Title

Optimal Maintenance Decision for Deteriorating Components in Miter Gates Using Markov Chain Prediction Model

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COVER SHEET

Title: *Optimal Maintenance Decision for Deteriorating Components in Miter Gates using Markov Chain Prediction Model* for Proceedings of the **12th International Workshop on Structural Health Monitoring 2019**

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ABSTRACT

Maintenance of miter gates in navigation locks is crucial to facilitate water navigation of cargo ships. Scheduled and unscheduled maintenance are the two types of actions performed to keep miter gates continuously operational. In practice, visual inspections and rating systems are used to monitor the current state of miter gate components in order to prioritize maintenance. This paper shows an example of how to find the optimal time to plan for maintenance using deterioration curves obtained from real visual inspection assessments of components in miter gates. Predictive deterioration curves are derived using a Markov Chain approach. In addition, the advantages of implementing Structural Health Monitoring (SHM) are discussed.

INTRODUCTION

The U.S. Army Corps of Engineers (USACE) owns and operates 236 locks at 191 sites in the United States [1]. According to Foltz [2], more than half of these assets have surpassed their economic design life, 50 years, and need frequent inspections to ensure their safe and reliable operation. Miter gates are the most common type in the United States among other designs including sector, tainter, and vertical lift [3]. Damage to critical components in miter gates may lead to closures of the lock chamber, which produce substantial economic losses on the marine cargo industry and their commercial clients.

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Lock closures for maintenance and/or repair are broadly classified as "scheduled" and "unscheduled." Scheduled maintenance allows commercial shippers to adjust their activities to optimize their benefit or minimize their losses by using alternative transportation options. However, essential (or emergency) maintenance (EM) needs can result from unscheduled closures, which can severely negatively impact marine transportation activities [4]. Generally, the downtime for unscheduled repairs is longer than for scheduled repairs. Therefore, there is a need to identify the optimal time to schedule maintenance activities to minimize the repair costs and the costs associated with the downtime in the lock gates.

Different engineers and lock operators from USACE [2] have mentioned that one of the primary concerns for inspection, maintenance, and repair are the condition of the quoin blocks. The condition of quoin blocks can be correlated with the bearing "gap"; these gaps are generated due to the loss of bearing contact between the quoin attached to the gate and the lock wall, which arise from fatigue, corrosion, or wear deterioration. A gap in the quoin block cause load redistribution leading to higher stresses on some places in the lock gate (e.g., the pintle), which further can lead to operational and/or structural failure. Therefore, monitoring the condition of quoin blocks can be used to suggest repairs and maintenance in a timely manner. Other concerns related to miter gates are fatigue deterioration and corrosion [5].

The paper first explains how to produce a deterioration curve using a Markov chain approach. Markov models are widely used to predict deterioration of bridges [6] and other structures [7]. With this deterioration curve, predictions of future states can be established based on the initial state of a component. A probability threshold is defined using the future state predictions to define when to plan for preventive maintenance (PM), which affects the amount of times that EM may be required. The cost function used in this paper gives certain weight to the PM and EM events, which allows to easily identify the optimal time between PM events for a specific component (ex. quoin blocks) in a miter gate. Additionally, the paper introduces the mapping from component level to system level and the benefits of integrating SHM into the life cycle of structural components.

MITER GATES

Miter Gates were invented by Leonardo Da Vinci, sometime around the late 15th century. Modern gates are made of steel and are used to facilitate navigation from different water levels in a river system. In the USA, many of gate's components (e.g. quoin blocks) are periodically inspected to ensure proper operation. Figure 1 shows a closed miter gated (miter position) and its function in helping ships to go from different water levels.

The USACE Asset Management team oversees the implementation and development of the OCA to assess structural component deficiencies by giving a category rating by an inspector, who base the evaluation on engineering knowledge and information of preexisting inspections. The ratings are classified as A (Excellent), B (Good), C (Fair), D (Poor), F (Failing) and CF (Completely Failed). More detailed definitions can be found in [2].

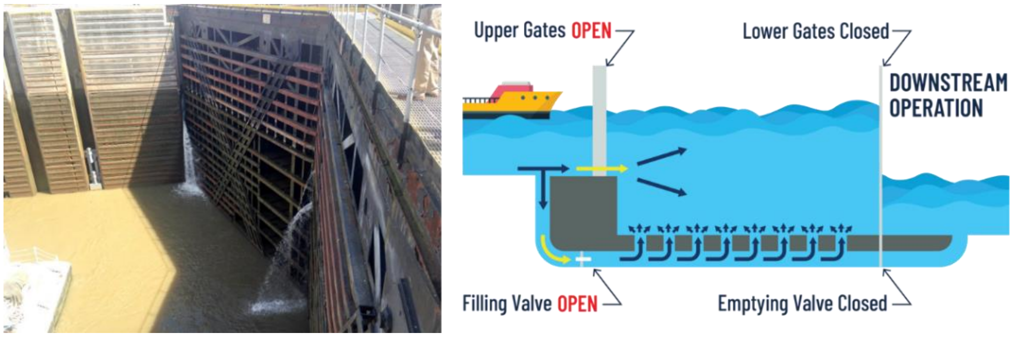


Figure 1. Navigation Lock Gates

$$P=\begin{bmatrix} 7.76e-1 & 2.13e-1 & 5.25e-3 & 2.16e-3 & 1.85e-3 & 2.47e-3 \\ 0 & 9.85e-1 & 9.33e-3 & 3.69e-3 & 1.68e-3 & 5.51e-4 \\ 0 & 0 & 8.70e-1 & 1.19e-3 & 6.64e-3 & 4.78e-3 \\ 0 & 0 & 0 & 9.40e-1 & 5.03e-2 & 9.39e-3 \\ 0 & 0 & 0 & 0 & 8.65e-1 & 1.35e-1 \\ 0 & 0 & 0 & 0 & 0 & 1.000 \end{bmatrix}$$

Figure 2. 1-step (1 year) Transition Matrix for quoin block components

TRANSITION PROBABILITY DERIVATION

Transition matrices, known also as stochastic matrices, have been widely used in different fields such as probability theory, economy and weather predictions [8]–[10]. These matrices are defined as a square matrix with nonnegative values. Each value in the transition matrix represents a probability and the sum of each row sums to 1. Based on an OCA database, the amount of times that a component transitioned from one rating category to another in a given year was determined. Only the upper triangle components were considered to simulate component deterioration. A transition matrix was found by normalizing the counts in each row as shown in Figure 2.

MARKOV CHAIN DEGRADATION MODEL

The Markov Chain degradation model is a discrete in time Markov process with finite state space. Equation 1 is used to build the Markov Chain degradation predictions where the vector $v^{(0)}$ represent the initial state vector. For instance, the state can be expressed as $v^{(0)}=[1\ \ 0\ \ 0\ \ 0\ \ 0\ \ 0]$ when the component is considered brand new.

$$v^{(n)}=v^{(0)}P^n, \tag{1}$$

The matrix P^n represents the n-step transition matrix, which can be obtained by raising the 1-step transition matrix, shown in Figure 2a, by the n-th power. The vector $v^{(n)}$ represent the state vector prediction at step n. This vector can also be expressed in the following manner:

$$v^{(n)}=[\mathrm{P}(A^{(n)})\quad \mathrm{P}(B^{(n)})\quad \mathrm{P}(C^{(n)})\quad \mathrm{P}(D^{(n)})\quad \mathrm{P}(F^{(n)})\quad \mathrm{P}(CF^{(n)})]\ . \tag{2}$$

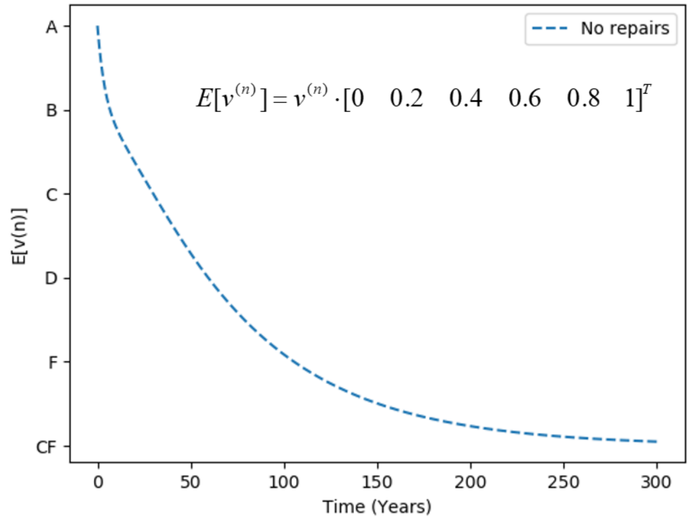


Figure 3. Expected degradation curve

A 300-yr prediction using the state vectors with different values of n was accomplished. To be able to calculate the expected value at each of these calculated state vectors, a proportional model mapping assigns values to each state. For example, the value of 0 is mapped to A, 0.2 is mapped to B, and so on.

Figure 3 shows the expected state value of the condition of the structural component. As shown in this figure as the time approaches to 300 years, the expected value of the state vector approaches the state 'CF'. Note that the figure above is shown for representation only. It is important to consider all the state probabilities (i.e., the state vector) at every step to take decision such as replacement or repair of a component. All these considerations are taken into account to build an improvement model, which is used to keep track of the effects of degradation in and repairs of a component.

IMPROVEMENT MODEL

An improvement model is a model that can capture the degradation of a component even after repair work has taken place. For this model, the degradation after repair work is assumed to deteriorate with the same rate as when it was good as new, in other word at the initial state. Recall that $v^{(n)}$ represents the state vector prediction at step n. To trigger an action such as repair, a probability threshold value is compared against the probabilities obtained at each *n*-step as follows:

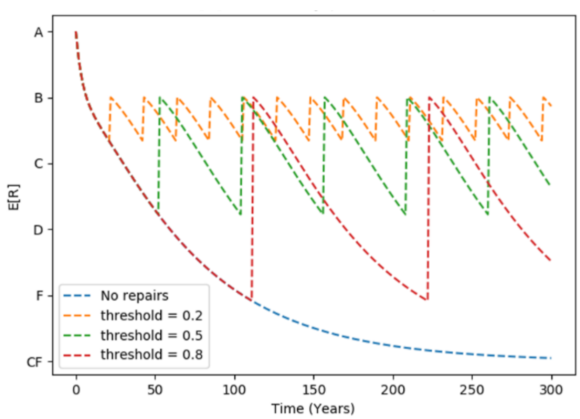
$$P(D^{(n)}) + P(F^{(n)}) + P(CF^{(n)}) > Threshold \in [0,1] \qquad (3)$$

The implementation shown in Figure 4b uses the transition matrix and initial state vector to do predictions for a structural component. Additionally, every time that the probability of being at a state equal or worse than state 'D', the state vector takes a value of $[0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0]$, which represent the state right after a repair. In other words, it assumes that a repair always results in a perfect condition 'B'.

Again, for representation only, Figure 4a shows the expected state value of the condition of the structural component. But this time, considering the effect of 3 different threshold values. From this figure, if the threshold is low then the amount of PM actions increases to maintain low the chances of being at state ‘D’ or worst. On the other hand, if the threshold is high, this means that you take a higher risk of being at state ‘D’ or worse, consequently the amount of PM actions decreases. Also, from Figure 4a, the time interval between PM actions can be observed and the number of PM event in a specific range of time can be extracted. Table I shows the probability threshold, the PM time interval and the number of scheduled events in the first 150 years of the life of a component.

So far, only one type of maintenance actions has been discussed (PM). However, the EM actions are another type of maintenance which is required to keep a component operational and safe. Accounting for both types of actions (PM and EM) will extend, if done properly, the life of the component or system.

The discrete cumulative probability distribution (CDF) of the state ‘CF’, obtained by the Markov process described earlier was used to account for EM actions. Figure 5a shows the CDF after calculating the probability of being at ‘CF’ from 1 to 300 years, including the effect of the PM actions based on different thresholds. Figure 5b shows the expected number of EM actions as a function of time, i.e., the expected occurrence of being in State 'CF' from year 1 to 300.



For n = 1:300 # time (years)

$v^{(k)} = v^{(0)} P^k$

If $P(D^{(k)}) + P(F^{(k)}) + P(CF^{(k)}) > \text{Threshold}$

$v^{(n)} = [0 \quad 1 \quad 0 \quad 0 \quad 0 \quad 0]$ # state after repair

k = -1 # reset time if there is a repair

else

$v^{(n)} = v^{(k)}$

k = k+1

Figure 4. a) Expected value of state vector at time *n* using improvement model and b) implementation of improvement model

Table I. PM EVENTS BASED ON THRESHOLD

Probability Threshold	**Time Interval**	**# PM events**
0.8	111	1
0.5	52	2
0.2	21	7
0.05	8	18

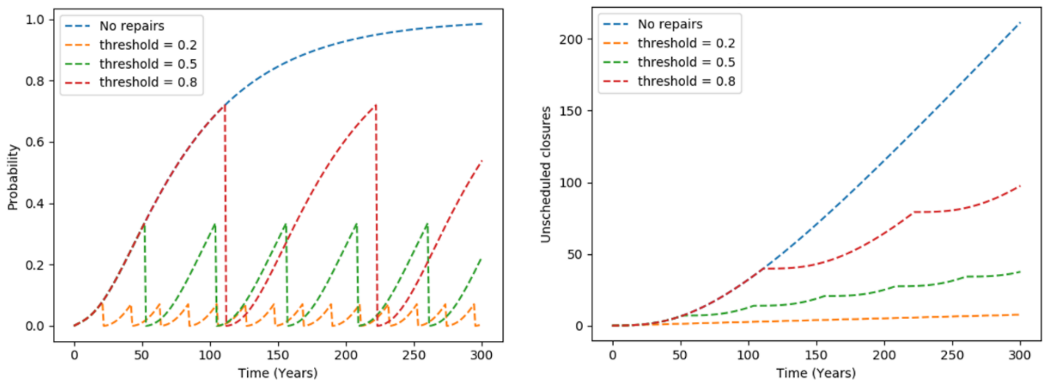


Figure 5. a) Probability of being at State 'CF' from step 1 to step 300 and b) Expected occurrence of being at State 'CF' from steps 1 to 300

COST FUNCTION

Using a cost function, the cumulative cost value can be calculated using a probability threshold (or time interval between PM actions) at a particular point in time. The long-term cost may be calculated by using Equation 4 where N_{PM} is the number of preventive events and N_{EM} is the number of essential maintenance events.

$$\text{Cost}(t, threshold) = 1 * N_{PM}(t, threshold) + W * N_{EM}(t, threshold), \qquad (4)$$

The variable W represents the ratio between the cost of an unplanned event (EM) and the cost of a planned event (PM). As shown in Table I, the probability threshold can be mapped to the time interval between PM actions.

Figure 6a shows the nonlinear relation between the time interval between PM actions and the probability threshold. Figure 6b shows the cumulative cost after 150 years with different ratios of W. As shown in this figure, the optimal time interval between PM actions can be obtained from different values of W.

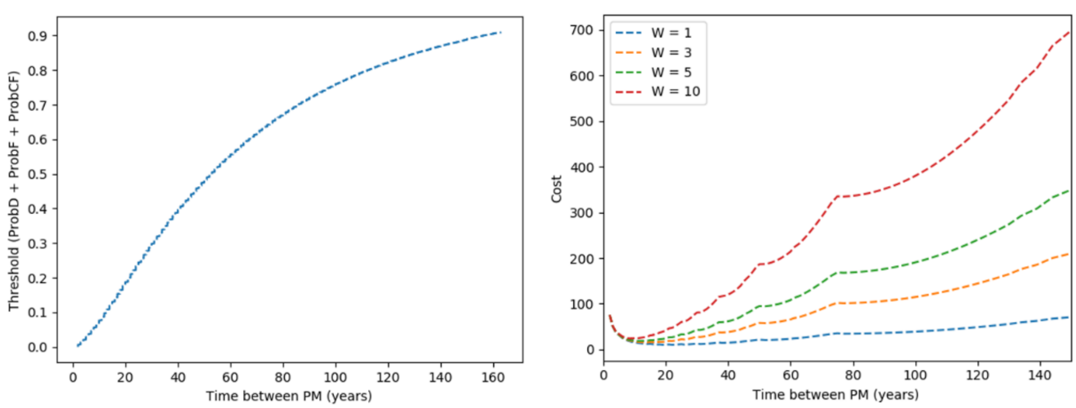


Figure 6. a) Mapping between probability threshold and PM interval and b) 150-yr cumulative cost for different PM intervals

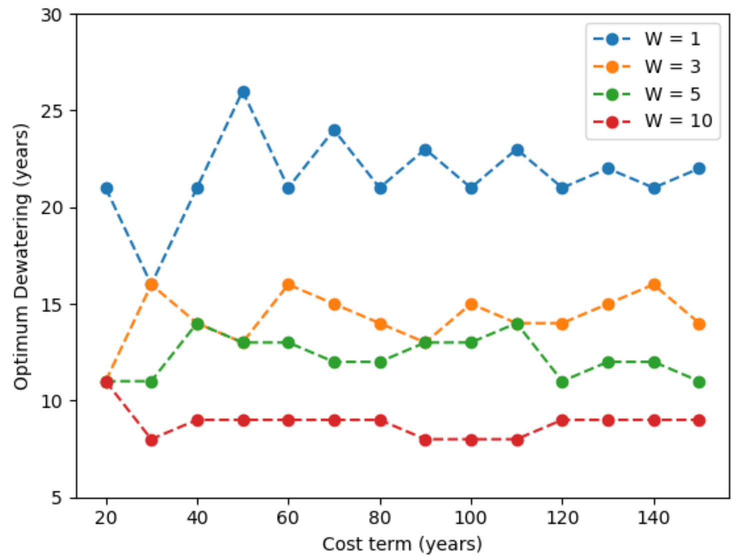


Figure 7. Optimal PM interval

OPTIMUM TIME INTERVAL BETWEEN PM ACTIONS

Figure 7 shows the optimal time interval to take planned maintenance actions for different values of *W* and for different cumulative time intervals. From this figure, it may be observed that the value of *W* has a strong effect on the optimal time interval between PM actions. For example, if the value of *W* is between 3 and 5. The recommended time interval between PM actions would be roughly between 10 to 15 years.

IMPLEMENTING SHM

Up to now, the long-term cost minimization has depended solely on the data from historical inspection. SHM can be a way to reduce the uncertainty of non-continuous monitoring such as visual inspections and to help to take more informed decision. Figure 8 shows SHM implementation flowchart to the miter gates.

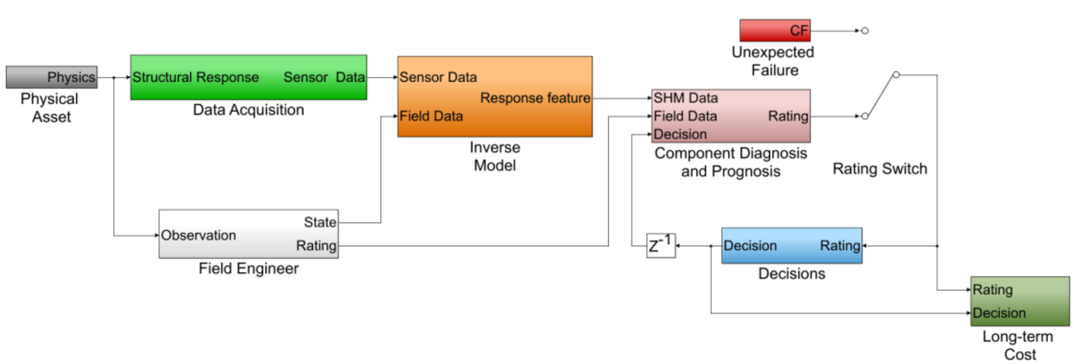


Figure 8. SHM implementation flowchart

Recently researchers such as Faber [11] and Thons [12] have studied theoretical and applied approaches to quantify the value of deploying a structural health monitoring. Studying the value of implementing SHM in miter gates may reduce the amount EM actions, which may lead to long-term cost savings. For SHM, the damage detection is an "inverse problem". Therefore, a Bayesian approach using the available sensor data or synthetic data from a finite element model (or a surrogate model) is generally used to infer the inverse problem.

CONCLUSION

A Markov process using transition matrices built from inspection data can be used to obtain the optimal time interval between PM. A simple loss or cost function was used to come up with the optimal value and assumptions about the condition after PM were made. Different component in mater gates may have different transition matrices values. This methodology can be extended from component to system level.

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