A Risk-Based Model for Construction Inspection in Highways

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ABSTRACT

The quality and durability of highway construction projects have been a major concern to highway agencies and contractors. Quality assurance (QA) of highway construction is defined as a tool or means by which the owner and contractors ensure that the roads are constructed in accordance with approved plans and specifications by the most economical, efficient, and safe method. To ensure the quality of highway construction projects, transportation agencies typically perform a series of tests for construction materials and inspect workmanship processes through their QA programs. Transportation agencies face the critical challenge of increased demand for highway system rehabilitation and construction work with limited inspection resources. These resources play a crucial role in asserting the quality of highway projects. The shortage of experienced QA inspection staff due to retirement or migration to the private sector has significantly impacted construction inspection capabilities. The objective of this dissertation is to develop a risk-based inspection (RBI) framework. This framework optimizes inspection and testing activities of highway construction projects based on criticality. It introduces a core list of QA inspection and testing activities for the rigid pavement, flexible pavement, bridge deck, and structural concrete. This list highly contributes to the QA of design service life and long-term performance of the highway. The prioritized list of activities may help transportation agencies allocate their limited resources to the most critical construction operations. Additionally, this dissertation provides a RBI model that serves as a risk assessment tools for highway construction quality levels and identifies causes of any quality shortfall. Bayesian belief network (BBN), fuzzy set (FS) theory, and Delphi techniques have been applied to develop the RBI model. Further, this dissertation discusses different strategies to alleviate the risk of highway construction inspection.

Dissertation Format

The entire dissertation was outlined to compose three journal papers, and the research plan consisted of three phases. The first research phase provided the first peer-reviewed journal article, published in the American Society of Civil Engineers (ASCE) *Journal of Construction Engineering and Management*. The main objective of this phase was to narrow down construction inspection activities to a core list and prioritize these activities in terms of safety, cost, and service interruption risk impact through the RBI framework. To attain this objective, a total of 108 core inspection activities were retrieved from QA documents. Risk data were collected, and a probabilistic risk assessment model was developed. For modeling the risk impact of the activities, FS and BBN were merged into a fuzzy Bayesian belief network (FBBN). The FS was employed to deal with the linguistic nature of collected data, which could not be represented precisely by a probability distribution. BBN dealt with the causal relationship between the model variables and inferred the risk impact in the form of the quantitative probability distribution. A case study from the Kansas Department of Transportation (KDOT) was conducted to verify and test the framework. The first paper contributes to the current construction body of knowledge by introducing a new framework to optimize QA inspections for highway projects. Further, the FBBN technique used to develop the RBI framework in this study can be adopted by other researchers to model the uncertainty of knowledge associated with qualitative data, which is common in the construction engineering and management area.

The second research phase produced the second journal article published by the ASCE *Journal of Construction Engineering and Management*. This phase investigated the causal relationship between QA inspection activities and the quality of hot mix asphalt HMA pavement (i.e., flexible pavement) by developing a risk-based analysis model. A core list of critical inspection activities of HWA pavement construction operations was included in the model. This list of activities was obtained based on synthesizing QA documents and verified with a wide range of experts. The model was developed based on FS and BBN. For validating the model, a case study from KDOT was applied. The model is capable of calculating the probability distribution of HMA risk levels, identifying the most likely potential causes of quality shortfall risk. Transportation agencies may benefit by using the model as a decision tool by updating risk level probabilities based on actual inspection results.

The third research phase produced the third journal paper, which is ready for submission to the construction engineering and management journal. During this phase, risk mitigation strategies have been investigated. Strategies such as inspector experience requirements, identifying the optimal inspection frequency for the activities, and activity documentation priority were investigated. A national questionnaire survey was conducted, and a series of workshops were convened to identify and assess these strategies. By following these strategies, transportation agencies may alleviate the risk of highway construction inspection and maintain quality requirements within the available inspection staff.

To my Family, Educators, and Friends

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I thank the Department of Civil, Environmental and Architectural Engineering at the University of Kansas for continuous encouragement with research and teaching opportunities, giving me a great platform to mound myself with great passion and intellectuality. I will always cherish this wonderful doctoral journey throughout my lifetime and proud to be a Jayhawk.

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CHAPTER 1

INTRODUCTION

OVERVIEW

Quality assurance (QA) plays a critical role in highway construction projects. QA is fundamental to meet the missions of the Federal Highway Administration (FHWA) and transportation agencies such as state departments of transportation (DOTs) to provide high-quality products and facilities that meet or exceed specified quality standards. State DOTs have historically specified quality standards based on detailed instructions describing the required materials and construction methods. Primary inspection areas typically include interpretation of contract plans and specifications; project recordkeeping and reporting; construction surveying; field inspection and testing procedures, techniques, and equipment; and supervisory techniques.

Federal regulation 23 CFR 637, subpart B: "Quality Assurance Procedures for Construction" requires that a comprehensive construction quality assurance (QA) program (including inspection and testing) should consist of the following six core elements: quality control (QC), acceptance, independent assurance (IA), dispute resolution, personnel qualification, and laboratory accreditation/qualification. According to the FHWA program evaluation reports and various QA stewardship reviews for 2003–2008, the risks of accepting non-conforming work are high. The FHWA recommended that risk-based evaluation tools should be developed to address risks for materials and workmanship, and 23 CFR 637 should be updated to address alternative delivery methods to more formally address construction inspection and processes for acceptance of manufactured products and to be more applicable to all federal-aid projects regardless of system, class, or type.

RESEARCH PROBLEM

During the last decade, transportation agencies have faced a critical challenge of increased demand for highway system rehabilitation and construction work with limited inspection resources. The shortage of experienced QA inspection staff due to retirement or migration to the private sector has substantially impacted construction inspection capabilities. Taylor and Maloney (2013) found that, between 2000 and 2010, the staff available to manage roads throughout the United States steadily declined by 9.8%, while the total lane miles of roads managed by state departments of transportation (DOTs) increased by 4.1%. As a result, state DOTs have attempted to leverage their limited inspection resources by outsourcing work to consultant engineering inspection (CEI), reducing inspection frequencies, or utilizing contractor test results for inspection acceptance. Although these approaches extend limited inspection resources, they often increase risk and uncertainty for inspection activities and processes. For instance, reducing the number of inspectors during construction may increase safety risks and functional failures and decrease the performance life of highways and bridges (Wani, and Gharaibeh 2013). Similarly, using contractor test results for acceptance can lead to erroneous pay decisions (Oechler et al. 2013). Effective inspection optimization approaches must be implemented to improve the QA process, increase the value of inspection with limited funding availability, and minimize inspection staff size.

RESEARCH OBJECTIVES

In order to address the underlying research gaps in the current construction industry, this dissertation aims to:

(1) Develop a comprehensive RBI framework that prioritizes inspection of construction processes and testing of materials based on criticality. The framework uses fuzzy

Bayesian belief network (FBBN) to consider uncertain knowledge and fuzziness associated with qualitative data, various sources of knowledge, incomplete data sets, and model causal relationships among risk factors.

(2) Identify a core list of QA inspection activities based on RBI assessment in terms of cost, safety, and service interruption. The core list includes QA inspection and testing activities for components such as rigid pavement, flexible pavement, bridge deck, and structural concrete. This may help transportation agencies conduct the most effective inspections for their QA processes when there is a shortage of inspection resources.

(3) Investigate the causal relationship between QA inspection activities and the quality of the HMA pavement in light of QA inspection results and identify the probability of any quality shortfall risk.

(4) Explore risk mitigation strategies for highway construction inspection. These strategies include inspector experience, identifying the optimal activity inspection frequency, and identifying activity documentation priority.

RESEARCH METHODOLOGY

This dissertation utilized the research framework shown in Figure 1. This framework includes comprehensive technical procedures where conceptual milestones are generated in each step. Figure 1 shows eight steps followed in the framework, including observed problems, intuitions and theoretical points of departure, research methods, research questions, research tasks, validation results, claimed contributions and predicted impacts. Figure 2 indicates a timeline of this dissertation research.

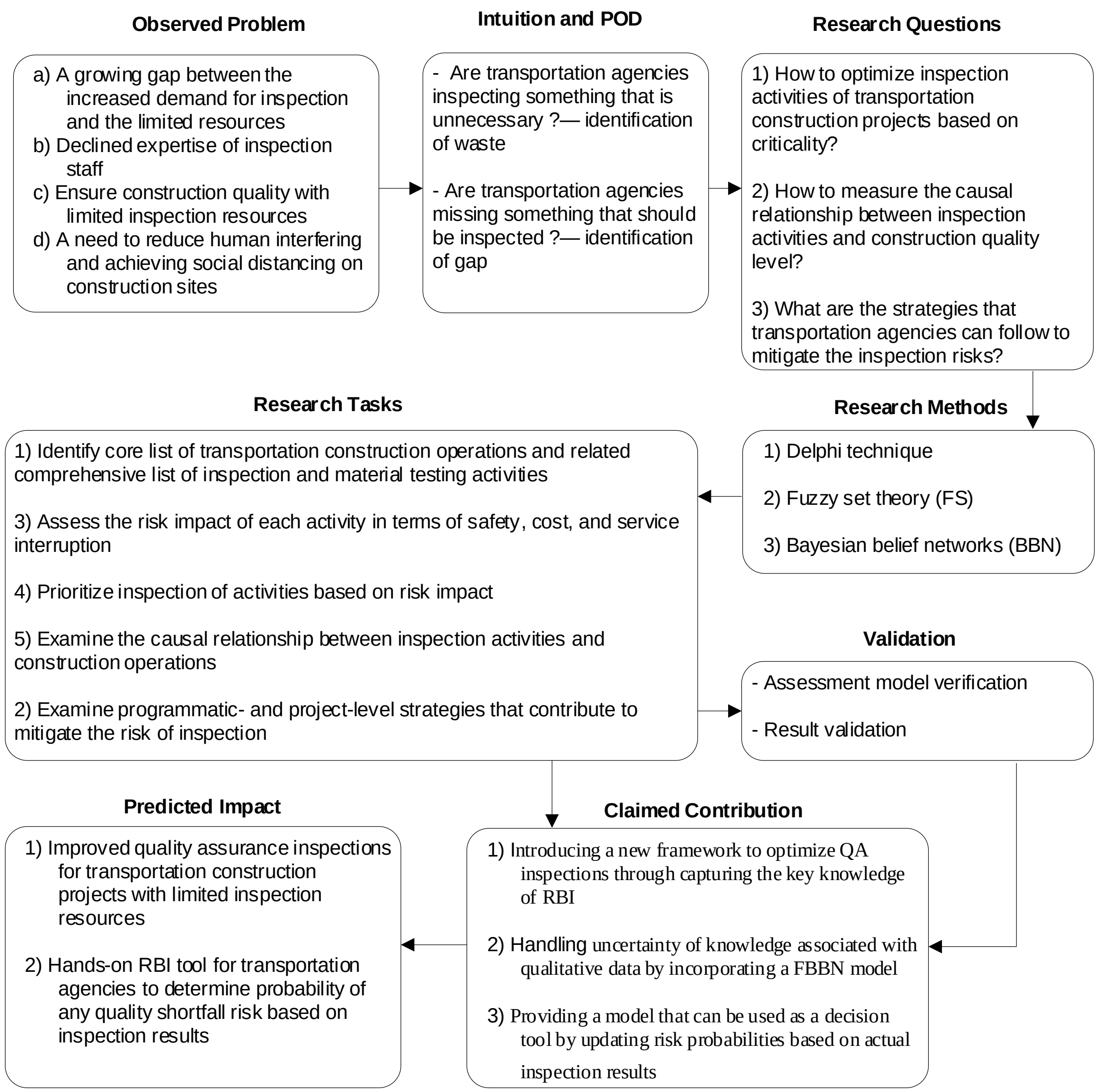

Figure 1. Research Methodology

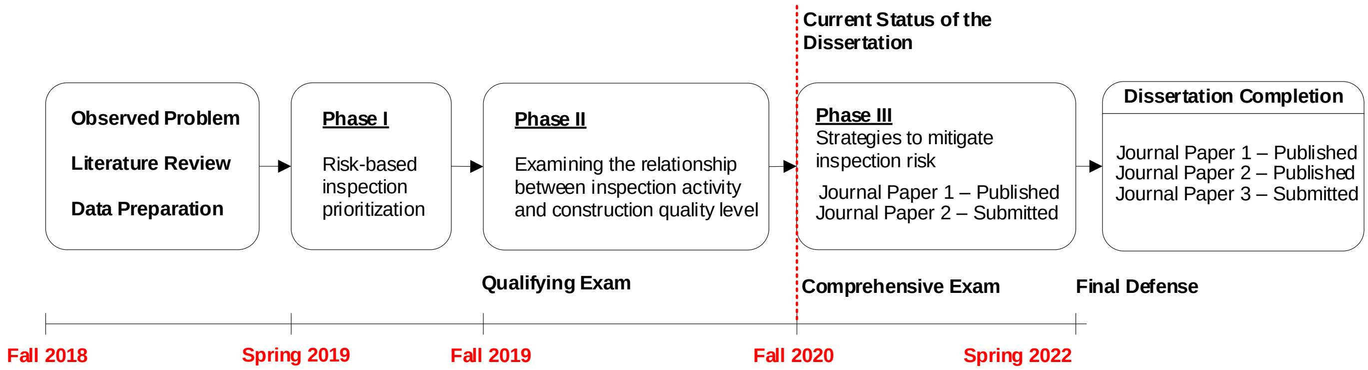

Figure 2. Dissertation Research Timeline

RESEARCH QUESTIONS

Research Question 1: Risk-Based Inspection Prioritization – Research Phase I

How can prioritized inspection approaches be used for material testing of transportation construction projects?

To address this question, the point of departure is to identify a comprehensive list of material inspection and testing activities and then refine these activities to a core list of critical inspections. This is followed by a risk impact assessment of each activity through the RBI approach. RI is the product of the probability of failure and the consequence of failure. The probability is defined as the extent to which the event of failure is likely to occur, potentially based on observing recurrence or on the degree of belief. The consequence of failure is an outcome of the failure event, including one or more consequences, and may be expressed qualitatively or quantitatively. Due to the qualitative nature of the collected data, FS and BBN were merged into a fuzzy Bayesian belief network (FBBN) to consider uncertain knowledge and fuzziness associated with qualitative data and the causal relationships among risk factors.

Research Question 2: Causality Between Activity Risk and Construction Quality Level – Research Phase II

What is the causal relationship between activity risk levels and construction quality levels?

To address the second research question, a risk-based analysis model was developed. This model investigates the causal relationship between the inspection activities and the quality of construction operations, hot mix asphalt (HMA) pavement was taken as an application example. A core list of critical inspection activities of HMA pavement was included in the model. This list of activities was obtained based on synthesizing QA documents and verified via a nationwide survey. RBI was used to assess the risk impacts of these activities. The model is developed based on FS and BBN. For model validation, a case study from KDOT was applied. The model infers the risk level of HMA and identifies the cause activities of any high risk.

Research Question 3: Risk Mitigation Strategies – Research Phase III

What strategies can transportation agencies use to mitigate the inspection risks?

To address the third research question, a number of inspection risk mitigation strategies were identified through literature review and focus group discussions. This includes strategies such as optimizing inspection workload, identifying the optimal inspection frequency for the activities, and identifying activity documentation priority to save time and cost. A step-by-step procedure was followed to identify and investigate these strategies through a national survey and a focus group workshop. The deliverables of this phase are discussed in Research Phase III.

RESEARCH PROCEDURE

To address the three proposed research questions, the general research procedures are provided below. Analyses processes through these procedures were conducted in Nvivo data analysis software, the R programming environment, and UnBBayes source for modeling, learning, and reasoning upon probabilistic networks.

1. Research Phase I – Journal Paper 1: Identify and prioritize a core list of material testing and construction inspection activities

    1.1 Development of a list of QA activities:

    - A total list of 302 inspection activities was retrieved from quality assurance (QA) documents.
    - This list was narrowed down to a core list of 108 inspection activities based on a series of focus groups discussion and professional interviews.
    - The core list includes activities for components such as rigid pavement, flexible pavement, bridge deck, and structural concrete.

    1.2 Risk assessment:

    - Risk impact (RI) of activity was expressed as the product of probability and consequence of failure
    - Probability and consequence of failure data were collected from experts as verbal expressions
    - Delphi technique was applied to minimize any biased results from the collected data
    - FS and BBN were amalgamated into a fuzzy Bayesian belief network (FBBN) for dealing with the linguistics of the collected data and

modeling the causality variables

1.3 Validation

- A case study from the Kansas Department of Transportation (KDOT) verified and tested the framework

2. Research Phase II – Journal Paper 2: Develop a risk-based inspection model for hot mix asphalt (HMA) pavement construction.

   2.1 Development of a comprehensive list of QA activities:

   - A total list of 33 HMA inspection activities was retrieved from quality assurance (QA) documents and Phase I.
   - This list was narrowed down to a core list of 14 inspection and testing activities based on a national survey.

   2.2 Risk assessment:

   - RI expressed as probability and consequence of failure data were collected from experts as verbal expressions.
   - Delphi technique was applied to minimize any biased results from the collected data and reach a consensus among the experts.
   - FS was applied to transfer the collected qualitative data into qualitative numbers. BBN modeled the causal relationship between the activity variables.

   2.3 Validation

   - The model was implemented in a case study to verify and test the model applicability

3. Research Phase III – Journal Paper 3: Identify and assess different strategies to mitigate the risk impact, RI, of highway construction inspection activities

    3.1 Identify strategies to mitigate the risk impact of QA inspection activities

    - Literature review of activity risk mitigation strategies
    - Focus groups to identify and validate the most appropriate strategies

    3.2 Assess procedures of each risk mitigation strategy

    - Description of strategy procedures
    - Validate strategy procedures via focus group discussions

    3.3 Inference of significant relationships

    - Examine the association and differences between these strategies and procedures in the QA inspection activities

CHAPTER 2

A Risk-Based Prioritization Approach to Construction Inspections for Transportation Projects

Research Phase I Dissertation – Journal Paper 1

(Published in ASCE JCEM)

A Risk-Based Prioritization Approach to Construction Inspections for Transportation Projects

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ABSTRACT

Construction inspections of transportation projects are essential for maintaining project quality and increasing driver safety throughout a highway construction project. Transportation agencies, however, have had to decrease the frequency of inspections due to current shortages of staffing and funding resources, consequently increasing safety risks and functional failures and decreasing performance life. This study proposes a risk-based inspection (RBI) framework for optimizing construction inspections based on criticality. A total of 108 core inspection activities were retrieved from quality assurance (QA) documents. Risk impact (RI) data were collected from experts and a probabilistic risk assessment model was developed. In addition, a fuzzy set (FS) and Bayesian belief network (BBN) were amalgamated into a fuzzy Bayesian belief network (FBBN) for modeling. The FS pertained to the linguistics of the collected data, which could not be represented precisely by probability distribution. The causal relationship between the model variables was converted into a quantitative probability distribution and inferred using the BBN. A case study from the Kansas Department of Transportation was conducted to verify and test the framework. Results of FBBN adoption indicated that the modular representation of uncertain knowledge increases the efficiency and functionality of QA inspection risk analysis. Moreover, the unification of FS and BN quantitatively measured the RI and modeled the relationship between risk factors and RI. The framework output showed that more than half of earthwork and bridge deck inspections are high RI, while hot mix asphalt (HMA) and Portland cement concrete pavement

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(PCCP) require the most high-RI inspections. This study contributes to the construction engineering and management body of knowledge by providing an RBI framework for optimizing construction inspection activities in highways. The findings of this study also provide guidelines for highway agencies to develop RBI strategies.

Author Keywords: Pavement, Quality Assurance, Risk-based Inspection, fuzzy Set, Bayesian belief network

INTRODUCTION

Construction inspection by transportation agencies plays a crucial role in maintaining quality of highway projects. These agencies currently face an increased demand for highway system construction and rehabilitation, but inspection staffing and funding resources are limited. The shortage of experienced quality assurance (QA) inspection staff due to retirement or migration to the private sector has significantly impacted construction inspection capabilities. From 2000 to 2010, the staff available to manage roads throughout the United States steadily declined by 9.78%, while the total lane-miles of roads managed by state departments of transportation (DOTs) increased by 4.1% (Taylor and Maloney 2013). As a result, state DOTs have attempted to leverage their limited inspection resources by outsourcing to consultants, reducing inspection frequencies, or utilizing contractor test results for inspection acceptance. Although these approaches extend limited inspection resources, they often increase risk and uncertainty for inspection activities and processes. For example, using contractor test results for acceptance can lead to erroneous pay decisions or decreasing the number of inspectors on construction activities may increase safety risks and functional failures and decrease performance life of highways and bridges (Wani and Gharaibeh 2012; Oechler et al. 2018). Effective inspection optimization approaches must be implemented to improve the QA process, increase the value of inspection, minimize inspection staff required, and consider budget constraints.

State DOTs have recently begun to consider risk-based inspection (RBI) approaches to optimize highway inspections. Typically, QA inspections are prioritized based on risk, expressed as expected values, by integrating the likelihood and consequences of construction failures via risk assessment methods. Selection of a suitable risk assessment method, however, depends on the number of inspection items, available resources, the nature and quality of available data, and complexity of the inspection processes (Scott et al. 2017). Mostafavi and Abraham (2013) used QA activities to prioritize inspection and testing activities of Indiana DOT for risk assessment. The researchers used a fuzzy set (FS) to assess probabilities of failure consequences, and they developed a protocol for inspection activities to prioritize highway construction inspection activities. Similarly, another study for Indiana DOT utilized a matrix with three levels of probability and consequence (i.e., low, moderate, high) to improve the RBI approach by studying the possibility of failing to meet specification requirements and the resulting impacts on quality, cost, time, and safety. A total of 90 critical inspection activities were included to assess risks associated with various inspection items during construction (Yuan et al. 2017). Additionally, Scott et al. (2017) developed an analytical framework based on analyzing QA cost and risks of material nonconformance to optimize QA inspection resources. The implementation of the analytical framework, however, required limited maintenance records and historical data from QA inspections.

Although previous RBI approaches have improved highway construction inspection practices, these approaches are primarily qualitative, and their risk assessment techniques have not provided comprehensive insight into the probability of failure and its associated consequences. Further, these assessment techniques do not consider causal relationships between risk factors.

Therefore, the objective of this study was to develop a comprehensive RBI framework based on a fuzzy Bayesian belief network (FBBN) to consider uncertain knowledge and fuzziness associated with qualitative data, various sources of knowledge, and incomplete data sets, as well as model causal relationships among risk factors. This study is one of the first attempts, if any, to investigate the causal relationships between risk factors of highway construction inspections using FBBN.

FBBN is a flexible, hybrid technique that combines FS theory and Bayesian belief networks (BBNs) into one model. This multicriteria method enables decision makers to arrange priorities and select the best alternative by considering tangible and intangible aspects of a problem (Sedki et al. 2010). Because FBBN highlights the interactions and interdependencies among variables, decision makers also can solve increasingly complex problems. FBBN has been widely used in construction research (Straub and Faber 2005; Luque and Straub 2019; Anbari et al. 2017; Mancuso et al. 2016), but limited studies, if any, have investigated its utilization for risk assessment of highway construction inspections. The FBBN risk assessment model in this study provides a systematic methodology to prioritize QA inspection activities for highway construction projects. The rest of this paper proceeds as follows: The next section describes theoretical background that derives the research hypotheses and the research methodology. This is followed by framework description and a case study, result, and discussion. Conclusions are drawn and provided in the final section.

LITERATURE REVIEW

Since the early 2000s, abundant literature has detailed the RBI technique. Although RBI has been widely applied in structural systems, sewer networks, industrial engineering, the oil and gas industry, and thermal and nuclear energy domains, it is relatively new to highway construction and maintenance. Several studies have investigated RBI as an approach for examining structural elements. Straub and Faber (2005) presented a model that considers entire systems in RBI planning instead of individual elements and responds to risk in terms of dependency between structural elements and failure consequences on the system. The model considers three basic factors when assessing risk: dependency of inspection cost, dependencies in deterioration performances, and dependency between inspection performances at different hot spots. Luque and Straub (2019) utilized the RBI approach to optimize the inspection of structural systems with many components. They implemented a heuristic approach to construct the optimization problem and used a dynamic Bayesian network and Monte-Carlo Simulation to capture system reliability based on inspection results and the expected cost of the resulting inspection plan.

Anbari et al. (2017) developed a risk assessment model to prioritize sewer network inspections using BBNs. The model counts for probability of failure and a weighted average method to calculate the consequences of failure values. Integration of probability and consequences of failure values using a fuzzy inference were also considered to capture uncertainty and subjective matters, thereby generating an inspection priority rating for sewer pipelines based on criticality. Mancuso et al. (2016) addressed the same issue of prioritizing inspection of an underground network of pipes by applying RBI methodology. The methodology implemented the multi-attribute value theory instead of BBN to assess the risk of each pipe in the network.

Many industries have implemented RBI. For example, the industrial engineering sector uses RBI to examine mechanical equipment and then define the optimal inspection program. Prioritization of inspection is determined by cost of inspection and a risk level, which is a product of the likelihood and consequences of failure (Das Chagas et al. 2015; Wang et al. 2011; Selvik and Aven 2011; Park and Yang 2010). The oil, gas and petrochemical industries are the leading sectors in RBI utilization. In fact, several researchers have investigated RBI implementation for maintenance procedures in oil refinery, crude oil tanks, pressure equipment, and chemical plants (Shuai et al. 2012; De Carlo et al. 2011; Bertolini 2009; and Wintle 2001). The studies developed models with prioritization techniques, such as heuristic methods, fuzzy logic, and BBNs, which allow efficient model extensions to include more RBI variables and represent discontinuous variables. In the thermal and nuclear energy domain, RBI is critical for safety of operation staff and public. Vinod et al. (2014) investigated RBI implementation into nuclear energy plants, but because the number of plant components is vast, evaluating the consequences of component failures (individually) is difficult. Therefore, critical components were screened using qualitative and semi-qualitative approaches that utilized damage consequence factors and health consequence factor (e.g., toxicity and flammability). Table 1 shows examples of the current research trends and RBI applications, including publications reviewed, areas of applications, and the purpose of application.

Table 1: Current Research Trends and Application Areas of RBI

Industry	Publication	Application Area	Specific problem(s)
Industrial engineering	Selvik et al. (2011)	Mechanical equipment	Examining mechanical equipment using RBI expressed as expected value
	Das Chagas et al. (2015)	Separation vessel	Defining the optimum inspection program in terms of cost of inspection and risk level by using multi-objective genetic algorithm
	Wang et al. (2011)	Polyethylene equipment	Prioritizing inspection of equipment parts using generic strategy
Infrastructure	Anbari et al. (2012)	Sewer pipelines	Prioritizing inspection of sewer networks using BBNs
	Marlow et al. (2017)	Water supply	Inspecting isolation valves of pipe networks using analytical hierarchy process
	Mancuso et al. (2016)	Underground network of pipes	Using MAVT to assess the risk of each pipe in the network
Oil, gas, and petrochemical industries	De Carlo et al. (2011)	Refinery plants	Inspection priority rating for chemical plant using BBN model and qualitative risk-based inspection procedures

	Topalis et al. (2011)	Offshore topside and processing plants	Assessing damage mechanism potential, degradation rate, probability of failure, consequence of failure, risk, and inspection intervals
	Bertolini et al. (2009)	Oil refinery	Developing RBI and maintenance procedures for an oil refinery using heuristic methods
	Ifezue and Tobins (2014)	Crude oil import/export line	Using a semi-quantitative RBI approach via threats identifying and ranking
Structural engineering	Lassen (2013)	Steel and concrete structures	Examining structural elements and fatigue cracks using a stochastic model and risk-based assessments to calculate for uncertainty analysis
Thermal and nuclear energy	Singh and Pretorius (2017)	Thermal power plant	Developing a semi-quantitative RBI program for thermal power plant components depending on expert input

FUZZY BAYESIAN BELIEF NETWORKS

Fuzziness and probability are related, but they have unique aspects. Fuzziness is a deterministic uncertainty that describes event-class ambiguity and measures the level to which an event occurs. On the other hand, probability arises from the question of whether or not an event occurs (Eleye et al. 2008). Although an FS can efficiently deal with uncertainty, it cannot infer by itself. Therefore, merging an FS with BBNs, creating an FBBN, provides an alternative to facilitate risk analysis.

Zadeh (1965) created the mathematical FS tool to model uncertain systems in the absence of precise and complete information. The theory of FS asserts that linguistic terms are less precise than crisp values (i.e., numbers). However, due to various construction information, observation data inaccuracy, lack of engineering experience, and other factors, a crisp value cannot satisfy the occurrence probability and severity of events, meaning the probability of verbal expressions must be transformed into fuzzy numbers. A fuzzy number, denoted by $P(\theta)$, refers to a continuous set of possible values, where each value has a membership function that varies between 0 and 1. Typically, FS uses triangular, trapezoidal, or Gaussian fuzzy numbers to convert crisp values into fuzzy numbers. Triangular fuzzy numbers are often utilized to provide precise descriptions and obtain accurate results (Li et al. 2012). A triangular fuzzy number includes three components $P(\theta) \cong (\theta_1, \theta_2, \theta_3)$, where θ_2 has the membership function of 1, and the values between θ_2 and θ_1 or θ_3 have membership functions between 0 and 1. Values less than θ_1 or greater than θ_3 have a membership function of zero (Emrouznejad and Ho 2017; Mostafavi and Abraham 2013). Assuming two triangular fuzzy numbers, $P(\theta_x): (\theta_{x1}, \theta_{x2}, \theta_{x3})$ and $P(\theta_y): (\theta_{y1}, \theta_{y2}, \theta_{y3})$, the operations of addition, subtraction, multiplication, and division between $P(\theta_x)$ and $P(\theta_y)$ can be defined by equations 1– 4:

$$P(\theta_x) \oplus P(\theta_y) \cong \left(\theta_{x1} + \theta_{y1}, \theta_{x2} + \theta_{y2}, \theta_{x3} + \theta_{y3}\right) \quad (1)$$

$$P(\theta_x) \ominus P(\theta_y) \cong \left(\theta_{x1} - \theta_{y1}, \theta_{x2} - \theta_{y2}, \theta_{x3} - \theta_{y3}\right) \quad (2)$$

$$P(\theta_x) \otimes P(\theta_y) \cong \left(\theta_{x1}\theta_{y1}, \theta_{x1}\theta_{y1}, \theta_{x1}\theta_{y1}\right) \quad (3)$$

$$P(\theta_x) \oslash P(\theta_y) \cong \left(\theta_{x1}/\theta_{y1}, \theta_{x1}/\theta_{y1}, \theta_{x1}/\theta_{y1}\right) \quad (4)$$

BBNs are an inference engine for calculating beliefs of events given the observation of other events (referred to as evidence). BBNs include conditional dependence assumptions and relationships between nodes (i.e., variables), represented by a directed acyclic graph (DAG), as shown in Figure 1. DAG allows joint probability distribution to be specified locally in terms of a conditional probability table (CPT). Relationships constructed among the nodes are called the model structure (Zhang et al. 2016; Sun et al. 2018).

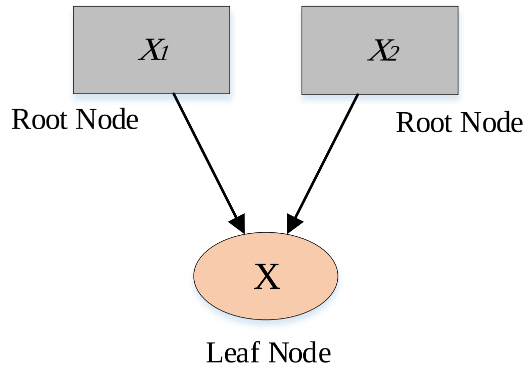

Figure 1: BBN with DAG and Uncertain Relationships Among Nodes

As shown in the equation 5, fuzzy conditional independence of leaf nodes (i.e., child nodes) can be calculated in terms of probability distribution of root nodes (i.e., parent nodes):

$$P(X) = P(X_1, X_2, \cdots X_n\ ) \cong \prod_{i=1}^{n} P\ (X_i |\ Root(X_i)) \qquad (5)$$

where $Root(X_i)$ is the parent node of (X_i) in DAG and the CPT of X_i equals $P(X_i|\ Root\ (X_i))$. Furthermore, due to the dependent relationships of the variables and knowing the probability distribution of the root nodes, the fuzzy joint probability distribution of leaf node $P(X_i)$ and the fuzzy marginalization rule were calculated using equations 6 and 7, respectively:

$$P\big(X_i, Root(X_i)\big) \cong\ \ P\big(Root(X_i)\big) \otimes P\ \big(X_i|\ Root(X_i)\big) \qquad (6)$$

$$P(X = x_i) \cong \sum_{i=1}^{n} P\ \ \big(Root(X_i)\big) \otimes P\ \big(X_i|\ Root(X_i)\big) \qquad (7)$$

Notably, θ_1 of all root nodes can be used to obtain θ_1 of a leaf node, θ_2 of root nodes can be used to obtain θ_2 of a leaf node, and θ_3 of root nodes can be used to obtain θ_3 of a leaf node (Sun et al. 2018).

DEVELOPMENT OF RBI FRAMEWORK

Figure 2 presents a framework to develop RBI protocol. First, QA inspection activities were identified, and then surveys and the Delphi technique were implemented to collect data. The risk assessment process was conducted to develop RBI protocol for highway construction projects. To elucidate the framework application, an illustrative case study from the QA program in the Kansas DOT (KDOT) was presented in detail with the framework description. The following sections present step-by-step development of the framework, application, and verification processes.

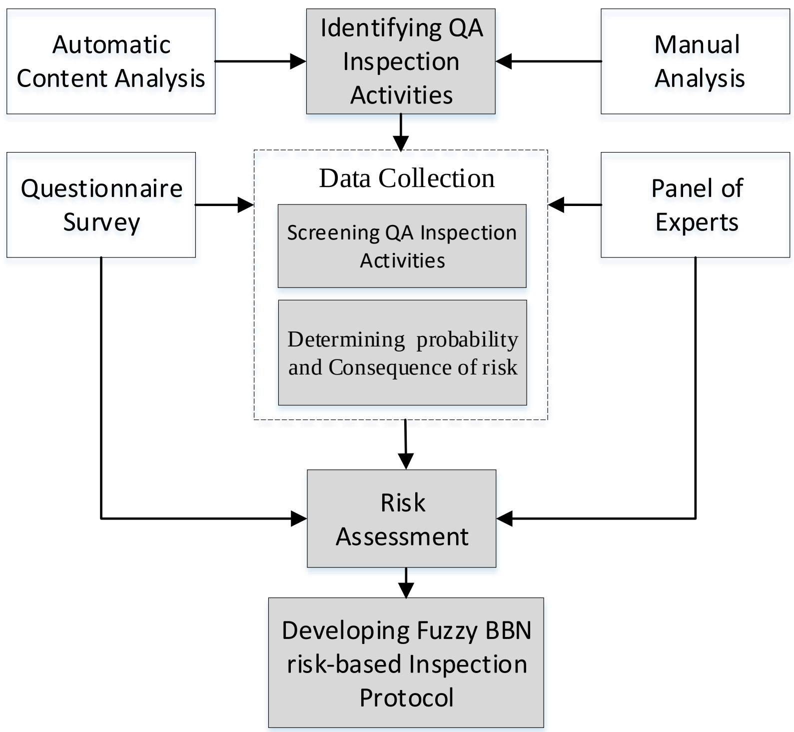

Figure 2: Framework for RBI Protocol Development

Identification of QA Inspection Activities

Highway construction projects typically contain certain elements that significantly impact a final product. The Federal Highway Administration (FHWA) has identified these elements as earthwork and embankment, base course and subbase, bridge deck and structural concrete, bituminous pavement, and rigid pavement (FHWA 2019). Focusing on elements' QA activities, as detailed in transportation agency construction manuals, specifications, and other relevant documentation, results in high-quality inspections. For example, to conduct the KDOT case study, the authors examined the KDOT construction manual, QA guidance, construction documentation manuals, KDOT specifications, and construction checklists and reports. For each document, the authors conducted the following two-stage scanning process:

- *Stage 1—Automated content analysis*: This stage utilized a qualitative data analysis computer software package (NVIVO) to develop a raw list of relevant inspection activities. NVIVO is ideal for qualitative researchers working with rich text-based and/or multimedia information, where deep levels of analysis on small or large volumes of data are required. The authors used the following key words for the searching process: inspection, acceptance, certification, quality assurance, quality control, risk, uncertainty, and test.
- *Stage 2—Manual analysis*: This stage refined and verified the list obtained from Stage 1. Based on the referent lines and sources identified from NVIVO in Stage 1, the authors performed a rigorous analysis to conservatively determine a comprehensive list of QA inspection activities by removing repeated activities or adding relevant activities.

Table 2 shows a comprehensive list of 302 QA activities in seven categories as described in KDOT documents. For example, for the earthwork and embankment division, Stage 1 generated 55 activities, but 28 of those activities were removed or combined with others in Stage 2 due to overlap. As a result, only 27 activities were retained for further analysis.

Table 2: Comprehensive List of QA Activities from KDOT Documents

Division	Scan Approach	
	Automated Content Analysis (NVIVO Software)	Manual Analysis
100 - General clauses	49	23
150 - Equipment	38	16

200 - Earthwork and embankment	55	27
300 - Subgrade, base, and shoulders	55	63
400 - Concrete (bridge deck)	42	39
500 - Rigid pavement (PCCP)	61	58
600 - Flexible pavement (HMA)	148	76
Total	448	302

Results from the two-stage scanning process also provided relevant inspection procedures for each activity. Table 3 presents a sample of the inspection activities associated with the acceptance methods, sample size, and reference sections for each activity. The relevant inspection procedures presented in Table 3 could help QA inspectors organize, understand, and compare information, including the inspection of each element, the required inspection activity, acceptance type and procedures, sample size and frequency of testing, and reference documents.

Table 3: Sample of KDOT QA activities

Division	QA activity	Acceptance		Sample size and frequency	Ref.
		Type	Procedures		
100-General	Testing facilities approval	Certificate	Review documents and approve	once	Specs 106.4, 602.2
200-Earthwork and embank-ment	Embankment layers approval	Field Inspection	Verify erosion, install pollution, approve preceding layer and dimensions	Intermittent	Specs 205, CM 4. 2.04
	Field density of compacted earthwork	Test	KT-13: measure the density of compacted soil	1000 ft (300 m)	CM 5.9.13, Specs 204
600-Flexible pavement (HMA)	Sieve analysis of aggregate	Test	KT-02: determine particle size distribution using standard sieves	1 per lot	CM 5.9.02, Specs 603

Data Collection

In the data collection phase, the qualitative research Delphi technique was implemented via two subjective data collection surveys. The purpose of the first survey was to screen and refine the comprehensive list in Table 2 to a core list of inspection activities. The purpose of the second survey was to determine occurrence probability and consequence of risk for each activity at each level of risk. The Delphi technique is typically used when objective data are unattainable, experimental research is unrealistic, or there is a lack of empirical evidence. The technique is particularly useful when participant heterogeneity must be preserved to assure validity of the results (Hallowell and Gambatese 2010).

Many construction-related studies have implemented the Delphi technique, but failure to satisfy the minimum requirements for Delphi characteristics in many of the studies has led to biased results (Hallowell and Gambatese 2010). In order to obtain high-quality results, the current study carefully considered Delphi selection characteristics for experts, number of rounds, type of feedback, and achievement of consensus. Experts were selected for the survey based on predefined criteria of more than 10 years of experience in highway construction and maintenance inspections, knowledge of inspection methods for various construction elements, and professional registration. Rowe and Wright (1999) and Hallowell and Gambatese (2010) pointed out that the number of Delphi panel members has ranged in peer-reviewed studies from 3 to 80 members. Hallowell and Gambatese (2010) suggested a minimum of eight experts. The purpose of multiple rounds was to achieve consensus and improve precision. After each round, the experts received group feedback in points of agreement listed in order of most- to least-often mentioned activities. The literature does not, however, indicate a certain level of variance that represents adequate consensus since data collected for every study is unique. Avella (2016) suggested a Delphi consensus of 70% as a standard agreement. In this study, respondent consensus was achieved when the absolute deviation was +/- 25% (i.e., 75% agreement). When a current round did not reach this percentage, the next round was conducted. Anonymity was incorporated to minimize the effect of judgment-based biases of dominance and collective unconscious when individuals tend to follow a popular opinion.

Screening QA Inspection Activities

When the number of factors or activities to be analyzed is relatively large, an initial-simple qualitative screening step is reliable and cost effective (FHWA 2006; API 2016). This study utilized a panel of five KDOT experts with an average of 15 years' experience in QA inspections. A list of 302 activities was provided to each expert, and they were asked to rate the activities using high, medium, low, and remote risk rankings. Figure 3 shows a sample of data collection form for the risk rating process.

Construction Division	No.	List of Inspection Activities	Risk Rating			
			Remote	Low	Moderate	High
Division 100 General Clauses and Covenants	1	Approval for personnel who should meet QC testing procedures	○	○	○	○
	2	Approval of testing facilities	○	○	○	○
⋮	⋮	⋮	⋮	⋮	⋮	⋮
Division 200 Earthwork	40	Clearing site and grubbing	○	○	○	○
	41	Check alignment	○	○	○	○
	42	Check grade elevations - preconstruction	○	○	○	○
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Figure 3. A sample of risk rating for QA inspection activities

Activities with high and medium risk levels were considered for further analysis, while low and remote risk activities required a minimum level of inspection. Following the Delphi technique, two rounds of assessment were conducted to ensure that the assumptions were valid and that consensus greater than or equal to 75% (i.e., four of five respondents) was achieved (Table 4). In the first round, an average consensus of 60% (three of five experts) was achieved for 124 activities, and then anonymous feedback from first-round results was presented to the experts. The second round of assessment achieved a consensus of 100%, meaning that 194 activities were eliminated and a core list of 108 activities was considered for further assessment. Table 5 shows a sample of seven activities identified as core inspections for earthwork and embankment.

Table 4. Core list of inspection activities

Division	Delphi-Method Meetings	
	Round 1	**Round 2**
100 - General clauses	3	0
150 – Equipment	4	0
200 - Earthwork and embankment	9	7
300 - Subgrade, base, and shoulders	50	47
400 - Concrete (bridge deck)	10	9
500 - Rigid pavement (PCCP)	15	12
600 - Flexible pavement (HMA)	33	33
Total	124	108
Consensus	(60%)	(100%)

Table 5. Example of core inspection activities for earthwork and embankment

Element	Activity ID	QA Activity
Earthwork and Embankment	1.1	Field density for compacted earthwork
	1.2	Field density of compacted backfilling works
	1.3	Moisture content of earthwork
	1.4	Moisture content for structure backfilling
	1.5	Field density of MSE walls foundation
	1.6	Field density of mechanically stabilized earth fill
	1.7	Check placement and compaction of granular drainage blanket

Determining Risk Probability and Consequence

As shown in equation 8, RI is the product of frequency of failure (FF) and consequence of failure (CF) (Mostafavi and Abraham 2013; API 2016). FF is defined as the extent to which the event of failure is likely to occur, potentially based on observing recurrence or on degree of belief and expectation. Qualitative scales, ranks, or categories such as “remote,” “low,” “moderate,” or “high” can be used to determine degrees of belief about probability of failure. On the other hand, CF is an outcome from the failure event, including one or more consequences, and may be expressed qualitatively or quantitatively (API 2016). Previous research identified three consequences, or sub factors, that represent CF, including increased maintenance cost or cost of rework (C), highway safety reduction and hazard for employees or the public (S), and highway service interruption (R) (Scott et al. 2017; Washer et al. 2014; Yuan et al. 2018).

$$RI = FF * CF_{C,\,S,\,R} \qquad (8)$$

To assess the risk impact (RI) of each QA activity, a questionnaire survey was used to collect data via the Delphi technique to effectively mitigate individual bias and error. In order to reduce uncertainty resulting from variation in the experts’ background knowledge, linguistic terms spread over five categories (i.e., 1 = Very low, 2 = Low, 3 = Moderate, 4 = High, and 5 = Very high) were used to describe risk levels. Eight experts from KDOT with an average experience of 20 years in highway construction inspections, including highway construction project managers, field engineers, and senior QA inspectors, participated in this questionnaire. Figure 4 shows a data collection form for the risk assessment process.

Element	ID	Activity	RISK ASSESSMENT																			
			Failure Frequency					Consequences														
								Cost					Safety					Service Interruption				
			Very low	Low	Moderate	High	Very High	Very low	Low	Moderate	High	Very High	Very low	Low	Moderate	High	Very High	Very low	Low	Moderate	High	Very High
1. Earthwork and Embankment	1.1	Field density for compacted earthwork																				
	1.2	Field density of compacted backfilling work																				
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Figure 4. A sample of QA risk assessment

Figure 5 shows the occurrence probability of C, S, R, and FF in terms of the five above-mentioned categories into nine intervals. The k^{th} interval was defined by $P(\theta) \cong (\theta_1, \theta_2, \theta_3)$. For example, $P(impossible) \cong (0.0, 0.0 0.125)$. The experts were asked to select the linguistic term/interval that reflected the occurrence probability of each category (Sun et al. 2018; Zhang et al. 2016).

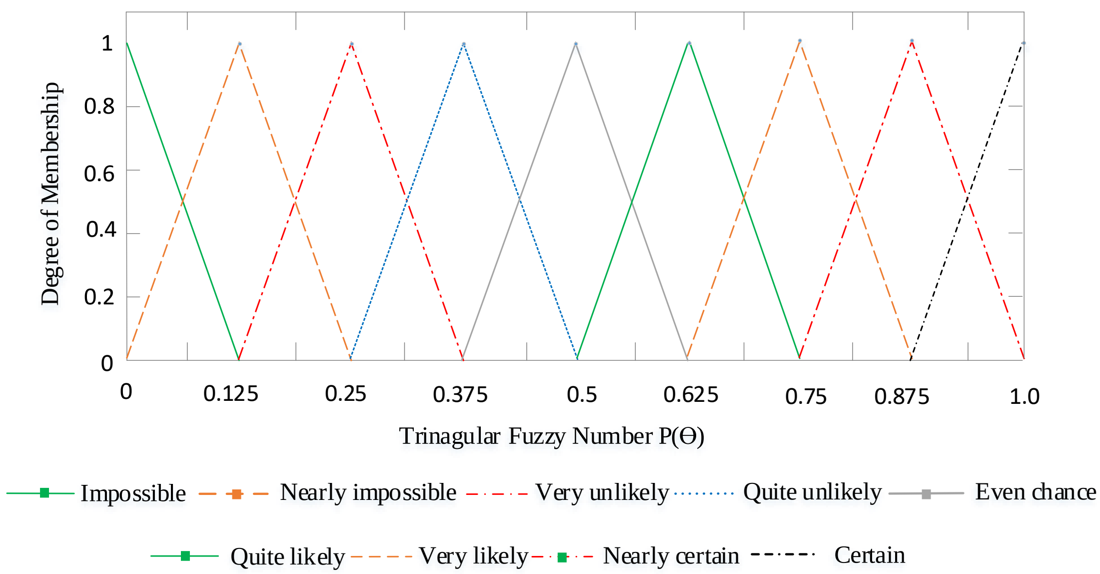

Figure 5. Set of triangular fuzzy numbers for probability of occurrence

The linguistic responses were fuzzified and analyzed when an average consensus of 87.5% was achieved after the second round of the survey. Table 6 shows a sample of results for probabilities selected by each expert for the five categories of C of activity 1.1 (field density for compacted earthwork). For example, Table 6 indicates that expert 1 assigned probabilities "*Impossible*/*Quite likely/Even chance/Very likely/Very unlikely*" for consequence C to be in categories "*1. Very low*; *2.Low/3.Moderate/4.High/5.Very high*" respectively. Similarly, expert 2 assigned the largest probability $P(very\ likely) \cong (0.625, 0.75, 0.875)$ to category 4 (High) and the lowest probability $P(Impossible) \cong (0.00, 0.00, 0.125)$ to category 1 (Very Low).

Table 6. Fuzzy probability distributions for cost factor C of activity 1.1

Expert	**Category**				
	1.Very Low	**2.Low**	**3.Moderate**	**4.High**	**5.Very High**
1	(0.0, 0.0, 0.125)	(0.50, 0.625, 0.75)	(0.375, 0.5, 0.625)	(0.625, 0.75, 0.875)	(0.125, 0.25, 0.375)
2	(0.0, 0.0, 0.125)	(0.375, 0.5, 0.625)	(0.375, 0.5, 0.625)	(0.625, 0.75, 0.875)	(0.125, 0.25, 0.375)
3	(0.0, 0.0, 0.125)	(0.375, 0.5, 0.625)	(0.375, 0.5, 0.625)	(0.50, 0.625, 0.750)	(0.000, 0.00, 0.125)
4	(0.0, 0.0, 0.125)	(0.25, 0.375, 0.50)	(0.50, 0.625, 0.75)	(0.625, 0.75, 0.875)	(0.125, 0.25, 0.375)
5	(0.0, 0.0, 0.125)	(0.375, 0.5, 0.625)	(0.375, 0.5, 0.625)	(0.625, 0.75, 0.875)	(0.125, 0.25, 0.375)
6	(0.0, 0.0, 0.125)	(0.375, 0.5, 0.625)	(0.375, 0.5, 0.625)	(0.750, 0.875, 1.00)	(0.375, 0.50, 0.625)
7	(0.0, 0.0, 0.125)	(0.375, 0.5, 0.625)	(0.25, 0.375, 0.50)	(0.625, 0.75, 0.875)	(0.125, 0.25, 0.375)
8	(0.0, 0.0, 0.125)	(0.375, 0.5, 0.625)	(0.375, 0.5, 0.625)	(0.625, 0.75, 0.875)	(0.125, 0.25, 0.375)
Consensus	(100%)	(75%)	(75%)	(75%)	(75%)

Table 6 shows that eight experts assigned the probability for the cost consequence factor of each category (Very Low; Low; Moderate; High; and Very High). To achieve the normalization condition, Zhang et al. (2016) proposed two steps to normalize P(θ) when various experts are involved in assessment. The first step involved using Equation (9) to combine probabilities assigned by the eight experts for each category; where, $\grave{P}_{ij}$ is the collective probability for category *j*, *M* is the number of experts (*m = 1, …, M*). The second step involved using Equation (10) to create normalized probability for category *j* (P_{ij}); where Q is the number of categories (*j = 1, …..,* *Q*).

$$P_{ij}^{`} = \sum_{m=1}^{M} p\ (\theta) \qquad (9)$$

$$P_{ij} = \frac{P_{ij}^{`}}{\sum_{j=1}^{Q} \theta_2} \qquad (10)$$

Table 7 shows a sample result of normalized probabilities of all four factors (C, S, R, FF) for activity 1.1 using Equations (9) and (10).

Table 7. Normalized probabilities of factors in activity 1.1

Factor	Category				
	1.Very Low	**2.Low**	**3.Moderate**	**4.High**	**5.Very High**
C	(0.000, 0.000, 0.062)	(0.187, 0.250, 0.312)	(0.187, 0.250, 0.312)	(0.312, 0.375, 0.437)	(0.062, 0.125, 0.187)
S	(0.062, 0.125, 0.187)	(0.312, 0.375, 0.437)	(0.312, 0.375, 0.437)	(0.000, 0.000, 0.062)	(0.062, 0.125, 0.187)
R	(0.000, 0.000, 0.062)	(0.062, 0.125, 0.187)	(0.312, 0.375, 0.437)	(0.437, 0.500, 0. 562)	(0.000, 0.000, 0.062)
FF	(0.187, 0.250, 0.312)	(0.000, 0.000, 0.062)	(0.437, 0.500, 0. 562)	(0.187, 0.250, 0.312)	(0.000, 0.000, 0.062)

Risk Assessment

Detailed risk assessment determines the RI of each activity by obtaining the main advantages of qualitative and quantitative approaches (i.e., less available data and speed of qualitative assessment and more rigor and accuracy of quantitative assessment) (API 2016). This study considers two aspects of risk assessment: fuzziness from using linguistic terms and uncertain knowledge; and representation of causal relationships between variables (i.e., risk factors of RI, C, S, R, and FF). FBBN was selected as an assessment technique because, compared to other machine learning models, all variables in FBBN have an understandable semantic interpretation (Guidotti et al. 2018). FBBN advantageously combines various sources of knowledge is suitable for small and incomplete data sets. It can be used to model causal relationships among variables, and explicitly handles uncertainty for decision analysis (Uusitalo 2007). The following four steps were conducted during risk assessment:

Step 1—Model construction: The first of two FBBN construction methods includes learning BN structures and parameters on the basis of historical data (Sun et al. 2018). However, this method often requires large amounts of training data. The second method, which is practical in most engineering areas, is based on knowledge and experience (Leu and Chang 2013; Nguyen et al. 2016). This study selected the second method after identifying the network structure and parameters from the literature and expert opinions. To infer RI of QA activity, a network of six variables was constructed, where C, S, R, and FF were root nodes; RI was a leaf node; and CF was an intermediate node (i.e., node that has parent and child nodes), as shown in Figure 6. It is noted that for the simplicity and practical application purpose, the CF node was valuated based on three different levels: Low, Moderate, and High.

Table 8 shows the CPT for the CF associated with three consequences (C, S, and R). The CPT of CF was developed by creating direct edges from C, S, R to CF as illustrated in Figure 6. As mentioned previously, the CF was categorized into three different levels: 1 = Low (minor effect on highway performance), 2 = Moderate (considerable effect on highway performance and repair works), or 3 = High (severe consequences such as loss of life or substantial economic loss). The weight of expert inputs was used to calculate the conditional probabilities. For example, when S, C, and R were rated as "Very Low," the CF was assigned at a low level. Mathematically, when C = 1 (Very Low), S =1(Very Low), and R = 1 (Very Low), the resulting CF conditional probabilities were $P(CF_{low}) = 1.0$, $P(CF_{moderate}) = 0.0$, and $P(CF_{high}) = 0.0$. The similar process was used to calculate other conditional probability values in Table 8.

To determine the CPT (Table 9), the direct edges from CF and FF to RI were created. As illustrated in Figure 6, the RI was evaluated based on three different levels: Low, Moderate, and High. The conditional probabilities in Table 9 were determined based on the weight of expert inputs. For instance, when FF received a "Very Low" rating (i.e., FF = 1) and CF was "Low" (i.e., CF = 1), the resulting RI conditional probabilities were $P(RI_{low}) = 1.0$, $P(RI_{moderate}) = 0.0$, and

$P(RI_{high}) = 0.0$. Other probabilities in Table 9 were determined using the same process.

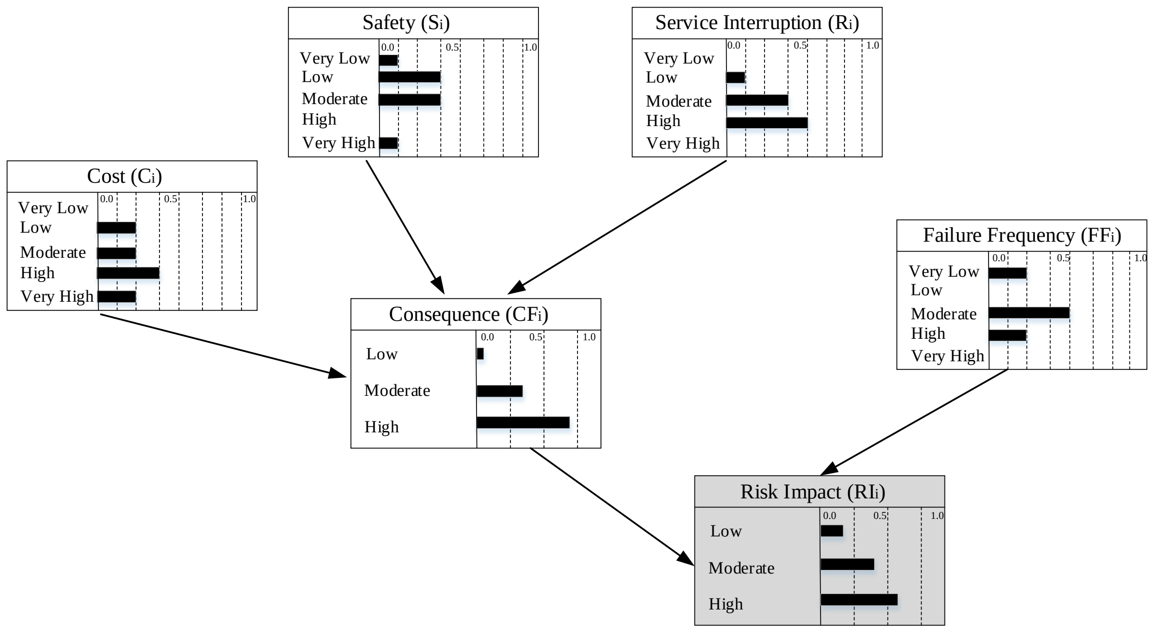

Figure 6. FBBN model for predicting the risk impact of QA activities

Table 8. Conditional probabilities of CF

C	S	R	P(CF =Low)	P(CF =Moderate)	P(CF =High)
1	1	1	1.00	0.00	0.00
1	1	2	0.50	0.50	0.00
1	1	3	0.25	0.75	0.00
⋮	⋮	⋮	⋮	⋮	⋮
3	3	2	0.06	0.94	0.00
3	3	3	0.00	1.00	0.00
3	3	4	0.00	0.38	0.62
⋮	⋮	⋮	⋮	⋮	⋮
5	5	3	0.00	0.03	0.97
5	5	4	0.00	0.01	0.99
5	5	5	0.00	0.00	1.00

Table 9. Conditional probabilities of RI

CF	FF	P(RI = Low)	P(RI = Moderate)	P(RI = High)
1	1	1.00	0.00	0.00
1	2	0.95	0.05	0.00
1	3	0.90	0.10	0.00
⋮	⋮	⋮	⋮	⋮

3	3	0.05	0.10	0.85
3	4	0.00	0.05	0.95
3	5	0.00	0.00	1.00

Step 2—Risk impact inference: Probabilities, expressed as triangle fuzzy numbers such as P (θ) in Table 7, of the root nodes (i.e., R, C, S, and FF) were considered as evidence. This study used FBBN to infer the RI probability at level/category *j*, represented by $P\ (RI = r_{i\ j}) = (\theta_{r1}, \theta_{r2}, \theta_{r3})$, where *j* represents the *j*th category of *i*th QA activity (*i* = 1, 2,…, 108; *j* = 1, 2, 3). Because of the space limitation, the key calculation steps of probability of RI_{1j} for activity 1.1 is described below.

For CF;

1. $\underline{Step\ 1}$: Applying Equation (7), we have

$$P\ (CF\ =\ cf_{1.low})\ \cong \sum_{C,S,R} P(C;S;R;CF\ =\ cf_{1.low}).$$

2. *Step 2:* Using Equation (6) and the conditional independence relationships, the following can be obtained

$$P\ (C;S;R;CF) \cong\ P(CF|C;S;R)\ \otimes P(C) \otimes P(S) \otimes P(R)$$

3. *Step 3:* Based on probabilities from Tables 7 for C, S, R, and Table 8 for CF, the probability of CF associated with the low, moderate, and high level was determined as follows.

$$P\ (CF\ =\ cf_{1.low})\ \cong \sum_{C,S,R} P(CF = cf_{1.low}\ |C;S;R)\ P(C)\ P\ (S)\ P(R)$$

$$\cong (0.02, 0.034, 0.040)$$

Similarly,

$P\ (CF\ =\ cf_{2.moderate}) \cong (0.355, 0.369, 0.48);$ *and* $P\ \left(CF\ =\ cf_{3.high}\right) \cong (0.50, 0.595, 0.604)$

The similar calculation process was applied for RI. Specifically, the three steps were used to calculate the probability of RI for the activity 1.1 as following:

4. <u>*Step* 1</u>: Applying Equation (7), we have

$$P\ (RI\ =\ ri_{1.low})\ \cong\ \sum_{CF,FF} P(CF;FF;RI\ =\ ri_{1.low}).$$

5. *<u>Step 2</u>:* Using Equation (6) and the conditional independence relationships, the following can be obtained

$$P\ (CF;FF;RI) \cong\ P(RI|CF;FF)\ \otimes P(CF) \otimes P(FF)$$

6. *<u>Step 3</u>:* Based on the probabilities from Tables 7 for C, S, R, Table 8 For CF, and Table 9 for RI, the probability of RI associated with low, moderate, and high are determined as follows.

$$P\ (RI\ =\ ri_{1.low})\ \cong\ \sum_{CF,FF} P(RI\ =\ ri_{1.low}|CF;FF)$$

$$\otimes \sum_{C,S,R} P(CF\ |C;S;R)\ P(C)\ P\ (S)\ P(R)$$

$\otimes\ P(FF) \cong$ (0.083, 0.089, 0.099)

Similarly,

$P\ (RI\ =\ ri_{2.moderate}) \cong (0.334, 0.362,\ 0.371); and\ P\ \left(RI\ =\ ri_{3.high}\right) \cong$

$(0.530, 0.548, 0.566)$*”*

It is noted that to reduce computational complexity and save computational time, a customized FBBN module was encoded in R software using BnLearn and gRain packages (Scutari, 2009). The major procedures to encode the module are as follows:

1. Identify the number of nodes and causal relationships of the network

> *Risk.dag = model2network("[C][S][R][CF|C:S:R][FF][RI|CF:FF]")*

2. Demonstrate the model graphically

```
> pp = graphviz.plot(risk.dag)
```

3. Identify prior probabilities for C, S, R, and FF

```
> C.prob  & > S.prob & > R.prob & > FF.prob
```

4. Identify conditional probabilities (CBTs)

```
> FF.prob & > RI.prob
```

5. Incorporate the variables into the network nodes

```
> cpt.list <- compileCPT(list(C = C.prob, S = S.prob, R = R.prob, FF = FF.prob, CF =
CF.prob, RI = RI.prob))
```

6. Infer RI

```
> bn <- grain(cpt.list)
> qgrain(bn, nodes=c("RI"))
```

Step 3—Defuzzification: The calculated P (RI_{ij}) for each QA activity were fuzzy triangular numbers in the previous risk analysis. In order to rank the risks, though, the fuzzy numbers were transformed into regular crisp numbers using the centroid method (Mostafavi and Abraham 2013). As shown in equation 11, the centroid of a triangular fuzzy number is equal to the average of the three components of the fuzzy number.

$$Centroid\ of\ triangular\ fuzzy\ number\ P_i(\theta){:}\ (\theta_1,\ \theta_2, \theta_3) = \frac{(\theta_1 + \theta_2 + \theta_3)}{3} \qquad (11)$$

The defuzzification process determined the most likely category to represent the RI of each activity. For example, defuzzification of activity 1.1 resulted in $P\ (RI_{1.low}) = 0.0903$, $P\ (RI_{2.moderate}) = 0.3556,\ P\left(RI_{3.high}\right) = 0.549$. Defuzzification results of the other activities are presented in result and analysis section below.

Step 4—Model validation: Validation of the proposed FBBN included data verification, model structure and parameter validation, and computerized module verification. Sargent (2013) asserted that data verification is essential for model integrity. In this study, the data used to build the model were from a list of QA activities from inspection reports and documents. This list was verified and refined by the collective judgment of experts, including two rounds of activity screening to reach consensus. The model variables (e.g., FF and CF) and causal relationships were identified in previous research and expert opinions. The authors presented the model variables and discussed the relationships among variables with senior superintendents, experienced project engineers, and knowledgeable inspectors responsible for QA inspections. The purpose of the discussions was to ensure that the model logically represented the RI of QA inspection activities. The model also was tested with a case example from KDOT to validate its output and applicability. The computerized module was verified to ensure that the R-based FBBN module was operating correctly. Results from the FBBN module in this study were compared to a commercial software. Table 10 compares output for activity 1.1. Outputs from these two computer programs were nearly identical and consistent.

Table 10. Comparison of $\mathrm{P}\left(\mathrm{RI}_{1.j}\right)$ for activity 1.1 between R-based FBBN and commercial software

Activity ID	Low	Moderate	High	RI
R-based FBBN	0.0900	0.3555	0.5490	High
Bayesialab software	0.0900	0.3550	0.5494	High
Difference	0.0000	0.0005	0.0004	N/A

RESULT AND ANALYSIS

The model output of defuzzification determined the most likely categories to represent RI of each activity. The computation of probabilities of RI categories for the 108 QA activities revealed that most activities were categorized as low and moderate RI: 42 were identified as low, 40 were moderate, and 26 were high. The probabilities of RI for the 108 activities are provided in Appendix. The resulting RI probabilities for the core inspection activities of earthwork and embankment are shown in Table 11. The category with the highest probability of the earthwork activity 1.1 was $P(RI_{3.high}) = 0.549$ as compared to $P(RI_{2.moderate}) = 0.355$ and $P(RI_{1.low}) = 0.090$. Therefore, the activity 1.1 was considered a high RI activity, meaning that this activity was designated a high priority for inspection. The activity 1.5, however, was given a moderate priority for inspection due to its $P(RI_{2.moderate}) = 0.449,$ as compared to $P(RI_{3.high}) = 0.440$ and $P(RI_{1.low}) = 0.111$. Overall results for earthwork activities indicated five earthwork activities with high RI, two activities with moderate RI, and no activities with low RI (Table 11). Therefore, the seven earthwork inspection activities were given high and moderate priorities for inspection.

Table 11. Probability of risk Impact for earthwork and embankment core QA activities

Activity ID	Low	Moderate	High	RI
1.1	0.090	0.355	0.549	High
1.2	0.059	0.258	0.682	High
1.3	0.126	0.430	0.443	High
1.4	0.081	0.419	0.499	High
1.5	0.111	0.449	0.440	Moderate
1.6	0.111	0.406	0.482	High
1.7	0.291	0.512	0.196	Moderate

Figure 7 shows probabilities of the top five activities for each category. Results showed that two density-related activities and two rigid pavement (PCCP) tests, including air content and slump and air content of concrete bridge deck, are high-priority inspection activities (red). Results indicated that three flexible pavement (HMA) tests, including mixture gradation (district lab), asphalt content, and voids in mineral aggregate, are moderate-priority inspection activities (blue). The other two moderate priority activities are plasticity of subgrade aggregate test and verification of the application rate of cement or fly ash for cement-treated base. Four base and subgrade tests, including percent solids of lime slurry in lime-treated subgrade, sieve analysis for aggregate of granular base, moisture test for combined aggregate of base course, and subgrade aggregate passing sieve number 200 via the wash method, as well as HMA sampling and storage for testing, are low-priority inspection activities (burgundy).

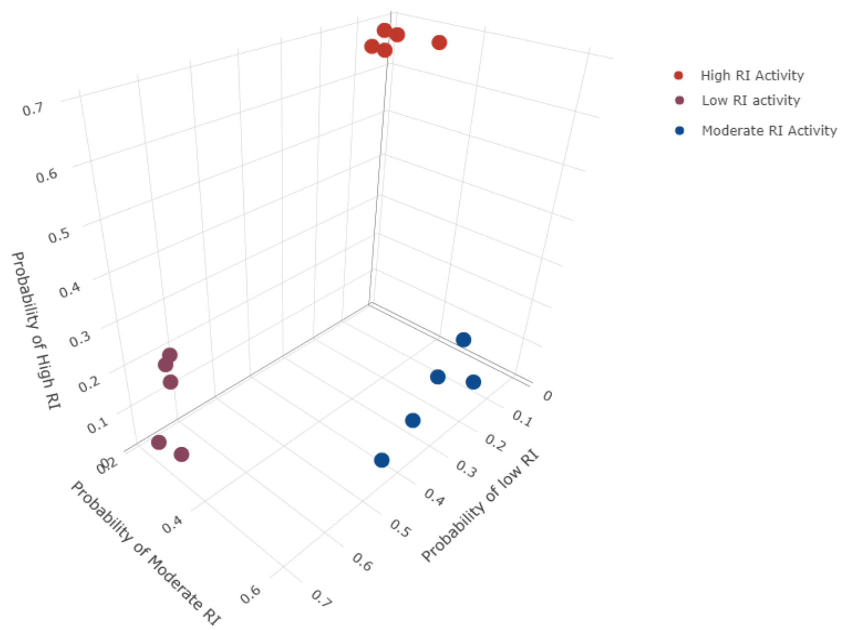

Figure 7. RI probabilities for the top five QA activities in each category

Figure 8 summarizes the result of the risk level of QA construction activities. Analysis results showed that on the construction element level, more than half the earthwork and bridge deck activities are high-risk inspections. The subgrade, base, and shoulder construction activities are comprising the lowest share of high-risk inspections (i.e., 9%). Although approximately half the HMA and PCCP inspections are in the moderate-risk category of inspection, the analysis showed that HMA and PCCP constructions are not covered by the largest number of inspection activities compared to subgrade and base constructions (Figure 8). One also can observe from Figure 8 that HMA and PCCP inspections contain the greatest number of high-risk inspection activities. These results highlight the criticality of HMA and PCCP construction inspections.

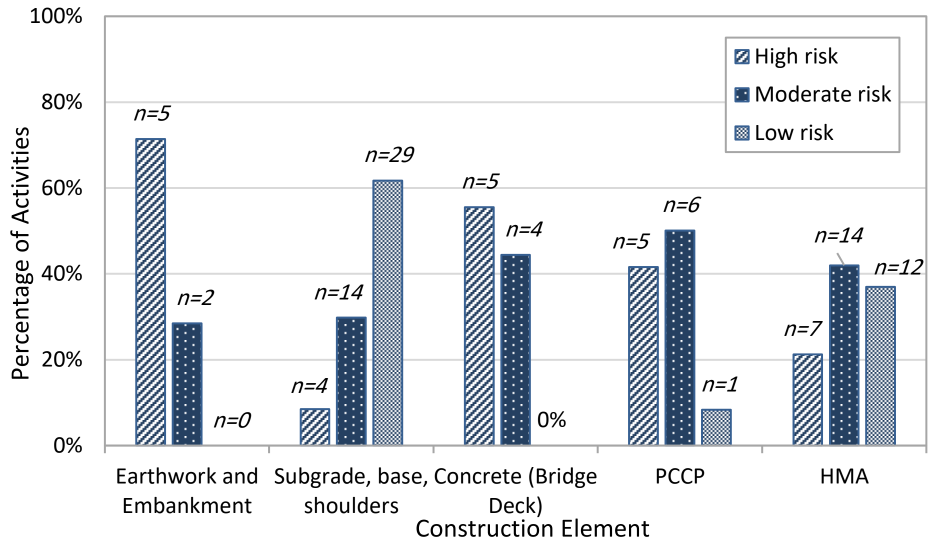

Figure 8. Percentage of high-, moderate-, and low-risk QA inspections for construction elements (*n = number of activities*)

The resulting RBI protocol included inspection priorities for 108 critical activities with their RI categorized as low, moderate, or high RI. Depending on the availability of inspection resources, transportation agencies can select the appropriate level of inspection for each activity..

DISCUSSION

The framework of this study included three phases: identification of inspection activities, data collection, and risk assessment. The identification phase involved collecting a comprehensive list of QA inspection activities from highway construction reports and documents. It is noted that the number of identified QA activities may vary from one transportation agency to another due to geographical and environmental factors, such as available materials and weather conditions (Scott et al. 2017). However, the framework and model implemented in this study are generic and replicable. During the data collection phase, qualitative expert opinions were obtained to refine the output of the previous phase. The result from this phase was a list of activities including qualitative descriptions of critical inspections and tests. Finally, the assessment phase aimed to quantify the RI of each activity.

The combination of qualitative and quantitative assessment in FBBN decreased the disadvantages of each approach while utilized the advantages of each (Washer et al. 2014; API 2016; Tserng et al. 2009). Quantitative risk assessment is defined as a numerical analysis of RI that utilizes numerical data based on performance and historical records. Although quantitative assessment provides valuable insight and accurate and objective results, it has limitations. Quantitative assessment is impractical for acquiring the data required for effective modeling. For example, data on past performance of a highway or bridge are typically incomplete or inaccurate (Andersen et al. 2001). The effort required to collect and analyze the data may surpass the value of the data for estimating the future performance of a highway, particularly when the data are sparse, include a large uncertainty, or contain evolving design characteristics. Therefore, due to the limited availability of quantitative data, the collected qualitative data (i.e., linguistic terms) for this research were aggregated via the Delphi method, and FS was used to transform the qualitative data to quantitative.

Conforming with previous studies, the amalgamation of BBN and FS in this study efficiently facilitated a probabilistic risk analysis under uncertainty during the assessment phase (Zhang et al. 2016; Ren et al. 2009; Eleye et al. 2008). FBBN prevented uncertainty that is typically presented in expert opinions and linguistics of the collected data. Input of the FBBN model was obtained from participants who were highly experienced in highway construction projects and primarily responsible for QA inspections. Therefore, the FBBN-based model proposed in this study provides an alternative for risk assessment and prioritization of QA inspections as described in the illustrative case. Compared to other statistical modeling techniques, such as Monte Carlo simulation, sensitivity analysis, ANN, and stochastic methodologies, FBBN effectively handled uncertainty, various sources of knowledge, and incomplete data sets (Uusitalo 2007). It also transformed the causal relationships among the variables (i.e., C, S, R, CF, FF, RI) into a probability distribution.

Regarding the framework output, processing many QA inspection activities became more achievable when the RI and inspection priorities were categorized into three levels of intensity. Furthermore, QA inspectors gained valuable inspection knowledge by identifying inspection type, procedure, and frequency for each construction element, as shown in Table 3. Using the generic framework and computational FBBN model developed in this study, transportation agencies can optimize the number and type of QA inspection activities. The framework output helps practitioners identify which inspections are the most effective to their QA process by offering three levels of RI based on availability of inspection staff. Expert opinions and RI analysis for 108 QA activities revealed 26 high-priority inspections for the first level when there is a significant shortage of inspection resources; these inspections specifically focus on mitigating the risk of life and substantial economic loss. A total of 66 high- and moderate-priority inspections were selected for the second level when there is a relative shortage of inspection resources. Because these inspections also focus on the aforementioned consequences, they extend to mitigating severe injuries and highway service interruptions. The total list of 108 critical inspection activities can be applied within the third level when there is little concern about the shortage of inspection resources.

CONCLUSIONS

Construction inspection is an essential component in QA programs to ensure the quality and long-term performance of highway systems. The scaling up of highway construction and maintenance projects requires increasing inspection resources. However, decreasing numbers of inspectors have caused a shortage of resources and knowledge for highway agencies to effectively inspect critical construction elements such as earthworks and embankments, bridge decks, flexible pavements, rigid pavements, subgrades, bases, and shoulders. The shortage of inspection resources has forced highway agencies to prioritize inspections based on criticality.

This study developed a methodology to help highway agencies overcome the shortage of inspection staffing by prioritizing QA inspections based on criticality. The framework included identifying a list of QA inspection activities, collecting data by surveying subjective matter experts, and assessing risk. In an illustrative case study, a comprehensive list of 302 testing and inspection activities were retrieved from KDOT's construction manuals, construction checklists, QA guides, documentation manuals, specifications, and design manuals. The Delphi technique and two rounds of interviews with experts were used to winnow this list to a core list of 108 critical activities. A questionnaire survey was then used to prioritize the core list of activities based on criticality. The experts assessed the risk associated with each inspection activity by considering the probability of failure and severity of failure consequences. The consequences included safety, service interruption, and the effect of failure on long-term performance of the highway and bridge expressed as cost of repair. The FBBN model was developed to assess the overall RI. FBBN dealt with the subjectivity and linguistic nature of the collected data and converted causal influence between the model variables into a quantitative probability distribution.

Results showed that the modular representation of uncertain knowledge due to randomness and vagueness increased the ease and functionality of QA inspection risk analysis. The model facilitated probabilistic risk analysis under uncertainty and fuzziness. The critical inspection activities were prioritized as low, moderate, or high levels. RBI protocol also equips highway construction inspectors with necessary inspection knowledge. The results of the KDOT case illustrative example indicated that more than half the KDOT earthwork and bridge deck QA activities were high-risk inspections. In addition, HMA and PCCP construction activities included the greatest number of high-risk inspections.

This study contributes to the construction engineering and management literature by introducing a new framework to optimize QA inspections for highway projects. Further, the FBBN technique used to develop the RBI framework in this study can be adapted by other researchers to model uncertainty of knowledge associated with qualitative data, which is common in the construction engineering and management area. The study also contributes to the construction industry by providing practical guidelines for highway agencies to adopt and validate RBI systems in their QA programs. Additionally, the finding from this study may help highway agencies better understand how to conduct their QA inspection activities to maintain the requirements of safety and quality with minimal resources.

The limitations of this study include a relatively small sample size of eight experts. In addition, the framework only prioritizes QA inspection activities and was tested on only one case study from KDOT. Another limitation of this study that warrants future research involves comparing the model results with actual project data. For example, future study may apply the model developed in this study to different types and sizes of highway construction projects to better understand how the result of the model can be used to mitigate inspection errors and optimize inspection resources and efforts. Finally, the authors suggest integrating RBI into e-construction inspection processes to reduce staff workload, enhance performance, and automate construction checklists.

DATA AVAILABILITY STATEMENT

Data generated or analyzed during the study are available from the corresponding author by request. Information about the Journal's data sharing policy can be found here: http://ascelibrary.org/doi/10.1061/%28ASCE%29CO.1943-7862.0001263

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CHAPTER 3

A Risk-based Inspection Model for Hot Mix Asphalt (HMA) Pavement Construction Projects

Research Phase II Dissertation – Journal Paper 2

(Published)

A Risk-based Inspection Model for Hot Mix Asphalt (HMA) Pavement Construction Projects

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ABSTRACT

Hot mix asphalt (HMA) is a critical component in highway construction projects. To ensure the quality of HMA, transportation agencies inspect construction materials and workmanship through quality assurance (QA) programs. However, there is a lack of studies that have investigated the causal relationship between QA inspection activities and quality of HMA pavement. This study addresses this knowledge gap by developing a risk-based analysis model. A total of 14 HMA inspection activities were obtained by synthesizing QA documents, verified with a wide range of experts, and then included in the model. The fuzzy set theory (FS) was incorporated into the model to overcome the linguistic nature of the collected data, which could not be represented precisely by probability distributions. Bayesian networks (BBN) also were used to investigate the causal relationship between the model variables. A case study was conducted to test and verify the model. Results indicated that the modular representation of uncertain knowledge about risk levels due to qualitative nature of the data increases the efficiency and functionality of QA inspection risk analysis. The model is capable of calculating the probability distribution of HMA risk levels, identifying the most likely potential causes of quality shortfall risk, and providing guidance to mitigate the risk via three risk scenarios. This study contributes to the body of knowledge by demonstrating how risk impacts inspection and providing FS and BBN in highway construction domain. The proposed model can be used by transportation agencies as a decision tool by updating

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probabilities based on actual inspection results.

Keywords*:* Hot mix asphalt, quality assurance, risk-based inspection, fuzzy set, and Bayesian belief networks.

INTRODUCTION

Pavement construction is a manufacturing process that takes materials and workmanship as inputs and generates pavement as the end product. The quality of the pavement depends on both material properties and construction practice and processes. Hot mix asphalt (HMA) is a key component in the pavement system. Different transportation agencies such as state departments of transportation (DOTs), local highway agencies, and others perform a series of quality assurance (QA) tests for construction materials and inspect workmanship processes to ensure the quality of HMA.

Transportation agencies are facing the critical challenge of an increased demand for highway system construction and maintenance work with reduced QA inspection resources such as funding and staff. For instance, Taylor and Maloney (2013) found that state DOTs are managing larger roadway systems with fewer in-house staff than they were before. The study pointed out that staff constraints and the lack of needed skills are virtually affecting all DOT functions, with major impacts on construction inspection capabilities. As a result, state DOTs are searching for effective approaches to accomplish construction and rehabilitation operations without being exposed to quality shortfall.

Reducing the occurrence likelihood of HMA damage requires identifying quality characteristics and the related inspection activities. A wide range of studies have discussed QA assessment of HMA based on examining each quality characteristic individually. For instance, Georgiou and Loizos (2019) conducted a study to evaluate surface texture characteristic using empirical models and experimental approaches. Plati and Loizos (2016) investigated QA of HMA compaction characteristic using the ground-penetrating radar technique. Radziszewski et al. (2014) examined bituminous binders quality based on viscoelasticity characteristic during QA inspections. However, there is no study that has examined the causal relationship between QA inspection activities and quality of HMA pavement.

The objective of this study is twofold. First, it introduces a core list of QA inspection activities for HMA. This core list helps state DOTs allocate their limited resources to the most critical inspection activities. Second, a risk-based inspection (RBI) model was developed to help state DOTs evaluate and mitigate a quality-related risk level of HMA early in the construction phase. The RBI model is based on Delphi, fuzzy set (FS) theory and Bayesian belief networks (BBNs) techniques. The Delphi techniques was applied to control bias during data collection process. FS was merged into the model to deal with linguistic nature of the collected data from subjective matter experts which cannot to be represented precisely by quantitative probability distributions. BBN was employed in the model to deal with the causal influence between the model variables and to infer probability distribution of quality risk levels. The model outcome provides transportation agencies with the probabilities of HMA quality shortfall based on actual observations of the current inspection activities. Additionally, it provides causal relationships between QA inspections and quality of HMA pavement.

The rest of the paper is organized as follows. The theoretical foundation and background of this study is presented in next section. It is followed by the development of the RBI model. Next, the model output and application scenarios are presented. Discussion of key findings is then provided. Finally, the conclusions of this research and future work are presented.

LITERATURE REVIEW AND BACKGROUND

This section provides literature review of RBI and an overview of three techniques employed to develop the RBI model for HMA paving construction projects. The techniques include Delphi, FS, and BBNs.

Risk-Based Inspection

RBI is implemented in many industries as a QA tool that focuses attention on the component representing the greatest risk. In industrial engineering fields, RBI is implemented as a technique to examine mechanical equipment with a focus on piping networks. The prioritization of inspection is based on risk that is expressed as expected values. Das Chagas et al. (2015) developed a multi-objective genetic algorithm to optimize cost of inspection and risk levels. The study provides an RBI example of oil and gas separator vessels subjected to internal and external corrosion. Researchers also examined implementation of RBI on polyethylene equipment, elevators, and mechanical devices (Wang et al. 2011, Park and Yang 2010).

Similarly, oil, gas and petrochemical industries are leading sectors in the area of implementing RBI. De Carlo et al. (2011) investigated implementation of BBNs in an RBI process for a chemical plant. The model adopted qualitative risk assessment including four main steps: (a) screening units within the facility; (b) estimating the risk level of the item and developing the risk matrix; (c) identifying the areas with higher risk; and (d) defining the inspection plan associated with the degree of risk. Similarly, studies by Bertolini (2009), Shuai et al. (2012), and Wintle (2001) addressed implementation of RBI for maintenance procedures in oil refinery, crude oil tanks, pressure equipment, using prioritization techniques such as heuristic methods and fuzzy logic.

In the water/wastewater infrastructure, Marlow et al. (2012) discussed the issue of inspecting isolation valves in the water sector. Marlow's study provided a pragmatic approach for risk-based inspection due to poor date on condition of these valves. An analytical hierarchy process was adopted as a technique to set relative weights between different criteria and alternatives. Anbari et al. (2017) developed a risk assessment model to prioritize inspection of sewer networks using Bayesian Networks. This model counts for probability of failure and weighted average method to calculate the consequences of failure values. Mancuso et al. (2016) provided an RBI methodology for a network of underground network of pipes. The methodology implemented multi attribute value theory to assess the risk of each pipe in the network.

For structural engineering, numerous studies have discussed RBI as an approach to examine structural elements. Straub and Faber (2005) presented a model for the consideration of entire systems in risk-based inspection planning instead of individual elements. Luque and Straub (2019) developed an RBI approach to optimizing the inspection process to a structural system that may include a large number of components. The procedures included implementation of a heuristic approach to construct the optimization problem, dynamic Bayesian Network to capture the system reliability, and Monte-Carlo simulation to compute the expected cost. Dong and Frangopol (2016) developed a probabilistic framework to identify inspection priority among multiple fatigue-sensitive details. Lassen (2013) discussed an RBI approach to inspection of fatigue cracks in welded offshore steel structures. A stochastic model with risk-based assessments was used to calculate for uncertainty and propose inspection time intervals.

Finally, in the thermal and nuclear energy domain, RBI is considered as a critical aspect in term of safety. Vinod et al. (2014) proposed an RBI approach to screening of critical components of nuclear energy plants. The approach uses damage consequence factors and health consequence factor (e.g., toxicity and flammability). Singh and Pretorius (2017) developed a semi-quantitative RBI process for thermal power plant components. The process included a multi-level risk analysis ranging from an initial screening step to a very detailed quantitative assessment. Table 1 exhibits examples of the current research trends and RBI applications, including articles reviewed, industry, and key findings.

Table 1. Application areas of risk-based inspection

Article	Area of Focus	Methodology/ Approach	Key Findings/Remarks
Anbari et al. (2017)	Sewer pipelines; Wastewater collection networks	BBN, Fuzzy Inference system	Possible damages to the sewer networks were divided into two categories: structural and hydraulic failures. Risk of a sewer pipe was obtained from integration of probability and consequences of failure values using a fuzzy inference system.
Singh and Pretorius (2017)	Thermal power plant	Risk Based Inspection and Maintenance Application Process (RIMAP) and expert input	Assessing damage mechanism and failure risk by RIMAP method. Where, RIMAP is a process for assessing the risk based on a combination of the probability and consequence of failure.
Marlow et al. (2017)	Water supply networks	Analytical hierarchy process	Prioritizing inspection of large number of isolation valves of pipe networks. Due to poor data on reliability or condition of the valves, the risk-based inspection concept and the analytical hierarchy process were used to set relative weights for each valve.
Mancuso et al. (2016)	Underground network of pipes	Multi-Attribute Value Theory (MAVT)	Assessing the risk of each pipe in the network in the presence of incomplete information about the network features and parameters. risk-based methodology was applied, including MAVT and Robust Portfolio Modeling (RPM) to identify Pareto-optimal portfolios of pipe inspections.
Das Chagas et al. (2015)	Separation vessel	Multi-objective genetic algorithm	Defining the optimum inspection program in terms of cost of inspection and risk level. The proposed approach provides information on how the inspection budget should be efficiently spent.
Ifezue and Tobins (2014)	Crude oil import/export line	Threats identifying and ranking	Semi-quantitative RBI and a line used to assess failure of import and export stabilized crude oil lines due to weld decay and corrosion under insulation. Potential threat from corrosion was therefore been considered and has been mainly targeted in

			inspection campaigns.
Lassen (2013)	Steel and concrete structures	Stochastic model	Examining structures to analyze uncertainty of fatigue cracks. Due to the uncertainty in the variables involved in the problem, the analysis has been carried out by stochastic modeling and risk based assessments.
Topalis et al. (2011)	Offshore topside and processing industry	Framework including a library of risk models	RBI software including a number of risk models is used for managing inspections in the process industry. The models Assess damage mechanism potential, degradation rate, failure risk, and inspection intervals.
Selvik et al. (2011)	Mechanical equipment	Expected value of risk by integrating the likelihood and consequences of failures	Planning of inspecting mechanical equipment using RBI. The inspections are prioritized based on risk, expressed as expected values.
Wang et al. (2011)	Polyethylene equipment	Risk assessment matrix	Due to a large number pressure pipes, the accumulation of the risk is higher in polyethylene devices. RBI risk assessment matrix is used to prioritize inspection of equipment parts.
Bertolini et al. (2009)	Oil refinery	Heuristic methods	Developing RBI and maintenance procedures for an oil refinery by taking into consideration the limits in term of time, budget and, human resources. This allows the refinery to minimize the overall risk.

Delphi Technique

Researchers have implemented the Delphi technique in several construction-related studies. This technique allows researchers to maintain significant control over bias in a well-structured academically rigorous process using the judgment of qualified experts (Hallowell and Gambatese 2010). It is noted that failure to satisfy the minimum requirements for Delphi characteristics has led to biased results. In order to obtain high-quality results, study should carefully consider Delphi selection characteristics for experts, number of rounds of interviews, type of feedback, and achievement of consensus among respondents. Experts should be selected for the survey based on predefined criteria such as number of years of experience in specialty discipline and professional registration. Rowe and Wright (1999) and Hallowell and Gambatese (2010) pointed out that the number of Delphi panel members has ranged in peer-reviewed studies from 3 to 80 members. The purpose of multiple rounds of interviews is to achieve consensus and improve precision. After each round, the experts receive group feedback in a form of points of agreement listed in order of most- to least-often mentioned. The literature does not, however, indicate a certain level of variance that represents adequate consensus for all studies since data collected for every study is unique. Avella (2016) suggested a Delphi consensus of 70% as a standard agreement. When the current round does not reach this percentage, a next round should be conducted.

Fuzzy Set Theory

Zadeh (1965) created a FS mathematical presentation to model uncertain systems in the absence of precise and complete information. The FS theory asserts that linguistic terms are less precise than crisp values (i.e., numbers). However, due to various construction information, inaccurate observation data, lack of engineering experience, and other factors, a crisp value cannot satisfy the occurrence probability and severity of events, meaning the probability of verbal expressions must be transformed into fuzzy numbers. A fuzzy number, denoted by $P(\theta)$, refers to a continuous set of possible values, where each value has a membership function that varies between 0 and 1. In general, FS uses triangular, trapezoidal, or Gaussian fuzzy membership functions to convert crisp values into fuzzy numbers. Triangular membership functions are often utilized to provide precise descriptions and obtain accurate results (Li et al. 2012). Thus, triangular fuzzy numbers were selected for this study. For all Θ, $\Theta \in$ a fuzzy set Θ, the triangular fuzzy number $P(\Theta)$ can be defined in terms of three components of a, b, and c as shown in Figure 1. The values between b and a or c have membership functions between 0 and 1. The value of b has a membership function of 1 (i.e., $P(\Theta) = 1$), and values less than a or greater than c have a membership function of zero (Emrouznejad and Ho 2017; Mostafavi and Abraham 2013).

$$P(\Theta) = \begin{cases} 0 & for\ \Theta < a \\ \dfrac{\Theta - \mathrm{a}}{\mathrm{b} - \mathrm{a}} & for\ \mathrm{a} \leq \Theta \leq \mathrm{b} \\ 1 & for\ \Theta = b \\ \dfrac{\mathrm{c} - \Theta}{\mathrm{c} - \mathrm{b}} & for\ \mathrm{b} \leq \Theta \leq \mathrm{c} \\ 0 & for\ \Theta > \mathrm{c} \end{cases}$$

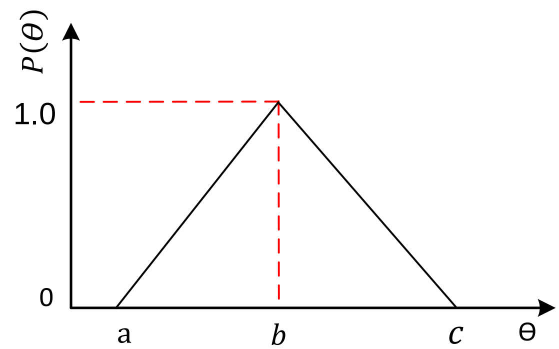

Figure 1. Triangular fuzzy number P(Θ)

Assuming two triangular fuzzy numbers, namely, $P(\theta_x)$: (a_x, b_x, c_x) and $P(\theta_y)$: (a_y, b_y, c_y), the operations of addition, subtraction, multiplication, and division between $P(\theta_x)$ and $P(\theta_y)$ can be conducted by using Equations 1- 4 (Zhang et al. 2016) as follows.

$$P(\theta_x) \oplus P(\theta_y) \cong (a_x + a_y, b_x + b_y, c_x + c_y) \qquad (1)$$

$$P(\theta_x) \ominus P(\theta_y) \cong (a_x - a_y, b_x - b_y, c_x - c_y) \qquad (2)$$

$$P(\theta_x) \otimes P(\theta_y) \cong (a_x a_y, b_x b_y, c_x c_y) \qquad (3)$$

$$P(\theta_x) \oslash P(\theta_y) \cong (a_x/a_y, b_x/b_y, c_x/c_y) \qquad (4)$$

Bayesian Belief Network

BBN is an inference engine for calculating beliefs of events given the observation of other events (referred to as evidence). BBN includes conditional dependence assumptions and relationships between nodes (i.e., variables), represented by a directed acyclic graph (DAG), as shown in Figure 2. DAG allows joint probability distribution to be specified locally in terms of a conditional probability table (CPT). Relationships constructed among the nodes are called the model structure (Sun et al. 2018; Borsuk et al. 2004).

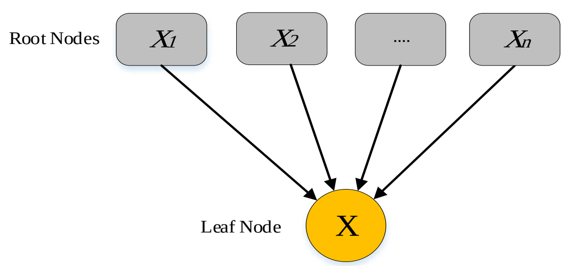

Figure 2. BBN with DAG and relationships among nodes

As shown in Equation (5), conditional independence of leaf nodes (i.e., child nodes) can be calculated in terms of probability distribution of root nodes (i.e., parent nodes).

$$P(\mathrm{X}) = P(X_1, X_2, \cdots X_n\ ) = \prod_{i=1}^{n} P\ (X_i |\ Root(X_i)) \qquad (5)$$

where $Root(X_i)$ is the parent node of (X_i) in DAG and the CPT of X_i equals $P(X_i|\ Root\ (X_i))$. Because of the dependent relationships of the variables and the known probability distribution of the root nodes, the joint probability distribution of the leaf node $P(X_i)$ and the marginalization rule can be calculated using Equations 6 and 7, respectively:

$$P\big(X_i, Root(X_i)\big) = \ P\big(Root(X_i)\big) \,.\, P\ \big(X_i |\ Root(X_i)\big) \qquad (6)$$

$$P(X = x_i) = \sum_{i=1}^{n} P\ \left(Root(X_i)\right).P\ \left(X_i|\ Root(X_i)\right) \qquad (7)$$

Finally, by knowing the probability distribution of the leaf nodes, the Bayesian rule can be applied to attain inverse operation of calculating probability of root nodes as shown in Equation (8).

$$P(Root(X_i)|\ X_i) = \frac{P\left(Root(X_i)\right).P\ \left(X_i|\ Root(X_i)\right)}{P(X_i)} = \frac{P(Root(X_i);\ X_i)}{P(X_i)} \quad (8)$$

DEVELOPMENT OF RISK-BASED INSPECTION MODEL

Figure 3 shows a step-by-step process for developing the RBI model to assess quality risk levels of HMA construction operations. The model includes three main modules, including: (1) identifying the critical inspection activities related to HMA quality; (2) evaluating risk parameters using the Delphi technique and FS; and (3) constructing a BBN model to investigate relationships between the parameters. The following sections discuss these modules in detail. To elucidate the model development and application, an illustrative case study from Kansas DOT (KDOT) was presented in detail. It is important to note that the model can be used for other state DOTs.

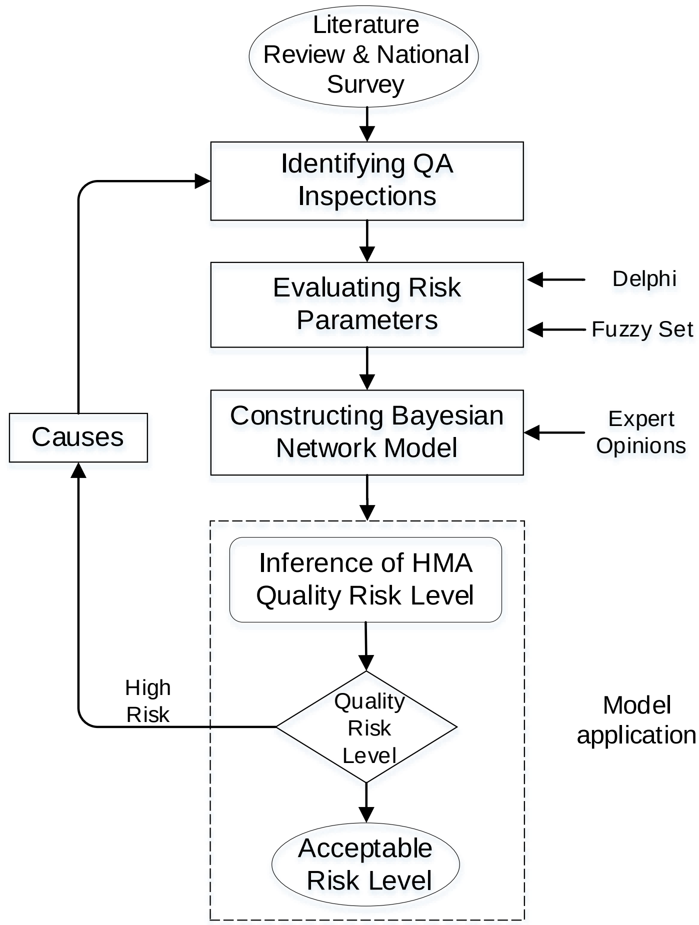

Figure 3. An overview of RBI model for HMA pavement

Identification of Critical QA Inspection Activities for HMA

To identify QA inspection activities of HMA, a rigorous literature review was conducted. This review process involves scanning and synthesizing a wide range of documents, including construction manuals, specifications, QA guides, documentation manuals, design manuals, and inspection checklists from FHWA and numerous state DOTs such as Washington, Ohio, Texas, California, Indiana, and Kansas. The review was performed through two main stages. The first stage, automated scanning, involves using a qualitative data analysis computer software package (NVIVO) to identify the pool of HMA inspection activities. NVIVO is a content analysis software package that has been designed for qualitative researchers working with rich text-based and/or multimedia information, where deep levels of analysis on small or large volumes of data are required. The key words used for this search include “HMA”, “pavement”, “inspection”, “QA acceptance”, and “test”. The second stage, evaluating and synthesizing, involves manual scanning, reviewing and checking the HMA inspection activities obtained from the first stage. The purpose of this stage is to remove repeated activities and combine or add any relevant inspection activities to generate a non-overlapped list of HMA inspection activities.

The outcome of this step generated a comprehensive list of 33 HMA inspection activities. To identify the critical inspection activities related to HMA quality, the list of these 33 activities was further evaluated and verified by a recent national survey questionnaire of 50 state DOTs. The survey questionnaire was distributed to the voting members of the American Association of State Highway and Transportation Officials (AASHTO) Committee of Construction. One question from this survey asked participants to identify the top five critical HMA inspection activities. A total of 38 valid responses was received (76% response rate). Based on the result of this survey, the 19 activities out of 33 HMA inspection activities were excluded. As a result, a core list of 14 activities was considered as critical activities for HMA pavement quality. Table 2 summarizes these 14 critical inspection activities for HMA pavement construction. As shown in Table 2, the activities are classified into two groups, aggregate related inspections (Y_1) and mixture related inspections (Y_2). These 14 activities were used to develop the model.

Table 2. Critical inspection activities for flexible pavement (HMA)

Component	QA Activity	Inspected Quality Characteristic
Aggregate (Y_1)	Sieve analysis of aggregate (X_1)	Particle size distribution using standard sieves to comply with specifications.
	Void content of aggregate (X_2)	Void content of a sample of HMA fine aggregate based on a given gradation

	Coarse aggregate angularity (X_3)	The percent, by mass, of particles, which by visual inspection, exhibit characteristics of crushed aggregate.
	Sand equivalent of HMA aggregate (X_4)	Relative proportions of fine dust or claylike material in HMA combined aggregates.
	Moisture content of combined aggregate (X_5)	Moisture of HMA combined aggregate to comply with specifications.
	Plasticity (X_6)	Liquid limit, plastic limit and plastic index of the minus No. 40 portions of aggregates.
Mixture and workman-ship (Y_2)	Density of HMA mixtures (X_7)	Density characteristics, and stability characteristics that satisfy specifications.
	Voids in mixture (X_8)	Void percent in a sample of HMA.
	Moisture content of mixture (X_9)	Moisture percent in a sample of HMA.
	Asphalt and binder content (X_{10})	Asphalt percent of hot mix paving mixtures by ignition of the asphalt cement at 932°F in a furnace.
	Surface smoothness/ tolerance (X_{11})	Smoothness, i.e. profile index, of asphalt pavement using the California type 25-foot profilograph.
	Construction joints control (X_{12})	Making transverse and longitudinal joints according to project plans, an acceptable surface texture, and applying a light coat.
	Compaction of asphalt pavement layer (X_{13})	Densifying, or reducing the volume of, the mass of asphalt layer.
	Theoretical maximum specific gravity (X_{14})	Sampling uncompacted asphalt paving mixtures and determining maximum specific gravity.

Evaluation of risk parameters

The primary purpose of QA inspections is to prevent mistakes and defects and to ensure that the finished product will meet all specifications and requirements. Thus, it is important to understand, measure, and optimize the trade-off between investment in quality and the expected value of quality risk (API 2016). The prevailing theory is that the expected value of quality risk decreases as the investment in QA programs of state DOTs increases. Expected value of risk is defined as the product of likelihood and consequence of occurrence. Likelihood is a prior probability that can be deduced logically by examining existing information, while consequence is potential payoff such as cost of rework or reduction in performance and service life (Mostafavi and Abraham 2013). For QA inspections, the risk impact (RI) of quality failure can be expressed as the product of inspection activity failure rate (FR) and the consequence of failure (CF) shown in Equation (9). The typical CF parameters include cost of rework (C), safety reduction (S), and highway service interruption (R) (Scott et al. 2017; Washer et al. 2014; Yuan et al. 2018).

$$\mathrm{RI} = \mathrm{FR} * \mathrm{CF}_{\mathrm{S,C,R}} \qquad (9)$$

It is noted that quantitative evaluation of RI often requires a large amount of information in a form of numerical historical data which is often difficult or impossible to obtain in the construction inspection domain. As a result, formally assessed expert opinions using verbal expressions (e.g., "very high") or interval value [e.g., (0.25, 0.35)] of probabilistic uncertainty may be more appropriate than numerical values. In order to reduce the uncertainty in interval value boundaries, linguistic terms spread over five categories of "1= very low", "2 = low", "3 = moderate", "4 = high", and "5 = very high" integrated with FS were used in this study. Specifically, the occurrence probability of each category was divided into nine interval FS, represented by "impossible to certain", as shown on the fuzzy scale in Figure 4. The k^{th} interval is defined by $P(\theta) \cong (\theta_1, \theta_2, \theta_3)$ such as $P(chance) = (0.375, 0.50, 0.625)$. Figure 4 shows that the most likely value of $P(\theta) =$ is 0.5, while 0.375 and 0.625 are the lower and upper least likely values of $P(\theta)$, respectively. The purpose of the discussion with subject matter experts was to collect information about occurrence probability of interval k. For the "probability interval k," the experts were required to select the interval that reflects the occurrence probability of each category

(Sun et al. 2018; Zhang et al. 2016). The following sections discuss the fuzzification and defuzzification that necessitate for developing the RIB model.

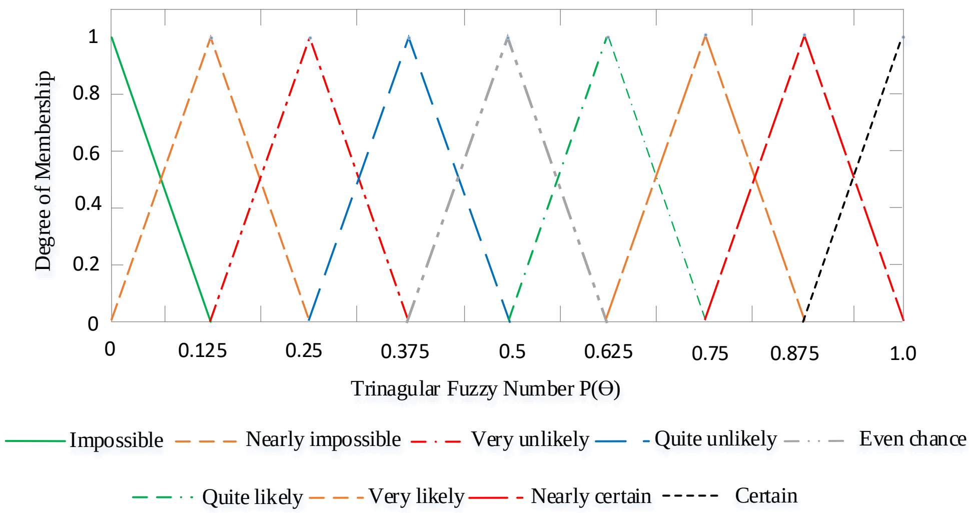

Figure 4. Set of triangular fuzzy numbers for probability of occurrence

Fuzzification

The fuzzification is the process of transforming linguistic responses into numerical fuzzy numbers. Accordingly, the probability intervals selected by each expert for the five aforementioned categories can be fuzzified into triangle fuzzy numbers, *P(θ)*, using Figure 4. To capture the wisdom of experts and differences in the risk attitudes, the assessment of *P(θ)* by experts can be aggregated using Equations (10), then incorporated using Equation (11) to satisfy normalization conditions (Sun et al. 2018; Zhang et al. 2016).

$$P_{ij}^{`} = \sum_{m=1}^{M} p\ (\theta) \qquad (10)$$

$$P_{ij} = \frac{P_{ij}^{`}}{\sum_{j=1}^{Q} \theta_2} \qquad (11)$$

Where, $P_{ij}^{`}$ is the collective probabilities for category *j*; *M* is the number of experts (m= 1, …, *M*); *Q* is the number of categories (*j = 1, ….., Q*); and P_{ij} is the normalized probability for category *j*.

Defuzzification

In the fuzzy-based risk assessment, the calculated results for each risk parameter remained fuzzy triangular numbers, represented by $P(\theta) \cong (\theta_1, \theta_2, \theta_3)$. Therefore, it is necessary to transform fuzzy values into crisp values via a defuzzification process for the purpose of risk analysis. Numerous defuzzification methods are used such as mean of maxima, center of maxima, and center of gravity (Detyniecki and Yager 2000). A study by Detyniecki and Yager (2000) mentioned that some information was lost during the transforming process in the above defuzzification methods. Detyniecki and Yager (2000) presented the α-weighted alternative method that efficiently reduced the information loss. As a result, the α-weighted valuation method was incorporated in this study for defuzzification. The fuzzy triangular number $P(\theta)$ shown in Figure 5 can be represented by crisp values *Val* (θ), then:

$$Val\ (\theta) = \int_0^1 Average\ (\theta_\alpha). d\alpha \quad (12)$$

Where $\theta_\alpha = \{x | F(x) \geq \alpha\}$ is the α-level of $\theta, a = \theta_1, b = \theta_2,$ and $c = \theta_3$. F(*x*) is a function to represent the membership of x in the fuzzy set, F (*x*) ∈ [0, 1]. The generalized formulation is shown in Equations (13) and (14):

$$Val\ (\theta) = \frac{\int_0^1 Average\ (\theta_\alpha).\ F\ (\alpha)\ .\ d\alpha}{\int_0^1 F\ (\alpha)\ .\ d\alpha} \quad (13)$$

$$Average\ (\Theta_{\alpha}) = \frac{d + \mathrm{e}}{2} \qquad (14)$$

Where: d and e represent the lower and upper bound of the α-level and can be calculated by Equations (15) and (16) as follows:

$$d = (b - \mathrm{a}) \times \alpha + a \qquad (15)$$

$$e = c - (c - b) \times \alpha \qquad (16)$$

For $F(\alpha)$= 1, the transformed exact value can be calculated by Equation (17)

$$Val\ (\theta) = \frac{\frac{1}{2}\int_0^1 [(b - \mathrm{a}) \times \alpha + \mathrm{a} + \mathrm{c} - (\mathrm{c} - \mathrm{b}) \times \alpha]}{\int_0^1 d\alpha} = \frac{\mathrm{a} + 2\mathrm{b} + \mathrm{c}}{4} \quad (17)$$

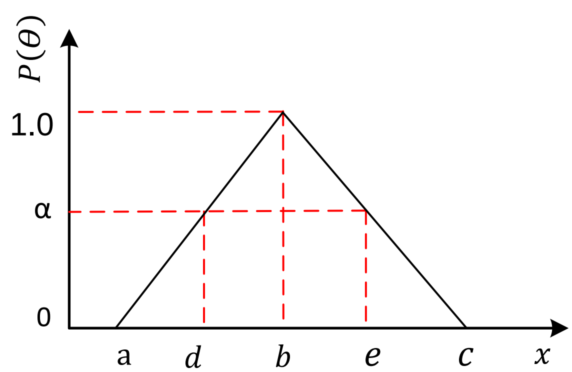

Figure 5. Membership functions of a triangular fuzzy number Θ

To illustrate the calculation process, a case study example was conducted with KDOT. In this case example, the Delphi technique and focus group interviews were employed for seeking subjective perceptions of eight experts from KDOT, including two construction engineers, one project manager, two senior inspectors, two material engineers, and a FHWA representative. The experts have an average experience of 20 years in highway construction inspections. These experts were asked to rate occurrence probability of FR and associated consequences (e.g., C, S, and R) in terms of the five above-mentioned categories (i.e., "1= very low", "2 = low", "3 = moderate", "4 = high", and "5 = very high").

Two rounds of the interviews with the experts were conducted to achieve consensus. The experts assigned probability of occurrence, expressed as linguistic responses, to each of the five categories to represent risk parameter. These responses were fuzzified into triangle fuzzy numbers. Table 3 shows a sample of results for probabilities selected by each expert for the five categories of the safety consequence (S_1) of activity X_1 "Sieve analysis of individual aggregate". For example, Table 3 indicates that the expert 1 assigned probabilities "*Impossible/Quite likely/Quite unlikely/ Nearly Impossible / Impossible*" for consequence S_1 to be in categories "*1. Very low*; *2.Low/3.Moderate/4.High/5.Very high*" respectively. Similarly, the expert 8 assigned the largest probability $P(Quite\ likely) \cong (0.50, 0.625, 0.75)$ to category 2 (Low) and the lowest probability $P(Impossible) \cong (0.00, 0.00, 0.125)$ to category 5 (Very High).

Table 3. Fuzzy probability distributions P (θ) for the safety (S_1) of activity X_1 "Sieve analysis of individual aggregate"

Expert	**Probability**				
	1. Very Low	**2. Low**	**3. Moderate**	**4. High**	**5. Very High**
1	(0.00; 0.00; 0.125)	(0.50; 0.625; 0.75)	(0.25; 0.375; 0.50)	(0.0; 0.125; 0.25)	(0.0; 0.0; 0.125)
2	(0.00; 0.125; 0.250)	(0.50; 0.625; 0.75)	(0.125; 0.25; 0.375)	(0.0; 0.125; 0.25)	(0.0; 0.0; 0.125)
3	(0.00; 0.125; 0.250)	(0.25; 0.375; 0.50)	(0.125; 0.25; 0.375)	(0.0; 0.125; 0.25)	(0.0; 0.0; 0.125)
4	(0.00; 0.125; 0.250)	(0.50; 0.625; 0.75)	(0.125; 0.25; 0.375)	(0.0; 0.125; 0.25)	(0.0; 0.0; 0.125)
5	(0.125; 0.25; 0.375)	(0.50; 0.625; 0.75)	(0.125; 0.25; 0.375)	(0.0; 0.00; 0.125)	(0.0; 0.0; 0.125)
6	(0.00; 0.125; 0.250)	(0.50; 0.625; 0.75)	(0.125; 0.25; 0.375)	(0.0; 0.00; 0.125)	(0.0; 0.0; 0.125)
7	(0.00; 0.125; 0.250)	(0.75; 0.875; 1.00)	(0.125; 0.25; 0.375)	(0.0; 0.125; 0.25)	(0.0; 0.0; 0.125)
8	(0.00; 0.125; 0.250)	(0.50; 0.625; 0.75)	(0.125; 0.25; 0.375)	(0.0; 0.125; 0.25)	(0.0; 0.0; 0.125)
Consensus	(75%)	(75%)	(87.5%)	(75%)	(100%)

The assessment of *P(θ)* by experts have been incorporated in Equations (10) and (11) to satisfy aggregation and normalization conditions. Table 4 shows the resulting normalized probabilities of C, S, R, FR for activity X_1 "Sieve analysis of individual aggregate."

Table 4. Normalized probabilities of activity X_1 "Sieve analysis of individual aggregate" parameters

Parameter	Category				
	1. Very Low	**2. Low**	**3. Moderate**	**4. High**	**5. Very High**
C_1	(0.000; 0.071; 0.142)	(0.285; 0.375; 0.428)	(0.428; 0.500; 0.571)	(0.00; 0.0714; 0.142)	(0.00; 0.00; 0.071)
S_1	(0.013; 0.109; 0.219)	(0.438; 0.548; 0.657)	(0.122; 0.232; 0.342)	(0.00; 0.1096; 0.191)	(0.00; 0.00; 0.109)
R_1	(0.000; 0.083; 0.166)	(0.333; 0.416; 0.500)	(0.333; 0.416; 0.500)	(0.000; 0.083; 0.166)	(0.00; 0.00; 0.083)
FR_1	(0.400; 0.466; 0.533)	(0.200; 0.266; 0.333)	(0.066; 0.133; 0.200)	(0.000; 0.066; 0.133)	(0.00; 0.06; 0.133)

For transforming fuzzy values, such as shown in Table 4, into crisp values via defuzzification, Equation (18) has been applied. For example, the resulting crisp *Val (Θ)* for activity X_1 "Sieve analysis of individual aggregate" is presented in Table 5. Probability of S_1 to be very low is "0.122"; low is 0.547; moderate is "0.232"; high "0.102"; and very high is "0.027". This result indicates that the consequence of X_1 failure on safety is most likely to be low, similarly for C_1, R_1, and FR_1 (Table 5).

Table 5. Crisp value probabilities for the parameters of activity *X1* "Sieve analysis of individual aggregate"

Parameter	Category				
	1. Very Low	**2. Low**	**3. Moderate**	**4. High**	**5. Very High**
C_1	0.071	0.365	0.499	0.071	0.017

S_1	0.122	0.547	0.232	0.102	0.027
R_1	0.083	0.416	0.416	0.083	0.020
FR_1	0.466	0.266	0.133	0.066	0.066

Constructing BBN Model

There are two typical methods for constructing BBN. The first method involves learning BBN structure and parameters on the basis of historical data. This method often requires large amounts of training data. The second method, which is more practical in most engineering areas, is constructed based on the knowledge and experience (Leu and Chang 2013; Nguyen et al. 2016). The second method was selected in this study. The network structure, model parameters, and CPTs were determined from literature review [e.g., incorporating Equation (9)] and expert opinions. Figure 6 (a) shows causal relationships of the key model parameters *Si, Ci*, and *Ri* and CF_i from the risk impact assessment (Eq. 9). To express this relationship, *Si*, *Ci*, and *Ri* were assigned as root nodes while CF_i was assigned as a leaf node. The causality between root and leaf nodes is expressed in CPT matrices. For example, in CPT 1, three levels of risk (i.e., categories) were assigned to CF_i, including "1 = low", "2 = moderate", and "3 = high". Specifically, when "*Ci* = 1.very low", "*Si* =1.very low", and "*Ri* = 1.very low", the resulting CF_i conditional probabilities are "$P(CF_{1.low})$ = 1.0", "$P(CF_{2.moderate})$ = 0.0", and "$P(CF_{3.high})$ = 0.0". Figure 6 (b) shows the causal relationship constructed between *CFi*, and *FRi* and *Xi* (i.e., RI for activity i) and represented by the CPT 2 matrix. Similarly, Figure 6 (c) shows the relationship between QA activities (X_1 through X_n) and construction component Y_k (i.e., aggregate and mixture). The causal relationship is represented by the CPT 3 matrix. In Figure 6 (d), the influential relationship was constructed between construction components of aggregate and mixture (Y_1, and Y_2) and the end product HMA. Under CPT 4, HMA quality risk has been categorized into three levels: "1 = low" when there is a minor effect on highway performance; "2 = moderate" when there is a considerable damage affecting highway performance and requiring repair works; and "3 = high" where there is a severe consequence of damage such as life loss and substantial economic loss. For instance, when $Y_{1,}$ and Y_2 are at the highest levels, "$Y_{1,}$ = 3.high" and "Y_2 = 3.high", the resulting HMA conditional probabilities are "P(HMA $_{low}$) = 0.0", "P(HMA $_{moderate}$) = 0.0", and "P(HMA $_{high}$) = 1.0".

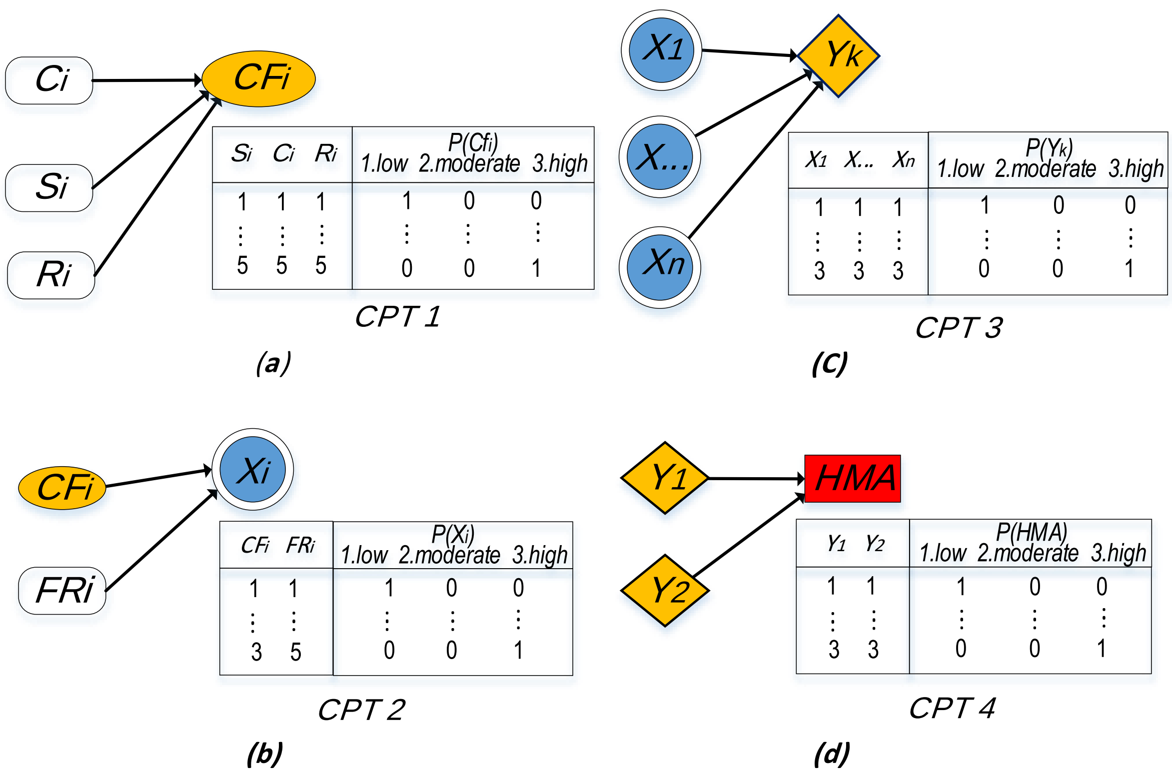

Figure 6. Model causal relationships and conditional probability tables

Figure 7 shows a complete BBN model for predicting and reasoning of the risk level of HMA quality based on QA inspections. The model includes 87 node variables representing risk parameters of 14 QA activities, aggregate and mixture components, and HMA. The following sections discuss the inference of HMA quality risk levels, model verification and validation.

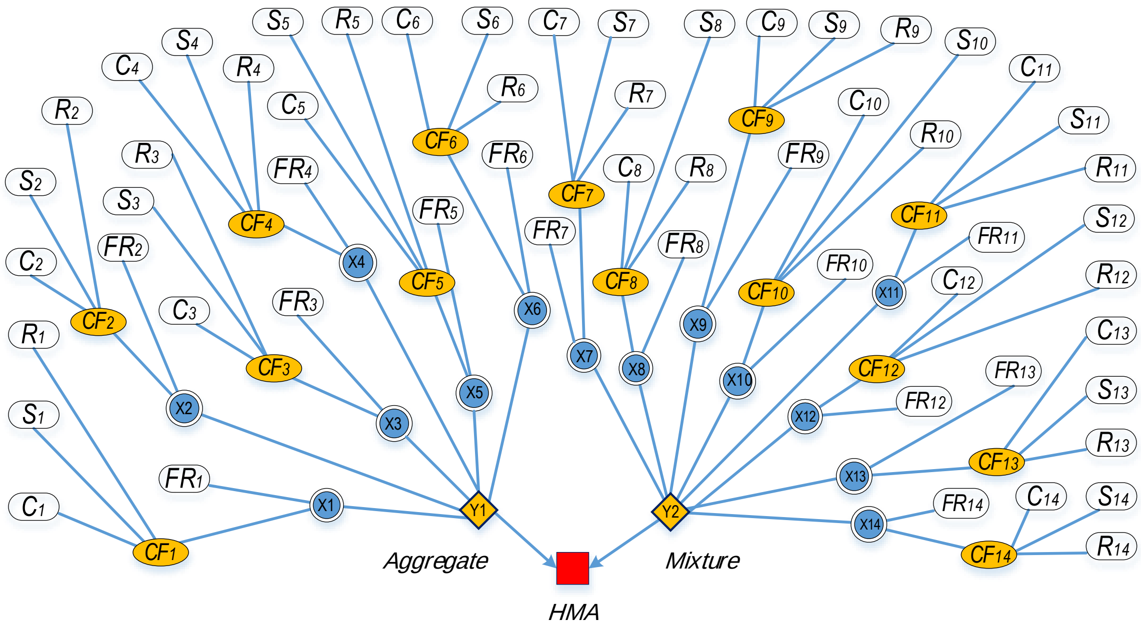

Figure 7. A BBN model for estimating the HMA quality risk levels

Inference of Quality Risk Level

Using the BBN model presented in Figure 7, the risk level of HMA quality shortfall can be evaluated based on input from all root nodes (i.e., *C*, *S*, *R*, and *FR*), which is considered as evidence of the inspection process. To illustrate the process, the calculation of probability of CF_1, X_1, Y_1, and HMA in the case study example is presented below. The same calculation process was conducted to determine the probability of other model parameters.

<u>For $\mathrm{CF_1}$:</u>

$$\mathrm{P}\ (CF_1\ =\ cf_{1.low}) = \sum_{C,S,R} \mathrm{P}(\mathrm{C_1};\mathrm{S_1};\mathrm{R_1};\mathrm{CF_1}\ =\ cf_{1.low})$$

Using the conditional independence relationships, the following can be obtained:

$$\mathrm{P}\ (\mathrm{C_1};\mathrm{S_1};\mathrm{R_1};\mathrm{CF_1}) \cong\ P(\mathrm{CF}|\mathrm{C_1};\mathrm{S_1};\mathrm{R_1})\ .\ P(\mathrm{C_1})\ .\ P(\mathrm{S_1})\ .\ P(\mathrm{R_1})$$

Hence;

$$\mathrm{P}\ (\mathrm{CF}_1\ =\ cf_{1.low}) = \sum_{C,S,R} \mathrm{P}(\mathrm{CF}_1 = cf_{1.low}\ |\mathrm{C}_1; \mathrm{S}_1; \mathrm{R}_1)\ P(\mathrm{C}_1)\ P\ (\mathrm{S}_1)\ P(\mathrm{R}_1)$$

$\cong (0.1716)$

Similarly,

$\mathrm{P}\ (\mathrm{CF}_1\ =\ cf_{2.moderate}) = (0.6207); and\ \mathrm{P}\ \left(\mathrm{CF}_1\ =\ cf_{3.high}\right) \cong (0.2077)$

<u>For X_1:</u>

$$\mathrm{P}\ (\mathrm{X}_1\ =\ x_{1.low}) = \sum_{CF,FR} \mathrm{P}(\mathrm{CF}_1; \mathrm{FR}_1; \mathrm{X}_1\ =\ x_{1.low})$$

Using the conditional independence relationships, the following can be obtained:

$\mathrm{P}\ (\mathrm{CF}_1; \mathrm{FR}_1; \mathrm{X}_1) = \ \mathrm{P}(\mathrm{X}_1|\mathrm{CF}_1; \mathrm{FR}_1)\ .\ \mathrm{P}(\mathrm{CF}_1)\ . \mathrm{P}(\mathrm{FR}_1)$

Hence;

$$\mathrm{P}\ (\mathrm{X}_1 =\ x_{1.low}) = \sum_{CF,FR} \mathrm{P}(\mathrm{X}_1\ =\ x_{1.low}|\mathrm{CF}_1; \mathrm{FR}_1)$$

$$.\ \sum_{C,S,R} \mathrm{P}(\mathrm{CF}_1|\mathrm{C}_1; \mathrm{S}_1; \mathrm{R}_1)\ \mathrm{P}(\mathrm{C}_1)\ \mathrm{P}\ (\mathrm{S}_1)\ \mathrm{P}(\mathrm{R}_1)$$

$.\ \ \mathrm{P}(\mathrm{FR}_1) = (0.3265)$

Similarly,

$\mathrm{P}\ (\mathrm{X}_1\ =\ x_{2.moderate}) = (0.4412); and\ \mathrm{P}\ \left(\mathrm{X}_1 =\ x_{3.high}\right) = (0.2323)$

<u>For Y_1:</u>

$$\mathrm{P}\ (\mathrm{Y}_1\ =\ y_{1.low}) = \sum_{X1:X6} \mathrm{P}(\mathrm{X}_1; \mathrm{X}_2; \mathrm{X}_3; \mathrm{X}_4; \mathrm{X}_5; \mathrm{X}_6; \mathrm{Y}_1\ =\ y_{1.low})$$

Using the conditional independence relationships, the following can be obtained:

$\mathrm{P}\ (\mathrm{X}_1; \mathrm{X}_2; \mathrm{X}_3; \mathrm{X}_4; \mathrm{X}_5; \mathrm{X}_6; \mathrm{Y}_1) = \ \mathrm{P}(\mathrm{Y}_1|\mathrm{X}_1; \mathrm{X}_2; \mathrm{X}_3; \mathrm{X}_4; \mathrm{X}_5; \mathrm{X}_6)\ .\ \mathrm{P}(\mathrm{X}_1)\ .\ \mathrm{P}(\mathrm{X}_2)$

$. \mathrm{P}(\mathrm{X}_3) \, . \, \mathrm{P}(\mathrm{X}_4) \, . \, \mathrm{P}(\mathrm{X}_5) \, . \, \mathrm{P}(\mathrm{X}_6)$

Hence;

$$\mathrm{P}\,(\mathrm{Y}_1 = y_{1.low}) = \sum_{X1:X6} \mathrm{P}(\mathrm{Y}_1 = y_{1.low} | \mathrm{X}_1; \mathrm{X}_2; \mathrm{X}_3; \mathrm{X}_4; \mathrm{X}_5; \mathrm{X}_6) \, .$$

$\sum_{\mathrm{CF1,FR1}} \mathrm{P}(\mathrm{X}_1|\mathrm{CF}_1; \mathrm{FR}_1)\ \mathrm{P}(\mathrm{CF}_1)\mathrm{P}\ (\mathrm{FR}_1) \ . \ \sum_{\mathrm{CF2,FR2}} \mathrm{P}(\mathrm{X}_2|\mathrm{CF}_2; \mathrm{FR}_2)\ \mathrm{P}(\mathrm{CF}_2)\ \mathrm{P}(\mathrm{FR}_2)$

$. \sum_{\mathrm{CF3,FR3}} \mathrm{P}(\mathrm{X}_3|\mathrm{CF}_3; \mathrm{FR}_3)\ \mathrm{P}(\mathrm{CF}_3)\mathrm{P}(\mathrm{FR}_3) \ . \ \sum_{\mathrm{CF4,FR4}} \mathrm{P}(\mathrm{X}_4|\mathrm{CF}_4; \mathrm{FR}_4)\ \mathrm{P}(\mathrm{CF}_4)\ \mathrm{P}\ (\mathrm{FR}_4)$

$. \sum_{\mathrm{CF5,FR5}} \mathrm{P}(\mathrm{X}_5|\mathrm{CF}_5; \mathrm{FR}_5)\ \mathrm{P}(\mathrm{CF}_5)\mathrm{P}(\mathrm{FR}_5) \ . \ \sum_{\mathrm{CF6,FR6}} \mathrm{P}(\mathrm{X}_6|\mathrm{CF}_6; \mathrm{FR}_6)\ \mathrm{P}(\mathrm{CF}_6)\ \mathrm{P}(\mathrm{FR}_6)$

$= (0.1943)$

Similarly,

$\mathrm{P}\,(\mathrm{Y}_1 = y_{2.moderate}) = (0.6152); and\ \mathrm{P}\,\left(\mathrm{Y}_1 = y_{3.high}\right) \cong (0.1905)$

<u>For HMA:</u>

$$\mathrm{P}\,(\mathrm{HMA} = hma_{1.low}) = \sum_{Y1,Y2} \mathrm{P}(\mathrm{Y}_1; \mathrm{Y}_1; \mathrm{HMA} = hma_{1.low})$$

Using the conditional independence relationships, the following can be obtained:

$\mathrm{P}\,(\mathrm{Y}_1; \mathrm{Y}_2; \mathrm{HMA}) = P(\mathrm{HMA}|\mathrm{Y}_1; \mathrm{Y}_2) \, . P(\mathrm{Y}_1) \, . P(\mathrm{Y}_2)$

Hence;

$$\mathrm{P}\,(\mathrm{HMA} = hma_{1.low}) = \sum_{Y1,Y2} \mathrm{P}(\mathrm{HMA} = hma_{1.low} | \mathrm{Y}_1; \mathrm{Y}_2)$$

$$. \sum_{X1:,X6} \mathrm{P}(\mathrm{Y}_1|\mathrm{X}_1; \mathrm{X}_2; \mathrm{X}_3; \mathrm{X}_4; \mathrm{X}_5; \mathrm{X}_6)\ \mathrm{P}(\mathrm{X}_1)\ \mathrm{P}(\mathrm{X}_2)\ \mathrm{P}(\mathrm{X}_3)\ \mathrm{P}(\mathrm{X}_4)\ \mathrm{P}(\mathrm{X}_5)\ \mathrm{P}(\mathrm{X}_6)$$

$$. \sum_{X7:X14} \mathrm{P}(\mathrm{Y}_2|\mathrm{X}_7; \mathrm{X}_8; \mathrm{X}_9; \mathrm{X}_{10}; \mathrm{X}_{11}; \mathrm{X}_{12}\ ; \mathrm{X}_{13}; \mathrm{X}_{14})\ \mathrm{P}(\mathrm{X}_7)\ \mathrm{P}\ (\mathrm{X}_8)\ \mathrm{P}(\mathrm{X}_9)$$

$\mathrm{P}(\mathrm{X}_{10})\mathrm{P}(\mathrm{X}_{11})\mathrm{P}(\mathrm{X}_{12})\mathrm{P}(\mathrm{X}_{13})\mathrm{P}(\mathrm{X}_{14}) = 0.1858$

Similarly,

$\mathrm{P}\,(\mathrm{HMA} = hma_{2.moderate}) = 0.4016; and\ \mathrm{P}\,\left(\mathrm{HMA} = hma_{3.high}\right) = 0.4126$

To reduce computational complexity, the authors developed a customized BBN module based on UnBBayes software. UnBBayes is an open source for modeling, learning and reasoning upon probabilistic networks (Matsumoto et al. 2011).

Model validation

The last step in developing a model is its validation. The key to model validation is to compare the model output with observation. Validation of the proposed BBN included (1) data verification, (2) model structure and parameter validation, (3) computerized module verification, and (4) model application. Sargent (2013) asserted that data verification is essential for model integrity. In this study, the data used to build the model were from a list of QA activities. This list was retrieved from construction inspection reports and documents. Further, the list was verified and refined by the collective judgment of experts through a national survey and KDOT experts. The model parameters (e.g., variables of C, S, R, FR and CF) and causal relationships were identified in previous research and reviewed by experts. The output of computerized BBN module (i.e., UnBBayes) was compared to the mathematical paper-based calculation above. In this research, the computer simulation BBN module was simplified by including only six nodes (i.e., variables). The result from this simplification was then compared with the manual calculation. Consequently, the verification procedure confirmed that the results from the risk-based model are practically the same (less than 3% compared with the manual calculation). The model also was tested with a case example from KDOT to validate its output and applicability. The result produced by the model for the current risk level of HMA was compared with the current KDOT inspections by interviews with experienced representatives from QA team members who were most knowledgeable of and fully responsible for the KDOT QA inspections program. Their recollection was that the resulting RI levels conform with the available historical records and field observations.

SCENARIO-BASED RBI MODEL APPLICATIONS

This section discusses the result and model application for the KDOT case study in detail. As presented previously, for the current KDOT construction practices, the inference of HMA quality risk level/category revealed that probabilities of risk for the three categories (i.e., low, moderate, and high) are P(HMA = $hma_{1.low}$) = 0.1858; P(HMA = $hma_{2.moderate}$) = 0.4016; and P(HMA = $hma_{3.high}$) = 0.4126. This result indicates that the current risk level of HMA quality is relatively moderate-to-high. Additionally, the model output also provides the probability of the 14 activities, expressed as X_i, associated with the high, moderate, and low risk levels of HMA quality (Figure 8). One can observe from Figure 8 that the nine activities including X_2, X_6, X_7, X_8, X_{10}, X_{11}, X_{12}, X_{13}, and X_{14} have the largest contribution to the high-risk level of HMA quality. The probability of the activities X_7, X_{10}, and X_{13} for the high-risk level of HMA is larger than 60%. Similarly, the four activities including X_1, X_3, X_4, X_5, X_9 have the largest contribution to the moderate-risk level of HMA quality. Figure 8 also indicates that the activities X_2 and X_4 have a similar impact on the high-risk or moderate-risk level of HMA with the probability approximately of 40%. None of 14 inspection activities have dominant for the low-risk level of HMA quality. All these results were validated through a comparison with the current KDOT field observations as discussed above in model validation section.

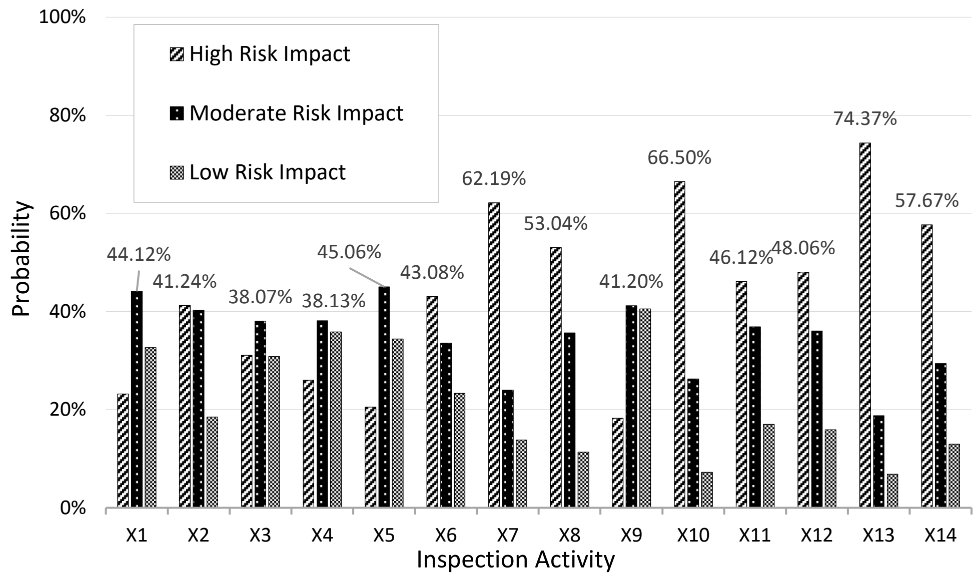

Figure 8. Risk impact of inspection activities for HMA quality

It is important to understand how each inspection activity affects HMA quality. Particularly, in the case of limited inspection resources, QA inspectors can focus on the most critical activities. To better understand how these 14 activities (X_i) influence HMA quality, three hypothetical scenarios were examined. The first scenario emphasizes on the high risk level by setting P(HMA = $hma_{1.low}$) = 0.0; P(HMA = $hma_{2.moderate}$) = 0.0; and P(HMA = $hma_{3.high}$) = 1.0. The second scenario emphasizes on the moderate risk level by setting P(HMA = $hma_{1.low}$) = 0.0; P(HMA = $hma_{2.moderate}$) = 1.0; and P(HMA = $hma_{3.high}$) = 0.0. The third scenario emphasizes on the low risk level by setting P(HMA = $hma_{1.low}$) = 1.0; P(HMA = $hma_{2.moderate}$) = 0.0; and P(HMA = $hma_{3.high}$) = 0.0. The following section discusses these scenarios in detail.

For the first scenario, using Bayesian rule (Eq.8), the probabilities of activity X_i were calculated. For example, the probabilities of the activity X_1 "Sieve analysis of individual aggregate" are calculated below.

$$\mathrm{P}\ (\mathrm{X}_1 = x_{1.low} | \mathrm{HMA} = hma_{3.high}) = \frac{\mathrm{P}\ (\mathrm{X}_1 = x_{1.low}; HMA = hma_{3.high})}{\mathrm{P}\ (\mathrm{HMA} = hma_{3.high})}$$

Where:

$$\mathrm{P}\left(\mathrm{X}_1 = x_{1.low}; \mathrm{HMA} = hma_{3.high}\right)$$

$$= \sum_{Xi,Yk} \mathrm{P}(hma_3|\mathrm{Y}_1;\mathrm{Y}_2)\,.\,\mathrm{P}(\mathrm{Y}_1|x_{1.low};\mathrm{X}_2;\mathrm{X}_3;\mathrm{X}_4;\mathrm{X}_5;\mathrm{X}_6)\,.\,\mathrm{P}(\mathrm{Y}_2|\mathrm{X}_7;\mathrm{X}_8;\mathrm{X}_9;\mathrm{X}_{10};\mathrm{X}_{11};\mathrm{X}_{12};\mathrm{X}_{13};\mathrm{X}_{14})$$

$$.\,\mathrm{P}(\mathrm{X}_1 = x_{1.low})\,.\,\mathrm{P}(\mathrm{X}_2)\,.\,P(\mathrm{X}_3)\,.\,\mathrm{P}(\mathrm{X}_4)\,.\,\mathrm{P}(\mathrm{X}_5)\,.\,P(\mathrm{X}_6)\,.\,\mathrm{P}(\mathrm{X}_7)\,.\,\mathrm{P}(\mathrm{X}_8)\,.\,P(\mathrm{X}_9)\,.\,\mathrm{P}(\mathrm{X}_{10})$$

$$.\,\mathrm{P}(\mathrm{X}_{11})\,.\,P(\mathrm{X}_{12})\,.\,\mathrm{P}(\mathrm{X}_{13})\,.\,\mathrm{P}(\mathrm{X}_{14})$$

Hence,

$$\mathrm{P}\left(\mathrm{X}_1 = x_{1.low} \middle| \mathrm{HMA} = xhma_{3.high}\right) = 0.2913$$

Similarly;

$\mathrm{P}\left(\mathrm{X}_1 = x_{2.moderate} \middle| \mathrm{HMA} = hma_{3.high}\right) = 0.4563$, and

$$\mathrm{P}\left(\mathrm{X}_1 = x_{3.high} \middle| \mathrm{HMA} = hma_{3.high}\right) = 0.2523$$

This result indicates that given the high-risk level of HMA, the probabilities of the activity X_1 "Sieve analysis of individual aggregate" at the low, moderate, and high levels are 29.13%, 45.63%, and 25.23%, respectively. The result means that the risk impact of the activity X_1 on the high-risk level of HMA performance is likely to be moderate. A similar calculation process was conducted for the other 13 inspection activities. Table 6 summarizes the result of analysis for all 14 activities. The probability of low, moderate, and high contribution of each activity to the high-risk level of HMA is presented. Nine activities, including X_2, X_6, X_7, X_8, X_{10}, X_{11}, X_{12}, X_{13} and X_{14}, have a high level of risk impact on HMA quality. The other five activity, including X_1, X_3, X_4, X_5 and X_9, have a moderate level of risk impact on HMA quality (Table 6). It is noted that six activities X_7, X_8, X_{10}, X_{11}, X_{13}, and X_{14} are the top contributing factors to the high-risk level of HMA with the probability larger than 50%.

A similar calculation process was conducted for the second and third scenarios. For the second scenario, with P(HMA = $hma_{1.low}$) = 0.0; P(HMA = $hma_{2.moderate}$) = 1.0; and P(HMA = $hma_{3.high}$) = 0.0, using Equation (8), the probabilities of 14 activities were calculated as follows:

$\mathrm{P}(\mathrm{X_i} = x_{1.low} | \mathrm{HMA} = hma_{2.moderate})$;

$\mathrm{P}(\mathrm{X_i} = x_{2.moderate} | \mathrm{HMA} = hma_{2.moderate})$; and

$\mathrm{P}\left(\mathrm{X_i} = x_{3.high} \middle| \mathrm{HMA} = hma_{2.moderate}\right)$.

Table 6 summarizes the result of calculations for these 14 activities. Eight activities, including X_6, X_7, X_8, X_{10}, X_{11}, X_{12}, X_{13} and X_{14}, have a high level of risk impact on HMA quality. Four activities, including X_1, X_2, X_3, and X_5, have a moderate level of risk impact on HMA quality. Two activities, including X_4 and X_9, have a low level of risk impact on HMA quality (Table 6). Four activities having the highest impact on the moderate-risk level of HMA with the probability larger than 50% are X_7, X_{10}, X_{13}, and X_{14}.

For the third scenario, with P(HMA = $hma_{1.low}$) = 1.0; P(HMA = $hma_{2.moderate}$) = 0.0; and P(HMA = $hma_{3.high}$) = 0.0., using Equation (8), the following probabilities were calculated:

$\mathrm{P}\ (\mathrm{X_i} = x_{1.low} | \mathrm{HMA} = hma_{1.low})$;

$\mathrm{P}\ (\mathrm{X_i} = x_{2.moderate} | \mathrm{HMA} = hma_{1.low})$; and

$\mathrm{P}\ \left(\mathrm{X_i} = x_{3.high} \middle| \mathrm{HMA} = hma_{1.low}\right)$.

Table 6 summarizes the result of calculations for these 14 activities. Seven activities, including X_7, X_8, X_{10}, X_{11}, X_{12}, X_{13} and X_{14}, have a high level of risk impact on HMA quality. Four activities, including X_1, X_2, X_5, and X_6, have a moderate level of risk impact on HMA quality. Three activities, including X_3, X_4 and X_9, have a low level of risk impact on HMA quality (Table 6). Five activities having the highest impact on the low-risk level of HMA with the probability larger than 50% are X_7, X_8, X_{10}, X_{13}, and X_{14}.

In summary, Table 6 indicates that mixture and workmanship-related activities (Y_2) are more dominant than aggregate-related activities (Y_1) due to the higher risk impact and higher rate of inspection failure of the workmanship. As a result, low quality of construction and mixing work such as compaction of HMA layer and asphalt content (i.e., X_7, X_{10}, or X_{13}) should be paid more attention during the inspection process. Further, these activities should be given the highest priority for inspection when there is a shortage of inspection staff. It is important to note that Table 6 summarizes the results of 14 HMA core inspection activities associated with three hypothetical scenarios. In practice, the probabilities of these 14 inspection activities can be calculated from any combination of these three risk scenarios. For example, state inspectors may have a desire to inspect the HMA construction project with 70%, 20%, and 10% of the high, moderate, and low risk level, respectively. Using the similar approach with P(HMA = $hma_{1.low}$) = 0.1; P(HMA = $hma_{2.moderate}$) = 0.2; and P(HMA = $hma_{3.high}$) = 0.7, the probability of each inspection activity can be calculated then the inspector can determine which inspection activities have the largest impact on the HMA quality.

Table 6. Risk impact results of three hypothetical scenarios

Activity	**High risk level of HMA (Scenario 1)**				**Moderate risk level of HMA (Scenario 2)**				**Low risk level of HMA (Scenario 3)**			
	Low (%)	Moderate (%)	High (%)	RI*	Low (%)	Moderate (%)	High (%)	RI*	Low (%)	Moderate (%)	High (%)	RI*
X_1	29.13	45.63	25.23	M	34.72	43.19	22.09	M	35.97	42.76	21.27	M
X_2	15.05	40.53	44.41	H	19.57	40.63	39.79	M	23.86	38.81	37.33	M
X_3	25.37	39.71	34.92	M	33.57	37.50	28.93	M	37.01	35.67	27.32	L
X_4	30.24	40.37	29.39	M	39.26	36.84	23.90	L	41.02	35.94	23.04	L
X_5	32.70	45.37	21.92	M	35.30	44.93	19.77	M	36.18	44.65	19.17	M
X_6	18.94	34.09	46.34	H	24.41	34.02	41.57	H	30.92	37.72	31.36	M
X_7	08.35	19.3	72.35	H	16.19	28.59	55.22	H	20.97	24.37	54.65	H
X_8	07.02	33.69	59.30	H	14.58	37.45	47.97	H	13.78	36.11	50.11	H
X_9	35.62	42.87	21.51	M	44.69	39.81	15.50	L	42.67	40.50	16.82	L

X_{10}	04.20	20.84	74.96	H	7.40	31.53	61.07	H	13.49	27.03	59.48	H
X_{11}	11.81	35.71	52.48	H	21.26	37.91	40.83	H	19.34	37.25	43.41	H
X_{12}	15.91	36.03	48.06	H	15.92	36.06	48.02	H	15.93	36.01	48.02	H
X_{13}	03.99	16.92	79.09	H	6.96	20.77	72.27	H	13.07	18.50	68.43	H
X_{14}	10.57	30.18	59.25	H	12.01	29.69	58.29	H	20.31	26.89	52.80	H

(*) RI = Risk Impact; H = High; M = Moderate; and L = Low.

DISCUSSION

The failure rate of HMA tests and inspections and their consequences is a direct indicator of construction work quality and the project performance. A higher failure rate of HMA activities often indicates low quality of material and workmanship and high risk of quality shortfall. In this study, RBI was developed to evaluate the risk impact of each inspection activity, expressed as X_i, in terms of the failure rate and consequences of failure. Further, the cause-effect relationships between the risk of HMA quality shortfall and QA inspection activities have been assessed by using FS and probabilistic BBN models. Because quantitative data on past performance are typically incomplete or inaccurate (Andersen et al. 2001), FS has been deployed to transform qualitative data collected directly from subjective matter experts into quantitative. FS avoided the complex process in dealing with vagueness in expert opinions and linguistic nature of the collected data (Zhang et al. 2016). Conforming with previous studies, BBN has provided an indispensable means to facilitate probabilistic risk analysis by taking uncertainty in consideration during the assessment phase (Zhang et al. 2016; Ren et al. 2009; Eleye et al. 2008). BBN is a powerful method to describe the causal relationships between the model variables.

The proposed model is able to infer risk levels of HMA quality shortfall and diagnose the causes of the current risk level. This diagnosis was performed by determining 14 QA inspection activities and their associated construction processes that contribute to the risk of HMA quality shortfall. For example, the output of Scenario 1 (a high-risk level of HMA) revealed that nine activities out of 14, presented above, have a high level of risk impact on HMA quality (Table 6). The model has also provided two risk mitigation scenarios (i.e., Scenarios 2 and 3). In Scenario 2, the high-risk level of HMA has been alleviated to a moderate-risk level by improving three HMA inspection activities (X_2, X_4, and X_9) out of the 14 activities (Table 6). Specifically, the risk impact of activity X_2 is downgraded from "high" to "low"; X_4 from "moderate" to "low"; and X_9 from "moderate" to "low." Similarly, in Scenario 3, the high-risk level of HMA has been decreased to a low-risk level by improving five HMA inspection activities (X_2, X_3, X_4, X_6, and X_9) out of the 14 activities (Table 6).

The proposed model can be used by state DOTs as a decision tool to perform real-time Bayesian inference by updating probabilities in light of actual observations of inspection results. Further, the probabilities of the 14 core HMA inspection activities can be calculated for any combination of three levels of risk (high, moderate, and low) from which an inspector can determine which inspection activities have the largest impact on the HMA quality. Additionally, incorporating S, R, and C in assessing the risk of quality shortfall at an early stage during construction may help state DOTs predict HMA performance and defects during design service life.

CONCLUSIONS

This study aimed at identifying a list of critical inspection activities for HMA construction projects. State DOTs could rely on this list when facing with a shortage of inspection resources such as funding and staff. The RBI model for evaluating risk levels of HMA quality was developed based on 14 critical inspection activities, FS, and BBN. The model development process included identifying model parameters and interdependencies. The parameters involved 87 nodes representing risk parameters of the 14 inspection activities for HMA classified into the aggregate and mixture components. Risk parameters of each inspection activity (X_i) are FR and CF including C, S, and R. The interdependent relationships between the nodes were represented by CPTs. These relationships were constructed based on the assumption that risk of each inspection activity (X_i) increases or decrease when FR, CF (e.g., C, S, and R) increase or decrease, respectively. A similar assumption was used to construct the relationship between X_i and HMA risk levels.

The findings of this study successfully addressed the need for a RBI model to help state DOTs evaluate and mitigate a quality-related risk level of HMA early in the construction phase. The model developed in this study has the potential to infer the HMA risk level based on the interdependence between HMA quality, activity X_i, and inspection results. For instance, in the KDOT case example, when nine activities showed high risk impact and five activities were moderate risk impact, the resulting HMA risk level was moderate-to-high to quality shortfall. The model also has the capability to examine causes of the HMA high risk level and determine related activities depending on the relationship between X_i and HMA. In the KDOT case example, when the HMA risk level was set to high (Scenario 1), the result showed that nine activities contributed to this high risk of HMA. The model provides scenarios to alleviate HMA risk to moderate and low levels. In KDOT example, by setting the HMA risk level to moderate (Scenario 2), the result showed that KDOT needs to improve construction and workmanship by focusing on three activities. Similarly, by setting HMA risk level to low (Scenario 3), the result showed that KDOT needs to improve construction and workmanship by focusing on five activities. As a result, the proposed model may serve as a tool for assessing the risk level of HMA quality shortfall and provides risk mitigation scenarios when the risk level is high. The model can be applied to highway construction inspections through updating probabilities based on inspection results. QA decision makers in transportation agencies may benefit from the model by taking an early action based on the inferred risk levels of HMA.

This study contributes to the body-of-knowledge by identifying the critical inspection and testing activities in HMA construction projects, capturing key knowledge of RBI and how risks impact HMA inspection activities, and handling uncertainty of knowledge associated with qualitative data by incorporating FS and probabilistic BBN models. The study also provides a practical hands-on decision tool for highway agencies to perform real-time Bayesian inference by updating probabilities in light of inspection results. Highway agencies such as state DOTs can explore cause-effect relationships between HMA quality levels and QA inspections and determine the most likely potential causes of HMA quality shortfall.

The limitations of this study include a relatively small sample size of eight experts in an illustrative case study. Additionally, the developed model was tested with only one case study. The study revealed several points that warrant future research. For example, the research approach and model can be applied to other types of roadway construction projects such as bridge inspection and concrete pavement. The authors recommend considering different inspection activities for each of these types of projects.

DATA AVAILABILITY STATEMENT

Data generated or analyzed during the study are available from the corresponding author by request. Information about the Journal's data sharing policy can be found here: http://ascelibrary.org/doi/10.1061/%28ASCE%29CO.1943-7862.0001263

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CHAPTER 4

Risk Mitigation Strategies to Highway Construction inspections

Research Phase III Dissertation – Journal Paper 3

Risk Mitigation Strategies to Highway Construction inspections

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ABSTRACT

Transportation agencies have increased the number and scope of highway construction projects with a simultaneous decrease in the resources of funding and inspectors. The reduced number of inspectors mirrors the risk of accepting inferior materials and workmanship and exposes construction projects to a quality shortfall. To offset this trend, this study proposes a framework including four strategies to mitigate inspection risks and minimize the need for inspectors. The four strategies are prioritizing inspection items based on risk impact, optimizing the frequency of inspection, optimizing inspection documentation effort, and allocating inspectors to items based on experience. Nine construction components, including 71 inspection activities, were retrieved from construction and quality assurance documents using natural language processing and manual desktop screening. Focus group discussions with highway inspection experts were conducted to evaluate the inspection items in terms of the four strategies. Correlation analysis was conducted to examine the relationship between item risk level and inspection strategies. Results show that the risk level of inspection activities is significantly associated with inspection frequency, documentation, and inspector experience. Thus, when the risk level of inspection activity increases, inspection frequency should increase with allocating experienced inspectors to that activity to mitigate the risk of a quality shortfall. This study contributes to the body of knowledge by examining the relationships between inspection risk, inspection frequency, documentation, and

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inspector experience. This study contributes to the construction industry by providing guidelines for highway agencies to develop risk mitigation strategies and improve inspection practices in their construction projects.

INTRODUCTION

The quality and durability of construction projects have been a major concern to highway agencies and contractors. To ensure the quality of construction work, state departments of transportation (DOTs) allocate resources to inspect their construction project through the quality assurance (QA) acceptance process. During the last two decades, the increased construction work and shortage of inspection staff in highway construction projects have led to an increasing inspection workload, which may result in accepting material or workmanship without examination. This may carry quality risks such as safety concerns, functional failures, and reduced performance life of the highway. For instance, a study by Taylor and Maloney (2013) found that between 2000 and 2010, the total lane miles of the roads managed by the 50 state DOTs increased by 4.1%, whereas the in-house staff available to manage these roads declined by 9.8% over the same period. This evolution occurs because experienced personnel are leaving state DOTs through retirement or migration to the private sector and being replaced by less experienced personnel or not being replaced at all (Li et al. 2019). Due to these circumstances, state DOTs have been looking to implement effective plans and strategies that aid the limited available staff and guide construction inspection activities (Li et al 2019; Taylor and Maloney 2013).

Previous studies attempted to provide a narrowed-down list of QA inspection items (Mostafavi et al. 2013; Yuan et al. 2018; TxDOT 2011). For instance, a study by Yuan et al. (2018) for the Indiana DOT utilized a risk assessment matrix with three levels (i.e., low, moderate, and high) of the possibility of failing to meet specification requirements and the resulting impacts on construction quality. The study chose 90 critical inspection items to assess risks associated with various construction activities. However, these studies did not provide a systematic methodology that took into account various risk factors such as experience and knowledge of inspector, inspection frequency to assure quality throughout the duration of construction work, documentation effort and time to record inspection results, and risk level of each inspection item in terms of safety, cost, and highway service. Therefore, It is necessary to order construction inspection items based on these factors and assign an optimal frequency of inspection and documentation to save time and cost of project QA examination.

This study aims at developing a framework including various strategies to mitigate inspection risks and minimize the need for inspectors. Thus, this study aims at addressing two main questions:

1. What are the available strategies to reduce inspection workload due to a shortage of inspection staff?
2. What are the value-added inspection strategies to mitigate the risks arising from a shortage of inspection staff?

To address these two questions, the proposed framework includes three steps. The first step involves refining QA inspection items to a core list and identifying the available risk mitigation strategies using literature review and natural language processing (NLP) technique. The second step includes assessing inspection items in terms of the four risk mitigation strategies using expert opinions. The third step involves examining the relationships between risk mitigation strategies and consequently recommending the best QA inspection practices. The remainder of this paper is organized as follows. First, the background section briefly discusses risk-based inspection techniques, inspection frequency and documentation, and NLP. Next, the framework development is presented. Finally, the analysis and the result were discussed, followed by conclusions and recommendations.

LITERATURE REVIEW AND BACKGROUND

This section provides background information and an overview of highway inspection practices in three areas related to this study: (1) risk-based inspection and its applications, (2) an overview of inspector experience and knowledge, inspection frequency, and inspection documentation, (3) NLP and its applications.

Risk-Based Inspection

The risk-based inspection aims to understand risk drivers in order to prioritize inspection and testing-related activities (Soares et al. 2015). Typically, the risk-based inspection and testing methodology require six main steps: data and information collection, risk assessment process, risk ranking, inspection plan, risk mitigation, and reassessment (in case of need) (API 2016). The American Petroleum Institute identified several benefits of using risk-based inspection. These include determining critical inspection activities, developing optimized inspection and testing plans, understanding the current risk, overall risk reduction, allocating inspection resources properly, and generating cost savings (API 2016).

The risk assessment process typically involves two main parameters: (1) likelihood of failure occurrence and (2) consequence of failure. The likelihood of occurrence is the probability of an adverse event or failure occurring during a given time period. The consequence of failure is defined as a measure of the event's impact. The consequence of failure may be measured in terms of safety, environmental, economic, social, or other impacts (Yuan et al. 2018; Anbari et al. 2017; Straub and Faber 2005). The risk impact can be estimated based on a product of the likelihood of an event and the consequences of event occurrence using Equation (1).

$$Risk\ Impact = Likelihood\ of Occurance\ x\ \ Consequences\ \ of\ Risk \qquad Equation\ (1)$$

The likelihood of risk and its possible consequences can be assessed quantitatively or qualitatively, depending on the project/system characteristics and the availability of historical data. The quantitative assessing process often utilizes the likelihood of failure and measures of consequences (e.g., cost impact of a risk event). The qualitative assessing process typically involves using an ordinal scale to rate the likelihood and consequences of risk events. For example, the likelihood and consequence of a risk event can be assessed qualitatively using a risk matrix of high, medium, or low levels. Researchers have shown that assessing risk qualitatively is an effective method of evaluating risk (Washer et al. 2014; Mahamid 2011). Project Management Institute (PMI) indicated that developing a risk matrix, it is typically defined by the organization that uses the matrix to perform a qualitative risk assessment (PMI 2004). The three main phases of developing a risk assessment matrix are (1) defining the risk levels, (2) determining the likelihood and consequence, and (3) modifying the probability and impact matrix if needed. The outcome of the risk matrix is an overall risk rating (i.e., risk impact) for each of the assessed items. (Ni et al. 2010).

Risk-based inspection has been applied in several civil and construction engineering areas. For instance, in the area of underground pipes, Anbari et al. (2017) developed a risk-based approach to prioritize the inspection of sewer networks. Marlow et al. (2017) used risk-based inspection in the area of water supply. Marlow et al. (2017) prioritized the examination of isolation valves of pipe networks using risk-based inspection and an analytical hierarchy process. Similarly, Mancuso et al. (2016) assessed the risk to the underground network of pipes. Mancuso et al. (2016) used MAVT to assess the risk of each pipe in the network. In the area of structural engineering, Lassen (2013) examined structural elements of steel and concrete structures for fatigue cracks. Lassen (2013) used a stochastic model and risk-based assessments to calculate uncertainty analysis.

Inspector Experience, Inspection Frequency and Documentation

Factors such as inspector experience and knowledge, inspection frequency, and time spent on inspection documentation may have an influence on the inspection process. For example, construction inspectors are at the frontline of ensuring the construction work is in accordance with approved plans and specifications, and it meets or exceeds quality standards (Von Quintus et al. 2009). The knowledge gained by the construction inspectors should be sufficient to verify the quality of a particular area of transportation infrastructure construction. This knowledge includes understanding the basic engineering principles of roadway design and construction, understanding contract documents such as plans and specifications, performing accurate mathematical calculations, performing inspection documentation, and understanding material testing principles (Marks and Teizer 2016). However, the current challenge facing state DOTs is the declined number of experienced and knowledgeable construction inspectors due to factors such as retirement or migration to the private sector, which has significantly impacted the construction inspection capabilities of these DOTs (Li et al 2019; Taylor and Maloney 2013).

The frequent inspection aims to ensure compliance of construction work with the contractual documents of a project (Caltrans 2017). Highway agencies follow two common approaches to specify the frequency of inspection. These two approaches can be specified as a time-based or quantity-based inspection frequency. For example, one time of inspection for each day’s production or construction is a time-based frequency. Quantity-based frequency is typically used for material testing (e.g., one time of inspection per ton). For instance, Maryland DOT maintains a standard guide for minimum testing frequencies that varies based on the criticality of materials (MDOT 2019). Kansas DOT reduces the frequency of material testing on a project basis when continued satisfactory and uniform production and construction are achieved (KDOT 2018).

However, reduction of inspection frequency should be applied cautiously. A study by TxDOT on sampling and testing rates showed that the department's risk of accepting "bad" material range from 20% to 40%. To reduce this risk, TxDOT increases the inspection rate during the initial production of construction materials (TxDOT 2018).

A significant amount of the inspector's time is spent on documentation rather than quality control (QC) and QA activities. Documentation of QA acceptance is defined as recording and filing evidence that construction material or work is in conformance with specifications and in the amounts required (ODOT 2009). The documentation of QA acceptance may include recording a quantity for payment and claims, documenting inspection results of construction deficiencies on the appropriate project form, and recording test results on the appropriate forms to verify the construction processes and materials are meeting the required contract requirements (MDOT 2021). The documentation may be in the form of daily reports, inspection forms or reports, certificates of compliance and product data for prefabricated and standard materials, or photo images providing indisputable supporting documentation (MDOT 2021; UDOT 2017). Project documentation should be clear, legible, and sufficiently detailed to describe inspection results and quantity measurement (ODOT 2009).

Natural Language Processing

In light of the increasing numbers of digitally recorded reports and electronics manuals in the construction industry, it is necessary to exploit these e-documents to improve our understanding of construction practices. However, it is a growing concern for several industries, including construction, to rely on human oversight to extract actionable information from these documents due to the volume of data and information overload (Baker et al. 2020). Further, gathering data from textual documents manually is time-consuming, subjective, and error-prone. There are other ways to examine the context of a long digital text, such as e-books and manuals, apart from reading it (Bird et al. 2009). NLP is an area of artificial intelligence. It is a computer manipulation of natural language. NLP could be as simple as counting word frequencies to compare writing styles. NLP Recognizes and retrieves textual content using algorithms and machine learning methods (Bird et al. 2009).

In order to improve document retrieval and analysis, attempts have recently been made to apply NLP in the construction sector. Cai et al. (2020) applied the NLP and machine learning algorithms to develop construction inspection checklists for Indiana DOT. Cai et al. (2020) aimed at eliminating the manual effort required to acquire construction inspection requirements and enhance the efficiency of the construction process. The inspection requirements were extracted from textual documents such as Indiana DOT standard specifications and restructured into the checklists. Similarly, Zhang and El-Gohary (2016) applied an NLP to extract the regulatory requirements and compliance checks from building codes. Baker et al. (2020) applied NLP with the deep learning technique of neural networks to develop a method that automatically retrieves construction injury precursors from safety reports. Information on injury precursors could be used proactively by safety decision-makers for analyzing construction hazards. Xu et al. (2020) used NLP algorithm, unified modeling language (UML), and object constraint language to automate utility permitting within the highway right-of-way. Traditional roadway agencies reviewed and tracked utility permit requests, documented utility conflicts, and verified compliance of newly installed utilities with the regulations manually. The NLP algorithm achieved an average precision of 90%. Similarly, Li et al. (2016) developed an NLP algorithm to retrieve spatial rules from utility regulations. The algorithm, through spatial reasoning in GIS, automated compliance checking of the utilities. Jafari et al (2021) developed a module to extract reporting requirements from construction contracts using NLP and machine learning. Ten contractual and specification documents of the project were used to develop and test the module. Jafari et al (2021) found that application of the module enhanced contract negotiations and reporting workflow processes.

FRAMEWORK DEVELOPMENT

The objectives of this study are to (1) identify and examine inspection strategies to reduce the need for inspection staff with maintaining the minimum construction quality requirements and (2) assess these strategies to better understand how highway agencies can adopt one or more of them with increasing value of inspection and mitigating quality risk. The authors employed a research framework including three primary steps, as shown in Figure 1. Step (1) included synthesizing existing literature publications related to construction inspection strategies of highway projects and inspection resources to identify inspection items and risk mitigation strategies. Step (2) included a risk assessment of the identified construction inspection items in terms of the inspection strategies using multiple rounds of focus group discussions. Step (3) consisted of analyzing the risk of construction inspection items and inferring association relationships between inspection strategies. The following sections present step-by-step development and validation of the framework.

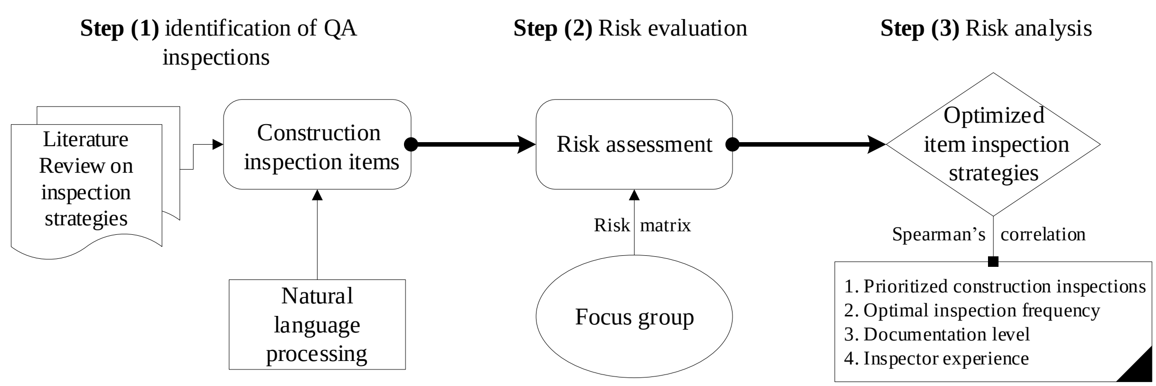
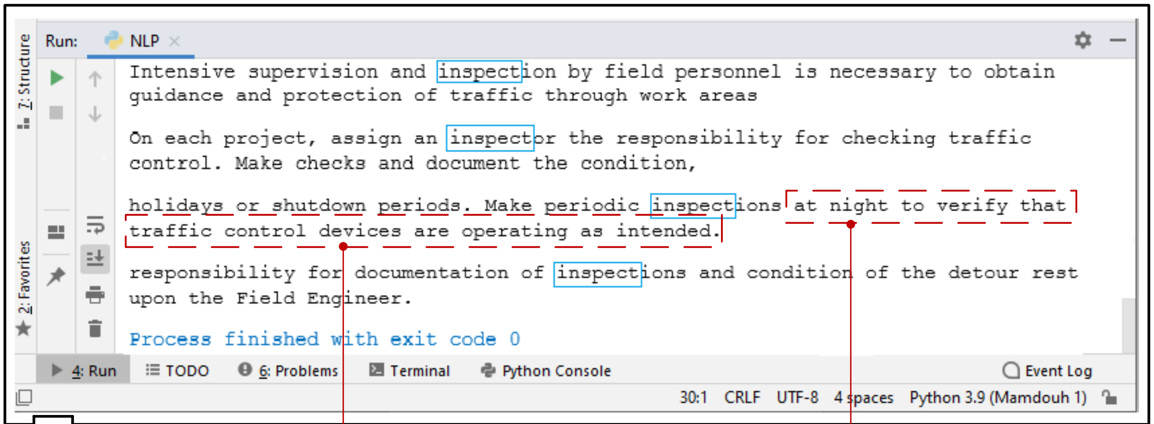


Figure 1. Research framework

Step 1: Identification of construction inspections

The Federal Highway Administration (FHWA) has identified components that major influence the quality of highway construction projects. These components include earthwork and embankment, base course and subbase, bridge deck and structural concrete, hot mix asphalt (HMA), concrete pavement, and others. Focusing on construction inspections of these components improves the quality of the final product (FHWA 2019). In this study, the authors identified and assessed the risk of construction inspection items of these components. To identify these inspection items, a rigorous desktop scan was conducted. This scan process involved collecting a wide range of electronic documents, such as construction manuals, standard specifications, documentation manuals, highway design manuals, bridge construction manuals, and inspection checklists from the FHWA and the 50 state DOTs, such as Texas, California, Washington, Ohio, Indiana, and Kansas. The scan process was performed through two main phases. Phase (1) was automated scanning and involved encoding the NLP into software to identify the pool of inspection items. It is worth noting that all the coding and associated analyses required for this phase of research were carried out in Python programming language. The software packages NLTK, NumPy, and Matplotlib were used to extract words from e-text and visualize the result. The NLTK package is designed for qualitative researchers working with a rich text-based dataset, where deep levels of analysis on small or large volumes of data could be obtained. The dataset consisted of 200 documents, including more than 150,000 pages. The keywords used for this search included “pavement,” “inspection,” “QA acceptance,” “documentation,” and others. Figure 2 provides an example of the software output for the word “inspect.” The outcome of this phase generated a comprehensive list of 105 construction inspection items.



Component	Inspection item	Description
Miscellaneous	Temporary Traffic Control	Check placing and maintaining temporary traffic control devices and related documentation to ensure the safety.
Earthwork	Placement Inspection	Inspect placement of fill material and review checklist including required construction operations and tests.
⋮	⋮	⋮

Figure 2. Example of the NLP output for scanning QA inspection documents

Phase (2) included manual scanning, reviewing, and verifying the field inspection items obtained from the first phase. This phase aimed to remove repeated inspection items and combine or add any relevant items to generate a nonoverlapped list of inspections. During this phase, 34 items out of 105 were eliminated. The 34 items were combined with other inspections due to overlap or removed because of repetitiveness. The focus group technique was employed in this study. Clemen and Winkler (1999) indicated that most of the knowledge could be achieved by interviewing three to five experts after removing outliers. Beyea and Nicoll (2000) and Krueger and Casey (2009) mentioned that an optimal focus group size of 5–10 participants is preferred to create a balance between depth and breadth of data collection. Krueger and Casey (2009) indicated that researchers should follow seven steps in the focus group research method, including brainstorming, phrase questions, sequence of questions, estimating time for each question, obtaining feedback from others, revising the questions, and testing the questions. By following these steps, four focus group sessions were conducted with 15 experts representing 15 state DOTs. The experts serve as members of the American Association of State Highway and Transportation Officials (AASHTO) Committee of Construction. The experts have an average experience of 15 years in pavement construction and QA inspection. The state DOTs represent different geographical areas of the U.S., such as Kansas DOT, PennDOT, RIDOT, SCDOT, TDOT, Utah DOT, WisDOT, and others. The focus group discussions were conducted to verify the final list of 71 inspection items. Table 1 summarizes the construction components, the number of inspection items for each component, and samples of highway inspection items. As shown in Table 1, the components are classified into nine groups, including 71 inspection items for highway construction projects.

Table 1: Highway construction components- 71 core field inspection activities

No.	Component	Number of inspection items	Sample of 71 inspection items
1	Earthwork and embankment	11	• Lift thickness inspection • Placement inspection
2	Subbase/base course	6	• Compaction control • Drainage layer inspection
3	Bridge deck and Girder	12	• Expansion joint inspection • Formwork/ falsework
4	Bridge foundation	10	• Vibration/placement of concrete • Survey checking
5	Cast-in-Place (CIP) Concrete	7	• Dimensions, thickness and grades • Rebar placement
6	Precast concrete	3	• Checking for damages before placement
7	Concrete pavement	8	• Joint inspection • Surface smoothness
8	HMA	8	• Coat and surface preparation • Longitudinal joint inspection

9	Miscellaneous	6	• Pavement marking • Guardrail and fencing

Step 2: Risk assessment of construction inspections

During this step, Four strategies were proposed based on literature and expert opinions to assess the risk associated with the 71 inspection items, minimize the need for inspection staff, and maintain the minimum QA requirements. These strategies include (ST1) risk-based prioritization of construction inspections, (ST2) optimization of inspection frequency, (ST3) optimization of inspection documentation, and (ST4) inspector experience. As mentioned above, multiple rounds of focus group sessions were conducted with the 15 experts to verify the construction inspection items, validate the four strategies, and assess the risk of construction inspection items. For assessing the four strategies, the experts were asked to:

- *ST1*: assign risk level expressed as the likelihood of inspection failure and consequence of failure for the 71 inspection items.
- *ST2:* identify the required inspection frequency for each of the inspection items,
- *ST3*: select the documentation level for each inspection item, and
- *ST4:* identify the required inspector experience for each of the construction inspection items.

Table 2 summarizes the rating system that could be used for assessing inspection items in terms of the four strategies. For example, inspection items could be prioritized for inspection by estimating the risk impacts for these items (ST1). The system includes a four-level scale ranging from “rare” when the likelihood of inspection failure is extremely small (e.g., unreasonable to expect failure) to “high” when the likelihood of inspection failure is increased. The system also includes a four-level scale for consequences ranging from “contractual impact” to “critical impact.” The “contractual impact” level is used to describe scenarios in which failure is very unlikely to have a significant effect on safety, cost, and serviceability, while the "critical impact" level is used to describe the major consequences of safety, and cost, or serviceability. Once likelihood and consequence ratings are determined, they can then be combined by using a likelihood-impact matrix similar to that shown in Figure 3 to arrive at a composite index (CI) (i.e., score) for each inspection item of interest. The matrix assists with generating a prioritized list of inspection items, where each color indicates a priority level for inspection (i.e., tier). Figure 3 indicates that the CI values range from "1" to "16". When a number of experts are involved in the assessment process, the CI represents the average risk score of each inspection item of interest.

Table 2. Risk rating systems for QA inspection strategies

Strategy	Rating system: Level/Category	Rating system: Description
ST1	▪ Likelihood of inspection failure	▪ Remote likelihood of failure/ non-conformance ▪ Low likelihood of failure/ non-conformance ▪ Moderate likelihood of failure/ non-conformance ▪ High likelihood of failure/ non-conformance
	▪ Consequence of inspection failure	▪ Contractual impact with minimal consequence ▪ Minor impact affects performance/highway service interruption ▪ Major impact results in economic loss/uselessness of component ▪ Critical impact Results in life loss/severe injury/critical safety issues
ST2	▪ Continues	▪ Inspection during the entire operation (80-100% of the work time)
	▪ Intermittent	▪ Inspection at critical times in the operation (30-80% of the work time)
	▪ End product	▪ Inspection after completion of the operation and during the operation when time permits (< 30 % of the work time)
ST3	▪ Level 1 ▪ Level 2 ▪ Level 3	▪ Minimum once per day ▪ Minimum once per item ▪ Minimum once per group of similar items
ST4	▪ Senior ▪ Intermediate ▪ Junior	▪ > 5 years of construction inspection ▪ 2 to 5 years of construction inspection ▪ < 2 years of construction inspection

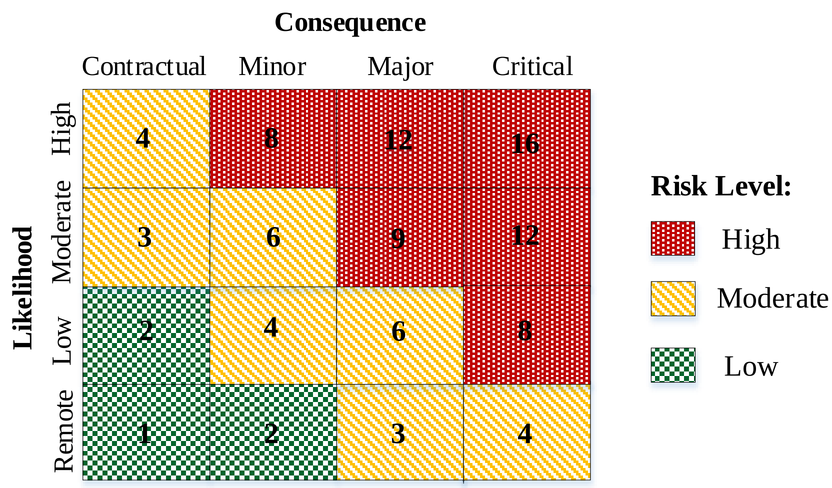


Figure 3. Likelihood-consequence matrix for construction inspection risk assessment

Step 3: Association between risk mitigation strategies

In this step, correlation analysis was conducted to examine the association between the four strategies. The primary objective of this step is to understand the relationship between the risk level of inspection items and recommend the best QA inspection practices based on these relationships. Correlation analysis is used to make inferences or judgments from the collected data to more general conditions (i.e., populations). In this study, a correlation test was conducted to infer the association between the four risk mitigation strategies. First, the sample was tested for normality using the Shapiro-Wilks test. The result of the Shapiro-Wilks test showed p-values smaller than 0.05. This result indicated that the sample is not normally distributed. Thus, the non-parametric tests of Spearman's correlation were selected, which do not require the assumption of normality. Spearman's rank-order correlation is a nonparametric measure of the strength and direction of ranking between two variables on an ordinal scale (Bagaya and Song 2016). In this study, Spearman's test was conducted to examine the existence of any association between ST1, ST2, ST3, and ST4.

RESULT

This section presents the result of the risk assessment for 71 inspection items in terms of the four inspection strategies. Appendix C shows the result of each item assessment. The following paragraphs present these results in more detail.

Figure 4 summarizes the result of assessing 71 inspection items of nine construction components in terms of ST1. It could be noted that, among the nine components, inspection items of miscellaneous and bridge decks have the highest risk impact with CI_{mean} of 6.33 and 7.8, respectively. In contrast, hot mix asphalt and concrete pavement have the lowest risk impact with CI_{mean} of 5.7 and 5.6, respectively. Overall, the least prioritized item for inspection is slope rounding and shaping of earthwork with CI = 2.7. The highest item for inspection is assembly and testing of steel girder of bridge dick with CI = 12.0. It could be noted that the risk impact of most of the inspection items lies between CI = 3.0 and CI = 8.0, with a total grand average of CI = 6.5. The top five items for inspection are assembly and testing of steel girder of bridge dick, rebar placement and concrete cover of cast-in-place structural concrete, traffic control, precast concrete deck and girders placement, and piles drilled shafts operations. As an example of component items, concrete pavement includes eight inspection items. The highest prioritized concrete pavement item for inspection is rebar placement and cover, with CI = 7.2, and the lowest prioritized item for inspection is dimensions and thickness and with CI = 4.4.

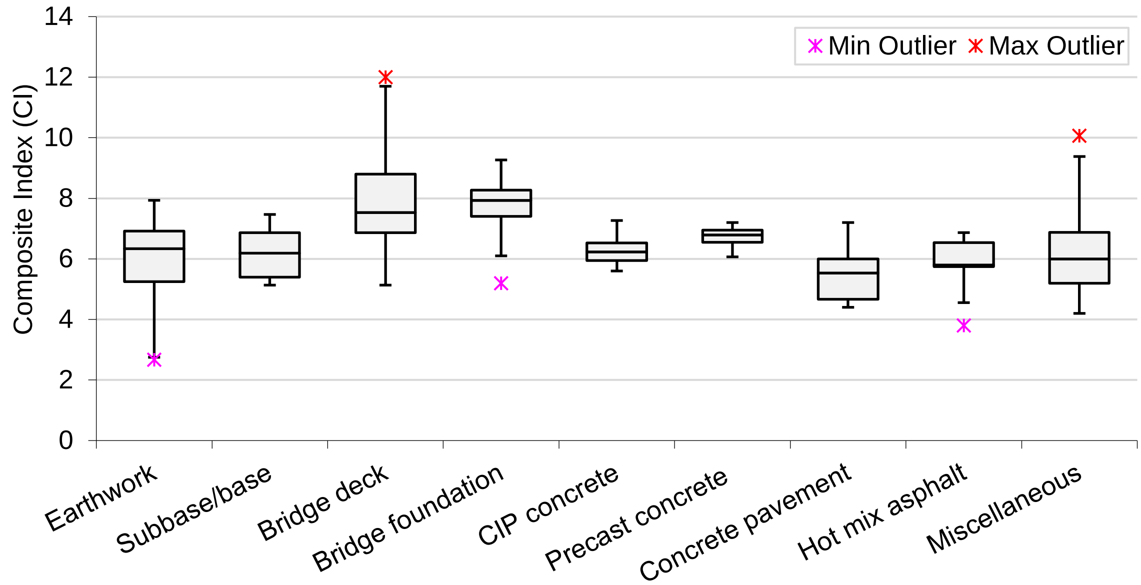


Figure 4. Risk composite index of nine construction components, including 71 inspection items

Figure 5 summarizes the result of assessing 71 inspection items of nine construction components in terms of ST2. Overall, it could be noted that "intermittent" is the most common frequency of inspection level, where 50 items (70%) require intermittent inspection. Only nine items (13%) require continuous inspection, and 12 items (17%) require end-product inspection. A comparison of the nine components indicates that, on average, bridge deck and bridge foundation components include the largest percentage of items that require the continual frequency of inspection, 33% of bridge deck items and 30% of bridge foundation items, respectively. Precast concrete, base course, and miscellaneous components include the largest percentage of items that require the intermittent frequency of inspection, 100% of precast concrete items, 83% of base course items, and 100% of the miscellaneous items, respectively. Asphalt pavement and bridge foundation components include the largest percentage of items that require end-product inspection, 25% of asphalt pavement items and 20% of bridge foundation items, respectively. All three items of precast concrete require intermittent inspection. None of the earthwork items, subbase items, precast concrete, concrete pavement, or miscellaneous items require continual inspection. The detailed result of assessing the inspection frequency of the nine components and 71 items is presented in Appendix C. For example, the hot mix asphalt component includes eight items. One item (i.e., laydown of hot mix asphalt) requires continual inspection, five items require intermittent inspection (i.e., field density, segregation, longitudinal joints, coat and surface preparation, dimension and thickness), and two items require end product inspection (i.e., surface smoothness, finish and skid resistance).

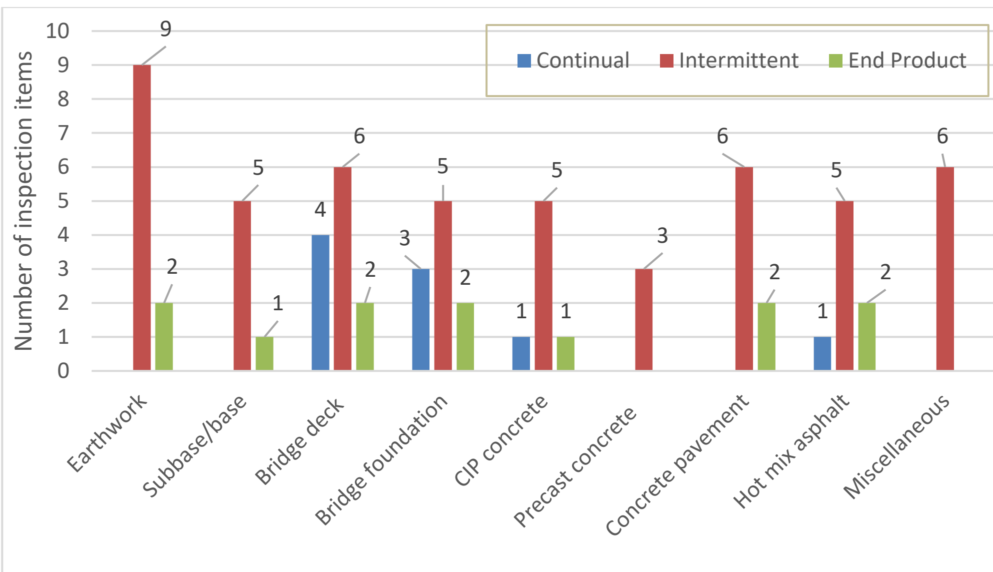


Figure 5. Inspection frequency of nine construction components including 71 inspection items

Figure 6 summarizes the result of assessing 71 inspection items of nine construction components in terms of ST3. Overall, it could be noted that the most common documentation level is level 3, where 44 items (62%) are required to be documented once per group of similar items. Twenty-one items (30%) lie in level 2 and are required to be documented once per item. Only six items (8%) are within documentation level 1 "once per day." Comparing documentation levels of the nine components indicates that, on average, bridge foundation and concrete pavement components include the largest percentage of items that require a high level of documentation (minimum once per day), 20% and 25%, respectively. Base course and precast concrete components include the largest percentage of items that require a moderate level of documentation (minimum once per item), 50% of base course items, and 67% of precast concrete items, respectively. Miscellanies and bridge deck components include the largest percentage of items that require a low level of documentation (minimum once per group of items), 83% of miscellanies items, and 75% of bridge deck items, respectively. The detailed result of assessing documentation levels of the nine components and 71 items is presented in Appendix C. For example, the bridge deck component includes 12 inspection items. One item (i.e., fresh concrete testing) requires level 1 of documentation, two items require level two of documentation (i.e., assembly and testing of steel girder elements and precast concrete deck and girders placement), and nine items require level 3 of documentation (e.g., surface smoothness/tolerance and monitoring concrete placement duration).

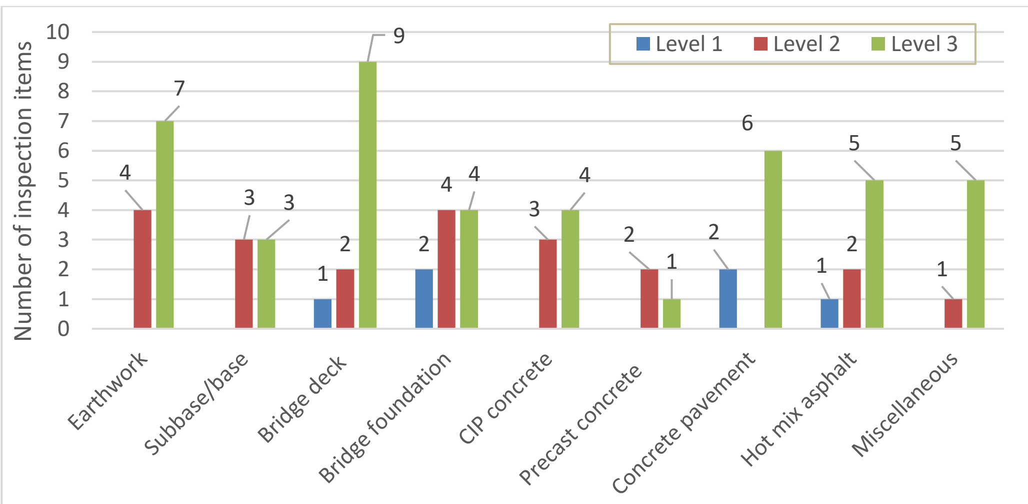


Figure 6. Documentation level of nine construction components, including 71 inspection items

Figure 7 shows the result of assessing 71 inspection items of nine construction components in terms of ST4. Among the three inspector experience levels, junior "less than two years" and intermediate "2 to 5 years" inspection experience are the most common levels, where 36 items (51%) and 31 items (44%) require these levels of experience. Only four inspection items (6%) require senior-level "more than five years" of inspection experience. The detailed result of assessing the required inspector's experience for the nine components and 71 items is presented in Appendix C. For example, the bridge foundation component includes ten inspection items. Two items (i.e., pile loading test and pile and drilled shaft operations) require an inspector with a senior experience level. Four items (e.g., rebar placement and formwork) require an inspector with an intermediate experience level. Four items (e.g., fresh concrete testing and vibration and placement) require an inspector with a junior experience level.

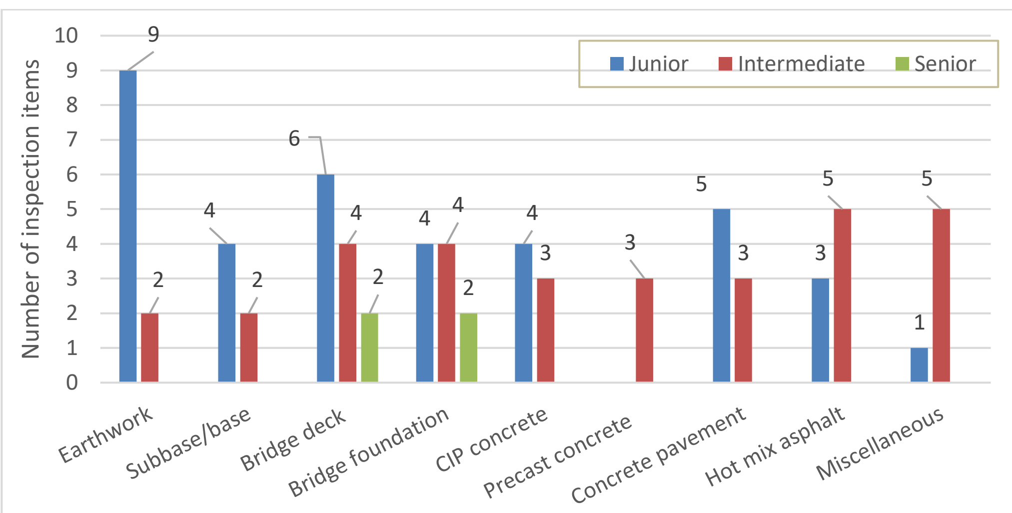


Figure 7. Inspector experience of nine construction components, including 71 inspection items

DISCUSSION

This study developed a new approach to optimizing inspection of highway construction through merging and integrating four risk mitigation strategies. The strategies include prioritizing inspection items based on CI (i.e., risk impact), optimizing the frequency of inspection, optimizing documentation level, and determining inspector experience expressed as ST1, ST2, ST3, and ST4. The result of analyzing 71 construction inspection items in terms of these strategies indicated that various levels of risk mitigation are required for each item to leverage the available inspection resources and minimize the likelihood of any quality shortfall occurrence.

ST1 aimed at allocating available project inspection resources to inspection items based on risk impact. Items with higher levels of risk impact are prioritized for inspection than those with lower levels of risk impact. For instance, fresh concrete testing (slump, air content, strength, thickness) of concrete pavement has a higher priority for inspection (*CI* = 6.6) than finish and skid resistance item (*CI* = 3.8) of the same component. This result complies with Yuan et al. (2018). Table 3 shows a comparison of the percentage of inspection items that lie in high, moderate, and low-risk impact levels for nine components. It is evident that most inspection items have a moderate risk level. For instance, seven items (63.5%) of earthwork and embankment components have a moderate level of risk, three items (27%) have a high level of risk, and one item from the same component (9%) has a low level of risk. It could also be noted that items of components such as subbase, CIP concrete, miscellaneous, and precast concrete have only moderate and high levels of risk. By taking the precast concrete component, as an illustration, it could be said that this component is prefabricated in a shop and typically requires less field control than the other components; therefore, around 90% of its inspection items lie at a moderate level of risk (Oechler et al. 2018). In contrast, components such as the bridge deck and girder require more scrutiny. Thus, the bridge deck and girder assessment result indicated that about 70% of its items are high risk. For instance, item of assembly and testing of steel girder of bridge dick has a high-risk impact with *CI* = 12. This could be explained that bridge girders may not fail very often, but failure would usually be catastrophic (Baker et al. 2010).

Table 3. Percentage of inspection items that lie in high, moderate, and low-risk impact levels

No.	Component	CI Risk Level		
		High	Moderate	Low
1	Earthwork	27%	64%	9%
2	Subbase/base	33%	67%	0%
3	Bridge deck	67%	33%	0%
4	Bridge foundation	80%	20%	0%
5	CIP concrete	29%	71%	0%
6	Precast concrete	33%	67%	0%
7	Concrete pavement	13%	88%	0%
8	Hot mix asphalt	0%	100%	0%
9	Miscellaneous	33%	67%	0%

The declined number of highway inspectors mirrors the risk of quality shortfall exposure in highway construction projects and urges the need to focus on optimizing the frequency of inspection and leveraging project inspection staff (Taylor and Maloney 2013). ST2 aimed at saving inspection time by minimizing the unnecessary frequency of inspection by categorizing inspection frequency into continual, intermittent, and end product. This strategy allocated inspection items into the appropriate frequency of inspection category instead of reducing the frequency of inspection for all items. It optimized the inspection rate for items by considering field observations of the failure rate of different construction materials and workmanship. However, it is recommended to increase the frequency of QA inspections when item inspection results do not meet specifications (Texas DOT 2017, Texas DOT 2018). For example, Caltrans does not use contractor quality control inspections and tests for acceptance or payment of work items unless allowed by the project specifications. However, quality control test results indicate quality issues should result in increased inspection frequency until quality issues have been resolved (Caltrans 2017).

A significant amount of inspection time is spent on documentation of quantities for payment, recordkeeping, and other administrative duties rather than quality control and quality assurance items, which exposes project construction processes to the risk of quality shortfalls. ST3 aimed to optimize documentation levels and minimize unnecessary documentation efforts for project inspection items to address this issue. ST3 categorized documentation efforts into three levels, once per day, once per item, and once per group of similar items. The documentation level for inspection items provides inspection staff with more time to focus on verifying the quality of construction processes. It is also important to maintain a documentation level that records project quality for other purposes such as potential claims and arbitrations, corrective actions, change orders, or future maintenance (Yamaura et al. 2015; Kangari 1995).

Inspection practices heavily rely on the experience of inspectors and their subjective interpretation of the project requirements (Xu et al. 2019; Li et al 2019). Accordingly, allocating construction inspectors to QA items based on experience can greatly enhance inspection efficiency and accuracy. ST4 aimed at reducing inspection risks by allocating inspectors based on experience and knowledge requirements for each item. Thus, inspector experience was categorized into three levels: junior, intermediate, and senior. While the integration of the four above-mentioned strategies has the potential to reduce inspection risk, they cannot minimize material and workmanship risks to zero level. Generally, risk cannot be reduced to zero level due to factors such as faults of design, natural disasters, and human errors (Soares et al. 2015).

Finally, Spearman's correlation analysis was conducted to understand the association between the four inspection strategies. Particularly the relationships between risk level of inspection item and frequency of inspection, documentation level, and inspector experience were examined. Table 4 shows that the risk level of the inspection item expressed as *CI* is significantly associated with ST2, ST3, ST4. Item risk level expressed as ST1 is significantly associated with inspection frequency ST2, where r_s = 0.50. The risk level of inspection item ST1 is significantly associated with documentation level ST3, where r_s = 0.27. The risk level of inspection item ST1 is significantly associated with inspector experience ST4, where r_s = 0.30. It could be noted that the association between item risk level and inspection frequency is higher than those between risk level and documentation level or inspector experience. Based on these findings, it could be concluded that when the risk level of inspection activity increases, inspection frequency should be increased to mitigate the risk of accepting inferior construction materials and workmanship by allocating experienced inspectors to such items. These findings concur with previous studies (Xu et al. 2019; Li et al 2019) and field observations by Caltrans (2017) and Texas DOT (TxDOT 2018, TxDOT 2017). These findings also reveal the importance of considering risk mitigation strategies by transportation agencies in their inspections of highway construction projects.

Table 4. Spearman's correlation of inspection risk mitigation strategies (alpha = 0.05)

No.	Strategy	ST1	ST2	ST3	ST4
ST1	Risk composite index	1.00	__	__	__
ST2	Inspection frequency	0.50*	1.00	__	__
ST3	Documentation level	0.27*	0.11	1.00	__
ST4	Inspector experience	0.30*	0.00	0.18	1.00

In terms of framework implementation, the highway agency's selection for inspection resources optimization strategy can significantly affect the long-term aspects of durability, safety, and lifecycle costs of its highway construction projects. The risk-based inspection is promising in the highway construction field because it could handle the probability of construction element failure with different consequences of cost, safety, and service interruption (Yuan et al. 2018). Integrating risk-based inspection with appropriate inspector experience, frequency of inspection, and documentation by state DOTs could improve the end product of highway construction projects and the level of service. Additionally, By following this framework, transportation agencies can tailor strategy rating scales based on their own agency's overall tolerance or appetite for risk.

CONCLUSION

The last periods of recessions forced highway agencies to cut budgets and reduce positions such as construction inspectors and technicians. Inspectors are at the frontline of ensuring the finished product of construction work meets or exceeds project specifications and quality standards. The reduced experience and number of construction inspectors mirror the potential risk of accepting inferior materials and workmanship, and consequently expose construction projects to the quality shortfall. This study has presented a framework integrating four strategies to mitigate inspection risks in highway construction projects. The four strategies included prioritizing inspection items based on risk impact, optimizing the frequency of inspection, optimizing documentation level, and determining inspector experience. Nine construction components, including 71 inspection items, were retrieved from construction and quality assurance documents using NLP and manual desktop screening. This was followed by several rounds of focus group discussions with highway inspection experts to evaluate and assess the risk level of the inspection items in terms of the four strategies. Finally, correlation analysis was conducted to examine the relationship between item risk level and inspection strategies.

The result indicated that most of the inspection items have a moderate risk level. The risk level of inspection items is significantly associated with inspection frequency, documentation, and inspector experience. Accordingly, items with higher risk levels require increased inspection frequency and experienced inspector to mitigate the risk of a quality shortfall. Finally, these findings were verified using three workshops, including 31 QA inspection professionals from state DOTs. The workshops discussed the 71 items, assessment process and results, and findings. The workshop participants confirmed that the result found from this study are reasonably supported by the available historical records and field observations.

This study contributes to the body of knowledge by examining the relationships between inspection risk, inspection frequency, documentation, and inspector experience in the area of highway construction. This study contributes to the construction industry by providing guidelines for transportation agencies to develop and implement risk mitigation strategies and inspection practices in their construction projects. A limitation of this study is that it included a relatively small sample size. Another limitation of this study that warrants future research involves comparing the framework results with actual project data. Future studies may include examining additional strategies such as using technology to improve highway construction inspection. Future studies can also examine the study result for different sizes of highway construction projects to better understand the relationship between project size and risk level.

Data Availability Statement

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

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CHAPTER 5

CONCLUSIONS

SUMMARY AND CONCLUSION

The quality and durability of construction and maintenance projects have been a major concern to transportation agencies and contractors. Quality assurance (QA) inspection of construction projects is defined as a tool or means by which the owner and contractors ensure that the project is constructed in accordance with approved plans and specifications by the most economical, efficient, and safe method (Von et al. 2009). When QA programs are well designed, they can provide confidence that project materials and workmanship will conform to plans and specifications (Rafalowski 2012). Typically, QA inspection and acceptance are managed by material certification, visual inspection, or sampling and testing. While the acceptance by the certificate is typically for standard and prefabricated materials with a low-risk level, the acceptance by testing and field inspection are often for project-produced materials and workmanship with higher levels of risk. To alleviate the inspection risk, transportation agencies often allocate resources to perform construction materials testing and inspect construction items as a part of their QA programs. Typically, the inspection staff is responsible for conducting and verifying the results of the material testing and inspection processes. The inspection process may be on-site such as visual field inspection, or off-site, such as shop and source inspection (Sillars et al. 2010). The current challenge that transportation agencies are facing is the declining availability of construction inspectors and material testing technicians. Declined number of qualified inspection personnel mirrors the risk of quality shortfall exposure in roadway construction projects and urges the need to focus on optimizing inspection processes. Currently, transportation agencies seek strategies that require a minimal number of construction inspections and material tests with maintaining quality requirements. Previous studies attempted to provide a narrowed-down list of QA tests (Mostafavi et al. 2013; Yuan et al. 2018; TxDOT 2011). However, these studies did not provide a systematic methodology that took into account various risk factors (such as safety and cost) as well as the best inspection and testing strategies such as frequency, inspector experience, and documentation effort.

This dissertation explores the impact of risk and uncertainty on highway project inspection. The body of this dissertation includes three papers that present the research problem, methodologies, results, contributions, and applications. The first, second, and third papers employ content analysis, survey questionnaires, and risk-based assessment to identify inspection activities that affect the quality of highway construction projects. In Chapter 2, the first paper focuses on developing a comprehensive RBI framework based on FBBN to consider uncertain knowledge and fuzziness associated with qualitative data, various sources of knowledge, incomplete data sets, and model causal relationships among risk factors. FBBN is a flexible, hybrid technique that combines FS theory and Bayesian belief networks (BBNs) into one model. This model enables decision-makers to arrange priorities and select the best alternative by considering tangible and intangible aspects of a problem (Sedki et al. 2010). The FBBN risk assessment model in this study provides a systematic methodology to prioritize QA inspection activities for highway construction projects. Additionally, a case study from KDOT was examined to demonstrate and validate the framework and model. The findings from this paper indicate that the modular representation of uncertain knowledge due to randomness and vagueness increased the ease and functionality of QA inspection risk analysis. The model facilitated probabilistic risk analysis under uncertainty and fuzziness. The model includes Delphi, fuzzy set (FS) theory, and Bayesian belief networks (BBNs) techniques. The Delphi technique was applied to control bias during the data collection process. FS was merged into the model to deal with the linguistic nature of the collected data from subjective matter experts, which cannot be represented precisely by quantitative probability distributions. BBN was employed in the model to deal with the causal influence between the model variables and to infer the probability distribution of quality risk levels. RBI protocol was also developed to equip highway construction inspectors with the necessary inspection knowledge. The results of the KDOT case illustrative example indicated that more than half the KDOT earthwork and bridge deck QA activities were high-risk inspections. In addition, HMA and PCCP construction activities included the greatest number of high-risk inspection activities.

Building upon the findings from the first paper, in Chapter 3, the second paper advances the understanding of how risk impacts construction inspection. The objective of the second paper aims at customizing the model developed in the first paper to measure the quality level of HMA projects through three steps. First, it introduces a core list of QA inspection activities for HMA. This core list helps state DOTs allocate their limited resources to the most critical inspection activities. Second, the RBI model using FBBN was developed to help state DOTs evaluate and mitigate a quality-related risk level of HMA early in the construction phase. Third, a case study from KDOT was examined to verify the applicability of the model. The findings of this study show that the RBI model developed in this study has the potential to infer the HMA risk level based on the interdependence between HMA quality, inspection activity, and inspection results. The model also has the capability to examine the causes of the HMA high-risk level occurrence and determine related activities depending on the relationship between inspection activities and HMA. In the KDOT case example, the result showed that KDOT needs to improve construction and workmanship by focusing on specific activities with a low construction quality level. QA decision-makers in transportation agencies may benefit from the model by taking an early action based on the inferred risk levels of HMA. QA decision-makers can apply the model to highway construction inspections by updating probabilities based on inspection results.

The results from the first and second papers provide a foundation to create various strategies to mitigate inspection risks and minimize the need for inspectors. Thus, in Chapter 4, the objectives of the third paper are (1) identifying the available strategies to reduce inspection workload due to a shortage of inspection staff and (2) increasing the value of inspection and mitigating the risks that may arise due to shortage of inspection staff. To attain these two objectives, the proposed study includes three steps. The first step involves refining QA inspection items to a core list and identifying the available risk mitigation strategies using literature review and natural language processing (NLP) technique. The risk mitigation strategies include item inspection prioritization, inspection frequency, documentation level, and inspector experience evaluation for each item. The second step includes assessing inspection items in terms of the four risk mitigation strategies using expert opinions. The third step involves examining the relationships between risk mitigation strategies and consequently recommending the best QA inspection practices.

The finding of this study indicated that most of the inspection items have a moderate risk level. The risk level of inspection items is significantly associated with inspection frequency, documentation, and inspector experience. However, the association of item risk level with inspection frequency is higher than with documentation or inspector experience. Accordingly, items with higher risk levels require increased inspection frequency and experienced inspector to mitigate the risk of a quality shortfall. These findings were verified using workshops, including QA inspection professionals from state DOTs. The workshops discussed the four strategies, the assessment process, and results. The workshop participants confirmed that the result of this study is reasonably supported by the available historical records and field observations.

CONTRIBUTIONS

To date, there is no research applying probabilistic risk analysis to quantify and prioritize project inspection in the construction industry. This research seeks to understand the interaction between inspection activities, inspection failure probabilities, and the consequences of failure occurrence for the activities and then offer risk-based strategies to alleviate this risk. This research offers three primary deliverables: (1) identifying the critical inspection activities that affect the project quality level in highway construction projects; (2) providing a risk-based model which can be used for assessing the quality level of highway construction projects and inferring any causes of quality shortfall; and (3) offering effective risk-based strategies for inspecting highway construction projects. There are several contributions to both theory and practice in all chapters of the dissertation.

Contribution to Theory

The dissertation provides a number of academic contributions. Overall, this dissertation offers a new risk-based framework and the FBBN model to identify and assess QA inspection activities in highway construction projects. A comprehensive literature review indicates that FBBN has been widely used in construction research (Straub and Faber 2005; Luque and Straub 2019; Anbari et al. 2017; Mancuso et al. 2016), but limited studies, if any, have investigated its utilization for risk assessment of highway construction inspections. Further, although the risk-based model was designed for highway projects, the logic and methodology can be used in other areas such as building, water and wastewater, and transit projects.

Chapter 2 provides a fresh RBI framework on the use of risk to determine the quality level of inspection activities in highway construction projects. It also adds novel insights into which inspection activities influence the quality of construction of highway projects. In addition, the FBBN technique used to develop the RBI framework in this study can be adapted by other researchers to model the uncertainty of knowledge associated with qualitative data, which is common in the construction engineering and management area. Studies by Yuan et al. (2017), Scott et al. (2017), and Mostafavi and Abraham (2013) developed protocols for QA inspection to prioritize highway construction inspection activities based on analyzing QA cost and risks of material non-conformance. The implementation of these studies, however, required maintenance records and historical data from QA inspections, which are limited. This study enhances these previous studies by identifying, categorizing, and grouping the risk of inspection activities based on their significance of the impact on the quality of highway construction projects. Specifically, Chapter 2 categorizes 108 critical inspection activities into tiers that have the most influence on the QA process of the highway. The findings of Chapter 2 study will help researchers focus on the most critical characteristics of highway construction materials and workmanship and lay the foundation for future work related to risk analysis and management of quality of highway construction projects.

Chapter 3 builds upon the results from Chapter 2 to develop a risk-based model to quantify the impact of inspection risk on project quality and determine any potential causes of the quality shortfall. Chapter 3 offers several theoretical contributions to construction engineering and management research. First, the risk-based model suggests a new method that combines the FS results with the BBN technique to solve decision problems under uncertainty. No research efforts have applied this method in the literature on highway quality management to the author's knowledge. Utilizing the FS results improves the accuracy of the experts' judgments and reduces the significant effort of knowledge acquisition required for the BBN analysis technique. Second, the risk-based model quantifies the probabilistic risk analysis by converting expert opinions into numerical values. Many previous studies have focused on developing a model for conducting conventional risk analysis techniques such as risk matrix (Mostafavi and Abraham 2013; Yuan et al. 2017), but there is limited research utilizing results from the probabilistic risk analysis the inspection of highways. Finally, the risk-based model suggests promising future research avenues on risk analysis and project quality management in the construction industry.

Chapter 4 provides various strategies necessary to consider in the highway construction inspection process, including a spectrum of four strategies: inspection risk level, frequency of inspection, documentation level, and inspector experience. Chapter 4 contributes to the construction engineering and management body of knowledge by optimizing the four strategies, minimizing the need for inspection staff, and increasing the value of the inspection process. It also noted that little research, if any, has examined the relationships between these four strategies. Innovatively, this study examines the relationships between inspection risk, inspection frequency, documentation, and inspector experience and provides guidelines for researchers and practitioners to develop risk mitigation strategies and improve inspection practices in highway construction projects.

Contributions to Practice

The overall focus of this dissertation is to identify and analyze the critical inspection activities and then develop a risk-based inspection model to help decision-makers understand the impact of risks on the quality of highway construction projects. The research and findings from this dissertation contribute to practice in highway construction projects in several ways. Chapter 2 identifies and categorizes a list of 108 critical inspection activities. These QA inspection activities are categorized into levels of intensity using the generic FBBN framework developed in this chapter. Transportation agencies can optimize the number and type of QA inspection activities. The framework output helps QA personnel identify which inspection activities are the most effective for the QA process by offering three levels of activity risk based on the availability of inspection staff. Thus, the framework developed in Chapter 2 helps highway agencies overcome the shortage of inspection staffing by prioritizing QA inspections based on criticality.

In Chapter 3, the RBI model developed based on FS and BBNs techniques can represent the risk level of QA precisely by quantitative probability distributions. The model outcome provides state DOTs with the probabilities of HMA quality shortfall based on observations of the actual inspection activity results. Additionally, it provides causal relationships between inspection activity and the quality of HMA pavement. Thus, the model can be used by transportation agencies as a practical hands-on decision tool to perform real-time Bayesian inference of quality risk levels in highway construction projects. The model provides three levels of risk, including high, moderate, and low, where an inspector can determine which inspection activities have the largest impact on the construction quality. Transportation agencies such as state DOTs can explore cause-effect relationships between HMA quality levels and QA inspections and determine the most likely potential causes of HMA quality shortfall.

Inspection practices heavily rely on the availability and experience of inspectors (Xu et al. 2019; Li et al 2019). The shortage of funding and decline in the number of inspection personnel mirrors the risk of quality shortfall exposure in highway construction projects. This situation urges the need to focus on optimizing inspection practices and leveraging project inspection staff (Taylor and Maloney 2013). Chapter 2 presents a framework integrating four strategies to mitigate inspection risks in highway construction projects. The four strategies included prioritizing inspection items based on risk impact, optimizing the frequency of inspection, optimizing documentation level, and determining inspector experience based on inspection risk level. Chapter 2 contributes to the construction industry by providing guidelines for transportation agencies to develop and implement risk mitigation strategies and inspection practices in their construction projects.

LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

Our current understanding of the fundamental relationship between risk and highway construction inspection remains incomplete. Data to support the use of empirical research on risk and project inspection are limited and largely qualitative. Although the research presented in this dissertation provides novel insights into the risk-based inspection process, several limitations warrant attention for future research, including:

1. Enhancing the framework and model testing and implementation.
2. Comparing the model output with actual project data.
3. Improving the understanding of the impact of inspection risk on alternative project deliver methods.
4. Using contractor quality control in acceptance decision.
5. Including other risk sources into the model.
6. Creating new models for different types highway projects.
7. Developing an interactive and practical computer tool.
8. Adopting more risk-based inspection strategies
9. Expanding the model to other sectors in the construction industry

The following paragraphs explain these limitations and suggestions for future research in more detail.

1. ***Enhancing the framework and model testing and implementation.*** The risk-based framework and model constructed in this research based on FBBN were tested with a case study from KDOT. The authors presented the model and discussed its results with senior KDOT superintendents, experienced project engineers, and knowledgeable inspectors responsible for QA inspections. The purpose of the discussions was to ensure that the model logically represented the risk levels of inspection activities. The practitioners confirmed that the model output complies with their field observations. While the result of the testing process was consistent with the inspection results from the agency, additional testing could ensure the accuracy of the results and provide more insights into the effects of risk on highway construction inspection.

2. ***Comparing the model output with actual project data***

   Comparing the model results with actual project data is critical to verifying the implementation of the model. For example, the model developed in this study could be applied to different types and sizes of highway construction projects to better understand how the result of the model can be used to mitigate inspection errors and optimize inspection resources and efforts.

3. ***Improving the understanding of the impact of inspection risk on alternative project delivery methods***. This study collected data from numerous relevant experts in the transportation industry, including representatives from 50 state DOTs examining KDOT QA practices as a case study. However, some experts mentioned that alternative delivery methods such as Design-Build (DB) and Construction Manager/General Contractor (CM/GC) delivery methods were limited in use in their states at the time of data collection. For instance, KDOT typically uses the traditional project delivery method of Design-Bid-Build (DBB) for its highway construction projects. As a result, the experts only responded to the survey questionnaire based on their perceptions or "learning" experience on the DBB delivery method. While the

DBB data satisfied the statistical assumptions for the input level of the risk-based model, more data on other project delivery methods such as DB and CM/GC will enhance the model validity and application. In the future, additional research is necessary to investigate the relationship between risk levels on inspection activities and project delivery methods.

4. ***Using contractor quality control in acceptance decision.*** The research presented in this dissertation only focused on QA inspection. In fact, QA by the transportation agency and QC by the contractor are interconnected. Future research could investigate how to integrate QA inspections by transportation agencies with contractor QC inspections. For example, using contractor QC inspections in acceptance decisions is becoming a more common method among state DOTs. It would be interesting to understand the risk associated with applying this method.

5. ***Including other risk sources into the model***. The risk-based model presented in this dissertation focused on the probability and consequence of the failure of material inspection activity. Other important inspection risk sources may be considered. For example, inspector experience is proven to be critical for the inspection process, as discussed in Chapter 4.

6. ***Creating a new model for different highway projects.*** The risk-based model in Chapter 3 was designed for HMA highway projects only. To overcome this limitation, similar models that combine risk assessment of inspection activities for other highway projects such as PCCP and bridge deck would be useful. These models will help agencies in understanding the impact of risk and uncertainty on their different types of projects.

7. ***Developing an interactive and practical computer tool***. Because the risk-based model relies heavily on mathematical structure and BBN simulation, it works separately from the data collection process and is complex for state DOTs to some degree. In the future, the author will develop a computer-based model that integrates the data collection phase into the model.

Additionally, a user-friendly interface will be developed where decision-makers can freely change the input based on inspection activity results to analyze the model output.

8. ***Adopting more risk-based inspection strategies.***

   Four risk-based inspection strategies were discussed in Chapter 4 to alleviate the risk of highway construction inspection. These strategies include priority inspection based on activity risk level, inspection frequency, inspection documentation, and inspector experience. Future research may include examining additional strategies such as using technology to improve highway construction inspection. Future research can also examine the study result for different sizes of highway construction projects to better understand the relationship between project size and risk level.

9. ***Expanding the model to other sectors in the construction industry.*** Another limitation was that this study only focused on the inspection of highway construction projects. Future research could expand the model to other sectors in the construction industry, such as buildings, water and wastewater, aviation, and transit. In addition, while the risk-based model was aimed at investigating the impact of risk and uncertainty on highway construction inspections, the computational structure of the model can be used to deal with other types of decision-making under uncertainty, such as asset management and maintenance risks.

ANTICIPATED IMPACT OF THE RESEARCH

There are several areas of impact anticipated from the results of this dissertation. First of all, this research will help highway agencies document inspection risks and benefits associated with using a risk-based inspection framework. This documentation will help state DOTs determine how to use risk-based inspection when there is a shortage of inspection staff. Additionally, risk-based inspection plays an important role in prioritizing construction activities for inspection based on criticality.

Second, the risk-based model developed from this dissertation leverages the current cutting-edge machine learning method of FBBN that has emerged in the transportation industry in the past few years. This research could provide the impetus for conducting risk analysis at the very beginning of the project construction and inspection processes to avoid quality shortfall and enhance risk management culture in state DOTs. The integration of probabilistic Bayesian risk analysis into the construction inspection process will play a pivotal role to the success of highway construction projects. By analyzing the outcomes of the risk-based model, state DOTs will identify which inspection activities are critical for each construction operation and how they influence project quality.

Finally, the third anticipated impact from this dissertation consists of a new approach to optimizing inspection of highway construction projects by integrating four risk mitigation strategies. The strategies include prioritizing inspections based on criticality (i.e., risk impact), optimizing inspection frequency, optimizing documentation level for each inspection activity, and determining inspector experience. The result of applying these strategies indicates that various levels of risk mitigation are required for each item to leverage the available inspection resources and minimize the likelihood of any quality shortfall occurrence. This approach also provides guidelines for highway agencies to develop risk mitigation strategies and improve inspection practices in their construction projects.

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APPENDIX A: Probabilities of RI for the 108 core inspection activities

Element	ID	Activity	RI Probabilities			Priority
			Low	Moderate	High	
1. Earthwork and Embankment	1.1	Field density for compacted earth works	0.09	0.355	0.549	High
	1.2	Field density of compacted backfilling works	0.059	0.258	0.682	High
	1.3	Moisture content of earthwork	0.126	0.430	0.443	High
	1.4	Moisture content for structure backfilling	0.081	0.419	0.499	High
	1.5	Field density of foundation of MSE walls	0.111	0.448	0.440	Moderate
	1.6	Field density of mechanically stabilized earth fill	0.111	0.406	0.482	High
	1.7	Check placement and compaction of granular drainage blanket	0.292	0.512	0.196	Moderate
2. Subgrade, base, shoulders	2.1	Sieve analysis of aggregate for subgrade	0.320	0.534	0.146	Moderate
	2.2	Check the application rate of cement or fly ash (CTB)	0.210	0.584	0.206	Moderate
	2.3	Material passing the no. 200 (75 μm) sieve by the wash method for subgrade aggregate	0.623	0.210	0.167	Low
	2.4	Plasticity of aggregate of subgrade	0.230	0.630	0.140	Moderate
	2.5	Moisture content for lime treated subgrade	0.320	0.200	0.480	High
	2.6	Sieve analysis for acceptance of lime treated subgrade	0.250	0.560	0.190	Moderate
	2.7	Percent solids of lime slurry in lime treated subgrade	0.710	0.205	0.085	Low
	2.8	Field density of lime treated subgrade	0.300	0.450	0.250	Moderate
	2.9	Sample of subgrade hydrated lime and pebble quicklime	0.480	0.320	0.200	Low
	2.10	Sieve analysis for acceptance of fly ash or cement treated subgrade	0.520	0.370	0.110	Low
	2.11	Field density of cement or fly ash treated subgrade	0.310	0.480	0.210	Moderate
	2.12	Sample of stabilization and cold recycle fly ash	0.630	0.230	0.140	Low
	2.13	Field density of crushed stone subgrade	0.527	0.320	0.153	Low

	2.14	Relative density of crushed stone subgrade	0.420	0.340	0.240	Low
	2.15	Sieve analysis for aggregate crushed stone of backfill	0.270	0.490	0.240	Moderate
	2.16	Sieve analysis for aggregate of base course	0.484	0.340	0.176	Low
	2.17	Sieve analysis for aggregate of binder material of base course	0.512	0.350	0.138	Low
	2.18	Plasticity for aggregate of binder material of base course	0.395	0.350	0.255	Low
	2.19	Sieve analysis for combined aggregate of base course	0.468	0.286	0.247	Low
	2.20	Plasticity of combined aggregate of base course	0.478	0.286	0.237	Low
	2.21	Moisture test for combined aggregate of base course	0.370	0.489	0.141	Moderate
	2.22	Field density of completed aggregate base course	0.321	0.495	0.184	Moderate
	2.23	Sieve analysis for individual aggregate of shoulders (non HMA)	0.476	0.347	0.177	Low
	2.24	Plasticity of individual aggregate of shoulders (non HMA)	0.423	0.358	0.219	Low
	2.25	Sieve analysis for aggregate of binder material of shoulders (non HMA)	0.427	0.342	0.231	Low
	2.26	Plasticity of binder material of aggregate shoulders (non HMA)	0.431	0.326	0.243	Low
	2.27	Sieve analysis for combined aggregate of shoulders (non HMA)	0.434	0.310	0.256	Low
	2.28	Plasticity of combined aggregate of shoulders (non HMA)	0.438	0.294	0.268	Low
	2.29	Moisture of combined aggregate of shoulders (non HMA)	0.441	0.278	0.281	Low
	2.30	Field density of completed aggregate shoulders (non HMA)	0.445	0.262	0.293	Low
	2.31	Moisture of completed aggregate shoulders (non HMA)	0.449	0.346	0.205	Low
	2.32	Sieve analysis for aggregate of cement treated base (CTB)	0.452	0.330	0.218	Low
	2.33	Moisture of cement treated base (CTB)	0.343	0.438	0.219	Moderate
	2.34	Density of cement treated base (CTB)	0.01	0.320	0.670	High
	2.35	Compressive strength of cement treated base (CTB)	0.192	0.331	0.477	High

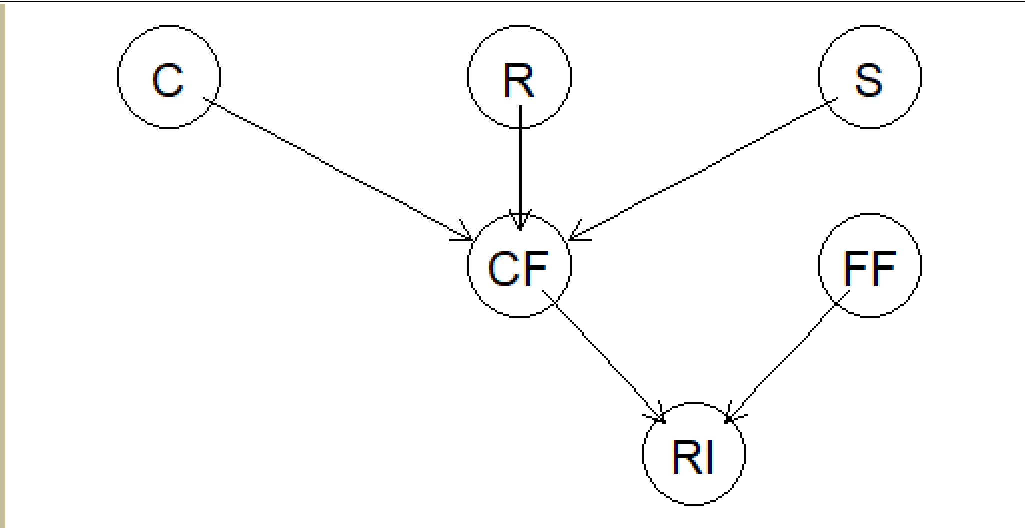
	2.36	Field density of completed cement treated base (CTB)	0.116	0.406	0.478	High
	2.37	Moisture of completed cement treated base (CTB)	0.359	0.438	0.203	Moderate
	2.38	Sieve analysis for aggregate of granular base	0.672	0.301	0.027	Low
	2.39	Plasticity of aggregate of granular base	0.505	0.217	0.277	Low
	2.40	Sieve analysis for aggregate of binder material of granular base	0.406	0.368	0.226	Low
	2.41	Plasticity of binder material of granular base	0.363	0.354	0.283	Low
	2.42	Sieve analysis for pulverized aggregate of granular base	0.405	0.346	0.249	Low
	2.43	Sieve analysis for combined aggregate of granular base	0.378	0.438	0.184	Moderate
	2.44	Plasticity of combined aggregate of granular base	0.527	0.275	0.198	Low
	2.45	Moisture of combined aggregate of granular base	0.535	0.233	0.233	Low
	2.46	Field density of completed granular base	0.340	0.447	0.213	Moderate
	2.47	Moisture of completed granular base	0.353	0.438	0.209	Moderate
3. Concrete (Bridge Deck)	3.1	Slump of concrete - bridge deck	0.366	0.454	0.180	Moderate
	3.2	Portland cement approval for concrete	0.339	0.480	0.181	Moderate
	3.3	Concrete temperature measurement	0.392	0.438	0.170	Moderate
	3.4	Concrete mass per cubic foot	0.189	0.357	0.454	High
	3.5	Concrete air content	0.102	0.234	0.664	High
	3.6	Moisture in aggregate	0.403	0.438	0.159	Moderate
	3.7	Density of fresh concrete	0.245	0.367	0.388	High
	3.8	Permeability of concrete	0.182	0.351	0.467	High
	3.9	Concrete strength (cylinders)	0.164	0.365	0.471	High
4. PCCP	4.1	Concrete mass per cubic foot - PCCP	0.148	0.319	0.533	High
	4.2	Sieve analysis of individual aggregates - PCCP	0.543	0.302	0.154	Low
	4.3	Check vibrator frequencies before placing PCCP	0.118	0.286	0.596	High
	4.4	PCCP temperature	0.103	0.270	0.627	High
	4.5	PCCP slump	0.088	0.254	0.658	High
	4.6	PCCP air content	0.073	0.238	0.689	High

	4.7	Moisture in PCCP aggregate	0.324	0.438	0.238	Moderate
	4.8	Cored PCCP thickness	0.315	0.458	0.228	Moderate
	4.9	Density of fresh PCCP	0.305	0.497	0.198	Moderate
	4.10	PCCP permeability	0.295	0.486	0.218	Moderate
	4.11	PCCP vibrator frequency	0.286	0.438	0.276	Moderate
	4.12	Unit weight of PCCP individual aggregate – lightweight aggregates only	0.276	0.544	0.180	Moderate
5. HMA	5.1	Sieve analysis of HMA individual aggregate	0.267	0.473	0.260	Moderate
	5.2	Compaction of asphalt pavement layer	0.081	0.312	0.607	High
	5.3	HMA sampling and storage for testing	0.61	0.208	0.182	Low
	5.4	Percentage of crushed particles in HMA crushed gravel (coarse aggregate angularity)	0.475	0.369	0.156	Low
	5.5	Uncompacted void content of HMA fine aggregate	0.354	0.438	0.208	Moderate
	5.6	Sieve analysis for HMA aggregate of mineral filler supplement	0.561	0.245	0.194	Low
	5.7	Plasticity of HMA mineral filler supplement	0.543	0.124	0.333	Low
	5.8	Sieve analysis of HMA combined aggregate	0.381	0.342	0.277	Low
	5.9	Coarse aggregate angularity for combined aggregate - HMA	0.510	0.314	0.176	Low
	5.10	Sand equivalent of HMA combined aggregate	0.471	0.338	0.191	Low
	5.11	Moisture content of HMA combined aggregate	0.414	0.237	0.350	Low
	5.12	Density of HMA mixtures (field lab)	0.253	0.290	0.458	High
	5.13	Voids of HMA mixtures (field lab)	0.178	0.364	0.458	High
	5.14	Moisture content of HMA mixtures (field lab)	0.469	0.360	0.171	Low
	5.15	HMA asphalt binder sampling for testing at plant	0.480	0.369	0.151	Low
	5.16	Density of HMA mixtures (district lab)	0.350	0.397	0.253	Moderate
	5.17	Gradation of HMA mixtures (district lab)	0.273	0.579	0.148	Moderate
	5.18	Asphalt content of HMA mixtures (district lab)	0.412	0.570	0.018	Moderate
	5.19	Maximum specific gravity of uncompacted plant mix asphalt (field lab)	0.321	0.412	0.266	Moderate
	5.20	Moisture content of uncompacted plant mix asphalt (field lab)	0.521	0.360	0.119	Low

	5.21	Air voids of plant mix asphalt (district lab)	0.278	0.468	0.254	Moderate
	5.22	Maximum specific gravity of uncompacted plant mix asphalt (district lab)	0.230	0.538	0.232	Moderate
	5.23	Gradation of plant mix asphalt (district lab)	0.201	0.487	0.312	Moderate
	5.24	Asphalt content of plant mix asphalt (district lab)	0.189	0.438	0.373	Moderate
	5.25	Field density (cores or nuclear) of completed HMA road work	0.167	0.289	0.544	High
	5.26	Voids in mineral aggregate (VMA)	0.340	0.580	0.080	Moderate
	5.27	Minimum, mix gradation	0.182	0.440	0.378	Moderate
	5.28	Binder content	0.350	0.430	0.220	Moderate
	5.29	Theoretical maximum specific gravity of asphalt paving mixtures- HMA (field lab)	0.178	0.321	0.501	High
	5.30	Voids filled with asphalt (VFA)- HMA	0.610	0.312	0.078	Low
	5.31	Voids in mineral aggregate (VMA) - HMA	0.380	0.458	0.162	Moderate
	5.32	Dust to effective binder content (d/b) ratio	0.217	0.320	0.463	High
	5.33	HMA construction joints control	0.208	0.380	0.412	High

APPENDIX B: BBN R CODE

```
R version 3.6.1 (2019-07-05) -- "Action of the Toes"
Copyright (C) 2019 The R Foundation for Statistical Computing
Platform: x86_64-w64-mingw32/x64 (64-bit)

R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.

R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

[Workspace loaded from ~/.RData]

Loading required package: graph
Loading required package: BiocGenerics
Loading required package: parallel
Loading required package: Rgraphviz
Loading required package: grid
Error: package or namespace load failed for 'Rgraphviz' in asNamespace(ns,
base.OK = FALSE):
 reached elapsed time limit
> library(bnlearn)

Attaching package: 'bnlearn'

The following objects are masked from 'package:BiocGenerics':

    path, score

The following object is masked from 'package:stats':

    sigma

> risk.dag = model2network("[C][S][R][CF|C:S:R][FF][RI|CF:FF]")
> pp = graphviz.plot(risk.dag)
Loading required namespace: Rgraphviz
> pp
A graphNEL graph with directed edges
Number of Nodes = 6
Number of Edges = 5
```




```
> #create probability distribution
> A.lv = c("very low", "low", "moderate","high", "very high")
> B.lv = c("low", "moderate", "high")
> C.prob = array(c(0.0, 0.25, 0.25, 0.375, 0.125), dim = 5, dimnames =
list(C = A.lv))
>
> S.prob = array(c(0.125, 0.375, 0.375, 0.0, 0.125), dim = 5, dimnames =
list(S = A.lv))
>
> R.prob = array(c(0.0, 0.125, 0.375, 0.5, 0.0), dim = 5, dimnames = list(R
= A.lv))
>
> FF.prob = array(c(0.25, 0.0, 0.5, 0.25, 0.0), dim = 5, dimnames = list(FF
= A.lv))

> CF.prob = array(c(1, 0, 0, 0.5, 0.5, 0, 0.25, 0.75, 0, 0, 0.5, 0.5, 0,
0.1, 0.9, 0.9, 0.1, 0, 0.6, 0.4, 0, 0.05, 0.95, 0, 0, 0.45, 0.55, 0, 0.08,
0.92, 0.04, 0.96, 0, 0.03, 0.97, 0, 0.02, 0.98, 0, 0, 0.25, 0.75, 0, 0.05,
0.95, 0, 0.3, 0.7, 0, 0.28, 0.72, 0, 0.26, 0.74, 0, 0.2, 0.8, 0, 0.05,
0.95, 0, 0.08, 0.92, 0, 0.07, 0.93, 0, 0.06, 0.94, 0, 0.05, 0.95, 0, 0.04,
0.96, 0.96, 0.04, 0, 0.94, 0.06, 0, 0.15, 0.85, 0, 0, 0.2, 0.8, 0, 0.08,
0.92, 0.65, 0.35, 0, 0.5, 0.5, 0, 0.2, 0.8, 0, 0, 0.4, 0.6, 0, 0.07, 0.93,
0.08, 0.92, 0, 0.07, 0.93, 0, 0.06, 0.94, 0, 0, 0.34, 0.66, 0, 0.06, 0.94,
0, 0.37, 0.63, 0, 0.35, 0.65, 0, 0.33, 0.67, 0, 0.31, 0.69, 0, 0.12, 0.88,
0, 0.19, 0.81, 0, 0.18, 0.82, 0, 0.17, 0.83, 0, 0.16, 0.84, 0, 0.03, 0.97,
0.14, 0.86, 0, 0.12, 0.88, 0, 0.07, 0.93, 0, 0, 0.39, 0.61, 0, 0.09, 0.91,
0.28, 0.72, 0, 0.26, 0.74, 0, 0.24, 0.76, 0, 0, 0.35, 0.65, 0, 0.21, 0.79,
0.07, 0.93, 0, 0.06, 0.94, 0, 0, 1, 0, 0, 0.38, 0.62, 0, 0.09, 0.91, 0,
0.29, 0.71, 0, 0.28, 0.72, 0, 0.27, 0.73, 0, 0.25, 0.75, 0, 0.05, 0.95, 0,
0.07, 0.93, 0, 0.06, 0.94, 0, 0.05, 0.95, 0, 0.04, 0.96, 0, 0.03, 0.97, 0,
0.13, 0.87, 0, 0.22, 0.78, 0, 0.21, 0.79, 0, 0.2, 0.8, 0, 0.11, 0.89, 0,
0.26, 0.74, 0, 0.25, 0.75, 0, 0.24, 0.76, 0, 0.23, 0.77, 0, 0.13, 0.87, 0,
0.3, 0.7, 0, 0.29, 0.71, 0, 0.28, 0.72, 0, 0.27, 0.73, 0, 0.12, 0.88, 0,
0.31, 0.69, 0, 0.3, 0.7, 0, 0.29, 0.71, 0, 0.5, 0.5, 0, 0.06, 0.94, 0,
0.09, 0.91, 0, 0.08, 0.92, 0, 0.07, 0.93, 0, 0.05, 0.95, 0, 0.03, 0.97, 0,
0.1, 0.9, 0, 0.09, 0.91, 0, 0.08, 0.92, 0, 0.07, 0.93, 0, 0.06, 0.94, 0,
0.2, 0.8, 0, 0.19, 0.81, 0, 0.18, 0.82, 0, 0.17, 0.83, 0, 0.07, 0.93, 0,
0.08, 0.92, 0, 0.15, 0.85, 0, 0.14, 0.86, 0, 0.13, 0.87, 0, 0.12, 0.88, 0,
0.09, 0.91, 0, 0.08, 0.92, 0, 0.07, 0.93, 0, 0.06, 0.94, 0, 0.03, 0.97, 0,
0.07, 0.93, 0, 0.04, 0.96, 0, 0.03, 0.97, 0, 0.01, 0.99, 0, 0, 1), dim =
c(3, 5, 5, 5), dimnames = list(CF = B.lv, R = A.lv, S = A.lv, C = A.lv))
> CF.prob
```

```
>

> RI.prob = array(c(1, 0, 0, 0.95, 0.05, 0, 0.9, 0.1, 0, 0.85, 0.1, 0.05,
0.05, 0.55, 0.4, 0.3, 0.65, 0.05, 0.4, 0.6, 0, 0, 1, 0, 0, 0.6, 0.4, 0.05,
0.25, 0.7, 0.1, 0.15, 0.75, 0.1, 0.1, 0.8, 0.05, 0.1, 0.85, 0, 0.05, 0.95,
0, 0, 1), dim = c(3, 5, 3), dimnames = list(RI = B.lv, FF = A.lv, CF =
B.lv))
> RI.prob
, , CF = low

          FF
RI          very low  low moderate high very high
  low              1 0.95      0.9 0.85      0.05
  moderate         0 0.05      0.1 0.10      0.55
  high             0 0.00      0.0 0.05      0.40

, , CF = moderate

          FF
RI          very low low moderate high very high
  low           0.30 0.4        0  0.0      0.05
  moderate      0.65 0.6        1  0.6      0.25
  high          0.05 0.0        0  0.4      0.70

, , CF = high

          FF
RI          very low low moderate high very high
  low           0.10 0.1     0.05 0.00         0
  moderate      0.20 0.1     0.10 0.05         0
  high          0.75 0.8     0.85 0.95         1
```

link the nnetwor and arc to the probability into BN

```
> cpt = list(C = C.prob, S = S.prob, R = R.prob, FF = FF.prob, CF =
CF.prob, RI = RI.prob)
> bn = custom.fit(risk.dag, cpt)
# Or To find marginal distribution of RI

> library(gRain)
> cpt.list <- compileCPT(list(C = C.prob, S = S.prob, R = R.prob, FF =
FF.prob, CF = CF.prob, RI = RI.prob))
> bn <- grain(cpt.list)
> #marginal distrbution of RI
> qgrain(bn, nodes=c("RI"))
$RI
RI
```

APPENDIX C

Component	No.	Field Inspection	Total CI	Inspection Frequency	Documentation Effort	Inspector Experience
Earthwork and Embankment (including structural backfills)	1	***Compaction Control:*** *Perform and document density and moisture tests.*	7.27	Intermittent	Level 2	Junior
	2	***Embankment Stability:*** *Ensure stability of embankment and slope against sliding by providing suitable materials, construction, foundation and a suitable bond.*	7.80	Intermittent	Level 3	Intermediate
	3	***Lift Thickness:*** *Verify material placement within specified lift thickness.*	6.40	Intermittent	Level 3	Junior
	4	***Drainage Work:*** *Check placement of traditional drainage stone or geotextile accordance to specifications.*	6.80	Intermittent	Level 2	Junior
	5	***Foundation Preparation:*** *Verify the foundation to be firm and uniform to line and grade as shown in the plans.*	7.93	Intermittent	Level 3	Junior
	6	***Erosion control:*** *Verify installation and maintenance of temporary erosion control devices and compliance with permits and Contract requirements*	6.27	Intermittent	Level 2	Junior
	7	***Geotextile Placement:*** *Verify placement of geotextile according to plans and specifications.*	6.60	Intermittent	Level 3	Junior

Component	No.	Field Inspection	Total CI	Inspection Frequency	Documentation Effort	Inspector Experience
	8	***Embankment Fine Grade Line:*** *Ensure embankment to be constructed according to plan limits, and finished to specified line and grade.*	4.60	End Product	Level 3	Junior
	9	***Excavation:*** *Check excavation limits, required undercuts, safety.*	5.47	Intermittent	Level 3	Intermediate
	10	***Placement Inspection:*** *Inspect placement of fill material and review checklist including required construction operations and tests.*	4.36	Intermittent	Level 2	Junior
	11	***Slope Rounding/Shaping:*** *Check slope rounding to be as shown in the plans.*	2.67	End Product	Level 3	Junior
Subbase/Base Course	1	***Base Patching:*** *Ensure all failed pavement is defined, sub-grade is structurally sound, and delaminated concrete is removed*	6.73	Intermittent	Level 3	Junior
	2	***Compaction Control:*** *Verify moisture content, watering operations, and compaction*	7.00	Intermittent	Level 2	Junior
	3	***Drainage Layer and Pipe Installation:*** *Verify construction of drainage layer, and check material approval and placement of drainage pipes.*	7.47	Intermittent	Level 2	Intermediate
	4	***Surface Smoothness/ Tolerance:*** *Inspect and document finished grade for smoothness and line and grade, and determine if all loose and segregated areas are repaired.*	5.53	End Product	Level 3	Intermediate

Component	No.	Field Inspection	Total CI	Inspection Frequency	Documentation Effort	Inspector Experience
	5	***Lift Thickness:*** *Verify base material placement within specified lift thickness.*	5.27	Intermittent	Level 3	Junior
	6	***Placement Inspection:*** *Inspect placement of base course material and review checklist including required construction operations and tests.*	5.13	Intermittent	Level 2	Junior
Bridge Deck and Girder	1	***Assembly, Erection, and Testing of Steel Girder Elements:*** *Verify assembly, erection, and testing of steel girder elements according to contract specifications and plans.*	12.00	Continual	Level 2	Senior
	2	***Precast Concrete Deck and Girders Placement:*** *Inspect placement of precast concrete deck and girders according to plans and specifications and check for any damage or cracks.*	9.53	Continual	Level 2	Intermediate
	3	***Rebar Placement/Concrete Cover:*** *Check placement of reinforced steel and concrete cover for length, location, size, and cover depth according to specifications and plans.*	10.13	Intermittent	Level 3	Intermediate
	4	***Formwork/ False Work:*** *Inspect formwork elements and erection to comply with the required loading capacity, dimensions, and project specifications.*	7.53	Intermittent	Level 3	Senior
	5	***Fresh Concrete Testing (Slump, Air Content, Strength,***	8.80	Intermittent	Level 1	Junior

Component	No.	Field Inspection	Total CI	Inspection Frequency	Documentation Effort	Inspector Experience
		and Thickness): *Cast strength specimens, perform required slump, temperature, air content, and probe tests*				
	6	***Curing:*** *Verify curing methods of concrete according to specified method and duration.*	7.13	Intermittent	Level 3	Junior
	7	***Vibration/Placement of Concrete:*** *Monitor placement of concrete and use of vibrators or other approved equipment to consolidate concrete.*	7.60	Continual	Level 3	Junior
	8	***Monitoring Concrete Placement Duration:*** *Verify concrete placement within specified duration to avoid hardening.*	6.87	Continual	Level 3	Junior
	9	***Expansion Joint Inspection:*** *Verify construction of expansion joints according to plans and specifications.*	7.00	Intermittent	Level 3	Intermediate
	10	***Finish/Texture/Skid Resistance:*** *Inspect the finishing of concrete and check skid resistance to comply with project specifications.*	5.47	End Product	Level 3	Intermediate
	11	***Surface Smoothness/Tolerance:*** *Determine of smoothness using a straightedge, profiler or any other approved tool certified by the Department.*	5.13	End Product	Level 3	Junior
	12	***Waterproofing Membrane:*** *Check approval of waterproofing materials and*	6.00	Intermittent	Level 3	Junior

Component	No.	Field Inspection	Total CI	Inspection Frequency	Documentation Effort	Inspector Experience
		provided documents, and inspect placement according to project specifications and plans.				
Bridge Foundation, Pile, Abutment, Column, and Pier	1	***Piles and Drilled Shafts Operations:*** *Ensuring proper placement and depth; Inspect piling for defects; splicing methods.*	9.27	Continual	Level 1	Senior
	2	***Formwork/ False work:*** *Inspect formwork elements and erection to comply with the required loading capacity, dimensions, and project specifications.*	8.20	End Product	Level 3	Intermediate
	3	***Pile Loading Test:*** *Check loading capacity of the pile according to specifications and design requirements.*	8.33	Intermittent	Level 2	Senior
	4	***Rebar Placement/Concrete Cover:*** *Check placement of reinforced steel and concrete cover for length, location, size, and cover depth according to specifications and plans.*	8.33	Intermittent	Level 2	Intermediate
	5	***Fresh Concrete Testing (Slump, Air Content, Strength):*** *Cast strength specimens, perform required slump, temperature, and air content tests*	8.20	Intermittent	Level 2	Junior
	6	***Vibration/Placement of Concrete:*** *Monitor placement of concrete and use of vibrators or other approved equipment to consolidate concrete.*	7.93	Continual	Level 3	Junior

Component	No.	Field Inspection	Total CI	Inspection Frequency	Documentation Effort	Inspector Experience
	7	***Monitoring Concrete Placement Duration:*** *Verify concrete placement within specified duration to avoid hardening.*	6.33	Continual	Level 3	Junior
	8	***Dimensions, Thickness and Grades:*** *Check dimensions, thickness and grades of foundation according to project plans.*	7.47	Intermittent	Level 2	Intermediate
	9	***Survey Checking:*** *Determine the precise location and elevations by surveying, staking, measurement, and calculations essential to different construction elements.*	7.33	Intermittent	Level 1	Intermediate
	10	***Finish/Texture:*** *Inspect that concrete finishing complies with specification.*	5.20	End Product	Level 3	Junior
Cast-in-Place Structural Concrete (Retaining walls, Box culverts, Drainage structure, Concrete bases)	1	***Monitoring Concrete Placement Duration:*** *Verify concrete placement within specified duration to avoid hardening.*	5.60	Continual	Level 3	Junior
	2	***Formwork/ False work:*** *Inspect formwork elements and erection to comply with the required loading capacity, dimensions, and project specifications.*	6.27	End Product	Level 3	Intermediate
	3	***Curing:*** *Verify curing method of concrete according to specified method and duration.*	6.00	Intermittent	Level 3	Junior
	4	***Fresh Concrete Testing (Slump, Air Content, Strength):*** *Cast strength specimens,*	7.13	Intermittent	Level 2	Junior

Component	No.	Field Inspection	Total CI	Inspection Frequency	Documentation Effort	Inspector Experience
		perform required slump, temperature, and air content tests				
	5	***Vibration/Placement of Concrete:*** *Monitor placement of concrete and use of vibrators or other approved equipment to consolidate concrete.*	5.80	Intermittent	Level 3	Junior
	6	***Rebar Placement/Concrete Cover:*** *Check placement of reinforced steel and concrete cover for length, location, size, and cover depth according to specifications and plans.*	7.27	Intermittent	Level 2	Intermediate
	7	***Dimensions, Thickness and Grades:*** *Check dimensions, thickness and grades of foundation or wall according to project plans.*	6.20	Intermittent	Level 2	Intermediate
Precast Concrete (Retaining walls, Box culverts, Drainage structure, Storm sewer)	1	***Monitoring Rebar Placement during Fabrication:*** *Visit the manufacturing workshop to verify rebar placement and size according to specifications and plans*	7.20	Intermittent	Level 2	Intermediate
	2	***Checking for Damages before Placement:*** *Check precast concrete elements for damages before placement.*	6.87	Intermittent	Level 3	Intermediate
	3	***Installation to Dimensions and Specifications:*** *Verify concrete element dimension and installation according to specifications and plans.*	6.07	Intermittent	Level 2	Intermediate

Component	No.	Field Inspection	Total CI	Inspection Frequency	Documentation Effort	Inspector Experience
Rigid Pavement (PCCP)	1	***Curing:*** *Verify the curing method of concrete according to the specified method and duration.*	6.00	Intermittent	Level 3	Junior
	2	***Rebar Placement/ Cover/Dowels:*** *Review reinforcing steel, joint detailing, and dowel placement plan and verify dowel bar cages.*	7.20	Intermittent	Level 3	Intermediate
	3	***Fresh Concrete Testing (Slump, Air Content, Strength, Thickness):*** *Cast strength specimens, perform required slump, temperature, air content, and probe tests*	6.60	Intermittent	Level 1	Junior
	4	***Vibration/Placement of Concrete:*** *Monitor placement of concrete and use of vibrators or other approved equipment to consolidate concrete.*	5.47	Intermittent	Level 3	Junior
	5	***Joint Inspection:*** *Verify joint spacing and reinforcement according to plans and specifications.*	5.53	Intermittent	Level 3	Junior
	6	***Surface Smoothness/Tolerance:*** *Determine the minimum International Roughness Index (IRI) for pavement smoothness using a profiler approved by the Department.*	4.67	End Product	Level 1	Intermediate
	7	***Dimensions, Thickness and Grades:*** *Check dimensions, thickness and cross-slope of PCCP pavement according to*	4.40	Intermittent	Level 3	Junior

Component	No.	Field Inspection	Total CI	Inspection Frequency	Documentation Effort	Inspector Experience
		specifications.				
	8	***Finish/Texture/Skid Resistance:*** *Verify the finishing of concrete and inspect skid resistance to comply with specifications.*	4.67	End Product	Level 3	Intermediate
Flexible Pavement (HMA)	1	***Laydown Inspection:*** *Make sure cleaning of the roadway, usually by brooming to help HMA bonds to the underlying pavement and coat is applied.*	6.87	Continual	Level 3	Junior
	2	***Density (nuclear Gage or other):*** *Check and document grade and density of underlying material.*	6.53	Intermittent	Level 1	Intermediate
	3	***Segregation:*** *Observe any possible segregation during pavement placement.*	6.73	Intermittent	Level 3	Intermediate
	4	***Coat and Surface Preparation:*** *Check placement of liquid or emulsified asphalt/coat to a prepared subgrade or untreated base course according to project specifications.*	5.80	Intermittent	Level 3	Junior
	5	***Longitudinal Joint Inspection:*** *Check construction and location of longitudinal joints according to plans and project specifications.*	5.80	Intermittent	Level 3	Intermediate
	6	***Dimensions, Thickness and Grade:*** *Verify HMA placement dimensions, thickness and grade according to specifications and plans.*	5.87	Intermittent	Level 2	Junior

Component	No.	Field Inspection	Total CI	Inspection Frequency	Documentation Effort	Inspector Experience
	7	***Surface Smoothness/ Tolerance:*** *Review profilograph/profile information as required for smoothness testing in accordance with specifications.*	4.53	End Product	Level 2	Intermediate
	8	***Finish/Texture/Skid Resistance:*** *Verify finishing HMA according to plans and inspect skid resistance to comply with specifications.*	3.80	End Product	Level 3	Intermediate
Miscellaneous	1	***Temporary Traffic Control:*** *Check the placing and maintaining temporary traffic control devices and related documentation to ensure the safety.*	10.07	Intermittent	Level 3	Intermediate
	2	***Guiderail and Fencing Installation:*** *Verify guardrail elements and post are installed and driven according to specifications to ensure that it performs correctly.*	7.40	Intermittent	Level 3	Intermediate
	3	***Pavement Marking:*** *Verify pavement marking according to specifications and plans.*	5.80	Intermittent	Level 3	Junior
	4	***Traffic Signals, Electrical, and Lighting:*** *Verify type, locations and elevations of traffic signal, foundations, and poles according to plans and specifications.*	6.00	Intermittent	Level 2	Intermediate
	5	***Traffic Signing:*** *Check traffic sign size, orientation, elevation, visibility and installation,*	4.60	Intermittent	Level 3	Intermediate

Component	No.	Field Inspection	Total CI	Inspection Frequency	Documentation Effort	Inspector Experience
		including supports and foundations.				
	6	***Coatings and Penetrating Sealants:*** *Verify and record field condition, thickness; Ensure proper cleaning and painting of misc. items and placement.*	4.20	Intermittent	Level 3	Intermediate