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Estimating Bridge Reliability by Using Bayesian Networks

Andrew B. Groeneveld, Stephanie G. Wood, Edgardo Ruiz, and
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Estimating Bridge Reliability by Using Bayesian Networks

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Abstract

As part of an inspection, bridge inspectors assign condition ratings to the main components of a bridge's structural system and identify any defects that they observe. Condition ratings are necessarily somewhat subjective, as they are influenced by the experience of the inspectors. In the current work, procedures were developed for making inferences on the reliability of reinforced concrete girders with defects at both the cross section and the girder level. The Bayesian network (BN) tools constructed in this work use simple structural mechanics to model the capacity of girders. By using expert elicitation, defects observed during inspection are correlated with underlying deterioration mechanisms. By linking these deterioration mechanisms with reductions in mechanical properties, inferences on the reliability of a bridge can be made based on visual observation of defects. With more development, this BN tool can be used to compare conditions of bridges relative to one another and aid in the prioritization of repairs. However, an extensive survey of bridges affected by deterioration mechanisms is needed to confidently establish valid relationships between deterioration severity and mechanical properties.

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Preface

This study was conducted for the U.S. Army Corps of Engineers under Project 476923, “Navigation Systems.” The program manager was Mr. Charles E. Wiggins, Technical Director for Navigation, U.S. Army Engineer Research and Development Center, Coastal and Hydraulics Laboratory (ERDC-CHL). The technical monitor was Mr. Edgardo Ruiz, Research Civil Engineer, U.S. Army Engineer Research and Development Center, Geotechnical and Structures Laboratory (ERDC-GSL).

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The work was led by the Structural Engineering Branch (StEB) of the Geosciences and Structures Division (GSD), ERDC-GSL, with contributions from the Concrete and Materials Branch (CMB) of the Engineering Systems and Materials Division (ESMD), ERDC-GSL, and the USACE Portland District (NWP). At the time of publication, Ms. Mariely Mejías-Santiago was Chief, StEB, and Mr. James L. Davis was Chief, GSD. The Deputy Director of ERDC-GSL was Mr. Charles W. Ertle II, and the Director was Mr. Bartley P. Durst.

COL Teresa A. Schlosser was the Commander of ERDC, and Dr. David W. Pittman was the Director.

1 Introduction

1.1 Background

As part of an inspection, bridge inspectors assign condition ratings to and identify any observed defects in the bridge's three main parts: the deck, the superstructure, and the substructure. The inspection team leader is relied on to consider the severity of the defects and their effect on component performance when assigning condition ratings. However, the judgment and past experience of the inspection team plays a large role in determining the ratings. Thus, ratings have an element of subjectivity, and ratings for the same structure can vary between different inspection teams.

There is a need for a quantitative way to interpret inspection findings and to determine the impact of any defects on bridge reliability. This work explores the use of Bayesian networks (BNs) for making inferences on bridge reliability based on observed defects. A BN is a type of probabilistic graphical model that expresses the causal relationships between variables. BNs can be used to model knowledge subject to uncertainty and to make inferences on the most likely state of variables in the model, given information or observations about other variables. The BNs constructed in this work use simple structural mechanics to model the capacity of girders and expert knowledge to connect defects, which can be observed during an inspection, to underlying deterioration mechanisms, which cannot be easily observed and must be inferred. By linking these deterioration mechanisms with reductions in mechanical properties, inferences on the reliability of a bridge can be made based on visual observation of defects.

1.2 Objective of current work

The objective of this work is to develop a process for using BNs to make inferences on reinforced concrete (RC) bridge reliability, incorporating findings about defects.

1.3 Outline

The remainder of this report is organized as follows. The most common material defects affecting concrete and their effects on mechanical properties are described in Chapter 2. The basic theory used to make inferences on reliability is introduced in Chapter 3 in the context of

analyzing the flexural capacity of an RC girder section with defects. For addressing practical problems when a bridge girder has multiple defects at different locations, an automated means of performing multiple analyses is needed. The basic framework for this automation is presented in Chapter 4, and details of its implementation are given in Chapter 5. Chapter 6 summarizes the key conclusions from this work and identifies possible areas for future work.

2 Material Defects

This chapter provides an overview of material defects specific to RC bridges. Section 2.1 lists the major deterioration mechanisms that cause the defects, and Section 2.2 describes how these defects affect mechanical properties.

2.1 Deterioration mechanisms

Defects in hardened concrete are linked to either damage or deterioration. Damage is the result of an external force, such as impact or overloading, and deterioration is caused by internal phenomena. Damage-induced defects listed in the American Association of State Highway and Transportation Officials (AASHTO)'s *Manual for Bridge Element Inspection (MBEI)* (2013) are largely self-explanatory and unrelated to concrete deterioration. They include abrasion/wear, distortion, settlement, scour, and damage. This study deals with the less obvious deterioration mechanisms and their consequential, observable defects. The most common concrete deterioration mechanisms include corrosion of internal steel reinforcement, freeze-thaw (FT) cycling, and alkali-silica reaction (ASR).

Corrosion of internal reinforcement is caused by the ingress of carbon dioxide and chlorides into the concrete and down to the depth of the reinforcement. The resulting rust occupies more volume than the steel and exerts tensile stresses on the concrete, resulting in cracking. In concrete bridges, the chlorides are commonly supplied by the application of de-icing salts. Surface symptoms of corrosion include rust staining, cracking, spalling, delamination, and exposed rebar.

FT cycling deterioration is caused when water inside the concrete pores cyclically freezes and thaws. As the water freezes, it exerts pressure inside the concrete pores and cavities. When this pressure exceeds the tensile strength of the concrete, the concrete cracks. Concretes placed prior to 1940, before the use of air-entraining admixtures, have a higher risk for FT deterioration. Additionally, concretes located in areas where nightly temperatures fall below freezing while daily temperatures rise above freezing are susceptible to this type of deterioration, particularly if lacking air entrainment and exposed to direct sunlight where cycles may be more severe. The most common manifestations of FT deterioration include efflorescence, cracking, spalling, and delamination.

ASR is a chemical reaction between the constituents of the concrete. Alkali hydroxides present in the concrete pore solution attack reactive forms of silica contained in some aggregates. In the presence of moisture, the product of this reaction, called ASR gel, swells and causes expansion and cracking of the concrete. The alkali hydroxides are typically supplied by the portland cement, which has necessitated limits on the cement alkalinity for many projects, but may also be contributed by supplementary cementitious materials, de-icing salts, or the aggregates themselves. Surface evidence of ASR includes pattern cracking, other cracking, efflorescence, and spalling.

2.2 Effects on mechanical properties

If unmitigated, these deterioration mechanisms eventually become evident on the concrete surface and result in reductions in the mechanical properties. Concrete stiffness, or the elastic modulus, is the most sensitive property to the deterioration, but compressive strength and tensile strength may also be affected.

No previous work has established correlations between rated visual inspections of bridges and the reductions of the concrete mechanical properties due to deterioration. Much of the existing literature involves small-scale laboratory studies in which the deterioration and subsequent symptoms are made rapidly severe and cannot be used to quantitatively predict deterioration of and effects on full-scale members. Therefore, relationships between deterioration severity and reductions in mechanical properties are based on expert elicitation, inferring threshold values from the literature and case studies. The following paragraphs are intended to serve as high-level summaries of the variable results taken from previous work rather than an extensive literature review.

Corrosion of internal reinforcement can cause debonding of the steel from the concrete, resulting in spalling and delamination of the concrete cover. The main concern in a reinforced concrete member affected by corrosion is the loss of the tensile and flexural strengths due to rebar section loss. That is to say that the mechanical properties of the concrete are not as affected as the mechanical properties of the steel. Unless the spalling or delamination is severe enough to expose the rebar, estimates of the remaining mechanical capacity of the steel remain nearly impossible to determine by using only visual observation.

Many studies on the relationship between FT deterioration and mechanical properties have been conducted on small-scale laboratory specimens subjected to FT cycles in a temperature-controlled chamber (Ji et al. 2008; Hanjari et al. 2011; Shang et al. 2014; Qin et al. 2016). Remaining capacities for mechanical properties from some of those studies are provided in Table 1. This sample of results from the literature highlights the variability and difficulty in defining conclusive ranges for these values. Contributing to that difficulty are the lack of visual ratings for the specimens and the inability to correlate the small-scale results with the behavior of large-scale structural members in the field.

Table 1. Sample of literature results for mechanical properties of FT-affected concrete in laboratory studies.

Study	Specimen Size and Type	Number of Cycles	Remaining Capacity (%)		
			Compressive Strength	Splitting Tensile Strength	Modulus of Elasticity
Ji et al. 2008	150-mm cubes	15	84	92	74-81
		30	74	84	47-53
		50	65	68	28-38
Shang et al. 2014	100-mm x 100-mm x 200-mm prisms	50	96-100	-	-
		100	92-99	-	-
		200	78-100	-	-
		400	54-77	-	-
Qin et al. 2016	100-mm cubes	25	99	-	100
		50	96	-	99
		100	91	-	98
		200	78	-	94
		325	44	-	75

The same inconsistencies among results of laboratory FT studies exist with laboratory ASR studies. Because ASR gel causes dimensional expansion of the affected concrete, the linear expansion of a specimen is used as the indicator of deterioration severity, and relationships are established between expansion levels and measured mechanical properties (Swamy and Al-Asali 1988; Smaoui et al. 2005; Giaccio et al. 2008; Liu et al. 2012). The amount an ASR-affected concrete specimen will expand depends on

multiple variables including aggregate mineralogy, pore solution alkalinity, available moisture, conditioning temperature, and other factors. Like the FT studies, the ASR studies do not contain visual ratings, and results on small-scale specimens do not scale up to capture the behavior of large-scale structural members in the field.

In addition to the literature on laboratory studies, case studies and previous experience involving other types of concrete structures were used to estimate the remaining mechanical property capacities in the BN. One report produced by the U.S. Army Corps of Engineers Waterways Experiment Station details the evaluation of navigation lock walls affected by FT cycling, ASR, or a combination of the two deterioration mechanisms (McDonald 1987). Compressive strength and modulus of elasticity were measured on extracted cores from many of the structures in the report. The data show remaining compressive strength and elastic modulus capacities as low as 70 and 45%, respectively, near the surface of the deteriorated concrete. For the cores taken from the same structure at the same depths, differences between reductions in compressive strength and elastic modulus were as high as 52%, emphasizing the higher sensitivity of elastic modulus to concrete deterioration. For instance, one core had retained 95% of its original compressive strength but only 45% of its original elastic modulus. Although no visual ratings were applied, photos of deterioration are provided in the report.

3 Inferences on Reliability at a Section

This chapter describes the underlying theory for analyzing the reliability of a girder at a section. Sections 3.1 and 3.2 give some brief background on BNs and structural reliability, respectively. Section 3.3 describes how conditional probabilities for material defects were established. Finally, section 3.4 presents a BN for making inferences on the reliability of a reinforced concrete girder section with defects.

3.1 Bayesian networks

A BN is a type of probabilistic graphical model that expresses the structure of interactions between variables and can be used to model knowledge subject to uncertainty (Heckerman and Wellman 1995; Pradhan et al. 1996). The BN takes the form of a directed acyclic graph, where nodes represent variables and links (or edges) represent causal relationships between variables. The graph is directed because the links represent causality, with edges running to a child node from one or more parent nodes. The graph is also acyclic, as circular dependencies between variables would be nonsensical. The relationships between variables are encoded in conditional probability tables (CPTs), which give the probability of each of a node's states given the states of its parent node(s). A simple example of a BN is shown in Figure 1. Node *E* is dependent on three nodes (*A*, *B*, and *C*), and node *D* is dependent on one node (*A*).

Figure 1. Example BN.

A key concept in the use of BNs is Bayes' theorem, which deals with conditional probabilities. It can be viewed in terms of a hypothesis, θ , which is formed at some initial time and has some probability of being true (often called the prior probability). When new data, x , are obtained, they can be used to update the prior probability based on the additional information that x provides about θ . This is expressed as

$$P(\theta|x) = \frac{P(x|\theta)P(\theta)}{P(x)} \quad (1)$$

where

$P(\theta)$ = the probability of the hypothesis' being true before the data are known (prior probability)

$P(\theta|x)$ = the probability of the hypothesis' being true, given the new data (posterior probability)

$P(x|\theta)$ = the probability of the data's being observed, given that the hypothesis is true (likelihood)

$P(x)$ = the probability of the data's being observed under any circumstances (essentially a scaling factor).

Bayesian inference is the process of using new data to update prior beliefs. Because this is a probabilistic approach, Bayesian inference will not necessarily result in the correct conclusion. However, it will give the probabilities of possible conclusions, and the most likely conclusion can be selected.

3.2 Structural reliability

The reliability of a structure is the probability of the structure's not failing. That is, if the probability of failure is P_f , then the reliability is $1 - P_f$. Thus, a definition of failure is needed to determine the reliability. Here, failure is defined as not performing as intended; specifically, having insufficient capacity to carry the applied loads. The performance (or limit) function, g , is defined as

$$g(R, Q) = R - Q \quad (2)$$

where

R = resistance (or capacity)

Q = load effect (or demand).

With this definition, $g > 0$ when the resistance exceeds the load effect, $g = 0$ when the resistance is exactly equal to the load effect, and $g < 0$ when the resistance is insufficient to support the load effect (i.e., failure). The probability of failure, P_f , is then

$$P_f = P(g < 0). \quad (3)$$

For a normally distributed limit state function, the reliability index, β , is defined as μ_g/σ_g , where μ_g and σ_g are the mean and standard deviation of g , respectively. The reliability index represents the number of standard deviations that separate the mean value of g from its value at the initiation of failure ($g = 0$). The reliability index can be approximated in a number of ways (Nowak and Collins 2012). The first order, second moment (FOSM) method uses a linear Taylor series expansion of the limit state function, $g(x_1, x_2, \dots, x_n)$, about the mean values of its arguments x_i . Assuming that the variables are uncorrelated,

$$\beta = \frac{g|_{x=\mu}}{\sqrt{\sum_{i=1}^n \left(\left. \frac{\partial g}{\partial x_i} \right|_{x=\mu} \sigma_i \right)^2}} \quad (4)$$

where the notation $\cdot|_{x=\mu}$ has been used to indicate evaluation at the mean values of the x_i . If all variables are normally distributed, then the expression further simplifies to

$$\beta = -\Phi^{-1}(P_f) \quad (5)$$

where Φ^{-1} is the inverse of the standard normal cumulative distribution function and P_f is defined according to equation (3).

The BN tools developed in the current project provide inferences on probability of failure [equation (3)] as their primary output, with the approximate reliability index [equation (5)] given for comparison.

3.3 Establishing conditional probability tables for defects

An observable defect can be due to a variety of causes. For example, cracking may be caused by drying shrinkage during concrete curing, overloading of the member, deterioration mechanisms, or other causes. Cracks from drying shrinkage, although aesthetically unpleasant, are largely harmless; but cracks caused by underlying deterioration mean

that the condition of the concrete will likely continue to worsen, producing more cracking and other symptoms.

To better estimate the remaining capacity of a concrete member, it is important to have an idea of the cause(s) for the observed defects. For this reason, the CPTs in this study were constructed by using a tiered approach. The most common defects associated with each of the three deterioration mechanisms were listed and centered on those provided in the *MBEI* with some deviation and one addition. These are provided in Table 2. Determination of the severity of each defect is based on guidance provided in the *MBEI*, and the severity ranges from 1 (good) to 4 (severe). The Federal Highway Administration provides a descriptive and visual guide for assessing the condition states of ASR-induced defects in transportation infrastructure, with the *MBEI* serving as the basis for evaluation (Thomas et al. 2012). There are no similar documents for defects related to corrosion and FT cycling with regard to bridge inspections.

Table 2. List of defects associated with common concrete deterioration mechanisms.

Defect	Deterioration Mechanism		
	Corrosion	FT Cycling	ASR
Cracking	x	x	x
Spalling	x	x	x
Delamination	x	x	
Efflorescence		x	x
Rust Staining	x		
Exposed Rebar	x		
Map Cracking			x

Tables were constructed in the BN for each defect, expressing the probability of that defect's being indicative of a particular deterioration mechanism at each of three levels of severity. An example table for ASR-induced cracking is provided in Table 3. Probabilities range from 1 to 100% and were based on expert elicitation using the following statement: Given the condition state of the defect (i.e., 1, 2, 3, or 4), then the probability distribution of the severity of the underlying deterioration mechanism (i.e., low, moderate, or severe) is inferred. For

instance, if the condition state of the cracking is 2, then the probability that the severity of the ASR is moderate is 35%.

Table 3. Example of probability table for ASR-induced cracking in concrete.

Severity of ASR	Probability Based on Condition State of Cracking (%)			
	Condition State 1	Condition State 2	Condition State 3	Condition State 4
Low	80	10	5	5
Moderate	25	35	30	10
Severe	3	15	42	40

The total probability that a particular deterioration mechanism is the underlying cause for the observed defects is based on combinations of those defects and their severities. In some cases, the concrete may be affected by more than one deterioration mechanism, and this is taken into account in the network.

The CPT files for the BN are saved in plaintext format to allow easy updating. Complete CPTs are presented in Appendix A.

3.4 Reinforced concrete girder with defects

This section describes a BN for inferences on RC girder reliability accounting for observed defects. This extends the BN from previous work (Roberts et al. 2019), which provided reliability estimates for girders under uncertainty about material properties, loading, and other parameters, but did not account for deterioration. Roberts et al. (2019) considered RC, prestressed concrete, and steel girders. Their analysis examined the capacity and moment demand at a section along the girder that was chosen as the location of the maximum moment.

The current work focuses on RC girders with defects. A rectangular cross section is assumed, and compression reinforcement (if any is present in the section) is neglected. It is also assumed that the controlling failure mode of the girder is the strength limit state for flexure. Model development and exploration were performed by using Netica 6.04 (Norsys 2017). Initially, the BN contained nodes for the area and centroid position of each rebar layer. This allowed fine-grained control of the uncertainty for the individual layers but resulted in excessive memory and computation time requirements. Therefore, the treatment of rebar

properties was changed as described in Appendix B. The user is still able to enter the area and centroid position for as many rebar layers as are needed. However, the program now approximates the distribution for the rebar area and first moment of area of the rebar. This greatly reduces the number of calculations required for performing inference on the BN.

The final BN, which includes this performance improvement as well as the effects of deterioration on concrete compressive strength, is shown in Figure 2. The user supplies girder properties as nominal values, which are represented in the BN by normally distributed random variables with the parameters listed in Table 4. The bias, λ , and coefficient of variation, COV, are defined as

$$\lambda = \frac{\mu}{x}, \quad (6)$$

$$\text{COV} = \frac{\sigma}{\mu}, \quad (7)$$

where

μ = mean value

x = nominal value

σ = standard deviation.

Figure 2. Full BN for analysis of an RC girder at a single section.

Table 4. Parameters of random variables.

Parameter			Distribution		
Description	Symbol	Units	Bias	COV	Reference
Concrete compressive strength	f'_c	ksi	1.10	0.18	LeBeau (2008)
Rebar yield strength	f_y	ksi	1.13	0.12	Nowak et al. (1994)
Area of steel in rebar layer i	A_i	in. ²	1.00	0.015	Nowak and Szerszen (2003)
Centroid position of rebar layer i	y_i	in.	1.00	St dev ¹ = 0.7 in.	Nowak and Szerszen (2003)
Total moment load effect	M_Q	kip-in.	1.10	0.18	Roberts et al. (2019); LeBeau (2008)

¹ Because the error in positioning rebar does not change based on the depth of the member, the variability is given in terms of the standard deviation rather than the COV.

Note that the normal distribution was chosen mainly due to a lack of information to support other more complex distributions. The BN approach is not limited to normal distributions; future models could incorporate other distributions, represented either analytically or empirically (e.g., as tabular data).

The top two rows of nodes in Figure 2 are the portion of the BN related to material defects. The top row contains the underlying deterioration mechanisms described in Chapter 2: ASR, FT cycling, and corrosion. The second row contains the observed defects (Chapter 2). Based on the observed defects entered for the section, an inference is made on the probability distributions for the severity of each of the underlying deterioration mechanisms. Inference is performed by Netica, using message passing in a junction tree of cliques (Spiegelhalter et al. 1993; Jensen 1996; Neapolitan 2012).

Currently, the effect of deterioration is incorporated only for concrete compressive strength. Plans for future work include updating the BN to include the effect of corrosion on the remaining area of reinforcing steel.

Approximate reductions to the concrete compressive strength for the three idealized ASR and FT severity levels are given in Table 5. These numbers were selected by expert elicitation based on laboratory data and should not be considered precise estimates due to the wide range of conditions that

may be encountered in the field. However, they are sufficient for performing inference.

Table 5. Concrete compressive strength reductions based on deterioration.

Severity of deterioration	Reduction to concrete compressive strength	
	ASR	FT
Low	0.98	0.95
Moderate	0.70	0.75
Severe	0.40	0.45

The minimum (i.e., most severe) reduction factor is applied to the concrete compressive strength as

$$f'_{c,\text{reduced}} = f'_c \min(r_{\text{ASR}}, r_{\text{FT}}) \quad (8)$$

where

r_{ASR} = reduction to concrete compressive strength due to ASR

r_{FT} = reduction to concrete compressive strength due to FT.

The nominal moment capacity at the section is calculated as

$$M_n = f_y A_{\text{total}} \left(h - \frac{S}{A_{\text{total}}} - \frac{1}{2} \cdot \frac{f_y A_{\text{total}}}{0.85 f'_{c,\text{reduced}} b} \right) \quad (9)$$

where

A_{total} = total area of steel, $\sum_i A_i$

h, b = height and width of the girder, respectively (assumed to be deterministic in this analysis)

S = first moment of area, $\sum_i A_i y_i$.

All other variables have been previously defined. For details on this calculation, refer to Appendix B. The individual rebar layers are “reduced” into A_{total} and S for efficiency, with the distributions of these two variables calculated prior to forming the BN.

The equation for the moment limit state is obtained by writing equation (2) in terms of the moment capacity and the moment demand for the girder.

$$g_M = M_n - M_Q. \quad (10)$$

The probability of failure, P_f , is the probability that $g_M < 0$. This probability is calculated based on the probability table computed by Netica for the node g_M .

4 Programmatic Generation of Bayesian Networks

The previous chapter described the process for making inferences on the probability of failure (or, equivalently, the reliability) of a girder at a particular cross section. Of course, for realistic problems, the probability of failure of an entire girder or bridge will be of interest. The remaining chapters in this report discuss progress made towards analyzing reliability at the system level. This process starts with analyzing the reliability of a single girder, which can be viewed as a system composed of multiple cross sections acting in series. Such an analysis involves multiple BNs, which would be time-consuming for the user to create. This chapter describes the framework used for automatic generation of BNs given model parameters as inputs. Chapter 5 provides details related to the implementation.

Model development and exploration were initially performed by using Netica 6.04 (Norsys 2017). This software allowed for creation and analysis of BNs within a convenient graphical user interface (GUI). However, a major thrust of this project was the development of a tool to create BNs automatically, given the relevant input, thus freeing the user from this somewhat tedious task. Automation is also a crucial steppingstone toward eventual application of the BN models developed in this work.

The Python API (application programming interface) for Netica (Norsys 2018) was used to create a prototype GUI for creation and analysis of BNs for bridge reliability. The Bayesian inference calculations were performed by the Netica API. Python (version 3.7.3) provided a high-level, interpreted language for rapid development of a GUI using the *tkinter* library to interface with Tcl/Tk (version 8.6).

The following two prototype programs were created. Currently, the programs support only reinforced concrete girder bridges. As future projects require, the programs may be expanded to include steel girder bridges and prestressed concrete girder bridges.

- Bridge Reliability: Create a sectional model of a bridge girder, enter defects, and make inferences on reliability (Figure 3).
- Girder Condition: Enter condition findings for a girder and automate analysis of the girder as a system (Figure 4).

Examples of the use of each program are given in Appendix C.

Figure 3. Example of Bridge Reliability program.

The screenshot shows the 'example.xml - Bridge Reliability' application window. A 'Results' dialog box is open, displaying the 'Probability of failure: 2.64%' and 'Reliability index: 1.94'. The main window contains the following sections:

Model information

Name: Default reinforced concrete bridge

Description: Calculate the Probability of Failure of the main girder

NBIS:

Number of:

Design type: ReinforcedConcrete

Girder properties

	Mean	Bias	COV	# bins	# st devs
Concrete compressive strength (ksi)	3.5	1.1	0.18	5	3
Rebar yield strength (ksi)	33.0	1.13	0.12	5	3
Moment load effect (kip-in.)	40200.0	1.1	0.18	5	3
Bearing-to-bearing length (in.)	642.0				
Height (in.)	83.0				
Width (in.)	28.0				

Load

☒ Enter load effect manually ☐ Auto-calculate for HL-93

Limit state discretization

Variable	Minimum	Maximum	# bins
Flexural capacity	45000	90000	7
Flexure limit state	-1000	60000	7

Buttons: Edit rebar layers... Edit condition... Run analysis

Time to generate, compile, and analyze Bayes net: 0.31 sec

Figure 4. Example of Girder Condition program.

5 Defects along the Girder Length

This chapter provides details on the analysis of a girder with multiple defects along its length. Section 5.1 presents the overall approach and the assumptions that were made. Section 5.2 describes the procedure used to break the girder into a number of segments to be analyzed by using sectional analysis. Section 5.3 documents the method used to determine the maximum moment in each segment. Finally, Section 5.4 deals with the determination of girder reliability based on the reliability calculated by sectional analysis for each segment.

5.1 Approach

Inspection findings for defects are modeled as one or more individual defects on the girder. Each individual defect has a defect type, defect severity, start location, and stop location. To make inferences on the effect of these defects, which vary along the length of the girder, the next step is to divide the girder into a number of segments. Segments are selected so that the defect type(s) and severity (severities) are constant along the length of the segment. This work deals with reinforced concrete girders and assumes that the girder is prismatic and that the reinforcing steel does not vary along the length of the girder. Thus, the moment capacity is also constant along the length of the segment. However, the moment caused by the applied load varies along the length of the segment. This work assumes that the probability of failure of the segment can be determined by performing a sectional analysis at the point in the segment where the moment demand is greatest. A simple load-marching scheme is used to determine the maximum moment caused by the moving load(s). The probability of failure of the girder is determined by idealizing the girder as a system composed of a number of segments in series.

5.2 Segmentation

The segmentation process for a girder with findings for three defect types is illustrated in Figure 5. In this example, each defect region has start and stop locations (denoted by x_i in the figure). Some of the defect regions overlap (defect 1 and defect 3) and others occur end-to-end (defect 2 and defect 3). In general, a girder is broken into segments as follows:

Figure 5. Illustration of segmentation process for a girder.

1. Determine the points, p_j , on the interior of the girder where divisions will be made. The number of division points is denoted m . These division points are all the *unique* values of x_i , where x_i is the position where a defect starts or stops. Note that it is not important whether any given point is the beginning or end of a defect region for this step.
2. Sort the p_j in ascending order.
3. Add the beginning and end of the girder to the division points: $p_0 := 0$ and $p_{m+1} := L$.
4. The girder is divided into $n = m + 1$ segments. For $k = 1, 2, \dots, n$, segment s_k starts at point p_{k-1} and ends at point p_k .
5. Finally, the defects are mapped onto the new segments.

This approach, dividing the girder into only as many segments as are needed, has two advantages over dividing the girder into uniform segments.

First, uniform segmentation can lead to inaccurate defect locations if the segments are not small enough. For example, suppose a 100-ft-long girder is divided into 5-ft segments starting from 0 ft. Suppose further that a defect occurs from 4 ft to 6 ft. The defect touches two segments (i.e., s_1 , from 0 ft to 5 ft and s_2 , from 5 ft to 10 ft). The defect can be applied to the uniform segments in four possible ways:

1. Apply the defect to s_1 ,
2. Apply the defect to s_2 ,
3. Apply the defect to both s_1 and s_2 , or
4. Apply the defect to neither segment.

None of these alternatives are a satisfying solution. Alternatives 1-3 artificially increase the size of the area affected by the defect, and alternative 4 simply ignores the defect.

If the segment size is decreased to overcome this limitation, the second disadvantage of uniform segmentation appears. The large number of segments needed for accurately locating defects results in longer analysis times.

5.3 Maximum moment

Currently, the program permits the specification of a uniformly distributed dead load along with a live load consisting of either of the following options:

- HL-93 (design truck or tandem, plus lane load) or
- Moving point load with specified magnitude.

A simple approach is used to determine the maximum moment. The program divides the girder into a number of finely spaced points at which the moment is computed. For each moment computation point, the load train (design truck, design tandem, or custom point load) is marched across the girder. The total moment due to the moving loads, lane load (if any), and dead load (if specified) is computed. If the total moment exceeds the previously maximum moment, then the maximum moment is updated. The location at which the maximum moment occurs and the position of the load train causing the maximum moment are also stored. If the HL-93 load combination is selected, three load trains are actually checked: design truck moving left-to-right, design truck moving right-to-left, and design tandem.

This approach uses one loop (load position) nested inside another loop (moment computation point). Thus, the number of moment calculations varies with the square of the number of points with which the girder is discretized. A slight coarsening of this discretization can result in a noticeable speedup.

It is worth noting that the time required for maximum load computation does not increase with the number of segments. The number of moment computation points and the number of possible load positions depend only on the length of the girder and the point spacing.

5.4 System reliability

At this point, the girder has been broken into n segments, with defect ratings and the maximum moment demand determined for each segment. The probability of failure, $P_{f,i}$, for each segment s_i is determined by using a sectional analysis (see Chapter 3) conducted at the location where the maximum moment occurs in that segment. The system probability of failure, $P_{f,sys}$, for a girder with n segments can be bounded as follows (Ayyub and McCuen 2003):

$$\max_{1 \leq i \leq n} P_{f,i} < P_{f,sys} < 1 - \prod_{i=1}^n (1 - P_{f,i}). \quad (11)$$

The lower bound applies when the failure events of the components (i.e., the segments) are completely dependent, and the upper bound applies when the failure events of the components are completely independent.

Assuming that the failure events of the segments are completely independent leads to unphysical results. Figure 6 shows a pristine girder (i.e., completely free of defects) with two segmentations: (a) one segment and (b) two segments. The girder is simply supported and is loaded by a moving point load of magnitude P . The maximum moment demand for all segments, for both case (a) and case (b), occurs when P is at midspan. Because the girder has no defects, the moment capacity is the same in all segments. Although both cases are the same girder, the upper bound from case (a) is $P_{f,sys} < x$, whereas case (b) gives $P_{f,sys} < 2x - x^2$. Clearly, however, the failure events of segments s_1 and s_2 are not independent. A load at midspan that caused s_1 to fail would also cause s_2 to fail. More generally, the failure of multiple segments may not be as completely dependent as this simple example. However, segments cannot be loaded in isolation; a load somewhere on a simply supported girder will result in some distribution of bending moment along the entire length of the girder. Therefore, the failure of girder segments is at least partially dependent. Further investigation is needed to determine how best to account for this dependence in system-level reliability.

Figure 6. Effect of segmentation on computed probability of failure.

(a) Pristine girder, 1 segment

$$S_1: \quad M_{\max} = PL/4 \quad P_{f,1} = x$$

$$\therefore x < P_{f,\text{sys}} < 1 - (1 - x)$$

(b) Pristine girder, 2 segments

$$S_1: \quad M_{\max} = PL/4 \quad P_{f,1} = x$$

$$S_2: \quad M_{\max} = PL/4 \quad P_{f,2} = x$$

$$\therefore x < P_{f,\text{sys}} < 1 - (1 - x)^2$$

6 Summary

This report summarizes progress on the development of BNs for making inferences on the reliability of RC girder bridges based on inspection observations. Key milestones in this development include the following:

- Relationships were determined both between observed defects and underlying deterioration mechanisms for concrete and between deterioration mechanisms and mechanical property reductions. These relationships are crucial to the incorporation of defects into reliability inference. At present, they are based largely on expert elicitation due to a lack of experimental data that match field conditions.
- A BN that incorporates the effects of ASR and FT deterioration on concrete compressive strength was developed for inferences on RC girder reliability.
- Two prototype programs were written to automate the procedure for reliability inference.
 - The program Bridge Reliability automatically creates and analyzes BNs for RC girders. This program provides a streamlined interface to enter the required girder and loading parameters.
 - The program Girder Condition performs reliability inference for an RC girder with spatially varying defects. The girder is automatically segmented for sectional analysis. The maximum moment for each segment is determined for a uniform dead load and a live load that can consist of either the HL-93 loading or a moving point load.

With more development, this BN tool can be used to compare conditions of bridges relative to one another and aid in the prioritization of repairs. However, an extensive survey of bridges affected by deterioration mechanisms is needed to confidently establish valid relationships between deterioration severity and mechanical properties. The survey would include visual inspections using *MBEI* guidelines followed by concrete sampling and testing. Bridges of varying deterioration should be evaluated.

The above survey is crucial to build confidence in the BN tool. Other possible areas for future work include the following:

- Update the BN to include the effect of corrosion on the remaining area of reinforcing steel.

- Explore the extent to which the failure events for girder segments are dependent or independent (see Section 5.4).
- Extend the analysis to operate at the level of a bridge rather than a single girder.
- Develop a similar procedure (BN and accompanying programs to automate analysis) for steel girder bridges.
- Apply this general procedure to steel navigation structures.

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Appendix A: Defect Conditional Probability Tables

This appendix presents the complete CPTs used to determine defect condition states based on the severity of the underlying deterioration mechanisms. These CPTs (Table A1 through Table B1) are based on expert elicitation. Note that all probabilities are expressed as percentages. To permit easy updating without requiring changes to the source code for Bridge Reliability, the CPTs are saved as tab-separated value files.

Table A1. CPT for cracking severity.

ASR	FT	Corrosion	1	2	3	4
Low	Low	Low	90	5	4	1
Low	Low	Moderate	10	37	38	15
Low	Low	Severe	5	10	15	70
Low	Moderate	Low	15	35	30	20
Low	Moderate	Moderate	8	15	27	50
Low	Moderate	Severe	2	10	13	75
Low	Severe	Low	5	15	30	50
Low	Severe	Moderate	2	8	37	53
Low	Severe	Severe	2	6	32	60
Moderate	Low	Low	5	30	40	25
Moderate	Low	Moderate	8	17	50	25
Moderate	Low	Severe	5	15	30	50
Moderate	Moderate	Low	5	25	30	40
Moderate	Moderate	Moderate	3	17	30	50
Moderate	Moderate	Severe	1	10	34	55
Moderate	Severe	Low	2	7	21	70
Moderate	Severe	Moderate	1	4	30	65
Moderate	Severe	Severe	1	2	27	70
Severe	Low	Low	1	7	12	80
Severe	Low	Moderate	1	4	13	82
Severe	Low	Severe	1	2	7	90
Severe	Moderate	Low	1	5	12	82
Severe	Moderate	Moderate	1	4	23	72
Severe	Moderate	Severe	1	1	8	90
Severe	Severe	Low	1	4	10	85
Severe	Severe	Moderate	1	1	8	90
Severe	Severe	Severe	1	1	3	95

Table A2. CPT for delamination severity.

FT	Corrosion	1	2	3	4
Low	Low	95	3	1	1
Low	Moderate	20	32	33	15
Low	Severe	10	26	26	38
Moderate	Low	10	38	40	12
Moderate	Moderate	10	25	35	30
Moderate	Severe	8	15	35	42
Severe	Low	3	12	35	50
Severe	Moderate	3	7	35	55
Severe	Severe	1	4	30	65

Table A3. CPT for efflorescence severity.

ASR	FT	1	2	3	4
Low	Low	90	5	4	1
Low	Moderate	50	30	15	5
Low	Severe	15	30	30	25
Moderate	Low	10	35	35	20
Moderate	Moderate	10	30	35	25
Moderate	Severe	5	20	35	40
Severe	Low	1	9	15	75
Severe	Moderate	1	4	20	75
Severe	Severe	1	1	18	80

Table A4. CPT for exposed rebar severity.

Corrosion	1	2	3	4
Low	90	5	4	1
Moderate	10	35	35	20
Severe	5	20	25	50

Table A5. CPT for pattern cracking occurrence.

ASR	Yes	No
Low	10	90
Moderate	80	20
Severe	90	10

Table A6. CPT for rust staining severity.

Corrosion	1	2	3	4
Low	90	5	4	1
Moderate	11	32	32	25
Severe	1	9	15	75

Table A7. CPT for spalling severity.

ASR	FT	Corrosion	1	2	3	4
Low	Low	Low	95	3	1	1
Low	Low	Moderate	15	25	35	25
Low	Low	Severe	5	25	30	40
Low	Moderate	Low	15	37	38	10
Low	Moderate	Moderate	10	20	25	45
Low	Moderate	Severe	3	12	25	60
Low	Severe	Low	5	20	25	50
Low	Severe	Moderate	3	10	22	65
Low	Severe	Severe	3	4	8	85
Moderate	Low	Low	15	45	30	10
Moderate	Low	Moderate	2	18	25	55
Moderate	Low	Severe	5	15	20	60
Moderate	Moderate	Low	10	32	33	25
Moderate	Moderate	Moderate	3	7	30	60
Moderate	Moderate	Severe	2	8	15	75
Moderate	Severe	Low	2	8	25	65
Moderate	Severe	Moderate	2	3	8	87
Moderate	Severe	Severe	2	3	5	90
Severe	Low	Low	4	10	26	60
Severe	Low	Moderate	2	10	23	65
Severe	Low	Severe	2	5	13	80
Severe	Moderate	Low	2	8	25	65
Severe	Moderate	Moderate	2	4	6	88
Severe	Moderate	Severe	1	4	5	90
Severe	Severe	Low	1	9	15	75
Severe	Severe	Moderate	2	3	5	90
Severe	Severe	Severe	1	2	2	95

Appendix B: Efficient Network Structure

The structure of a BN has a large influence on the efficiency of analysis, from creating CPTs to compiling the network to performing inference. This appendix begins by examining the efficiency of the BN for RC moment capacity introduced in Section 3.3. All of the nodes in the model represent continuous numeric variables, and CPTs for the nodes are generated by random sampling. The size of the CPTs directly influences the number of function evaluations that must be performed when randomly sampling, as well as the amount of memory required to perform inference on the BN. Thus, the amount of time required for analysis can be decreased by reducing the size of the CPTs. Two methods are discussed for reducing the size of the CPTs by reducing the dimensionality of a CPT.

Cause of the problem

Initial model development for RC bridges created nodes for the area, A_i , and centroid position, y_i , of each rebar layer. This allows fine-grained control of the uncertainty for the individual layers. Inference can also be performed on individual layers. The main disadvantage to this approach is that the size of the CPT for the nominal moment capacity, M_n , grows exponentially with the number of rebar layers, n .

An example with three rebar layers is shown in Figure 7. The other nodes appearing in the BN are the 28-day concrete unconfined compressive strength, f'_c , and the steel tensile yield strength, f_y . If all nodes are discretized into d bins, then the size of the CPT inputs for M_n is d^{2n+2} . The total number of CPT entries in the BN is $d^{2n+3} + (2n + 2)d$. Clearly, a better solution is needed.

Figure B1. Naïve BN for RC moment capacity.

Variable reduction

One idea is to take arbitrarily many A_i 's and y_i 's as input and reduce them into a fixed number of variables that are included in the BN. This can be done by recognizing that the equation for M_n requires only the total area of steel and the centroid of all steel layers.

$$M_n = f_y A_{\text{total}} \left(h - \bar{y} - \frac{1}{2} \cdot \frac{f_y A_{\text{total}}}{0.85 f'_c b} \right) \quad (\text{B1})$$

where

A_{total} = total area of steel, $\sum_i A_i$

h, b = height and width of the girder, respectively, (assumed to be deterministic in this analysis)

$\bar{y}$ = centroid of all steel layers, $(\sum_i A_i y_i) / \sum_i A_i$.

Now, the task is to analytically determine (or approximate) the distributions of A_{total} and $\bar{y}$. As will be shown, it is convenient to rewrite $\bar{y}$ to allow for easier approximation. Calculating these distributions outside the BN will significantly reduce the size of the network.

Currently, A_i and y_i are assumed to be normally distributed. The total area of steel is the sum of n normally distributed variables, $\sum_i A_i$, which is also normally distributed. The expectation and variance of the sum (Ayyub and McCuen 2003) are simple to express and are given below.

$$E(A_{\text{total}}) = \sum_i E(A_i), \quad (\text{B2})$$

$$\text{Var}(A_{\text{total}}) = \sum_i \text{Var}(A_i), \quad (\text{B3})$$

where

$E(\cdot)$ = expectation operator

$\text{Var}(\cdot)$ = variance operator.

Analytically determining the distribution of the centroid location would be complicated, as $\bar{y}$ is a rational function. However, $\bar{y}$ can be rewritten as $\bar{y} = S/A_{\text{total}}$, where $S = \sum_i A_i y_i$ is the first moment of area. The first moment of area is the sum of n products of normally distributed variables. Although S cannot be represented exactly by using a normal distribution, it can be approximated sufficiently well for these purposes, as will be shown below.

The product of two normally distributed random variables, $X \sim \mathcal{N}(\mu_x, \sigma_x^2)$ and $Y \sim \mathcal{N}(\mu_y, \sigma_y^2)$, is the sum of two χ^2 random variables:

$$XY = \frac{1}{4}(X + Y)^2 - \frac{1}{4}(X - Y)^2. \quad (\text{B4})$$

The sum (or difference) $X \pm Y$ follows a normal distribution, and therefore its square follows a χ^2 distribution.

This would be overly complex for making inferences based on (semi-) subjective inspection findings. However, as shown by Seijas-Macías and Oliveira (2012), the distribution of XY can be approximated as normal. The quality of this approximation depends on the inverse coefficient of variation (COV), defined as

$$\delta_x = \frac{\mu_x}{\sigma_x}, \quad \delta_y = \frac{\mu_y}{\sigma_y}. \quad (\text{B5})$$

The product XY approaches the distribution $\mathcal{N}(\mu_x\mu_y, \mu_x^2\sigma_y^2 + \mu_y^2\sigma_x^2)$ as δ_x and δ_y increase. Seijas-Macías and Oliveira (2012) showed that the approximation was generally acceptable when $\delta_x > 1$ and $\delta_y > 1$. In our

case, the COV for A_i was assumed to be 0.015 (Nowak and Szerszen 2003), corresponding to $\delta_{A_i} = 1/0.015 \approx 66.7 \gg 1$. Nowak and Szerszen (2003) gives a standard deviation of 0.7 in. for rebar vertical position. Due to clear cover requirements, the rebar height y_i is unlikely to be less than 2.5 or 3 in. for the lowest layer. This corresponds to a δ_{y_i} of at least $2.5/0.7 \approx 3.57$. Thus, this approximation is judged to be sufficient for our purposes.

Having found a normal distribution approximation for the product $A_i y_i$, the distribution of the sum $\sum_i A_i y_i$ can also be approximated as normal. The expectation and variance are then

$$E(S) \approx \sum_i E(A_i) E(y_i), \quad (\text{B6})$$

$$\text{Var}(S) \approx \sum_i (E(y_i))^2 \text{Var}(A_i) + (E(A_i))^2 \text{Var}(y_i). \quad (\text{B7})$$

The variance, equation (B7), assumes that the variables are uncorrelated. The resulting reduced BN is shown in Figure B2. The total size of the inputs to the CPT for M_n is d^4 and is *independent* of the number of layers of rebar. The total number of CPT entries is $d^5 + 4d$.

Figure B2. BN for RC moment capacity using reduced variables for rebar geometric properties.

Network unraveling

The node with the most parents typically dominates the size of the CPT. This is because a node with p parents requires a CPT with $p + 1$ dimensions. The BN can be “unraveled” to yield a new BN where every

node has at most two parents*, thereby limiting the CPTs to three dimensions. This reduces the memory required to store the CPT and the number of function evaluations required to populate the CPT by random sampling. However, there are two primary difficulties associated with unraveling. First, the number of nodes will still increase linearly with the number of rebar layers. Second, an appropriate discretization needs to be chosen for all of the intermediate nodes.

The issue of choosing appropriate discretizations for the intermediate nodes is significant, as it affects the accuracy of the probability distribution for the intermediate nodes as well as their child nodes. A discretization should cover the likely range of values the node can take on and provide enough bins so that the shape of the distribution is represented reasonably well. An appropriate discretization for an input variable, such as concrete 28-day compressive strength, may be determined so that the bins cover the mean value plus and minus a certain number of standard deviations, perhaps 3. Having to determine, or even roughly estimate, the bins for a large number of intermediate nodes would be onerous.

The terms A_{total} and S , defined previously, are straightforward to decompose into two-operand subexpressions. The moment capacity, equation (B1), can be expressed as follows, remembering that b and h are assumed to be deterministic (constant) in the calculations.

$$T = f_y A_{\text{total}}, \quad (\text{B8})$$

$$\bar{y} = \frac{S}{A_{\text{total}}}, \quad (\text{B9})$$

$$a = \frac{T}{0.85 f'_c b}, \quad (\text{B10})$$

$$\text{arm} = h - \bar{y} - \frac{a}{2}, \quad (\text{B11})$$

* This is possible because the formulas in our simple BN are composed of the usual arithmetic operations, which take two operands. If, for example, functions or operators with an arity of three were present, then nodes in the unraveled BN would have at most three parents.

$$M_n = T \cdot \text{arm}. \quad (\text{B12})$$

The completely unraveled BN is shown in Figure B3. The number of CPT entries is broken down in Table B1. The total number of CPT entries is $(3n + 3)d^3 + (2n + 2)d$.

Figure B3. Completely unraveled BN.

Table B1. CPT size for completely unraveled BN example.

Group of nodes	Number of nodes	CPT size for each node
Inputs	$2n + 2$	d
Computation of A_{total}	$n - 1$	d^3
Computation of S	$2n - 1$	d^3
Computation of M_n	5	d^3

Summary

Although motivated by issues particular to the BN shown in Figure B1, the techniques discussed in this appendix can be applied to any BN. These

techniques are useful when a BN has a node with a large number of parent nodes. The dimensionality of the node's CPT is proportional to the number of its parents. This increases the memory requirements and, if the CPT is constructed by random sampling, also increases the computation time. Variable reduction is well-suited for a BN that has a large number of input variables, x_i , that are used to calculate some intermediate result, $f(\mathbf{x})$. However, variable reduction requires that the distribution of $f(\mathbf{x})$ can be expressed either in closed form or via approximation. In practice, therefore, variable reduction is limited to cases in which $f(\mathbf{x})$ is a simple function. Network unraveling is simple and straightforward (if slightly tedious) to apply, but requires the determination of good discretizations for all of the intermediate nodes that are created.

The programs developed in this work currently use variable reduction to achieve reasonably fast run times for analysis of sections and single girders. For an RC section, generating the BN, compiling the BN, and determining the probability of failure typically takes 0.3-0.4 sec. For a girder analysis, a significant amount of time is actually spent on moving load calculations. A girder analysis with eight segments and a live load consisting of a moving point load takes roughly 1.1 sec, of which about 1.0 sec is used for moving load calculations. If the automated HL-93 live load option is selected, the analysis takes roughly 7.5 sec, of which about 7.4 sec is used for moving load calculations. The girder in these examples was 642 in. long, and the moving load calculations used a step size of 1 in. to "march" the load(s) across the girder. An increased step size can be used to achieve faster analysis times.

Appendix C: Example Reliability Analysis

This appendix provides brief examples of the Bridge Reliability and Girder Condition prototype programs. First, the Bridge Reliability program is used to create a model of an RC girder for reliability analysis at a section. Second, the Girder Condition program is used to create a “map” or list of defects and apply it to the girder model from the first step.

Creating a reinforced concrete girder model

To begin, create a new model by selecting **File > New Model...** or pressing Ctrl + N. A dialog (Figure C1) pops up prompting the user to select the girder type. The default (and only type currently supported) is “Reinforced Concrete.” Select **OK** to continue.

Figure C1. New Model dialog.

The model is populated with default values from the template (rc_default.xml), as shown in Figure C2. The specifics of this default template can easily be changed.

The interface (Figure C2) is organized into a number of panels. At the top, the **Model information** panel provides fields for metadata related to the model. These fields are optional and are intended to help document the model. These fields are not used in the analysis. The design type (in this case, “reinforcedConcrete”) is shown and cannot be changed; it is for information only.

The **Girder properties** panel contains fields for the input of the girder parameters described in Section 3.3. Some variables (bearing-to-bearing length, height, and width) are assumed to be deterministic and have only fields for a nominal value. The other variables have fields for input of the nominal value, bias, and COV. The number of bins with

which to discretize the CPT can also be specified. The discretization will span a given number (# st devs) of standard deviations above and below the mean of the variable. Note that Netica will automatically extend the first or last bin of the discretization as needed during the analysis if a value falls outside the current discretization.

The **Load** panel allows the choice of manually entering the moment load effect or letting the program automatically calculate the maximum moment load effect caused by the HL-93.

The **Limit state discretization** panel provides control over the discretization of the nodes for flexural capacity (M_n) and flexure limit state (g_M). Because these variables do not have means and standard deviations that are known *a priori* (and their distributions are not expected to be normal), the discretization is determined based on a minimum value, maximum value, and number of bins. Again, Netica will automatically extend the first or last bin of the discretization as needed if a value falls outside the current discretization.

Figure C2. Default reinforced concrete girder model created from template.

Untitled - Bridge Reliability

File Edit View Help

Model information

Name	Default reinforced concrete bridge
Description	Calculate the Probability of Failure of the main girder
NBIS	
Number of spans	1
Design type	reinforcedConcrete

Girder properties

Variable	Nominal	Bias	COV	# bins	# st devs
Concrete compressive strength (ksi)	3.5	1.1	0.18	5	3
Rebar yield strength (ksi)	33.0	1.13	0.12	5	3
Moment load effect (kip-in.)	40200.0	1.1	0.18	5	3
Bearing-to-bearing length (in.)	642.0				
Height (in.)	83.0				
Width (in.)	28.0				

Load

☒ Enter load effect manually ☐ Auto-calculate for HL-93

Limit state discretization

Variable	Minimum	Maximum	# bins
Flexural capacity	45000	90000	7
Flexure limit state	-1000	60000	7

Edit rebar layers... Edit condition... Run analysis

The visibility of the distribution details can be toggled by **View > Distribution details on/off** or by pressing the keyboard shortcut Ctrl + D. When details are hidden, only the nominal value fields are shown (Figure 12). The **Limit state discretization** panel is also hidden.

Figure C3. Model with distribution details hidden.

The screenshot shows a software window titled "Untitled - Bridge Reliability" with a menu bar (File, Edit, View, Help) and a toolbar. The main area is divided into sections: "Model information" and "Girder properties".

Model information

Name	Default reinforced concrete bridge
Description	Calculate the Probability of Failure of the main girder
NBIS	
Number of spans	1
Design type	reinforcedConcrete

Girder properties

Variable	Nominal
Concrete compressive strength (ksi)	3.5
Rebar yield strength (ksi)	33.0
Moment load effect (kip-in.)	40200.0
Bearing-to-bearing length (in.)	642.0
Height (in.)	83.0
Width (in.)	28.0

Load

☒ Enter load effect manually ☐ Auto-calculate for HL-93

Buttons: Edit rebar layers... Edit condition... Run analysis

Click **Edit rebar layers...** to add or change layers of rebar. The “Rebar Layers” dialog box is shown in Figure C4. Inputs are given for each *layer* of rebar, not for individual bars. For each layer, enter a line consisting of the height of the layer’s centroid above the bottom of the girder (in.), a comma, and the area of the layer (in.²). Spaces can also be used in addition to the comma. Spaces between numbers and commas are ignored; spaces are not allowed in the middle of numbers.

Figure C4. Rebar layer editing.

The image shows a software dialog box titled "Rebar Layers". It contains a text area with the following instructions: "Enter description of rebar below. Use one line for for each layer. Each line should consist of the y value (in.), a comma, and the area (in.^2). Spaces are optional." Below the instructions, there are three lines of text: "2.750, 10.920", "6.500, 10.920", and "10.250, 5.080". At the bottom of the dialog box, there are two buttons: "OK" and "Cancel".

Y Value (in.)	Area (in. ²)
2.750	10.920
6.500	10.920
10.250	5.080

Click **Edit condition...** to enter defect findings for the girder at the section to be analyzed. The resulting dialog box allows ratings for seven defect types to be input by using drop-down menus, as shown in Figure C5(a). The full set of defects used for the example analysis is shown in Figure C5(b).

Figure C5. Reinforced concrete girder condition editing.

a. Example of entering a condition finding by using the drop-down menu.

Condition	Value
Pattern cracking	Yes
Efflorescence	Yes
Cracking	
Spalling	1
Delamination	1
Rust staining	1
Exposed rebar or prestressing strands	1

b. Complete condition findings for example analysis.

Condition	Value
Pattern cracking	Yes
Efflorescence	4
Cracking	3
Spalling	2
Delamination	1
Rust staining	3
Exposed rebar or prestressing strands	1

a. Example of entering a condition finding by using the drop-down menu.

b. Complete condition findings for example analysis.

Running a sectional reliability analysis

To run an analysis, click **Run analysis** at the bottom of the window, select **File > Run analysis**, or press F5. Note that you must save the model file before running an analysis. If you try to run an analysis before saving, the program will notify you (Figure C6) and then provide a standard “Save File” dialog so you can save the file (Figure C7). After saving, the analysis will run; results are shown in Figure C8. With the defects entered in Figure C5(b), the estimated probability of failure is 6.73%. For comparison, without defects (all fields in Figure C5 set to “No” or 1), the estimated probability of failure is 2.64% (Figure 18).

Figure C6. Attempting to run an analysis with an unsaved file.

Figure C7. “Save File” dialog.

Figure C8. Results of analysis for an RC girder with defects.

Figure C9. Results of analysis for an RC girder without defects.

example.xml - Bridge Reliability

File Edit View Help

Model information

Name: Default reinforced concrete bridge

Description: Calculate the Probability of Failure of the main girder

NBIS:

Number of:

Design type: ReinforcedConcrete

Girder properties

	Normal	Bias	COV	# bins	# st devs
Concrete compressive strength (ksi)	3.5	1.1	0.18	5	3
Rebar yield strength (ksi)	33.0	1.13	0.12	5	3
Moment load effect (kip-in.)	40200.0	1.1	0.18	5	3
Bearing-to-bearing length (in.)	642.0				
Height (in.)	83.0				
Width (in.)	28.0				

Load

☒ Enter load effect manually ☐ Auto-calculate for HL-93

Limit state discretization

Variable	Minimum	Maximum	# bins
Flexural capacity	45000	90000	7
Flexure limit state	-1000	60000	7

Edit rebar layers... Edit condition... Run analysis

Time to generate, compile, and analyze Bayes net: 0.31 sec

Results

Probability of failure: 2.64%

Reliability index: 1.94

Close

Creating a defect “map” for a girder

The Girder Condition program is primarily designed to create lists, or “maps,” of defects for RC girders. To start entering defects, click **Add finding...** at the bottom of the window. A “Finding Entry” dialog pops up, as shown in Figure C10. Figure C11 shows the dialog box without the drop-down menu. The defect type, defect rating, and defect start and stop locations can be entered. For the example of pattern cracking, the defect rating field is disabled (grayed out); pattern cracking is treated as a binary finding (either pattern cracking is present or it is not). If a user is entering a finding for pattern cracking, that finding is obviously going to be that pattern cracking is present. For the other defect types, the defect rating is from 1 to 4 with 4 being the most severe. For the example, four defects will be entered. The result is shown in Figure C12.

Figure 7C10. Girder Condition program showing “Finding Entry” dialog box.

Figure C11. Defect start and stop locations.

Figure C12. Defects for example analysis.

Any of the defect findings can be edited by clicking the **Edit** button to the right of the finding description. Editing brings back the same “Finding Entry” dialog box that was used to create the defect finding. Any of the inputs can be changed, including the defect type. To delete a defect finding, click the **Delete** button to the right of the finding description.

Save the findings by selecting **File > Save findings** or by pressing Ctrl + S. Call the file “defects.txt.”

Defining load case for whole girder analysis

Click the **Edit loads...** button at the bottom of the window to enter (or change) the loads applied to the girder during the analysis. The resulting

dialog box is shown in Figure 22. Currently, the options are fairly simple. A uniformly distributed dead load can be applied. For live load, either the HL-93 or a moving point load with a user-specified magnitude can be used. Loads can be saved by selecting **File > Save load case as...** (Ctrl + L). An existing load case can be opened by selecting **File > Open load case** (Ctrl + Shift + O). Loading and saving load cases is for convenience; the load case does not need to be saved to a file to perform an analysis. The loads currently in memory, whether manually entered in the dialog box or opened from a file, are used for analysis.

Figure C13. "Girder Loads" dialog box.

Applying defects to a girder

Click the **Apply findings to model...** button at the bottom of the window to analyze the reliability of a girder with the defect map. A dialog (Figure C14) opens to allow a girder model to be opened. For the example, select the RC girder model that was previously created with the Bridge Reliability program. The analysis will then be run. When the analysis concludes, a dialog box will provide summary information about the number of segments used, the time required, and the output files that were generated (Figure C15). Detailed information and diagnostics are also printed to the console window, a portion of which is reproduced below. Some lines have been omitted for brevity, and these are indicated by an italicized comment on what was omitted (... *like this* ...). The probability of girder failure, assuming dependent failure events, is 7.99%.

```
Current Bayes Net file found, using it ...
```

```
Note: Using custom moment envelope defined by 250.0-kip moving point  
load
```

Netica 5.04 Win (AF), (C) 1992-2012 Norsys Software Corp.

... license information omitted ...

Segment 0 from 0.0 to 36.0

=====

Max moment = 9586.13 at 36.0 -- User load function controls with
rightmost wheel at 36.0

Entered Efflorescence finding CS1

Entered PatternCracking finding no

Entered Cracking finding CS1

Entered Spalling finding CS1

Entered Delamination finding CS1

Entered Rust_Staining finding CS1

Entered Exposed_Rebar finding CS1

Segment 0 probability of failure = 0.015033083967864513

... output for 7 more segments omitted ...

Leaving Netica.

Run Summary

=====

Prob. of girder failure: 0.0799 (dependent failure events)

Segments analyzed: 8

Total run time: 1.057 s

Moving load calcs 0.980 s

Netica inference 0.023 s

Saving BN segments 0.046 s

Other 0.009 s

Figure C14. Select the RC girder model for the example analysis.

Figure 8C15. Analysis summary information.

Visualizing results

For easy viewing of results, “Girder Condition” generates a VTK file that can be read by the open-source visualization program ParaView (Ayachit 2018). ParaView can be run on Windows, Linux, or macOS.

Open the file “example.vtk” in ParaView (**File > Open...** or Ctrl + O). Be sure to click “Apply” to tell ParaView to load the data from the file into memory (see Figure C16). You will also need to change the representation from “Outline” to “Surface With Edges.” After completing these two

actions, a rendering of the girder will be shown. When a file is first opened in ParaView, the “Solid Color” variable is plotted, which shows the geometry and does not take long to render. A number of other variables can be selected from (see Figure C17).

The results in the VTK file are presented as a simple 3-D model of a girder. The view in ParaView can be manipulated with the mouse as follows:

- Rotate view – click and hold left mouse button
- Pan – click and hold middle mouse button
- Zoom – click and hold right mouse button

Complete details on using ParaView can be found in the User’s Guide (Ayachit 2018).

Figure C16. ParaView visualization setup.

Figure C17. Variables available to visualize.

The inputs for defect location and severity can be visualized, as shown in Figures C18 through C20. Note that the girder has been segmented as needed to deal with overlapping defect regions. The VTK file also contains a number of probabilities output from the model. The variable `p_failure` is the probability of failure of a segment determined by reliability analysis at a section. There is also a series of variables that gives the inferred probability of having a given deterioration mechanism and severity in a segment. For example, `p_low_ASR` is the probability of having ASR with low severity. For each segment, `p_low_ASR`, `p_moderate_ASR`, and `p_severe_ASR` sum to 1. The probability of failure for each girder segment is shown in Figure C21. The highest probability of failure is for the fifth segment from the left, which also has the highest probability of moderate ASR (Figure C22).

Figure C18. Rendering of pattern cracking location.

Figure C19. Rendering of spalling location and severity.

Figure C20. Rendering of efflorescence location and severity.

Figure C21. Rendering of probability of failure for girder segments.

Figure C22. Rendering of probability of moderate ASR for girder segments.

Unit Conversion Factors

Multiply	By	To Obtain
degrees Fahrenheit	$(F-32)/1.8$	degrees Celsius
feet	0.3048	meters
inches	0.0254	meters
pounds (force)	4.448222	newtons
pounds (force) per square inch	6.894757	kilopascals
pounds (mass)	0.45359237	kilograms

Acronyms and Abbreviations

Term	Definition
API	Application Programming Interface
ASR	Alkali-Silica Reaction
BN	Bayesian Network
COV	Coefficient of Variation
CPT	Conditional Probability Tables
FOSM	First Order, Second Moment
FT	Freeze-Thaw
GUI	Graphical User Interface
<i>MBEI</i>	<i>Manual for Bridge Element Inspection</i>
RC	Reinforced Concrete

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14. ABSTRACT As part of an inspection, bridge inspectors assign condition ratings to the main components of a bridge's structural system and identify any defects that they observe. Condition ratings are necessarily somewhat subjective, as they are influenced by the experience of the inspectors. In the current work, procedures were developed for making inferences on the reliability of reinforced concrete girders with defects at both the cross section and the girder level. The Bayesian network (BN) tools constructed in this work use simple structural mechanics to model the capacity of girders. By using expert elicitation, defects observed during inspection are correlated with underlying deterioration mechanisms. By linking these deterioration mechanisms with reductions in mechanical properties, inferences on the reliability of a bridge can be made based on visual observation of defects. With more development, this BN tool can be used to compare conditions of bridges relative to one another and aid in the prioritization of repairs. However, an extensive survey of bridges affected by deterioration mechanisms is needed to confidently establish valid relationships between deterioration severity and mechanical properties.					
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