Novel trends on the assessment and management of maritime infrastructures: Outcomes from GIIP project

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Abstract. Climatic conditions, load, fatigue, aging and other factors causes a deterioration in civil infrastructures. As a consequence, repair and maintenance work actions are needed, being the former considered as more expensive than the latter ones. Indeed, an accurate method for measuring corrosion is a fundamental prerequisite for the detection of damaged areas and for planning an effective repairing of concrete maritime structures. In this article a comparation between two surrogate models, Markov Chains and Neuronal Networks, is presented and applied to predict the results of corrosion sensors of an infrastructure data set. The proposed methodology benefits from current monitoring practice and have the objective to develop a modular decision support system for the integrated asset management, taking into account operational, economic and environmental criteria. The results could contribute to the possibility of adapting these degradation models to aggressive environments and repaired structures, thus generating accurate maintenance strategies, and reducing costs. This methodology is part of the ongoing study “GIIP- Intelligent Port Infrastructure Management”.

Keywords: Maintenance actions, Neuronal networks, Markov chains, Monitoring practice, Corrosion, Maritime infrastructures.

1 Introduction

Infrastructures are key assets in modern society; consequently, guaranteeing their operation over time by considering quality and safety standards is a fundamental activity. Therefore, the control and effective management of assets are essential for organizations to perceive the risk associated with their activities and to achieve the desired balance between cost, risk, and performance, thus creating an added value to the economic activity [1].

Currently, ninety percent of international trade is performed by sea due to the morphology of our planet [2]. Thus, the service industry of shipping represents a crucial factor in national and international trade. Given the importance of port infrastructures, particularly from the perspective of the country's development, foreign trade, and the exposure of these infrastructures to the aggressive environment and the maritime climate, an instrument of administration that allows the allocation of increasingly scarce resources to the management and preventive maintenance based on advanced predictive models will provide great value in the management of assets during their useful life.

The deterioration of long-term performance of reinforced concrete or steel infrastructure assets is defined as the loss of capacity, and it’s have been associated with the material disintegration caused by chemical or electrochemical reactions due to the corrosion of the reinforcement [3]. Therefore, it is not surprising that fifty percent of construction industry expenses in most European countries are allocated to repair, rehabilitation, and maintenance actions [4], [5].

Degradation models were developed as key tools to determine the long-term performance of assets, and have been applied in different types of infrastructures maintenance systems [6], [7]. Currently, degradation models are a necessity for the implementation of an adequate maintenance strategy that ensures the system's proper operation and prevents breakdowns.

The present research develops surrogate degradation models to describe the long-term performance from a database of a bridge exposed to coastal aggressive environment conditions. This structure was selected due to its repairment, and the data recorded after the instrumentation process. The concrete resistivity information collected between 2006 and 2020 through corrosion sensor, will be used in the development of two surrogate models: Markov chain and artificial neural networks. Same implementation that will be implemented on a larger scale in the Port of Leixões, the case study of GIIP project. The paper is organized as follows, section 1 presents an introduction about the subject, the GIIP project and the structure analyzed, section 2 describes the procedure used for the determination of degradation models, section 3 presents and compare the results, and finally, section 4 describes the conclusions of the research.

1.1 The GIIP Project

The project entitled ‘Intelligent Port Infrastructure Management’ (GIIP), has the main objective to develop a modular decision support system for integrated asset management, based on new functional and structural degradation models considering operational, economic, and environmental criteria. GIIP solution will involve three conceptual levels:

1. Development of global architecture for a management system of port infrastructures, which will address some advanced sensor frameworks.
2. Development of performance degradation models of port assets, which allow the assessment in the short, medium, and long term, of the condition and related risk.
3. Development of a modular platform that allows prioritizing intervention, and inspection needs, considering the optimum uses of resources.

The decision support system developed by the GIIP project will represent an innovative solution by allowing a truly integrated approach for asset management, promoting transports intermodality and interoperability. Additionally, the project will involve the participation of the academy in conjunction with a software development company

(3MAPS) and public entities such as Portuguese Civil Engineering National Laboratory (LNEC), and Administração dos Portos do Douro, Leixões e Viana do Castelo, S.A. (APDL), company in charge of the administration of the Port of Leixões. This will lead to solutions adapted to the need of the industrial sector promoting adequate economic exploitation, conservation, and development of ports, also covering the exercise of powers and prerogatives of the port authority.

1.2 GIIP case study

Leixões Port was selected as case study to develop the integrated system (Fig. 1). Since materials degradation phenomena are slow processes, it was also necessary to have older data on different pathologies for the development of the models. In this context, data from the corrosion monitoring system installed in the Edgar Cardoso bridge was used [8]. Also know as the Figueira da Foz bridge, the structure, is located over the river Mondego on the central coastline of Portugal (See **Fig. 1**). The bridge was opened in 1982 but was subjected to a general rehabilitation that finished in 2005 [8]. The bridge has a long cable-stayed bridge geometry with a steel deck with a longitude of 405m, and the main span of 225m. The bridge has two prestressed concrete approach viaducts with a length of 905m. The bridge has a clearance of 85m, and it is supported by hollow rectangular columns.

Fig. 1. Leixões seaport.

A detailed inspection of the structure found voids in prestressed concrete and low concrete cover [8]. This low quality of construction led to the appearance of reinforcement corrosion. Alkali silica reactions and sulfate attacks were identified on the foundation of the columns. The rehabilitation process was focused on the strengthening of the cable-stayed system, external prestressing of the viaducts decks, and local repairing and addition of cover protection for steel and concrete elements [9]. Additionally, work was performed on the approach viaducts abutment to fulfill recent seismic regulations. Finally, a corrosion monitoring system was installed during the rehabilitation with the objective of gathering information about the effect of migrating corrosion inhibitors and coating system, the progress of despassivation, and the implications of cracking in the progress of reinforcement corrosion [8].

A total of 33 embedded sensors were installed in different locations of the bridge, considering the influence of differential exposure conditions [8]. The sensors provide galvanic cells, corrosion potential, resistivity, and temperature measurements. The present research considers data obtain from the resistivity sensor from 2006 to 2020. The resistivity sensor has been taking a measurement per day, however, some data wasn't able to recover, such as the data between June 2008 and May 2009. Despite the missing data, it is possible to develop degradation models from the data available.

2 Degradation process

Understanding the deterioration process is crucial to assure the correct use of the structures throw their lifespan. Degradation models contribute to determining the performance of the assets in time, this data is essential for defining maintenance actions and costs. The degradation models could be mechanistic, statistical, or metaheuristics. Due to the high cost of data requirement and modeling, mechanistic models are used to determine the current state of the structure. Therefore, statistical and metaheuristic projects are widely used for the analysis of the long-term performance of infrastructures.

2.1 Markov chain models

Statistical models are based on historical and failures data to estimate future performance. Models with a stochastic nature perform better under the uncertainty of complex phenomena and have been widely used in the estimation of bridge deterioration [10]. Initially, the Markov Chain (MC) model was used to predict pavement behavior but was later adapted for structural analysis models [11]. The model has been applied to predict bridge deterioration with a variety of structural materials and climatic conditions [12]–[14]. More recently Muñoz et al. [10], clustered and determined the performance of the bridges in the Indiana state in the USA, considering geometry, material, and traffic proprieties. MC models have also been applied to coastal infrastructures, such as in [5], which presented a sustainable maintenance assessment considering a Markovian approach for RC port structures.

The MC is based on degradation levels or states. The model estimates the degradation of the structure after a period of time (t), Eq. 1, as a function that depends only on the present state C_o and a transition probability matrix calculated from the historic records.

$$C\ (t) = C_o * P^t \tag{1}$$

The present research used the information collected from 11 resistivity sensors located at the piers of the Edgar Cardoso bridge. Damage was associated with 7 resistivity levels; therefore, each measurement has a possible damage scale. Within this scale, the transition probability matrix is established, and the damage to the structure can be simulated.

2.2 Artificial neural networks model

Another surrogate degradation models frequently used, are the model based on metaheuristic algorithms. These models are established based on biological or natural processes to solve highly complex problems and have been applied for the solution for a variety of engineering problems. Within these models' artificial neural networks (ANN) have become popular, as they overcome the deficiencies of current mechanistic and statistical models in degradation prediction.

ANN is based on the understanding of the human brain, where each neuron processes information separately and simultaneously [15]. ANN models have existed since 1943 [16], however, only be applied to simulate the degradation process in structures since 2004 when Ukrainczyck et al. [17], applied an ANN to establish the expected future degree of damage considering steel corrosion on three concrete structures in a marine environment. Since then, different studies have used these models, such as [18], which developed an ANN-based model to analyze the performance of concrete decks in the state of Wisconsin (USA), based on inspection records. Recently, Chou et al. [19], used five metaheuristic models in the prediction of corrosion risk and marine corrosion rate.

ANN models save the information to estimate the performance through a training phase. In the training phase, a set of input and output data is used for the network to identify the relationships between the degradation and the sensors [20]. The present research used the information of one sensor, labeled CS5R-P, to determine the degradation process of the structure.

3 Results

MC and ANN models were developed using the resistivity data record to determine the degradation of the bridge. The MC establish 7 levels of deterioration associated with the sensors' data. Each day measure is categorized into these levels which are the basis of the generation of the probability transition matrix. Fig. 2 represents the performance of the structure according to the MC model with initial category 1, over 15 years of service.

For the development of the ANN model, the MATLAB Neural Network Toolbox [21] was used. 70%, 15%, and 15% were used for training, validating, and testing the network respectively, and the number of hidden layers and neurons were selected to be 2 and 20 respectively, as they present the best performance. Fig. 3 represents the performance of the ANN model with initial category 1, over 15 years of service.

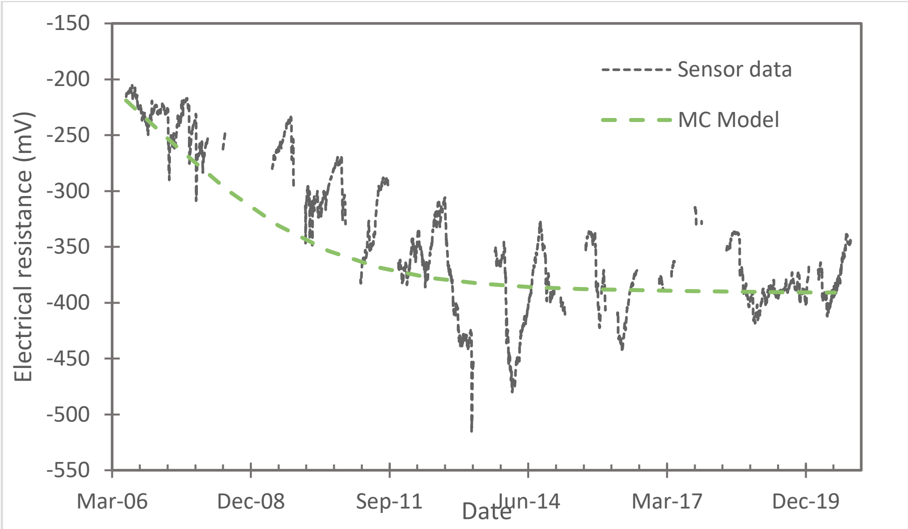

Fig. 2. MC model for degradation prediction.

The ANN model, on average, keeps a good condition rating for longer than the MC model. It can be observed that the models' deterioration curves yield varied degradation pathways over the bridge's lifetime. Due to the high volatility of the data, it's impossible to assure which of the models provides a better reflection of the bridge's overall deterioration process. As a result, the predictions are compared to the measurement in an attempt to quantify the fitness of each model. The mean square error was used to measure the fitness according to the measured data (MSE). The ANN model achieves the lowest errors, as shown in **Table 1**.

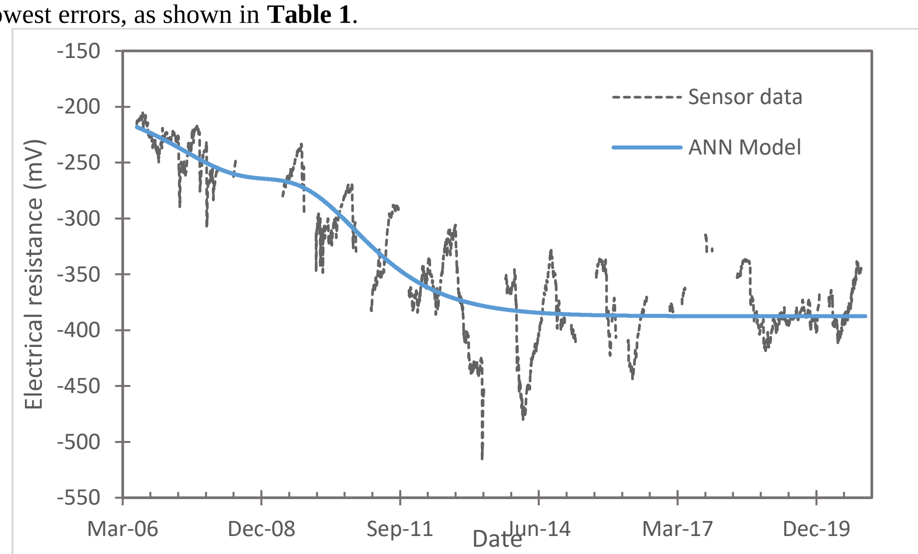

Fig. 3. ANN model for degradation prediction.

Table 1. Mean square error of the models considered.

Model	MSE
ANN Model	**767.35**
MC Model	**1697.48**

4 Conclusions

Two different deterioration models namely MC and ANN models were implemented in the present work to predict and compare the degradation of bridges based on the electric resistivity data monitored from 2006 to 2020.

The ability to capture the variability and randomness of the degradation process is the main advantage of the MC model and the principal reason for its implementation in the field. However, the transition probability matrix is severely criticized because its not time dependent. The ANN model is proposed as an alternative to compare the impact of the assumption of the MC model on the prediction results.

The models present a distinct degradation curve, and the ANN model achieved the lowest errors. Therefore, for this example, an ANN model becomes a more convenient alternative to be implemented on existing bridges to predict the condition degradation through time. Further simulations and analysis are required to confirm this finding.

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