Bridge Condition Assessment using Supervised Decision Trees

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Abstract. Bridges are at risk from aging, fatigue and deterioration processes. Many countries are facing with large stocks of existing bridges approaching the end of the service life and the preservation of their structural performance and functional adequacy is a priority for administrations, public authorities, and decision makers dealing with bridge condition rating and infrastructure management. Visual inspections are at the base of an effective and reliable bridge condition assessment. Inspection strategies and procedures determine how results are returned, stored and managed leading to the formulation of different bridge condition indicators. The collection of information over time provides a great amount of bridge data which can be properly elaborated to get useful insights for supporting the decision-making process. Classification tools, such as Decision Trees (DTs) can be exploited to prioritize maintenance and rehabilitation interventions within the transportation network. This paper presents the application of a supervised DT for the assessment of bridge condition. The proposed approach is applied to classification in Good, Fair, or Poor status of a stock of existing bridges located in California. The DT is trained using visual inspection results stored in public United States National Bridge Inventory (NBI).

Keywords: Condition assessment, Visual inspections, Decision Tree.

1 Introduction

Most developed countries worldwide are facing the urgent need of prioritizing maintenance and repair of many bridges approaching the end of service life. As an example, according to ASCE Report Card for America's Infrastructure, almost the 42% of 617,000 US bridges is over 50-years and the 7.5% are considered structurally deficient, meaning they are in "poor" condition [1]. Limited available resources for maintenance and repair interventions must be optimally allocated within the whole transportation network considering risk-based bridge prioritization procedures [2]. An informed decision-making process can be effectively supported by a proper Bridge Management System (BMS) which can provide condition assessment of the bridge asset on the base of data stored in inventories [3,4]. Bridge inventories can include data obtained from different monitoring sources, such as visual inspection, Non-Destructive Tests (NDT) and Structural Health Monitoring (SHM) and a great effort is ongoing to create bridge databases and gather information from experimental testing on existing bridges [5, 6, 7]. This information plays an important role in the reduction of epistemic uncertainty usually affecting quantities involved in life-cycle assessment of aging bridges [8, 9, 10]. NDTs results can be exploited for calibration of mechanical properties of materials and components. Data from SHM can be used for updating prediction models in a life-cycle perspective [11, 12, 13]. Despite the rapid growth of NDT and SHM applications over the last decades [14], visual inspections still play a prominent role in bridge condition assessment even if affected by subjectivity related to expert judgments [15]. To overcome this drawback, visual inspection standards and protocols have been developed and updated over time [16].

Data from bridge monitoring and inspection can be processed by advanced numerical techniques to get useful insights and machine learning techniques are particularly suitable for the elaboration of visual inspection results under uncertainty [17, 18]. In this paper, a supervised Decision Tree (DT) is implemented for the condition assessment of an existing bridge stocks. Results of element-level bridge inspections in terms of local numerical condition indicators are exploited for the classification of bridges in Good, Fair and Poor status. The DT is trained and applied for the classification of Reinforced Concrete (RC) girder bridges located in California.

2 Bridge Condition Assessment

2.1 Bridge Classification

The US National Bridge Inventory (NBI) was established in 1968 after the collapse of Silver Bridge [19]. Starting from 1979 a visual inspection routine was adopted based on the condition rating of four mayor bridge elements [20, 21]. A total of 116 bridge features are annually collected by transportation agencies in the NBI. Items 58, 59 and 60 are devoted to the condition rating of major elements of the bridge. Deck, superstructure, and substructure condition are evaluated with a score from 0 to 10 according to indications provided by [20].

According to [22] three bridge status are determined on the base of NBI condition ratings for deck, superstructure and substructure, according to rules included in Tab. 1. If the lowest rating among the three is no lower than 7 the bridge is classified as Good. If it is no larger than 4, the classification is Poor. Bridges with rating equal 5 or 6 are classified as Fair. From 1992 NBI is annually published [23].

Table 1. Definition of bridge condition classes [22]

RULE	STATUS
ITEM 58 $\geq$ 7 or ITEM 59 $\geq$ 7or ITEM 60$\geq$ 7	GOOD
5 $\leq$ ITEM 58 $\leq$ 6 or 5 $\leq$ ITEM 59 $\leq$ 6 or 5 $\leq$ ITEM 60 $\leq$ 6	FAIR
ITEM 58 $\leq$ 4 or ITEM 59 $\leq$ 4 or ITEM 60 $\leq$ 4	POOR

2.2 Bridge Health Index

In 1990s the element-level inspection routine was also introduced in US to meet the need of a more detailed level of bridge descriptions [24]. The element level inspection consists in a detailed breakdown of the major components. The Bridge Health Index (BHI) can be computed on the base of results from such inspection routine [25]. For each element *e*, severity and extent of the deterioration are simultaneously captured (Tab. 2). According to [26], four different condition states (CS_i) are identified: Good (CS_1), Fair (CS_2), Poor (CS_3) and Severe (CS_4). Condition information about bridge components is collected through the indication of the element portion subjected to the considered condition state (Q_i) using the appropriate unit of measure (*u*). The summation of Q_i provides the Total Element Quantity (TEQ). Moreover, a weighting factor can be computed for each condition state *i* (W_i) as:

$$W_i = 1 - \frac{CS_i - 1}{N_{CS} - 1} \tag{1}$$

where N_{CS} is the total number of condition states. BHI is defined as:

$$BHI = \frac{\sum_{i=1}^{4} Q_i \cdot W_i}{TEQ} \tag{2}$$

From 2015 this kind of data is collected for all bridges within the US National Highway System (NHS) and annually published [27].

Table 2: Example of bridge component condition information format [26]

Element	Unit	TEQ	CS1	CS2	CS3	CS4
e	*u*	$\sum_{i=1}^{4} Q_i$	Q_1	Q_2	Q_3	Q_4

3 Decision Tree

Decision trees are machine learning methods for building prediction models from data. In a classification problem given training vectors of features $\mathbf{x}_i$ to which label $k_i = 1,...,K$ is associated, models are obtained recursively partitioning the feature space [28, 29]. Let S_m denote a set of labeled examples $(\mathbf{x}_i, k_i)$ with $i = 1,\ldots,N$ included in the start node of the tree (root). S_m must be split into 2 subsets through the partition of the variables space. To this aim a feature *j* and a threshold value t_m can be identified for the definition of a split function $\theta = \theta(j, t_m)$, such as (Fig. 1):

$$S_m^{left} = \{(\mathbf{x}_i, k_i) \mid (\mathbf{x}_i, k_i) \in S_m, \mathbf{x}_i(j) \le t_m\} \tag{3}$$

$$S_m^{right} = \{(\mathbf{x}_i, k_i) \mid (\mathbf{x}_i, k_i) \in S_m, \mathbf{x}_i(j) > t_m\} \tag{4}$$

More than one split θ can be selected for partitioning the feature space. Among all the possible splits, the optimal one is chosen minimizing the following split impurity function:

$$H(S_m^{left}, S_m^{right}) = \frac{N_m^{left}}{N_m} H(S_m^{left}(\theta)) + \frac{N_m^{right}}{N_m} H(S_m^{right}(\theta)) \tag{5}$$

in which $H(S_m^{left}(\theta))$ and $H(S_m^{right}(\theta))$ are entropy functions, measuring the impurity of the generic node *m*:

$$H(S_m) = -\sum_k p_{mk} \log_2(p_{mk}) \tag{6}$$

where p_{mk} is the proportion of class *k* observations in node *m.* The described process is recursively applied to the nodes and the tree can grow until a node is pure (i.e. it is composed only by examples associated to the same *k* class). A limit is imposed to the minimum decreasing of the impurity function needed for the splitting.

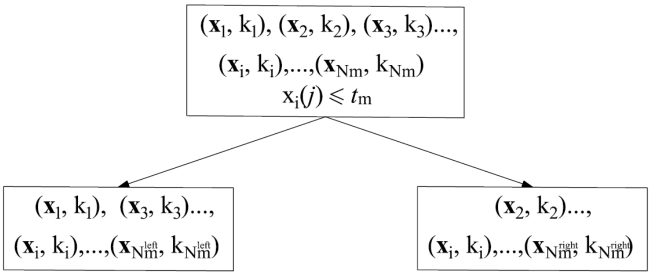

Fig. 1. Decision Tree.

4 Decision Tree for Bridge stock classification

A DT is trained for the classification of a stock of RC/PC girder bridges included in the NBI located in California. Average BHIs have been computed for deck (BHI_d), girder (BHI_g), piers (BHI_p), and abutment (BHI_a) for a set of 2309 bridges according to the element breakdown described by Fig. 2 and Tab. 3. Fig 3 provides the frequency distribution of the three bridge condition classes. The DT is trained on a set of 1847 examples to obtain a model which provides the classification of the structure condition in Good, Fair or Poor, as defined in Tab.1 taking as input the BHIs. The obtained DT is then applied to identify the condition of the remaining 462 bridges. Fig. 4 shows the trained DT. Each node displays information about number of bridges and the rule identifying the next split. Nodes are also characterized by different colors identifying the most frequent class at that stage. Purity of nodes is identified by the transparency of colors, with pure nodes associated to full color. It is interesting to note that BHI_d and BHI_g are the features most influencing the classification. BHI_p and BHI_a are affecting only the distinction between Good and Fair status in the last layers of the tree. In this case, the expert judgment evaluating bridge major element and global condition is most influenced by the girder and deck bridge components, since they are associated to most of the splits in the DT.

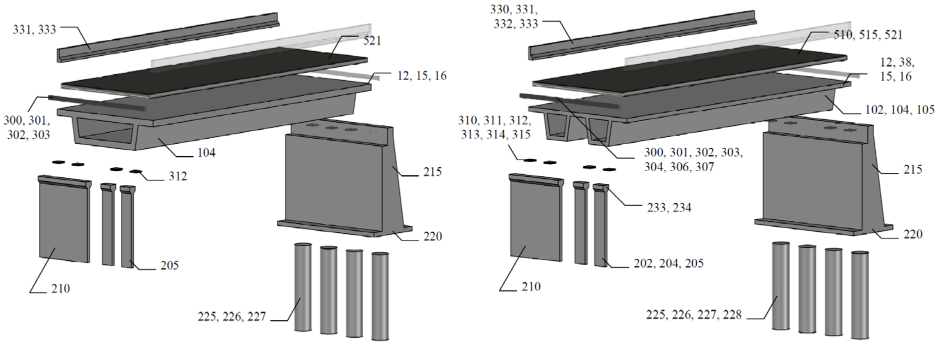

Fig. 2. Subdivision in bridge components.

Table 3. Library of bridge components.

MAYOR ELEMENT	BRIDGE COMPONENT	ID	UNIT*
Deck	RC Deck/Slab	12/38	A
	RC/PC Top Flange	15/16	A
	Railings	330, 331, 332, 333	L
	Joints	300 - 307	L
Superstructure	Closed web/Box Girder	104,105,106	L
Substructure	Column/Pile Extension	202, 204, 205, 206	EA
	Submerged Pile	225, 226, 227, 228	EA
	Pile Cap/Footing	220	EA
	Bearings	310-315	EA
	Pier Cap	233, 234	EA
	Pier Wall	210	L
	Abutment	215	L
Wearing Surface & Protection System	Wearing surface	510	A
	RC Protective Coating	521	A

*A=Area; L=Length; EA=Each Element

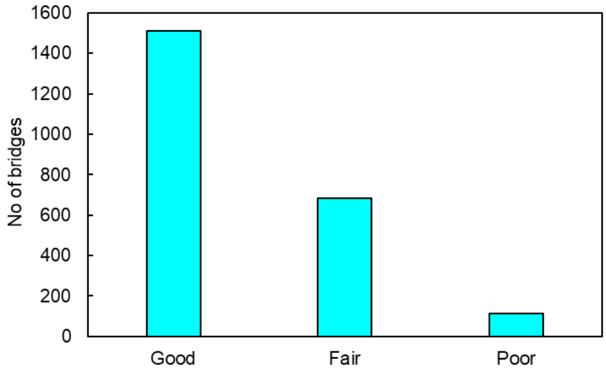

Fig. 3. Frequency distribution of bridges in Good, Fair, and Poor states.

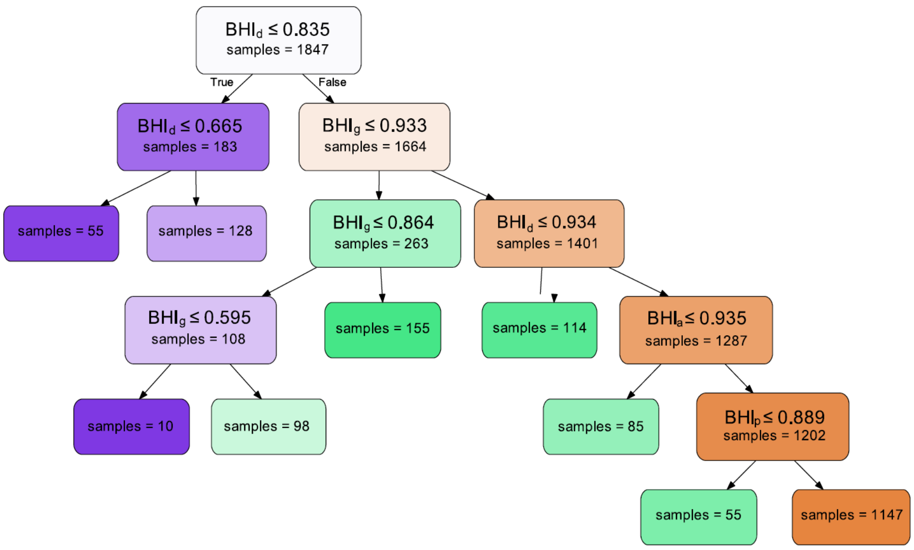

Fig. 4. Decision Tree. Colored nodes are associated with Poor (purple), Fair (green), and Good (orange) condition.

Fig. 5 shows the localization of bridges included in the test dataset along with the actual status (Fig.5a) and the status predicted by the DT (Fig 5b). The quality of the output classifier applied to the test dataset is described in Tab. 6 by means of a confusion matrix **C** summarizing how successful the classification model is at predicting the bridge status. Each row of this matrix is associated to the actual status and each column to the predicted status. The diagonal terms indicate the number of bridges correctly classified and the terms out of the diagonal represent the misclassifications. Precision and recall can be used to assess the quality of the model [30]. Precision (*P*) of a status can be computed as the ratio of bridges correctly classified and the total number of bridges predicted as belonging to that status:

$$P_{GOOD} = \frac{267}{267+8+0} = 0.97 \quad P_{FAIR} = \frac{107}{35+107+4} = 0.73 \quad P_{POOR} = \frac{15}{2+24+15} = 0.36 \tag{7}$$

Recall (R) of a status classification can be computed as the ratio of number of correct classifications and total number of bridges associated to the considered actual status:

$$R_{GOOD} = \frac{267}{267+35+2} = 0.88 \quad R_{FAIR} = \frac{107}{8+107+24} = 0.77 \quad R_{POOR} = \frac{15}{0+4+15} = 0.79 \tag{8}$$

High values of P_{GOOD} and R_{POOR} indicates the capability of the model to distinguish between bridges associated to good and poor evaluations. In particular, none of bridges labeled as poor is predicted as good, meaning that a reliable indication is provided to bridge managers about the structures which need a more in-depth analysis.

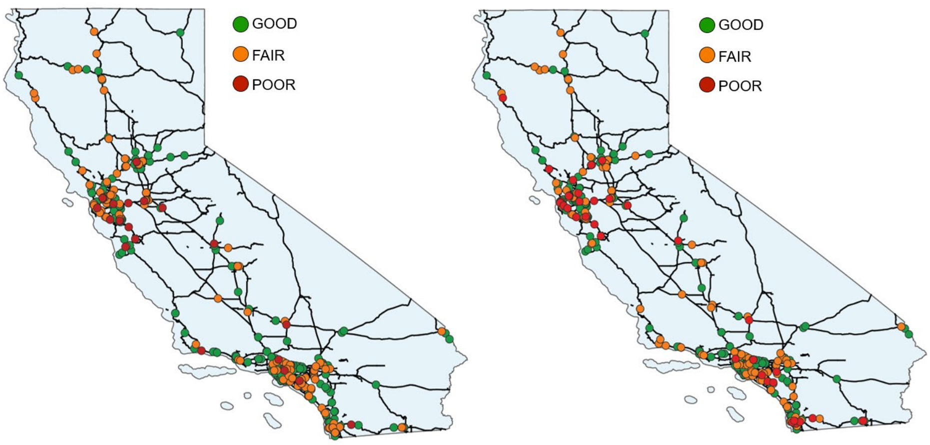

Fig. 5. Localization of 462 bridges of the test subset with the indication of (a) actual status and (b) predicted status.

Table 6. Confusion matrix.

ACTUAL STATUS	PREDICTED STATUS: GOOD	FAIR	POOR
GOOD	267	35	2
FAIR	8	107	24
POOR	0	4	15

5 Conclusions

In dealing with large bridge assets visual inspections play an important role in the bridge condition assessment. Evolution of visual inspection protocols try to reduce the uncertainty associated to the subjectivity of expert judgments moving from a condition assessment related to global evaluation of bridge major elements towards the computation of the BHI based on the results of standardized element-level inspections. The paper presented a supervised DT trained for the condition assessment of existing RC box girder bridges. The DT takes as input the results of the element-level inspection and automatically classifies the bridge condition, according to Good, Fair or Poor status. The DT has been then applied to a test dataset. The goodness of condition predictions has been quantified through the computation of precision and recall indicators. Furthermore, a confusion matrix shows that a reliable indication is provided by the model to bridge managers on the structures which need a more in-depth analysis, since none of bridges labeled as poor is predicted as good and very few structures labeled as good are predicted as poor. Moreover, the trained DT can be assessed to identify the input variables which mainly influence the classification. In the investigated case, the expert judgment evaluating bridge major element and global condition is most influenced by the girder and deck components.

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