Predictive Group Maintenance Model for Networks of Bridges

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ABSTRACT

The progress in infrastructure condition monitoring and prediction, using sensing technologies, in recent years, has motivated researchers and infrastructure owners to explore the benefits of asset predictive maintenance, compared to reactive maintenance. However, the application of predictive group maintenance for multi-system multi-component networks (MSMCN) has not seen much attention in literature and in practice. Presented herein is an approach that prioritizes the maintenance of MSMCN of bridges, using a deterioration model of components with uncertainty, a lifecycle cost model, a predictive model for the optimal time for maintenance based on the latest inspection, a group maintenance model to reduce setup cost, and a scheduling model considering budget constraints. This model has been applied in a network of fifteen bridges constituted by multiple heterogeneous components, and compared to the Structures Investment Toolkit, showing potential for a substantial decrease in maintenance cost, and thus, highlighting the practical significance of the presented approach.

Keywords: Infrastructure Deterioration, Lifecycle Cost Model, Group Maintenance, Scheduling, Transportation Systems, Asset Management

INTRODUCTION

Transportation systems are an essential requirement of social development of any country since the economic growth is directly connected with the accessible resources to society and the effectiveness of their usage (*1*). They impact public prosperity by contributing to productivity and serving mobility (*2*). Specifically, bridges consist the vulnerable elements of highway and railway networks. A disruption, due to degradation, in bridges, which are mainly positioned at intersections of highways/railways, can have numerous undesirable influences not only on users but also on the society at large. Possible broad effects are the loss of reachability to isolated areas, rerouting of traffic, decrease of productivity, as well as increase of travel distance, time and consequently of environmental pollution.

Highway and railway bridges progressively deteriorate over their lifetime. A range of events, such as extreme weather conditions (e.g. floods), natural disasters (e.g. earthquakes), man-made events (e.g. bridge strikes), heavy traffic and inadequate maintenance, accelerate their deterioration (*3*). Only in the U.S., there are 614,387 bridges, from which around 40% are over 50 years old and 9.1% are structurally deficient, with 188 million trips/day happening across structurally deficient bridges. The average age of bridges in the U.S is constantly growing, while many bridges are close to the end of their design life. The latest approximation for the amount needed for bridge rehabilitation equals $123 billion (*4*).

Traditional bridge maintenance programs normally focus on achieving optimized life-cycle cost (LCC) of individual bridges, ignoring the interactions between bridges within a transportation network. Nevertheless, the failure or degradation of a bridge, as well as its maintenance prioritization, timing and cost directly affect the performance of the bridge network and the maintenance scheduling of other bridges. Bridge managers have realized the significance of a network perspective, over the years, trying to strategically allocate their resources to optimize network performance. The adoption of a network perspective adds new dimensions in decision support systems for bridge management such as the improvement of transportation network reliability and functionality (*3*).

Bridge managers face challenges in maintenance prioritization of bridge elements, in a network scale, due to budget constraints. They need to take crucial decisions on how to allocate and distribute limited maintenance resources in an optimal manner in order to ensure functionality of transportation networks and achieve safety requirements as defined by transportation authorities. Bridge managers try to minimize the present value of life-cycle maintenance cost, and, at the same time, satisfy performance constraints (*5*). Other separate objective functions, formulating the bridge maintenance planning, along with LCC, might be conflicting performance indicators that consider structural reliability, safety, durability and condition (*6*). Bridge managers are responsible to find a solution for the resulting multi-objective optimization problem, balancing several objectives, based on their experience, opinion and bridge owners' requirements. Summarizing, the current maintenance prioritization techniques for bridge systems are not standardized and have room for improvement.

With the aforementioned in mind, the subsequent section of the paper presents the state of research in maintenance of bridge networks and other MSMCN, as well as element deterioration methods based on Markov chain models (which are used for the proposed methodology), the identified gap in knowledge, and the objectives of the present study. The sections that follow describe the proposed methodology, and the way each phase of the methodology is applied on a case study. Lastly, findings, conclusions, and future research are discussed.

BACKGROUND

Overcoming the barriers of current practices in bridge maintenance prioritization, regarding consideration of bridges as part of a network and solving multi-objective optimization problems, has attracted the interest of researchers, in the last two decades. Maintenance policies for network-level problems seek for balance between agency cost and network performance. Several research studies have quantified the former using LCC analysis and the latter using graph-theoretic indicators of reliability or connectivity, while attending to maximize operational performance. Concerning this, Orcesi and Cremona (*7*) presented a method for bridge network management utilizing visual bridge evaluation and Markov chains. Another study worth mentioning (*8*, *9*) defined a bridge reliability significance factor, correlating single bridge reliability to the network of bridges. This study also presented a mathematical model that assesses the overall users' comfort and the structural performance of critical bridges. Finally, it optimizes the maintenance of bridge networks, using genetic algorithms to solve the multi-objective problem. Hu and Madanat (*10*) expanded this algorithm to multiple nodes at a later stage, developing a network topology-based indicator. These indicators can effectively assess post-disaster network performance in case of extreme events as they consider the failed links. Another class of indicators, termed network functionality-based, evaluates the level of network service to the community. In addition, Chen et al. (*11*) investigated the probability of a network serving a specific travel demand utilizing a user equilibrium model as well as the sensitivity of the model to capacity variations of links. Nojma (*12*) proposed a prioritization model that uses maximum traffic flow as a performance indicator that measures the significance of every network element.

Beyond bridges, there is an increased research interest in the predictive maintenance prioritization of MSMCN in general. MSMCN are networks composed by numerous systems which are in turn constituted by numerous components. For instance, a bridge can be considered as a system of multiple components (e.g. primary deck element), while belonging in a network of multiple bridges. Predictive maintenance is the decision-making for maintenance procedures based on the predicted service life. The advancement in infrastructure condition evaluation and prediction using sensors as well as in data analysis methods (*13*, *14*), in recent years, has motivated researchers and infrastructure managers to examine the benefits of asset predictive maintenance, compared to reactive maintenance. Predictive maintenance has the potential to enhance systems reliability, while decreasing maintenance cost. The benefits of predictive maintenance approach can be further expanded, when combined with a systematic approach that aims to improve the reliability and connectivity of a network, rather than maintenance policies focusing on separate components. Systematic maintenance approaches can be divided into the following three classes: selective, opportunistic and group maintenance.

Selective maintenance includes inactive periods of time, proposing which components should be repaired to assure the reliability of the system until the next period of maintenance. A selective maintenance methodology, proposed by Dao and Zuo (*15*), considers s-dependence amongst elements of a multi-state series system. Additionally, Liu et al (*16*) presented another selective maintenance system that aims to increase the possibility of a following successful maintenance period, utilizing a tailored ant colony algorithm. The second category of systematic maintenance approaches, namely opportunistic, proposes the maintenance of elements meeting some criteria, normally related to age or condition, when an opportunity appears due to the repair of neighboring components. This approach is characterized by lower cost and downtime for the system maintenance, compared to tactics concentrated on individual assets (*17*). A bi-level maintenance method, designed by Xia et al. (*18*), conducts real-time scheduling for batch production, integrating production-driven opportunistic maintenance in the system level and a multi-attribute model in the machine level. Furthermore, Aizpurua et.al (*19*) proposed a prognostic-enhanced maintenance policy for complex dynamic systems that combines dynamic fault tree and stochastic activity networks, allowing the repair of failed non-critical assets in case of maintenance of a critical asset.

The third class of systematic maintenance approaches, termed group maintenance, combines numerous maintenance actions, with a shared cost and system downtime, to decrease cost. For instance, Sheu and Jhang (*20*) designed an exact algorithm for generalized two-phase group maintenance of identical units. Their methodology identifies the optimal distinction between two maintenance stages and which elements need to be repaired in order to minimize the long-term cost per element. Scarf and Cavalcante (*21*) proposed hybrid block replacement and inspection policies for a n-identical component series network. Their study uses a mixed Weibull distributed defect arrival time and a three-state failure algorithm for elements deterioration, while it was tested on traction motor bearings of a commuter railway. Another related method, formulated by Chalabi et.al (*22*), optimizes the cost and availability of a series production system, exploiting a particle swarm algorithm. Finally, Ruiz-Castro (*23*) used a discrete marked Markov arrival process to model a complex multi-state warm standby system with repairable and non-repairable failure, prevented by group maintenance.

Systematic maintenance approaches are normally combined with asset predictive models. Several researchers have developed Markov chain-based bridge element deterioration models, with a similar technique being used in the current paper, as described in “Methodology” section. Cesare et al. (*24*) determined and used Markovian transition matrices for the condition rating of bridge elements as well as for the modelling of effects of repair strategies. Morcous (*25*) assessed the impact of two specific assumptions, normally made for the performance prediction of bridge decks, using transition probability matrices. Another related study (*26*) utilized Markov chain modeling to predict the condition of timber bridge elements, while testing it on data acquired from the Roads Corporation of Victoria, Australia. Finally, Wellalage (*27*) proposed a Metropolis-Hasting algorithm-based Markov chain Monte Carlo simulation technique to identify the optimum transition probability matrix and to calibrate the state-based Markov deterioration models of railway bridge elements.

Summarizing, although element deterioration models as well as methods that enhance group maintenance in the system level exist, there is a research gap in applicable maintenance policies in the network scale. Predictive maintenance of MCMSN might be more challenging, compared to network level, due to the heterogeneity of systems constituting the network as well as the economic dependence in such hierarchical network configuration. A practical example of a heterogeneous network is a bridge network. Thus, the problem, which motivates the current study, can be briefly stated as follows: A bridge network is composed of diversified bridge types, which are constituted of various element types. Managers of such networks face challenges in maintenance prioritization due to budget constraints. Group maintenance policies for such networks require investigation since they might be able to reduce setup cost of maintenance procedures as well as bridges downtime due to contraflow and lane closure, by simultaneously repairing elements of the same bridge.

Given the aforementioned problem, the current paper modifies and tests a developed framework by our research group (*28*) on a real-life network of fifteen bridges, evaluates its efficiency, and compares the results with those from the Structures Investment Toolkit (SIT) (*29*). SIT is a decision support tool created by Atkins to enable Highways England to carry out lifecycle planning on their structures asset. It is one of the limited number of tools that makes calculations at the component level, considering external factors such as traffic and other components condition within the same system to approximate the deterioration rate. Presented herein is the optimization of dynamic maintenance scheduling in bridge networks by utilizing positive economic dependencies in both network and system levels. It should be noted that the current descriptive paper does not present in detail the mathematical equations of the model since its purpose is to give an understanding of the framework behind our work and to highlight the significant potential of a predictive group maintenance model for MSMCN of bridges for asset owners, researchers and users.

METHODOLOGY

The hierarchical structure of the proposed methodology is divided into three stages, termed element, system and network levels. The presented model is formulated under the following assumptions:

(1) In the element level, a generalized model is designed to describe the stochastic deterioration of elements, utilizing continuous-time Markov chain (CTMC). CTMC is a multi-state stochastic procedure which assumes that the time of staying at every condition state (sojourn time) is exponentially distributed. The parameterization of the model is based on periodic bridge inspections.

(2) Operating environment worsen over time in a stochastic manner that can cause extreme elements deterioration.

(3) Upon inspection, minor or major maintenance can be proposed. The former type (e.g. anti-corrosion printing) refines the declined operating environment or enhances the resistance against environmental hazards, without disrupting the system operation. The latter type can eliminate damages and restore the element condition to the same level as new.

(4) Downtime of elements, during maintenance, depends on their functionality and criticality. The element that requires the highest-level of operation interruption has a dominant effect.

(5) In case of multiple components of the same system being repaired together, the setup cost is shared.

(6) Downtime of a system might affect the operation of other systems. For example, a lane closure of a bridge can impact the traffic of other bridges. The system with the higher level of operation interruption dominates the lower level operation.

(7) Penalty function of elements assumes that postponing a repair timing will cause a postponing of sequential repair timings so that the predicted service life of the element will remain the same.

The proposed predictive group maintenance approach for MSMCN of bridges follows five main phases, as explained bellow.

Phase 1: Elements deterioration model

The deterioration of elements is formulated, while the condition-based maintenance threshold is optimized based on the long-term average cost. In practice, bridge condition inspections allow the capture of elements deterioration rates based on the time of an element staying in a specific condition state. However, the asset owner that provided the data for this paper (like most asset owners) has a limited number of inspection data points (i.e. 1-6 in the current dataset) for every bridge component and thus, the accurate estimation of bridge deterioration rate is challenging.

Most asset owners have been saving data only for the last few decades, while their inspection rate range between one to seven years. For this purpose, work in progress by the authors includes collaborative prognostics in transport assets. Though, the deterioration rate (in the component level) in the current paper is calculated based on the equation defined by the SIT (*29*). The input needed from a bridge owner for the calculation of the deterioration rate consists of the following: structure type; location (e.g. rural, urban); structure usage, including route supported, obstacle crossed and traffic; structure size consisting of number of spans and dimensions; level of service requirements (e.g. high visual standard required, loading requirements); construction type, material and elements condition. Weather is also a variable of the used deterioration rate equation but it should be noted that the proposed methodology has been tested only in the UK where the weather does not significantly vary. Thus, the method can be applicable in places with different weather conditions only if data and experts' knowledge are available to confirm the rate that weather will affect the deterioration rate.

This study designed a discrete state stochastic procedure to quantify elements aging. A continuous-time Markov chain (CTMC) was selected because of its mathematical tractability, practicality and generalizability when combined with a phase-type estimation. The parameter setting of the deteriorating elements can be readjusted, if needed. The state transition diagram describing the element deterioration process with periodic inspections is illustrated in **Figure 1**. Compared with conventional models for multi-state system, the deterioration mechanism, adopted in this paper, is formulated as a deterioration path that captures non-memoryless deterioration behaviors. The deterioration paths, under different operating environments, are enabled, with strong explanatory power characterizing the heterogeneity of deterioration rates. The parameterization of the model relies on the knowledge about the expected time of staying in each condition state, which is practically available. Here, the deterioration rate of the component at the rated operating condition and under detrimental are denoted by $\lambda_{n,u(i,j)}^{(v)}$ and $\lambda_{d,u(i,j)}^{(v)}$ respectively, while the decline rate of the external factor is represented by $\lambda_{f,u(i,j)}^{(v)}$. Two types of maintenance activities are modeled, termed major maintenance and minor maintenance. If the condition of a specific component drops under a predefined threshold, major risks may arise. A major maintenance must be activated with a cost of $C_{M,u}^{v}$ during a duration of $1/\mu_{M,u}^{v}$. To prolong the lifetime of elements, minor maintenance needs to be implemented to protect the elements against external factors. The cost of minor maintenance denotes $C_{c,u}^{v}$ with a duration of $1/\mu_{c,u}^{v}$. Using the CTMC model, an optimal condition threshold b_{u}^{v} for activating minor maintenance activity can be calculated by minimizing the long-term average cost, including both inspection cost, minor maintenance cost, and costs induced by major maintenance and replacement.

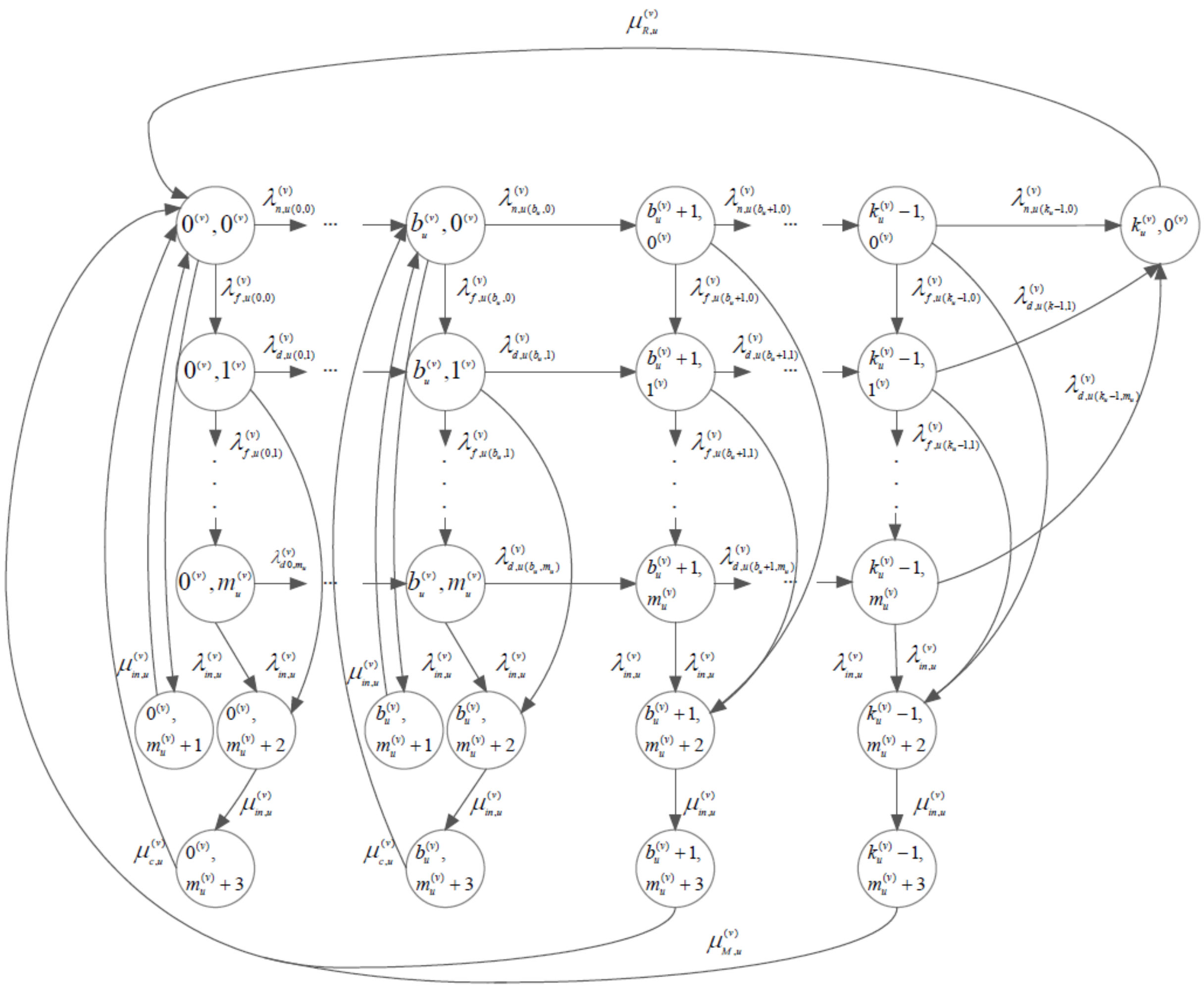

Figure 1 State transition diagram including maintenance for element u in system v (*28*)

Phase 2: Optimal time prediction for maintenance

The optimal maintenance time for every element is estimated, based on life-cycle cost analysis, its latest condition evaluation and outputs from phase 1. Every component at every condition state is linked with specific maintenance actions. The action cost type can be set as fixed (i.e. applied under specified conditions and/or a point in time); constant (regardless of element condition); or variable (i.e. dependent on the element condition). The bridge owner needs to define theses costs.

An element might deteriorate in a different rate than expected (i.e. slower or faster) due to the stochastic nature of element deterioration. As the deterioration and maintenance model are formulated by a CTMC, matrix Λ_u^v can be constructed containing the information of transition rates amongst all transitive states. The holding time at each state is exponentially distributed with a rate that equals to the diagonal elements of Λ_u^v. Thus, the phase-type prediction is applied to predict the optimal time to major maintenance and replacement as well as their probability densities. In case of a change in condition state after inspection, phase 2 is recalculated.

Phase 3: Penalty cost function

The proposed approach collaboratively plans maintenance actions in the network level due to the interdependencies within the MSMCN. The optimal timing for maintenance in the network level might differ from the optimal timing of individual elements that is estimated in Phase 2. Hence, the SIT penalty function, which is crucial for grouping maintenance activities in the network level, is applied to calculate cost of postponing or advancing maintenance procedures.

The penalty cost function was designed to be robust with respect to the changing planning horizon. It is complemented by the optimized condition based maintenance policy. Cost function was constructed for elements under two deferent scenarios. Scenario 1 represents the expected cost when the first lifecycle ends and is renewed by a major maintenance action, whilst scenario 2 represents the expected cost when first lifecycle is terminated and the element is replaced.

Phase 4: Group maintenance

Group maintenance is proposed, exploiting the positive economic interdependencies at both the network and system levels. A joint execution of maintenance procedures can decrease operation interruption as well as setup cost. Though, the shifts in maintenance timing of elements are penalized using the penalty function of phase 3. Therefore, the presented approach checks whether the penalty cost of shifting is lower than the benefit of grouping due to decreased operational disruption and setup cost. This phase looks for the optimal way of combining different maintenance actions.

On the one hand, setup cost represents the design of the maintenance process and preparation of maintenance resources. By grouping some maintenance activities, the setup cost can be shared and prepared jointly. On the other hand, the penalty cost caused by operation interruption is calculated by integrating the temporal profiles of systems' downtime. For a group of elements with overlapped durations, it is always beneficial to start all maintenance activities at the same time. For instance, if a bridge requires both contraflow and lane closure at the same time, the calculation will only consider the contraflow.

However, it is not always easy to implement the group maintenance procedure. The optimal solution of the group maintenance policy involves a time complexity of (2^n), which can be reduced to (n^2) if every group has consecutive activities. For optimizing the maintenance schedule of stochastic aging assets, a genetic algorithm (GA) was used as a prevalent choice that provides robust results with limited computational capability.

Phase 5: Scheduling

Scheduling is conducted using rolling horizon, which is an established method for decreasing computational complexity of scheduling (*30*). It is a repeated procedure that disintegrates long-term scheduling into numerous time planning periods and composes them in a rolling horizon manner. In every repetition, this method executes the maintenance schedule only for the current horizon. The condition state of elements at the end of the current planning horizon is estimated and updated so that the maintenance of the next planning horizon will be scheduled by repeating phases 2, 3 and 4. Summarizing, long-term maintenance planning is conducted with low computational complexity.

CASE STUDY

The proposed predictive group maintenance model was applied to a network of 15 bridges, which are composed of a number of heterogeneous elements ranging from 10 to 19. Data processing was performed in the MATLAB programming language and environment, on a PC with the following specifications: Intel Xeon CPU E5-2680 v4, 2.40 GHz, and 64 GB RAM. The processing time was 1.5 minutes for the presented case study of 15 bridges, and less than 7 minutes for 50 bridges. The proposed model is able to efficiently analyze large network of bridges since real-time data processing is not required. The used data has been provided by a large transport infrastructure owner in the UK. The organization name cannot been provided for confidentiality reasons. Bridge elements serve different functionalities (i.e. primary deck, abutment), are made of different materials (e.g. steel, concrete), and are exposed to different environment conditions (e.g. traffic load, weather).

Elements deterioration rate estimation (Phase 1) uses a scale that describes bridge elements condition. Their condition is divided into five major discrete states, namely 1 to 5, where 1 indicates a perfect novel condition and 5 represents failure, following infrastructure owners' guidelines. These states are then further divided into the following sub-states: 1A, 2B to 2E, 3B to 3E, 4B to 4E and 5B to 5E. The deterioration rate of each component is described by three exposure levels that are classified into mild, moderate and severe. For bridge elements, the exposure level is determined by various factors including their type, location, usage, and other key adjacent elements. We assumed that the exposure level defined at year 0 is constant thereafter. However, in reality, the exposure level could be updated upon the occurrence of extreme weather conditions, such as freeze-thaw and flooding. Figure 2 illustrates the deterioration rate of the primary deck of bridge 2 in the case study. Year 0 presents the date of inspection where the bridge had an excellent condition (i.e. 1A), while in Year 30 the bridge is expected to be characterized by condition 2E, if no maintenance activity is conducted in this span of 30 years.

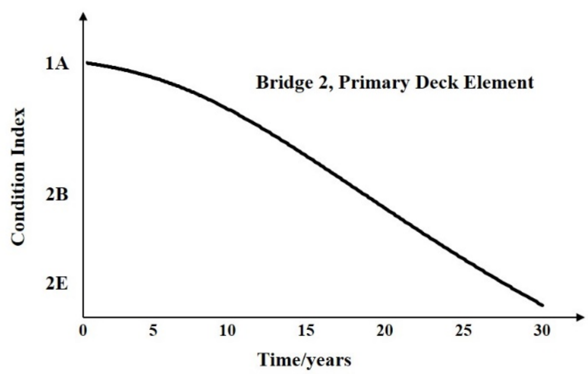

Figure 2 Example of deteriorate rate calculation of a bridge element

Phase 2, termed optimal time for maintenance of each element, can be estimated based on the minimum long-term average cost. The continuous time Markov chain is capable of inferring the stochastic deterioration condition with time, according to the last inspection. Figures 2, 3 and 4 illustrate the relationship between the estimated maintenance cost of elements and the first scheduled maintenance activity (Phase 2) in the planning horizon that can have three typical trends. Monotonic increase trend indicates that it is necessary to maintain the element immediately (**Figure 3**). Monotonic decrease trend indicates that no maintenance is needed during the planning horizon (**Figure 4**). Lastly, a trend containing one minimum suggests that it is beneficial to maintain the component at the time of minimum (**Figure 5**). After running the developed model, it is proposed that 244 out of 262 elements should be maintained within the next 30 years planning horizon. By the means of minimizing the average cost, thresholds for different elements are adapted dynamically. The maintenance budget is decreased and outperforms the conventional fixed maintenance threshold scheme.

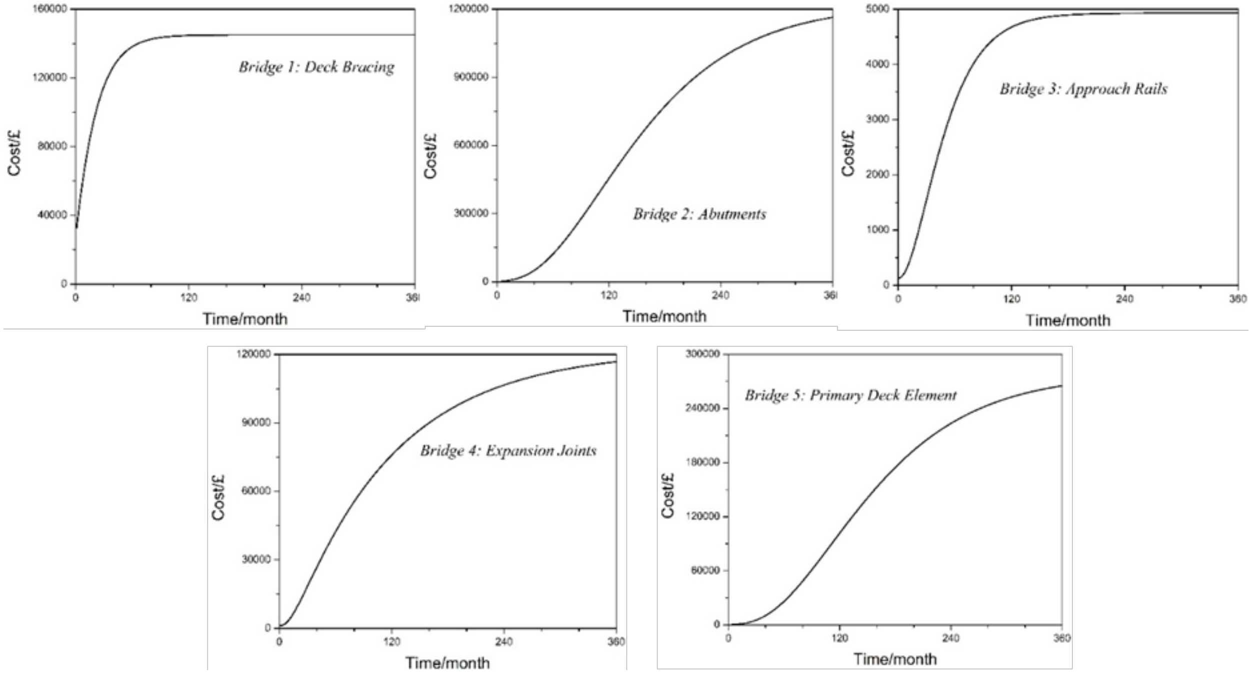

Figure 3 Examples of elements with increasing trend in cost

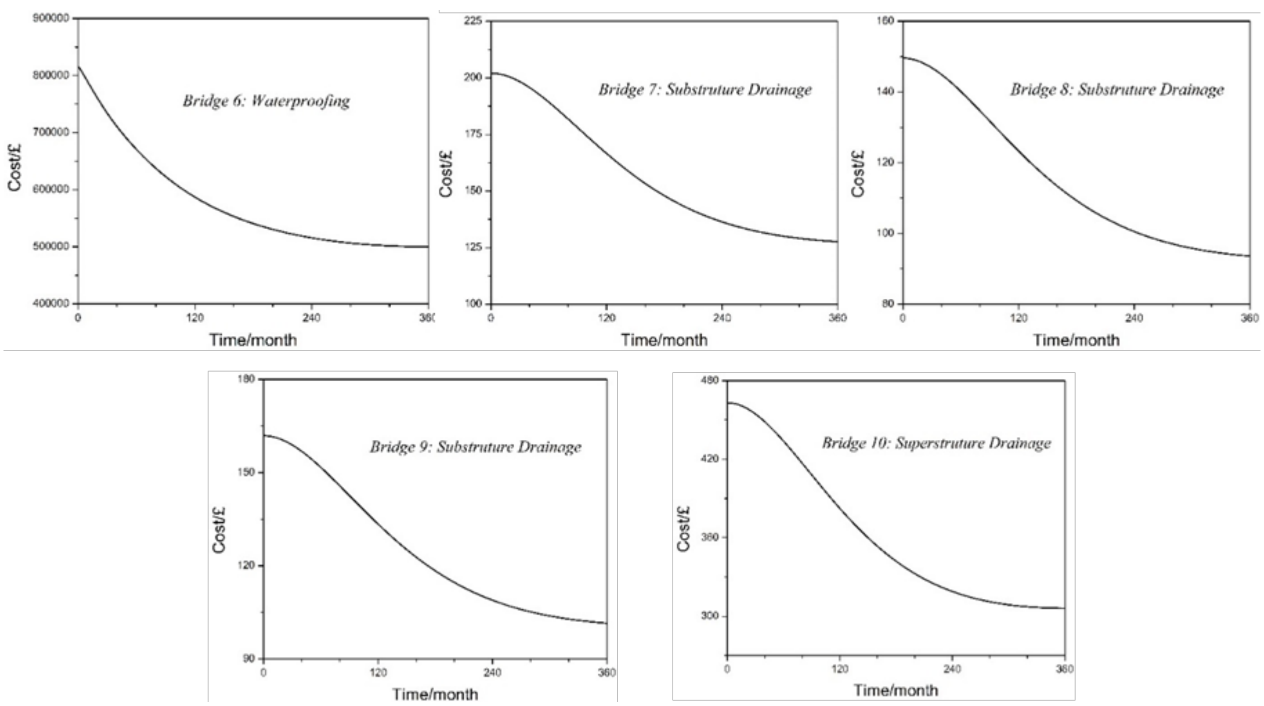

Figure 4 Examples of elements with decreasing trend in cost

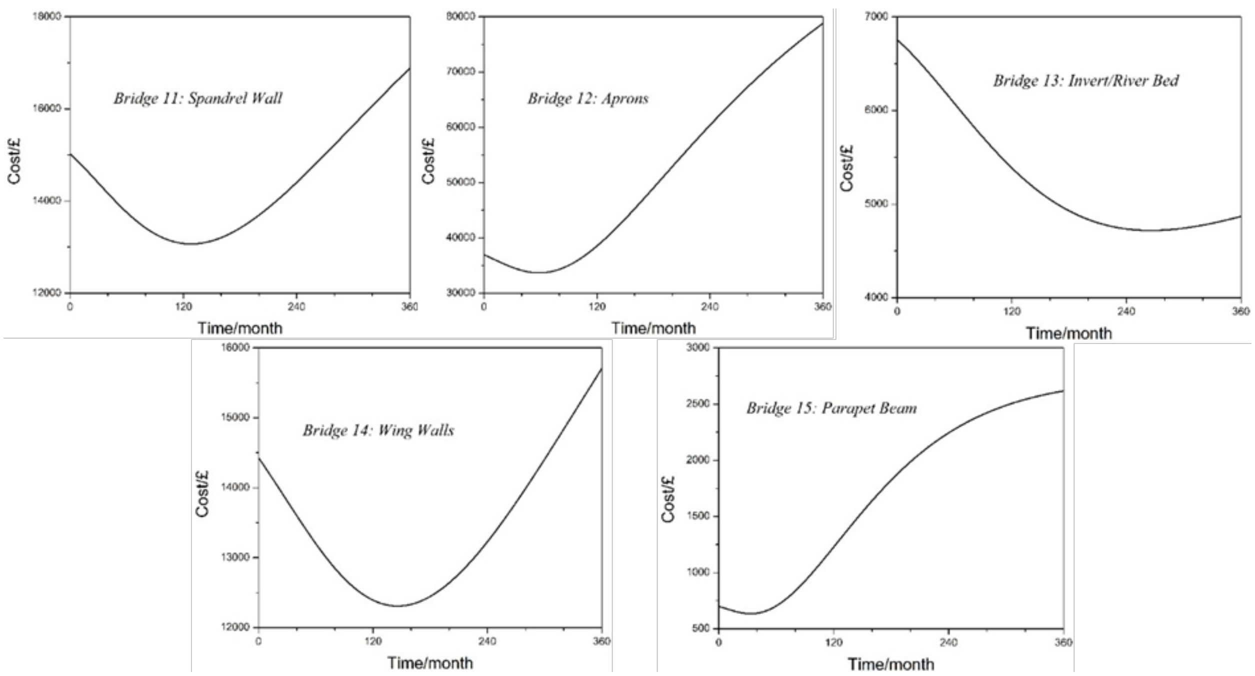

Figure 5 Examples of elements containing a minimum value of cost

Phase 3, termed penalty cost function, presents the risks in cost terms associated with not undertaking and/or delaying maintenance activities. In the presented case study, the penalty cost function considers the impact on loss of service and safety risk. The former is divided into the impact on availability (e.g. lane closure) and the impact on other routes supported and/or crossed by the examined bridge. The latter constitutes of public safety risk (i.e. deteriorated elements that impact the running surface and consequently can cause vehicle accidents) and structural integrity risk (i.e. structural failure that is associated with accidents, vehicle delays and reconstruction).

Phase 4, named group maintenance, is conducted to cluster different maintenance activities, during same period for each bridge, into a joint execution to reduce traffic management cost, caused by traffic interruptions in network level. Traffic interruptions can be contraflow, lane closure or any other insignificant traffic interruption. Bridge 1 and bridge 2 are presented as examples from the conducted case study. **Table 1** demonstrates the optimal timing for maintenance of elements before grouping.

Table 2 presents the maintenance scheduling results after implementing group maintenance (Phase 4) and scheduling (Phase 5). In order to reduce the traffic interruption, maintenance activities in near months would be conducted at the same time in a year. After group maintenance, if there is not enough budget for maintaining a formed group of elements, then the maintenance of this group is moved to the next year (Phase 5). This is a dynamic process where the yearly budget is allocated in the optimal way so that the cost will be minimum in the examined time planning horizon. The total maintenance cost of Bridge 1 and Bridge 2 after grouping, during the 30 years planning horizon, is £ 1117000 and £ 643200, respectively, whose sum is approximately 11% lower than the maintenance schedule plan before grouping.

TABLE 1 Maintenance schedule before grouping for Bridge 1 and Bridge 2

System	Element	Optimal time to maintain (month/year)

Bridge 1		
	Primary Deck Element	1/1
	Deck Bracing	1/1
	Abutments	20/2
	Spandrel Wall	37/4
	Expansion Joints	2/1
	Finishes: Deck Elements	22/2
	Finishes: Substructure Elements	21/2
	Finishes: Parapets	18/2
	Handrail	1/1
	Invert/River Bed	11/1
	River Training works	1/1
	Wing Walls	92/8
	Embankments	148/13
Bridge 2		
	Primary Deck Element	58/5
	Parapet Beam	357/30
	Deck Bracing	75/7
	Abutments	1/1
	Substructure Drainage	360/30
	Waterproofing	333/28
	Expansion Joints	2/1
	Finishes: Parapets	105/9
	Handrail	218/19
	Invert/River Bed	46/4
	Wing Walls	1/1
	Embankments	192/16
	Approach Rail	2/1

TABLE 2 Maintenance schedule after grouping for Bridge 1 and Bridge 2

System	Element	Optimal time to maintain (year)
Bridge 1		
	Primary Deck Element Deck Bracing Abutments Expansion Joints Finishes: Deck Elements Finishes: Substructure Elements Handrail River Training works	Group 1 - year 1
	Finishes: Parapets Invert/River Bed	Group 2 - year 2
	Spandrel Wall	Group 3 - year 4

	Wing Walls	Group 4 - year 8
	Embankments	Group 5 - year 13
Bridge 2		
	Abutments Expansion Joints Invert/River Bed Wing Walls Approach Rail	Group 1 - year 1
	Primary Deck Element Deck Bracing Finishes: Parapets	Group 2 - year 5
	Embankments	Group 3 - year 16
	Handrail	Group 4 - year 19
	Waterproofing	Group 5 - year 28
	Parapet Beam Substructure Drainage	Group 6 - year 30

CONCLUSIONS

A bridge network is normally composed of various types of bridges that are in turn contain various elements. Dependence in such hierarchical networks could be diversified. Presented herein is a dual-positive economic dependence which includes the setup cost dependence in the system level as well as operation downtime dependence in the network level. A predictive group maintenance model is developed to proactively seek the potential benefits of the described dual-positive economic dependence. The risk of the decaying operating environment is highlighted in the element deterioration model in order to enhance the practicality of the model. With this setting, the approach can be applicable to long-lifetime assets that are exposed to external risks. Numerous measures have been taken to enhance the performance of the presented method. Firstly, the deterioration and the condition-based maintenance models for elements are designed based on CTMC which enables an analytical explanation of the lifecycle cost and decreases computational complexity. Secondly, the developed GA-A algorithm contributes to the avoidance of local optimums caused by the dual- positive economic dependence. It also assists the algorithm to converge to a better result. Thirdly, the rolling horizon approach reduces the computation time of the dynamic maintenance scheduling in MSMCNs and have no significant impact on the operation cost. Summarizing the proposed model combines numerous prevalent concepts in reliability engineering, such as predictive maintenance, lifecycle cost, condition-based maintenance dependence, and dynamic maintenance scheduling.

The proposed predictive group maintenance model was applied to a case study. The real-life network was constituted of 15 bridges (i.e. systems), which were composed of a number (i.e. 10-19) of heterogeneous elements. The case study showed the following three possible trends for the relationship between the estimated maintenance cost of components and the first scheduled maintenance activity: monotonic increase that indicates an immediate need for maintenance; monotonic decrease that shows no need for maintenance throughout the planning horizon; and a trend including a minimum point, which is the proposed time point for maintenance. After running the algorithm for a period of 30 years and a relatively high budget, almost all elements are proposed to be maintained. This shows that possible budget constraints (that are common in transportation authorities) delay the maintenance of elements that required to be maintained and thus, maintenance prioritization becomes dramatically important for the operation and safety of bridges. Additionally, the case study showed a reduction on operation cost (i.e. 11%), caused by group maintenance, highlighting the practical significance of the presented approach.

The proposed methodology can be supported by common software, used by transportation agencies, only after modifications. Existing software relies on deterioration profiles that are non-adjustable to time-variant environment, while the presented method introduces several novel techniques, such as a deterioration model that considers different exposure levels as well as the group maintenance phase. Additionally, there is novel software, used by agencies, that considers interdependencies amongst deterioration of various elements. Future work for improvement of the proposed technique also includes the consideration of interdependencies, by modifying a model developed in our lab (*31*) and applying it to bridge infrastructure.

This research work can have a positive impact on researchers and asset managers motivating them to investigate maintenance strategies in complex and hierarchical networks. There are several possible extensions of the model. The deterioration of components is modeled by CTMC, which assumes the holding time at each state is exponentially distributed. This assumption could be relaxed by using a semi-Markov model or approximated by phase-type distribution. However, it will increase the computation complexity of the problem. Future work also includes further study of the GA-A algorithm, under different contexts. Factors that are more practical should be included, such as the constraints of maintenance resources. Different types of imperfect maintenance and their resulting type shift in the grouping policy will also be explored. Finally, the authors are in collaboration with transportation asset owners in order to improve, expand and test this approach in real-life networks of bridges and other assets.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: A. Parlikad, X. Xie, G. Hadjidemetriou; analysis and interpretation of results: X. Xie, G. Hadjidemetriou; draft manuscript preparation: G. Hadjidemetriou, X. Xie. All authors reviewed the results and approved the final version of the manuscript.

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DATA ACCESSIBILITY

Data available on request from the authors.

REFERENCES

1. Ivanová, E., and J. Masárová. Importance of Road Infrastructure in the Economic Development and Competitiveness. *Economics and Management*, Vol. 18, No. 2, 2013. https://doi.org/10.5755/j01.em.18.2.4253.
2. Chan, C. Y., B. Huang, X. Yan, and S. Richards. Investigating Effects of Asphalt Pavement Conditions on Traffic Accidents in Tennessee Based on the Pavement Management System (PMS). *Journal of Advanced Transportation*, Vol. 44, No. 3, 2010, pp. 150–161. https://doi.org/10.1002/atr.129.

3. Zhang, W., and N. Wang. Bridge Network Maintenance Prioritization under Budget Constraint. *Structural Safety*, Vol. 67, 2017, pp. 96–104. https://doi.org/10.1016/j.strusafe.2017.05.001.
4. ASCE. Bridges. ASCE's 2017 Infrastructure Report Card, , 2017.
5. Frangopol, D. M., M. P. Enright, E. Gharaibeh, and A. C. Estes. Towards Optimal Reliability-Based Bridge Maintenance Planning. Presented at the Case Studies in Optimal Design and Maintenance Planning of Civil Infrastructure Systems, 1999.
6. Liu, M., and D. M. Frangopol. Multiobjective Maintenance Planning Optimization for Deteriorating Bridges Considering Condition, Safety, and Life-Cycle Cost. *Journal of Structural Engineering*, Vol. 131, No. 5, 2005, pp. 833–842. https://doi.org/10.1061/(ASCE)0733-9445(2005)131:5(833).
7. Orcesi, A. D., and C. F. Cremona. A Bridge Network Maintenance Framework for Pareto Optimization of Stakeholders/Users Costs. *Reliability Engineering & System Safety*, Vol. 95, No. 11, 2010, pp. 1230–1243. https://doi.org/10.1016/j.ress.2010.06.013.
8. Liu Min, and Frangopol Dan M. Probability-Based Bridge Network Performance Evaluation. *Journal of Bridge Engineering*, Vol. 11, No. 5, 2006, pp. 633–641. https://doi.org/10.1061/(ASCE)1084-0702(2006)11:5(633).
9. Liu Min, and Frangopol Dan M. Optimizing Bridge Network Maintenance Management under Uncertainty with Conflicting Criteria: Life-Cycle Maintenance, Failure, and User Costs. *Journal of Structural Engineering*, Vol. 132, No. 11, 2006, pp. 1835–1845. https://doi.org/10.1061/(ASCE)0733-9445(2006)132:11(1835).
10. Hu Xiaofei, and Madanat Samer. Determination of Optimal MR&R Policies for Retaining Life-Cycle Connectivity of Bridge Networks. *Journal of Infrastructure Systems*, Vol. 21, No. 2, 2015, p. 04014042. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000226.
11. Chen, A., H. Yang, H. K. Lo, and W. H. Tang. Capacity Reliability of a Road Network: An Assessment Methodology and Numerical Results. *Transportation Research Part B: Methodological*, Vol. 36, No. 3, 2002, pp. 225–252. https://doi.org/10.1016/S0191-2615(00)00048-5.
12. Nojima, N. Performance-Based Prioritization for Upgrading Seismic Reliability of a Transportation Network. *Journal of natural disaster science*, Vol. 20, No. 2, 1998, pp. pp57-66.
13. Hadjidemetriou, G. M., and S. E. Christodoulou. Vision- and Entropy-Based Detection of Distressed Areas for Integrated Pavement Condition Assessment. *Journal of Computing in Civil Engineering*, Vol. 33, No. 3, 2019, p. 04019020. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000836.
14. Chuang, T.-Y., N.-H. Perng, and J.-Y. Han. Pavement Performance Monitoring and Anomaly Recognition Based on Crowdsourcing Spatiotemporal Data. *Automation in Construction*, Vol. 106, 2019, p. 102882. https://doi.org/10.1016/j.autcon.2019.102882.
15. Dao, C. D., and M. J. Zuo. Selective Maintenance for Multistate Series Systems With S-Dependent Components. *IEEE Transactions on Reliability*, Vol. 65, No. 2, 2016, pp. 525–539. https://doi.org/10.1109/TR.2015.2494689.
16. Liu, Y., Y. Chen, and T. Jiang. On Sequence Planning for Selective Maintenance of Multi-State Systems under Stochastic Maintenance Durations. *European Journal of Operational Research*, Vol. 268, No. 1, 2018, pp. 113–127. https://doi.org/10.1016/j.ejor.2017.12.036.
17. Zhou, X., Z. Lu, and L. Xi. Preventive Maintenance Optimization for a Multi-Component System under Changing Job Shop Schedule. *Reliability Engineering & System Safety*, Vol. 101, 2012, pp. 14–20. https://doi.org/10.1016/j.ress.2012.01.005.
18. Xia, T., X. Jin, L. Xi, and J. Ni. Production-Driven Opportunistic Maintenance for Batch Production Based on MAM–APB Scheduling. *European Journal of Operational Research*, Vol. 240, No. 3, 2015, pp. 781–790. https://doi.org/10.1016/j.ejor.2014.08.004.
19. Aizpurua, J. I., V. M. Catterson, Y. Papadopoulos, F. Chiacchio, and D. D'Urso. Supporting Group Maintenance through Prognostics-Enhanced Dynamic Dependability Prediction. *Reliability*

Engineering & System Safety, Vol. 168, 2017, pp. 171–188. https://doi.org/10.1016/j.ress.2017.04.005.

20. Sheu, S.-H., and J.-P. Jhang. A Generalized Group Maintenance Policy. *European Journal of Operational Research*, Vol. 96, No. 2, 1997, pp. 232–247. https://doi.org/10.1016/S0377-2217(96)00073-2.
21. Scarf, P. A., and C. A. V. Cavalcante. Hybrid Block Replacement and Inspection Policies for a Multi-Component System with Heterogeneous Component Lives. *European Journal of Operational Research*, Vol. 206, No. 2, 2010, pp. 384–394. https://doi.org/10.1016/j.ejor.2010.02.024.
22. Chalabi, N., M. Dahane, B. Beldjilali, and A. Neki. Optimisation of Preventive Maintenance Grouping Strategy for Multi-Component Series Systems: Particle Swarm Based Approach. *Computers & Industrial Engineering*, Vol. 102, 2016, pp. 440–451. https://doi.org/10.1016/j.cie.2016.04.018.
23. Ruiz-Castro, J. E. Complex Multi-State Systems Modelled through Marked Markovian Arrival Processes. *European Journal of Operational Research*, Vol. 252, No. 3, 2016, pp. 852–865. https://doi.org/10.1016/j.ejor.2016.02.007.
24. Cesare, M. A., C. Santamarina, C. Turkstra, and E. H. Vanmarcke. Modeling Bridge Deterioration with Markov Chains. *Journal of Transportation Engineering*, Vol. 118, No. 6, 1992, pp. 820–833. https://doi.org/10.1061/(ASCE)0733-947X(1992)118:6(820).
25. Morcous, G. Performance Prediction of Bridge Deck Systems Using Markov Chains. *Journal of Performance of Constructed Facilities*, Vol. 20, No. 2, 2006, pp. 146–155. https://doi.org/10.1061/(ASCE)0887-3828(2006)20:2(146).
26. Ranjith, S., S. Setunge, R. Gravina, and S. Venkatesan. Deterioration Prediction of Timber Bridge Elements Using the Markov Chain. *Journal of Performance of Constructed Facilities*, Vol. 27, No. 3, 2013, pp. 319–325. https://doi.org/10.1061/(ASCE)CF.1943-5509.0000311.
27. Wellalage, N. K. W., T. Zhang, and R. Dwight. Calibrating Markov Chain–Based Deterioration Models for Predicting Future Conditions of Railway Bridge Elements. *Journal of Bridge Engineering*, Vol. 20, No. 2, 2015, p. 04014060. https://doi.org/10.1061/(ASCE)BE.1943-5592.0000640.
28. Liang, Z., and A. K. Parlikad. Predictive Group Maintenance for Multi-System Multi-Component Networks. *Reliability Engineering & System Safety*, Vol. 195, 2020, p. 106704. https://doi.org/10.1016/j.ress.2019.106704.
29. Hesketh, O., L. Tachtsi, R. Hickey, I. Hassan, B. Besra, and S. Mikhaylov. A Toolkit for Structures Asset Management. Presented at the Asset Management Conference 2015, London, UK, 2015.
30. Kreipl, S., and M. Pinedo. Planning and Scheduling in Supply Chains: An Overview of Issues in Practice. *Production and Operations Management*, Vol. 13, No. 1, 2004, pp. 77–92. https://doi.org/10.1111/j.1937-5956.2004.tb00146.x.
31. Liang, Z., and A. K. Parlikad. A Condition-Based Maintenance Model for Assets With Accelerated Deterioration Due to Fault Propagation. *IEEE Transactions on Reliability*, Vol. 64, No. 3, 2015, pp. 972–982. https://doi.org/10.1109/TR.2015.2439132.