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A CLUSTERING-BASED MODEL FOR RATING CONCRETE BRIDGES USING *K*-MEANS TECHNIQUE

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Abstract: Bridge Maintenance, Repair and Replacement (MRR) decisions need accurate condition assessment and rating methods to ensure safety and serviceability of bridge infrastructure. In North America, the common practices to assess condition of bridges are through visual inspection. Further, the thresholds that define the severity of bridge deterioration are subjectively assigned based on the experience and judgment of the inspector or expert. The current research discusses the main deteriorations and defects identified during visual inspection and Non-Destructive Evaluation (NDE). NDE techniques are becoming popular in augmenting the visual examination during inspection to detect subsurface defects. Quality inspection data and accurate condition assessment and rating are the basis for determining appropriate MRR decisions. Thus, in this paper, a novel method for bridge condition assessment using the Quality Function Deployment (QFD) theory is proposed to develop an integrated condition rating index while identifying clear thresholds between the different ratings. The threshold identification technique is based on using *k*-means clustering. *k*-means is one of the simplest unsupervised learning algorithms that solves the subjective determination of threshold values problem. The QFD method was applied and the developed rating index was implemented on twenty case studies in the province of Quebec. The results from the analyzed case studies show that the proposed threshold model produces robust MRR recommendations consistent with decisions and recommendations made by bridge managers on these projects. The proposed method is expected to advance the state of the art of bridges condition assessment and rating.

1 INTRODUCTION

Bridge structures play a critical role in the transportation system as they serve millions of people daily. Any failure in these structures will result in both human life and economic loss. Consequently, condition assessment is performed on routine or scheduled basis to ensure public safety and prevent such catastrophic events. Bridge assessment is mainly an interpretation that identifies the appropriate Maintenance, Repair or Replacement (MRR) action. With the increasing number of deteriorated bridges in Canada, the US and around the globe, condition assessment and rating techniques of concrete bridges are evolving.

Similar to any reinforced concrete structures, bridges experience loss of integrity over time due to degradation. It is important to understand different deterioration processes as each process leads to different types of defects such as cracking, scaling, spalling, concrete delamination and corrosion of reinforcing steel. It is also important to identify the basic causes of deterioration that require MRR actions;

otherwise, ineffective technique may be selected. Corrosion of steel reinforcement, for instance, is considered as the most leading cause of deterioration (Bolar, Tesfamariam, and Sadiq 2013) and has always been viewed as the biggest problem that reasons in many consequent damages as the structure ages. Deterioration comes from the fact that rust, the final product of the electrochemical process of corrosion, occupies much larger volume than the original steel over the years. This causes internal stresses in the surrounding concrete leading to cracking. As corrosion gets more severe, those internal cracks progressively cause partial separation of concrete at the level of reinforcement known as delamination. Several delaminated areas eventually form spalling of concrete, which results in structural disintegration. Cracking, delamination, and other discontinuities can occur due to overloading as well. Such defects in some cases could threaten public safety. The main objective of this research is to develop a clustering-based threshold model for rating bridges to facilitate the MRR decision making for bridge managers. To achieve this objective, the following sub-objectives are sought: i) assess and evaluate both the surface and subsurface defects, and ii) develop an integrated condition model for rating concrete bridges. Defects assessment and evaluation are captured through a QFD-based condition assessment model developed by the first author while a clustering-based model using *k*-means technique is proposed to rate the condition of concrete bridges.

2 BACKGROUND

2.1 Condition Assessment of Bridges

The commonly used technique to assess condition of bridges is through visual inspection and close observation to bridge elements because it is inexpensive and requires a minimal level of experience. Information from routine visual inspections is being used to update lifetime reliability assessments and set life-cycle MRR strategies (Estes and Frangopol 2003). The visual examination provides valuable information on bridges condition. However, this practice is not always reliable because it is limited to detect surface defects and external flaws. Subsurface defects are mostly measured with the aid of Non-Destructive Evaluation (NDE) techniques. Moreover, NDE technologies are involved in objectifying the inspection process and making it more reliable. These techniques are becoming popular in augmenting the visual inspections (Alampalli 2010). Among the most effective technologies, the Ground Penetrating Radar (GPR) has been considered for many years as a highly promising technique for deterioration mapping. Thus, in this research, GPR is integrated with visual inspection technique to assess the condition of concrete bridge decks using Quality Function Deployment (QFD) theory in order to enhance the reliability of bridge condition assessment.

2.2 Condition Rating Systems for Bridges

Once condition assessment is executed, a score is provided to interpret the bridge condition rating. National Bridge Inventory (NBI) condition rating system is the oldest rating used in the US to evaluate the bridge under three main components, namely: deck, superstructure, and substructure. Two performance measures are deduced from the NBI ratings, namely: structurally deficient (SD) and functionally obsolete (FO). Another measurement from NBI data is called the sufficiency rating (SR) which is a numeric value that is used to allocate federal funds. The less a bridge's SR is, the more it is eligible for MRR funds. Although NBI program is wildly in use the US, its ratings and condition metrics (SD, FO, and SR) are not providing detail measurement and considered to be general in identifying maintenance strategies and cost estimates for federal or state funds distribution.

Due to NBI rating system limitations, FHWA and the California Department of Transportation (CalTrans) decided to develop the first bridge management system in the US (Pontis) where Commonly Recognized (CoRe) elements level condition is described instead of dividing a bridge into several main components. Although deterioration of bridges is a continuous process, the Federal Highway Administration (FHWA) uses an ordinal bridge deck rating system (FHWA 2005). FHWA bridge deck ratings, for example, range from 9 to 0, with 9 representing an excellent condition or new condition and 0 representing a deck that has deteriorated to a failed condition. Discrete ratings are used instead of continuous condition measures mainly to simplify the computational complexity of the MRR decision-making process (Madanat, Mishalani, and Ibrahim 1995).

Later, the California Department of Transportation (Caltrans) came up with a new concept called Bridge Health Index (BHI) based on element level condition data obtained from implementing Pontis system. The BHI is a ranking system for bridge maintenance ranging between 0-100, with 100% indicating the best state and 0% indicating the worst. Caltrans has developed a visual representation of the BHI (Fig. 1). The index accuracy comes from the fact of using element weighting factors aggregation where failure elements that could threaten the public safety, for example, receive more weight than the ones have a relatively little economic effect. Although the BHI enhances bridge performance measure, Dinh (2015) noticed that condition state weighting factors are simply calculated. Moreover, the values for the economic effect of element failure are difficult to obtain. Thus, it is concluded that a more appropriate method to calculate condition rates is needed in which weighting factors should consider defects interdependencies at the element level.

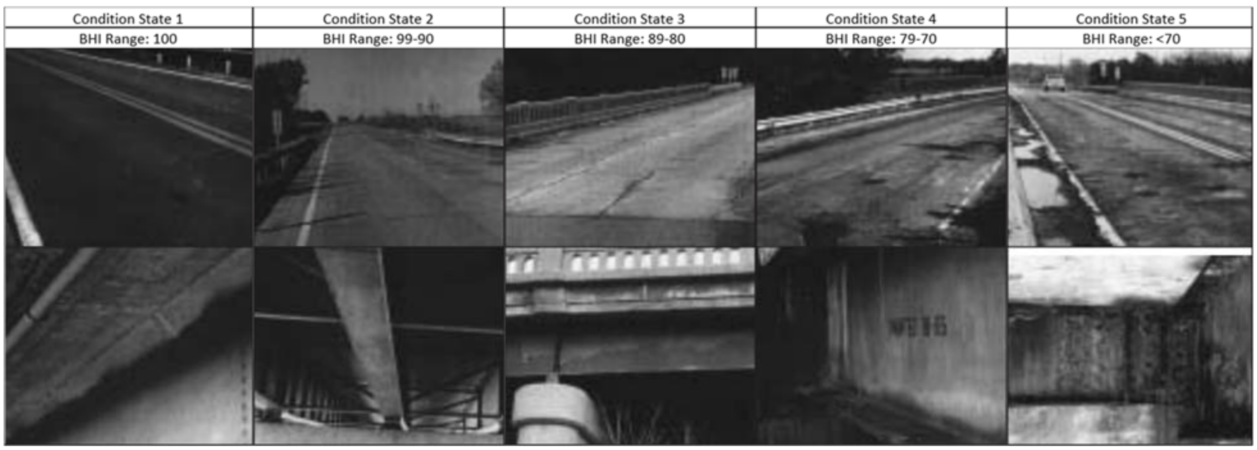

Figure 1: Visual representation of BHI values (Shepard and Johnson 2001, 6-11)

In Canada, bridge management systems have been developed like most states in the US. Some Canadian transportation agencies adopt Pontis system with minor modifications to suit their inventories while others like Ontario, Alberta, Quebec and Nova Scotia provinces use their own condition ratings similar to the NBI ratings described previously. Hammad et al. (2007) reviewed Canadian Bridge Management Systems (BMSs) in deep and compared between diverse provinces and territories management systems of bridge. In his research, he took a further step and proposed a unified National Bridge Inventory (NBI) development for Canada. While many condition ratings have been developed, all of them are computed based on visual inspections. Also, most of them are limited to certain defect types without integrating both surface and subsurface defects. Furthermore, the thresholds that define the severity of concrete deterioration is selected arbitrarily. Prior to explaining the methodology, k-means clustering, the utilized technique in this research, is explained below.

2.3 *k*-Means Clustering Technique

Among clustering formulations, *k*-means clustering is one of the most popular types of clustering algorithm because of its ease of implementation, efficiency, empirical clustering, and simplicity (Jain 2010). *k*-means clustering is a partitioning technique that is based on minimizing a formal objective function. The problem of object clustering was widely used and studied in various scientific areas such as machine learning (Thompson and Langley 1991), data mining and knowledge discovery (Fisher 1987; Huang 1998), pattern recognition and pattern classification (Sung and Poggio 1998; Kanungo et al. 2002; Duda, Hart, and Stork 2012). The three main user-defined parameters required to perform *k*-means clustering are i) the number of clusters *k*; ii) cluster initialization; and iii) distance metric. In general, *k*-means clustering starts by randomly selecting *k* initial cluster centers c_j and adjusting them by repeating the following steps: i) calculate the Euclidean distance using Eq. 1, where x_i is the data point and c_j is the centroid of the cluster of *j*; and ii) each cluster center c_j is updated to be the mean of its constituent points. The two steps are repeated until the centroids and points no longer move where the clustering process stops (Wagstaff et al. 2001, 577-584).

[1] $d(x_i, c_i) = \left(\sum_{d=1}^{D} |x_{id} - c_{id}|\right)^{\frac{1}{2}}$

where:

x_i = data point *i*,

c_j = centroid of cluster *j*,

d = d^{th} dimension, and

D = dimension of the data needed to be classified.

3 METHODOLOGY AND MODEL DEVELOPMENT

The proposed methodology and model's development process are illustrated in Fig. 2 and discussed in the following sections. Inspection data are gathered and collected from two sources: i) visual inspection reports and ii) GPR scans. Visual examination process can evaluate surface defects. Moreover, GPR technology evaluate subsurface defects such as chloride contamination and corrosion of steel reinforcements. This can be obtained from the condition map generated from performing the amplitude analysis to the GPR profiles. Once inspection data are analyzed, quantified surface and subsurface defects are fed into a QFD-based condition assessment model. The QFD model output is an integrated condition crisp value. Using *k*-means technique, integrated condition values from different case studies are divided into four clusters. Based on the result of clustering, the threshold value for each condition category will be determined. The final output of this methodology is a clustering-based rating model represented by an integrated condition index.

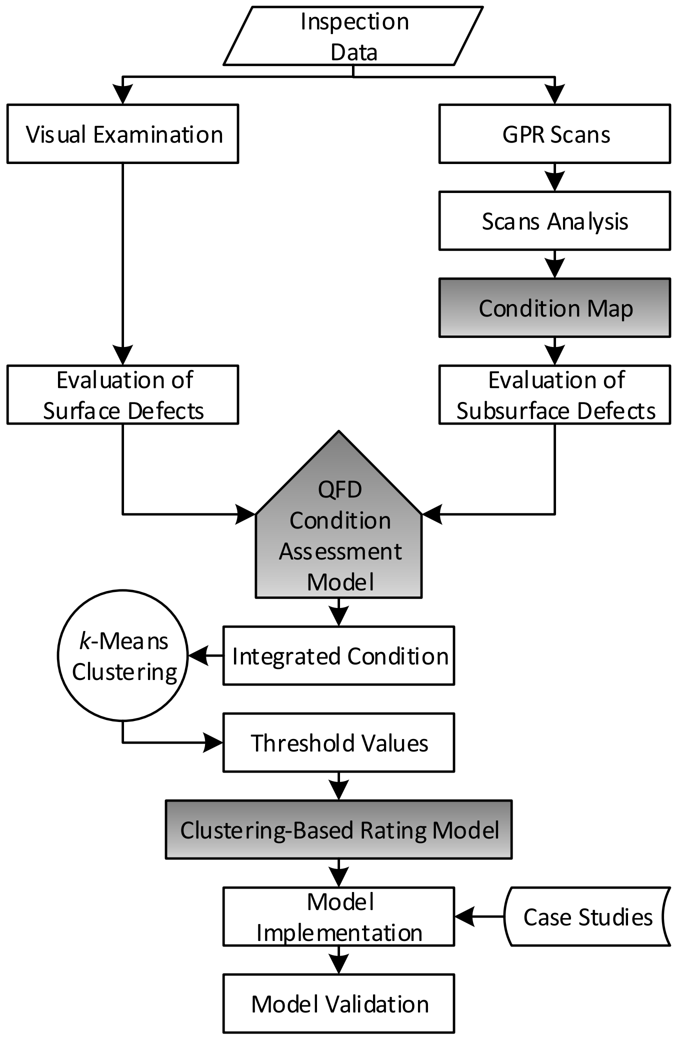

Figure 2: Schematic flow diagram for proposed methodology

3.1 Data Collection and Analysis

Two approaches of data collection are employed in this research. The first approach of data collection is by gathering inspection reports from the Ministère des Transports du Québec (MTQ) to get info related to surface defects detected from visual inspections. The second approach of collecting data is done by the research team where the same inspected bridge decks are scanned using GSSI ground-coupled radar system. This approach is important in order to detect corrosion of steel reinforcements, which is a subsurface defect.

After scanning bridge decks, the GPR profiles are imported to GSSI RADAN 7® software to find the amplitude of the reflected wave of the top reinforcing bars by picking the peak of the parabolic shapes that represent the location of the reinforcing bars as shown in Fig. 3. This step had been repeated for all profiles of bridge decks, then each profile with its corresponding amplitude values is exported to create an attenuation map. This attenuation (decibel) output map is used for evaluating the bridge deck corrosion condition.

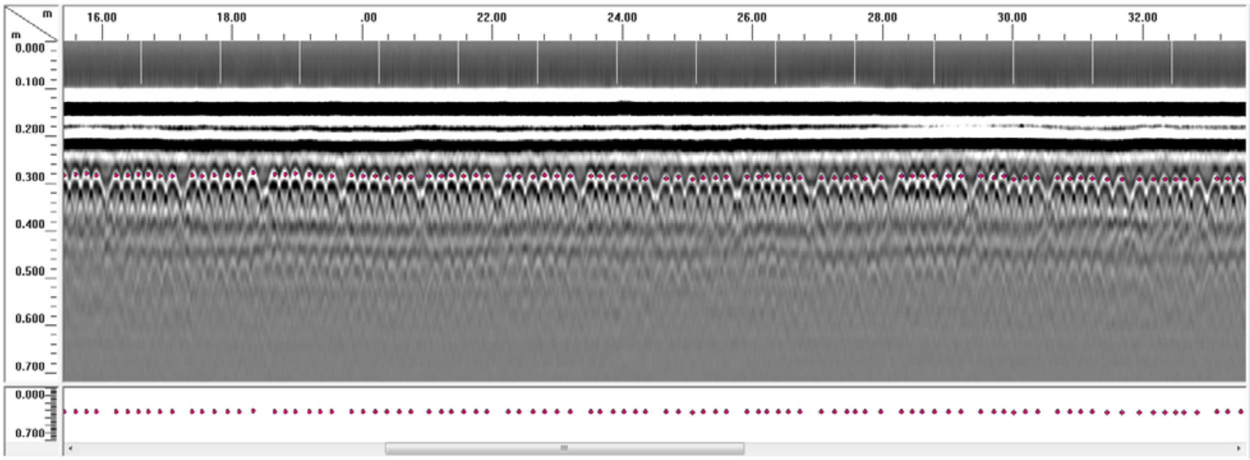

Figure 3: Example of picking the top reinforcing bars

3.2 Quality Function Deployment Model

In order to assess bridge deck condition, a Quality Function Deployment (QFD) condition assessment model is utilized. The QFD model is able to integrate surface defects detected by visual inspection and subsurface defects using NDE techniques in one framework (Alsharqawi, Zayed, and Abu Dabous 2018). The research extended the traditional QFD guidelines from their typical use (extracting the "voice of the customer" to produce a product that meets the customer needs) and applied the approach to perform bridge condition rating (meeting the need of infrastructure facility based on its condition assessment). By applying the QFD model, a final crisp integrated condition value C_I is calculated representing the bridge deck overall condition using Eq. 2:

[2] $C_I = (1 \times Good + 3 \times medium + 6 \times Severe + 9 \times V.Severe)/9$

where: C_I = integrated component condition; and $1, 3, 6, 9$ = numerical rating scale following a geometric progression where severity (condition ratings) is scored proportionally. The crisp value calculation is similar to a material condition rating used by MTQ (2012) inspection manual "Cote de Matériau Intégré (CMI)".

3.3 Clustering-Based Threshold Model

Commonly, the determination of the condition thresholds is subjective and selected arbitrarily. This can misrepresent the obtained assessment result and may cause wrong intervention decision. In this research, a robust method based on *k*-means clustering technique is proposed to solve this issue. For the proposed method of clustering, the value of *k* is chosen to be 4 indicating the number of clusters we would like to form from our data. The data set contains twenty crisp integrated condition values after analyzing real case studies using the QFD model. Since parameter *k* was set to 4, four clusters are generated. The final output is a rating model represented by an integrated condition index. The developed index recommends suitable MRR actions based on the integrated condition as displayed in Table 1.

Table 1: Bridge Deck Integrated Condition Index Interpretation

Integrated Condition		Action
Linguistic	**Numeric**	
- Excellent	0.00-0.23	No action is needed
- Good	0.23-0.46	Bridge needs routine maintenance
- Poor	0.46-0.65	Bridge needs repair
- Critical	0.65-0.76	Bridge needs replacement
- Failed	0.76-1.00	Close bridge until the deck is replaced

4 DISCUSSION AND CONCLUSION

Beside accurate assessment of bridge condition, agencies/departments of transportation require a rating system to interpret their bridge condition. Subjective determination of threshold values between condition categories may lead to selecting improper maintenance, repair and replacement decisions. This research proposes a robust method for resolving that issue. Similar to the idea of the BHI, the integrated condition index provide ratings and recommendations for intervention actions. However, this index has some distinguished features as follows. First, the index is based on assessing concrete bridge decks while integrating surface and subsurface defects. Therefore, an enhancement to the condition rating is achieved at the defect level. Second, the condition threshold values are selected using the *k*-means technique, which eliminates the subjectivity associated with the traditional method for threshold selection. The proposed clustering-based threshold model was implemented on several case studies. Results showed effectiveness of the model with high validity. The proposed method is expected to advance the state of the art of bridges condition assessment and rating. Moreover, it is certainly a useful tool the will help agencies/departments of transportation in allocating limited funding on the most deserving bridges at a network level.

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