



SHM-based Decision Support System for bridge scour management

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Abstract

Scour is the leading cause of bridge failures worldwide. In the United States, 22 bridges fail every year, whereas in the UK scour contributed significantly to the 138 bridge collapses recorded in the last century. Monitoring an entire infrastructure network against scour is not economically feasible. This limitation can be overcome by installing monitoring systems at critical locations, and then extend the pieces of information gained to the entire asset through a probabilistic approach. This paper proposes a Decision Support System (DSS) for bridge scour management that exploits information from a limited number of scour monitoring systems (SMSs) to achieve a more confined estimate of the scour risk for a bridge network. A Bayesian network (BN) is used to describe conditional dependencies among the involved random variables, and it allows estimating the scour depth distributions using information from monitoring of scour depth and river flow characteristics. Data collected by SMSs and BN's outcomes are then used to inform a decision model and thus support transport agencies' decision frameworks. A case study consisting of several road bridges in Scotland is considered to demonstrate the functioning of the DSS. The BN is found to estimate accurately the scour depth at unmonitored bridges, and the decision model provides higher values of scour thresholds compared to the ones implicitly chosen by the transport agencies.

1 Introduction & background

Bridge scour is the removal of sediment from around bridge abutments and piers (Kirby et al., 2015). The total scour at a bridge site results from the combination of different types of scour, namely natural, constriction and local scour. While the first type is due to the natural evolution of the river bed, the interaction between the bridge and the water flow causes the other two. Constriction scour is the result of confining river channel width between bridge abutments and piers, while local scour is caused by the interference of structural elements with water flow. When the scour depth becomes significant, the bridge stability may be compromised, leading to structural instability and failure.

Scour is the principal cause of bridge failures worldwide. In the UK, there are around 95,000 bridge spans susceptible to scour processes, and, according to van Leeuwen & Lamb (2014), scour was identified as the most common cause of 138 bridge failures in 1846-2013. Briaud et al., (2007)

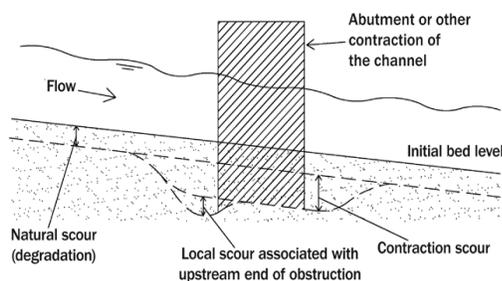


Figure 1: Types of scour (Kirby et al., 2015)

shows that scour was the cause of 58% of the 1,502 bridge failures recorded in the USA in 1966-2005. Network Rail (NR) owns 19,000 bridges nationally: 45% are held in a National Scour Database. In Scotland, 1,750 railway bridges are inspected for scour, and 58 are at high risk. Transport Scotland (TS) manages the Scottish road network including 1,567 bridges over water. Around 8% need scour monitoring and protection measures.

The scour risk assessment is an important component of any bridge scour management system. This assessment should combine information on the scour hazard, the bridge vulnerability, and the consequences of failure. It should involve a probabilistic approach due to the many uncertainties inherent to the future flood occurrence and intensity, the bridge state, and capability to withstand the effects of the scour action (Tubaldi et al., 2017). Structural health monitoring (SHM) can be very helpful in supporting decision-makers involved in bridge management. SHM and decision-making are two separate processes, occurring one downstream of the other. Monitoring is about acquiring information on the bridge state while decision-making is about choosing the best action to undertake based on the structural state assessed via SHM and the estimated risk.

The current practice for bridge scour inspection depends on visual checks carried out at regular intervals. TS and NR assess the scour risk using the Procedures BD 97/12 (Department of Transport, 2012) and EX2502 (HR Wallingford, 1993), respectively. The decision frameworks followed by TS and NR are defined by their own plan (Transport Scotland, 2018; Network Rail, 2016). They provide a framework for the management of bridges after an extreme weather event.

In this paper, the prototype of a DSS for bridge scour management is presented; it consists of a scour hazard model and a decision model. The former model is based on a Bayesian network (BN) able to estimate the scour depth in the surrounding of bridge foundations. In particular, the BN can estimate, and update, the scour depth using information from a scour monitoring system (SMS) and river flow characteristics. The latter model can update the scour threshold after which bridges are closed by exploiting BN's outcomes and data collected by a SMS. Section 2 illustrates the BN for scour estimation and the decision model. Section 3 describes the network built to demonstrate the functioning of the DSS. Three bridges located over the same river are considered, with only one instrumented with a SMS. Section 4 shows the results obtained by applying the proposed framework.

2 Methodology

Monitoring scour at any location of a bridge stock is not economically feasible. One way to overcome this issue is to install SMS only at critical locations and use a probabilistic approach to extend the information to the entire asset. A Bayesian network can be used for this purpose. A BN is a probabilistic graphical model describing a set of random variables and their conditional dependencies via a directed acyclic graph (Jensen & Nielsen, 2007). In BN terminology, a node is a parent of a child if there is a link from the former to the latter. Probabilistic inference in BNs takes

two forms: predictive analysis that is based on evidence on parent nodes and Bayesian learning where observations enter into the BN through child nodes (Ben Gal, 2007). BNs started to be used for Bayesian modelling in engineering risk analysis due to their ability to deal with uncertainties in complex systems (Faber et al., 2002).

The BN employed in the scour hazard model is developed according to the BD 97/12 (Department of Transport, 2012). Starting from the river flow characteristics, the total scour depth D_T (Figure 2) is estimated by summing the effects of constriction scour (D_C) and local scour (D_L). Model uncertainties are added to reproduce the randomness of the estimation processes.

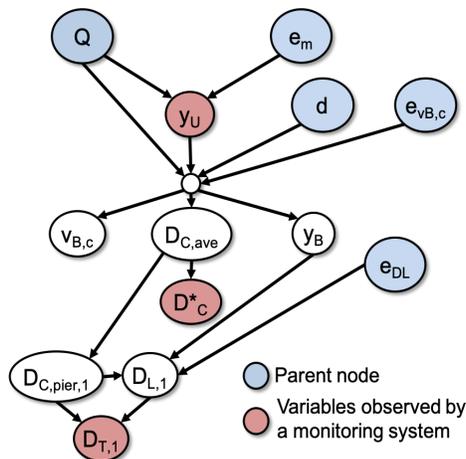


Figure 2: BN for scour estimation at a single bridge location

Manning equation is used to describe the relationship between river flow Q and upstream river level y_U . Two model uncertainties are employed: e_M is the correlated error of the Manning equation and $^{(j)}e_M$ is the uncorrelated error in the j^{th} bridge. Q , y_U and the bed material grain size d are the input of a nonlinear system consisting of 3 equations - the Colebrook-White (C-W) equation (Kirby et al., 2015), the conservation of fluid mass, and the Bernoulli equation - uses to evaluate the average constriction scour $D_{c,ave}$, the water level through the bridge y_B , and the threshold velocity $v_{B,c}$. Model errors, $e_{vB,c}$ and $^{(j)}e_{vB,c}$, are added to the C-W equation alone. The mechanism causing local scour at piers is the formation of vortices at their base, primarily controlled by the pier width W_P . Two model uncertainties are again added: the correlated one, e_{DL} and the uncorrelated one, $^{(j)}e_{DL}$.

With reference to the presented BN, three quantities are monitored: y_U , D_T and the constriction scour D^*_C measured in the middle of the channel. Environmental agencies can provide water level data from gauging stations while SHM sensors to detect scour exist in the market (Prendergast & Gavin, 2014). When new observations become available, the BN model allows propagating information through the network to update probabilities (Jensen & Nielsen, 2007). The BN solution can be broken down into three steps: (i) defining the prior probability distribution functions (pdfs) of the parent nodes; (ii) splitting the BN into three sub-networks to have three different updating: y_U updates e_M ; D^*_C and y_U update $e_{vB,c}$ and d ; D_T , y_U and D^*_C update e_{DL} ; and (iii) updating the descendant nodes.

The BN can be extended to a second bridge with N piers because the scour estimation is based on the same models; therefore, the correlated model errors are the same ones. These connections allow the BN to spread information gained from a SMS to each sub-network (i.e., unmonitored bridge).

2.1 Decision model

The actions to be taken by TS and NR after a flooding event are defined by their plans (Transport Scotland, 2018; Network Rail, 2016). They provide the triggers that determine what actions needs to take place and a “visual” decision scheme based on water level markers. TS defines a red marker in correspondence of the 1 in 200-year flood level whereas NR as the water level associated with a Priority Score ≥ 16 . The transport agencies fix these thresholds by choosing a level of risk they are willing to accept, such that the losses due to the bridge closure equal those due to bridge failure.

The idea behind the proposed decision model is to use the updated scour depth to inform decision about bridge scour management. In particular, the relative scour depth D_R (i.e., ratio between D_T and the foundation depth D_F), employed by transport agencies to categorise bridges at high risk of scour, is used as quantity to trigger actions.

The scour failure probability P_F is the probability that the relative scour demand is greater than the relative scour capacity of the bridge. The prior relative scour demand D_{Pr} (Figure 4) can be expressed as a Normal distribution:

$$D_{Pr} \sim \mathcal{N}(\bar{D}_0, \sigma_{D_0}) \quad (1)$$

where \bar{D}_0 is the prior threshold of D_R corresponding to a high risk of scour according to transport agencies, and σ_{D_0} is the prior standard deviation of D_R obtained with the BN. A fragility function F_C , consistent with the risk class given by BD97/12 (Figure 4), relates D_R to the probability of failure P_F , and the unconditional prior probability of failure P_{F,D_0} can be written as:

$$P_{F,D_0} = \int_{D_R} \mathcal{N}(\bar{D}_0, \sigma_{D_0}, D_R) F_C(D_R) dD_R \quad (2)$$

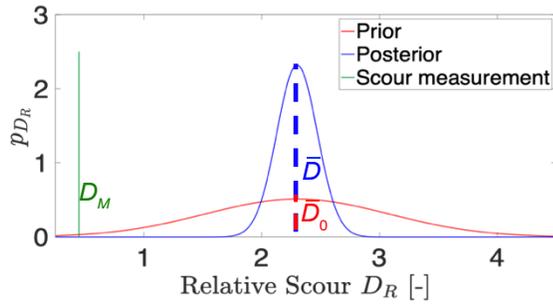


Figure 4: Scour demand pdfs

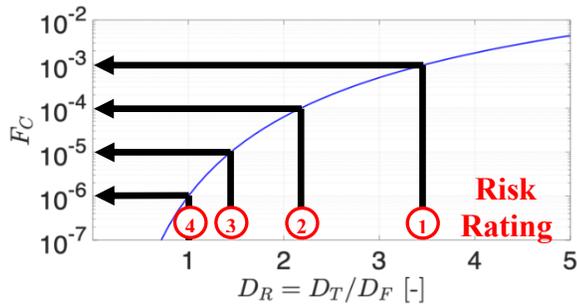


Figure 4: Fragility function for the scour capacity F_C

Eq. (2) expresses the failure probability implicitly chosen by transport agencies when they fix their thresholds (i.e., the mean value of the prior scour demand D_{Pr} is the agency’s threshold). The BN provides an updating of the D_T distribution (i.e., posterior pdf in Figure 4). This BN’s outcome can be used to express the posterior scour demand D_P :

$$D_P \sim \mathcal{N}(\bar{D}, \sigma_P) \quad (3)$$

where \bar{D} is the posterior scour threshold and σ_P is the posterior standard deviation updated by the BN. The probability of failure must remain equal to the one “a priori”, shown in Eq. (2), to be consistent with the threshold defined by transport agencies. Thus:

$$P_{F,D} = \int_{D_R} \mathcal{N}(\bar{D}, \sigma_P, D_R) F_C(D_R) dD = P_{F,D_0} \quad (4)$$

where P_{F,D_0} is expressed in Eq. (2). The updated demand threshold corresponding to a high risk of scour is the value of \bar{D} that satisfies Eq. (4).

3 Case study

A small bridge network, consisting of bridges managed by TS in south-west Scotland (Figure 5), is used to test the functioning of the DSS. The three bridges have experienced significant scour in the past. They cross the same river (River Nith), and only the first one is instrumented with a PSMS:

- **Bridge 1:** A76 200 bridge in New Cumnock. It is a 3-span stone-masonry arch bridge, with two piers in the riverbed founded on spread footings.
- **Bridge 2:** A76 120 Guildhall bridge in Kirkconnel. It is a 3-span masonry arch bridge, with one pier in the riverbed founded on spread footings.
- **Bridge 3:** A75 300 Dalscone bridge in Dumfries. It is a 7-span steel-concrete composite bridge, with one pier in the riverbed founded on pile foundations.

The final BN for the estimation of the total scour at every pier of the three bridges is depicted in Figure 6; each subnetwork related to each bridge is identifiable.



Figure 5: (a) Map; (b) A76 200 bridge; (c) A76 120 Guildhall bridge; and (d) A75 300 Dalscone bridge

4 Results

Normal pdfs are employed for every variable except for river flows described with a log-normal pdf. The prior pdfs of the model errors are set as Normal distributions defined by a zero mean and a coefficient of variation (CoV). The parameters of the log-normal pdf are based on the SEPA’s gauging station data of the last ten years.

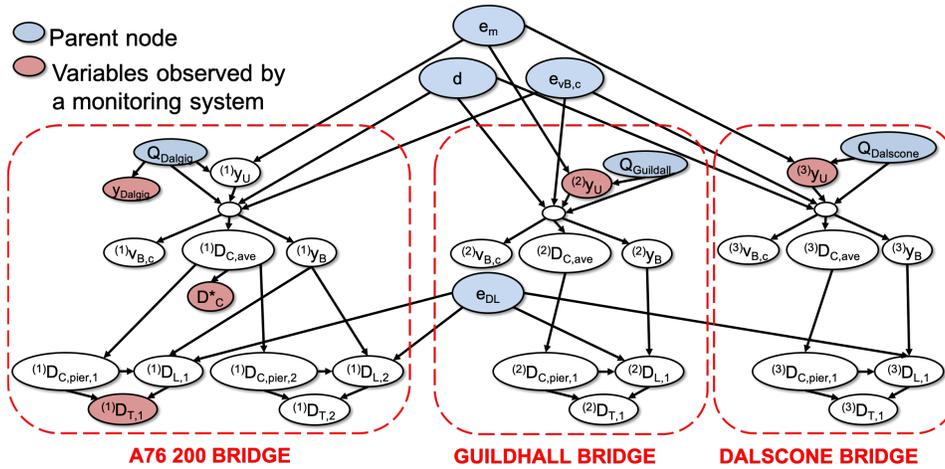


Figure 6: BN developed for the case study

The predictive analysis is carried out by running a Monte Carlo method. The outcomes are displayed in grey in the second column of Figure 7. The accuracy of the estimation at unmonitored piers is not satisfactory (i.e., $\sigma \approx 75$ cm). The Transitional Markov Chain Monte Carlo (TMCMC) algorithm (Ching & Wang, 2016) is used to perform the Bayesian learning analysis and update the parent nodes. The peak value of y_U is chosen to simulate a heavy river flood condition and scour data are assumed to represent a critical situation: 20 cm for constriction scour depth D^*_C and 45 cm for total scour depth D_T at pier 1 of A76 200 bridge. The algorithm estimates a mean value of D_T on pier 2 that is equal to the one measured at pier 1. It is the most probable result since the piers belong to the same bridge, their geometry and the bed material are the same. However, it is an uncertain variable, with a standard deviation of 17 cm. It is noteworthy that the standard deviation has reduced from 76 cm to 17 cm, which is a decrease of around 80%, due to the added information. The total scour D_T at the unmonitored bridges can also be evaluated. A value of standard deviation close to 21 cm is obtained. This constitutes an increase (more than 70%) in the accuracy compared to the prior results.

The third column of Figure 7 shows the outcomes of the scour threshold updating by exploiting the results obtained from the BN. The graphs depict the plotting of Eq. (4) by varying the value of

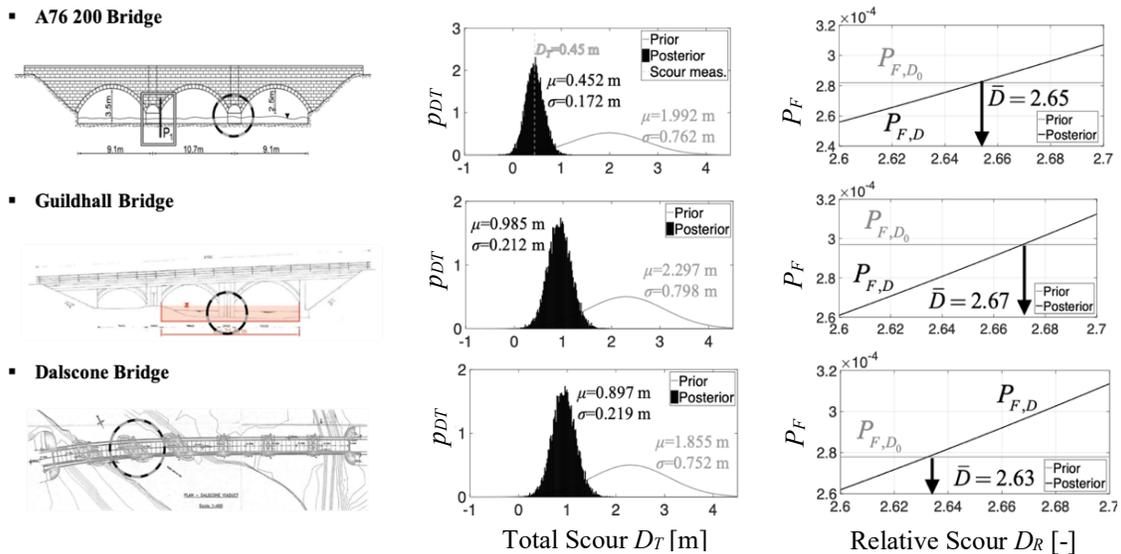


Figure 7: Updating of the scour threshold from BN's outcomes of unmonitored components

threshold \bar{D} . The failure probability $P_{F,D0}$ is a constant value because the threshold was chosen “a priori”. The intersection of the straight lines provides the updated threshold that satisfies Eq. (4). According to the scour risk classification performed by TS, the prior threshold \bar{D}_0 is chosen equal to 2.3, the one that defines the boundary between class 3 and class 2, by assuming a priority factor equal to 2. Figure 7 shows that, starting from $\bar{D}_0=2.3$, the posterior estimation of the scour depth updated by the BN allowed increasing the scour threshold to a value of around $\bar{D}=2.66$.

5 Conclusion

In this paper, a prototype of a DSS for scour risk management for rail and road bridges is presented. It consists of a scour hazard model and a decision model. The former model is based on a BN, which can estimate the scour depth using information from a SMS and river flow characteristics. The latter model can update the scour threshold after which the bridge is closed by exploiting BN’s outcomes and observations collected by a SMS. Case study consisting of three bridges managed by TS in South-West Scotland is used to demonstrate the functioning of the DSS.

The probabilistic framework shows that data from SMSs increase the accuracy on scour estimation of unmonitored, but correlated bridges. This increase is in the order of 70% (from 76 cm to 17 cm). BN’s outcomes and observations of the PSMS are used to update the scour threshold that triggers the bridge closure. The outcomes present an increase of the scour threshold that could help transport agencies in reducing the times that bridges might be closed unnecessarily as a precautionary action.

6 References

- Ben Gal, I. (2007) Bayesian Networks. In F. Ruggeri, F. Faltin & R. Kennett, eds. *Encyclopedia of Statistics in Quality & Reliability*. Chester: Wiley.
- Briaud, J.L., Brandimarte, L., Wang, J. & D’Odorico, P. (2007) Probability of scour depth exceedance owing to hydrologic uncertainty. *Georisk*, 1(2), pp.77-88.
- Ching, J. & Wang, J.S. (2016) Application of the transitional Markov chain Monte Carlo algorithm to probabilistic site characterization. *Engineering Geology*, 203, pp.151-67.
- Department of Transport. (2012) *The assessment of scour and other hydraulic actions at highway structures (BD 97/12)*. UK: Design manual for roads and bridges.
- Faber, M.H., Kroon, I.B. & Kragh, E. (2002) Risk assessment of decommissioning options using Bayesian networks. *Journal of Offshore Mechanics and Arctic Engineering*, 124, pp.231-38.
- HR Wallingford. (1993) *Hydraulic Aspects of Bridges - Assessment of the Risk of Scour, Report EX2502*. HR Wallingford.
- Jensen, F.V. & Nielsen, T.D. (2007) *Bayesian networks and decision graphs*. 2nd ed. Berlin: Information Science and Statistics, Springer.
- Kirby, A.M. et al. (2015) *Manual on scour at bridges and other hydraulic structures*. London: CIRIA.
- Network Rail. (2016) *Scotland route: extreme weather plan*. Glasgow: Network Rail.
- Prendergast, L.J. & Gavin, K. (2014) A review of bridge scour monitoring techniques. *Journal of Rock Mechanics and Geotechnical Engineering*, 6, pp.138-49.
- Transport Scotland. (2018) *Scour Management Strategy and Flood Emergency Plan*. Glasgow: Transport Scotland.
- Tubaldi, E. et al. (2017) A framework for probabilistic assessment of clear-water scour around bridge piers. *Structural safety*, 69, pp.11-22.
- van Leeuwen, Z. & Lamb, R. (2014) *Flood and scour related failure incidents at railway assets between 1846 and 2013*. Railway Safety & Standards Board.