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A custom building deterioration model

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Abstract. Developing accurate prediction models for deterioration behavior represents a challenging but essential task in comprehensive Infrastructure Management Systems. The challenge may be a result of the lack of historical data, impact of unforeseen parameters, and/or the past repair/maintenance practices. These realities contribute heavily to the noticeable variability in deterioration behavior even among similar components. This paper introduces a novel approach to predict the deterioration of any infrastructure component. The approach is general as it fits any component, however the prediction is custom for a specific item to consider the inherent impacts of expected and unexpected parameters that affect its unique deterioration behavior.

Keywords: IMS; deterioration modeling; Markov chains; optimization; repair and maintenance.

1. Introduction

The process of deterioration prediction in its current form can be described as "A General Prediction Process" as it ends up with a set of prediction curves for a certain category of infrastructure components. Considering the large number of components in a building, hundreds of curves need to be created then stored to be able to predict the deterioration of all building components. An organization that manages buildings, such as schools, hospitals, etc. is faced with this challenge. A building can have more than 100 components that can be split into various types. If only three types per component are considered, the prediction model should involve 300 curves. Creating such a large database is neither easy nor practical. Alternatively, this paper presents a model which perform an analysis for each inspected item or component to determine its unique deterioration curve (i.e., custom). Customization as such will account for all factors that might affect the component deterioration without investigating these factors. The novelty of the proposed model stems from three main aspects: (1) utilizing existing condition assessment data to provide the needed data for deterioration predication; (2) developing a generic deterioration curve of any type of components (in this paper Markov chain approach in a simplified spreadsheet format is used); and

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(3) customizing the generic deterioration curve to create a custom deterioration behavior for each item using optimization.

2. Deterioration models

In infrastructure management systems (IMS) the future condition is as important as the current condition for making decisions related to repair and maintenance fund allocation. Researchers in the literature proposed many models which are essential for any infrastructure management system (Madanat *et al.* 1995, Madanat *et al.* 1997, Morcous *et al.* 2002a). Prediction models or deterioration modeling in general can be categorized in three main research domains (Morcous *et al.* 2002b): Deterministic, Stochastic, and Artificial Intelligence models (Fig. 1). A brief description of these categories is as follows, with their pros and cons highlighted in Table 1.

(1) Deterministic Models: These models vary from simple straight-line extrapolation (Fig. 2(a)) to more involved regression models (Fig. 2(b)). In the straight-line extrapolation model a line is stretching between two points (a) and (b) with known conditions, then it is possible to extrapolate the future condition at any time e.g., point (c, Fig. 2(a)). This type of models needs only one point as the condition at construction time is known (i.e., excellent condition). On the other hand, regression can be used if enough historical data is provided (Fig. 2(b)). Regression tries to determine the best function that minimizes the square error between the assumed function and the real data used.

(2) Stochastic Markovian Models: Markovian models are the most common stochastic techniques that have been used extensively in modeling the deterioration of infrastructure facilities (Butt *et al.* 1987, Jiang *et al.* 1988). These models use the Markov Decision Process (MDP) that predicts the deterioration of a component by defining discrete condition states and accumulating the probability of transition from one condition state to another over multiple discrete time intervals (Puterman 1994). The main challenge in this type is how to obtain the transition probability matrix which describes the deterioration from one condition state to another during a specified time interval.

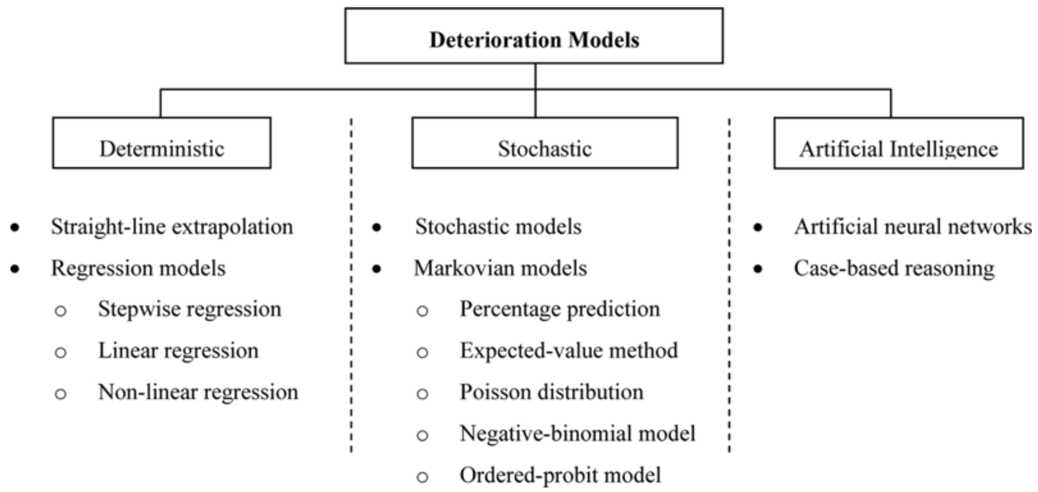
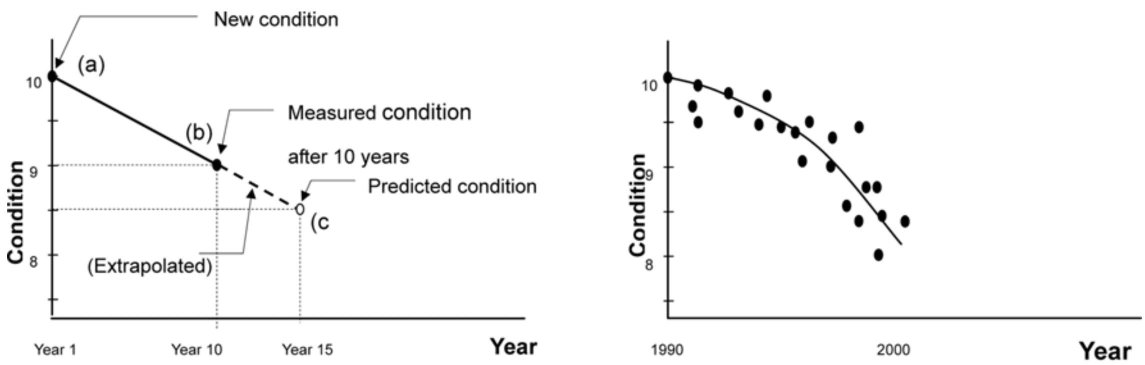


Fig. 1 Categories of deterioration models, adapted from (Morcous *et al.* 2002b)

Table 1 Prediction Models: Pros and Cons

	Methodology	Advantageous	Disadvantageous
Regression	Mathematical or statistical formulation.	Simple to use; Efficient when a lot of data is available (Morcous *et al.* 2002a).	Predicts the average condition at the system level, which ignores the measured condition of individual components (Shahin *et al.* 1987, Jiang and Sinha 1989); Do not predict the condition improvement after repair (Sanders and Zhang 1994); Neglects the uncertainty due to the stochastic nature of infrastructure deterioration (Jiang and Sinha 1989, Madanat *et al.* 1995); Neglects the interaction among different asset components (Sianipar and Adams 1997); and Difficult to update when new data is obtained (Morcous *et al*. 2002a).
Markov	Defines condition states the probabilities of transition from one state to another.	Captures the uncertainty of the deterioration process; Future condition is a function of current condition;	Assumes fixed transition probabilities (Collins 1972); Assumes state independence for simplicity (DeStefano and Grivas 1998, Madanat *et al.* 1997); Do not predict the condition improvement after repair (Madanat and Ibrahim 1995); Difficult to consider the interaction among different components (Sianipar and Adams 1997); and Require updates when new data are obtained from inspection.
Neural Networks	Uses train-by-example approach.	Most useful for non-linear mappings; Works well with noisy data; and Has inspired many new learning algorithms.	Sometimes difficulty to train from case history; Black box; Sometime difficult to design; and Require balance between over-training and generalization.



(a) Straight-Line Extrapolation (b) Regression Analysis

Fig. 2 Deterministic models

(3) Artificial Neural Networks: An Artificial Neural Network (ANN) can be defined as a type of information processing system whose architecture is inspired by the structure of biological systems. Such a network has been found to be capable of carrying out parallel computations for different tasks, such as pattern recognition, linear optimization, speech recognition, and prediction. In 1997, the multi-layer ANN was used to predict the deterioration behavior of bridge decks (Sobanjo 1997). After training on data from 50 bridges, the ANN became able to predict the deck condition as a function of age.

3. Key definitions

Before describing the proposed model, it is important to give brief definition of the common terms used in this paper.

Condition Assessment Survey: is the whole inspection process and covers all components related to an organization, the assessment survey evaluate, for each inspected item, the severity level (%) of its possible defects.

Deterioration Index (DI): for an inspected item represents a measure of its deterioration level or condition. It ranges from 0 to 100 with 100 represents the most critical condition; *Predicted condition or future DI*: is the DI after a certain time interval (i.e., if the current is 2009) then the inspected DI is DI_{2009} or DI_1 and the predicted future DIs in yearly bases is DI_{2010}, DI_{2011}, DI_{2012}, and DI_{2013} or DI_2, DI_3, DI_4, and DI_5, respectively, covering a five-year prediction horizon; *Condition State:* where each 10 points on the DI scale represents one condition state. This means, the 100-DI scale is divided into 10 condition states to match Markov chain process; and *TPM:* is the transition probability matrix that shows the probabilities to move from one condition state to another.

4. The proposed approach: a two-stage deterioration analysis

The proposed model is shown in Fig. 3 and it is obvious that even though similar items can be at same age, they often exhibit different deterioration (DIs). The reason behind this is that the deterioration is affected by many factors, other than age. This includes but not restricted to the following: maintenance history, surrounding environmental conditions, surrounding components' conditions, component location/ altitude, users' behaviors, etc. Trying to realize all factors that might affect the deterioration of a certain component is neither easy nor practical, but more important is to consider their impacts during the prediction process.

To consider the multitude of factors affecting an item, this research deals with each single inspected item individually and generates a custom deterioration behavior for it. It relies on the condition assessment data (DIs) gathered during a complete condition assessment survey. Fig. 1 shows the two-stage process of the deterioration model. First, for any component (e.g., aluminum windows) the model develop a *generic deterioration curve* from the assessment data related to aluminum windows; and second, generates for each individual item (e.g., east-side aluminum window(s)) a deterioration curve that imitates the generic deterioration curve, but customized to its actual data (*Custom deterioration curve*).

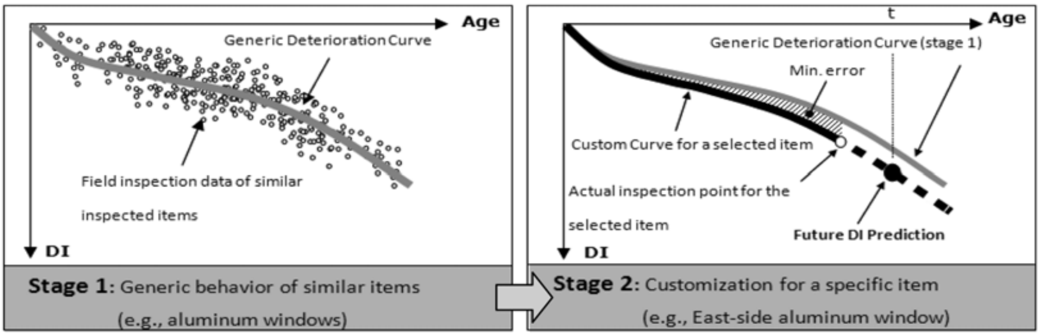


Fig. 3 Two-stage deterioration prediction model

Stage1: Generic Deterioration Behavior (Curve): In case of large organizations which manage hundreds of buildings, an assessment survey is expected to cover a wide spectrum of assets with various components and types. Consequently, an assessment survey will provide measurements for the condition in the form of (DIs) for thousands of items. With the fact that similar items at different buildings have various ages at the inspection time, inspection data can be used to plot the age versus DI relationship (Fig. 3-Stage 1), representing a generic deterioration behavior. For example, if 25 buildings out of 100 buildings managed by an organization, have “aluminum windows”, and each building has four items only (i.e., east, west, north, and south), the total number of inspected aluminum windows is 100 items. At the inspection year when all (DIs) are measured, each item has its own age, once all points are plotted, a generic deterioration behavior for this type of items can be obtained. Markov chain approach or any other approach can then be used to determine the generic deterioration curve (i.e., Age versus DI similar to Fig. 3-Stage 1). In this paper Excel-based Markov chain with optimized TPM of Elhakeem and Hegazy, 2005 had been used.

Stage2: Custom Deterioration Behavior (Curve): To adapt the generic deterioration curve to account for the actual deterioration behavior of a specific item, the Markov chains approach is also used. The TPM matrix obtained from stage 1 which describes the generic deterioration is used to guide the creation of the custom deterioration prediction. Using constrained optimization, a new TPM can be determined which force the custom curve to go through the actual measured DI for that specific item under consideration, (Fig. 3-Stage 2). As shown in the figure this stage minimizes the error between the generic deterioration trend and the prediction resulted from the custom TPM by changing its probabilities and going through the actual point. Both processes in stage 1 and 2 are then repeated for all types of components and their items as a double loop analysis.

5. Case study example

In order to validate the approach described in this paper, the proposed model is tested using a real case study. One of the Egyptian organizations that manage many buildings facilitated site visits to its assets to inspect the building and their sub components. The collected data was then used in the deterioration analysis. As the organization requires deterioration analysis every three months, the analysis was done considering a quarter of year time interval.

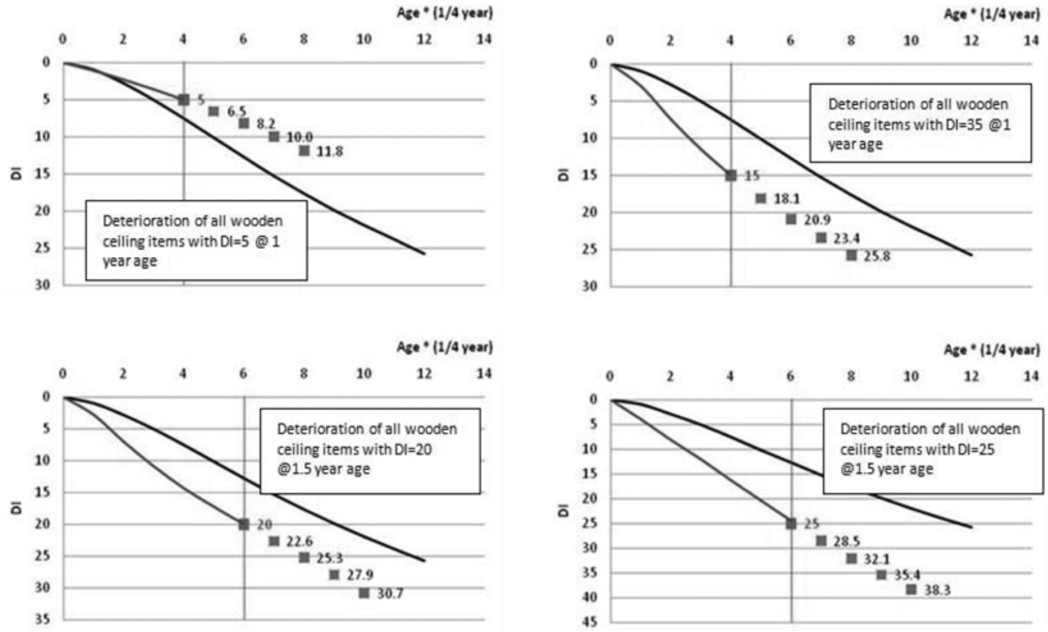


Fig. 4 Sample of custom deterioration analysis of wooden ceiling items

(1) The Assessment Survey: The inspection covered the following types of building components: Wooden windows (90 records) - Wooden ceiling (94 records) - Wooden doors (76 records) - Terrazzo Tiles (32 records) - Sanitary (16 records) - Room Electricity and Lights (67 records).
(2) Generic Deterioration Curves: after classification and clustering the inspection data into various types, records for each type were averaged at each age then the TPM that best describes the average is calculated using optimization. This process is repeated for each component type.
(3) Custom Deterioration: For each inspected item, a custom curve was generated through a loop analysis which considers each item at a time and optimizes its custom TPM.

Sample result for wooden ceiling is shown in Fig. 4 where the solid thick curve represents the generic trend. The figure shows the custom deterioration for each single item, (gray solid line) considering its influential parameters. Using extrapolation on the custom deterioration curve, predicted future deterioration are marked as individual points. In the top part of the figure two types of items aging one year old can be compared. The one to the left has a slower than average deterioration rate and continues better than the average in the future, the right one however behaves poorly than average and keeps behaving worse in the future. The proposed model overlooks the reasons for such a behavior, however considers them in the prediction. It is notable that as many items have same DI and Age, the number of custom curves can be reduced accordingly as well as the time for the analysis.

6. Conclusions

The introduced model for deterioration prediction is novel in its formulation and its integration with the condition assessment which provides reliable data to make accurate deterioration predictions. The model is generic where it can be applied on any type of asset/component according to the data gathered through the condition assessment of similar assets. In the paper, the model was applied on building asset that constitutes of diversified building components. The assessment data used embodies the maintenance history of the specific organization owning/operating the building. Using this data, the proposed deterioration model dynamically produces a custom deterioration curve for each item in the building network using optimization. Customization considers the implicit impact of the specific working environment of each item and any other unforeseen parameters that might affect the item's rate of deterioration, including the interaction with other components.

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