process can delay the GMP negotiations.

The results from the correlation analysis show that delays in completing in railroad agreements had a moderate correlation with the delays in a ROW process in all three delivery methods. Under D-B, delays in completing in railroad agreements also had a correlation with project complexity and delays in completing utility agreements with coefficients of 0.315 and 0.311, respectively. Under CM/GC, delays in completing in railroad agreements had a correlation with unexpected utility encounter with a coefficient of 0.538.

Project Complexity

This risk factor involves complex structures, unexpected ground conditions, unforeseen design and technical issues, challenges in the level of interaction between stakeholders, and difficulties in obtaining an agreement with third-party. Project complexity was ranked first in CM/GC, second in D-B-B, and fifth in D-B (Table 12). Under D-B-B, the delivery process is clear and well understood, but it has limited coordination among project participants to deal with project complexity effectively. One engineer explained that "the more complex and unique a project is, the more risk exists for delays, changes and problems due to a lack of communication between the designer/owner and constructor."

Under D-B, agencies define the project scope and requirements through initial design documentation in the request for dissertations (RFP) and then procure both the final design and construction through an evaluation of technical and price dissertations. Construction can start at

30% of design complete or earlier. The feeling of loss of direct control and oversight and challenges in developing the project scope is the main concern. One public owner explained that "on some projects, the D-B delivery method should not be used due to the complexity and unknown variables. Loss of direct control and oversight, challenges in the management of the desired end product, and performance have a big impact on the D-B selection."

Communication and collaboration of the designer, contractor, and owner plays a pivotal role in dealing project complexity in CM/GC. The process of addressing complexity issues and adding innovation depends heavily on the relationship between contractor and designer and the facilitation of the process by the owner. One contractor stated that "under CM/GC, the line of communication can be indirect or uncertain that may lead to delays in review processes."

The results from the correlation analysis show that the risk associated with project complexity was highly or moderately correlated with almost all risk factors across three delivery methods (Tables 4, 7, and 10). The correlation coefficient value of project complexity with other risk factors ranged from 0.335 to 0.574 in D-B-B, from 0.442 to 0.626 in D-B, and from 0.30 to 0.759 in CM/GC. It is noted that project complexity has a weak correlation (the coefficient less than 0.30) with unexpected utility encounter in CM/GC (Table 10).

Uncertainty in Geotechnical Investigation

Uncertainty in geotechnical investigation involves unforeseen ground conditions, inappropriate design, contamination, ground water, settlement, chemically reactive ground, incomplete survey, and inadequate geotechnical investigation. This risk factor was ranked second in D-B, fourth in both the CM/GC and D-B-B (Table 12). Under D-B-B, the design required 100% complete before construction is the main reason for the low impact of this risk when comparing to D-B and CM/GC delivery methods.

Under D-B, uncertainty in geotechnical investigation is a critical risk factor. NCHRP Synthesis Report 429, "Geotechnical Information Practices in Design-Build Projects," found that geotechnical uncertainty in D-B projects is always high until the post-award site investigation and geotechnical design report can be completed (Gransberg and Loulakis 2014). This report also emphasized that geotechnical uncertainty is one of the highest pre-award uncertainties and the owner "needs to reduce the impact of geotechnical uncertainty as expeditiously as possible" (Gransberg and Loulakis 2014).

One of the main advantages of the CM/GC method is to provide a forum to communicate and discuss geotechnical uncertainty in the design phase. These risks can then be allocated to the party most able to control them to optimize project cost. NCHRP Project 15-46 found that for some projects a construction manager conducts its own geotechnical investigation as part of the preconstruction services contract (Minchin et al. 2014). This may explain why geotechnical uncertainty under the CM/GC delivery method was ranked lower in comparison with D-B-B, but higher when comparing D-B.

The results from the correlation analysis show that the uncertainty in geotechnical investigation was highly or moderately correlated with the project complexity delays in right-of-way process across three delivery methods (see Tables 4, 7, and 10). Under D-B-B, the uncertainty in geotechnical investigation had correlation only with four other risk factors with low the correlation coefficient ranged from 0.35 to 0.49 (Table 4). Under D-B, the uncertainty in geotechnical investigation had a correlation with eight other risk factors with the correlation coefficient ranged from 0.33 to 0.67 (Table 7). Under CM/GC the uncertainty in geotechnical investigation had a correlation with seven other risk factors with the correlation coefficient ranged from 0.35 to 0.74 (Table 10).

Delays in a Right-of-Way (ROW) Process

Challenging in a ROW acquisition process can have a substantial impact on project delivery method selection across all three delivery methods (Table 12). Generally, government agencies have more power and control over the ROW acquisition process. Under D-B-B, the ROW acquisition and relocations are usually achieved prior to construction. ROW issues are often resolved by the time the project is let. One public owner mentioned that "some deadlines cause projects to go to construction before all ROW is acquired, which often lead to potential time delays and cost overruns."

Under D-B, highway agencies can transfer part or all of this risk to the design-builder. In this case, the RFP must clearly and sufficiently define all aspects related to the ROW acquisition process. One public owner explained that "ROW can be in flux. The best way to do D-B is to acquire the land first, then let the design-builder within the footprint. Only the states have powers to condemn the property if needed. If the D-B team is responsible for the ROW acquisition, it could be very high risk. We have challenges when [the design-builder] tries to buy ROW as part of the contract."

Under CM/GC, early collaboration with the designer and construction manager can minimize ROW risk by properly structuring construction packages. NCHRP Project 15-46 highlighted that one of the successful strategies to implement CM/GC projects is to break a project into “mini” phases so that the construction manager can start work early in areas where ROW and permits have been obtained (Minchin et al. 2014).

The results from the correlation analysis show that the delays in right-of-way process had a correlation with railroad agreements, project complexity, unexpected utility encounter, and geotechnical investigation across three delivery methods (see Tables 4, 7, and 10). Additionally, the delays in right-of-way process had a correlation with all nine other risk factors in D-B with the correlation coefficient ranged from 0.31 to 0.64 (Table 7).

Unexpected Utility Encounter

Similar to delays in a ROW acquisition process, utility risk can have a substantial impact on project delivery method selection across all three delivery methods (Table 12). Utility relocation is typically a two-step process. The first step is to identify existing utilities. The second step is to remove or relocate the utilities. Obtaining utility agreements is a potentially high-risk process that can influence both project schedules and costs. Under D-B-B, the owner assumes the risk. One respondent stated that “utility delays are often uncontrolled third party risk that creates schedule problems and usually leads to more payouts.”

Under D-B, the highway agency can choose to shift the responsibility for obtaining utility agreements to the design-builder, but these RFPs should include all provisions related to the utility work. The level of communication and coordination between the design-builder and utility companies is key to success. It is challenging for the design-builder to acquire utility agreements because highway agencies have traditional relationships with utility companies and will likely have more influence than the design-builder.

Under CM/GC, the construction manager may have greater flexibility in negotiating with a utility company. NCHRP Project 15-46 emphasized that the CM/GC approach partially transfer some risk of utility coordination to the construction manager who takes responsibility for accelerating utility relocations and the overall project schedule and budget (Minchin et al. 2014). A word from a public owner "there is stronger collaboration earlier between the contractor and designer that can minimize the likelihood of an unexpected utility encounter."

The results from the correlation analysis show that the unexpected utility encounter had a correlation with most of the D-B-B and D-B delivery risk factors. Specifically, in D-B-B, the unexpected utility encounter had a correlation with eight other risk factors with the correlation coefficient ranged from 0.30 to 0.49 (Table 4). Under D-B, the unexpected utility encounter had a correlation with nine other risk factors with the correlation coefficient ranged from 0.32 to 0.77 (Table 7). However, the unexpected utility encounter only had a correlation with three risk factors in CM/GC with correlation coefficient ranged from 0.32 to 0.77 (Table 10).

Work Zone Traffic Control

This risk factor involves potential problems with maintenance of traffic, unexpected plans, and detours, and/or seasonal restrictions. Work zone traffic control is more critical to D-B-B than D-B and CM/GC (Table 12). Under D-B-B, designers specify the traffic control/maintenance according to the Manual of Uniform Traffic Control Devices (MUTCD) and requirements of the project. Contractors awarded the contract typically comply with the plans for traffic control. There is a lack of input from contractors to effectively manage this risk.

Under D-B, the traffic control plan is often included in the technical proposal and evaluated as part of the selection decision. As a result, this risk factor was not dominant in D-B projects. One contractor stated that "the performance specifications are the key to reducing work-zone traffic control risk." Under CM/GC, early collaboration with the designer and construction manager can minimize the impact of work-zone traffic control risk. The construction manager often actively participates in producing the traffic control and construction plans during the design phase (Minchin et al. 2014).

The results from the correlation analysis show that the risk related to work zone was highly correlated with construction sequencing/staging/phasing in both D-B-B and CM/GC. Additionally, the risk related to work zone traffic control had a correlation with other four risk factors with the coefficient ranged from 0.35 to 0.61 in D-B-B (Table 7). Similarly, the risk related to work zone traffic control had a correlation with other six risk factors with the coefficient ranged from 0.30 to 0.59 in CM/GC (Table 10).

Challenges to Obtain Environmental Documentation

This risk factor involves changing environmental regulations, unforeseen formal NEPA consultation, an insufficient environmental study, or environmental clearance for staging required. This risk factor was ranked seventh in D-B, and eighth in D-B-B, but was not in the top 10 risk factors in CM/GC (Table 12). Under D-B-B, the owner complete environmental documentation prior to the commencement of design and a bidding process. Under D-B, poorly defined environmental criteria can directly lead to project delays and cost overrun. Because the D-B delivery method limits the agency's control in obtaining environmental permits when the design is incomplete, environmental commitments may be a challenge for the design-builder during construction. Furthermore, when the design deviates from the original plan, some permits must be reissued before the construction can be resumed. In CM/GC projects, since the owner, designer, construction manager, and consultants work together early in the project plan, environmental documentation risk is often identified and effectively resolved, not identified in top 10 critical risks.

The results from the correlation analysis show that the challenge to obtain environmental documentation was correlated with project complexity, delays in right-of-way process, and unexpected utility encounter in both D-B-B and D-B, but not in CM/GC. Under D-B-B, the challenge to obtain environmental documentation had a correlation with other four risk factors with the coefficient ranged from 0.34 to 0.51 (Table 4). Under D-B, the challenge to obtain environmental documentation had a correlation with all other eight risk factors with the coefficient ranged from 0.41 to 0.67 (Table 7).

Delays in Delivery Schedule

Delays in delivery schedule involves uncertainty in the overall project delivery schedule from scoping through design, construction, and opening to the public. This risk factor was ranked seventh in D-B-B and ninth in CM/GC, but was not in the top 10 risk factors in D-B (Table 12). The nature of a non-overlapping process between design and construction in the D-B-B project delivery method may cause schedule delays. Additionally, due to lack of input from contractor experience and expertise in the design phase, design and construction schedules can be unrealistic. Under D-B, delays in delivery schedule may depend on selecting an appropriate procurement method. The low-bid selection may lead to schedule delays and other adverse outcomes when contractors cannot perform ideal projections (Minchin et al. 2014). Under CM/GC, delays in delivery schedule often involve the final establishment of a GMP. The process of managing GMPs not only requires an element of trust between the owner, designer, and construction, but also demands maintaining trust when changes are being negotiated (Gransberg and Shane 2010).

The results from the correlation analysis show that the delay in delivery schedule was correlated with several risk factors in both D-B-B and CM/GC, but not in D-B. Specifically, under D-B-B, the delay in delivery schedule had a correlation with other six risk factors with the coefficient ranged from 0.35 to 0.57 (Table 4). Under CM/GC, the delay in delivery schedule had a correlation with all other seven risk factors with the coefficient ranged from 0.35 to 0.76 (Table 10).

CONCLUSIONS

Project delivery selection has recently received considerable attention in the highway industry. Determining an appropriate delivery method for highway projects is a complex decision due to risk and uncertainty. Decision makers must have a clear understanding of how risks impact each delivery method to select the most suitable delivery method for their projects. This paper determined the top 10 risk factors associated with D-B-B, D-B, and CM/GC through analyzing 274 completed highway projects. The eight risk factors that were found to be the most influential on the project delivery selection process include: delays in completing in railroad agreements ; project complexity; uncertainty in geotechnical investigation; delays in a ROW process; unexpected utility encounter; work zone traffic control; challenges to obtain environmental documentation; and delays in delivery schedule. These risks were discussed and cross-validated using the content analysis of opinion-based risk data and the literature and the internal reliability and correlation analysis.

The results of this study showed that the top 10 risk factors of each delivery method were not independent, but correlated with other risks. Overall, the correlation coefficients of the top 10 risk factors in D-B-B were lower than that of D-B and CM/GC. One possible reason for these differences was the requirement of the design completed before construction in D-B-B projects. This requirement may lead to more certain information available to make a decision in D-B-B Thus, the risk factors in D-B-B had less dependent on other risks when comparing with D-B and CM/GC.

The risk assessment and risk management plays a pivotal role in the success of highway projects. This study was one of the first attempts in the literature that investigates project delivery risk using empirical data in that the rating of each risk factor was based on a completed project. The findings from this study advance the understanding of risk on project delivery selection. Additionally, the findings from this study will encourage public agencies to perform a risk assessment early in the project development process. It also promotes a better understanding of risk management cultures and enhances collaboration among project participants. The rankings of risk factors and their impact on each project delivery method may help highway agencies to improve appropriate risk allocation and thoughtful risk taking that can result in more efficient project delivery.

There are several limitations in this study. First, the sample size of CM/GC projects was smaller than that of D-B-B and D-B due to the fact that CM/GC is a still new delivery method in the highway industry. It is expected that increasing the sample size would reduce sampling errors and enhance the validity of this study. Future research may need to collect more completed CM/GC highway projects to overcome this limitation. Second, although the findings from this study contribute to both body of knowledge and practices, the study did not take into account project size and types when evaluating risk factors. It is expected that for certain types or sizes of projects, there may exist an appropriate risk profile for each delivery method. This limitation may warrant future research to investigate the interaction between risk and project characteristics and delivery. Finally, this study only collected data based on highway projects. Future research may collect non-highway projects to further investigate the impact of risk on project delivery selection.

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REFERENCES

AASHTO (2008). Design-Build Procurement Guide, American Association of State Highway and Transportation Officials, Washington, D.C., 2008.

AASHTO (2014). *MAP-21: Overview of Project Delivery, Environmental, and Planning Provisions.*

Alder, R. (2007). *UDOT Construction Manager/General Contractor (CM/GC) Annual Report*. Utah DOT- Project Development Group, Salt Lake City.

Blanding, J., and Lewis, J. (2012) “Shortening project delivery- Design-Build.” U.S. Department of Transportation Federal Highway Administration (FHWA) Every Day Counts (EDC).

Design-Build Institute of America (DBIA) (2016). *Design-Build Authorization for Transportation*, http://www.dbia.org/advocacy/state/Pages/default.aspx

Ellis, R.E., Herbsman, Z. J., and Kumar, A. (1991). “Evaluation of the FDOT Design/Build Program.” Final Report, Florida Department of Transportation, Tallahassee, Florida.

Federal Highway Administration (FHWA). (2006). *Design-build effectiveness study. U.S. Dept. of Transportation*, Washington, DC.

FHWA (2002). *Design-Build Contracting: Final Rule*. Federal Register.

Federal Highway Administration (FHWA). (2006). *Design-build effectiveness study*. U.S. Dept. of Transportation, Washington, DC.

Gransberg, D. D., Koch, J. A., and Molenaar, K. R. (2006). “Preparing for Design-Build Projects: A Primer for Owners, Engineers, and Contractors.” American Society of Civil Engineers.

Gransberg, D. D., and Shane, J. S. *NCHRP Synthesis 402 Construction manager-at-risk project delivery for highway programs*. Washington, D.C., 2010, 137 pp

Gransberg, D.D. and Loulakis, M.C. (2014). *NCHRP Synthesis 429 Geotechnical Information Practices in Design-build Projects*, Washington, D.C., 124.

Gransberg, D. D., Koch, J. A., and Molenaar, K. R (2006). *Preparing for Design-Build Projects: A Primer for Owners, Engineers, and Contractors.* American Society of Civil Engineers.

Kline, P. (2000). *The handbook of psychological testing (2nd Ed.)*. London: Routledge

Minchin, E., Ptschelinzew, L., Migliaccio, G.C., Gatti, U., Atkins, K., Warne, T., Hostetler, G. and Asiamah, S. (2014). *NCHRP Report 787: Guide for design management on design-build and construction manager/general contractor projects*, Washington, D.C.

Rahm, E. and Do, H. H. (2000). "Data Cleaning: Problems and Current Approaches." *In Bulletin of the IEEE Computer Society Technical Committee on Data Engineering*, 23(4), 3-13.

Sheskin, D.J. (2011). *Handbook of Parametric and Nonparametric Statistical Procedures (5th Edition)*. Chapman & Hall/CRC

Tran, D. Q., and Molenaar, K. R. (2014a). "Impact of risk on design-build selection for highway design and construction projects." *Journal of Management in Engineering*, 30(2), 153-162.

Tran, D. Q. and Molenaar, K. R. (2014b). "Exploratory critical delivery selection risk factors for transportation design and construction projects." *Engineering Construction and Architectural Management*, 21 (6), 631-647

Tran, D.Q., Harper, C.M., Molenaar, K.R., Haddad, N.B., and Scholfield, M.M. (2013). "Project Delivery Selection Matrix for Highway Design and Construction." *In Transportation Research Record: Journal of the Transportation Research Board, No. 2347, National*

Academies, Washington, D.C., 3–10.

Tran, D.Q., and Molenaar, K.R. (2015). "Risk-Based Project Delivery Selection Model for Highway Design and Construction." *Journal of Construction Engineering and Management*, 141 (12), 1-9

CHAPTER 4

IMPLEMENTING BAYESIAN NETWORKS FOR SELECTING PROJECT DELIVERY METHOD: THEORETICAL FRAMEWORK

ABSTRACT

Decision making during early stages of the project development process has a critical impact on project outcomes. Especially, decisions like selecting an appropriate project delivery method (PDM) may significantly impact the project performance. Historical observations or expert opinions strengthen an argument that no single PDM is suitable for any types/conditions of highway construction. In this paper, the authors proposed a theoretical framework to select an appropriate PDM for highway construction projects typically delivered using design-bid-build (D-B-B), design-build (D-B), and construction manager/general contractor (CM/GC). This paper employed grounded theory, resulted from extensive literature review about selecting PDM, and a survey questionnaire to develop the decision framework. The decision driving factors for selecting PDM were retrieved from the survey questionnaire comprising: project attributes, complexity, cost factor, time factor, and risk profile. The decision framework was developed based on Bayesian Networks (BN). The theoretical framework involves determining the interrelationships between the decision factors and how to implement the BN for selecting a PDM. The outcomes of the framework provide with probabilistic inferences associated with the three delivery methods (D-B-B, D-B, and CM/GC). The findings of this paper contribute to implementing BNs as a quantitative delivery selection tool in the construction industry. The theoretical framework facilitates the owners as an effective tool to make a reliable and statistically supported selection of PDM in their highway constructions.

Keywords: Bayesian Networks, Decision Making, Project Delivery Method, Highways

INTRODUCTION

Currently, many state departments of transportation (DOTs) have been adopting three fundamental project delivery methods to deliver their projects: design-bid-build (D-B-B), design-build (D-B) and construction manager/general contractor (CM/GC). Each delivery method has certain strengths and limitations. D-B may be a better choice than D-B-B and CM/GC for a specific project, but it may not be the suitable delivery method for others. It is widely acknowledged that there exists an optimal delivery method for each project, but no single delivery method is the most appropriate for any project type (Touran et al. 2011; Ibbs et al. 2003; Gordon 1994). Selecting a suitable project delivery method can have a major impact on the achievement of project goals and objectives. Researchers (Oyetunji and Anderson 2006; Luu et al. 2003; Love et al. 1998) have shown that using a suitable project delivery method can increase the efficiency and the success rate of a construction project. In fact, the selection of an appropriate delivery method could decrease the total project cost by an average of 5% (Love et al. 2012; Gordon 1994). On the other hand, applying an inappropriate project delivery method may impede a project's performance and even lead to project failure (Rwelamila and Meyer 1999).

Choosing an appropriate delivery method is a complex and challenging task for decision makers. The primary challenges of selecting the optimal delivery method include (1) a set of alternatives available (i.e., D-B-B, D-B, and CM/GC); (2) a variety of criteria that must be assessed; and (3) a large number of risks and uncertainties involved in the decision making process. Researchers have been developing models with improving tools and techniques like Gordon's (1994) flowchart model, the experiential knowledge approach (Kumaraswamy and Dissanayaka 2001), analytical hierarchical processes (Al Khalil 2002; Alhazmi and McCaffer 2000), the fuzzy logic selection models (Ng et al. 2002; Chan 2007). Multi-attribute utility/value theory approaches (Skitmore and Marsden 1988; Love et al. 1998; Molenaar and Songer 1998; Mahdi and Alreshaid 2005; Oyetunji and Anderson 2006). These models and tools have a common feature that they rely on subjective responses from industry practitioners and that the results are still somewhat devoid of relation to empirical project performance. Even some of the recently developed project delivery selection methods (Tran et al. 2013; Tran et al. 2014; Harper 2014) contain subjective elements in the project delivery method selection process, and some are designed for only a few types of projects or circumstances. Although such methods have their virtues, they fall short of capturing uncertainty propagation and the interaction between variables inherent in the selection process. To improve the accuracy of the project delivery decision process, this paper employed BNs to capture the impact of uncertainty on the decision and the relationships among decision variables.

BACKGROUND

A Bayesian Network (BN), popularly termed as a belief network or a causal network, is a powerful tool for knowledge representation and reasoning under uncertain conditions (Cheng et al. 2002). It visually presents the probabilistic relationships among a set of variables (Heckerman 1997). It is a convenient graphical expression for high-dimensional probability distributions representing complex relationships between large numbers of variables (Tran 2013). A convenient feature of BNs is the ability to learn about the structure and parameters of a system based on observed data (Kragt 2009). Knowledge of the structure of a system can reveal the dependence and independence of variables and suggest a direction of causation. It evaluates the ‘optimal’ BN structure, based on the highest probability score for possible candidate structures, given the data provided and perhaps penalized for the level of complexity (Norsys 2005). Different score metrics can be used to evaluate the BN structure, varying from entropy methods to genetic algorithms. It is frequently applied to real-world problems such as diagnosis, forecasting, automated vision, sensor fusion, and manufacturing control (Heckerman et al. 1995). It has been extended to other applications including transportation (Ulegine et al. 2007), ecosystem and environmental management (Uusitalo 2007), and software risk management (Fan and Yu 2004). BNs have many advantages such as suitability for small and incomplete data sets, structural learning possibility, a combination of different sources of knowledge, explicit treatment of uncertainty and support for decision analysis, and fast responses (Uusitalo 2007).

BNs deal with the decision scenarios under uncertainties and correlated decision variables. Because a BN constructs a cause and consequence diagram easily, it could be a suitable methodology for project risk management with systematic and integrated processes. Such a tool will expect to provide a valuable option for project delivery selection body of knowledge. In fact, some researchers have applied BN in the construction engineering and management domain. For example, McCabe et al. (1998) combined the BN with simulation models for automatic resource optimization on earth-moving operations; in their research, BNs were used to suggest remedial actions that will improve the project performance. Chung et al. (2006) applied BNs into a tunneling project for updating the penetrating rate based on accumulated evidence on project performance. Bayraktar and Hastak (2009) used BNs in the decision support system for evaluating different construction strategies based on a set of project performance indicators. Recently, Nguyen and Tran (2015) developed a model using BN to predict construction safety risk from falls. Though these studies demonstrated the effectiveness of BNs in predicting under complex and uncertain conditions, the networks were manually constructed and cause-effect relations were identified primarily by matter experts.

This study used empirical data in developing a prompt, accurate and unbiased decision support framework for highway construction agencies to select project delivery methods. It is expected that the proposed decision framework will be advantageous to the previous approaches by providing the specific quantitative results in the delivery selection process using BNs.

LITERATURE REVIEW

The project success is dependent on the selection of delivery method. Each project has unique features, and no single delivery method is the best. It is anticipated that a more efficient and quantitative way of determining the delivery method based on probabilistic results is needed. Table 1 summarizes typical project delivery selection approaches. Table 1 indicates that the project delivery decision varies widely ranging from the flow chart, multiple linear regressions, analytical hierarchy process (AHP), cased based reasoning, fuzzy case-based reasoning, and risk-based reasoning.

Table 1. Methodologies for selecting project delivery method

Researcher	Methodology for selecting project delivery method
Luu et al. (2005)	Case-based reasoning (CBR)
Oyetunji and Anderson (2006)	Multi-criteria decision analysis method
Zhao and Liu (2006)	Non-structural fuzzy decision method (NSFDM)
Mafakheri et al. (2007)	AHP coupled with rough approximation concepts
Chan (2007)	Fuzzy procurement selection model (FPSM)
Ojiako et al. (2008)	Data envelopment analysis (DEA)
Zhuo et al. (2008)	Multi-Attribute fuzzy evaluation
Mostafavi and Karamouz (2010)	Fuzzy multi-attribute decision making (FMADM) model
Chen et al. (2011)	DEA-bound variable (BND) model

Moon et al. (2011)	Logistic regression analysis
Love et al. (2012)	Participatory action based approach
Tran (2013)	Risk-based model

Oyetunji and Anderson (2006) pointed out that, "Structured, quantitative decision analysis processes possess many advantages than the simplistic, holistic, and informal processes that typically characterize subjective evaluations." Over the time, many researchers made attempts to derive quantitative approaches from investigating project delivery methods. Consequentially, multi-attribute utility/value theories were developed in which the encompassing decision-making process was broken down into smaller components which could then be ranked and scored for comparison. For example, AHP was used to select a suitable PDM in many studies. The priority of PDMs can be determined through the pairwise comparison matrix (Al Khalil 2002; Mahdi and Alreshaid 2005). The accuracy of AHP is interfered by the experts' uncertain and subjective judgments. Mafakheri (2007) utilized the interval AHP to determine the interval priorities for alternative PDMs and set theory to fully rank the alternatives. However, the full ranking depends on a higher risk, which increases the inaccuracy. Moreover, AHP tends to require a set of established indicators, including project participants, project characteristics and external environment (Alhazmi and McCaffer 2000; Mafakheri Dai, Slezak, and Nasiri, 2007; Mahdi and Alreshaid, 2005). It is very complex if a large number of indicators are used. Careful selection of indicators is needed to reduce the number as well as their correlation.

The multi-attribute utility can be utilized for PDM selection (Chan et al., 2001; Love, Skitmore, and Earl, 1998). The overall utility is calculated by multiply the weights by the utility of indicators. Speed, certainty, flexibility, quality, complexity, risk allocation, responsibility, arbitration and dispute, and price competition are often identified as its common indicators. The simplicity makes this model easy to practical use. However, the utility values of indicators often fail to reflect the actual status and the project may not achieve the specified objectives as initially expected.

Even some of the recently developed project delivery selection frameworks (Tran, 2013; Molenaar et al., 2014; Harper, 2014) contain subjective elements in the delivery selection process, and some are designed for specific projects or circumstances. Tran (2013) developed a risk-based model for the selection of project delivery methods for highway constructions projects in which the delivery selection model is innovatively connected with probabilistic risk analysis processes using a complex statistical and computational approach. The model developed by Tran (2013) produced approximate cost distributions for D-B, D-B-B and CM/GC methods along with a sensitivity analysis showing exactly which risk impacting the cost of the delivery methods. A major limitation is that it cannot be used without probabilistic risk-based cost estimating which remains a difficult concept in the construction industry to some extent. Tran et al. (2014) developed a project delivery selection matrix that can be used to validate the project delivery method decision. The process incorporates workshops with agency personnel directly involved in project delivery and encourages discussion during the evaluation of project attributes, goals, and constraints as they are compared and rated, by a non-numerical system, among different delivery methods. The result is the selection of the optimal delivery method among D-B-B, D-B, and CM/GC methods for a given project. Building upon form the literature, this study proposed a BN-based framework for selecting project delivery methods.

OVERVIEW OF BAYESIAN NETWORKS

Baye's theorem

BNs relies on Baye's theorem, postulated by Rev. Thomas Bayes (1702-1761). Rev. Bayes has addressed the probability distributions for both the discrete and continuous data. To understand the Baye's rule in practical approach, considering two events A and B (A→B; B is dependent of A). Transferring basic concepts of Baye's theorem to certainties in causal networks relates the conditional and marginal probabilities of events A and B as shown in Equations 1 and 2, provided that the probability of B, not equal zero:

$$P(A|B) = \frac{P(B|\mathrm{A})\, P(A)}{P(B)} \qquad \text{Eq (1)}$$

$$P(A|B) = \frac{P(B|\mathrm{A})P(A)}{P(B|\mathrm{A})\, P(\mathrm{A}) + P(B|\mathrm{A})\, P(B|\mathrm{A}^{\mathrm{c}})\, P(\mathrm{A}^{\mathrm{c}})} \qquad \text{Eq (2)}$$

- P(A) is the prior probability (unconditional or marginal probability) of A. It is *prior* in the sense that it does not take into account any information about B; however, the event B needs not occur after event A. P(B) is the prior or marginal probability of B and acts as a normalizing constant.
- P(A|B) is the posterior probability (conditional probability) of A, given B. P(A|B) is conditional because it is derived from or depends upon the specified value of B. Similarly, P(B|A) is the conditional probability of B given A.

In the above example, for a pair of variables A and B, the occurrence probability of a variable A, denoted as P(A), was simply calculated by the number of the experts who judge the occurrence of the variable A over the number of all judgments. The conditional probability of variable B given event A, denoted as P (B|A), was calculated by the number of experts who judge the occurrence of both variables A and B over the number of all experts who predict the occurrence of variable A. Although this approach has some advantages to obtain a consistent estimation of occurrence and conditional probabilities, it requires a significant number of experts.

Crossing the boundaries between theory and data (as shown in Figure 1), BNs have special qualities about causality. Under certain conditions and with specific theory-driven assumptions, BNs facilitate causal inference. The fundamental development of BN is widely applied in many fields, including science, engineering, medicine, and law. Its use in conjunction with prior knowledge and a system able to compute inference data can be very effective.

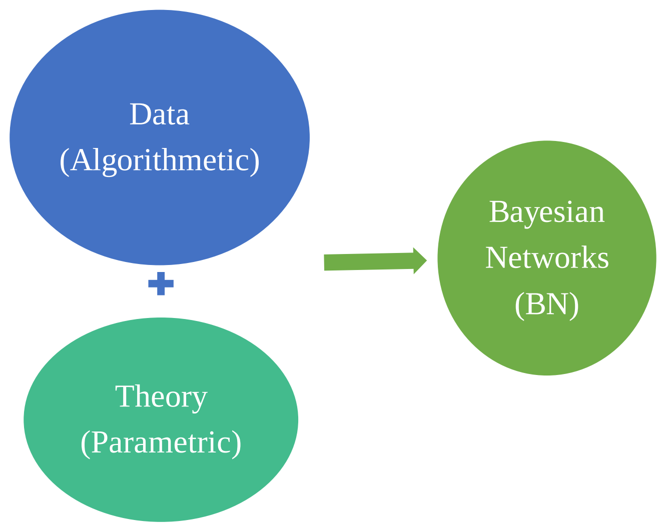


Figure 1. Fundamental theory of BNs

BN has a multidisciplinary theoretical base. The basic theory of the BN formalism was applied in numerous disciplines, including Computer Science, Probability Theory, Information Theory, Logic, Machine Learning, and Statistics. BNs can be utilized in virtually all disciplines. Stuart Russell in Darwiche (2009) indicated that BNs are closely relevant to artificial intelligent (AI) and machine learning. Bouhamed (2015) mentioned that BNs are emerging as one of the most complete, self-sustained and coherent formalisms used for knowledge acquisition, representation and application through computer systems.

Table 2. Implementing BNs to Develop Decision Models

Researcher	Application of BNs
Martín et al. (2009)	Case-based reasoning (CBR)
Liao (2012)	Participatory action based approach
Zhao et al. (2012)	Application on Safety Science
Martins and Maturana (2013)	Reliability engineering and system safety
Akhtar and Utne (2014)	Application on Safety Science
Hanninen et al. (2014)	Expert systems with applications
Zhao et al. (2012)	Application on Safety Science

Albeit many researchers have been striving to enhance the realistic application of BNs (as shown in Table 2), there is a need to emphasis software tools and algorithms in use. Advanced research should be made to implement large scale BNs in a wide range of multi-disciplinary applications. Innovative technical advancements can be effectively adaptable to enhance the BNs application. Many tools like TRACS, QinetiQ, AID tool, and MODIST are examples of application improvement using software. AgenaRisk is one such recent advanced development of BNs that possess the following advantages:

- Manual discretization of continuous nodes is not required. AgenaRisk can automatically discretize into suitable number of intervals.
- The software facilitates the users with pre-defined functions regarding ranked nodes that reduces the cumbersome work of manually constructing large BNs.
- Node probability tables (NPT) are generated from the simulation with the given mathematical conditions.

The critical applications of BNs include computer-assisted hypothesis testing, automated scientific discovery, and automated construction of probabilistic expert systems. It is noted that although the BN is an effective decision tool to describe probabilistic comparisons of different alternatives to make a decision and has been used successfully in many areas, it is still challenging to develop decision framework in the construction industry. This challenge is even more severe for problems involving various risks and uncertainty (i.e., project delivery selection). Overcoming such challenges, this paper integrates the results from multivariate analyses into the basics of BN in developing a decision framework for selecting an appropriate PDM.

Though the project success is crucially dependent on the selection of delivery method, each project has unique features. No single delivery method is the best for any projects. As a result, it is anticipated that a more efficient and quantitative way of determining the delivery method based on probabilistic results is needed. To develop an effective decision model of selecting a PDM and visualize the likelihood probabilities of each option (D-B-B, D-B, and CM/GC), this study developed a framework based on BNs to quantitatively identify the most suitable delivery method for a given project. The proposed framework improves the accuracy of making a delivery decision when compared with existing selection methodologies.

MODEL DEVELOPMENT

A convenient feature of BNs is the ability to learn about the structure and parameters of a system based on observed data (Kragt 2009). Knowledge of the structure of a system can reveal the dependence and independence of variables and suggest a direction of causation (Kragt 2009). It evaluates the optimal BN structure, based on the highest probability score for possible candidate structures, given the data provided and perhaps penalized for the level of complexity. Different score metrics, varying from entropy methods to genetic algorithms, can be used to evaluate the BN structure (Norsys 2005). Structure learning addresses the general problem of determining the existence of statistical dependencies among variables. If variables of influencing factors or events are represented as graphical nodes in the BN, structure learning identifies the directed edges between nodes with each one indicating a pair of the cause (arrow start) and effect (arrow end). In structure learning, the algorithm searches for an optimum structure in the space of all possible structures for a given set of variables representing the application domain (Luger 2009).

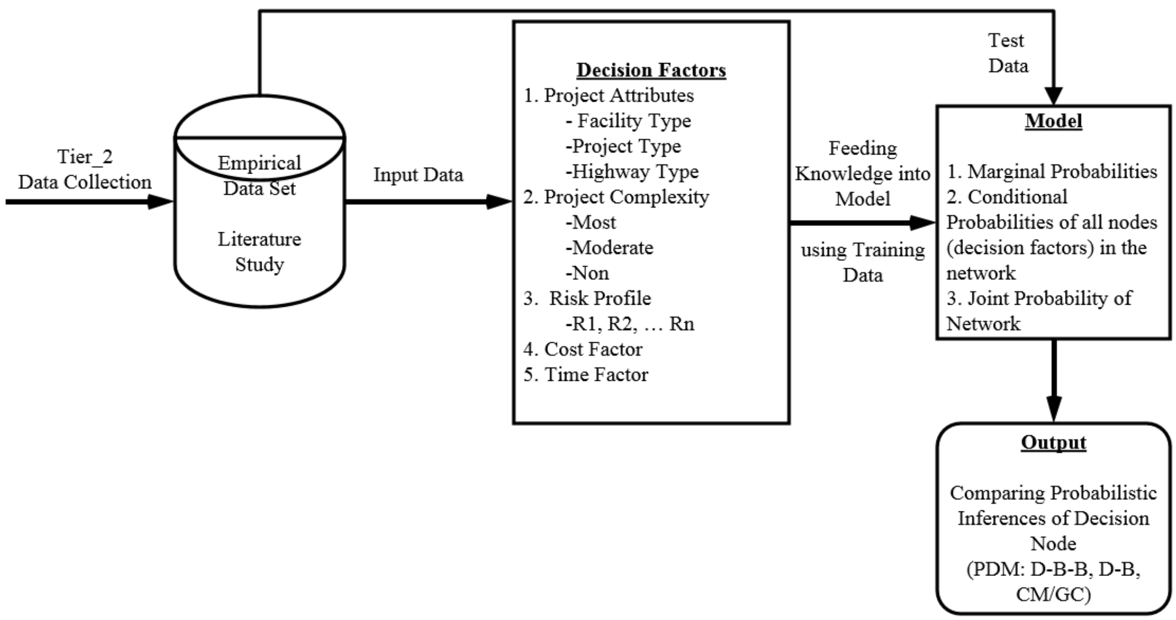


Figure 2. Steps to Developing Theoretical Decision Framework

Figure 2 illustrates the steps in developing the theoretical decision framework. Tier 2 data collection has totally 291 highway projects that were completed between 2004 and 2015. These projects were collected from state DOTs, FHWA, and Office of Federal Lands Highway. For each project, the authors developed a detailed questionnaire to collect pertinent information related to evaluating the influence of 31 risk factors on project outcomes. Combining the literature study and empirical data set from survey questionnaire, delivery decision factors were identified. The delivery decision factors includes: project attributes, project complexity, risk profile, cost factor, and time factor. The empirical data was screened and analyzed to building BN model. It is noted that only projects that have cost growth +/-5% were used to feed the knowledge into the model. The project cases excluded from building the model were retained for testing the model accuracy and case studies. The model outputs probabilistic comparison of the three delivery methods.

Proposed theoretical framework

The BN-based decision framework aims to quantify risk, project attributes and uncertainty that affects the project outcomes (e.g., cost and schedule performance). The model was developed based on the interrelation between the risk profile, project characteristics, and delivery method. The study has utilized BayesiaLab software, a graphical user interface, in developing the proposed decision framework. Figure 3 shows an overview of the BN-based model to select an appropriate delivery method. In the input level, the identified delivery decision factors are scrutinized and developed as nodes using BayesiaLab (BN software) and then the marginal (prior) probabilities were calculated. In processing level, the probabilistic dependence between the delivery decision factors were identified and the conditional probabilities were calculated. In addition, BN structure was tested for accuracy during the processing level. Finally, in the output level, joint probability of each delivery method (D-B-B, D-B, and CM/GC) were compared to select the highest likelihoods. All these three levels were explained detail in the later sections of the paper.

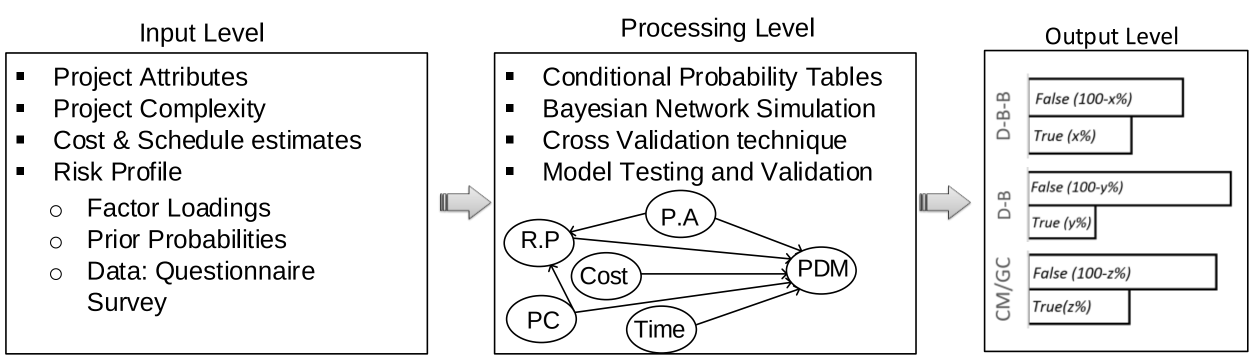


Figure 3. Research methodology to building a BN Computational Model

In Figure 3, R.P. represents the risk profile; P.A. accounts for the project attributes; Cost indicates the cost factor; Time indicates the time factor; PC represents the project complexity; finally, PDM represents, the target variable, project delivery method to be predicted (true and false probabilistic inferences).

Many commercial or open-source software packages are available for automatic BN learning. However, the fully automatic learning procedure can be difficult to apply for large number of variables, either the system or the variables are not well defined in the first place (Fan and Yu 2004). Further, different learning algorithms can produce different network structures, from the simplest star structure (with the target in the center and influencing variables outside) to the compound bushy tree-type structure (Fan and Yu 2004). A hybrid approach is based on the predefined BN. After obtaining operational data, the factual data can be used to update the parameters and the structure based on similar learning procedure. During the learning process, certain known relations or node information can be refined through the learning algorithm. The logical network represents the qualitative part of the domain knowledge; arcs represent the probabilistic interrelationships between the nodes. The quantitative part of the knowledge is contained in the conditional probability tables (CPT), which is associated with each node.

To explore the CPT's in detail, each node can be seen at its state level, probability distribution. The knowledge stored in the network can be utilized by the decision makers in the selection process of a delivery method for new highway construction projects. The model structure, identified based on the decision perspectives, depends on how the factors are organized in the model. Same factors can be modeled in different structures based on the decision analysis requirements. In this paper, the model structure learnt knowledge from the data (Salini and Kenett 2009).

Learning the BN structure from data is challenging. Finding an optimal structure over a large data set is a Non-deterministic polynomial-time hard problem due to the directed acyclic graph constraint (Chickering et al. 2004; Guo and Hsu 2007). Approximate solutions using heuristics are computationally efficient but suboptimal. Datasets may include noisy and irrelevant variables that can cause unnecessary complexity for the model. Therefore, before applying the BN model, a suitable variable selection procedure must be adopted to eliminate the trivial variables while capturing the most relevant ones (Shih et al. 2014). To find the best subset of variables, a heuristic feature selection algorithm is proposed by Sun and Shenoy (2007) where they eliminate the redundant variables based on correlations and partial correlations among variables (Sun and Shenoy 2007).

The BN can be constructed based on the expert opinions (Bayesian Belief network), or statistical evidence (Bayesian probability network). Compared with other decision models such as decision trees, BN models have some unique advantages in problem modeling and analysis. The graphical representation of BNs are easy to interpret and represents the probabilistic dependence of casual factors. In addition, BNs can be updated timely using computer algorithms.

Construction of a Bayesian Network

Two methods to construct the network are available: (a) manually with the help of an expert, and (b) analytically by learning the structure from the data using advanced mathematical methods.

Building a manual modest-sized network requires a skilled knowledge engineer. When the size of the network increases, the expert time increases dramatically (Koller and Friedman 2009). In some cases, it is also challenging to find a knowledgeable engineer for that particular domain. Previous studies provide various techniques that use data for learning the structure. The naive Bayes classification is a simple model that assumes conditional independence between all predictor variables and the given target variable to learn the structure (Domingos and Pazzani 1996). Based on the Bayes rule, as shown in Equations 1 and 2, probability target variable is computed for each given attribute variable and then the highest prediction is chosen for the structure.

Learning Method

Pearl (1986) developed a message-passing scheme that updates the probability distributions for each node in BNs in response to observations of one or more variables. Researchers, for example Lauritzen and Spiegelhalter (1988), Jensen et al. (1990), and Dawid (1992), proposed an efficient algorithm that first transforms a BN into a tree where each node corresponds to a subset of variables in the original graph. The algorithm then exploits several mathematical properties of this tree to perform probabilistic inference. There are a variety of BN learning algorithms. Of these, best known are probabilistic logic sampling (Henrion 1988), likelihood sampling (Shachter and Peot 1990; Fung and Kuo-Chu 1990), backward sampling (Fung and Del Favero 1994), Adaptive Importance Sampling AIS-BN (Cheng and Druzdzel 2000), and Approximate Posterior Importance Sampling APIS BN (Yuan and Druzdzel 2003). Approximate belief updating in BNs has also been shown to be worst-case NP-hard (Dagum and Luby 1993).

BayesiaLab Software Version 6.0.8

Implementing the knowledge of building BNs, many advanced statistical software packages such as Netica, BayesiaLab, Hugin, Analist, and Genie are available. In this study, BayesiaLab 6.0.8 with abundant modeling features, better visual representation, and adaptive questionnaire was used for developing the theoretical framework. The detailed step-by-step approach of building the theoretical framework using BayesiaLab is demonstrated in the following sections.

Data Preparation

This study collected 291 highway projects that were completed between 2004 and 2015. These projects were collected from state DOTs, FHWA, and Office of Federal Lands Highway. For each project, the research team developed a detailed questionnaire to collect pertinent information related to evaluating the influence of 31 risk factors on project outcomes. The research team sent the questionnaire survey to the agency's project representative by email and following up with phone correspondences as required for data verification. Based on the specific characteristics of each project, the project representative (e.g., project manager) were asked to rate the impact of risk on project cost and schedule performance before or at the time that the project delivery decision was made. The data collection process took more than a year. The theoretical framework was developed based on 177 highway projects including, 71 of D-B-B, 87 of D-B and 19 of CM/GC projects. Data import and discretization are the initial steps in data preparation. To import the empirical data collected from the survey questionnaire, using the command shown in Figure 4, the Comma Separated Values (CSV) formatted file is imported into the BayesiaLab. To define the sample data, each column is examined while importing. Missing values are defined, notable to follow, to avoid discrepancy and noise in the analysis.

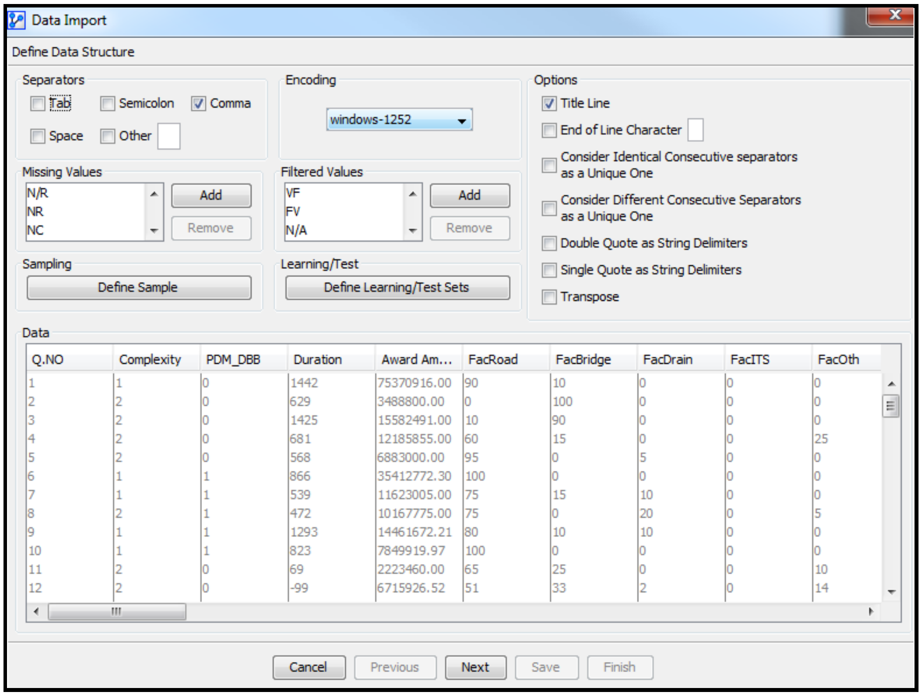


Figure 4. Data import for developing theoretical framework

Discretization and aggregation of the data involve dealing with continuous data. To build the computational model, the input fields of project attributes (facility type, project type, highway type) are of continuous data. To facilitate BayesiaLab in building marginal and conditional probability tables, discretized data was used. Based on the density function and distribution of each variable, bins are set to describe the continuous data into intervals. The distribution curve helps in identifying the critical points (changing trend), and care should be taken while setting the bin size. Figure 5 provides an illustrative example of discretizing the continuous data of time factor. Based on the density function and distribution, bin sizes of these data are set at suitable intervals. These bins can represent the marginal and conditional probabilities of the nodes/variables in the network. The likelihood of discretized bins is even used in the interpretation of probabilistic inferences. In the BN, each node is described by a probability distribution dependent on its direct predecessors. Nodes with no predecessors are described by prior probability distributions.

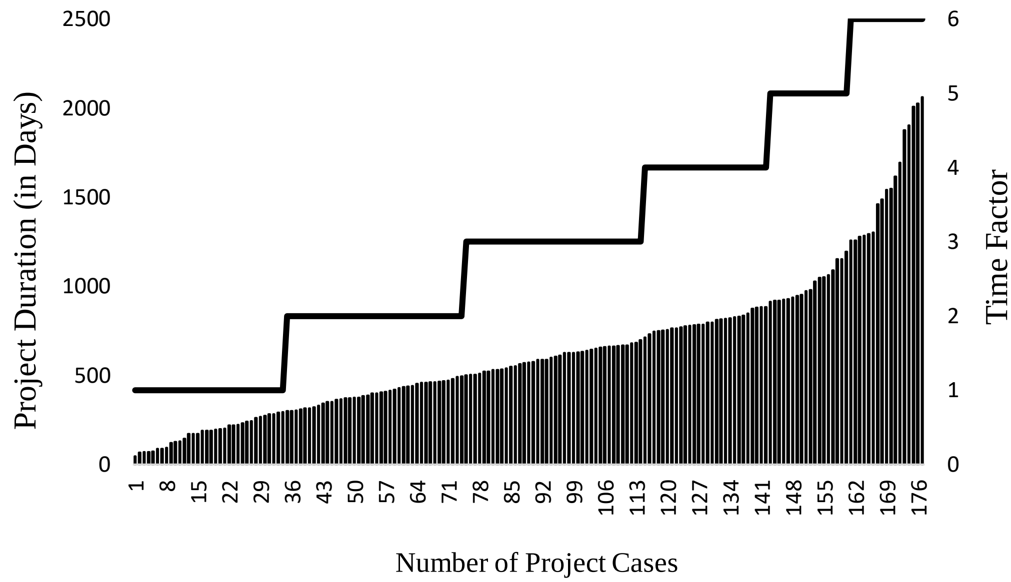


Figure 5. Discretizing the continuous data of time factor (sample node)

Establishing interrelationships between the Decision Factors (Nodes)

Decision factors include cost, time, project complexity, project attributes, and risk profile (as shown in Figure 6). It is noted that because decision factors of cost, time are continuous, they were categorized into suitable number of bins (discussed in the previous section). The project complexity was categorical. To reduce the complexity of BN structure, using cluster analysis technique, project characteristics with 14 variables (from the survey questionnaire- see Appendix VI) including facility type (road, bridge, drainage, ITS, others), project type (new construction/expansion, rehabilitation/reconstruction, resurfacing/renewal, others), and highway type (rural interstate, urban interstate, rural primary, urban primary, rural secondary) were clustered into a single variable, (Project attributes) with three levels. Project attributes is treated as an intermediate node in the network.

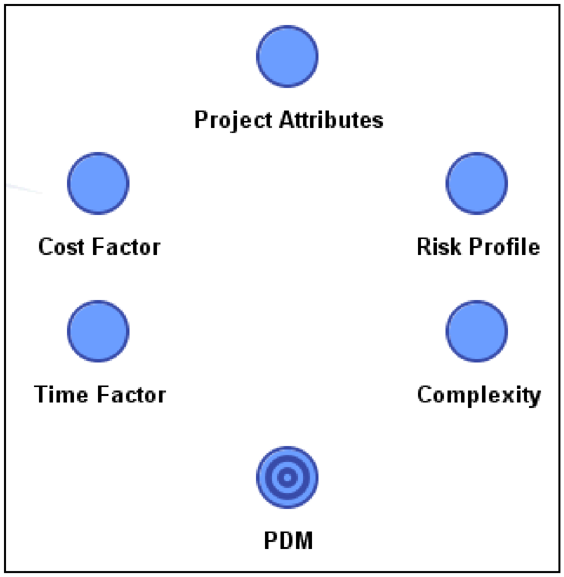


Figure 6. Decision Factors to Selecting PDM

Similarly, risk components for D-B-B, D-B, and CM/GC identified from factor analysis results, adapted from Tran and Molenaar (2014), see Appendices II, III, and IV, were clustered into a single risk profile variable with three levels. Generating risk profile based on the risk components were shown in Figures 14, 15, 16, and 17. Detailed results of data clustering for project attributes and risk profile were explained in the following sections.

A cluster is simply a group of objects considered similar by one or more metrics. With applications in biology (Alon et al. 1999; Fathian et al. 2007), computer science (Frey and Dueck 2007; Broder et al. 1997), and social science (Hillhouse and Adler 1997; Cook 2005), among many others, clustering analysis is an efficient data mining method for grouping objects with similar characteristics (Moser et al. 2007).. Many methods for determining clusters within a data set exist, each with their own benefits and downsides. Generally the clustering methods fall into one of two categories—partitioning and hierarchical algorithms. Partitioning algorithms (e.g., k-means, an algorithm used later in this paper) divide the dataset, whereas hierarchical algorithms decompose the dataset into a nested partition (Ankerset et al. 1999). Some algorithms are distinctively partitioning or hierarchical algorithms whereas others are hybrids, blurring the definitions of both. The clustering method chosen by the user is heavily context dependent, and the outcomes depend on the method selected. The clustering algorithm is the fastest known exact algorithm for belief updating in BNs. It was originally proposed by Lauritzen and Spiegelhalter (1988) and improved by several researchers such as Jensen et al. (1990) or Dawid (1992).

The clustering algorithm includes two phases: (1) compilation of a directed graph into a junction tree, and (2) probability updating in the junction tree. It has been a common practice to compile a network, and then perform all operations in the compiled version. Research in relevance reasoning (Lin and Druzdzel 1997) has challenged this practice and shown that it may be advantageous to pre-process the network before transferring it into a junction tree. . The belief updating algorithm for singly connected networks (polytrees) was proposed by Pearl (1986). It is the belief updating algorithm that is of polynomial complexity. However, this result and the algorithm works only in singly connected networks (i.e. networks in which any two nodes are connected by at most one undirected path).

Cost Factor

From the empirical data collected 291 completed highway projects, the projects were analyzed. Only projects with cost growth within +/- 5% were only used for feeding the knowledge in building the BN framework. As a result, the sample data used to build the BN framework was 177. Table 3 represents both the survey data and the sample data distribution of cost factor, into six bins: less than $3M, $3M to $10M, $10M to $20M, $20M to $30M, $30M to $50M, and greater than $50M.

Table 3. Sample Data Distribution of Cost Factor

Category	Project Size (in Million)	Survey Data (before Scrutiny, n=291)	Sample Data (After Scrutiny, n=177)
1	Less than 3M	60	42
2	$3M- $10M	54	36
3	$10M- $20M	60	38
4	$20M- $30M	43	21
5	$30M- $50M	36	17
6	Greater than $50M	38	23

Time Factor

Table 4 represents both the survey data and the sample data distribution of time factor (e.g., construction duration), into six bins: Less than 300 days, 300 to 500 days, 500 to 700 days, 700 to 900 days, 900 to 1200 days, and greater than 1200 days.

Table 4. Sample Data Distribution of Time Factor

Category	Duration Size (in Days)	Survey Data (before Scrutiny, n=291)	Sample Data (After Scrutiny, n=177)
1	Less than 300	60	34
2	300- 500	54	40
3	500- 700	52	40
4	700- 900	46	28
5	900- 1200	37	18
6	Greater than 1200	41	17

Project Complexity

Table 5 represents the characteristics of a highway construction that determines the project complexity. From the sample data of 177 projects, majority of project cases are of most and moderate complex categories with 43% and 40% respectively. Only 17% of the sample data are of non-complex projects.

Table 5. Project Complexity from Survey Questionnaire

Most Complex (Major) Projects	Moderately Complex Projects	Non-complex (Minor) Projects
•New highways; major relocations •New interchanges •Capacity adding/major widening •Major reconstruction (4R; 3R with multi-phase traffic control) •Congestion management studies are required •Environmental Impact Statement or complex Environmental Assessment required	•3R and 4R projects which do not add capacity •Minor roadway relocations •Non-complex bridge replacements with minor roadway approach work •Categorical Exclusion or non- complex Environmental Assessment required	•Maintenance betterment projects •Overlay projects, simple widening without right-of-way (or very minimum right-of-way take) little or no utility coordination •Non-complex enhancement projects without new bridges (e.g. bike trails) •Categorical Exclusion

Project Attributes

Table 6 represents the project attributes data collected from the survey questionnaire (Appendix VI). Respondent was assigned the percentages from 0 to 100 (continuous data), contributing portion, based on the highway construction project conditions. The facility type comprises of road, bridge, drainage, ITS, and other. The project type comprises of new construction/expansion, rehabilitation/reconstruction, resurfacing/renewal, and others. The highway type details about the rural interstate, urban interstate, rural primary, urban primary, and rural secondary.

Table 6. Project Attributes from Survey Questionnaire

Project Attributes		
Facility Type	**Project Type**	**Highway Type**
• Road • Bridge • Drainage • ITS • Other	• New Construction /Expansion • Rehabilitation/Reconstruction • Resurfacing/Renewal • Ohers	• Rural Interstate • Urban Interstate • Rural Primary • Urban Primary • Rural Secondary

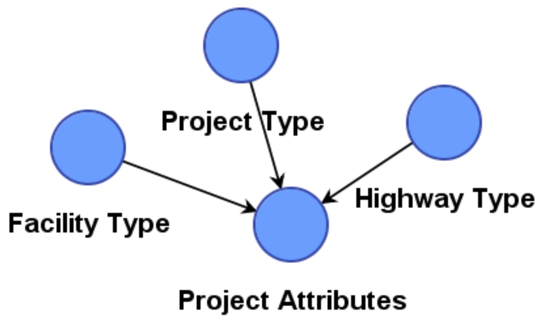


Figure 7. Establishing Project Attributes Node

It is noted that the data clustering at the input level of facility/project/highway type variables with project attribute (as shown in Figure 7) remains the same for D-B-B, D-B and CM/GC. The data clustering of project attributes resulted in three fixed states with a clustering average purity of 95.33%. Cluster 1 has marginal probability of 40.11% and cluster purity of the 94.78%. Cluster 2 has marginal probability of 10.18% and cluster purity of the 96.29%. Cluster 3 has marginal probability of 49.71% and cluster purity of the 94.78%. The results of data clustering of project attributes with corresponding mutual information and relative significance were presented in Table 7.

Table 7. Data Clustering of Project Attributes

Project Attributes		Mutual Information	Normalized Mutual Information	Relative significance	Mean Value	G-test
Facility Type	Bridge	0.665	48.67%	1.000	37.36	163.09
	Road	0.533	39.07%	0.803	42.72	130.89
	Drainage	0.213	15.59%	0.320	7.44	52.25
	ITS	0.143	10.47%	0.215	2.10	35.07
	Oher	0.125	9.17%	0.189	10.72	30.74
Project Type	New Construction/ Expansion	0.283	20.74%	0.426	43.95	69.51
	Reconstruction/ Rehabilitation	0.196	14.37%	0.295	40.47	48.14
	Resurfacing/ Renewal	0.043	3.15%	0.065	4.06	10.55
	Other	0.088	6.46%	0.133	11.57	21.65
Highway Type	Rural Interstate	0.132	9.67%	0.199	11.76	32.41
	Rural Primary	0.085	6.19%	0.127	28.47	20.73
	Rural Secondary	0.090	6.59%	0.136	10.76	22.09
	Urban Interstate	0.072	5.29%	0.109	24.15	17.74
	Urban Primary	0.047	3.44%	0.071	24.94	11.54

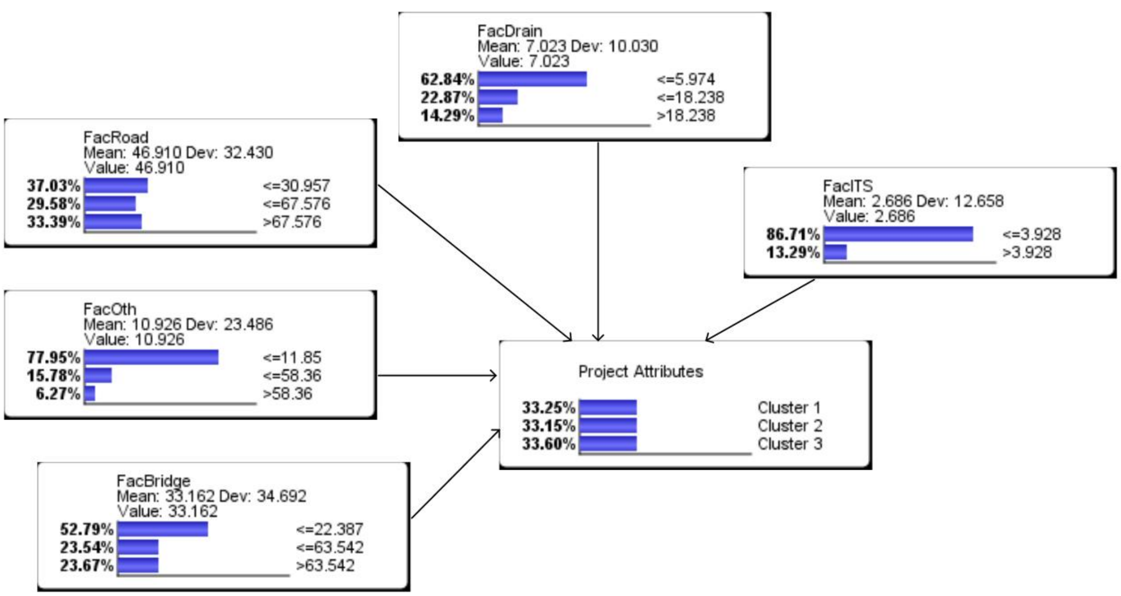


Figure 8. Interrelationship between facility type variables and Project attributes

Figure 8 represents the contribution of facility type to the single project attributes variable. For facility type, road has the highest mean value of 43%. Bridge has a mean value of 37%. Other and drainage has a mean values of 11% and 7% respectively. ITS has the least mean value of 2.10%.

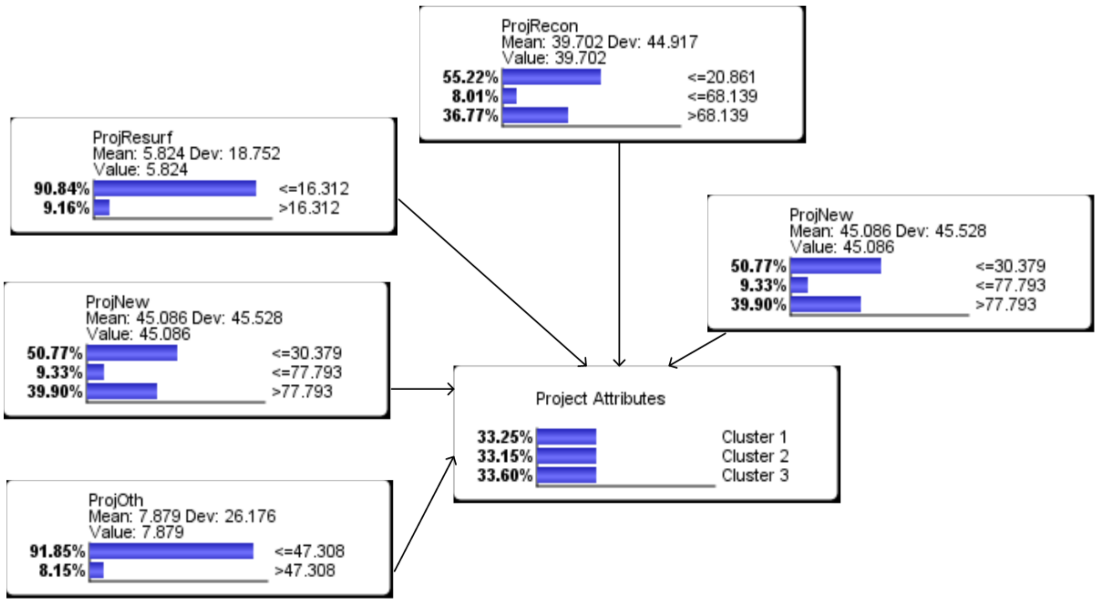


Figure 9. Interrelationship between project type variables and Project attributes

Figure 9 represents the contribution of project type to the single project attributes variable. For project type, new construction/expansion has the highest mean value of 44%. Reconstruction/ rehabilitation has a mean value of 40%. Other has a mean value of 11%. Resurfacing/ renewal has the least mean value of 4%.

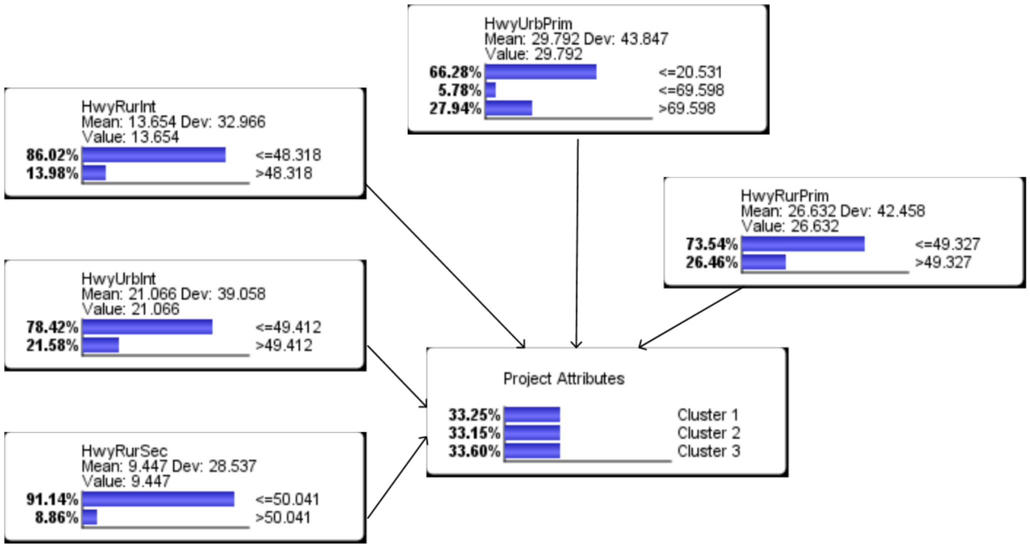


Figure 10. Interrelationship between highway type variables and Project attribute

Figure 10 represents the contribution of highway type to the single project attributes variable. For Highway type, rural primary has the highest mean value of 28%. Bothe urban interstate and primary interstate has approximately equal mean value of 24%. Rural interstate has a mean value of 12%. Reconstruction/ rehabilitation has a mean value of 40%. Rural secondary has the least mean value of 11%.

Risk Profile

Risk profiles in the BN are differently associated with each delivery method. Each delivery method (D-B-B, D-B, and CM/GC) has their unique set of interrelationships between the risk factors in the project case and risk profile, as shown in Figure 11. The different combinations of risk profiles based on the delivery method are illustrated in the Figures 12, 13, and 14 and explained as follows. The factor loadings (factor analysis results on critical risk factors under each PDM are documented in Appendices II, III, and IV) were used to construct the interrelationships among risk components.

As mentioned previously, the major challenge of using BN to select an appropriate project delivery method is a large number of variables involved in the decision. For instance, with 31 delivery risk factors in the analysis, at least 3 * 31*31 = 2883 assessments are required when three delivery methods (D-B-B, D-B, and CM/GC) are present in the analysis. To reduce the complexity in building BN, data clustering was carried out for risk profiles of the three delivery methods.

Table 8. Risk Profile from Survey Questionnaire

Risk Profile		
Design-Bid-Build (D-B-B) • Construction Risk • Schedule Risk • Third Party and Complexity Risk • Constructability Risk • Market Risk • ROW Risk	**Design-Build (D-B)** • Scope Risk • Third Party and Complexity Risk • Construction Risk • Utility and ROW Risk • Level of Design and Contract Issues • Management Issues • Regulation Risk and Railroad	**Construction Manager/General Contractor (CM/GC)** • Constructability and Documentation Risk • Construction Risk • Complexity Risk • Management Issues and Schedule Risk • Third Party Risk • Regulation Risk and ROW

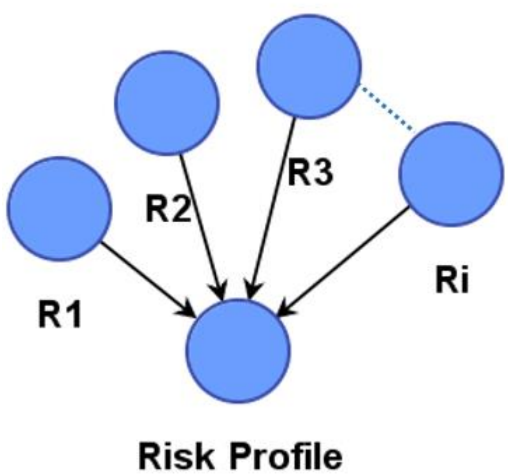


Figure 11. Establishing risk profile node

Figure 11 represents an example risk profile (building the network) by data clustering the risk components identified (Appendices II, III, and IV). The data clustering results of risk profile are presented in Table 9.

Table 9. Data Clustering of Risk Profile

Risk Profile		Mutual Information	Normalized Mutual Information	Relative significance	Mean Value	G-test
Design-Bid-Build (D-B-B)	Construction Risk	0.605	41.31%	0.629	4.84	243.97
	Schedule Risk	0.846	57.80%	0.881	4.32	341.40
	Third Party and Complexity Risk	0.961	65.63%	1.000	3.92	387.66
	Constructability Risk	0.659	45.02%	0.686	3.37	265.92
	Market Risk	0.468	31.94%	0.487	1.48	188.62
	ROW Risk	0.336	22.96%	0.350	0.70	135.63
Design-Build (D-B)	Scope Risk	0.487	37.39%	0.603	4.80	119.60
	Third Party and Complexity Risk	0.646	49.55%	0.799	4.21	158.48
	Construction Risk	0.681	52.27%	0.843	4.43	167.18
	Utility and ROW Risk	0.434	33.31%	0.537	1.93	106.54
	Level of Design and Contract Issues	0.654	50.14%	0.809	2.08	160.40
	Management Issues	0.808	62.00%	1.000	1.34	198.32
	Regulation Risk and Railroad	0.300	22.98%	0.371	1.05	73.50
Construction Manager/ General Contactor (CM/GC)	Constructability and Documentation Risk	0.967	65.19%	1.000	4.60	237.30
	Construction Risk	0.801	53.99%	0.828	2.24	196.53
	Complexity Risk	0.765	51.56%	0.791	3.66	187.70
	Management Issues and Schedule Risk	0.763	51.42%	0.789	4.68	187.18
	Third Party Risk	0.388	26.14%	0.401	1.53	95.16
	Regulation Risk and ROW	0.353	23.80%	0.365	0.88	86.65

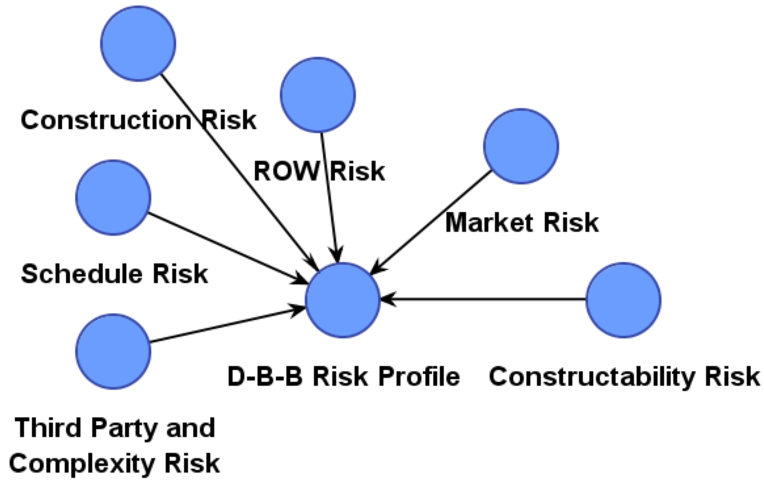


Figure 12. Risk Profile for D-B-B Delivery Method

The risk profile for the D-B-B delivery method is shown in Figure 12. The data clustering of D-B-B risk profile resulted in three fixed states with a clustering average purity of 93.38%. Cluster 1 has marginal probability of 51.88% and cluster purity of the 98.69%. Cluster 2 has marginal probability of 29.21% and cluster purity of the 94.65%. Cluster 3 has marginal probability of 18.90% and cluster purity of the 90.96%. Construction risk comprises of uncertainty in geotechnical investigation, environmental impacts, work zone traffic control, construction QC/QA process. Schedule risk comprises of construction sequencing/staging/phasing, unexpected utility encounter, unclear contract documents, and delays in delivery schedule. Third party and complexity risk comprise of difficulty in obtaining other agency approvals, defined and non-defined hazardous waste, project complexity, delays in completing utility agreements. Constructability risk comprises of delays in procuring materials, labor, and equipment, constructability of design, and a significant increase in material, labor, and specialized equipment cost. Market risk comprises of construction market conditions and annual inflation rates. Row risk is about delays in right-of-way (ROW) process.

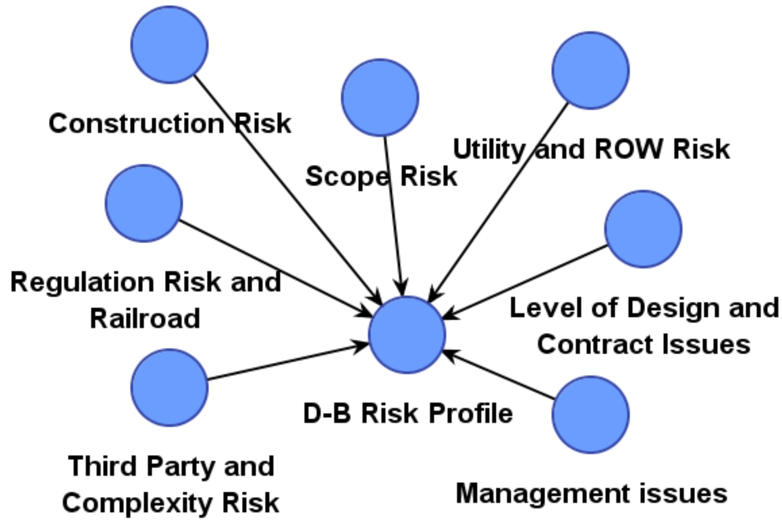


Figure 13. Risk Profile for D-B Delivery Method

The risk profile for the D-B delivery method is shown in Figure 13. The data clustering of D-B risk profile resulted in three fixed states with a clustering average purity of 95.69%. Cluster 1 has marginal probability of 19.78% and cluster purity of the 99.22%. Cluster 2 has marginal probability of 63.82% and cluster purity of the 94.79%. Cluster 3 has marginal probability of 16.39% and cluster purity of the 95.38%. Scope risk comprises of project definition, scope definition, staff experience/availability, conformance with regulations/guidelines /design criteria, a challenge to appropriate environmental documentation. Third-party and complexity risk consists of delays in completing utility agreements, difficulty in obtaining other agency approvals, project complexity, defined and non-defined hazardous waste, legal challenges and changes in the law. Construction risk comprises of uncertainty in geotechnical investigation, work zone traffic control, environmental impacts, and construction QC/QA process. Utility and ROW risk comprises of unexpected utility encounter, delays in right-of-way (ROW) process. The level of design and contract issues comprises of design completion, single or multiple contracts, unclear contract documents. Management issues comprise of project and program management issues, insurance in the contract. Regulation risk and railroad comprise of intergovernmental agreements and jurisdiction and delays in railroad agreements.

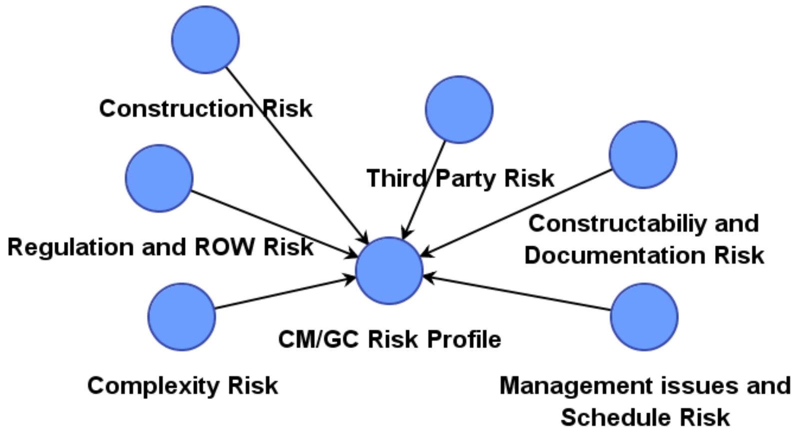


Figure 14. Risk Profile for CM/GC Delivery Method

The risk profile for CM/GC delivery method is shown in Figure 14. The data clustering of CM/GC risk profile resulted in three fixed states with a clustering average purity of 94.59%. Cluster 1 has marginal probability of 20.91% and cluster purity of the 98.78%. Cluster 2 has marginal probability of 50.84% and cluster purity of the 92.24%. Cluster 3 has marginal probability of 20.91% and cluster purity of the 95.95%. Constructability and documentation risk consists of conformance with regulations/guidelines/design criteria, a significant increase in material, labor and equipment cost, constructability of design, delays in procuring critical materials, labor, and specialized equipment, challenges to obtain appropriate environmental documentation. Construction risk comprises of work zone traffic control, uncertainty in geotechnical investigation, construction QC/QA process, and environmental impacts. Complexity risk comprises of project complexity, difficulty in obtaining other agency approvals, design QC and QA process, defined and non-defined hazardous waste. Management issues and schedule risk comprises of project and program management issues, insurance in contract and delays in delivery schedule. Third-party risk comprises of delays in railroad agreements and delays in completing utility agreements. Regulation risk and right-of-way (ROW) comprises of intergovernmental agreements and jurisdiction, and delays in the ROW process.

Mathematical Expression

The proposed BN built and detailed in the previous section can be represented in the form of mathematical expressions. A BN containing n nodes, X_1 to X_n, joint distribution is represented by $P(X_1=x_1, X_2=x_2 \ldots X_n=x_n)$. Pearl et al. (1991) showed that BNs allow representing the joint probability distribution compactly on the set of *n* variables. The chain rule of probability theory yields to factorize joint probabilities as represented by Equation 2.

$$P(X) = \mathrm{P}(\mathrm{X}_1, X_2 \ldots . X_n) = \prod_{i=1}^{n} P[X_i \mid X_{j(i)}] \qquad \text{Eq (2)}$$

To formulate the mathematical expressions, generic model of BN, as shown in Figure 17, is used to present probabilistic dependence between the decision delivery factors (nodes). In the following equations the acronyms of RP represents the risk profile; PA represents the project attributes; C i represents the cost factor; T represents the time factor; and PC represents the project complexity. Finally, the target variable, PDM, represents project delivery methods to be predicted (true and false probabilistic inferences).

$$P(PDM|\mathrm{PA}, \mathrm{RP}, \mathrm{C}, \mathrm{T}, \mathrm{COM}) = P(PA) * P(\mathrm{COM}) * P(\mathrm{C}) * P(\mathrm{T}) * P(RP|\mathrm{PA}, \mathrm{COM}) \qquad \text{Eq(3)}$$

$$P(PA) = P(PA_1) * P(PA_2) * P(PA_3) \qquad \text{Eq(4)}$$

$$P(COM) = P(COM_1) * P(COM_2) * P(COM_3) \qquad \text{Eq(5)}$$

$$P(C) = P(C_1) * P(C_2) * P(C_3) * P(C_4) * P(C_5) * P(C_6) \qquad \text{Eq(6)}$$

$$P(T) = P(T_1) * P(T_2) * P(T_3) * P(T_4) * P(T_5) * P(T_6) \qquad \text{Eq(7)}$$

$$P(RP) = P(RP_1|\text{PA, COM}) * P(RP_2|\text{PA, COM}) * P(RP_3|\text{PA, COM}) \qquad \text{Eq(8)}$$

$$P(PDM|\text{PA , RP, C, T, COM}) = P(PDM|\text{PA}) * P(PDM|\text{C}) * P(PDM|\text{T}) * P(PDM|RP) * P(PDM|\text{COM}) * P(RP|\text{PA, COM}) * P(\text{PA}) * P(\text{C}) * P(\text{T}) * P(COM) \qquad \text{Eq(9)}$$

$$P\ (PDM|\text{PA , RP, C, T, COM}) = \left[P(PA|\text{PDM}) * \frac{P(PDM)}{\text{P(PA)}}\right] * \left[P(C|\text{PDM}) * \frac{P(PDM)}{\text{P(C)}}\right] * \left[P(T|\text{PDM}) * \frac{P(PDM)}{\text{P(T)}}\right] * \left[P(RP|\text{PDM}) * \frac{P(PDM)}{\text{P(RP)}}\right] * \left[P(COM|\text{PDM}) * \frac{P(PDM)}{\text{P(COM)}}\right] * \left[P(PA|\text{RP}) * \frac{P(RP|COM)}{\text{P(PA)}}\right] * P(PA) * P(\text{C}) * P(\text{T}) * P(COM) \qquad \text{Eq(10)}$$

As represented in Figure 15, the likelihoods (true %) of a project case falling under each PDM type: D-B-B, D-B and CM/GC are determined by *x%*, *y%*, and *z%* respectively. For D-B-B, the false (%) likelihood indicating the project can either be D-B or CM/GC is represented by *100-x%*. For D-B, the false (%) likelihood indicating the project can either be D-B-B or CM/GC is represented by 100- *y%.* For CM/GC, the false (%) likelihood indicating the project can either be D-B-B or D-B is represented by 100- *z%.* The true likelihood probabilities of *x%, y%* and *z%* and the false likelihood probabilities of *100- x%, 100- y%, and 100- z%* are compared with each project case to determine the most suitable one. The highest true likelihood probability is considered as the most appropriate PDM.

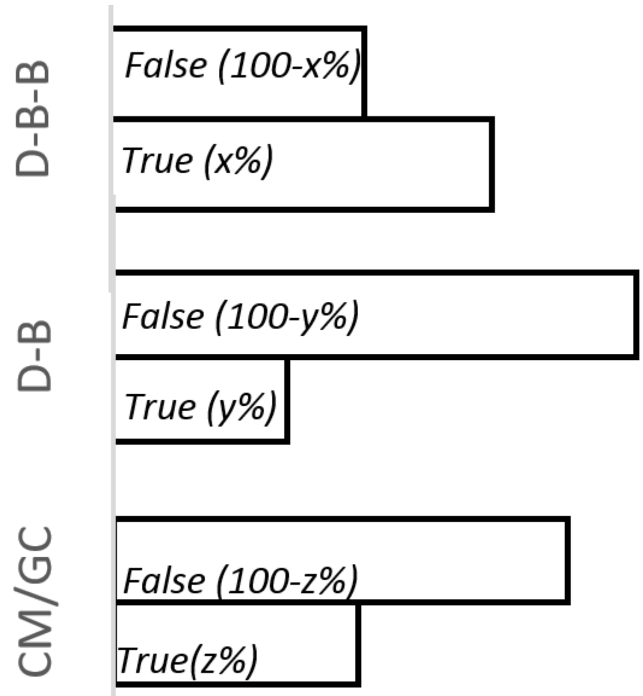


Figure 15. Comparing probabilistic inferences

The following Equation 11 can be used to check whether the highest true likelihood is correct based on the probabilistic inferences. The joint probabilities of three delivery methods are shown in Table 10.

Max $\{P(x), P(y), P(z)\}$ =100- Min $\{(P(100-x), P(100-y), P(100-z)\}$ Eq (11)

Table 10. Selecting the PDM with highest true likelihood

Joint Probability	True Likelihood	False Likelihood
$P(PDM\|\mathrm{PA, RP, C, T, COM})_{\mathrm{D-B-B}}$	$P(x)$	$P(100-x)$
$P(PDM\|\mathrm{PA, RP, C, T, COM})_{\mathrm{D-B}}$	$P(y)$	$P(100-y)$
$P(PDM\|\mathrm{PA, RP, C, T, COM})_{\mathrm{CM/GC}}$	$P(z)$	$P(100-z)$

The probabilistic dependence and interrelationships of decision factors, as shown in Figure 16, indicates the direction of influence. After several iterations, with different combinations, it is determined that project attributes and complexity are parent nodes to risk profile. On the other hand, cost factor and time factor independently acts as parent nodes to PDM (target node). Combining these all individual relationships between the variables/nodes in the network ties to PDM. This establishment of interrelationships is a major input for developing the BN-generic model.

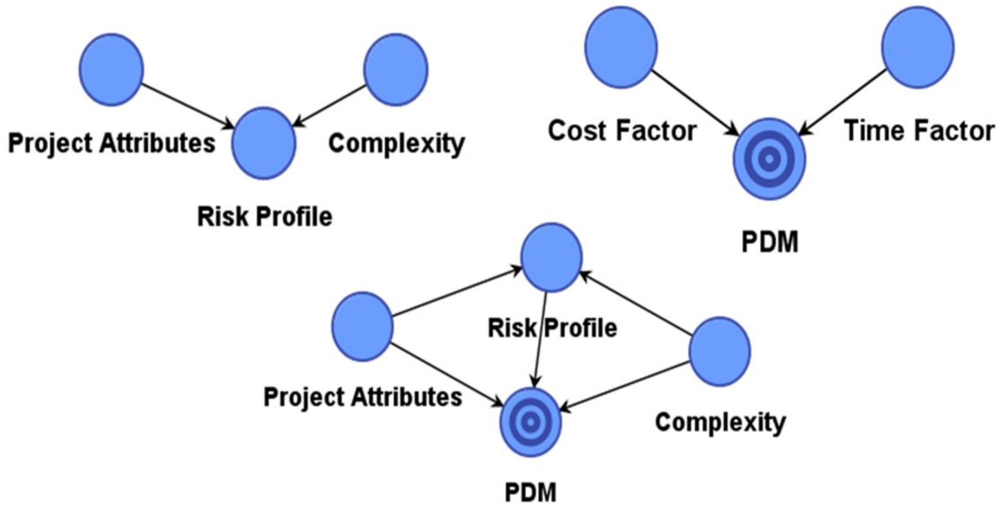


Figure 16. Interrelationships between the decision factors

Figure 17 represents the generic model of the BN decision framework. After several iterations, combining interrelationships between the delivery decision factors, construct validity of the structure was examined. For each PDM (D-B-B, D-B, and CM/GC), the combination of risks (R1, R2, R3…Ri) varies to form a single risk profile variable. Project complexity, cost factor, and time factor are parent nodes. Project attributes and risk profile are intermediate nodes. Finally, PDM is the target node in this BN model.

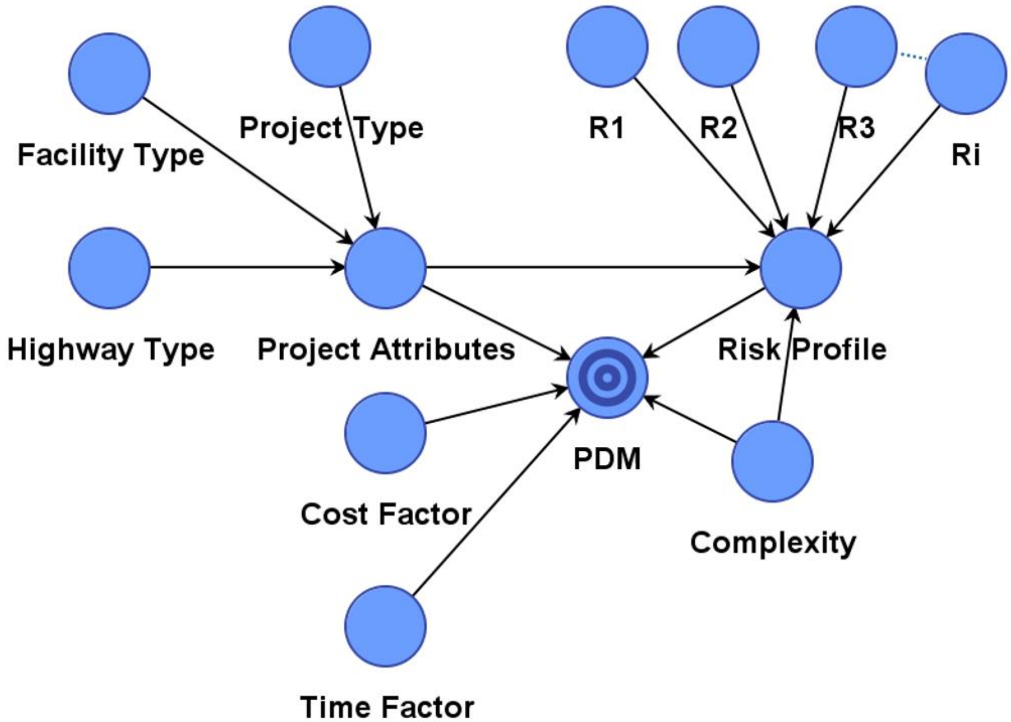


Figure 17. Generic Model of BN Theoretical Framework

SUMMARY AND CONCLUSIONS

State DOTs are often required to make an important decision of selecting a project delivery method in early stages of project development process. It is well recognized that no single project delivery method is suitable for all types/conditions of highway construction, but existing a delivery method that is optimal for a given project. This paper presents a decision framework for selecting delivery method using BNs. Implementing BN is a challenging task, including data preparation, identifying and establishing probabilistic interrelationships between the decision factors. The decision factors to selecting PDM were retrieved from the survey questionnaire comprising project attributes, complexity, cost factor, time factor, and risk profile. Although the empirical data collected from questionnaire has 291 completed highway projects, only 177 projects that have better cost performance were treated as data sample. The scrutinized data sample used as training data, fed knowledge regarding highway construction with different project conditions. The theoretical framework developed in this paper makes a logical understanding of a need for implementing an advanced statistical tool that facilitates effective decision making.

The theoretical framework in this paper is efficient in visualizing the comparison of probabilistic inferences to selecting suitable PDM. It effectively handles the decision factors and their corresponding probabilistic interrelationships. Although the theoretical framework was built using a commercial software BayesiaLab 6.0.8, the structure maps with the literature findings from the previous chapters.

Although the findings from this paper provide insights into the implementing BNs to selecting project delivery methods, there are some constraints that caution future steps in this research area. First, the sample data used for building this theoretical framework was scrutinized from the survey questionnaire based on cost performance, it does not inculcate schedule performance for filtering the training and testing data sets. The knowledge fed into the theoretical framework was built based on ccompleted highway projects that have better cost performance. Further research should explicitly address schedule performance of the training data set. The decision factors may include more performance parameters like quality, intensity, etc. to reinforce this proposed decision framework.

Finally, the result of this study may provide transportation agencies with a quantitative approach to selecting a project delivery method . The theoretical framework facilitates the owners as an effective tool to make a reliable and statistically supported selection of project delivery method in their highway constructions. The research work will be continued to next chapter with more practical application by developing computational models demonstrated with experimental case examples.

REFERENCES

Bayraktar, M.E., and Hastak, M. (2009). "Bayesian Belief Network Model for Decision making in Highway Maintenance: Case Studies." Journal of construction engineering and management,

Corcoran, J.N., Tran, D., and Levine, N.D. (2014). "An Efficient Strategy for aggregation and discretization of attributes of Bayesian Networks using Minimum Description Length."

Cooper, G.F., and Herskovits, E. "A Bayesian method for constructing Bayesian Belief Networks from databases."

Luu, V., Kim, S., Tuan, N., and Ogunlana, S. (2009). "Quantifying schedule risk in construction projects using Bayesian belief networks." International Journal of Project Management,10.1016/j.ijproman.2008.03.003,39-50.

Lee, E., Park, Y., and Shin, J.G. (2009) "Large engineering project risk management using a Bayesian belief network," Expert systems with applications, 5880-5887.

Muleta, M. (2012) A Formal, Bayesian Approach for Uncertainty Analysis of a Watershed Model. World Environmental and Water Resources Congress 2012: pp. 3732-3739.

Yates, J.K. (1993), "Construction decision support system for delay analysis," Journal of construction delay analysis, 119 (2), 226-244.

Bensi, M. and Kiureghian, A. (2011) A Bayesian Network Approach for Identification of Critical

Components of a System. Vulnerability, Uncertainty, and Risk: pp. 541-548.

Joseph, S., Adams, B., and McCabe, B. (2010). ”Methodology for Bayesian Belief Network Development to Facilitate Compliance with Water Quality Regulations.” Journal of Infrastructure Systems. 16(1), 58–65.

Augeri, M., Colombrita, R., Greco, S., Lo Certo, A., Matarazzo, B., and Slowinski, R. (2011). ”Dominance-Based Rough Set Approach to Budget Allocation in Highway Maintenance Activities.” Journal of Infrastructure Systems. 17(2), 75–85.

Kirnbauer, M. and Baetz, B. (2014). ”Prototype Decision-Support System for Designing and Costing Municipal Green Infrastructure.” Journal of Urban Planning and Development. 140(3), 04014004.

Njardardottir, H., McCabe, B., and Thomas, M. (2005). "Concrete bridge deck deterioration model using belief networks." Computers and Concrete, 10.12989/cac.2005.2.6.439, 439-454.

D. Nasir, B. McCabe, L. Hartono, (2003), “Evaluating risk in construction–schedule model (ERIC-S): construction schedule risk model,” Journal of Construction Engineering and Management ASCE, 129 (5) (2003), pp. 518–527.

McCabe, B., AbouRizk, S., and Goebel, R. (1998). ”Belief Networks for Construction Performance Diagnostics.” Journal of Computing in Civil Engineering. 12(2), 93–100.

Kim, S. (2011). "Bayesian Model for Cost Estimation of Construction Projects." Journal of the Korean Institute of Building Construction, 10.5345/JKIC.2011.02.1.091, 91-99.

Bayraktar, M. and Hastak, M. (2009). ”Bayesian Belief Network Model for Decision Making in Highway Maintenance: Case Studies.” Journal of Construction Engineering and Management. 135(12), 1357–1369.

Faddoul, R., Raphael, W., Soubra, A., and Chateauneuf, A. (2013). ”Incorporating Bayesian Networks in Markov Decision Processes.” Journal of Infrastructure and Systems. 19(4), 415–424.

Ames, D. and Neilson, B. (2001) A Bayesian Decision Network Engine for Internet-Based Stakeholder Decision-Making. Bridging the Gap: pp. 1-10. doi: 10.1061/40569(2001)169

Williams, B. and Cole, B. (2013). "Mining monitored data for decision-making with a Bayesian network model." Ecological Modelling, 10.1016/j.ecolmodel.2012.07.008, 26-36.

Mkrtchyan, L., Podofillini, L., and Dang, V. (2015). "Bayesian belief networks for human reliability analysis: A review of applications and gaps." Reliability Engineering and System Safety,10.1016/j.ress.2015.02.006,1-16.

Tesfamariam, S. and Liu, Z.. 2013. Seismic risk analysis using Bayesian belief networks. Handbook of Seismic Risk Analysis and Management of Civil Infrastructure Systems175-208.

Jha, M. (2006) Applying Bayesian Networks to Assess Vulnerability of Critical Transportation Infrastructure. Applications of Advanced Technology in Transportation (2006): pp. 1-6.

Cockburn, G. and Tesfamariam, S. (2012). "Earthquake disaster risk index for Canadian cities using Bayesian belief networks." Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards, 10.1080/17499518.2011.650147, 128-140.

Joseph, S., Adams, B., and McCabe, B. (2010). ”Methodology for Bayesian Belief Network Development to Facilitate Compliance with Water Quality Regulations.” J. Infrastruct. Syst., 16(1), 58–65.

Kabir, G., Demissie, G., Sadiq, R., and Tesfamariam, S. (2015). "Integrating failure prediction models for water mains: Bayesian belief network based data fusion." Knowledge-Based

Systems, 10.1016/j.knosys.2015.05.002.

Deublein, M., Schubert, M., and Adey, B. (2014). "Prediction of road accidents: comparison of two Bayesian methods." Structure and Infrastructure Engineering, 1394-1416.

Vieira, E. M. A., Silva, J. M. N., & Silva, L. B. (2017). Modeling Bayesian Networks from a conceptual framework for occupational risk analysis. Production, 27, e20162239.

CHAPTER 5

IMPLEMENTING BAYESIAN NETWORKS FOR SELECTING PROJECT DELIVERY METHOD: PRACTICAL APPLICATION

ABSTRACT

Selecting an appropriate project delivery method (PDM) can substantially influence project performance. This paper demonstrated the practical application of a Bayesian Networks (BN) based decision framework for selecting PDM in highway construction, including: design-bid-build (D-B-B), design-build (D-B) and construction manager/general contractor (CM/GC). The proposed BN decision framework was developed based on the data collection from 177 highway comprising 71 D-B-B, 87 D-B, and 19 CM/GC projects. The proposed framework comprises of three main levels: (1) Input level collects information regarding project attributes, complexity, cost and schedule estimates, and risk profile; (2) Processing level determines the interrelationship between the predicting variables, develops computational model, conditional probability table for each predicting variable in the network; and (3) Output level produces probabilistic inferences in selecting each delivery method, cross-validating and testing the BN.The proposed BN decision framework was tested and cross- validated using K-fold technique and case studies. The test results indicate that statistical predicting of an appropriate PDM, belonging to the testing dataset, was observed with suggestible accuracy and decent standards. Also, a detailed discussion was made on the illustration of three randomly selected case studies which are excluded from the survey data while building the BN decision framework. The model facilitates the owners as an effective tool to make a reliable and statistically supported project delivery decision for their highway constructions. The findings of this paper contribute to the implementation of BNs as a defensible decision-making tool in the construction industry.

Keywords: Bayesian Networks, Decision Making, Project Delivery Method, Highways, Probabilistic Inferences

INTRODUCTION

State departments of transportation (DOTs) have used three basic project delivery methods (PDM) for their highway construction: traditional design-bid-build (D-B-B), design-build (D-B) and construction manager/general contractor (CM/GC). Each PDM is unique with certain individual strengths and limitations. Choosing an appropriate delivery method is a complex and challenging task for decision makers. The primary challenges of selecting the optimal delivery method include a set of alternatives PDMs (D-B-B, D-B, and CM/GC); a variety of criteria that must be assessed; and a large number of risks and uncertainties. Researchers have been developing models with improving tools and techniques like Gordon's (1994) flowchart model, the experiential knowledge approach (Kumaraswamy and Dissanayaka 2001), hierarchical analytical processes (Al Khalil 2002; Alhazmi and McCaffer 2000), the fuzzy logic selection models (Ng et al. 2002; Chan 2007). Multi-attribute utility/value theory approaches (Skitmore and Marsden 1988; Love et al. 1998; Molenaar and Songer 1998; Mahdi and Alreshaid 2005; Oyetunji and Anderson 2006). These models and tools have a standard feature that they rely on subjective responses from industry practitioners and that the results are still somewhat devoid of relation to empirical project performance. Although such methods have their virtues, they fall short of capturing uncertainty propagation and the interaction between variables inherent in the selection process. To improve the accuracy of prediction and also to understand the uncertainty in decision making, an advanced statistical tool like BNs, structural equation modeling or multivariate analysis is an indefinite requirement.

This study used an empirical data in developing a prompt, accurate and unbiased decision support framework for highway agencies to select project delivery methods. It is expected that the proposed decision framework will add value to the previous approaches by providing the specific quantitative results in the delivery selection process. This chapter was organized into following sections: literature review, research questions, objectives developing computational BN model, experimental case examples, model application and discussion, limitations and future research, and conclusions.

LITERATURE REVIEW

Bayesian Network (BN) constructs a cause and consequence diagram. It could be a suitable methodology for project risk management with systematic and integrated processes. Some researchers have applied BN in the construction engineering and management domain. For example, McCabe et al. (1998) combined the BN with simulation models for automatic resource optimization on earth-moving operations; in their research, BNs are used to suggest remedial actions to improve the project performance. Chung et al. (2006) applied Bayesian technique into a tunneling project for updating the penetrating rate based on accumulated evidence on project performance. Bayraktar and Hastak (2009) applied BN in decision support system for evaluating different construction strategies based on a set of project performance indicators. Recently, Nguyen and Tran (2015) developed a model using BN to predict construction safety risk from falls. Though these studies demonstrated the effectiveness of BN in prediction under uncertain and complex conditions, all the networks were manually constructed, and cause-effect relations were identified primarily by matter experts.

The selection of project delivery involves uncertainties. To quantify the uncertainty is challenging even though many classes of models such as decision trees, artificial neural networks, mixtures of basic functions, Markov networks can be used to represent uncertain domains. BN is a probabilistic graphical model representing a set of variables and their interdependencies. The key advantages of using the BN (Bayraktar and Hastak 2009) in modeling uncertainty are listed as follows:

- Graphical models, capable of displaying relationships clearly and intuitively.
- The directional interaction is helping to represent cause-effect relationships.
- A practical tool to model uncertainty.
- Handling uncertainty through the traditional theory of probability.
- Being able to represent indirect in addition to direct causation.

Under BNs, directed acyclic graphs (DAGs) are powerful yet intuitive tools for solving complicated causal problems. The DAGs are mainly used to (1) determine the causal effects and (2) derive the testable implications of a causal model. DAGs are also useful for illuminating the causal assumptions behind widely used statistical estimation techniques.

Although the BN is an effective decision tool to describe probabilistic comparisons of different alternatives to make a decision and has been used successfully in many areas, it is still challenging to develop a decision framework in the construction industry. This challenge is even more severe for problems involving various risks and uncertainty (i.e., project delivery selection). Overcoming such challenges, this paper integrates the results from multivariate analyses into the basics of BN in developing a decision framework for selecting a project delivery method.

RESEARCH QUESTIONS

The main research questions of this study are:

1. How to enhance the decision making of project delivery by using a Bayesian Networks?

2. What are the significant advantages of incorporating project attributes, risk profile, project complexity, and cost and schedule factors in project delivery decision?
3. How to examine the interaction between predictors (project attributes, risk profile, project complexity, and cost and schedule factors) of project delivery decision based on probabilistic inferences?

OVERVIEW OF BAYESIAN NETWORKS

It is easy to define the problems and list possible decision options but difficult to quantify uncertainty. Thomas Bayes studied the probability of a particular event occurring about the occurrence of another event in 1765, and the mathematician Laplace extended this work in 1774. Bayesian inference (Bayes 1958) provides a means for determining the probability of an event based on the probabilities of other events. In decision analysis theory, the Bayesian inference is closely related to discussions of subjective probability. BNs deal with inferences and the probabilities of variables within the system. It indicates a set of random variables and their conditional dependencies on a directed acyclic graph (Thulasiraman and Swamy 1992).

BNs can also be coined as recursive graphical models, belief networks, causal probabilistic networks, and influence diagrams among others (Daly et al. 2011). A BN can be expressed as two components: qualitative and quantitative (Nadkarni and Shenoy 2001, 2004). The qualitative expression is represented as a directed acyclic graph (DAG), which consists of a set of variables (denoted by nodes) and relationships between the variables (denoted by arcs) (Salini and Kenett 2009). BN modeling techniques can be used to discover and describe the interdependencies and causalities linking failure events. A graphical node denotes causal events or factors, while the arrowed edge connecting two nodes denotes a pair of a cause-effect relationship, with edge start (parent) as the cause, and edge end (child) as the effect. Some fundamental features of the proposed BN model are: (1) parent-child relationships are cause-effect, or influence-result with probability values (0 or 1) depicting the degree of causality; (2) parent-child relationships are based on Bayesian' theorem (e.g., any node (event occurrence) is dependent on the joint probability of its parent nodes); and (3) no acrylic edges in the graph. The BN can be constructed based on the expert opinions (Bayesian Belief network), or statistical evidence (Bayesian probability network). In BNs, nodes represent variables and arcs encode the conditional dependencies between the nodes (variables). The conditional dependencies are obtained from known statistical and computational methodologies.

DEVELOPING COMPUTATIONAL MODEL

Structure learning has the capability of determining the existence of statistical dependencies among variables. If the variables of influencing factors or events are represented as graphical nodes in the BN, structure learning identifies the directed edges between nodes with each one indicating a pair of the cause and an effect. In structure learning, the algorithm scrutinized for an optimal structure in the space of all possible structures for a given set of variables representing the application domain (Luger, 2009).

In this study, the computational model framework includes three main levels (as shown in Figure 1): input, processing, and output levels. In the input level, the identified delivery decision factors are scrutinized and developed as nodes using BayesiaLab (BN software) and then the marginal (prior) probabilities were calculated. In processing level, the probabilistic dependence between the delivery decision factors were identified and the conditional probabilities were calculated. In addition, BN structure was tested for accuracy during the processing level. Finally, in the output level, joint probability of each delivery method (D-B-B, D-B, and CM/GC) were compared to select the highest likelihoods. All these three levels were explained detail in the later sections of the paper.

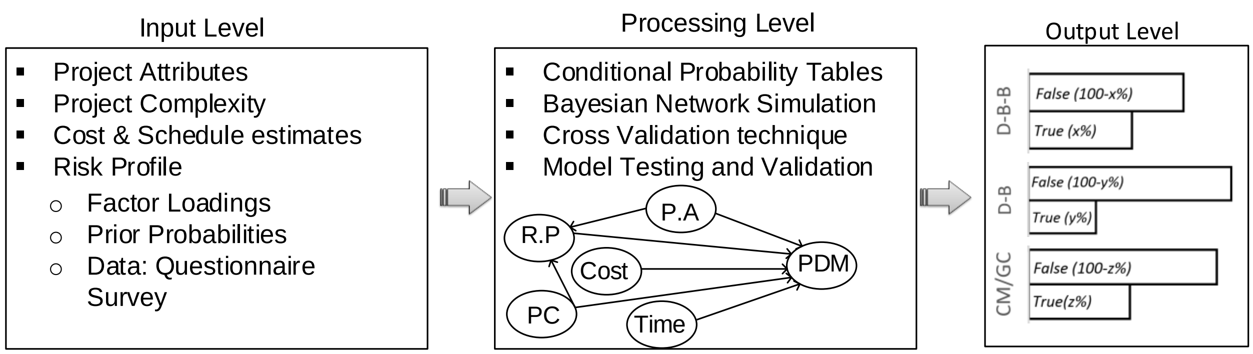


Figure 1. Research methodology to building BN Computational Model

In Figure 1, R.P. represents the risk profile; P.A. accounts for the project attributes; Cost indicates the cost factor; Time indicates the time factor; PC represents the project complexity; Finally, PDM represents, the target variable, project delivery method to be predicted (true and false probabilistic inferences). The following section details the practical implementation of the proposed BN decision framework including a three nodal sample BN, BN updating, model testing and validation, running analysis and performance evaluation, and cross validation

Three Nodal Sample BN

A sample model including three nodes is built to make the process understandable and briefed out. Table 1 summarizes data for the three-node/variables network. Complexity, project size, and PDMs are used to build this network. The marginal, conditional probabilities were determined from the network (Figures 2 and 3).

Table 1. Data Table for Three Nodal Sample BN

Project#	Complexity	Project Size	PDM
1	Most	1	D-B-B
2	Moderate	2	D-B
3	Non	3	D-B-B
4	Non	2	D-B-B
5	Moderate	2	CM/GC
6	Moderate	2	CM/GC
7	Most	1	D-B
8	Most	1	D-B
9	Non	1	D-B
10	Moderate	3	CM/GC

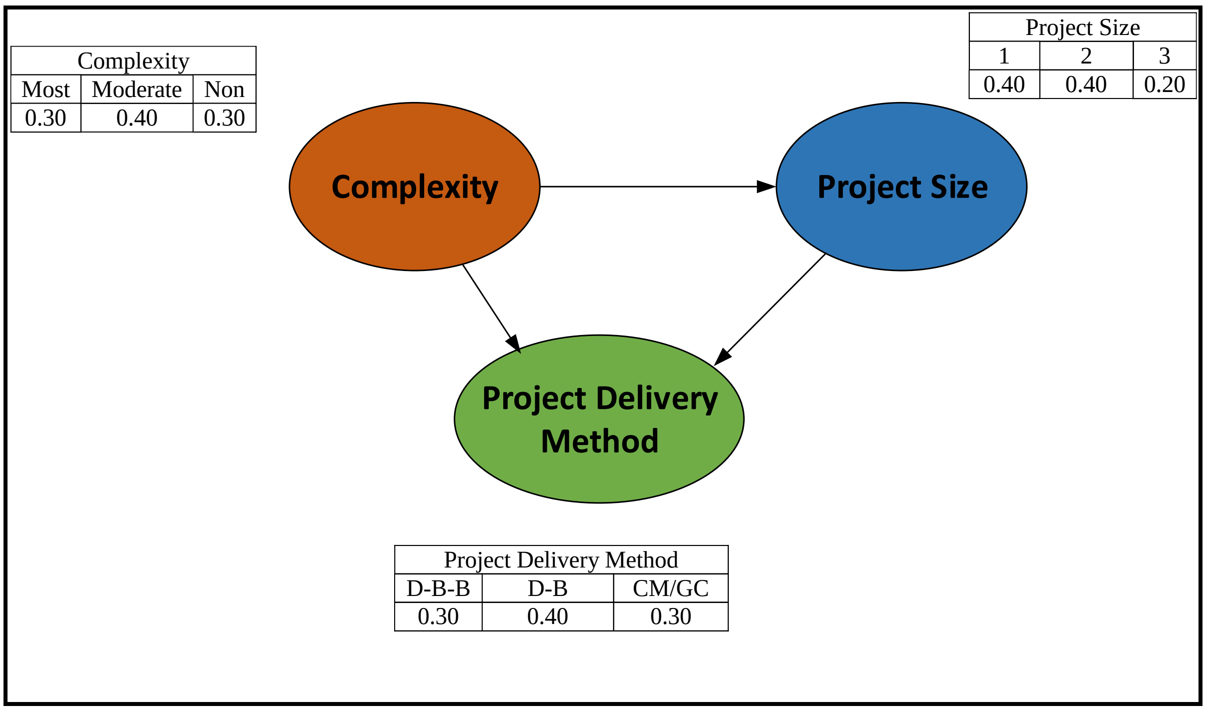
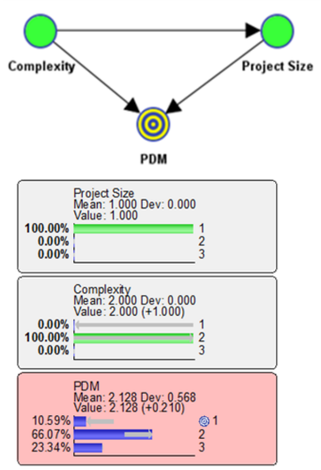


Figure 2. Marginal Probabilities of Three Nodal Sample BN

For example, the model is tested input as evidence of a project case (highlighted case in Figure 2) having moderate complexity (or the value of 2) and project size as (1). At the output level, probabilities of selecting each of the three delivery methods can be compared. Based on the result from this example, the probability of D-B-B, D-B, and CM/GC is 0.11, 0.66, and 0.23 respectively.

One can refer to these results that D-B is the most suitable choice for this project because the probability of D-B is higher than that of D-B-B and CM/GC. It is noted that this simple example of BN is limited to consideration of only the interrelationship between the complexity (C) and project size (PS) in the project delivery decision process.

	Project Size		
Complexity	1	2	3
Most	0.50	0.33	0.17
Moderate	0.30	0.45	0.25
Non	0.03	0.29	0.68



		Project Delivery Method		
Complexity	*Project Size*	*D-B-B*	*D-B*	*CM/GC*
Most	1	0.33	0.42	0.25
Moderate	1	0.11	0.66	0.23
Non	1	0.30	0.35	0.35
Most	2	0.33	0.27	0.40
Moderate	2	0.42	0.33	0.21
Non	2	0.60	0.30	0.10
Most	3	0.37	0.59	0.04
Moderate	3	0.50	0.48	0.02
Non	3	0.17	0.48	0.33

Figure 3. Conditional Probabilities of Three Nodal Sample BN

Bayesian Network Updating

Updating the BN is one of the motivating features of this advanced statistical tool. The decision maker can verify and modify these relationships based on the project conditions and characteristics. The proposed model was adjusted by the new project case information or change in probability tables (based on expert opinion). However, updating BN can be a time-taking process. In some cases, the weighting of a variable was increased by using more extreme values from the probability table for the variable concerned (closer to 0 or closer to 1, depending on the desired effect). The BayesiaLab allows a validation mode, to analyze the built network and also to predict an appropriate PDM based on the new project information.

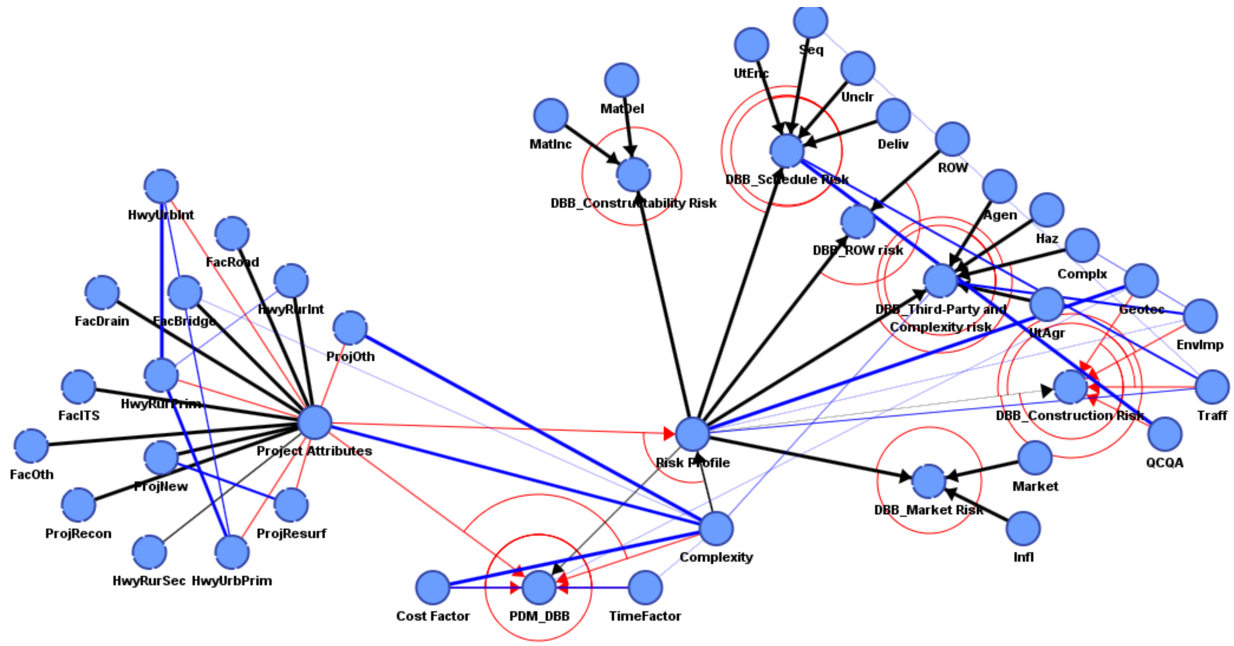


Figure 4. Network comparisons of Computational Model

Based on Augmented Markov Blanket algorithm, network structures were compared. Figure 4 is an example of comparison of D-B-B computational model. This helps in comparing the updated BN, with any required changes, to the original structure. Common arcs in red color visualizes the differences from the original structure. In this scenario, except few project attributes related nodes, majority of the nodes are dynamic and showing differences with the original network. The network comparisons will be more useful while customizing the BN computational model.

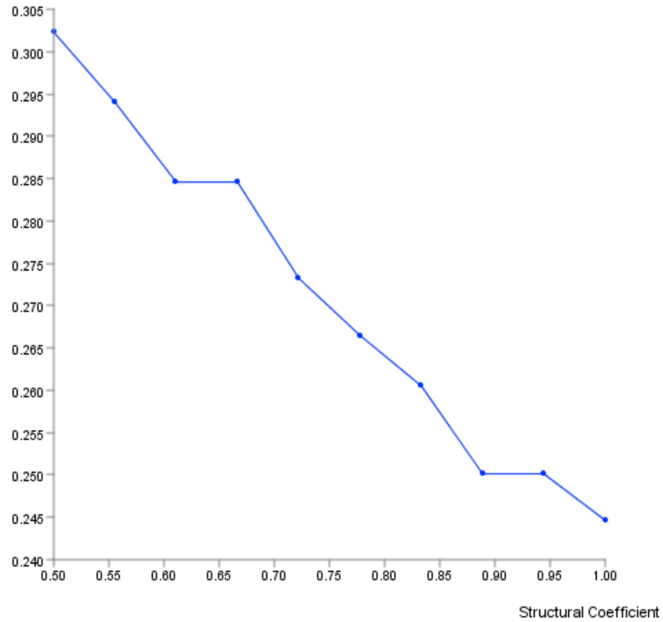


Figure 5. Structure/Target Precision Ratio

The Structure/Target Precision Ratio (as shown in Figure 5) is a constructive measure for making tradeoffs between predictive performances versus network complexity. This plot can be best interpreted when following the curve from right to left. Moving to the left along the x-axis lowers the structural coefficient, which, in turn, results in a more complex structure. It becomes problematic when the structure increases faster than the precision. Typically, the elbow of the L-shaped curve identifies this critical point. Here, visual inspection suggests that the elbow is just below SC=0.3 (as shown in Figure 5). The portion of the curve further to the left on the x-axis, i.e., SC>0.3, shows that Structure is increasing without improving Precision, which can be a potential cause of over-fitting. Hence, it is concluded that SC=0.3 is a reasonable choice for proceeding further.

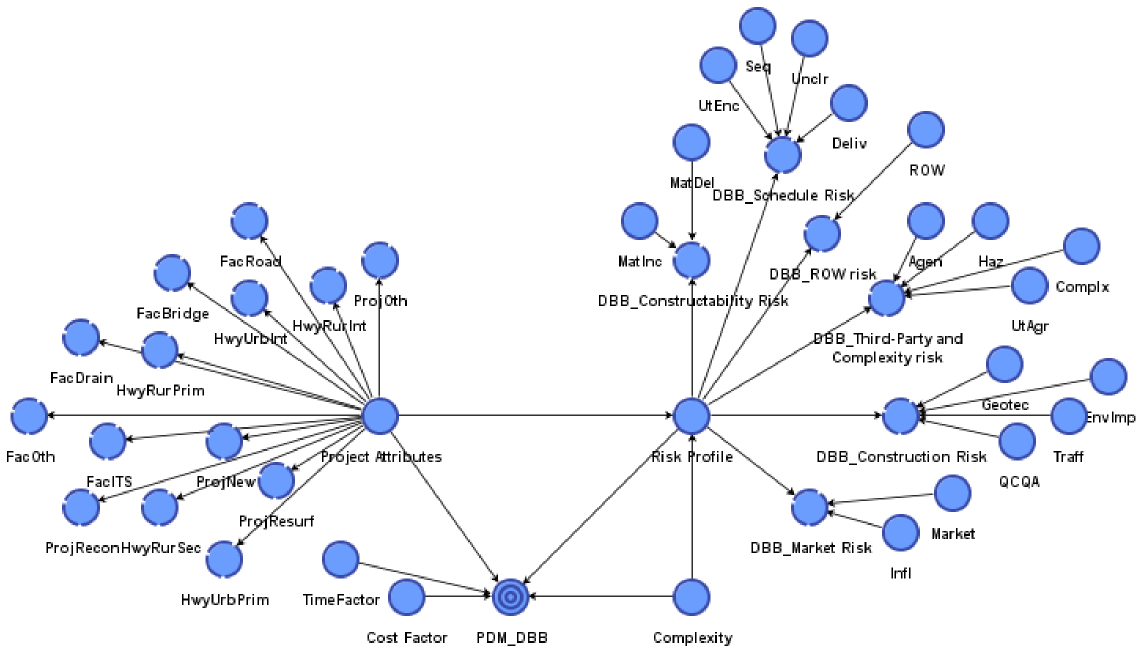


Figure 6. BN Computational Model for D-B-B

Figure 6 represents the computational model for D-B-B with varied risk profile including constructability risk, right-of-way risk, schedule risk, third party and complexity risk, construction risk, and market risk.

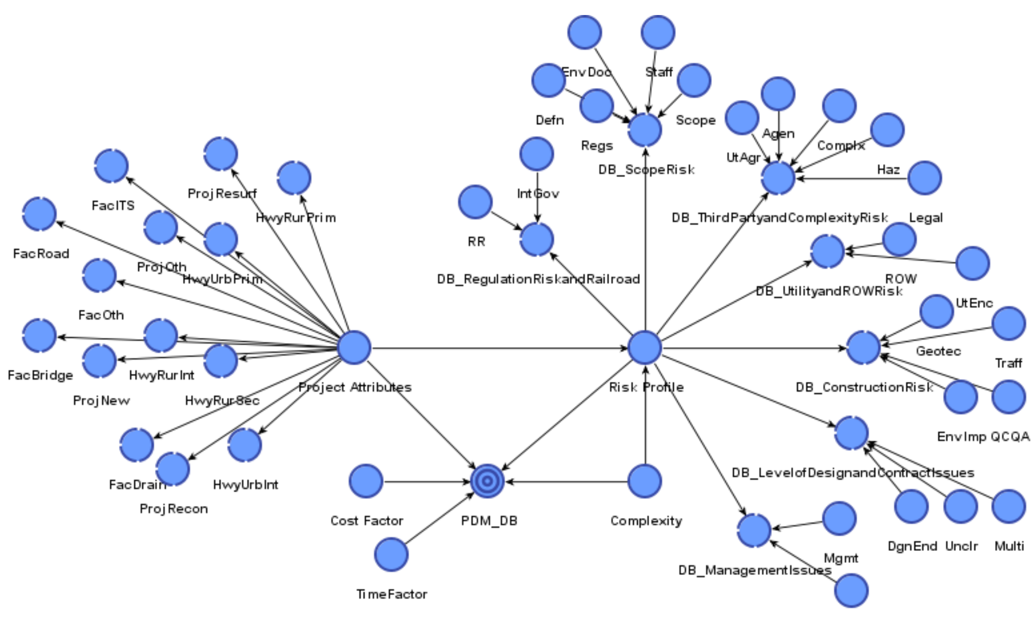


Figure 7. BN Computational Model for D-B

Figure 7 represents the computational model for D-B with varied risk profile including constructability risk, right-of-way risk, schedule risk, third party and complexity risk, construction risk, and market risk.

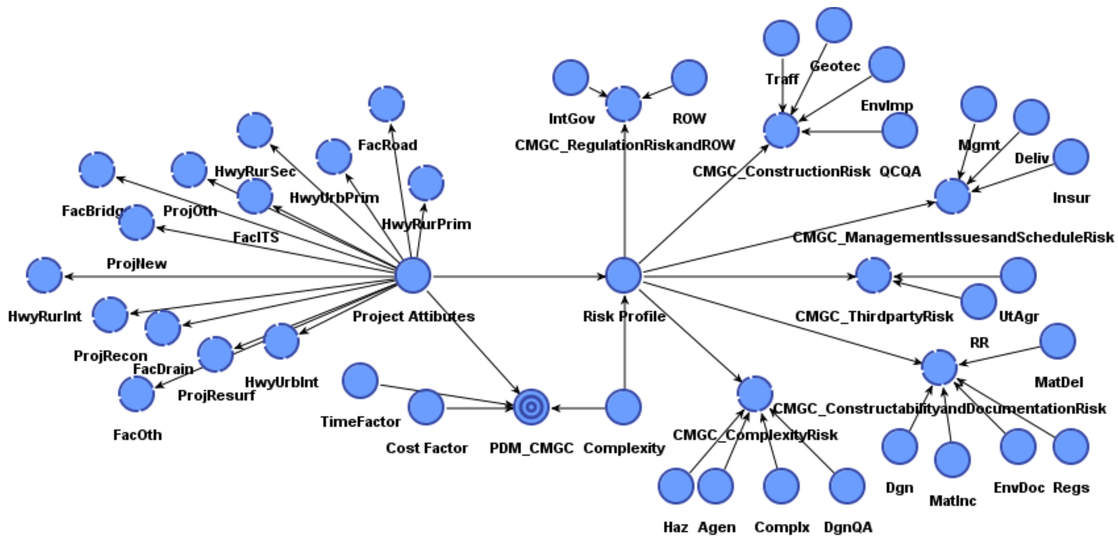


Figure 8. BN Computational Model for CM/GC

Figure 8 represents the computational model for CM/GC with varied risk profile including regulation risk and right-of-way, construction risk, management issues and schedule risk, third party risk, constructability and documentation risk, and complexity risk.

Figure 9 presents the likelihoods (true %) of a project case falling under each PDM type: D-B-B, D-B and CM/GC are determined by *x%, y%,* and *z%* respectively. For D-B-B, the false (%) likelihood indicating the project can either be D-B or CM/GC is represented by *100- x%.* For D-B, the false (%) likelihood indicating the project can either be D-B-B or CM/GC is represented by 100- *y%.* For CM/GC, the false (%) likelihood indicating the project can either be D-B-B or D-B is represented by 100- *z%.* The true likelihood probabilities of *x%, y%* and *z%* and the false likelihood probabilities of *100- x%, 100- y%, and 100- z%* are compared with each project case, and the highest true likelihood probability is considered as most appropriate PDM.

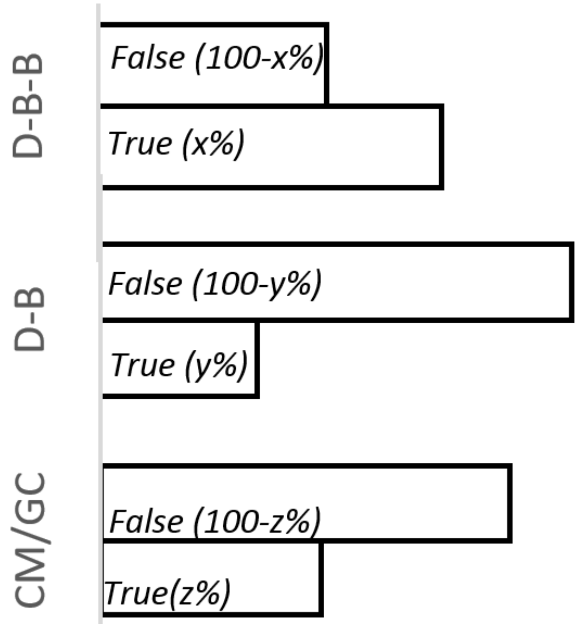


Figure 9. Comparing probabilistic inferences

Model Testing and Validation

The model testing and validation are organized in two phase: running analysis and performance evaluation, and cross-validation. In this paper, the objectives were identified from the empirical data. Importantly, the BN's outcomes should be reviewed in the light of an objective, to ensure that the model is representing the objective adequately and providing outputs that are informative about the objective. Experts can examine the model's structure to confirm that the model accurately represents the system of interest. In some cases, the network and its sub-networks can be validated against other data or literature.

The conditional probability Tables in the BN model can be validated with the help of domain experts and compared with other summarized information or reports if available. The internal consistency of the CPTs can also be evaluated, for example by deleting some nodes and assessing the validity of the collapsed CPTs. If sufficient information is available, the reliability of the CPTs can be evaluated using replicated sub-samples of the data. The model can be validated either by domain experts or using any analytical tool.

Running Analysis and Performance Evaluation

To execute the analysis, BayesiaLab requires the mode change from structure building to modeling. The proposed BN requires the input level information which feeds the knowledge to the model. The effective modeling practice often involves evaluation of confidence in the models' outcomes and evaluating the contribution of each input to the model output. Quantitative model evaluation includes sensitivity analyses and assessments of predictive accuracy. Predictive accuracy refers to a quantitative assessment of the model, by comparing model predictions with observed data (Pollino et al. 2007). Sensitivity analysis tests the sensitivity of model outcomes to variations in model parameters. Sensitivity analysis in BNs can measure the sensitivity of outcome probabilities to changes in input nodes or other model parameters, such as changes in node's type of states. It was performed using entropy measure of mutual information (Pearl 1988). The entropy measure is based on the assumption that the uncertainty or randomness of a variable X, characterized by probability distribution P(x), can be represented by the entropy function H(x) as below.

$$H(x) = \sum P_i(x) * \log(P_i(x)) \qquad \text{Eq (3)}$$

Reducing H(X) by collecting information in addition to the current knowledge about variable X is interpreted as reducing the uncertainty about the actual state of X (Barton and de Vladar 2009).

Cross-Validation

The performance of the proposed BN is examined using the k-fold cross-validation technique for low bias and low variance (Kohavi 1995). The dataset is split into k subsets of equal size. For each k subset, k–1 folds (as shown in table 2) are used to construct the predictive model, and the remaining one is utilized for testing the model. These mutually exclusive parts of the dataset are used k times for training and testing of the models. Then the average performance of the cross-validation is calculated by the following equation

$$\text{Average Performance} = 1/K \sum_{i=1}^{K} P_i$$

Where K is the number of mutually exclusive subsets, and P_i represents the performance of the fold i (Kohavi 1995; Olson and Delen 2008).

Table 2. Visual Representation of K-Fold Cross-Validation Technique (K=10)

	1st Fold	2nd Fold	3rd Fold	4th Fold	5th Fold	6th Fold	7th Fold	8th Fold	9th Fold	10th Fold
Round 1										
Round 2										
Round 3										
Round 4										
Round 5										
Round 6										
Round 7										
Round 8										
Round 9										
Round 10										

Testing Fold	
Training Fold	

After developing the model's structure and estimating the conditional probabilities, the BN model was evaluated. The typical model evaluation tools include qualitative feedback from experts and stakeholders, or comparing model predictions with literature data or with results from similar models (Kragt 2009). In this study, the proposed BN model was developed based on 177 highway projects including, 71 of D-B-B, 87 of D-B and 19 of CM/GC projects. There are several ways to verifying the accuracy or validity of the proposed BN model. K-fold technique was performed along with three randomly selected project cases to verify the model performance. The verification process shows how accurate the model can predict the probability of selecting each PDM.

As shown in table 3, the D-B-B model used data clustering on project attributes and risk profile. The project attributes were categorized into three classes with a cluster purity of 93.38%. The risk profile was also categorized into three categories with a cluster purity of 95.61%. The K-fold test was carried on D-B-B projects, and the average overall prediction and reliability percentages were 54.57% and 53.94% respectively. Similarly, the D-B model used data clustering on project attributes and risk profile. The project attributes were categorized into three classes with a cluster purity of 93.38%. The risk profile was also categorized into three categories with a cluster purity of 95.61%. The K-fold test was carried on D-B projects, and the average overall prediction and reliability percentages were 53.06% and 54.93%, respectively. Finally, the CM/GC model has used data clustering on project attributes and risk profile. The project attributes were categorized into three classes with a cluster purity of 93.38%. The risk profile was also categorized into three categories with a cluster purity of 95.61%. The K-fold test was carried on CM/GC projects, and the average overall prediction and reliability percentages were 53.75% and 51.47%, respectively.

Table 3. K-Fold Cross-Validation Results (K=10)

	D-B-B	D-B	CM/GC
Data Sample (n)	71	87	19
Average Precision	54.57%	53.06%	53.75%
Maximum Precision	84.61%	66.67%	76.47%
Average Reliability	53.94%	54.93%	51.49%
Maximum Reliability	75.00%	66.25%	75.00%
Average Relative Gini Index	34.18%	39.97%	80.77%
Maximum Relative Gini Index	69.35%	40.26%	59.66%
Average Relative Lift Index	72.75%	60.89%	65.49%
Maximum Relative Lift Index	84.27%	81.89%	91.86%

EXPERIMENTAL RESULTS AND DISCUSSION

This section illustrates the application of the proposed BN decision framework to select an appropriate PDM. Three random projects, one for each delivery method, with high project performance (e.g., cost, schedule, and quality) were selected from the data set (Table 4). The data collected from these projects was input into the BN. The probabilistic inference of three delivery methods is compared to select the most appropriate delivery method. The highest probabilistic value indicates the optimal delivery method. The following sections discuss these three projects in detail.

Table 4. Input data retrieved from the three test cases

Input Field	Case #1 (Missouri DOT)	Case #2 (Louisiana DOT)	Case #3 (Arizona DOT)
Complexity	Most Complex	Most Complex	Moderate Complex
Cost	$ 229,450,505.00	$ 334,656,245.00	$ 32,035,665.66
Time	1467 Days	1827 Days	145 Days
Project Type	New Construction	New Construction	Reconstruction
Highway Type	Urban Interstate	Rural Primary	Rural Secondary
Facility Type	Bridge-100%	Road- 30% Bridge- 65% Drainage- 5%	Road- 80% Drainage-15% Other- 5%

Case Study 1
Introduction

The randomly selected project case was Missouri DOT's new Mississippi River Bridge D-B-B project. It is a 1,500-foot cable-stayed bridge across the Mississippi River between Metro East and St. Louis, Missouri. The bridge is two lanes in each direction but broad enough to be restriped for three lanes in each direction if traffic volumes warrant and additional funding is secured. The project is most complex and has a budget of $229 million and schedule of 1467 days. This new construction comes under the urban interstate, and the facility type is bridge only.

Modeling Process and Result

The project data was input into the BN model. The decision framework updates the marginal probabilities of each node in the network and calculates joint probabilities by adapting the Bayes' chain rule. The output level showcases true and false scenarios for each of three delivery methods (D-B-B, D-B and CM/GC). These probabilistic inferences were compared to select appropriate delivery decision. The absolute probability value indicates the best possible case based on the knowledge fed to the model from the questionnaire data.

Figure 10 shows that the true likelihood of D-B-B is 100%, and the false probability is 0%. The false values of D-B and CM/GC of 100% indicate that D-B or CM/GC is not suitable project delivery for the selected project case. The predicted delivery method is consistent with the selected delivery method of D-B-B from Missouri DOT. As a result, it can be concluded that the model is reliable for this case project

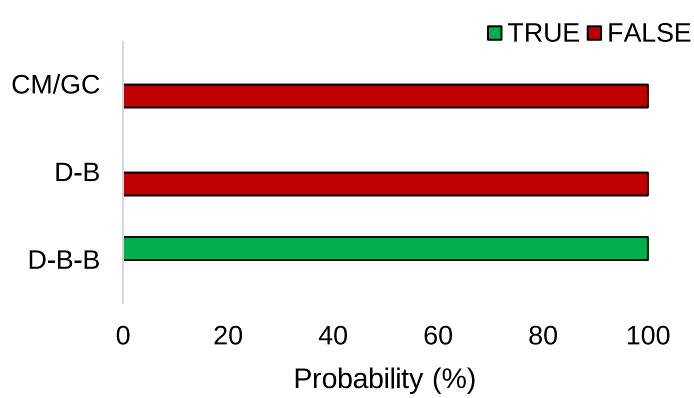


Figure 10. Comparing probabilistic inferences from test case 1

Case Study 2

Introduction

The randomly selected project case was from the Louisiana DOT. The main scope of this project involves Hurricane Katrina affecting the Mississippi river levels. This project is also a part of the Transportation Infrastructure Model for Economic Development (TIMED) program. This cable-stayed bridge, with the longest main span in the Western Hemisphere at 1581ft and 520 foot high towers, was constructed utilizing D-B by Audubon Bridge Constructors managed by Louisiana TIMED Managers (LTM). It replaces the existing ferry between Pointe Coupee and West Feliciana Parishes, providing a reliable, safe and efficient crossing of the river. .The project is most complex and has a budget of $334 million and schedule of 1827 days.

Modeling Process and Result

The project data was used to run the BN model. This new construction comes under rural primary, and the facility type comprises 65%-bridge; 30%-road and 5% of drainage. Figure 11 shows the true probability of D-B is 100%, and the false probability is 0%. The false probability values of D-B-B and CM/GC were 100% and 67.1%, respectively. This infers that D-B-B or CM/GC was not suitable delivery methods for this project. The model result provided the optimal delivery method (D-B) same as the delivery method selected by Louisiana DOT.

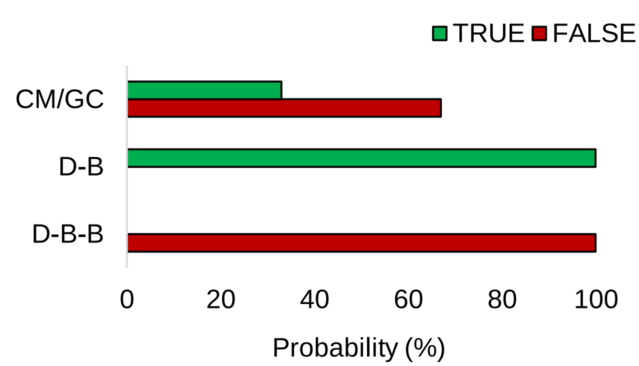


Figure 11. Comparing probabilistic inferences from test case 2

Case Study 3

Introduction

The randomly selected project case was Arizona DOT's N20 detour delivered by CM/GC. The projected $40 million repair was expected to take more than two years to complete and included significant environmental and right-of-way clearances before construction. The project is moderate complex and has a budget of $ 32 million and schedule of 145 days.

Modeling Process and Result

From the data collection process, it shows that this is a reconstruction project comes under rural secondary. The project is predominantly road with 80%, 15% of drainage, and only 5% of other. The project data was used to run the BN model. Figure 12 summarizes the model results. One can observe from Figure 12 that the true probability of CM/GC is 69.78%, and the false probability of CM/GC is 30.22%. The false values of D-B-B and D-B indicate 100% meaning that D-B-B or D-B is not suitable for delivering this project. In other words, the model generated the optimal delivery method (CM/GC) same as project delivery selected by Arizona DOT.

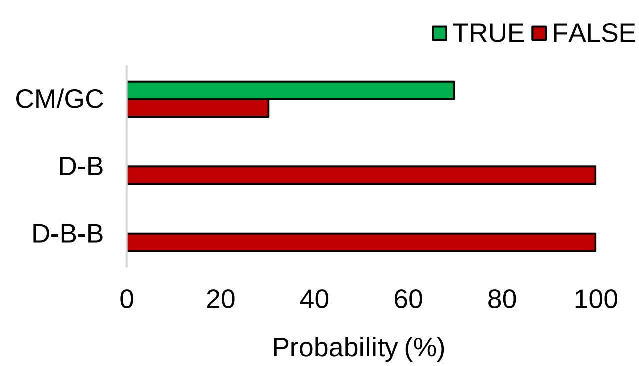


Figure 12. Comparing probabilistic inferences from test case 3

There are many benefits of using BNs as a statistical tool in selecting a project delivery method for highway construction projects. The statistical inferences are evident to probabilistically support the decision, especially in handling complex projects with cost and time uncertainties. It is not an easy task to selecting an appropriate PDM as a significant amount of ambiguous information exists. The paper aims to develop a PDM selection model to help owners to make a decision. An important step of the BN model development is to create the modes by which the BN results can be communicated to the project manager and other stakeholders.

DISCUSSION

It is well recognized that no single project delivery method is suitable for all types/conditions of highway construction, but existing a delivery method that is optimal for a given project. This paper presents a BN-based decision framework for selecting a project delivery method. The framework involves numerous risks and uncertainties, complex relationships among predictors, various possible decision alternatives, and risk profiles. It is noted that the majority of quantitative research on project delivery method selection was used small sample sizes (Hale et al. 2009; Debella and Ries 2006; Ibbs et al. 2003). The data collected in this research was one of the largest empirical data set exclusive to the topic of highway construction project delivery. Thus, results would be highly specific and relevant to US highway construction sector.

There are several limitations of this study. First, the CMGC delivery method was limited in use in their states at the time of data collection. While the CMGC data satisfied the statistical assumptions for the factor analysis, more data on CMGC projects will enhance the model validity and application. Further, other important project performance aspects such as project quality, repair or maintenance cost, or sustainability issues could be added to the structure to investigate further the benefits and drawbacks of each delivery method. Analyses of these results will determine if it improves accuracy or provides additional insights for decision makers.

CONCLUSION

The main objective of this research is to develop a reliable predictive model for selecting project delivery methods within the US highway construction industry using the extensive empirical data set. The selection of delivery decision has a significant effect on project outcomes. Incorporating project attributes (facility type, project type, and highway type), estimated cost and schedule factors, project complexity, risk profile as inputs to the BN-based decision framework is proven to be an efficient way to select an approporiate delivery method. The decision framework also provides a defensible selection and drives state DOTs to integrate the probabilistic risk-cost analysis into the delivery decision. This integration will promote a better understanding of DOT risk management cultures and enhances collaboration among project participants. The innovation of this paper is the formalization and presentation of a general approach for developing BN models based on survey data.

The proposed decision framework was demonstrated on the delivery decision of three completed highway projects, and the test results are discussed in detail. The findings from this paper provide a new decision framework for selecting project delivery method. The model benefits the owners and decision makers by providing an effective tool to make an accurate project delivery decision. The study also presents a chance to learn how highway construction variables (project attributes, complexity, cost and schedule estimates, and risk profile) interacts with the project delivery decision.

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REFERENCES

Ames, D. and Neilson, B. (2001) A Bayesian Decision Network Engine for Internet-Based Stakeholder Decision-Making. Bridging the Gap: pp. 1-10. doi: 10.1061/40569(2001)169

Augeri, M., Colombrita, R., Greco, S., Lo Certo, A., Matarazzo, B., and Slowinski, R. (2011). ”Dominance-Based Rough Set Approach to Budget Allocation in Highway Maintenance Activities.” J. Infrastruct. Syst., 17(2), 75–85.

Bayraktar, M. and Hastak, M. (2009). ”Bayesian Belief Network Model for Decision Making in Highway Maintenance: Case Studies.” J. Constr. Eng. Manage., 135(12), 1357–1369.

Bensi, M. and Kiureghian, A. (2011) A Bayesian Network Approach for Identification of Critical Components of a System. Vulnerability, Uncertainty, and Risk: pp. 541-548.

Cockburn, G. and Tesfamariam, S. (2012). "Earthquake disaster risk index for Canadian cities using Bayesian belief networks." Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards, 10.1080/17499518.2011.650147, 128-140.

Cooper, G.F., and Herskovits, E. (1991). “A Bayesian method for constructing Bayesian Belief Networks from databases.” Uncertainty proceedings, seventh conference, pp. 86-94.

D. Nasir, B. McCabe, L. Hartono, (2003), “Evaluating risk in construction–schedule model (ERIC-S): construction schedule risk model,” J Construct Eng Manage ASCE, 129 (5) (2003), pp.

518–527.

Deublein, M., Schubert, M., and Adey, B. (2014). "Prediction of road accidents: comparison of two Bayesian methods." Structure and Infrastructure Engineering, 1394-1416.

Faddoul, R., Raphael, W., Soubra, A., and Chateauneuf, A. (2013). ”Incorporating Bayesian Networks in Markov Decision Processes.” J. Infrastruct. Syst., 19(4), 415–424.

Jha, M. (2006) Applying Bayesian Networks to Assess Vulnerability of Critical Transportation Infrastructure. Applications of Advanced Technology in Transportation (2006): pp. 1-6.

Joseph, S., Adams, B., and McCabe, B. (2010). ”Methodology for Bayesian Belief Network Development to Facilitate Compliance with Water Quality Regulations.” J. Infrastruct. Syst., 16(1), 58–65.

Kabir, G., Demissie, G., Sadiq, R., and Tesfamariam, S. (2015). "Integrating failure prediction models for water mains: Bayesian belief network based data fusion." Knowledge-Based Systems, 10.1016/j.knosys.2015.05.002.

Kim, S. (2011). "Bayesian Model for Cost Estimation of Construction Projects." Journal of the Korean Institute of Building Construction, 10.5345/JKIC.2011.02.1.091, 91-99.

Kirnbauer, M. and Baetz, B. (2014). ”Prototype Decision-Support System for Designing and Costing Municipal Green Infrastructure.” J. Urban Plan. Dev., 140(3), 04014004.

Lee, E., Park, Y., and Shin, J.G. (2009) “Large engineering project risk management using a Bayesian belief network,” Expert systems with applications, 5880-5887.

Luu, V., Kim, S., Tuan, N., and Ogunlana, S. (2009). "Quantifying schedule risk in construction projects using Bayesian belief networks." International Journal of Project Management,10.1016/j.ijproman.2008.03.003,39-50.

McCabe, B., AbouRizk, S., and Goebel, R. (1998). ”Belief Networks for Construction Performance Diagnostics.” J. Comput. Civ. Eng., 12(2), 93–100.

Mkrtchyan, L., Podofillini, L., and Dang, V. (2015). "Bayesian belief networks for human reliability analysis: A review of applications and gaps." Reliability Engineering and System Safety,10.1016/j.ress.2015.02.006,1-16.

Muleta, M. (2012) A Formal, Bayesian Approach for Uncertainty Analysis of a Watershed Model. World Environmental and Water Resources Congress 2012: pp. 3732-3739.

Njardardottir, H., McCabe, B., and Thomas, M. (2005). "Concrete bridge deck deterioration model using belief networks." Computers and Concrete, 10.12989/cac.2005.2.6.439, 439-454.

Tesfamariam, S. and Liu, Z.. 2013. Seismic risk analysis using Bayesian belief networks. Handbook of Seismic Risk Analysis and Management of Civil Infrastructure Systems175-208.

Tran, D. (2013). “An Efficient Strategy for aggregation and discretization of attributes of Bayesian Networks using Minimum Description Length.” Applied mathematics graduate theses & dissertations, 41.

Williams, B. and Cole, B. (2013). "Mining monitored data for decision-making with a Bayesian network model." Ecological Modelling, 10.1016/j.ecolmodel.2012.07.008, 26-36.

Yates, J.K. (1993), “Construction decision support system for delay analysis,” Journal of construction delay analysis, 119 (2), 226-244.

CHAPTER 6

CONCLUSIONS

This dissertation proposed a quantitative approach for selecting project delivery method (PDM) using Bayesian Network (BN). This dissertation capitalizes on the opportunity to apply an advanced probabilistic comparison and selecting one of the three delivery methods (D-B-B, D-B and CM/GC) in a highway construction. The project success is typically dependent on the selection of delivery method. Each project has unique features and no single delivery method is the suitable for any projects. With more project data available in the highway sector with the increasing use of alternative contracting methods, it is anticipated that a more effective and quantitative approach to determining the delivery method is needed. From the related literature, delivery selection methodologies can be categorized based on the flow chart, multiple linear regressions, analytical hierarchy process, cased based reasoning, fuzzy case based reasoning and risk based reasoning. In developing the quantitative decision framework for selecting PDM, this research study used BNs to enhance the existing selection methodologies. The proposed framework can visually represent the comparison of likelihoods of different PDM options (D-B-B, D-B, and CM/GC). Additionally, a number of delivery decision factors including project attributes, complexity, cost factor, time factor, and risk profile were integrated into the decision framework for selecting an appropriate PDM. This dissertation addressed a research gap of comparison of project performance between D-B-B and D-B based on project size. The proposed decision framework also serves as a supportive tool to assist state DOTs for better understanding the project delivery selection process. The proposed framework was demonstrated using three case studies. The framework was cross validated using k-fold techniques for testing the accuracy of the model prediction.

Research Contributions

There are several contributions to both theory and practice in every chapter of this dissertation.

Research contribution includes developing a statistical tool in supporting project delivery decision, previously developed models are more of qualitative approaches. This new quantitative approach investigates the delivery decision of complex highway projects using probabilistic comparisons. This research offers three primary deliverables that contribute to the body of knowledge of PDMs. First, a comprehensive evaluation of cost and schedule performance between D-B-B and D-B was examined based on project size. Second, identification and evaluation of critical risk factors under each delivery decision. Finally, the dissertation proposed a BN based decision framework for selecting an appropriate PDM. To date, there is no research applying probabilistic comparison using BNs to quantify and select project delivery methods in the construction industry. The framework was developed based on integrating a number of decision delivery factors including project attributes, cost factor, time factor, risk profile, and project complexity.

The proposed decision framework and consequential results in this research study allow the departure from previous researchers who have made attempts to model project delivery decision in several ways:

- The proposed research is based on empirical project information. This presents an advantage over the use of qualitative PDM selection approaches by reducing the possibility of inherent biases, and other subjective elements.
- The majority of quantitative research on PDM have used smaller sample sizes (Hale et al., 2009; Debella and Ries, 2006; Konchar and Sanvido, 1998; Ibbs et al., 2003; Molenaar and Songer, 1998). The data collected in this research was one of the largest empirical data sets related to the highway construction project delivery at the time of this writing.

- In the process of conducting this research, there is an opportunity not only determine the probabilistic dependence of decision delivery factors but also integrating them in developing a decision framework. This research has fewer restrictions posed by limited options of computational/statistical methods. The use of new/improved multivariate statistical methods which have not been employed by previous researchers in Construction Engineering and Management is now possible as a result of recent advances in statistical software capabilities and enhancements of computational developments.
- This research avoids several ambiguities in the explanations of parameters, variables and criteria used in highway construction project delivery by referencing what is now well-established and documented attributes of highway construction project delivery as defined by practicing state DOTs and the FHWA.
- This study is first of its kind in implementing the advanced probabilistic approach by using BNs for project delivery decision in highway construction.

Future Research

The fundamental aspect in this dissertation is to implement statistical evidence to project delivery decisions. Current project delivery decision frameworks was often constrained to industry trends and subjective experts of practicing delivery decisions. This study developed the BN-based decision framework to quantitative evaluate and determine the most suitable project delivery for highway construction projects. Albeit this dissertation contributes to the body of knowledge, there are number of limitations and potential future research areas to extend from this study, including:

1. Creating a mathematical code to customize the decision framework to fit for user needs
2. Demonstrating the model application with more testing data set.

3. Improving the decision framework by including more decision elements like design criteria, owner's quality expectations, payment and procurement prospects.
4. Exploring the impact of project size on cost and schedule performance of Construction manager/ general contractor (CM/GC) projects.
5. Integrating other delivery methods such as Integrated Project Delivery (IPD), Public Private Partnership (P3) to the model.
6. Using sensitivity analyses to identify significance of decision factors for different parameters (project type, facility type, highway type)

INTEGRATED REFERENCES

AASHTO (2008). Design-Build Procurement Guide, American Association of State Highway and Transportation Officials, Washington, D.C., 2008.

AASHTO (2014). *MAP-21: Overview of Project Delivery, Environmental, and Planning Provisions.*

Abad-Grau, M., M., Ierache, J., Cervino, C., and Sebastiani, P. (2008). Evolution and challenges in the design of computational systems for triage assistance. Journal of biomedical informatics, 41(3):432-41.

Abimbola, M., Khan, F., Khakzad, N., and Butt, S. (2015). Safety and risk analysis of managed pressure drilling operation using Bayesian network. Safety Science, 76:133-144.

Aflaki, S., and Memarzadeh, M. (2011). "Using two-way ANOVA and hypothesis test in evaluating crumb rubber modification (CRM) agitation effects on rheological properties of bitumen." *Construction and Building Materials*, 25 (2011) 2094–2106.

Al Khalil, M. I. (2002). "Selecting the appropriate project delivery method using AHP." International Journal of Project Management, 20(6), 469-474.

Alder, R. (2007). *UDOT Construction Manager/General Contractor (CM/GC) Annual Report*. Utah DOT- Project Development Group, Salt Lake City.

Alhazmi, T., and McCaffer, R. (2000). "Project procurement system selection model." Journal of Construction Engineering and Management, 126(3), 176–184.

Ames, D. and Neilson, B. (2001). A Bayesian Decision Network Engine for Internet-Based Stakeholder Decision-Making. Bridging the Gap: pp. 1-10. doi: 10.1061/40569(2001)169

Aspinall, W., Carniel, R., Jaquet, O., Woo, G., and Hincks, T. (2006). Using hidden multi-state

Markov models with multi-parameter volcanic data to provide empirical evidence for alert level decision-support. Journal of Volcanology and Geothermal Research, 153(1-2):112-124. 5 2006.

Associated General Contractors (2004). Project delivery systems for construction, Associated General Contractors of America, Arlington, VA.

Associated General Contractors. (2004). *Primer on project delivery*, Washington, D.C.

Augeri, M., Colombrita, R., Greco, S., Lo Certo, A., Matarazzo, B., and Slowinski, R. (2011). Dominance-Based Rough Set Approach to Budget Allocation in Highway Maintenance Activities. J. Infrastructure. Syst., 17(2), 75–85.

Batchelor, C., and Cain, J. (1999). Application of belief networks to water management studies. Agricultural Water Management, 40(1):51-57.

Bayraktar, M. and Hastak, M. (2009). ”Bayesian Belief Network Model for Decision Making in Highway Maintenance: Case Studies.” Journal of Construction Engineering and Management, 135(12), 1357–1369.

Beard, J. L., Loulakis, M. C., Wundram, E. C. (2001). Design-Build: Planning Through Development, McGraw-Hill, New York, NY.

Bennett, J., Pothecary, E., and Robinson, G. (1996). "Designing and Building a World-Class Industry." The University of Reading Design and Build Forum Report. *The University of Reading,* Centre for Strategic Studies in Construction.

Bensi, M. and Kiureghian, A. (2011) A Bayesian Network Approach for Identification of Critical Components of a System. Vulnerability, Uncertainty, and Risk: pp. 541-548.

Black, K. (2010) “Business Statistics: Contemporary Decision Making” 6th edition, John Wiley & Sons

Blanding, J. and Lewis, J (2012) "Shortening project delivery- Design-Build," U.S. Department of Transportation Federal Highway Administration (FHWA) Every Day Counts (EDC). http://www.fhwa.dot.gov/innovation/everydaycounts/edc-2/designbuild.cfm. Accessed July 27, 2016.

Bonafede, C. and Giudici, P., (2007). Bayesian Networks for enterprise risk assessment. Physica A: Statistical Mechanics and its Applications, 382(1):22-28. 8 2007.

Bouejla, A., Chaze, X., Guarnieri, F., and Napoli, A. (2014). A Bayesian network to manage risks of maritime piracy against offshore oil fields. Safety Science, 68:222-230.

Box, G. E. P., (1953) "Non-normality and tests on variances." *Biometrika* 40 (3/4), 318–335.

Bulu, H., Alpkocak, A., and Balci, P. (2013). Uncertainty modeling for ontology-based mammography annotation with intelligent BI-RADS scoring. Computers in biology and medicine, 43(4):301-11.

Buriticá, J., A., and Tesfamariam, S. (2015). Consequence-based framework for electric power providers using Bayesian belief network. International Journal of Electrical Power & Energy Systems, 64:233-241.

Chan, C. T. W. (2007). "Fuzzy procurement selection model for construction projects." Construction Management and Economics, 25(6), 311-618.

Chen, Q., Jin, Z., Xia, B., Wu, P., and Skitmore, M. (2016). "Time and cost performance of design-build projects." Journal of Construction Engineering and Management, 142(2)

Choy, E. and Ruwanpura, J. (2006). Predicting construction productivity using situation-based simulation models. Canadian Journal of Civil Engineering, 10.1139/l06-088, 1585-1600.

Cockburn, G. and Tesfamariam, S. (2012). "Earthquake disaster risk index for Canadian cities using Bayesian belief networks." Georisk: Assessment and Management of Risk for

Engineered Systems and Geohazards, 10.1080/17499518.2011.650147, 128-140.

Construction Industry Institute (CII). (1997). “Project delivery systems: CM at risk, design-build, and design-bid-build.” The University of Texas at Austin. Austin, Texas.

Construction Industry Institute. (CII) (2002). “Measuring the Impacts of the Delivery System on Project Performance-Design-Build and Design-Bid-Build. (NIST Publication No. BMM 2002-10).” The University of Texas at Austin. Austin, Texas.

Cooper, G.F., and Herskovits, E. “A Bayesian method for constructing Bayesian Belief Networks from databases.”

Corcoran, J.N., Tran, D., and Levine, N.D. (2014). “An Efficient Strategy for aggregation and discretization of attributes of Bayesian Networks using Minimum Description Length.”

Cornalba, C., and Giudici, P. (2004) Statistical models for operational risk management. Physica A: Statistical Mechanics and its Applications, 338(1-2):166-172.

D. Nasir, B. McCabe, L. Hartono, (2003), “Evaluating risk in construction–schedule model (ERIC-S): construction schedule risk model,” Journal of Construction Engineering and Management ASCE, 129 (5) (2003), pp. 518–527.

Design Build Institute of America (DBIA), 2016 Design-Build Authorization for Transportation, http://www.dbia.org/advocacy/state/Pages/default.aspx, Accessed July 25, 2016.

Design-Build Institute of America (2017) “Design-Build Authorization for Transportation” http://www.dbia.org/advocacy/state/Documents/design_build_maps.pdf (accessed January 25, 2017)

Deublein, M., Schubert, M., and Adey, B. (2014). "Prediction of road accidents: comparison of two Bayesian methods." Structure and Infrastructure Engineering, 1394-1416.

Dlamini, W., (2011). A data mining approach to predictive vegetation mapping using probabilistic graphical models. M. Ecological Informatics, 6(2):111-124.

El Asmar, M., Hanna, A., and Loh, W. (2013). "Quantifying Performance for the Integrated Project Delivery System as Compared to Established Delivery Systems." *Journal of Construction Engineering Management*, 139(11), 04013012, DOI: 10.1061/(ASCE)CO.1943-7862.0000744. ASCE.

Ellis, R. D., Pyeon, J., Herbsman, Z. J., Minchin, E. and Molenaar, K.R. (2007). “Evaluation of Alternative Contracting Techniques on FDOT Construction Projects.”

Ellis, R.E., Herbsman, Z. J., and Kumar, A. (1991). “Evaluation of the FDOT Design/Build Program.” Final Report, Florida Department of Transportation, Tallahassee, Florida.

Ernzen, J., and Schexnayder, C. (2000). “One Company's Experience with Design/Build: Labor Cost Risk & Profit Potential.” *Journal of Construction Engineering and Management*, 126(1), 10-14.

Faddoul, R., Raphael, W., Soubra, A., and Chateauneuf, A. (2013). Incorporating Bayesian Networks in Markov Decision Processes. J. Infrastruct. Syst., 19(4), 415–424.

Fan, C.F., and Yu, Y.C., (2004) BBN-based software project risk management, Journal of systems and software, 73(2), 193-203.

Federal Highway Administration (FHWA). (2006). *Design-build effectiveness study. U.S. Dept. of Transportation*, Washington, DC.

FHWA (2002). *Design-Build Contracting: Final Rule*. Federal Register.

FHWA. Quantification of Cost, Benefits, and Risk Associated with Alternative Contracting Methods and Accelerated Performance Specifications. Federal Highway Administration

Project, Contract No. DTFH61-11-D-00009, 2013-2016.

Florida Department of Transportation. (2004). “Design Build Program Evaluation.” Project Management, Research & Development Office, FDOT, Tallahassee, Florida.

Gastwirth, J. L., Gel, Y. R., & Miao, W. (2009). “The impact of Levene's test of equality of variances on statistical theory and practice.” *Statistical Science*, 343-360.

Goftar, V. N., El Asmar, M., and Bingham, E. (2014). “A meta-analysis of literature comparing project performance between design-build (D-B) and design-bid-build (D-B-B) delivery systems.” In Construction in a Global Network. Atlanta: *Construction Research Congress*, 1389-1398.

Gordon, C. M. (1994). “Choosing appropriate construction contracting method.” Journal of construction engineering and management, 120(1), 196–210.

Goulding, R., Jayasuriya, N., and Horan, E. (2012). A Bayesian network model to assess the public health risk associated with wet weather sewer overflows discharging into waterways. Water Research, 46(16):4933-4940.

Gransberg, D. D., and Shane, J. S. NCHRP Synthesis 402 Construction manager-at-risk project delivery for highway programs. Washington, D.C., 2010, 137 pp.

Gransberg, D. D., Koch, J. A., and Molenaar, K. R. (2006). Preparing for Design-Build Projects: A Primer for Owners, Engineers, and Contractors. American Society of Civil Engineers.

Gransberg, D., and Shane, J. (2010). “NCHRP Synthesis of Highway Practice 402: Construction Manager-at-Risk Project Delivery for Highway Programs.” Transportation Research Board of the National Academies, Washington, DC.

Gransberg, D.D. and Loulakis, M.C. (2014). *NCHRP Synthesis 429 Geotechnical Information*

Practices in Design-build Projects, Washington, D.C., 124.

Gransberg, D.D. and Loulakis, M.C., 2012. NCHRP Synthesis 429 Geotechnical Information Practices in Design-build Projects, Washington, D.C., 2014, 124 pp

Hale, D., Shrestha, P., Gibson, G., Jr., and Migliaccio, G. (2009). “Empirical Comparison of Design/Build and Design/Bid/Build Project Delivery Methods.” *Journal of Construction Engineering and Management*, 135(7), 579–587.

Ibbs, C. W., Kwak, Y. H., Ng, T., and Odabasi, A. M. (2003). "Project Delivery Systems and Project Change: Quantitative Analysis." *Journal of Construction Engineering and Management* 129 (4), 382-387.

Jaccard, J., & Guilamo-Ramos, V. (2002). Analysis of variance frameworks in clinical child and adolescent psychology: Advanced issues and recommendations. *Journal of Clinical Child Psychology*, 31, 278 –294

Jellinek, S., Rumpff, L., Driscoll, D., A., Parris, K., M., and Wintle, B., A. (2014). Modelling the benefits of habitat restoration in socio-ecological systems. Biological Conservation, 169:60-67. 1 2014.

Jha, M. (2006) Applying Bayesian Networks to Assess Vulnerability of Critical Transportation Infrastructure. Applications of Advanced Technology in Transportation (2006): pp. 1-6.

Jiang, X., Wallstrom, G., Cooper, G., F., and Wagner, M., M. (2009). Bayesian prediction of an epidemic curve. Journal of biomedical informatics, 42(1):90-9. 2 2009.

Johnson, S., Mengersen, K., de Waal, A., Marnewick, K., Cilliers, D., Houser, A., M., and Boast, L. (2010). Modelling cheetah relocation success in southern Africa using an Iterative Bayesian Network Development Cycle. Ecological Modelling, 221(4):641-651.

Joseph, S., Adams, B., and McCabe, B. (2010). ”Methodology for Bayesian Belief Network

Development to Facilitate Compliance with Water Quality Regulations.” Journal of Infrastructure Systems. 16(1), 58–65.

Kabir, G., Demissie, G., Sadiq, R., and Tesfamariam, S. (2015). "Integrating failure prediction models for water mains: Bayesian belief network based data fusion." Knowledge-Based Systems, 10.1016/j.knosys.2015.05.002.

Kahn, C., E., Roberts, L., M., Shaffer, K., A., and Haddawy, P. (1997). Construction of a Bayesian network for mammographic diagnosis of breast cancer. Computers in Biology and Medicine, 27(1):19-29. 1 1997.

Keppel, G., and Wickens, T. D. (2004). *Design and analysis: A researcher’s handbook*.

Keshtkar, A., Salajegheh, A., Sadoddin, A., and Allan, M. (2013). Application of Bayesian networks for sustainability assessment in catchment modeling and management (Case study: The Hablehrood river catchment). Ecological Modelling, 268:48-54.

Kim, S. (2011). "Bayesian Model for Cost Estimation of Construction Projects." Journal of the Korean Institute of Building Construction, 10.5345/JKIC.2011.02.1.091, 91-99.

Kirnbauer, M. and Baetz, B. (2014). Prototype Decision-Support System for Designing and Costing Municipal Green Infrastructure. J. Urban Plann. Dev., 140(3), 04014004.

Klann, J., G., Szolovits, P., Downs, S., M., and Schadow, G. (2014). Decision support from local data: creating adaptive order menus from past clinician behavior. Journal of biomedical informatics, 48:84-93.

Kline, P. (2000). *The handbook of psychological testing (2nd Ed.)*. London: Routledge

Konchar, M., and Sanvido, V. (1998). “Comparison of US project delivery systems.” *Journal of Construction Engineering and Management*, 124(6), 435-444.

Kreng, V. and Chang, C. (2003). Bayesian network based multiagent system—application in e-marketplace. Computers & Mathematics with Applications, 10.1016/S0898-1221(03)90036-8, 429-444.

Kumaraswamy, M. and Dissanayaka, S. (2001). “Developing a decision support system for building project procurement.” Building and Environment, 36(3), 337-349.

Kuzel, AJ. (1999). “Sampling in qualitative inquiry.” In BF Crabtrree and WL Miller (Eds.) Doing Qualitative Research (second edition). Thousand Oaks, CA: *Sage Publications*, 33-45.

Laws, R., J., and Kesler, D., C. (2012). A Bayesian network approach for selecting translocation sites for endangered island birds. Biological Conservation, 155:178-185.

Lee, E., Park, Y., and Shin, J.G. (2009) Large engineering project risk management using a Bayesian belief network, expert systems with applications, 5880-5887.

Lee, S., and Abbott, P., A. (2003). Bayesian networks for knowledge discovery in large datasets: basics for nurse researchers. Journal of Biomedical Informatics, 36(4-5):389-399.

Liao, Y., Wang, J., Guo, Y., and Zheng, X. (2010). Risk assessment of human neural tube defects using a Bayesian belief network. Stochastic Environmental Research and Risk Assessment,10.1007/s00477-009-0303-5,93-100.

Liedloff, A., C., and Smith, C., S. (2010). Predicting a ‘tree change’ in Australia's tropical savannas: Combining different types of models to understand complex ecosystem behavior. Ecological Modelling, 221(21):2565-2575.

Lin, J., and Haug, P., J. (2008). Exploiting missing clinical data in Bayesian network modeling for predicting medical problems. Journal of biomedical informatics, 41(1):1-14.

Love, P. E .D. Edwards, D. J., Irani, Z., and Sharif, A. (2012). Participatory action research approach to public sector procurement selection. ASCE Journal of Construction Engineering and Management, Vol.138, No.3, 2012, pp. 311–22

Love, P. E. ., Skitmore, M., and Earl, G. (1998). “Selecting a suitable procurement method for a building project.” Construction Management & Economics, 16(2), 221–233.

Luu, D. T., Ng, S. T., and Chen, S. E. (2003). “Parameters governing the selection of procurement system–an empirical survey.” Engineering, Construction and Architectural Management, 10(3), 209–218.

Luu, D. T., Ng, S. T., Chen, S. E. and Jefferies, M. (2006). “A Strategy for evaluating a fuzzy case based construction procurement selection system.” Advances in Engineering Software, 37, 159-171.

Luu, V., Kim, S., Tuan, N., and Ogunlana, S. (2009). Quantifying schedule risk in construction projects using Bayesian belief networks. International Journal of Project Management,10.1016/j.ijproman.2008.03.003,39-50.

Mahdi, I. M., and Alreshaid, K. (2005). “Decision support system for selecting the proper project delivery method using analytical hierarchy process (AHP).” International Journal of Project Management, 23(7), 564–572.

Malekmohammadi, B., Kerachian, R., and Zahraie, B. (2009). Developing monthly operating rules for a cascade system of reservoirs: Application of Bayesian Networks. Environmental Modelling &Software,10.1016/j.envsoft.2009.06.008,1420-1432.

Matthews, P. and Philip, A. (2012). Bayesian project diagnosis for the construction design process. Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 10.1017/S089006041200025X,375-391.

McCabe, B., AbouRizk, S., and Goebel, R. (1998). Belief Networks for Construction Performance Diagnostics. J. Comput. Civ. Eng., 12(2), 93–100.

McVittie, A., Norton, L., Martin-Ortega, J., Siameti, I., Glenk, K., and Aalders, I. (2015). Operationalizing an ecosystem services-based approach using Bayesian Belief Networks: An application to riparian buffer strips. Ecological Economics, 110:15-27.

Mediero, L., Garrote, L., and Carrasco, M. F. (2007). A probabilistic model to support reservoir operation decisions during flash floods. Hydrological Sciences Journal,523-537.

Migliaccio, G., Gibson, G., O'Connor, J., and others. (2009). "Procurement of Design-Build Services: Two-Phase Selection for Highway Projects." Journal of Management in Engineering, 25, 29.

Miller, J. B., Garvin, M. J., Ibbs, C. W., and Mahoney, S. E. (2000). "Toward a new paradigm: Simultaneous use of multiple project delivery methods." Journal of Management in Engineering, 16(3), 58–67.

Minchin, E., Ptschelinzew, L., Migliaccio, G.C., Gatti, U., Atkins, K., Warne, T., Hostetler, G. and Asiamah, S. NCHRP Report 787: Guide for design management on design-build and construction manager/general contractor projects, Washington, D.C., 2014, 226 pp.

Minchin, R., Jr., Li, X., Issa, R., and Vargas, G (2013). Comparison of Cost and Time Performance of Design-Build and Design-Bid-Build Delivery Systems in Florida. *Journal of Construction Engineering and Management*, 139(10).1-5.

Mkrtchyan, L., Podofillini, L., and Dang, V. (2015). "Bayesian belief networks for human reliability analysis: A review of applications and gaps." Reliability Engineering and System Safety,10.1016/j.ress.2015.02.006,1-16.

Molenaar, K. R., Songer, A. D., and Barash, M. (1999). "Public-sector design/build evolution and performance." *Journal of Management in Engineering*, 15(2), 54-62.

Moser, B. K., and Stevens, G. R., (2016). "Homogeneity of Variance in the Two-Sample Means Test," S.l.: *American Statistical Association*, Taylor & Francis, Ltd.

Muleta, M. (2012) A Formal, Bayesian Approach for Uncertainty Analysis of a Watershed Model. World Environmental and Water Resources Congress 2012: pp. 3732-3739.

Navidi, W. C. (2008). *Statistics for engineers and scientists*. McGraw-Hill Higher Education.

Ng, S. T., Luu, D. T., Chen, S. E. and Lam K. C. (2002). "Fuzzy membership functions of procurement selection criteria." Construction Management and Economics, 20, 285–296

Nicholson, A., E., and Flores, M., J. (2011). Combining state and transition models with dynamic Bayesian networks. Ecological Modelling, 222(3):555-566.

Nielsen, J. D., Salmerón, A., and Gámez, J., A. (2014). A tool based on Bayesian networks for supporting geneticists in plant improvement by controlled pollination. International Journal of Approximate Reasoning, 55(1):74-83.

Njardardottir, H., McCabe, B., and Thomas, M. (2005). Concrete bridge deck deterioration model using belief networks. Computers and Concrete, 10.12989/cac.2005.2.6.439, 439-454.

Oyetunji, A. A., and Anderson, S. D. (2006). "Relative effectiveness of project delivery and contract strategies." Journal of Construction Engineering and Management, 132(1), 3–13.

Park, H. S., and Kwak, Y. H. (2017). "Design-Bid-Build (DBB) vs. Design-Build (DB) in the U.S. public transportation projects: The choice and consequences." *International Journal of Project Management*, 35(3), 280–295.

Patton, M.Q. (1990). *Qualitative evaluation and research methods* (2nd Ed.). Newbury Park, CA: Sage, 532.

Peelen, L., de Keizer, N., F., Jonge, E., d., Bosman, R., Abu-Hanna, A., and Peek, N. (2010). Using hierarchical dynamic Bayesian networks to investigate dynamics of organ failure in patients in the Intensive Care Unit. Journal of biomedical informatics, 43(2):273-86.

Pollino, C., A., White, A., K., and Hart, B., T. (2007). Examination of conflicts and improved strategies for the management of an endangered Eucalypt species using Bayesian networks. Ecological Modelling, 201(1):37-59.

Rahm, E. and Do, H. H. (2000). “Data Cleaning: Problems and Current Approaches.” *In Bulletin of the IEEE Computer Society Technical Committee on Data Engineering*, 23(4), 3-13.

Riley, D. R, Diller, B. E., and Kerr, D. (2005). “Effects of delivery systems on change order size and frequency in mechanical construction.” *Journal of Construction Engineering and Management*, 131(9), 953–962.

Rumpff, L., Duncan, D., Vesk, P., Keith, D., and Wintle, B. (2011). State-and-transition modelling for Adaptive Management of native woodlands. Biological Conservation, 144(4):1224-1236.

Sahely, B. and Bagley, D. (2001). Diagnosing Upsets in Anaerobic Wastewater Treatment Using Bayesian Belief Networks. Journal of Environmental Engineering, 10.1061/(ASCE)0733-9372(2001)127:4(302),302-310.

Saunders, M., Lewis, P. & Thornhill, A. (2012) “Research Methods for Business Students” 6th edition, Pearson Education Limited

Schapaugh, A. W., and Tyre, A., J. (2012). Bayesian networks and the quest for reserve adequacy. Biological Conservation, 152:178-186.

Sheskin, D.J. (2011). *Handbook of Parametric and Nonparametric Statistical Procedures (5th*

Edition). Chapman & Hall/CRC

Shrestha, P., Connor, J., and Gibson, G. J. (2011) "Performance Comparison of Large Design-Build and Design-Bid-Build Highway Projects." *Journal of Construction Engineering and Management*, 138(1), 1-13.

Shrestha, P., Fernane, J, (2016) "Performance of Design-Build and Design-Bid-Build Projects for Public Universities." *Journal of Construction Engineering and Management*, 0733-9364, 1-10.

Shrestha, P., Migliaccio, G., O'Connor, J., & Gibson Jr, G. (2007). "Benchmarking of large design-build highway projects: One-to-one comparison and comparison with design-bid-build projects." *Journal of the Transportation Research Board*, 17-25.

Skitmore, R. M. and Marsden, D. E. (1988). "Which procurement system? Towards a universal procurement selection technique." Construction Management and Economics, 6, 71-89.

Smid, J., H., Verloo, D., Barker, G., C., and Havelaar, A., H. (2010). Strengths and weaknesses of Monte Carlo simulation models and Bayesian belief networks in microbial risk assessment. International journal of food microbiology, 139 Suppl :S57-63.

Songer, A. D., and Molenaar, K. R. (1997). "Project characteristics for successful public-sector Design-Build." *Journal of Construction Engineering and Management*, 123(1), 34–40.

Stevens, J. P. (1999) "*Intermediate Statistics: A Modern Approach* (2nd ed.). Mahwah, NJ: Lawrence Erlbaum Associates.

Tang, Z. and McCabe, B. (2007). Developing Complete Conditional Probability Tables from Fractional Data for Bayesian Belief Networks. Journal of Computing in Civil Engineering, 10.1061/(ASCE)0887-3801(2007)21:4(265),265-276.

Tesfamariam, S. and Liu, Z.. 2013. Seismic risk analysis using Bayesian belief networks. Handbook of Seismic Risk Analysis and Management of Civil Infrastructure Systems175-208.

Touran, A., Gransberg, D. D., Molenaar, K. R., and Ghavamifar, K. (2011). "Selection of project delivery method in transit: drivers and objectives." Journal of Management in Engineering, 27(1), 21–27.

Tran, D. Q. and Molenaar, K. R. (2014b). Exploratory critical delivery selection risk factors for transportation design and construction projects. *Engineering Construction and Architectural Management*, 21 (6), 631-647

Tran, D. Q., and Bypaneni, S.P.K. Impact of correlation on cost-risk analysis for construction highway projects, Construction Research Congress 2016, pp. 668-678.

Tran, D. Q., and Molenaar, K. R. (2013). Impact of risk on design-build selection for highway design and construction projects. Journal of Management in Engineering, 30(2), 153-162.

Tran, D., and Molenaar, K.R. (2014). Exploring critical delivery selection risk factors for transportation design and construction projects. Engineering, Construction and Architectural Management, 21(6), 631-647.

Tran, D., Cameron Lampe, J., Bypaneni, S., and Molenaar, K. (2016). An empirical comparison of cost growth between highway design-bid-build and design-build projects by project size. *Construction Research Congress 2016*, ASCE, Reston, VA, 2029–2038.

Tran, D.Q., and Molenaar, K.R. (2012). Critical risk factors in project delivery method selection for highway projects, Construction Research Congress 2012, pp. 331-340.

Tran, D.Q., and Molenaar, K.R. (2015). Risk-Based Project Delivery Selection Model for Highway Design and Construction. *Journal of Construction Engineering and Management*, 141 (12), 1-9

Tran, D.Q., Harper, C.M., Molenaar, K.R., Haddad, N.B., and Scholfield, M.M. (2013). "Project Delivery Selection Matrix for Highway Design and Construction." *In Transportation esearch Record: Journal of the Transportation Research Board*, *No. 2347, National Academies*, Washington, D.C., 3–10.

Van der Heijden, M., Lucas, P., J., F., Lijnse B., Heijdra, Y. F., and Schermer, T., R., J. (2013). An autonomous mobile system for the management of COPD. Journal of biomedical informatics, 46(3):458-69.

Van Tol, A. and AbouRizk, S. (2006). Simulation modeling decision support through belief networks. Simulation Modelling Practice and Theory, 10.1016/j.simpat.2005.10.010, 614-640.

Vieira, E. M. A., Silva, J. M. N., & Silva, L. B. (2017). Modeling Bayesian Networks from a conceptual framework for occupational risk analysis. Production, 27, e20162239.

Warne, T. R. (2005). "*Design-build contracting for highway projects: A performance assessment*." Tom Warne & Associates, LLC, 2005.

Wiegerinck, W., Kappen, H., ter Braak, E., ter Burg, W., Nijman, M., O, Y., and Neijt, J. (1999). Approximate inference for medical diagnosis. Pattern Recognition Letters, 20(11-13):1231-1239.

Williams, B. and Cole, B. (2013). Mining monitored data for decision-making with a Bayesian network model. Ecological Modelling, 10.1016/j.ecolmodel.2012.07.008, 26-36.

Wilson, D., S., Stoddard, M., A., and Puettmann, K., J. (2008). Monitoring amphibian populations with incomplete survey information using a Bayesian probabilistic model.

Ecological Modelling, 214(2-4):210-218.

Yang, G., Lin, Y., and Bhattacharya, P. (2010). A driver fatigue recognition model based on information fusion and dynamic Bayesian network. Information Sciences, 180(10):1942-1954.

Yates, J. (1995). Use of design/build in E/C industry. Journal of Management in Engineering, 11(6), 33–38.

Yates, J.K. (1993), Construction decision support system for delay analysis, journal of construction delay analysis, 119 (2), 226-244.

Yet, B., Perkins, Z., B., Rasmussen, T., E., Tai, N., R., M., and Marsh, D., W., R. (2014) Combining data and meta-analysis to build Bayesian networks for clinical decision support. Journal of biomedical informatics, 52:373-85.

APPENDIX I: RISK FACTORS FOR DELIVERY DECISION

No	Risk Factor	Risk Description
1	Challenges to obtain appropriate environmental documentation	Changing environmental regulations, unforeseen formal NEPA consultation, unexpected Section 106 issues, an insufficient environmental study, and environmental clearance for staging required, etc.
2	Environmental impacts	Unexpected environmental constraints during planning and construction (e.g., historic site, endangered species, wetland, coastal and scenic zone, and wildlife; Environmental Assessment vs. Environmental Impact Statement).
3	Uncertainty in geotechnical investigation	Unforeseen ground conditions, inappropriate design, contamination, ground water, settlement, chemically reactive ground, incomplete survey, and inadequate geotechnical investigation.
4	Work zone traffic control	Potential problems with maintenance of traffic, unexpected plans, and detours, and/or seasonal restrictions
5	Unexpected utility encounter	Unforeseen utility conditions (e.g., seasonal requirements during utility relocation, unknown utility relocation, utility company workload, financial condition or timeline).
6	Delays in completing utility agreements	The risk relates to disagreement over responsibility to move, over cost-sharing or inadequate pool of qualified appraisers.
7	Delays in right-of-way (ROW) process	Challenges or general delays in the acquisition of ROW.
8	Delays in completing in railroad agreements	Obtaining railroad agreement takes longer to complete than anticipated.
9	Difficulty in obtaining other agency	Primarily relating to new permits, new information required for permits, delays in agreements from Federal, State, or local agencies, or unforeseen agreements required.
10	Defined and non-defined hazardous waste	Incomplete analysis of hazardous waste site, unexpected environmental constraints or unanticipated cumulative impact issues (e.g., on-site storage, additional costs to dispose).
11	Project complexity	Complex structures, unexpected ground conditions, environmental issues, unforeseen design and technical issues, and challenges in the level of interaction between stakeholders, and difficulties in obtaining an agreement with third-party, etc.
12	Scope Definition	Incomplete scope definition or unclear description of all major project deliverables and project boundaries that may lead to new or revised designs, added workload or time, rework and change orders (i.e., scope creep).

No	Risk Factor	Risk Description
13	Project definition	Project goals and objectives (schedule, cost, and quality) are not well-defined or insufficient description of project conditions and challenges.
14	Staff experience/availability	Lack of experienced of staff (e.g., the staff's comfort and confidence using a specific contract method; the quality and competence of staff to complete the duties; and concern about the retirement of experienced staff or losing critical staff at crucial point of the project).
15	Project and program management issues	A lack of understanding of complex internal procedures or functional units not available, overloaded (e.g., inconsistent cost, time, scope, and quality objectives; overlapping of one or more project limits).
16	Constructability in design	The risk relates to unresolved constructability items, complex project features, incomplete quantity estimates, and unforeseen construction window
17	Delays in procuring critical materials, labor, and specialized equipment	Unexpected constraints, unforeseen requirements, complex structure, unresolved constructability items may lead to delays in procuring materials, labors, and equipment.
18	Significant increase in material, labor and equipment cost	The risk relates to incomplete quantity estimates, increase in material cost due to market forces, unanticipated escalation in material, labor, and equipment costs.
19	Conformance with regulations/guidelines/design criteria	Challenges in conforming to guidelines, design criteria, and regulations (e.g., new or revised design standard, consultant design not up to department standards, and unforeseen design exceptions required).
20	Intergovernmental agreements and jurisdiction	Challenges in an intergovernmental agreement between the agency and other agencies (e.g., political factors for project changes, local communities pose objections, permits or agency actions delayed or take longer than expected).
21	Legal challenges and changes in law	The threat of lawsuits due to new permits or additional information required.
22	Unclear contract documents	Ambiguities in the contract documents (e.g., incentive/disincentive payment clauses, the impact of long lead items, changes during construction required additional coordination with resources agencies.
23	Single or multiple contracts	Difficulties in multiple contractor interfaces (e.g., lack of coordination/communication, additional coordination with resource agencies required).

No	Risk Factor	Risk Description
24	Insurance in contract	Uncertainty in the availability of insurance coverage under which contractors accepts significant insurance risk from agencies.
25	Annual inflation rates	A change in value caused by a deviation of the actual market consistent value of assets and/or liabilities from their expected value due to inflation.
26	Construction market conditions	A change in construction market (e.g., considerable variation of bid prices on similar work components; higher procurement costs for major project components).
27	Delays in delivery schedule	Uncertainty in the overall project delivery schedule from scoping through design, construction, and opening to the public.
28	Construction sequencing/staging/phasing	The risk often involves insufficient or limited construction or staging areas, unforeseen construction window, rainy season requirements, and street or ramp closures not coordinated with the local community.
29	Construction QC/QA process	The risk involves continued evaluation and assessments of the activities of planning, construction, and maintenance (e.g., contractor testing, agency verification, and possible dispute resolution).
30	Design Quality Assurance	The risk involves continued evaluation and assessments of the activities of the development of plans, design, and specifications, advertising and awarding of the contract.
31	Design Completion	This risk relates to inaccurate assumptions on technical issues, unforeseen design exception, incomplete quantity estimates at the level of design completion at the time of the contract method selection.

APPENDIX II: CRITICAL RISK FACTORS FOR D-B-B DELIVERY METHOD

Critical Risk Components	Risk Factors	Loading
Construction Risk	Uncertainty in geotechnical investigation	0.77
	Environmental impacts	0.77
	Work zone traffic control	0.75
	Construction QC/QA Process	0.63
Schedule Risk	Construction sequencing/staging/phasing	0.74
	Unexpected utility encounter	0.72
	Unclear contract documents	0.72
	Delays in delivery schedule	0.70
Third-party and Complexity Risk	Difficulty in obtaining other agency approvals	0.82
	Defined and non-defined hazardous waste	0.73
	Project complexity	0.71
	Delays in completing utility agreements	0.70
Constructability Risk	Delays in procuring critical materials, labor, and specialized equipment	0.81
	Constructability in design	0.80
	Significant increase in material, labor and equipment cost	0.71
Market Risk	Construction market conditions	0.75
	Annual inflation rates	0.72
ROW Risk	Delays in right-of-way (ROW) process	0.62

Source: Adapted from Tran and Molenaar (2014)

APPENDIX III: CRITICAL RISK FACTORS FOR D-B DELIVERY METHOD

Critical Risk Components	Risk Factors	Loading
Scope Risk	Project definition	0.82
	Scope definition	0.78
	Staff experience/availability	0.75
	Conformance with regulations/guidelines/design criteria	0.70
	Challenge to obtain appropriate environmental documentation	0.64
Third-party and Complexity Risk	Delays in completing utility agreements	0.74
	Difficulty in obtaining other agency approvals	0.74
	Project complexity	0.72
	Defined and non-defined hazardous waste	0.71
	Legal challenges and changes in law	0.66
Construction Risk	Uncertainty in geotechnical investigation	0.77
	Work zone traffic control	0.73
	Environmental impacts	0.66
	Construction QC/QA process	0.48
Utility and ROW Risk	Unexpected utility encounter	0.84
	Delays in right-of-way (ROW) process	0.63
Level of Design and Contract Issues	Design completion	0.81
	Single or multiple contracts	0.78
	Unclear contract documents	0.41
Management Issues	Project and program management issues	0.79
	Insurance in contract	0.72
Regulation Risk and Railroad	Intergovernmental agreements and jurisdiction	0.79
	Railroad agreements	0.53

Source: Adapted from Tran and Molenaar (2014)

APPENDIX IV: CRITICAL RISK FACTORS FOR CM/GC DELIVERY METHOD

Critical Risk Components	Risk Factors	Loading
Constructability and Documentation Risk	Conformance with regulations/guidelines/design criteria	0.74
	Significant increase in material, labor and equipment cost	0.69
	Constructability of design	0.66
	Delays in procuring critical materials, labor, and equipment cost	0.65
	Challenge to obtain appropriate environmental documentation	0.65
Construction Risk	Work zone traffic control	0.81
	Uncertainty in geotechnical investigation	0.77
	Construction QC/QA process	0.67
	Environmental impacts	0.58
Complexity Risk	Project complexity	0.77
	Difficulty in obtaining other agency approvals	0.69
	Design QC and QA process	0.64
	Defined and non-defined hazardous waste	0.61
Management Issues and Schedule Risk	Project and program management issues	0.77
	Insurance in contract	0.71
	Delays in delivery schedule	0.71
Third-party Risk	Delays in completing railroad agreements	0.72
	Delays in completing utility agreements	0.55
Regulation Risk and ROW	Intergovernmental agreements and jurisdiction	0.85
	Delays in right-of-way (ROW) process	0.61

Source: Adapted from Tran and Molenaar (2014)

APPENDIX V: LITERATURE REVIEW OF BNS APPLICATION

Researcher	Research Area/Topic	Methodology and Model Validation
Yates (1993)	Construction decision support system for delay analysis	Built upon solid data of actual industry experience, sample case study was presented
Heckerman (1995)	A Tutorial on Learning With BNs	Methods for constructing BNs from prior knowledge and summarize Bayesian statistical methods
Kahn et al. (1997)	Construction of a BN for mammographic diagnosis of breast cancer	BN provide a potentially useful tool for mammographic decision support (implementation and evaluation)
McCabe et al. (1998)	Belief Networks for Construction Performance Diagnostics	Computer simulation is used to model the construction operations and to validate the changes
Batchelor and Cain (1999)	Application of belief networks to water management studies	Belief and decision networks can provide a mathematical framework, allowing a simple, integrated methodology
Wiegerinck et al. (1999)	Approximate inference for medical diagnosis	Equipped with approximate methods to study the practical feasibility and the usefulness in medical practice
Ames and Nielson (2001)	A BN Engine for Internet-Based Stakeholder Decision-Making	Bayesian Decision Network (BDNs) are presented here as a useful tool for diagramming the decision process
Sahely and Bagley (2001)	Diagnosing Upsets in Anaerobic Wastewater Treatment using BN	Monte Carlo Simulation was used in determining the conditional probabilities of the states of the variables
Nasir et al. (2003)	Evaluating risk in construction–schedule model (ERIC-S)	Sensitivity analysis was performed. The model was tested using 17 case studies with very good results
Kreng and Chang (2003)	BN based multiagent system—application in e-marketplace	Evaluated qualitative and quantitative decision factors to construct multiagent system
Aspinall et al. (2003)	Evidence-based volcanology: application to eruption crises	A formalism may aid decision-making in future: BNs performs the necessary numerical procedures

Lee and Abbot (2003)	BNs for knowledge discovery in large datasets	BNs allow investigators to combine domain knowledge with statistical data
Fan and Yu (2004)	BN-based software project risk management	BN using a feedback loop to predicts potential risks, analytical and simulated cases were reported
Cornalba and Giudici (2004)	Statistical models for operational risk management	Developed valid statistical models to measure and, consequently, predict, operational risks
Njardardottir (2005)	Concrete bridge deck deterioration model using belief networks	Sensitivity analysis was performed to determine which probabilities in the model, two case studies
Jha (2006)	Applying BN to Assess Vulnerability of Transportation Infrastructure	BN model is developed for predicting likelihood of a terrorist strike with an example study
Van and Abourizk (2006)	Simulation modeling decision support through belief networks.	The knowledge encapsulation for the agents is provided via belief networks
Choy and Ruwanpura (2006)	Predicting construction productivity using situation-based simulation models	Model the cause-and-effect relationships among various triggering situations
Aspinall et al. (2006)	Using hidden multi-state Markov models with multi-parameter volcanic data	A multi-state Markov process provides one simple model for defining states and for switching estimating rates
Mediero et al. (2007)	A probabilistic model to support reservoir operation decisions during flash floods	Monte Carlo simulation was implemented, a case study was conducted
Tang and McCabe (2007)	Developing Complete Conditional Probability Tables from Fractional Data for BN	Techniques for using fractional data to develop complete conditional probability tables were examined
Bonafede and Giudici (2007)	BNs for enterprise risk assessment	Building a BN in which only prior probabilities of node states and marginal correlations between nodes
Pollino et al. (2007)	Conflicts and improved strategies for the management of an endangered Eucalypt species using BN	BN model has been developed for E. camphora and used to explore the differences between hypotheses

Abad-Grau et al. (2008)	Evolution and challenges in the design of computational systems for triage assistance	principled approaches from machine learning can be used to increase accuracy and robustness
Lin and Haug (2008)	Exploiting missing clinical data in BN modeling for predicting medical problems	Networks were built based on a naive Bayes, a human-composed, and structural learning algorithms
Wilson et al. (2008)	Monitoring amphibian populations with incomplete survey information using a BN	probabilistic approach incorporated survey information for co-occurring species to help make better predictions
Luu et al. (2009)	Quantifying schedule risks in construction projects	Expert interview survey to develop a BN model, Validated with two case studies
Lee et al. (2009)	Large engineering project risk management using a BN	Twenty-six different risks were deduced from expert interviews and a literature review
Bayraktar and Hastak (2009)	Bayesian Belief Network Model for Decision Making in Highway Maintenance	Decision support system was used for predicting the influence of decisions, two case studies were conducted
Bayraktar and Hastak (2009)	DSS for selecting the optimal contracting strategy in highway work zone projects	a dynamic relationship between the involved parties and the performance of any highway work zone project
Malekmohammadi et al. (2009)	Developing monthly operating rules for a cascade system of reservoirs using BN	Varying chromosome Length Genetic Algorithm (VLGA-II) was used along with fuzzy linear regression
Jiang et al. (2009)	Bayesian prediction of an epidemic curve	Developed a model for estimating an epidemic curve early in an outbreak, and results of experiments testing its accuracy.
Joseph et al. (2010)	BN Development to Facilitate Compliance with Water Quality Regulations	Expert judgment was used in developing structure and in quantifying the required probability relationships
Liao et al. (2010)	Risk assessment of human neural tube defects using a Bayesian belief network	Bayesian belief network was used to quantify the probability of Neural Tube Defects with 95% accuracy
Smid et al. (2010)	Strengths and weaknesses of MCS models and BN in microbial risk assessment	BBNs were used as an alternative for Monte Carlo modelling with an illustrative example

Peelen et al. (2010)	Using hierarchical dynamic BNs to investigate dynamics of organ failure	Developed a set of complex Markov models based on clinical data, logistic regression was used along with BN
Liedloff and Smith (2010)	Predicting a 'tree change' in Australia's tropical savannas	Combined modelling approach with a case study, sensitivity and diagnostic analysis was conducted
Yang (2010)	A driver fatigue recognition model based on information fusion and dynamic BN	First-order Hidden Markov Model to compute the dynamics of the BN
Johnson et al. (2010)	Modelling cheetah relocation success in southern Africa using an Iterative BN	Benefit of relocation BNs goes beyond the identification and quantification of the factors
Bensi and Kiureghian (2011)	BN Approach for Identification of Critical Components of a System	Max-propagation algorithm of the BN was used, two simple examples were used for demonstration
Augeri et al. (2011)	Dominance-Based Rough Set Approach (DRSA) to Budget Allocation in Highway	This approach enables an interaction between the analyst and the decision maker, case study was performed
Kim (2011)	Bayesian Model for Cost Estimation of Construction Projects	The Markov Chain Monte Carlo (MCMC) method is applied to estimate parameter distributions
Rumpff et al. (2011)	State-and-transition modelling for Adaptive Management of native woodlands	Application of the model is demonstrated using case-study and simulation data
Nicholson and Flores (2011)	Combining state and transition models with dynamic BNs	Combining state and transition models (STMs) with BNs for decision support tools
Dlamini (2011)	A data mining approach to predictive vegetation mapping using probabilistic graphical models	The classification uses BNs (BN) and the parameterization is based on the expectation-maximization (EM) algorithm
Muleta (2012)	Bayesian Approach for Uncertainty Analysis of a Watershed Model	Markov-Chain Monte Carlo (MCMC) scheme was used; maximum likelihoods were used for validation
Cockburn and Tesfamariam (2012)	Earthquake disaster risk index for Canadian cities using BN	Expert knowledge derives the subjective probabilities of the BN, A case study illustrates model versatility

Matthews and Philip (2012)	Bayesian project diagnosis for the construction design process	Monte Carlo approach is used to parameterize a Bayesian estimator, Quasi-Markov chain was also used
Goulding et al. (2012)	BN model to assess public health risk with sewer overflows into waterways	Highlights the benefits of the probabilistic inference function of the BN in prioritising management options
Laws and Kesler (2012)	A BN approach for selecting translocation sites for endangered island birds	Conditional probabilities were allocated using information from the literature, expert opinions, and a training set
Schapaugh and Tyre (2012)	BNs and the quest for reserve adequacy	BN assigns an expected value to a property based on criteria arrayed into a causal diagram,
Faddoul (2013)	Incorporating BNs in Markov Decision Processes	Partially observable Markov decision process with an illustrative example
Williams and Cole (2013)	Mining monitored data for decision-making with a BN model	The approach to incorporating elicited data is described and some simple scenario testing is also presented
Tesfamariam and Liu (2013)	Seismic risk analysis using Bayesian belief networks	BBN structure is generated from historical data through different machine learning algorithms
Bulu et al. (2013)	Uncertainty modeling for ontology-based mammography annotation	Experimentations in terms of accuracy, sensitivity, precision and uncertainty level measures
Keshtkar at al. (2013)	BN application for sustainability assessment in catchment modeling and management	Integrated BN model framework was applied to evaluate the sustainability, a case study was conducted
Vander et al. (2013)	An autonomous mobile system for the management of COPD	Probabilistic model using cross-validation and ROC analyses; Pilot study was conducted to test feasibility
Kirnbauer and Baetz (2014)	Decision-Support System for Designing and Costing Municipal Green Infrastructure	DECO is designed to allow the user to perform a series of “what-if” scenarios/sensitivity analyses
Deublein et al. (2014)	Prediction of road accidents: comparison of two Bayesian methods	Empirical Bayes (EB) and Bayesian Probabilistic Networks (BPNs) were compared

Bouejla et al. (2014)	BN to manage risks of maritime piracy against offshore oil field	BN was used to manage this large number of parameters and identify appropriate counter-measures
Jellinek et al. (2014)	Modelling the benefits of habitat restoration in socio-ecological systems	BN can be used to integrate ecological and social data and expert opinion, illustrated with a case study
Klann (2014)	Decision support from local data: creating adaptive order menus from past clinician behavior	This study demonstrates that local clinical knowledge can be extracted from treatment data for decision support.
Yet et al. (2014)	Combining data and meta-analysis to build BNs for clinical decision support	Meta-analysis with a clinical dataset and expert knowledge to construct multivariate BN models
Nielsen et al. (2014)	BN for supporting geneticists in plant improvement by controlled pollination	A system designed for assisting geneticists in vegetal genetic improvement tasks using BN
Yet et al. (2014)	Not just data: a method for improving prediction with knowledge	BN model predict and reason with latent variables, using a combination of expert knowledge and available data
Mkrtchyan et al. (2015)	Bayesian belief networks for human reliability analysis	Analyses the process for building BBNs and in particular how expert judgment is used
Kabir et al. (2015)	Integrating failure prediction models for water mains	BN based data fusion model was developed, The proposed model can be integrated with the GIS
Abimbola et al. (2015)	Safety and risk analysis of managed pressure drilling operation using BN	Bow-ties were mapped into BN to minimize difficulties in modeling dependencies and operational data
McVittie et al. (2015)	Operationalizing an ecosystem services-based approach using BBN	Discussed key issues raised as a result of the probabilistic nature of the BBN model
Buritica and Tesfamariam (2015)	Consequence-based framework for electric power providers using BBN	Sensitivity analysis was undertaken to identify importance of the indicators on the decision framework

U.S. Department of Transportation
Federal Highway Administration

University of Colorado Boulder

KU THE UNIVERSITY OF KANSAS

HILL

FHWA PROJECT DELIVERY QUESTIONNAIRE

Purpose: You are invited to submit a questionnaire for a project from your agency as part of an FHWA study to quantify the cost, benefits and risks associated with alternate contracting methods and accelerated performance specifications. The objective of this study is to *empirically* investigate and compare the costs, benefits and risks associated with the use of design-bid-build (D-B-B), design-build (D-B), construction manager general contractor (CM/GC) and alternative technical concept (ATC) contracting methods, as well as those related to use of early completion incentives/disincentives (I/Ds). Results of this study will benefit state transportation agencies by providing empirical evidence on selecting the various project delivery methods and determining appropriate incentive/disincentive levels.

Participation/Confidentiality: Your expertise and experience is critical to the success of this important study. Your individual privacy will be maintained in all published and written data resulting from this study. The project questionnaire should take approximately 30 minutes to complete. To save time and promote efficiency, please have the following information available before you start:

- Project size and type (lane miles, structures, etc.)
- Project delivery method (D-B-B, D-B and CM/GC)
- Overall project and construction costs (initial and final contracted costs)
- Project schedule (initial/final design, award and construction completion dates)

Contact: We thank you in advance for your time and thoughtful consideration. Please let us know if you have any questions or comments

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I. GENERAL INFORMATION

1. First Name: ____________________
Last Name: ____________________
Phone #:__________Email: ____________________
Organization: ____________________
State in which you are employed: ____________________

2. What group/section do you work in?
◯ Design group/section ◯ Construction group/section ◯ Operations group/section
◯ Alternative project delivery group/section ◯ Contracts/procurements group/section
◯ Other, please specify: ____________________

3. Have you completed a highway project within the past five years?
◯ Yes, continue with the next questions ◯ No, go to a *"Thank you"* page

II. PROJECT CHARACTERISTICS

4. Project Name: ____________________
Project Location: ____________________
Owner Agency: ____________________
Additional Project Identifier (e.g., project number): ____________________

5. Please approximately *estimate approximate percentage of total project cost* that falls into each category.

Project Description	***Approximate*** **percentage of total project cost**
Facility Type	______% Road ______% Bridge(s) ______% Drainage ______% ITS ______% Others, please specify:__________ ______% **Total** *(must total 100%)* or ☐ I do not know
Project Type	______% New Construction/Expansion ______% Rehabilitation/Reconstruction ______% Resurfacing/Renewal ______%Others, please specify:__________ ______% **Total** *(must total 100%)* or ☐ I do not know
Highway Type	______% Rural Interstate ______% Urban Interstate ______% Rural Primary ______% Urban Primary ______% Rural Secondary ______% **Total** *(must total 100%)* or ☐ I do not know

6. Given the complexity definition in the table below, please rate the complexity of this project.
◯ Most Complex (major) ◯ Moderately Complex ◯ Non-Complex (minor)
◯ Information not available

Complexity Definitions

Most Complex (Major) Projects	Moderately Complex Projects	Non-complex (Minor) Projects
• New highways; major relocations • New interchanges • Capacity adding/major widening • Major reconstruction (4R; 3R with multi-phase traffic control) • Congestion management studies are required • Environmental Impact Statement or complex Environmental Assessment required	• 3R and 4R projects which do not add capacity • Minor roadway relocations • Non-complex bridge replacements with minor roadway approach work • Categorical Exclusion or non-complex Environmental Assessment required	• Maintenance betterment projects • Overlay projects, simple widening without right-of-way (or very minimum right-of-way take) little or no utility coordination • Non-complex enhancement projects without new bridges (e.g. bike trails) • Categorical Exclusion

Note: 4R is rehabilitation, restoration, resurfacing, or reconstruction

III. PROJECT PERFORMANCE

7. Please indicate the *cost performance* of this project in the table below. Please separate Construction Cost if known; otherwise, enter Total Project Costs only.

	Construction
STIP Amount ($) (if available)	
Engineer's Estimate ($)	
Contract Award ($)	
Final Cost ($) (= Contract Award + Cost of all Change Orders)	

* If other project cost data is available, please complete the table below.

	Design	ROW	CEI
Original Estimate ($)			
Final Cost ($)			

CEI: Construction Engineering and Inspection

◯ Other ____________________

8. How many change/extra work orders were approved for this project?
#_______of change orders $_______ value of change orders

☐ I do not know

9. If known, please approximate the total value of the change/extra work orders into the following categories:
___% Agency directed changes
___% Changes in planned quantities
___% Unforeseen or external project conditions
___% Errors and omissions in the plans
___% Other, please specify:____________________
___% **Total** (must equal 100%)

☐ I do not know

10. Please indicate the *schedule performance* of this project in the table below. If planned dates are not known, please include only actual dates.

(*For D-B, Design Start = agency start date RFP development ; Design End = best estimate of D-B design completion (e.g., last D-B design payment)*)	Planned *(mm/dd/yy)* (if available)	Actual *(mm/dd/yy)*
Total Project Time (Days)		
Design start date *(Notice to proceed)*		
Design end date *(Plans or RFP complete)*		
Date advertised		
Construction start date *(Notice to proceed)*		
Construction end date *(Substantial completion)*		

11. Were there any major unanticipated (or external) schedule delays encountered that should be noted in relation to schedule performance?
- ◯ Yes, please specify below: ◯ No ◯ I do not know

____

12. For CM/GC or D-B projects, did the original scope of work change significantly as a result of recommendations made by either the CM firm or successful design-builder? If so, briefly describe the modified scope.

____

[Note: Branching section of questionnaire begins here. Respondents will be able to skip sections for which they do not have information.]

IV. DELIVERY METHODS

13. Are you able to answer questions about the delivery methods for this project?
- ◯ Yes [proceed to question 14]
- ◯ If no, can provide contact information for someone who can answer delivery method questions? [answer below and proceed to question 19]

Name: ____________________
Phone #:__________ Email:__________

14. Which project delivery method was used for this project?
- ◯ Design-Bid-Build (D-B-B) ◯ Design-Build (D-B)
- ◯ Construction Manager/General Contractor (CM/GC or CM at Risk)
- ◯ Other, please specify: ____________________

15. Which procurement procedure was used for this project?
- ◯ Low bid ◯ Best value (Consideration of factors in addition to cost) ◯ Qualification-based (Quals. only, no price)
- ◯ A+B (Cost + Time)
- ◯ Other, please specify: ____________________
- ◯ I do not know

16. Which payment method was used for this project?
- ◯ Lump sum ◯ Cost reimbursable ◯ Unit price
- ◯ Guaranteed maximum price (or agreed upon contract price in CM/GC or similar)
- ◯ Other, please specify: ____________________
- ◯ I do not know

17. How many firms bid or proposed on this project?
- ◯ If D-B-B, # of construction firms: _______
- ◯ If D-B, # of D-B firms: ______
- ◯ If CM/GC, # of construction firms: _______
- ◯ I do not know

18. If D-B, were stipends provided to unsuccessful proposers?
- ◯ Yes If yes, please provide amount if known: _____________
- ◯ No ◯ I do not know

V. ALTERNATIVE TECHNICAL CONCEPTS

19. Are you able to answer questions about ATCs for this project?
- ◯ Yes [proceed to question 20]
- ◯ Yes, but no ATCs were used. [proceed to question 24]
- ◯ No. Please provide contact information for someone who can answer ATC questions? [answer below and proceed to question 24]

Name: ____________________
Phone #:__________ Email: __________

20. Approximately how many ATCs were submitted for this project?
____
- ☐ I do not know

21. Were costs available for the evaluation of ATCs?
- ◯ Yes ◯ No
- ◯ Information not available

If yes, what was the total value of all ATCs from proposers?
$ ______
Comments: ____________________
- ☐ I do not know

If Yes, what was the total value of the ATC incorporated into the winning proposal?
$ ______
Comments: ____________________
- ☐ I do not know

22. Was time considered for the evaluation of ATCs?
- ◯ Yes ◯ No
- ◯ Information not available

If yes, what was the total value of all ATCs from proposers?
Days ______
Comments:__________________
- ☐ I do not know

If Yes, what was the total value of the ATC incorporated into the winning proposal?
Days ______
Comments: __________________
- ☐ I do not know

23. Were confidential one-on-one meetings held to discuss ATCs with proposers?
- ◯ Yes ◯ No

Comments ____________________
- ☐ I do not know

VI. INCENTIVE/DISINCENTIVE PROVISIONS FOR EARLY COMPLETION

24. Are you able to answer questions about I/D provisions for early completion on project?
- ◯ Yes [proceed to question 25]
- ◯ Yes, but no I/D provisions were used. [proceed to question 30]
- ◯ No. Please provide contact information for someone who can answer I/D provision questions? [proceed to question 30]

Name: ____________________
Phone #:__________ Email: __________

25. What was the amount of ***Incentive*** available for early completion and ***Disincentive*** for late completion?

26. What was the amount of I/D for early completion *earned* by the contractor of record?
$_______Incentive earned
$_______Disincentive assessed
- ☐ I do not know

27. What components was I/D based upon (please check all that apply)?
- ☐ User cost ☐ Agency cost
- ☐ Contractor cost ☐ Project acceleration cost
- ☐ Agency standard policy ☐ Other, please specify:
- ☐ I do not know

____

28. What components of time extension were used on I/D (please check all that apply)?
- ☐ A + B bidding
- ☐ Time extension granted for an owner-caused delay
- ☐ Time extension granted for a third-party-caused delay
- ☐ Only disincentive provision used
- ☐ Other, please specify: ____________________
- ☐ I do not know

Please explain the basis for the time extension in more detail:

29. Did the project team use a formal partnering agreement ? ◯ Yes ◯ No
If Yes, please explain:

VII. RELATIVE PROJECT QUALITY

30. Are you able to answer questions about the relative quality for this project?

○ Yes [proceed to question 31]

○ If no, can provide contact information for someone who can answer relative quality questions for this project? [answer below and proceed to question 32]

Name:____

Phone #:_______________Email: _____________________________

31. Please rate the relative project quality on the scale from 1 to 6 as compared to other projects you have completed in your career.

Quality Criteria	Low 1	2	3	4	5	High 6
Conformance with the original project scope, objective, and need	○	○	○	○	○	○
Conformance with standards/specifications	○	○	○	○	○	○
Conformance with user expectations	○	○	○	○	○	○
Compliance with warranty provisions	○	○	○	○	○	○
Overall project satisfaction	○	○	○	○	○	○

VIII. PROJECT RISK PROFILE

32. Are you able to answer questions about the impact of risk on this project?

○ Yes [proceed to question 33]

○ If no, can provide contact information for someone who can answer questions regarding project risks? [answer below and proceed to question 35]

Name: ____

Phone #:_______________Email:_______________________________

Project risk profiles can influence the selection of a project delivery method and overall project performance. Please use the following scale to rate the impact of risks on the cost and schedule performance of your project. *NOTE: to the best of your ability, please rate these risks **prior to** or **at the time** of the project delivery decision is made.*

Rating system	1	2	3	4	5
	Very Low	Low	Moderate	High	Very High
Cost Impact	Insignificant cost increase	< 2% cost increase	2-5% cost increase	5-10% cost increase	> 10% cost increase
Schedule Impact	Insignificant slippage	< 2% schedule slippage	2-5% schedule slippage	5-10% schedule slippage	> 10% schedule slippage

Note: NA (Not Applicable) is used to rate risk that is not materialized.

Risk Description / Rating

1. **Challenges to obtain appropriate environmental documentation**—changing environmental regulations, unforeseen formal NEPA consultation, unexpected Section 106 issues, an insufficient environmental study, environmental clearance for staging required, etc.

	NA	1	2	3	4	5
Cost Impact	○	○	○	○	○	○
Schedule Impact	○	○	○	○	○	○

2. **Environmental impacts**—unexpected environmental constraints during planning and construction (e.g., historic site, endangered species, wetland, coastal and scenic zone, and wildlife; Environmental Assessment vs. Environmental Impact Statement).

	NA	1	2	3	4	5
Cost Impact	○	○	○	○	○	○
Schedule Impact	○	○	○	○	○	○

3. **Uncertainty in geotechnical investigation**—unforeseen ground conditions, inappropriate design, contamination, ground water, settlement, chemically reactive ground, incomplete survey, and inadequate geotechnical investigation.

	NA	1	2	3	4	5
Cost Impact	○	○	○	○	○	○
Schedule Impact	○	○	○	○	○	○

4. **Work zone traffic control**— potential problems with maintenance of traffic, unexpected plans and detours, and/or seasonal restrictions

	NA	1	2	3	4	5
Cost Impact	○	○	○	○	○	○
Schedule Impact	○	○	○	○	○	○

5. **Unexpected utility encounter**—unforeseen utility conditions (e.g., seasonal requirements during utility relocation, unknown utility relocation, utility company workload, financial condition or timeline).

	NA	1	2	3	4	5
Cost Impact	○	○	○	○	○	○
Schedule Impact	○	○	○	○	○	○

6. **Delays in completing utility agreements**—the risk relates to disagreement over responsibility to move, over cost-sharing or inadequate pool of qualified appraisers.

	NA	1	2	3	4	5
Cost Impact	○	○	○	○	○	○
Schedule Impact	○	○	○	○	○	○

7. **Delays in right-of-way (ROW) process**—challenges or general delays in acquisition of ROW.

	NA	1	2	3	4	5
Cost Impact	○	○	○	○	○	○
Schedule Impact	○	○	○	○	○	○

8. **Delays in completing in railroad agreements**—obtaining railroad agreement takes longer to complete than anticipated.

	NA	1	2	3	4	5
Cost Impact	○	○	○	○	○	○
Schedule Impact	○	○	○	○	○	○

9. **Difficulty in obtaining other agency approvals**—primarily relating to new permits, new information required for permits, delays in agreements from Federal, State, or local agencies, or unforeseen agreements required.

	NA	1	2	3	4	5
Cost Impact	○	○	○	○	○	○
Schedule Impact	○	○	○	○	○	○

10. **Defined and non-defined hazardous waste**— incomplete analysis of hazardous waste site, unexpected environmental constraints or unanticipated cumulative impact issues (e.g., on-site storage, additional costs to dispose).

	NA	1	2	3	4	5
Cost Impact	○	○	○	○	○	○
Schedule Impact	○	○	○	○	○	○

11. **Project complexity**—complex structures, unexpected ground conditions, environmental issues, unforeseen design and technical issues, and challenges in level of interaction between stakeholders, and difficulties in obtaining an agreement with third-party, etc.

	NA	1	2	3	4	5
Cost Impact	○	○	○	○	○	○
Schedule Impact	○	○	○	○	○	○

12. **Scope Definition**—incomplete scope definition or unclear description of all major project deliverables and project boundaries that may lead to new or revised designs, added workload or time, rework and change orders (i.e., scope creep).

	NA	1	2	3	4	5
Cost Impact	○	○	○	○	○	○
Schedule Impact	○	○	○	○	○	○

13. **Project definition**—project goals and objectives (schedule, cost, and quality) are not well-defined or insufficient description of project conditions and challenges.

	NA	1	2	3	4	5
Cost Impact	○	○	○	○	○	○
Schedule Impact	○	○	○	○	○	○

14. **Staff experience/availability**—lack of experienced of staff (e.g., the staff's comfort and confidence using a specific delivery method; the quality and competence of staff to complete the duties; and a concern about the retirement of experienced staff or losing critical staff at crucial point of the project).

	NA	1	2	3	4	5
Cost Impact	○	○	○	○	○	○
Schedule Impact	○	○	○	○	○	○

15. **Project and program management issues**—a lack of understanding of complex internal procedures or functional units not available, overloaded (e.g., inconsistent cost, time, scope, and quality objectives; overlapping of one or more project limits).

	NA	1	2	3	4	5
Cost Impact	○	○	○	○	○	○
Schedule Impact	○	○	○	○	○	○

Risk Description	Rating					
16. Constructability in design—the risk relates to unresolved constructability items, complex project features, incomplete quantity estimates, and unforeseen construction window.	NA	1	2	3	4	5
	Cost Impact					
	Schedule Impact					
17. Delays in procuring critical materials, labor, and specialized equipment— Unexpected constraints, unforeseen requirements, complex structure, unresolved constructability items may lead to delays in procuring materials, labors, and equipment	NA	1	2	3	4	5
	Cost Impact					
	Schedule Impact					
18. Significant increase in material, labor, and equipment cost—the risk relates to incomplete quantity estimates, increase in material cost due to market forces, unanticipated escalation in material, labor, and equipment costs.	NA	1	2	3	4	5
	Cost Impact					
	Schedule Impact					
19. Conformance with regulations/guidelines/design criteria—challenges in conforming to guidelines, design criteria, and regulations (e.g., new or revised design standard, consultant design not up to department standards, and unforeseen design exceptions required).	NA	1	2	3	4	5
	Cost Impact					
	Schedule Impact					
20. Intergovernmental agreements and jurisdiction—challenges in intergovernmental agreement between the agency and other agencies (e.g., political factors for project changes, local communities pose objections, permits or agency actions delayed or take longer than expected).	NA	1	2	3	4	5
	Cost Impact					
	Schedule Impact					
21. Legal challenges and changes in law—threat of lawsuits due to new permits or additional information required.	NA	1	2	3	4	5
	Cost Impact					
	Schedule Impact					
22. Unclear contract documents—ambiguities in the contract documents (e.g., incentive/disincentive payment clauses, impact of long lead items, changes during construction required additional coordination with resources agencies.	NA	1	2	3	4	5
	Cost Impact					
	Schedule Impact					
23. Single or multiple contracts—difficulties in multiple contractor interfaces (e.g., lack of coordination/communication, additional coordination with resource agencies required).	NA	1	2	3	4	5
	Cost Impact					
	Schedule Impact					
24. Insurance in contract—uncertainty in the availability of insurance coverage under which contractors accepts significant insurance risk from agencies.	NA	1	2	3	4	5
	Cost Impact					
	Schedule Impact					
25. Annual inflation rates—a change in value caused by a deviation of the actual market consistent value of assets and/or liabilities from their expected value due to inflation.	NA	1	2	3	4	5
	Cost Impact					
	Schedule Impact					
26. Construction market conditions—a change in construction market (e.g., considerable variation of bid prices on similar work components; higher procurement costs for major project components).	NA	1	2	3	4	5
	Cost Impact					
	Schedule Impact					

Risk Description	Rating					
27. Delays in delivery schedule—uncertainty in the overall project delivery schedule from scoping through design, construction, and opening to the public.	NA	1	2	3	4	5
	Cost Impact					
	Schedule Impact					
28. Construction sequencing/staging/phasing—the risk often involves insufficient or limited construction or staging areas, unforeseen construction window, rainy season requirements, and street or ramp closures not coordinated with local community.	NA	1	2	3	4	5
	Cost Impact					
	Schedule Impact					
29. Construction QC/QA process—the risk involves continued evaluation and assessments of the activities of planning, construction, and maintenance (e.g., contractor testing, agency verification, and possible dispute resolution).	NA	1	2	3	4	5
	Cost Impact					
	Schedule Impact					
30. Design Quality Assurance—the risk involves continued evaluation and assessments of the activities of development of plans, design and specifications, advertising and awarding of contract.	NA	1	2	3	4	5
	Cost Impact					
	Schedule Impact					
31. Design Completion—this risk relates to inaccurate assumptions on technical issues, unforeseen design exception, incomplete quantity estimates at the level of design completion at the time of the project delivery selection.	NA	1	2	3	4	5
	Cost Impact					
	Schedule Impact					
32. Please describe any other risk factors that significantly influenced project schedule and cost performance. ______ ______ ______	NA	1	2	3	4	5
	Cost Impact					
	Schedule Impact					
33. Please describe any other risk factors that significantly influenced project schedule and cost performance. ______ ______ ______	NA	1	2	3	4	5
	Cost Impact					
	Schedule Impact					

IX. LESSONS LEARNED FROM THIS PROJECT

34. Did the project delivery, ATC and/or I/D provisions in the contract significantly impact the outcome of the project in fulfilling its intended purpose?
   - Yes
   - No
   - I do not know

If YES, in what way(s)?

35. Based on your experience with alternative contracting delivery approach, could this project have been delivered more successfully?
   - Yes
   - No
   - I do not know

If YES, in what way(s)?