GPR-Based Fuzzy Model for Bridge Deck Corrosiveness Index

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Abstract: Ground-penetrating radar (GPR) is a rapid technology for evaluating condition of concrete bridge decks subject to rebar corrosion. In this paper, based on a threshold model recently proposed in the literature, a bridge deck corrosiveness index (BDCI), is developed to have an idea where a bridge deck is during its continuous service life and to suggest corresponding maintenance activity. Based on fuzzy set theory, expert opinions were used to calibrate fuzzy membership function for each condition category found by GPR. Then, for a particular bridge deck, area percentages of all condition categories would be utilized to aggregate these functions into a BDCI using weighted fuzzy union (WFU) operation. The benefit of the developed system is twofold. First, it is based on GPR, a more accurate inspection technology. Second, it employs the knowledge provided by bridge community, and, in the meantime, has the capability to deal with fuzzy information associated with expert responses. Using an automated software, the system is illustrated for several concrete bridge decks in North America. Because the case studies show that the developed system is easy to be implemented, it would be an effective tool for transportation agencies in North America where the corrosion of rebar in concrete bridge decks is one of biggest concerns. **DOI: 10.1061/(ASCE)CF.1943-5509.0000815.**

Author keywords: Ground penetrating radar; Concrete bridge decks; Bridge inspection; Condition rating.

Introduction

The corrosion of concrete bridge decks is one of the biggest problems facing transportation agencies in North America. The ASCE (2013) estimated that an annual investment of $20.5 billion would be needed to eliminate the United State's bridge deficient backlog by 2028, and the largest portion of this expected expenditure would be allocated to bridge decks (Gucunski et al. 2013).

Ground-penetrating radar (GPR) is a rapid technology for detecting corrosion in concrete bridge decks, and its use has been standardized in an ASTM standard (ASTM 2008). In the simplest form, the output provided by GPR is a contour map of attenuation at top rebar layer in which the region with low reflection amplitude would be diagnosed as a potentially corroded area. However, because of increasing expectations from bridge owners, recent studies tend to employ specific terms for describing various conditions found by GPR (Gucunski et al. 2013; Tarussov et al. 2013; Dinh et al. 2015). Although these linguistic scales may be intuitive and useful for understanding the condition of a specific bridge deck, the condition information expressed in this form cannot be incorporated for further analysis at a network level. Built on a GPR threshold model recently developed by Dinh et al. (2015), such a research gap will be addressed in this study.

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Research Objectives

As discussed previously, although a linguistic description provides intuitive information about the corrosion deterioration of a specific bridge deck area, a systematic rating framework for bridge decks based on GPR output should be devised. In the simplest manner, the rating helps to identify bridge decks those are structurally deficient or to rank them according to maintenance priority. Based on the physical principles of GPR and its main capability in assessing concrete corrosion (Tarussov et al. 2013; Dinh et al. 2015), that rating is termed bridge deck corrosiveness index (BDCI) in this study. Specifically, the objectives of the current research are as follows:

1. Understand GPR output from management perspective,
2. Study and select the appropriate theory and techniques for interpreting GPR output, and
3. Develop and implement the bridge deck corrosiveness index (BDCI) model.

Bridge Condition Rating

The results obtained from the bridge inspection reveal different types of defects that exist on a bridge structure. However, because different flaws on different elements may not have the same implication to the overall bridge performance, transportation agencies need to have a rational framework to assess the condition of bridges under their responsibility. According to AASHTO (1994), the bridge condition rating is defined as the result of determining the functional capability and physical conditions of bridge components.

In the United States, the two most commonly used bridge condition rating systems are the national bridge inventory (NBI) and Pontis (Golabi and Shepard 1997). Although the former assesses a bridge according to three main components, i.e., deck, superstructure, and substructure, with the rating ranges from zero to nine, the latter rates a bridge in a greater level of detail, of up to

108 standardized elements (Thompson and Shepard 2000). The ratings of all the elements can then be integrated to come up with a bridge health index (BHI) that is considered to represent the health of the entire bridge structure.

According to Scherschligt and Kulkarni (2003), the BHI was developed to bridge the communication gap between bridge inspectors, bridge managers, elected officials, and the public concerning bridge conditions. The index, in percentage, ranges from 0 to 100, in which the value of 100 indicates the best state, whereas 0 indicates the worst, failure condition. Basically, it is a ranking system for bridge maintenance, and the idea of the rating is to think of the condition of a bridge, or an element, at a given time as a point along a continuous timeline, and the health index simply indicates where the bridge or element is along this continuum (Thompson and Shepard 2000).

The health index can be calculated for an element, a single bridge, or a group of bridges (Thompson and Shepard 2000). Its computation, shown in Eq. (1), is based on the total element quantity, element quantity in each condition state, failure cost of each element, and the so-called condition state weighting factors. The aggregation of the index, at bridge or network level, is based on the element weighting factors that are determined as the relative economic consequence of the failure of each element. The idea is that the elements that have failures with relatively little economic effects should receive less weight than the elements that have failures that could threaten public safety, or force the bridge to be closed

$$\text{Health Index(HI)} = \frac{\sum \text{CEV}}{\sum \text{TEV}} \times 100 \qquad (1)$$

where total element value$(\text{TEV}) =$ total element quantity $\times$ failure cost of element (FC); current element value$(\text{CEV}) = [\sum(\text{quantity in condition state} i \times \text{WF}_i)] \times \text{FC}$; and weighting factor of condition $i(\text{WF}_i) = 1 - [(i-1) \div (\text{number of states} - 1)]$.

According to Roberts and Shepard (2000), the BHI is used in California for several purposes including: (1) as a performance measure; (2) for allocation of resource; (3) level-of-service indicator; (4) for showing budget-based network condition; and (5) for measuring improved condition following preservation actions.

Although the current BHI is considered by the bridge management community to be an excellent performance measure, this study noticed that it has several limitations. First, it is based on visual inspection that provides only defects visible on the surface. Second, as can be realized from Eq. (1), the way in which condition state weighting factors (WF) are calculated makes the BHI model deterministic that does not take into consideration any inherent uncertainty. For example, if an element has three defined condition states and the entire element is found in condition state two, the health index of this element would be 50%, indicating the element just exactly passes a half of its service life. Obviously, this is not the case and drawing the health index, based on inspected condition states, as an arbitrarily predetermined point in a continuous timeline is not an appropriate conclusion. This situation is the same as when one has to guess the exact room temperature based on his sensing. The circumstance like this should be best dealt with using fuzzy theory that is presented in the next section.

Fuzzy Set Theory

Introduced the first time by Zadeh (1965), fuzzy set theory has developed rapidly and been applied in numerous areas. The usefulness of this theory is that it helps solve many decision making and control problems that are associated with fuzziness and the imprecision of human languages. Study efforts in the application of fuzzy set theory for evaluating the performance of constructed facilities in general can be found in Yao (1980), Hadipriono (1988), Tee (1988), Liang et al. (2001), Zhao and Chen (2002), Yan and Vairavamoorthy (2003), Kawamura and Miyamoto (2003), Najjaran et al. (2005), Sasmal et al. (2006), Kumar and Taheri (2007), Sasmal and Ramanjaneyulu (2008), Tarighat and Miyamoto (2009), Zhou et al. (2009), and Sun and Gu (2011).

For bridge condition assessments in particular, one of the initial efforts that applied fuzzy set theory can be found in Tee (1988). In his study, a model to assess conditions of bridge components based on mathematical operations on fuzzy sets was proposed. Specifically, the model makes use of fuzzy weighted average (FWA) arithmetic to combine bridge element ratings and their corresponding importance into the overall rating for each component. For example, suppose that a bridge superstructure has three subcomponents, including stringers, floor beams, and girders, in which the stringers have a good condition rating, the floor beams have a fair condition rating, the girders have a poor condition rating, and the importance coefficient of each element is given. Using the model that he proposed will provide the answer whether that superstructure is in good, fair, or poor condition. In the model, the output of the fuzzy weighted average operation is also a fuzzy set. Therefore, to determine which language term (rating expression), i.e., good, fair, or poor, best represents the overall superstructure condition, is based on the shortest distance between this resultant fuzzy set to the fuzzy set corresponding to each linguistic rating expression. The model was aimed to support NBI rating.

Kawamura and Miyamoto (2003) developed a rating system for assessing concrete bridges based on a neuro-fuzzy technique. In the model, bridge elements were evaluated in terms of load-carrying capability and durability, with the inputs including technical specifications, environmental conditions, traffic volume, and visual inspection. The neuro-fuzzy technique, also called soft-computing technique, is the fusion of a fuzzy inference system and an artificial neural network (ANN) in which the purpose of using a neural network is to refine the knowledge base of the fuzzy system.

Tarighat and Miyamoto (2009) proposed a fuzzy inference system to evaluate reinforced concrete bridge decks. The system utilizes multidistress inputs collected from inspection including crack-widths, spalls, delamination, hammer-tapping, and corrosion probability with a set of 162 different rules. The output of the model is a bridge deck condition rating that ranges from 0 to 100, in which 0 and 100 indicate perfect and worst conditions, respectively. The proposed system was expected to provide an excellent means to assess concrete bridge decks. However, the drawback of the model is that it treats a bridge deck as a whole and bases the assessment only on existing global distresses. This is not in line with current practices of bridge inspection in the United States and Canada which record condition states for an element according to its quantities. Therefore, it may be the case that the condition is bad with only a small deck region, but good in the remaining area. In such case, the model will rate the deck to be in bad condition.

Based on the early work of Tee (1988) and using fuzzy mathematical operations, Sasmal et al. (2006) proposed a condition assessment model for rating existing reinforced concrete bridges. The improvement of their approach was that they combined fuzzy weighted average (FWA) with an eigenvector-based priority setting methodology. In their model, each bridge is divided into three main components in which each of them, in turn, composed of a number of elements. The method first based on the inspected ratings and importance factors of all the elements of a component to combine these ratings into the overall component rating. The component ratings are then incorporated to produce the overall bridge rating by the same method. Because the product of such combinations is also a fuzzy set, a defuzzification procedure is therefore necessary. Similar to Tee (1988), the defuzzification is also performed based on minimum Euclidian distance.

Sasmal and Ramanjaneyulu (2008) proposed a very complicated condition rating system for the evaluation of reinforced concrete bridges. The system employs an analytic hierarchy process (AHP) and fuzzy logic to solve rating problem in a fuzzy environment. The rating process can be divided into several steps. First, the conditions of various reinforced concrete bridges are ranked and prioritized. Then based on the result of this prioritization, the rating of the most deserved bridge is carried out using multiattribute decision making (MADM). The inputs for the model are data collected using the NBI inspection standard.

Research Methodology

Similar to the idea of BHI when it uses the scale from 0 to 100 to represent the overall bridge condition, the question has to be answered in this research is how to convert bridge deck corrosion map found by GPR (Dinh et al. 2015) to a numerical format of BDCI.

As noticed previously, the way in which BHI calculates condition state weighting factors (WF) makes it a deterministic method that does not model any inherent uncertainty associated with inspection result. In reality, similar to other elements, bridge decks deteriorate gradually over time. Where corrosion-induced deterioration is concerned, the process starts with chloride ingression in concrete cover, then corrosion initiation, corrosion propagation, and finally delamination and spalls. Normally, a bridge deck will stay in each of these stages for a long period of time, and with current inspection methods, no one can specify exactly at which point the deck is on the rating scale. In other words, uncertainty modelling is needed to solve the research question. The uncertainty in this situation arises from fuzziness instead of randomness.

Based on the same scale used for BHI, this study visualizes that each condition category of a bridge deck during its service life would occupy certain sections along the continuum from 100 to 0, starting from excellent to failure conditions (Fig. 1). Because there is no way to directly measure the exact value of BDCI from a GPR corrosion map, expert opinion appears to be the only available option. Specifically, it was found that a group of bridge and GPR experts can be used to solicit the values regarding the boundaries of each condition category in the BDCI continuum. The sections corresponding to various condition categories can then be determined based on the aggregation of these opinions.

According to Hisdal (1986), to deal with a fuzzy problem appropriately, first the source of the fuzziness or uncertainty has to be identified. Specifically, he provided a list of fourteen different sources of fuzziness in which three main sources were considered giving rise to the membership function itself. Readers are advised to refer Hisdal (1986) for the full list of fuzziness sources, whereas the three main sources are explained here, including: (1) the fuzziness attributable to inexact conditions of observation, (2) the fuzziness attributable to classification in an underdimensioned or overdimensioned universe, and (3) the fuzziness attributable to the intersubject differences with respect to universe partitioning.

As the name implies, the first source of fuzziness discussed previously refers to the case when the concerned attribute values of objects can only be estimated with some possibility of making an error. For example, suppose that one already has his own clear criterion for defining hot weather. However, there would be the circumstance in which he does not know the exact temperature, and he has to judge whether the weather is hot or not, based on his perception. In such case, although the hot boundary is not fuzzy, the fuzziness still arises as a result of nonexact conditions of observation.

The second type of fuzziness occurs when an attribute is classified in a universe with the number of dimensions lower than it should be for purpose of classification. Because of that, nonfuzzy classification in the lower-dimensional universe is not correct, and a partial grade of membership is assigned to take into account the resulting fuzziness. This membership function is specified based on the estimated frequency of occurrence of different values in the excluded dimensions.

The problem of partitioning BDCI is related to the last type of fuzziness (Fig. 1). It refers to the case when the quantitative variation exists between different people in the choice of universe partitioning. For example, regarding the temperature again, one may consider a day cool when the temperature lies between 15 and 25°C, whereas the others may choose different ranges.

In comparison to the visual inspection method, bridge deck inspection using GPR technology considerably reduces the fuzziness extent, specifically the fuzziness attributable to inexact condition of observation explained in the preceding paragraphs. As pointed out by the FHWA (2001), it is very difficult in many cases for bridge inspectors to determine whether a given element is in this state or in its adjacent ones.

In industrial control and decision making, the membership function plays a very important role in determining the success of a fuzzy logic application. Realizing this, numerous studies have been performed investigating techniques for membership function generation such as Yang et al. (1991), Valliappan and Pham (1993), Beliakov (1996), Tamaki et al. (1998), Arslan and Kaya (2001), Lin and Chen (2002), Dombi and Gera (2005), and Yang and Bose (2006). These techniques are classified by Medasani et al. (1998) including: (1) subjective perception-based, (2) heuristic based, (3) multidimensional histogram, (4) probability distributions to possibility distributions transformation, (5) fuzzy K-nearest neighbor techniques, (6) neural network-based, (7) clustering technique, and (8) mixture decomposition technique.

As is shown, a vast number of techniques for generating membership functions have been proposed. Unfortunately, it was found that there are no guidelines or rules that can be used to select the appropriate membership generation technique. Also,

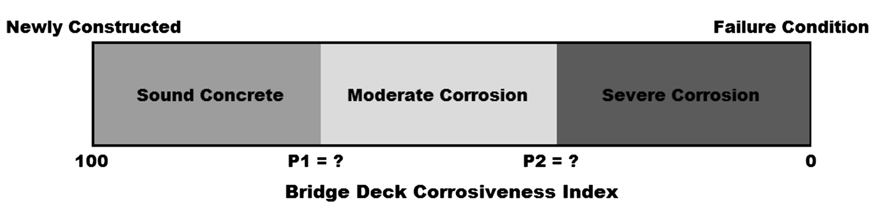


Fig. 1. Visualization of bridge deck corrosiveness index

Medasani et al. (1998) believed that it would be impossible to come up with a single membership generation method that would work for most applications.

Based on studying the literature, it was found that the integration of the first two techniques can be used for generating BDCI membership functions in this study. These two techniques are therefore described in detail in the subsequent paragraphs.

According to Medasani et al. (1998), membership function generation based on a subjective perception of vague or imprecise categories has been applied in many decision-making problems. In this category, several techniques can be used, for example, direct or reverse rating, polling, or the relative preference method. Specifically, in the direct rating procedure, a subject is presented with a random series of objects and then asked to indicate the membership degree to rate each one regarding an attribute. In the reverse rating procedure, the subject is presented with an ordered series of objects and asked to select the one best corresponding to the indicated degree of membership in the predefined category of the attribute. Thinking of the membership function as a cumulative distribution function, the polling technique assumes that semantic uncertainty is simply a statistical uncertainty in the information-theoretic sense.

More specifically, the values of membership functions are calibrated by randomly and repeatedly presenting a subject with elements and acquiring either a yes or a no response to the question: Does $\mathbf{x}$ belong to $\mathbf{A}$? The polling method implies that probability of a positive answer is proportional to membership value. Regarding relative preference method, the so-called pairwise comparison alternative matrix, denoting as $\mathbf{A}$, is used to compute membership values. In the matrix, element $\mathbf{a}_{ij}$ represents the relative membership value of an element $\mathbf{x}_i$ in a fuzzy set $\mathbf{F}$ with respect to the membership value of an element $\mathbf{x}_j$ in $\mathbf{F}$. The larger the value of $\mathbf{a}_{ij}$, the greater the membership of $\mathbf{x}_i$ compared with that of $\mathbf{x}_j$. The membership values are then determined by finding the eigenvector of $\mathbf{A}$.

Heuristic method assumes a predefined shape for a membership function. This technique has been employed successfully in many rule-based pattern recognition applications (Ishibuchi et al. 1993) in which some commonly used shapes for heuristic membership function include piecewise linear functions and piecewise monotonic functions. Realizing some clear advantages of piecewise linear membership functions, such as providing a reasonably smooth transition or easily being manipulated by fuzzy operators; however, Medasani et al. (1998) also had some criticisms. First, because heuristic methods are chosen to fit the given problem, they work well only for problems for which they are intended. Second, the shapes of the heuristic membership functions are not flexible enough to model all kinds of data. Third, the parameters associated with the membership functions must be provided by experts, and in some applications, they have to be fine-tuned until the performance is acceptable. This tuning process is however not a trivial task, especially in a high-dimensional system attributable to the interactions between variables and local minima.

The method used for finding membership function in this study is quite simple. First, it is assumed that membership functions are

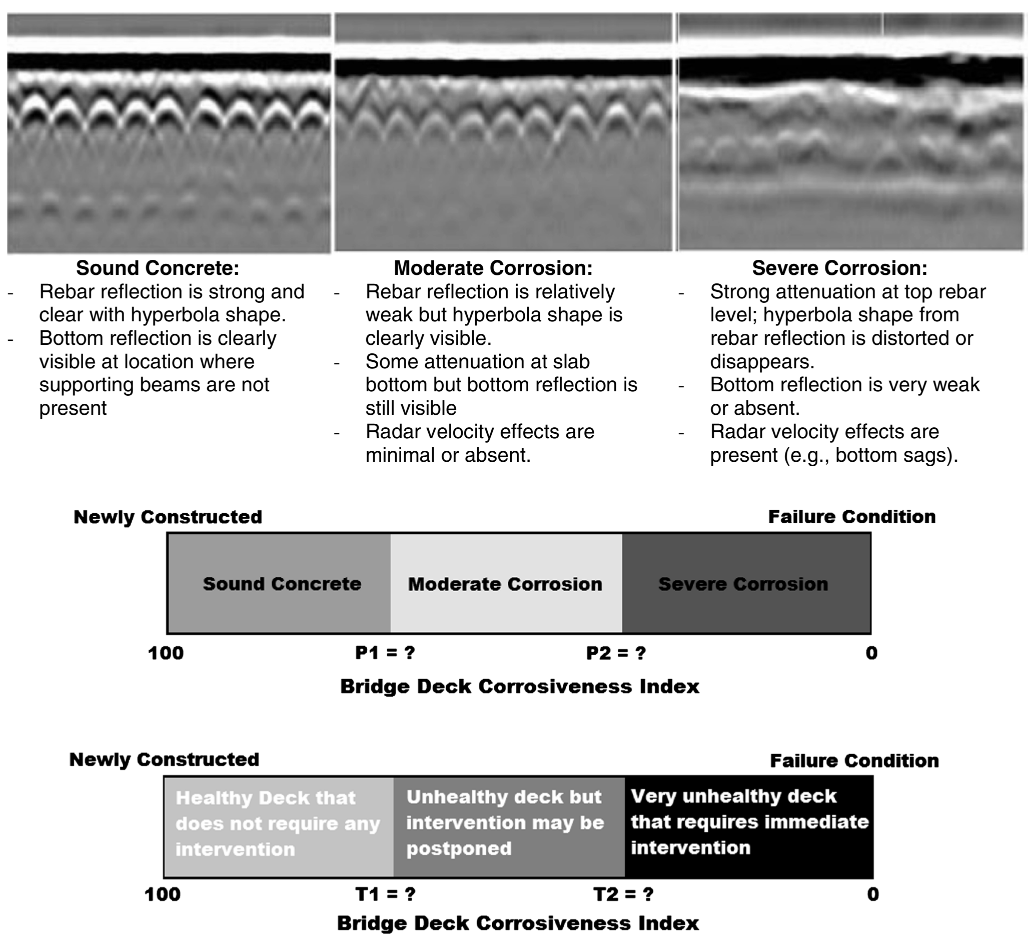


Fig. 2. Explanation of the survey

piecewise linear. Through a questionnaire survey, the parameters will then be determined based on linear regression analysis with an assumption the same as polling technique, i.e., the probability of a positive answer is proportional to the membership value.

Because the result of concrete bridge deck inspections using GPR is area percentages of various condition categories, and aggregation of this information is required. As discussed previously, Tee (1988) found in the literature two techniques that can be used for combining fuzzy information or knowledge, namely fuzzy weighted average (FWA) and weighted fuzzy union (WFU).

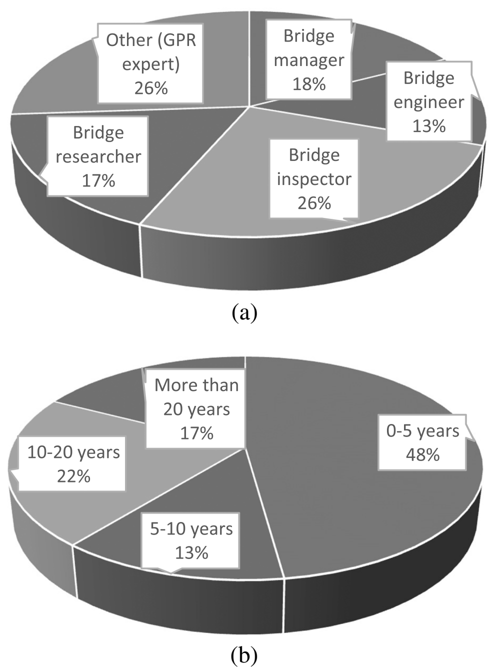


Fig. 3. Respondents based on (a) expertise; (b) experience

Table 1. Summary of the Responses for P1, P2, T1, and T2

Response number	P1	P2	T1	T2
1	90	50	75	30
2	70	40	80	60
3	60	40	60	40
4	80	30	60	30
5	80	60	80	60
6	70	30	70	40
7	70	30	75	25
8	75	55	70	45
9	85	70	75	50
10	80	60	80	60
11	60	40	80	60
12	80	50	70	40
13	75	55	80	60
14	75	45	60	40
15	80	40	70	30
16	70	50	60	40
17	80	50	70	50
18	75	25	75	25
19	70	30	70	30
20	66	33	66	33
21	60	30	50	30
22	85	65	80	60
23	80	60	80	70

Basically, the former technique is used when weighting factors are fuzzy sets themselves, whereas the latter is more appropriate if the weights are crisp numbers. The mathematical form of WFU is presented in Eq. (2). As is shown, the result obtained from the equation is also a fuzzy set itself

$$\bar{F} = U\left(\sum_{i=1}^{n} W_i F_i\right) \tag{2}$$

where F_i = fuzzy set ith; $\bar{F}$ = resultant fuzzy set; U = fuzzy union operator; and W_i = nonfuzzy weighting factors.

As in the case of fuzzy inference system and fuzzy control, the resultant fuzzy output always needs to be defuzzified to make a concrete decision or control action. Because there is no systematic procedure for choosing a good defuzzification strategy (Lee 2005), the present study will compare the two most commonly used methods, namely centroid and bisector defuzzification. Although the first technique finds the center of gravity, the bisector is the vertical line that divides the possibility distribution of the resultant fuzzy set into two subregions of equal area. The horizontal position of the point or the line represents the crisp output for making decisions or taking control action.

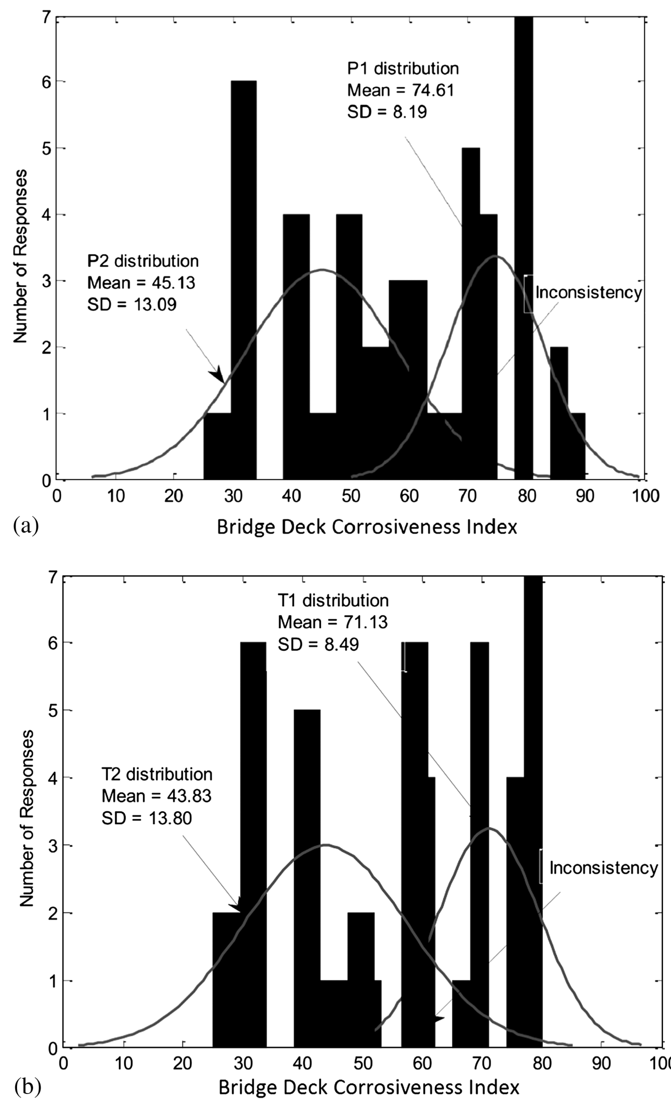


Fig. 4. Inconsistency: (a) between P1 and P2; (b) between T1 and T2

Data Collection and Analysis

As explained previously, a questionnaire survey was used in the research methodology. Its main purpose was to solicit opinions from bridge and GPR experts for building membership functions that will finally be used to convert GPR condition map to the numerical format of BDCI. However, because another research question was also raised regarding how that index will be used by bridge managers for deck maintenance decision making, extra questions were added in the survey.

Concerning the questionnaire design, it consists of two main sections. The first section asked the respondents to give some information about themselves such as their name (optional), expertise and experience. In the second and also the main section of the survey, they were requested to provide specific percentages for partitioning (P1 and P2), for thresholds (T1 and T2), (Fig. 2), and to suggest intervention actions corresponding to these thresholds. The questionnaire was developed on the web survey website http://www.surveymonkey.com. The link was then delivered either directly to bridge and GPR expert, or through LinkedIn, a business-oriented social networking service. In addition to special feedback representing the collective opinion of the Ministry of Transportation of Quebec (MTQ), other received responses are described in the next section.

Response Rate

Response rate refers to the number of experts who answered the survey divided by the number of experts in the sample. However, because of the manner in which the survey was delivered, resulting in unknown sample size, the number of experts who did open the link and responded to at least one question is considered instead as the number of experts in the sample. With that number being 83 and 23 experts completing the survey, the response rate is therefore 27.7% in this study.

Response rate has long been considered by many people as an indicator for the quality of a research survey. Although it is believed that higher response rates assure more accurate survey results, satisfactory number is still of controversy. To address this issue, Baruch (1999) conducted a study that explored what could and should be a reasonable response rate for academic research in which statistics from 141 journal papers were investigated. Based on that study, he found that reasonable response rate for the survey that targets populations such as employees, managers or professionals was approximately 60 ± 20 (%). He suggested that for future studies that use questionnaire survey, any downward deviation in response rate from this norm should be explained.

Given the suggestion from Baruch's research, there are some justifications for a fairly low response rate obtained in this study. First, although many bridge experts are not familiar with GPR and cannot understand even rebar pattern explained in the survey, some of them had direct correspondence with the authors informing that they had bad experience with the technology. Second, some experts expressed their concern about the BHI itself when in their agencies, it rarely enters the discussion on what strategies to take for planning deck intervention. Finally, but possibly the main reason, many respondents may not be

Table 2. Rearranged Responses for P1, P2, T1, and T2

Response number	P1	P2	T1	T2
1	**60**	25	**50**	25
2	**60**	30	**60**	25
3	**60**	30	**60**	30
4	**66**	30	**60**	30
5	**70**	30	**60**	30
6	**70**	30	**66**	30
7	**70**	33	**70**	30
8	**70**	40	**70**	33
9	**70**	40	**70**	40
10	75	40	**70**	40
11	75	40	**70**	40
12	75	45	**70**	40
13	75	50	75	40
14	80	50	75	45
15	80	50	75	**50**
16	80	50	75	**50**
17	80	55	80	**60**
18	80	55	80	**60**
19	80	**60**	80	**60**
20	80	**60**	80	**60**
21	85	**60**	80	**60**
22	85	**65**	80	**60**
23	90	**70**	80	**70**

Note: Bold values indicate the conflicted values in the responses and therefore be candidates for removal.

Table 3. Distance Calculation for Inconsistency Removal

Sample	Mean (1)	SD (2)	Candidate removal (3)	Distance (1–3)/2
P1	74.61	8.19	60	**1.78**
P2	45.13	13.09	60	1.13

Note: Bold value indicates the final decision where 60 is to be removed from P1 sample, not P2 sample.

Table 4. Retained and Removed Values for P1, P2, T1, and T2

Response number	P1	P2	T1	T2
1	**60**	25	**50**	25
2	**60**	30	**60**	25
3	**60**	30	**60**	30
4	66	30	**60**	30
5	70	30	**60**	30
6	70	30	66	30
7	70	33	70	30
8	70	40	70	33
9	70	40	70	40
10	75	40	70	40
11	75	40	70	40
12	75	45	70	40
13	75	50	75	40
14	80	50	75	45
15	80	50	75	50
16	80	50	75	50
17	80	55	80	60
18	80	55	80	60
19	80	60	80	60
20	80	60	80	60
21	85	60	80	60
22	85	**65**	80	60
23	90	**70**	80	**70**

Note: Bold values indicate the conflicted responses to be removed based on distance calculation.

familiar with the way in which the main questions were asked when instead of multiple-choice options, they were requested to provide specific numbers which was proposed for the first time by this study.

Respondent's Information

Summary information for 23 respondents who completed the survey are presented based on their expertise in Fig. 3(a), and their experience in Fig. 3(b). As is shown, although all expertises favorable for answering the questionnaire were covered, the highest numbers of respondents were equally shared between bridge inspector and GPR expert groups, each with 26%. The numbers of bridge managers and bridge researchers participated were the same, approximately 18% for each group. Finally come bridge engineers, the last group with only 13%.

Regarding experience, interestingly, the highest participant rate belong to youngest professionals with 48% followed by the senior group with 22% responses. The most senior respondents accounted for 17%, whereas the experts with 5–10 years of experience shared the smallest portion of the pie with only 13%.

Membership Function Calibration

Although all the responses for P1, P2, T1, and T2 values are provided in Table 1, the calibration process is described in the setions that follow.

Step 1. Check the First Level of Consistency

As advised in the questionnaire, experts were expected to provide consistent opinions, i.e., P1 value should be greater than P2 and the same with T1 and T2. However, because one expert did not know what would be the number provided by the others. As a result, the consistency should be checked at both levels, individual, expert, and the entire group. As is shown in Table 1, for the first level check, no individual expert provided inconsistent judgment.

Step 2. Check the Second Level of Consistency

To check the second level of consistency for the entire group, a histogram and assumed normal distribution fitting is plotted for each number couple, i.e., P1 and P2 and T1 and T2. Although this plot is shown in Figs. 4(a and b), as is shown, they show some inconsistency at group level that need to be eliminated.

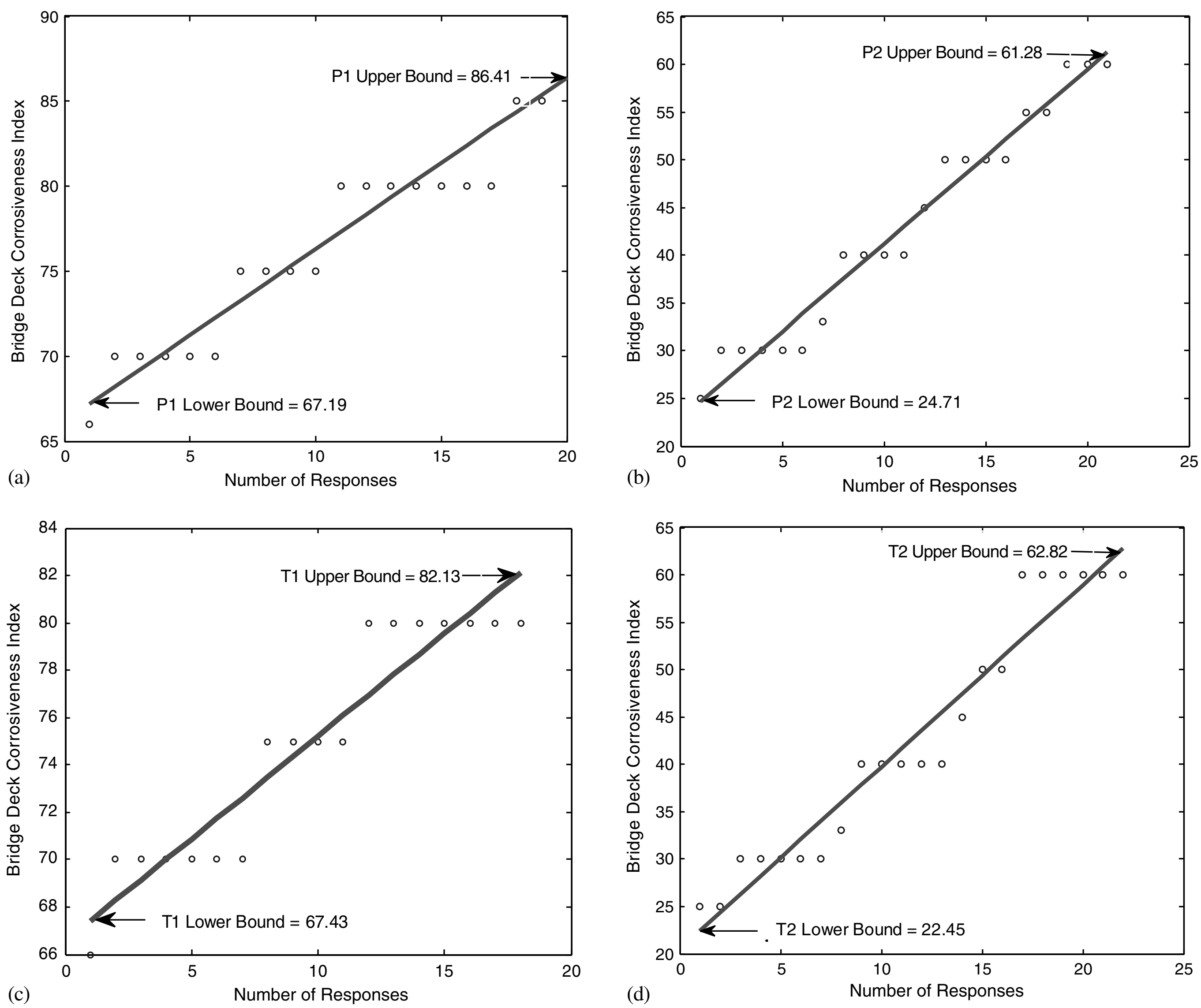


Fig. 5. Linear regression for (a) P1; (b) P2; (c) T1; (d) T2

To do that, it is proposed that first, the responses in Table 1 are rearranged in increasing order for each column as shown in Table 2. Then any value in Table 2 that lies in inconsistency zone is highlighted and will be considered as a candidate for removal. The removal is done based on the distance from normal distribution model, using standard deviations. For instance, 60 appears to be present in both P1 and P2 columns. To consider whether that value should be removed from P1 or P2 sample, a calculation illustrated in Table 3 is used. As is shown, because the value, 60, is closer to the mean of P2, it should be removed from P1 sample.

Following the same procedure, all the removed values from each sample are highlighted and shown in Table 4. As can be realized, this inconsistency removal method also results in the lowest number of responses being removed.

Step 3. Linear Regression for Determining Membership Function Boundaries

With the retained values for each sample in Table 4, and because membership functions were assumed to be piecewise linear, the boundaries for membership functions are determined based on linear regression as shown in Fig. 5. Finally, the membership functions based on the results in Fig. 5 is shown in Fig. 6.

Selection of Defuzzification Method

Ideally, the BDCI should have the range from 100 to 0; however, because of fuzzy information provided by GPR corrosion map, this range can never be achieved for the BDCI computed from the model. Therefore, between the centroid and bisector methods for defuzzifying the resultant fuzzy set, this research selected the strategy that provides maximum range of the index. As is shown in Fig. 7, although showing small difference, bisector defuzzification was the selected technique.

Intervention Actions

Regarding intervention action, as is shown in Fig. 8(a), 65% respondents suggest repair for bridge decks those are unhealthy but intervention can still be postponed. None of them consider total deck replacement, 18% recommend do nothing and more frequent monitoring, and 17% think of other solutions such as chloride or additional NDE testing.

For bridge decks those are very unhealthy [Fig. 8(b)], and 57% of respondents suggest total deck replacement, 30% of them recommend repair, and 13% propose other actions. These newly-proposed intervention actions include: (1) deck reinforcement and (2) partial deck replacement for safety until plans can be developed for total deck replacement.

Although the majority of experts responded by choosing one intervention action in the list provided in the survey, not all of them felt satisfactory. Their reaction for this was either (1) to correspond and discuss directly with the authors or (2) to choose an action different from those listed. Regarding BDCI thresholds and corresponding intervention actions, MTQ recommended the two following scenarios. The first scenario is when only one threshold value T is used. Then, if the BDCI is greater than T: do-nothing; otherwise, intervention should be planned in a 5–20 year horizon for the deck in question. The second scenario is the one in which two threshold values T1 and T2 are employed. Then, if BDCI is more than T1: no repair or replacement intervention; if BDCI is below T1 and more than T2: an intervention planned in a 10–20 year horizon; and below T2: an intervention planned in a 5–10 year horizon.

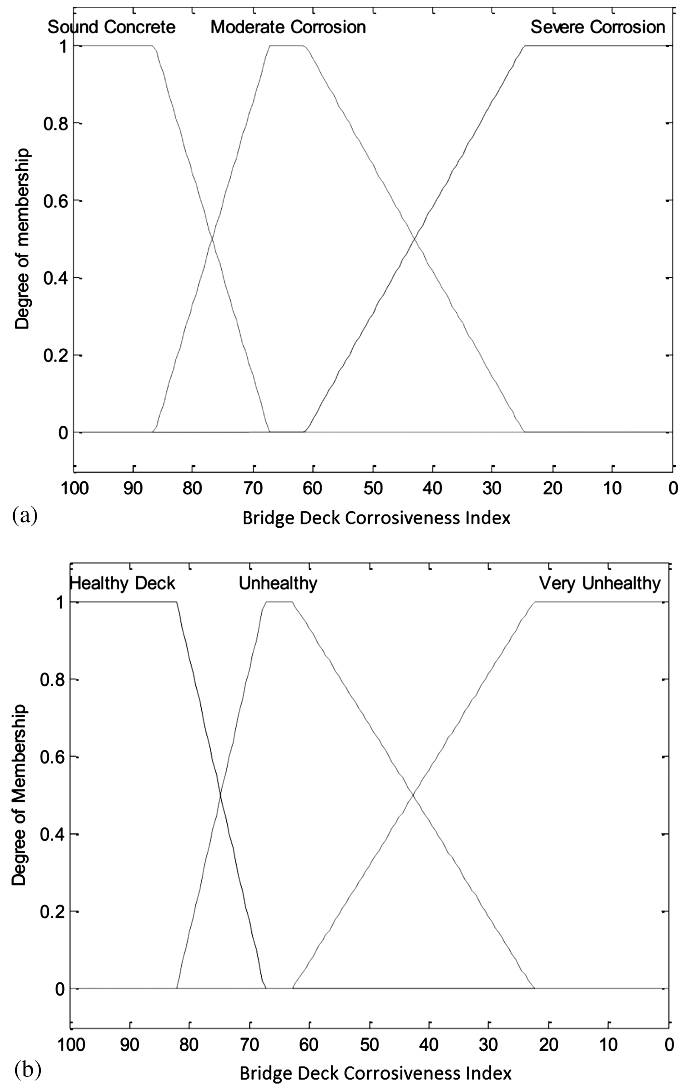


Fig. 6. Calibrated membership functions based on (a) P1 and P2; (b) T1 and T2

On the contrary, the authors also received a suggestion from an expert who participated in the survey that they should consider more decision points (thresholds), instead of the two (T1 and T2) used in the questionnaire. Benefited from all these suggestions, a comprehensive strategy for using BDCI is proposed in the next section.

Strategic Use of Bridge Deck Corrosiveness Index

As is shown, fuzzy partitioning exists with both threshold T1 and T2 when each of them has lower and upper bound as shown in Figs. 5(c and d). What that indicates is, for the same BDCI value that lies in these fuzzy areas, experts do not share the same opinion regarding intervention needed for bridge deck with a specific BDCI in question. For example, if a bridge deck has a BDCI value of 80.00, some experts would consider the deck being completely healthy whereas others would think it is unhealthy and needs intervention. Considering these fuzzy regions along with recommendations discussed previously, it is reasonable to redefine the levels of intervention needs that integrate lower and upper bounds of T1

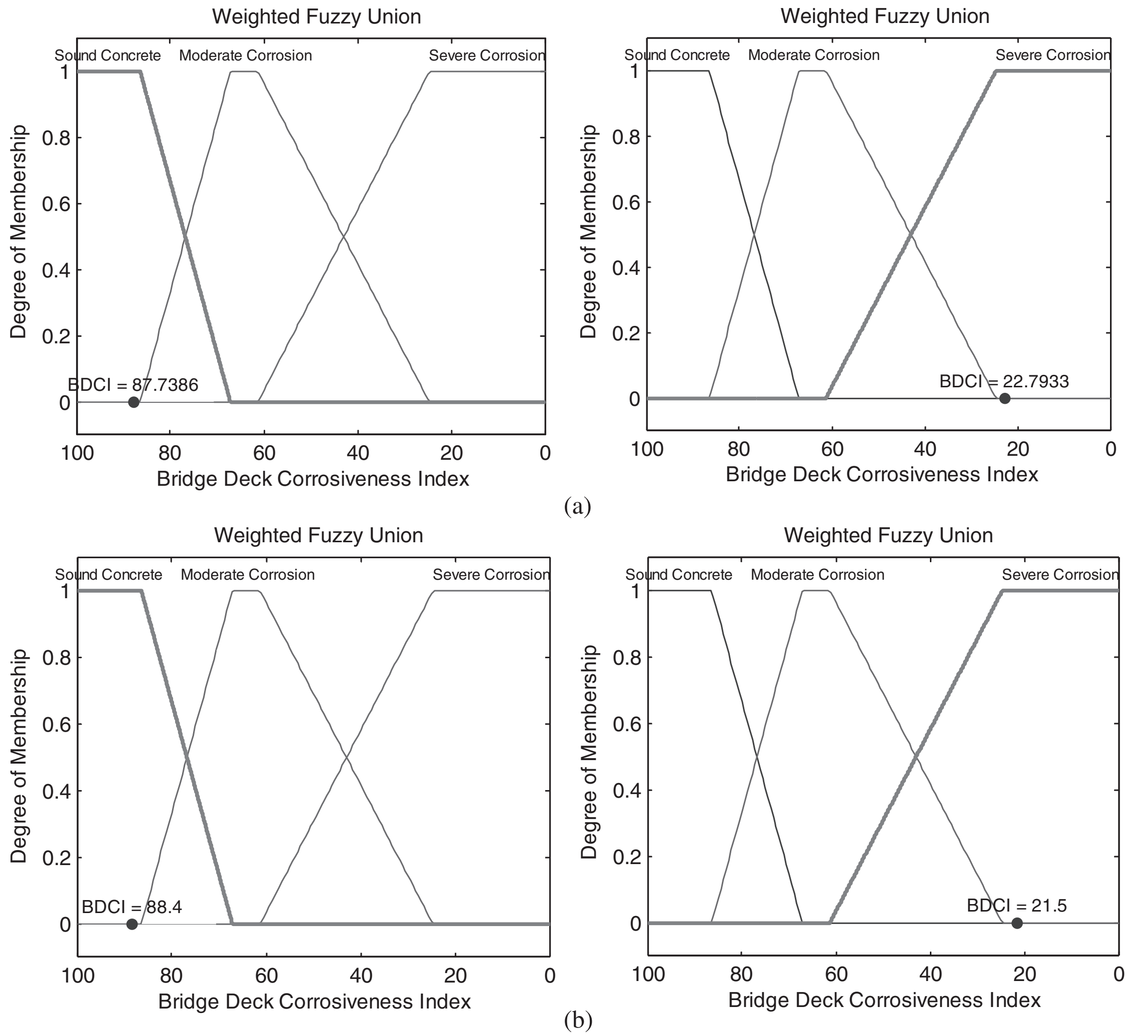


Fig. 7. Defuzzification with (a) centroid method; (b) bisector method

and T2. The proposed levels of BDCI and corresponding recommended actions are provided in Table 5.

Table 5 shows that at some levels of BDCI, instead of a single intervention type, a list of feasible actions may be provided. If that is the case, intervention actions are put in recommendation priority order, indicating that the first type of action is recommended more strongly than the second one and so on. This approach is more practical than providing a single action, considering the fact that bridge decks competing with one another for the limited maintenance budget.

Justification exists for specifying maximum 10–20 years of separation between GPR scans. With commonly high deterioration rate of bridge decks, considerable corrosion might have built up on healthy decks but undetected if this period is set too long. In contrast, for bridge decks those have shown some unhealthy sign, Table 5 suggests that if intervention action is not taken, GPR inspection frequency should be increased.

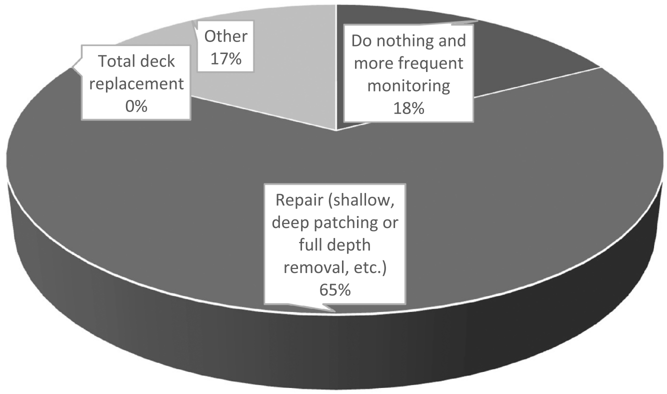
In addition to provide important input that will be used by bridge maintenance planner and bridge program manager, the BDCI model developed in this research also provides an useful tool for high-level decision-makers or elected authority. For example, these agencies can use the index for communication with the public to gain more attention about bridge deck conditions or to justify the budget that they ask for fixing bridge problems.

Case Study Implementation

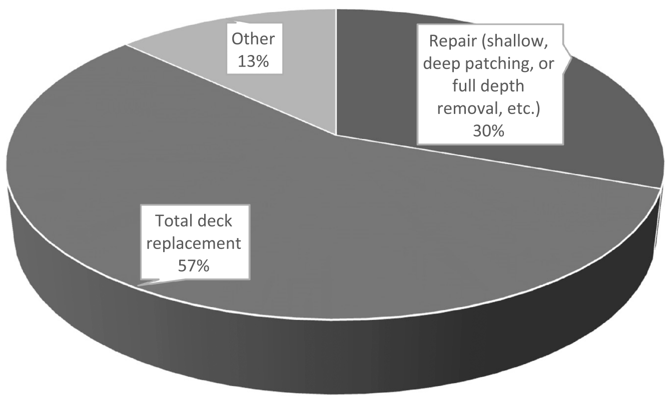
To implement the BDCI model, a software named GPR-based bridge deck condition assessment system (GPR-BriDCAS) has been developed in this study. Coded in C#, the software has two main components. The first one is to determine threshold values and to calculate area percentages of various condition categories based on K-means clustering (Dinh et al. 2015). In the second component, the area percentages obtained will be employed to compute the BDCI. Using the software, the developed model is implemented for several concrete bridge decks in North America, specifically, one bare concrete bridge deck in New Jersey, United States; and two asphalt-covered concrete bridge decks in Quebec, Canada.

Bridge A in New Jersey, United States

Bridge A in Warren County, New Jersey, was built in 1978 with a bare concrete slab resting on five steel girders. The bridge has been extensively studied and monitored by Rutgers University where other NDE technologies are also deployed frequently on the bridge deck. Although the corrosion map found by GPR has been confirmed by other NDE techniques, this paper only focuses on management aspect of using GPR result.



(a)



(b)

Fig. 8. Suggested intervention actions for (a) an unhealthy bridge deck with BDCI smaller than threshold T1; (b) a very unhealthy bridge deck with BDCI smaller than threshold T2

As is shown in Fig. 9(a), the output provided by the software are: (1) amplitude threshold values based on K-means clustering; (2) area percentages of each condition category; and (3) bridge deck corrosiveness index (BDCI). The threshold values are then used to change conventional amplitude contour map to the map in Fig. 9(b), with specific linguistic description of each condition category, i.e., sound concrete; moderate corrosion and severe corrosion.

Regarding WFU algorithm to determine BDCI value, in the figure, the thick, magenta line represents the fuzzy membership function of the resultant fuzzy set which was determined based on the area percentage of each condition category, i.e., sound concrete, moderate, severe corrosion; and the corresponding fuzzy membership functions developed in the previous section. As is shown, with the BDCI value of 68.94, the bridge deck is Category B, indicating it is slightly unhealthy, but intervention is not yet necessary.

Bridge B in Quebec, Canada

The Bridge B in Quebec, Canada was built in 1966, consisting of a 30-cm reinforced concrete deck with asphalt overlay that rests on five I-shaped steel girders. The deck has a width of eight m and a total length of approximately 55 m with three continuous spans. The bridge is a little skewed and in some areas at the bottom of the slab, spalls can be easily observed. As is shown, the result in Fig. 10 suggests that the deck of Bridge B is in category C, indicating it is unhealthy, intervention is needed but may be postponed. Based on Table 5, the recommendation for the bridge owner is that they should repair the bridge in the next 5–10 year programming horizon using available techniques such as shallow patching, deep patching, or full depth removal. The selection of which technique should depend on level of chloride contamination on each specific area. However, in case the intervention is postponed, the deck should be monitored with GPR for that same period.

Bridge C in Quebec, Canada

Bridge C in Quebec, Canada, was built in 1965 with a total length of 64.5 m. It consists of four spans in the north-south direction. The bridge is formed by a deck varying in thickness (between 60 and 110 cm) resting directly on piers and abutments. The total width of the deck is 12.8 m with nine m of traveled way. As is shown in Fig. 11, with BDCI value of 60.26, the deck of bridge C is classified as category D, indicating it is a very unhealthy deck and intervention is strongly recommended. The recommendation for this deck is that it should be totally replaced in the coming 5–10 year programming period.

Discussion

The case studies clearly illustrate the implementation of the BDCI model developed in this study. Similar to the idea of the BHI, however, BDCI possesses some distinguished features as follows. First, the BDCI assesses concrete bridge decks based on GPR, a more accurate evaluation technology. Second, it employs the knowledge provided by bridge community and in the meantime has the capability to deal with fuzzy information associated with expert responses.

Table 5. Strategic Use of BDCI and Inspection System

Level of intervention need (category)	Value of BDCI	Intervention need description	Recommended actions within 20-year horizon
A	100–82.13	Healthy deck, no intervention is required	Do nothing, next GPR inspection is planned in 10–20 year horizon
B	82.13–67.43	Slightly unhealthy deck, intervention is not yet necessary	Do nothing, next GPR inspection is planned in 5–10 year horizon
C	67.43–62.82	Unhealthy deck, intervention is needed but may be postponed	1. Deck repair is planned in 5–10 year horizon 2. Next GPR inspection is planned in 5–10 year horizon
D	62.82–22.45	Very unhealthy deck, intervention is strongly recommended	Total deck replacement is planned in 5–10 year horizon
E	22.45–0.00	Completely unhealthy deck, immediate intervention is required	Total deck replacement is planned in 0–5 year horizon

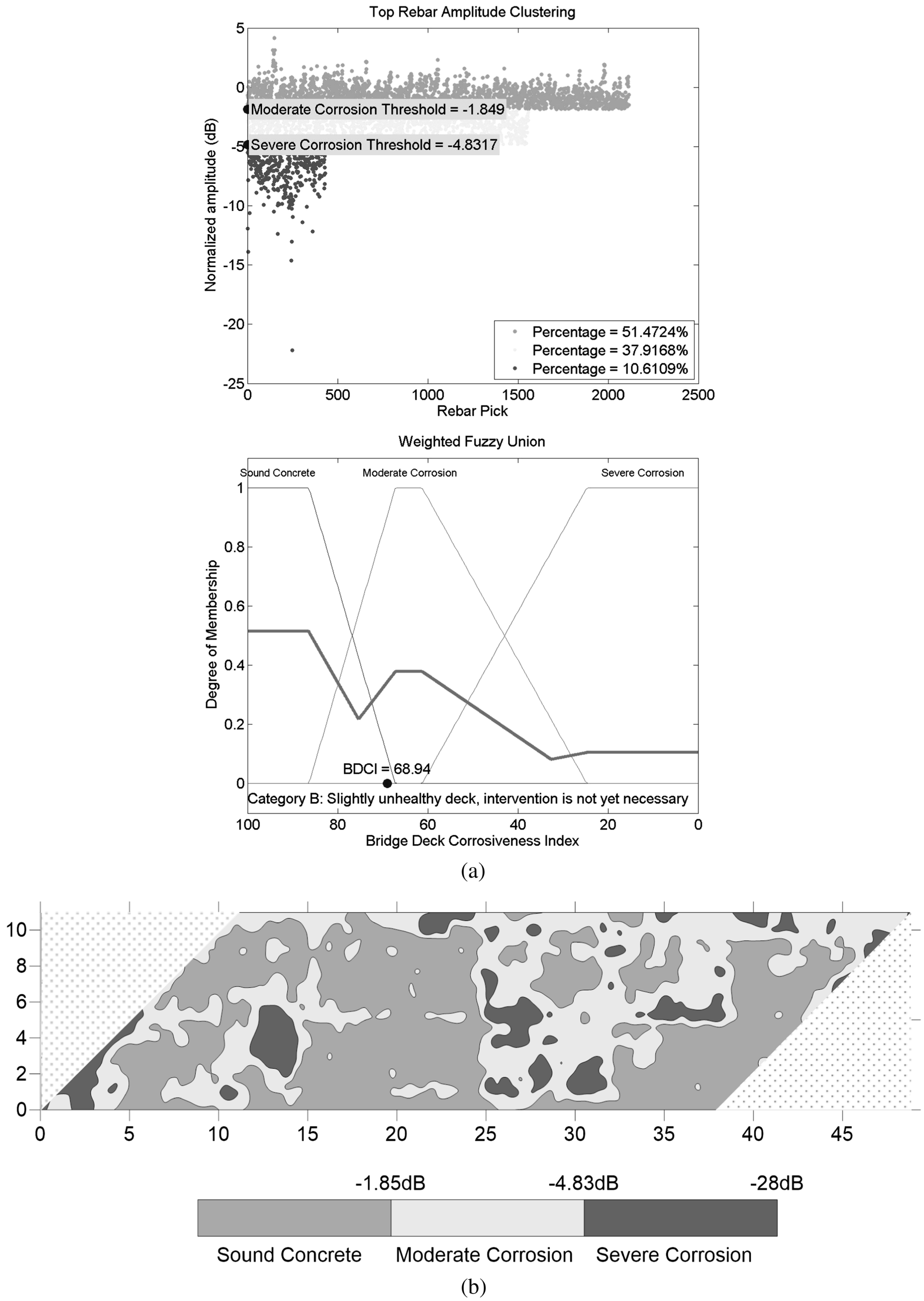


Fig. 9. (a) Output provided by the software; (b) corrosion map for bridge A

However, because the developed model is completely based on GPR, some limitations of this evaluation technique should also be noted. Specifically, GPR is not a technology that can work well for all bridge decks. For example, the variation of pavement and cover thickness, or rebar spacing, might significantly affect the interpretation of amplitude data. Moisture trapped underneath waterproofing membrane might absorb most of the radar because of its dielectric property and lead to a misinterpreted condition map. In addition, local variation of moisture in bridge deck might affect the accuracy of depth correction technique. In such extraordinary cases, it may be more reasonable to interpret GPR data using the image analysis method developed by Tarussov et al. (2013). The final output is still a GPR condition map appropriate for the BDCI model proposed in this research.

Although the proposed BDCI model is certainly a useful tool for project programming at a network level, one might suspect the adequacy of GPR survey for preparation of rehabilitation contract. What is suggested is that in certain cases in which the output of

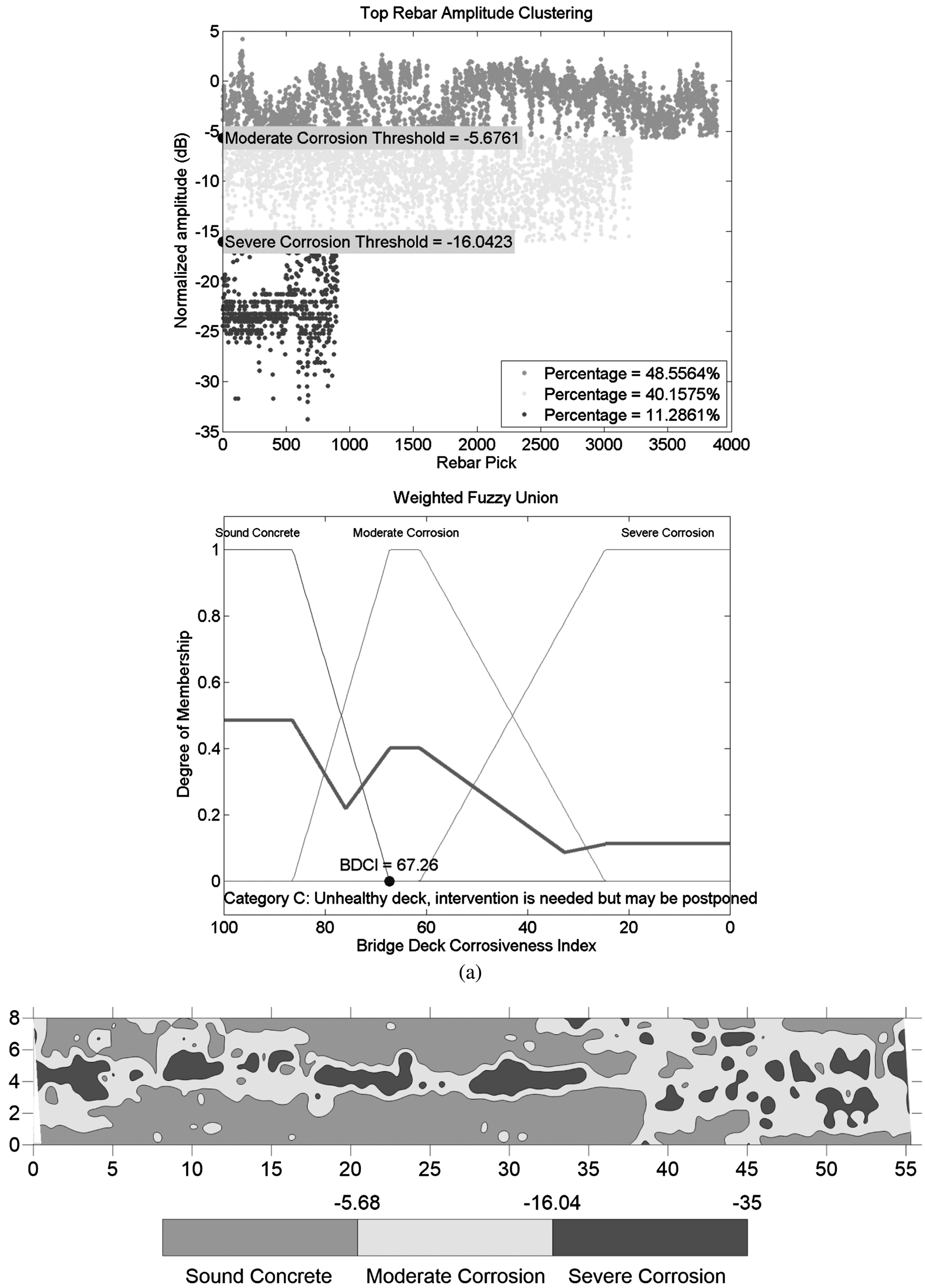


Fig. 10. (a) Output provided by the software; (b) corrosion map for bridge B

GPR seems to be questionable, additional evaluation methods such as hammer sounding, half-cell potential, chloride analysis or other techniques might be used. Even if that is really the case, the BDCI still helps to identify deficient bridge decks better than visual inspection method.

It is not necessary for transportation agencies to use the exact numbers obtained in this study. Instead, they are encouraged to apply the proposed methodology. Specifically, a group of bridge engineers and bridge inspectors in their agency can provide the information that was asked in the questionnaire. The responses can then be analyzed in the same manner described in this study and be fine-tuned by a second round of survey if necessary.

Conclusions

Beside accurate inspection technologies, transportation agencies are required to have a rational framework for communicating their

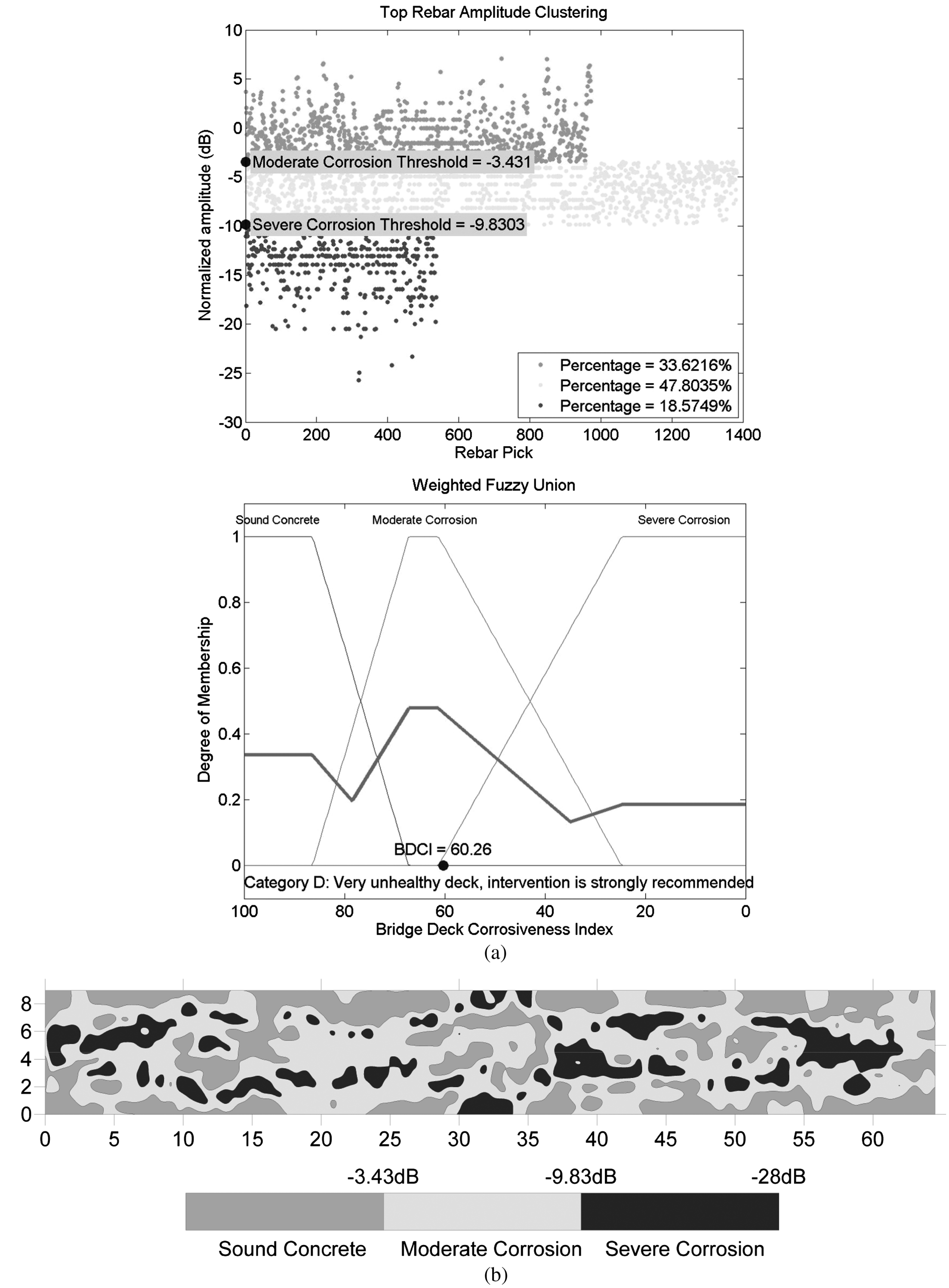


Fig. 11. (a) Output provided by the software; (b) corrosion map for bridge C

bridge condition internally, and with the public. The BDCI model developed in this study was aimed for that need. As an indication of corrosive environments in bridge decks, the index can be used, along with other performance measures, for planning deck maintenance activity for an individual or a network of bridges. As has been seen, for an individual bridge, the BDCI can be used to specify maintenance need and to suggest intervention activity. At network level, they can be employed to rank bridge deck maintenance projects according to maintenance priority, or to justify to the public the budget that they ask for fixing bridge problem. Therefore, the proposed BDCI model should certainly be of interest to transportation agencies in North America where corrosion of rebar in concrete bridge decks is one of the biggest concerns.

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