Markov-based deterioration prediction and asset management of floodway structures

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Markov-based deterioration prediction and asset management of floodway structures

Floodway structures are sections of roads which have been designed to be overtopped by floodwater and to fully return to serviceable level after the flood water recedes. Floodway structures are an alternative cost-effective solution to bridges and culverts while they play a significant role in the economy of a country by connecting regional communities, farmlands and agricultural areas to urban cities. Reactive asset management of floodway structures can lead to isolating regional communities and hindering the supply of agricultural products to other regions. To support proactive asset management of floodway structures, this study has developed a Markov deterioration model to predict the rate of deterioration for a network of floodway structures by using their visual inspection data. Based on the Markov deterioration model, a computational algorithm has also been developed for estimating the lowest-cost inspection interval for floodway structures. A case study with real floodway structures is used to demonstrate the practical application of this study. From the case study data, the effects of maintenance assumption, traffic count and underneath drainage culverts on deterioration rate of floodway network are investigated. A budget estimation for proactive asset management based on Markov deterioration model is also presented.

Introduction

In Australia, floodway structure is a small road section apart from bridges and culverts, that is designed to carry road traffic with underneath drainage pipes in some cases and is also designed to be overtopped to allow flood crossing during flood events. Figure 1 shows an example of type 4 floodway structure used in the Lockyer Valley Region of Queensland in Australia, which often have a road surface with road substructure, a reinforced concrete slab with apron and cut-off wall, rock protection against scouring and drainage pipes or culverts. There are several design types of floodway structures, which differ by various arrangements of rock protection, apron and cutoff wall at upstream and downstream (floodways of Main Roads Western Australia).

[Figure 1 near here]

Floodway structures are used generally, under the following circumstances:

- Where flow across the road is infrequent or of short duration.
- Where traffic volumes and serviceability requirements are not high, and the cost of a bridge or major culvert structure is not justified.
- Where floodways can provide flood relief for nearby bridges and culverts during large flows.

Floodway structures are commonly used as a cost-effective alternative solution to bridges and culverts in rural and urban areas to support local community. For example, the Western state of Australia is managing 2,878 floodway structures with average road length of 200 meters (floodway dataset of Mainroads Western Australia) across its vast land area of 2,527,013 square kilometers for a population of only 2.6 million people (Wikipedia of Western_Australia). Floodway structure is also used in urban city to mitigate the impact of urban flooding. For example, a floodway structure comprising of an open channel and a control road was built in a Taiwan urban city (Cheng, et al., 2016). However, only 20 days in operation, the urban floodway structure in Taiwan collapsed in a heavy rainfall event due to erosion of floodway bed (Cheng, et al., 2016). The failure of that particular floodway structure not only highlighted the challenge for safety design of individual floodway structures but also had a significant implication on risk-cost optimal asset management for network of floodway structures in Australia.

Existing literature on floodway structures tends to focus on safety design. For example, hydraulics design guide of floodway structure was introduced by Main Road Western Australia (Main Roads Western Australia, 2006) and Queensland Department of Transport Main Roads (Queensland Department of Transport Main Roads, 2019).

Wahalathantri et al (2016) conducted review of design guide of floodway structures. They found that design process is mainly governed by the hydraulic aspects and very limited attention is paid to studying the effect of extreme loading on safe performance and integrity of the floodway structure. Since then, Lokuge et al. (2019) developed three-dimensional structural analysis approach for floodway structures to provide a basis for their structural design graphs and adjacent soil/rock protection vulnerability analysis. Greene et al. (2020) investigated finite element method approach for the inclusion of a simplified structural design method into design procedures of floodway structure against extreme flooding load. While the newly developed design guides can be heavily used for the construction of new floodways, it is of utmost importance to look after the existing floodways so that they are resilient during and after an extreme flood event.

The existing floodway structures can be managed through asset management of floodway structures at project and network level to ensure maximal asset performance and minimal failure risk and maintenance cost during service life. Similar to bridges, drainage pipes and road pavements, the asset management of floodway structures require knowledge of failure process, condition monitoring and rehabilitation strategy.

For failure process of floodway structures, Allen and Rickards (2012) identified four main failure zones within floodway structures, which include upstream zone, downstream zone, floodway structure and a peripheral zone outside the previous three zones. Wahalathantri et al (2016) summarized man-made and natural factors contributing to failure of floodway structure. The man-made factors include qualities of design, construction and maintenance and the main natural hazards include erosion, scouring, aging, debris, deterioration. Traffic overload can be an added factor, which might occur during normal traffic or detour route. Cheng et al (2020) investigated the failure of urban floodway in Taiwan and concluded that the failure cause is due to the incision of channel bed, erosion of floodway bank and the loose soil caused by piling construction with water-jetting method.

For condition monitoring, Wahalathantri et al (2016) developed a 5-level damage index to rate damage condition of floodway structure with regards to ratio of damage repair cost and replacement cost. However, they did not elaborate on defect types and defect severity for each level of damage index. Floodway industry currently adopts 5 state condition rating to assess visual damages and deteriorated conditions of floodway structure. On the other hand, the 4-state condition rating is commonly used for condition inspection of bridge structures in Australia (Sonnenberg, 2014). The visual assessment is often conducted by trained inspector and the assessment report can be used for rehabilitation planning.

For rehabilitation strategy, the literature review of this study found no published work for floodway structures. The rehabilitation strategy for bridges and drainage pipes, on the other hand, can be used to understand the current best practices applicable to floodway structure. The rehabilitation strategy can be divided into time-based and condition-based rehabilitation (Alaswad and Xiang, 2017; Pham and Wang, 1996). With the time-based rehabilitation strategy, assets are replaced at a predefined time or at failure, whichever occurs first. In contrast, the condition-based rehabilitation (CBR) strategy is based on regular condition inspection and monitoring for timely detecting deterioration and damage of assets and then maintenance actions such as do-nothing, minor repair, major repair or replacement (Hassan, et al., 2019; Xie and Tian, 2018). The above mentioned CBR strategy is often used for bridges and road pavements, and is also suited for drainage pipes and floodway structures. The key driver of the CBR strategy is the deterioration model that can provide predictive information for inspection frequency, estimation of annual rehabilitation budget and prioritized rehabilitation program. At the network level, the stochastic Markov deterioration model, which is based on Markov chain theory, is commonly adopted for infrastructure assets with discrete condition data and random damage events (Micevski et al. 2002; Baik et al. 2006; Lokuge et al. 2019). For industrial assets such as steel bearings and machinery with time-failure data and wear and tear process, the other statistical models such as Weibull, Gamma and Poison are applicable (Luo et al., 2020; Mouais et al., 2021). However, the stochastic deterioration models are based on statistics and therefore are not accurate for a particular asset, which can be handled by physical failure models and reliability theory (Tu et al., 2019; Shakouri, 2021). The main issue of the physical failure models is the requirement of site data, which is time consuming and costly to obtain.

This study aims to develop a Markov deterioration model for network of floodway structures using their visual condition data and to derive the low-cost inspection frequency algorithm based on the deterioration model. The methodology is applied to a real case study of floodway structures managed by a local Government in Australia. The outcome of this study can support proactive management for network of floodway structures, which is consistent with the goal of strengthening resilience in Sendai Framework for disaster risk reduction (2015-2030) issued by the United Nation Office for Disaster Risk Reduction (UNISDR). The main contribution of this study to the knowledge literature is the development of Markov model for floodway structure deterioration that has not been done before. Based on the reported literature in the public domain, the Markov model has been applied to other infrastructure assets (e.g. bridges, pavements) except the floodways. The result of this study shows that Markov model can be used for floodway structures to assist in their asset management. The derivation of low-cost inspection algorithm and the data preparation method are additional contribution together with the investigation of maintenance assumption, annual average daily traffic

(AADT) and drainage culvert on deterioration of floodway structures. The low-cost inspection algorithm has been developed for stormwater pipes but has not been applied for floodway structures previously. The impacts of influential factors are also investigated in this study. The last but not least is the demonstrated application of Markov model for budget estimation of proactive asset management. The budget estimation for inspection and replacement of floodway is derived from this study, which has not been done for proactive management of floodway structures in the previous studies.

This study addresses the lack of knowledge on deterioration and asset management of floodway structures as highlighted in the main contribution. The use of the stochastic Markov model in this study can account for uncertainty in deterioration process and can model floodway network with a large number of assets, discrete condition rating and snapshot inspection. This strength is supported by the pass of statistical fitness test. The use of case study with real data shows the practicality of this study which appeals to industry and academic readers.

Case study

The Lockyer Valley Regional Council (LVRC), a local government of Australia started proactive inspection framework for floodway structures after the 2011 and 2013 extreme flood events in which flood-damaged floodway structures were rebuilt together with other infrastructure assets. Services to culverts and floodways were provided on a need-basis. Two issues arose from this reactive approach after the floods. First, repair was delayed as inspectors needed to understand what caused the failures of the structures. This was difficult to achieve as the condition states of the structures prior to the floods were unknown. Delayed repair means that communities take longer to recover. Secondly, a reactive approach can mean that the needs are not recognized until after major failure.

In partnership with the LVRC, researchers from the University of Southern Queensland (USQ) have been studying the maintenance of floodways and culverts in Queensland by aiming to develop an appropriate methodology to assess these structures during routine maintenance or after flood events.

The establishment of an Inspection Framework has been an area of interest. An inspection framework is expected to evaluate structures to a more consistent standard. This is a more proactive approach. Other advantages of an Inspection framework include:

- Identifying how assets deteriorate over time
- Predicting future asset conditions
- Identifying low-cost condition monitoring program
- Prolong the service life of treatments
- Estimating rehabilitation budgeting and providing accounting report

An issue with this proactive approach is that it can be very costly, especially over the short-term. Inspecting assets, as often as possible is very proactive but might not be viable due to limited budget allocations. Hence a cost estimation could be particularly helpful.

The recently established proactive inspection framework of LVRC affected the availability of condition data available. As such, the data provided was of snapshot nature. This means, the condition data are provided for each structure at one particular date. This affects the prediction model as most models make use of multiple inspection records spanning multiple years in order to develop transition probabilities.

The current floodway structures of LVRC are presented within their own register database. The available data includes the location, the type of material, the size of the structure and its elements, the construction years, the traffic count and finally, the visually inspected condition state. A 5-state condition rating is currently used by LVRC to rate the overall condition state of floodway structures from their inspected visual defects. A rating of 1 represents a structure in perfect condition which is equivalent to 100% of its overall condition or a value of 1. A rating of 5 represents a structure in failure imminent condition and requiring immediate replacement. There are 346 floodway structures, which were evaluated over the period of 2014 to 2018. Of these structures, 267 were inspected in 2011 and only 72 were inspected in 2009. The average-built year of these floodway structures is 1991 (the oldest asset being built 1938) and average road length of 20 meters and road width of 5 meters. Furthermore, only 239 out of 346 floodway structures have traffic count AADT (average annual daily traffic) with median value of 118.

Figure 2a shows the snapshot condition distribution of 267 visually inspected floodway structures in 2019. The figure shows that the majority of floodway structures are in condition 3,4,5 (total of 80%) and the remaining 20% are in conditions 1 and 2. Figure 2b shows the snapshot condition distribution of 346 visually inspected floodway structures between 2014-2018. The figure shows that the majority of floodway structures are in condition 1, 2 and 3 with more or less of 30% for each and the remaining 10% is condition 4. Only one floodway structure is found in condition 5. A comparison of Figures 2a and 2b suggests that some repair and replacement have been carried out to improve the condition of floodway structure network.

[Figure 2a near here]

[Figure 2b near here]

Methodology

Markov deterioration model

The Markov chain model is adopted to model the deterioration of floodway structures because it has been shown to be suitable with proven prediction performance in modelling works for not only drainage pipes (Micevski, et al., 2002; Tran, 2007) but also other linear assets such as pavements (Thomas and Sobanjo, 2013), sewers (Baik, et al., 2006) and bridges (Ranjith, et al., 2013).

The Markov model (Ross, 2012) is based on the assumption that future condition of assets is dependent on the current condition (i.e. memory-less) and is expressed as a probability Pij that a pipe can move from condition i at year t to condition j at year t + 1. Since there are 5 conditions derived from condition data, a 5x5 transition probability matrix M can be established as shown in Equation (1). Equation 2 shows the Kolmogorov equation (Ross, 2012) for predicting future condition given the current known condition (shown in Equation 3) and transition matrix M.

$$\boldsymbol{M} = \begin{bmatrix} P_{11} & P_{12} & P_{13} & P_{14} & P_{15} \\ 0 & P_{22} & P_{23} & P_{24} & P_{25} \\ 0 & 0 & P_{33} & P_{34} & P_{35} \\ 0 & 0 & 0 & P_{44} & P_{45} \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (1)$$

$$\boldsymbol{P}^{t+1} = \boldsymbol{P}^{t} * \boldsymbol{M} \quad (2)$$

$$\boldsymbol{P}^{t} = [p_1^t,\ p_2^t,\ p_3^t,\ p_4^t,\ p_5^t\ ] \quad (3)$$

where p_i^t is probability in condition *i* at time *t* and *i*=1 to 5.

The transition matrix M of the Markov deterioration model is calibrated using Bayesian Markov chain Monte Carlo simulation (Micevski, et al., 2002; Tran, 2007) on sample of observed condition data. The validation of Markov model is based on Chi-square test by separating sample data into calibration data (80%) and validation data (20%) (Micevski, et al., 2002; Tran, 2007). This means that using a random sample condition data of drainage network, the future condition of drainage network can be predicted.

The test hypothesis, with the test statistics being the Chi-square value, is that the observed frequency is consistent with the predicted frequency for a particular condition rating at a particular observed age. The Chi-square value for the Markov model can be calculated using Equation 4 (Micevski, et al., 2002):

$$\chi_M^2 = \sum_{i=1}^{5} \frac{(O_i - E_i)^2}{E_i} \qquad (4)$$

where *Oi* is observed number of elements in condition *i* and *Ei* is predicted number of elements in condition *i*. If the test statistic χ_M^2 is larger than the critical value of Chi-square distribution at 95% confidence level and a specified degree of freedom, the hypothesis is rejected (Greenwood and Nikulin, 1996). The degree of freedom is calculated as (row number – 1) multiplying with (column number – 1) where row number is number of observed ages and column number is number of observed condition states at an observed age.

Lowest-cost inspection model

Monte Carlo simulation (MCS) (Melchers, 1999) is a versatile and commonly used technique for uncertainty study, risk assessment and optimization. In this study, the Markov deterioration model and MCS are used to find the lowest cost inspection interval based on the following observations and ideas.

- The shorter the inspection interval, the more likelihood to detect the poor condition of floodway for timely repair/replacement but the higher the inspection cost. For example, if the inspection interval is 1 year, it is almost certainty to timely detect the poor condition of floodway structure asset for repair and replacement. However, the inspection cost might be unnecessarily high if asset deterioration is slow such that asset condition does not move to poorer condition in 5 or 10 years. In this case, it is not needed to inspect the asset every year, i.e. 1-year inspection interval.

- On the other hand, if the inspection interval is 10-year, for instance, the floodway might fail before the inspection. In this case, the inspection cost is low but the failure consequence cost such as traffic accident and emergency repair cost due to unexpected failure could be far more than the inspection cost.
- A penalty cost is applied when pipe failure or pipe in poor condition is not timely detected due to long inspection interval (the focus of this study) and other causes (explained in Discussion). The penalty cost can include the tangible cost (e.g. extra cost for emergency repair and cost of traffic delay and accident cost) and intangible cost (e.g. reputation and public discomfort).
- The lowest-cost inspection interval over a planning horizon for a given deterioration rate could be the point where the total of inspection cost is balanced with the total of penalty cost.
- The rate of deterioration can be simulated with the Markov model since the model can provide the predicted probabilities in 5 condition states over time.
- The MCS is used to generate random sequences of floodway condition change over time based on the provided probabilities being in 5 condition states from the Markov model.

The algorithm written in Matlab to find the lowest-cost inspection interval is summarised in the step flow chart of Figure 3. The first step is to select a planning horizon, which can be 5 years as an example. The second step is to use Markov deterioration model to generate a random sequence of condition change as shown by an example where failure condition 5 occurs at year 4. The third step is to select an inspection interval, which is 3-year interval as an example. Steps 4 and 5 can be explained as follows. It can be seen that for a particular random sequence in Step 2, the 4-year inspection interval can timely detect the failure condition 5 with only one inspection trip. The 1-year and 2-year inspection intervals can also detect failure condition 5 but the inspection cost is higher. The 3-year inspection interval is unable to detect the failure condition in a timely manner and therefore, penalty cost is added to inspection cost. Step 6 is repeat of steps 3-5 for various inspection intervals. Step 7 is repeat of step 6 for 10,000 random sequences as per MCS. Step 8 takes average cost for each inspection interval over 10,000 random sequences and compared the average cost to find the inspection interval with lowest cost. More details of this inspection model can be found in Tran et al. (2021)

[Figure 3 near here]

Data preparation for Markov model

The case study shows that repeat inspections were carried out for some floodway structures. These inspection data can be processed to produce data points for calibration and validation of Markov deterioration model as follows. Table 1 shows 3 scenarios with 1, 2 and 3 inspections for a floodway asset and the resulted number of data points for 2 points of view called long-term and short-term. The short-term view is based on the assumption that repair might be carried out between the built year until the first inspection year if their time gap is relatively large (for example, 10 years or more). This means the condition at the first inspection year cannot be used to show deterioration from built year. This view results in fewer data points than the long-term view, which assumes no repair had been done between built year and first inspection year. This is because the long-term view can use the condition at the first inspection to reflect the deterioration from built year, which then contribute to overall rate of deterioration. To cover all possible cases encountered in the inspection dataset, the scenario 1 in Table 1 shows the case of only one inspection. The scenario 2 shows a data case (sometimes encountered) that at first inspection in 2011, the asset is in condition 4 (very poor) and at the subsequent inspection in 2015, the asset is in condition 1 (very good). This is the case of condition getting better due to maintenance. The scenario 3 shows the commonly encountered case that asset condition stays in the same condition or gets poorer over time.

For scenario 1, the floodway asset has only one inspection (e.g. at 2015) since the built year. Since the time gap between built year 1980 and first inspection at 2015 is relatively large (i.e. 35 years for the example), the long-term view produces one data point while the short term view produces zero data point.

For scenario 2, the floodway asset has two inspections (e.g. at 2011 and 2015). Since the time gap between built year 1980 and first inspection at 2011 is relatively large (i.e. 31 years for the example), the long-term view produces one data point while the short term view produces zero data point. Between 2011-2015, the condition is improved from condition 4 to 1, this mean a repair has been done and the long-term and short-term views produce zero data point.

For scenario 3, the floodway asset has three repeated inspections (e.g. at 2009, 2011 and 2015) in which condition 3 is unchanged at 2009 and 2011 then moved to condition 5 at 2015. For scenario 3, the long-term view produces 2 data points instead of 3 data points because a data point between built year and 2009 is combined with a data point between 2009 and 2011 to produce the first data point because of unchanged condition at 2009 and 2011. This combination is to reflect the fact that the asset stayed in the same condition from built year until 2011. If combination is not made, 2 data points will be resulted but the data does not reflect the true fact. The second data point is between 2011 and 2015 because the condition changes from condition 3 to condition 5. The short-term view produces one data point between 2009-2011 and one data point between 2011-2015. Both short-term and long-term view uses the same combination method if such observations occur.

[Table 1 near here]

Table 2 shows the summary of data points obtained from case study data, which are used for calibration and validation of Markov model. As expected, the long-term view produces significantly more data than the short-term view as shown in Table 2. The long-term view data is further split into 2 datasets to compare deterioration of floodway structures subjected to low and high AADT and to compare deterioration between floodway structure with and without drainage culvert (Figure 1 in the Introduction section shows a floodway design with drainage culvert). It is noted that the data points for low and high AADT are fewer than all data points because only 239 out of 346 floodway structures have AADT information. Furthermore, the obtained data of short-term view is not sufficient to investigate impacts of AADT and drainage culvert.

[Table 2 near here]

Results

Fitness test of Markov deterioration model

A calibration dataset of 85% data points and a test dataset of 15% data points, respectively, for calibrating and testing of the Markov model are randomly selected from the entire dataset. Furthermore, floodway structure assets are assumed in good condition at the time of installation (i.e. $P^0 = [1\ 0\ 0\ 0\ 0]$).

The calibrated transition matrix is shown in Table 3 for the case of all data of long-term view as a demonstration. The first row of Table 3 shows the transition probabilities from condition 1 to conditions 1, 2, 3, 4 and 5 in which the largest probability is found for staying in the same condition (i.e. condition 1 to condition 1). The multi-step transition probabilities from condition 1 to 3,4, 5 and from 2 to 4, 5 are not zero suggesting the probable occurrence of damage events such as extreme flooding and over-load traffic.

[Table 3 near here]

The Markov deterioration models for various datasets passed the Chi-square test for goodness-of-fit as shown in Table 4. For example, for all the data of long-term view dataset, the calculated Chi-square value of 12.94 is found smaller than the Table Chi-square value of 18.04 at 5% significance and 10 degrees of freedom suggesting the adequacy of Markov model and assumptions of multi-step jumps and initial conditions.

[Table 4 near here]

Network deterioration rate

The network deterioration curve of floodway structures is shown in Figure 4. This curve is derived from the calibrated Markov deterioration model and can be used and explained as follows.

For a particular floodway structure, the vertical axis shows the probability values of the structure being in 5 condition states over time as represented by horizontal axis. For example, at year 0, which can be assumed to be installation year, Figure 4 shows that there is 100% of probability that the structure is in condition 1 and zero probability of being in other poorer condition. After 10 years, the probability of the floodway structure being in good condition 1 decreases while probabilities being in poorer conditions 2-5 increase.

For a network of floodway structures, the vertical axis shows the percentage of network in 5 condition states by applying the frequency concept of statistical theory. For example, at year 0, which can be assumed to be installation year of the network, Figure 4 shows that 100% of network is in good condition 1. The installation year of floodway structure network can be assumed to take average construction year of all floodway structures since individual structures were constructed at various years in the past. For LVRC, the average construction year is 1991 and at the current year of 2021, the network age is 30 years.

- At current year 2021 and network age of 30 years, the Markov model predicts that 0.78% of floodway structures being in condition 1, and 16.2% in condition 2, and 42.2% in condition 3, 31.6% in condition 4 and 9.2% in failure condition 5. This is shown by drawing a vertical line at 30 years and reading the cross values between the deterioration curves and the vertical line.

- At any future year such as 2030 at network age of 40 years, the prediction can be made by using the similar technique at year 2021. This shows that the percentage of floodway structures in failure condition 5 is increased from 9.2% to 13.2%, which is considered slow to mild deterioration.

[Figure 4 near here]

Effect of maintenance assumption

The data choice of long-term view and short-term view can affect the predicted deterioration of floodway network. The deterioration of floodway network using long-term view (Figure 4) is different with short-term view (Figure 5) at conditions 4 and 5. The poor condition 4 of long-term view appears to have slower rate than that of short-term view while the failure condition 5 of long-term view shows faster rate of deterioration than that of short-term view. This is because the first inspection in 2009 (since the built year) has more condition 5 but it cannot be used as condition data for short-term view as explained in the data preparation section.

[Figure 5 near here]

Effect of AADT

It is useful to understand if traffic AADT has any effect on deterioration of floodway structures. The long-term view condition data has sufficient data to split the dataset into low and high AADT by the median value of 118. Figure 6a shows that group of floodways with low traffic AADT are more deteriorated than floodways with high

AADT (figure 6b). This can be seen by slope of condition 5 curve and the percentage of floodways in condition 5 at any future time. One possible explanation for this finding is that the floodways with higher traffic AADT could be designed with more safety factor resulting in more durability.

[Figure 6a near here]

[Figure 6b near here]

Effect of add-in drainage culvert

Floodway design allows the choice of adding drainage culvert underneath road surface to ensure the continuous flow of creek. It is useful for asset management practice to understand if there are any differences in deterioration between floodways with and without drainage culvert. The data shows that floodways with underneath drainage culvert deteriorates faster than without drainage culvert as shown by the condition 5 curves in Figure 7a and 7b.

[Figure 7a near here]

[Figure 7b near here]

Lowest-cost inspection interval

The lowest-cost inspection model is used to estimate the lowest-cost inspection interval for the proactive inspection of floodway structures with the following assumed cost values. The unit cost of inspection is assumed $1, which can be easily scaled up to any real values. The planning horizon is taken as 20 years and the failure condition to be detected by inspection is assumed condition 5.

Figure 8 shows how the lowest-cost inspection interval is obtained for the case of the known condition being 1 and penalty cost being equal to unit cost of inspection. As can be seen, the shorter inspection interval results in higher inspection cost and as the inspection interval gets longer, the inspection cost decreases until the minimal point where longer inspection interval after this point result in higher inspection cost due to the penalty cost.

[Figure 8 near here]

The lowest-cost inspection intervals for various current conditions of floodway structures and various penalty costs, with the particulate rate of deterioration calibrated with the Markov model for the case study, are shown in Table 5. For example, if the current condition of a floodway structure is known in condition 2 then the next inspection interval with lowest-cost is 7 years for detecting failure condition 5 if penalty cost is equal to the unit cost of inspection. Table 5 also shows that the choice of penalty cost affects the inspection interval with lowest cost. For the example, of current condition 2, the inspection interval of 7 years is unchanged for small penalty costs up to 3 times inspection cost and changes from 7 year to 3 years when the penalty cost being 5 to 8 times inspection cost.

[Table 5 near here]

Budget estimation for proactive asset management

There are 346 floodway structures in the case study region. If it is assumed that at current year 2021, all floodway structures in failure condition 5 have already been repaired or replaced, then the budget for proactive asset management over the next 10 years (selected as an example) can be estimated as:

- Unit cost of visual inspection is assumed $500 AUD per structure and unit cost of major repair or replacement is $80,000 AUD per structure for its average road length 15 m. The penalty cost is assumed being equal to unit cost of inspection.
- The proactive visual inspection within 10-year planning is one time for all structures (as per Table 2), resulting in inspection budget equal to $173,000 AUD (which is 346 times $500 AUD).
- The Markov deterioration model predicts the increase by 4.0% of 346 floodway structures (i.e. approximately 14 structures) that will be in failure condition 5, that require major repair or replacement. The replacement budget is therefore $1,120,000.0 (which is 14 times $80,000).
- The total budget for proactive asset management is $1,293,000 over 10-year planning (which is sum of inspection budget and replacement budget)

As a demonstration for the benefit of this study, the budget for proactive management is compared with a reactive management, which conducts no regular inspection and carries out repair/replace after the failure occurs. For this reactive management, the cost of regular inspection is zero, but the cost of replacement is expected to be more than 20% the normal replacement process. This is called emergency replacement, which requires emergency inspection to identify the failure extent, then the emergency arrangement of resources and man power to conduct replacement. These emergency actions often require more cost and longer period of traffic detour with potential traffic accident. Therefore, with the above simplified assumption, the total cost of reactive management is estimated as $1,344,000 (which is 1.2 times normal replacement cost of $1,120,000.0). This reactive cost is higher than the proactive cost of $1,293,000.

Discussion

This study has shown that data assumption on maintenance can result in longer or shorter data span (i.e. long-term and short-term datasets in this study) and can significantly affect the estimated rate of deterioration for floodway network. Furthermore, after repair or replacement, the deterioration rate of assets might change due to the use of better maintenance material or technology as noted by the study by Saeed et al. (2017). Since the Markov method is based on the assumption that the deterioration of assets can be predicted based on the current condition and a transition matrix of condition change, the transition matrix should be re-calibrated to account for such possible maintenance effects on deterioration of assets. Due to lack of maintenance data, the re-calibration of the transition matrix is not investigated in our study. This highlights again the importance of keeping record of maintenance over asset lifetime. When maintenance data are available, an alternative deterioration model with maintenance effects developed by Saeed et al. (2017a) can also be investigated to find the best suited model for floodway assets. With the limited data available from the case study, the effects of other contributing factors such as soil type and flood flow rate on deterioration of floodway structures could not be investigated for the Markov deterioration model in this study, either.

In this study, the longer inspection interval is considered as the main cause for not being able to detect poor condition in a timely manner. Other causes such as varied quality of inspectors and the error of automated inspection vehicle can be explored in future study.

Penalty cost is used in this study to represent for consequences of not being able to detect failure condition in a timely manner. The methodology to estimate the penalty cost should involve tangible costs such as traffic delay, freight delay and emergency repair cost and intangible costs such as reputation, road user discomfort. The methodology for estimating the penalty cost in this study is not yet developed and this can be developed in future study.

The assumed unit cost of inspection and replacement cost in this study are based on discussion with floodway engineers. However, these cost values are not actual values due to commercial confidential. The use of assumed unit cost for inspection and replacement due to commercial confidential could be viewed as a weakness. However, the actual values, when available, can be used with the methodology easily.

The limited data in this study is a weakness in terms of producing results with high confidence and reliability. However, the methodology is fully demonstrated for future use and development when more data are available.

There is currently no standard guide by industry or researchers on rating condition of floodway structures. The rated condition data in the case study is based on the view of inspectors and could be varied among inspectors. Future research should develop a more objective and consistent condition rating scheme for floodway structures. Furthermore, the efficacy of various maintenance activities on improving condition of floodway structures could also be important information as shown by the study on bridge deck and pavement by Saeed et al. (2017b)

The budget estimation for proactive asset management of floodway network has been demonstrated based on average rate of network deterioration. If maintenance priority is placed on group of floodways with high traffic AADT, the budget estimation process can be easily calculated using average rate of deterioration of high AADT. For a particular floodway asset, the Markov model can only provide the probability values in 5 condition states, which are not easily interpreted. Alternatively, physical deterioration models and reliability analysis can be carried out to obtain desirable outcomes.

Conclusion

Floodway structures are part of road infrastructures, which are crucial for community activities. The considerable large network of floodway structures in Australia requires risk-cost effective asset management strategy, which is addressed by the contribution of this study. The Markov deterioration model and lowest-cost inspection algorithm and data preparation method have been developed in this study and demonstrated on a case study of floodway structure with real condition data from visual inspection. The results of case study based on Markov deterioration model calibrated with limited data show that:

- Floodway structures can be subjected to extreme damage events resulting in significant condition changes from good to very poor or failure with small probability.
- If maintenance is assumed to occur between built year and first inspection year (resulting in short term condition data), the deterioration of floodway network with regards to failure condition 5 is much slower than when maintenance is not carried out (resulting in long-term condition data).
- The deterioration of floodway network with regards to failure condition 5 is not necessarily correlated with traffic AADT. In fact, the case study data shows that low AADT has higher rate of deterioration than high AADT.

- It is found that deterioration of floodway structures with underneath drainage culvert is more than without drainage culvert.
- With penalty cost being equal to unit cost of inspection, the lowest-cost inspection interval for flood structures is 7 years if the current condition is 1, 2 and 3. For penalty cost being four times unit cost of inspection, the inspection interval becomes 3 years.
- The total budget for proactive asset management (including one-time visual inspection and replacement of 4% of floodway network) over 10-year planning is estimated as $1,393,000 based on assumed values in this study.

Data Availability Statement

All data, models, or code generated or used during the study are available from the corresponding author by request.

Disclosure statement

No potential conflict of interest.

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References

Alaswad, S. and Xiang, Y. (2017). A review on condition-based maintenance optimization models for stochastically deteriorating system. *Reliability Engineering and System Safety*, 157, 54-63.

Allen, G. and Rickards, R. (2012). Floodway research report. In. South Australia, Australia: Local Government Association of South Australia.

Baik, H.S., Jeong, H.S. and Abraham, D.M. (2006). Estimating Transition Probabilities in Markov Chain-Based Deterioration Models for Management of Wastewater Systems. *Journal of Water Resources Planning and Management*, ASCE, 132(1),15-24.

Cheng, M.H., Huang, M-W., Pan, Y-W., and Liao, J-J. (2016).Lessons from a failure case of an excavated floodway supported by precast cantilever pile walls. *Engineering Geology*, 209,106-118.

Floodways Mainroads Western Australia, access September 2021, https://www.mainroads.wa.gov.au/technical-commercial/technical-library/road-traffic-engineering/drainage-waterways/floodways/

Floodway dataset of Mainroads Western Australia, accessed September 2021, https://catalogue.data.wa.gov.au/dataset/mrwa-floodway

Greene, I., Lokuge, W. and Karunasena, W. (2020). Structural design of floodways under extreme flood loading. *International Journal of Disaster Resilience in the Built Environment*, 11(4), 535-555.

Greenwood, C. and Nikulin, M.S. (1996). A guide to chi-squared testing. New York, Wiley.

Hassan, S.I., Dang, L. M., Mehmood, I., Im, S., Choi, C., Kang, J., Park, Y-S., Moon, H. (2019). Underground sewer pipe condition assessment based on convolutional neural networks. *Automation in Construction*, 106, 102849

Lokuge, W., Greene, I., Etemadi, E., and Karunasenaa, W. (2019). Role of structural analysis in floodway design process. *Australian Journal of Civil Engineering*, 17(2), 110-119.

Lokuge, W., Wilson, M., Tran, H. & Setunge, S. (2019). Predicting the probability of failure of timber bridges using fault tree analysis. *Structure and Infrastructure Engineering,* 15(6), 783-797.

Luo, H., Alkhaleel, B.A., Liao, H. and Pascual, R. (2021). Resilience improvement of a critical infrastructure via optimal replacement and reordering of critical components, *Sustainable and Resilient Infrastructure*, 6(1-2), 73-93.

Main Roads Western Australia (2006). Floodway design guide. In. Western Australia, Australia. Government of Western Australia, Australia.

Micevski, T., Kuczera, G. and Coombes, P. (2002). Markov Model for Storm Water Pipe Deterioration. *Journal of Infrastructure Systems*, 8(2),49-56.

Mouais, T., Kittaneh, O.A. and Majid, M.A. (2021). Choosing the Best Lifetime Model for Commercial Lithium-Ion Batteries. *Journal of Energy Storage*, 41, 102827.

Pham, H. and Wang, H. (1996). Imperfect maintenance. *European Journal of Operational Research*, 94(3),425-438.

Queensland Department of Transport Main Roads. (2019). Road Drainage Manual. In. Brisbane, Australia: Queensland Department of Transport Main Roads.

Ranjith, S., Setunge, S., Gravina, R. and Venkatesan, S. (2013). Deterioration Prediction of Timber Bridge Elements Using the Markov Chain. *Journal of Performance of Constructed Facilities*,27(3), 319-325.

Ross, S. (2012). Simulation. US, Academic Press.

Saeed TU., Qiao Y., Chen S., Gkritza K. and Labi, S (2017a) Methodology for probabilistic modeling of highway bridge infrastructure condition: Accounting for improvement effectiveness and incorporating random effects. Journal of Infrastructure Systems. 23(4).

Saeed, T. U., Qiao, Y., Chen, S., Alqadhi, S., Zhang, Z., Labi, S., & Sinha, K. C.(2017b). Effects of bridge surface and pavement maintenance activities on asset rating (Joint Transportation Research Program Publication No. FHWA/IN/JTRP-2017/19). West Lafayette, IN: Purdue University.

Shakouri, M. (2021).Time-dependent concentration of chlorides at the concrete surface revisited, *Sustainable and Resilient Infrastructure*, AHEAD-OF-PRINT, 1-18, https://doi.org/10.1080/23789689.2021.1892965

Sonnenberg, A. (2014). Australian Bridge Inspection Processes. *6th Australian Small Bridges Conference 2014*. Sydney.

Thomas, O. and Sobanjo, J. (2013). Comparison of Markov Chain and Semi-Markov Models for Crack Deterioration on Flexible Pavements. *Journal of Infrastructure Systems*, 19(2),186-195.

Tran, H., Setunge, S. and Shi, L. (2021) A Markov chain-based inspection and maintenance model for stormwater pipes *ASCE Journal of Water Resources Planning and Management.* (doi/full/10.1061/(ASCE)WR.1943-5452.0001469).

Tran, H.D. (2007). Investigation of Deterioration Models for Stormwater Pipe Systems, PhD Thesis. Melbourne, Australia, Victoria University.

Tu, B., Dong, Y. and Fang, Z. (2019). Time-Dependent Reliability and Redundancy of Corroded Prestressed Concrete Bridges at Material, Component, and System Levels. *Journal of Bridge Engineering*, 24(9), 20.

Wahalathantri, B.L., Lokuge, W., Karunasena, W. and Setunge, S. (2016). Vulnerability of Floodways under Extreme Flood Events. *Natural Hazards Review*, 17(1).

Wikipedia of Australia, https://en.wikipedia.org/wiki/Western_Australia (accessed September 2021)

Xie, M. and Tian, Z. (2018). A review on pipeline integrity management utilizing in-line inspection data. *Engineering Failure Analysis*, 92,222-239.

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Table 1. Various inspection cases of a floodway asset and resulted data points for calibration of Markov model

Inspection Scenario	Rated condition at built year and inspection year				Resulted data points (long term)	Resulted data points (short term)
	Built year 1980	2009 inspection	2011 inspection	2015 inspection		
1	1	n/a	n/a	3	1	0
2	1	n/a	4	1	1	0
3	1	3	3	5	2	2

Table 2. Summary of data points used for calibration and validation of Markov model

Data type	Number of data points		
	All	Low / High AADT	With / Without drainage culvert
Long-term view	532	193 / 176	326 / 206
Short-term view	276	n/a	n/a

Table 3. Calibrated transition matrix of Markov model for the case of all data of long-term view

	Cond. 1	Cond. 2	Cond. 3	Cond. 4	Cond. 5
Cond.1	0.8507	0.1354	0.0001	0.0137	0.0001
Cond.2	0	0.9252	0.0572	0.014	0.0036
Cond.3	0	0	0.9805	0.0157	0.0038
Cond.4	0	0	0	0.9944	0.0056
Cond.5	0	0	0	0	1

Table 4. Results of goodness of fit test using Chi-square values on test data of various datasets

Test Dataset	Calculated Chi-square value	Degree of freedom (df)	Table Chi-square value (5%, df)	Test result
All data (long-term)	12.94	10	18.04	Pass
All data (short term)	1.35	3	7.82	Pass
Low AADT	13.74	7	14.07	Pass
High AADT	7.16	6	12.6	Pass
With Drainage culvert	10.07	7	14.07	Pass
Without drainage culvert	5.42	4	9.49	Pass

Table 5. Lowest-cost inspection frequency for various current conditions of floodway structures and penalty costs (CI is unit cost of visual inspection)

Current Conditions	Next inspection time (years) to detect failure condition 5			
	Penalty cost = 1*CI	Penalty cost = 3*CI	Penalty cost = 5*CI	Penalty cost = 8*CI
1	7	7	7	3
2	7	7	3	3
3	7	7	3	3
4	7	3	3	3