Eslam Mohammed Abdelkader*,†, Mohamed Marzouk†and Tarek Zayed‡
*Department of Building, Civil and Environmental Engineering, Concordia University, Montreal, QC Canada
†Structural Engineering Department, Faculty of Engineering, Cairo University, Egypt
‡Department of Building and Real Estatethe Hong Kong Polytechnic University, Hong Kong

An Invasive Weed Optimization-based Fuzzy Decision-making Framework for Bridge Intervention Prioritization in Element and Network Levels

ABSTRACT

Recently, the number of deteriorating bridges has drastically increased. Furthermore, tight maintenance budgets are cut down; imposing escalating adverse implications on the safety of bridges. This state of affairs entails the development of decision support systems for the effective management of bridges within the allocated budget. As such, the present study introduces an invasive weed optimization-based fuzzy decision-making framework designated for bridge intervention prioritization in both element and network levels. The proposed decision-making platform encompasses three main tiers. The first tier is an optimized fuzzy analytical network process model that aims at computing the weighting vector of the bridge defects, namely corrosion, delamination, cracking, spalling and scaling. In this model, a genetic algorithm optimization model is formulated to improve the consistencies of judgment matrices through circumventing the imprecisions encountered by the classical judgment assignment. The second tier encompasses establishing an integrated bridge deck condition assessment model capitalizing on ground penetrating radar and inspection reports. In it, the severities of the bridge defects are demonstrated in the form of fuzzy membership functions to address the inherent uncertainties of inspection. Subsequently, a variable-length invasive weed optimization model is structured to automatically calibrate the fuzzy membership functions. The third model is designed for structuring a bridge maintenance decision-making strategy stepping on the integrated condition index. The capabilities of the proposed framework were validated through several levels of comparisons. For instance, it significantly outperformed some of the current condition assessment models. Additionally, it inferred that the thresholds separating the four categories of the integrated bridge deck condition index are: 75.651, 67.769 and 60.318.

Keywords:

Decision-making framework; bridge intervention; optimized fuzzy analytical network process; ground penetrating radar; invasive weed optimization; fuzzy membership functions

Electronic version of an article published as International Journal of Information Technology & Decision Making, Vol. 19, No. 05, 2020, pp. 1189-1246, https://doi.org/10.1142/S0219622020500273, © World Scientific Publishing Company, https://www.worldscientific.com/worldscinet/ijitdm

1. INTRODUCTION

In the recent years, the number of worldwide deficient bridges has increased radically owing to the fact there are limited available funds for maintenance, repair and rehabilitation. This motivated researchers and decision-makers to pay more attention to the maintenance planning of deteriorating bridges, whereas the backlog of maintenance activities can result in the increase of repair costs to the extent that repairing the deteriorating bridges is more expensive than building new ones (Miyamoto et al., 2001).

In Canada, the instantaneous and serious economic and environmental impacts of bridge collapses besides the high owner and user costs have drawn the attention to the importance of bridge management systems. Bridges experience accelerated aging and extensive deterioration and larger portion of them require urgent rehabilitation or replacement. The bridges consumed approximately 57% of their service life, whereas their average age is considered as the second highest among the five main assets, namely roads, bridges, water supply systems, wastewater treatment facilities and sewer systems. Bridges in Quebec reached higher levels of deterioration such that they reached 72% of their service life, which is regarded as the highest average age among all the provinces of Canada. On the other hand, bridges in Prince Edward Island have the smallest average age, which is 15.6 years. This can be attributed to that about 70% of the bridges in Quebec were built between the 1960s and 1980s (Farzam et al., 2016; Viami International Inc. and the Technology Strategies Group, 2013).

Another aspect that amplifies the deterioration in the bridges is the decline in the public investment. The public investment peak was 3% of the gross domestic product (GDP) in the late 1950s and it declined steadily until the mid of the 2000s. The decline in the investment is over 40 years from the late 1950s to the mid of the 2000s. Most of the decline was in the first 20 years, where the investment dropped from 1.6% of GDP in 1959 to 0.4% of GDP in 1979. This induced a backlog of bridge maintenance, rehabilitation and replacement of $10 billion (Sennah et al., 2011).

In the light of foregoing, it is essential to build efficient bridge management systems (BMSs) to aid decision makers in maximizing the safety, functionality and serviceability of bridge networks while maintaining cost-effective repair, rehabilitation and replacement plans within available budget. Condition assessment is regarded as one of the main pillars of bridge management systems, which aids in presenting an in-depth evaluation of the performance of element level components. Transportation agencies need comprehensive condition assessment models to evaluate the condition of the bridge elements. The accurate documentation for the extent of deterioration of the bridge decks provides well-established deterioration curves. Accordingly, the infrastructure managers can plan the optimal maintenance, repair and rehabilitation (MR&R) actions for both project and network levels.

The primary objective of the present study is to develop an invasive weed optimization fuzzy decision-making framework that enables the asset managers to define and prioritize the maintenance requirements of the concrete bridge decks based on an integrated condition index. Moreover, the developed framework enables the decision maker to define in detail the extent of severity for each type of the bridge defects separately. The main objectives of the present study can be summarized as follows:

1. Review the previously developed models and define their shortcomings.
2. Develop an integrated bridge deck condition index (IBDCI) that supports both element and network levels decisions.
3. Build a bridge maintenance decision-making strategy based on the IBDCI.
4. Define the most influential bridge defect that affects the IBDCI.
5. Validate the developed framework through several case studies.

2. LITERATURE REVIEW

Literature review is composed of three main sections, namely condition assessment of the bridges, calibration of the fuzzy membership functions and research gaps. It is worth mentioning that the IBDCI is obtained based on an optimization-based model that requires an efficient paradigm for the purpose of calibration of fuzzy membership functions.

2.1 Condition Assessment of Bridges

Several efforts were performed to develop maintenance prioritization models for reinforced concrete bridges. Alsharqawi et al. (2020) developed a numerical ground penetrating radar scale to evaluate the corrosiveness in reinforced concrete bridges. K-means clustering method was applied to compute the thresholds of the amplitude values. Some statistical analysis tests were adopted to define the best-fit distribution of the thresholds, namely Kolmogorov-Smirnov test, Anderson Darling, and chi-squared test. They highlighted that the thresholds that separate the “Very Poor” category from “Poor” category, “Poor” category from “Medium” category, and “Medium” category from “Good” category follow logistic distribution, logistic distribution and triangular distribution, respectively. Then, Weibull distribution was adopted to simulate the deterioration of the bridge decks using the output of the ground penetrating radar. Dromey et al. (2020) developed a model to rank the rehabilitation priority of bridges based on a set of characteristic attributes. Linear regression analysis was used to predict the annual degradation in the condition ratings of the bridges. The prioritization index was established based on ten influencing factors including: overall structural condition, number of spans, bridge material, rehabilitation cost, etc. Additionally, stepwise multiple regression analysis was conducted to generate the best combination of independent variables that constitute the prioritization index. They highlighted that the developed model could serve as a robust process to optimize the annual investments designated for bridge network rehabilitation.

Bukhsh et al. (2019) presented an approach for network level maintenance planning using multi-attribute utility theory. The proposed approach prioritized the bridges by accommodating different attributes which were: improving assets’ reliability, minimizing agency cost, minimizing impact on users and maintaining the bridge network safety. They suggested that the proposed approach can improve the decision-making of maintenance planning through modeling performance, economic and social aspects. Prasetyo et al. (2019) presented an approach for the purpose of prioritization of bridge maintenance. Analytical hierarchy process was utilized to compute the weighting vector of a set of attributes, namely average daily traffic, bridge length, bridge width, population, etc. Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE II) was applied to obtain a unified ranking index based on the evaluation of the bridge inventory across the different attributes. It was revealed that the condition rating attribute constituted the highest priority among the different criteria.

Mahdi et al. (2019) developed a decision support system to prioritize the maintenance strategies of concrete bridges using dynamic programming. The evaluation criteria of the bridges depended on some performance indicators which include: structural performance, functional performance and external factors. They highlighted that the developed model can compute the optimal maintenance plan for each bridge within the network while taking the budget constraints within limitations. Amiri et al. (2019) adopted a group of multi-criteria decision-making techniques for sorting maintenance actions taking into consideration the risks that may threaten the bridges during the operational stage. The multi-criteria decision-making models involved analytical hierarchy process (AHP), analytical network process (ANP) and technique of order preference by similarity to ideal solution (TOPSIS). Furthermore, the risks on bridges were analyzed using failure mode and effects analysis (FMEA) method. Fitriani et al. (2019) presented a maintenance prioritization model of truss bridges using analytical hierarchy process. The prioritization model was designed with respect to a set of attributes, namely level of damage, technical aspects, financial aspects, vehicle load and resources. Level of damage represented the highest weight (27.6%) while resources constituted the lowest weight (12.1%) as per the feedback of 12 respondents. They highlighted that the developed model could provide transportation agencies with efficient bridge maintenance program.

Yossyafra et al. (2019) presented a hybrid multi-criteria decision making model for maintenance prioritization of bridges in West Sumatra Province. They utilized fuzzy analytical hierarchy process to compute the weights of attributes, which were technical condition, age, average daily traffic, economic benefits, road function, budget fund, disaster impact and spatial conditions. Then, a multi-criteria ranking index was calculated using VIKOR method, which mapped the priority order of bridges to be repaired prior to others. Gao et al. (2019) introduced a multi-criteria decision making method to rank the reinforced concrete bridge repair projects. They adopted VIKOR (Vlse Kriterijumska Optimizacija I Resenje) to compute the prioritization index designated for sorting the bridge repair projects. They utilized criteria importance through inter-criteria correlation (CRITIC) to compute the weights of attributes in an objective manner. They took into consideration a set of attributes, namely structural deficiency, functional obsolesce, average daily traffic, average daily truck traffic, corrosion damage potential environment, and service years. They validated their model through application to a transportation network of 21 bridges.

Contreras-Nieto et al. (2019) introduced a geographical information system (GIS)-based multi-criteria decision making model for bridge maintenance prioritization. They established a weighted bridge rating system using AHP by analyzing responses from local bridge experts. The bridge rating system was designed as per weighted average of deck, substructure, superstructure and scour with respect to resiliency, riding comfort, safety and serviceability. They concluded that the developed model can visualize the prioritization of bridges for maintenance, which improves the decision-making process in the departments of transportation. Markiz and Jrade (2018) presented a fuzzy-based decision support system integrated with bridge information management system to emulate the bridge deterioration modeling and to prioritize the maintenance, repair and rehabilitation actions at the conceptual design stage. They applied time-dependent gamma shock model to forecast the bridge deterioration. Furthermore, TOPSIS was deployed to design the maintenance prioritization platform of bridges. They highlighted that the developed model was capable of attaining approximately 10%-15% error in the prediction accuracy of bridge deterioration.

Gao and Li (2018) proposed a simplified corrosion index to evaluate the actual corrosion of reinforced concrete superstructure. Fuzzy analytical hierarchy process was applied to compute the weighting factors, namely corrosion damage, environment change factor and material vulnerability factor. They pointed out the developed model signified promise results when dealing with the assessment of the extent of severities of corrosion. Yoon and Hastak (2017) developed a multi-tiered method for the prioritization of bridge deck rehabilitation relying on urgency scale and total prioritization scale. The urgency scale was based on computing the timeframe that the rehabilitation process of the bridge deck can be delayed until its structural condition goes beyond the acceptable limit. The total prioritization scale integrated the normalized magnitudes of the performance, economic and criticality scales. Dinh et al. (2017) utilized a combination of image processing techniques and deep convolutional neural network to automatically locate and detect the rebars from ground penetrating radar B-scans of concrete bridge decks. The proposed method helps detecting the rebars automatically because picking the rebars manually is time-consuming and labor intensive. The overall accuracy of the detection process was 99.6% ±0.85%.

Rashidi et al. (2017) presented a decision support system to rank the remedial actions of steel bridges using analytical hierarchy process. They considered a set of attributes to model the remedial actions such as safety, service life, remediation cost, traffic disruption, environmental impact and heritage significance. They considered four alternatives of rehabilitation actions which were: splice plates, steel plate strengthening, fiberglass reinforced plastic strengthening and partial member replacement. They concluded that the presented model can enable asset managers to manage the bridges through balanced modeling of multiple attributes. Nurdin et al. (2017) developed a multi-criteria decision making model to set a priority scale for bridge maintenance and rehabilitation. Three attributes were introduced to set the maintenance prioritization index, whereas the criteria for condition of damage represented the largest weight followed by the volume traffic and criteria policy. The weights of attributes were computed based on analytical hierarchy process by aggregating the feedback of 27 respondents using geometric mean. ArcGIS was utilized to visualize the output of the maintenance prioritization model.

Suthanaya and Artamana (2017) proposed a multi-criteria decision making model for the prioritization of bridge maintenance in developing countries. The ranking system was capitalized on four criteria which were: road network system, institutional system, land use system and movement system. They concluded that the most influential attributes were bridge condition, road narrowing, transportation strategic area, traffic volume and bridge function. They deduced that the developed model was efficient in building a bridge maintenance ranking system in Bali province. Nurani et al. (2017) suggested a bridge maintenance prioritization model using a set of multi-criteria decision making models, namely AHP, fuzzy AHP and TOPSIS. The prioritization model was established with respect to bridge condition and average daily traffic, whereas bridge condition was evaluated according to pier, expansion joint, foundation, girder system, etc. Results signified that different multi criteria decision-making models yielded different ranking outcome.

Moufti et al. (2016) applied fuzzy hierarchical evidential reasoning (HER) to provide a detailed condition assessment under uncertainty. The proposed methodology modeled the three levels of the concrete bridge, which were: bridge components, elements, and measured defects. Dempster-Shafer (D-S) theory was implemented to aggregate the multiple sources of information. The weights of the bridge elements and the structural defects were calculated based on AHP. Dinh and Zayed (2016) introduced an automated software that calculates the bridge deck corrosiveness index (BDCI) based on the weighted fuzzy union (WFU) operation. The proposed model was capable to deal with the fuzziness associated with the expert opinions. The corrosion index was calculated based on the ground penetrating radar (GPR) to evaluate the corrosion of the rebar in the concrete bridge decks.

Deng et al. (2014) presented a methodology for the bridge condition assessment using D numbers, which is an extension of the Dempster-Shafer theory. The proposed methodology was divided into four main stages, which were: establishing a hierarchical model for the bridge condition assessment model, calculating the weight and assessment rating for each factor, aggregating the assessment results of the bottom factors, and aggregating of all the assessment results by stepwise weighting to calculate the overall condition index. Bolar et al. (2013) applied HER for the condition assessment of the bridges. The HER framework classified the bridge data to primary, secondary, tertiary or life safety-critical elements. The information and bodies of evidence were aggregated using Dempster–Shafer ($\mathrm{D}-\mathrm{S}$) and Yager rule of combination in order to deal with aleatory and epistemic uncertainties.

2.2 Calibration of the Fuzzy Membership Functions

Several studies were conducted to develop fuzzy-based decision-making models. These models capitalized on subjected-based paradigms to calibrate the fuzzy membership functions designated to build the assessment model. Anbari et al. (2019) presented a risk assessment model for the prioritization of sewer pipes inspection in wastewater collection networks using Bayesian network. Triangular membership functions were proposed to simulate the probabilities and consequences of failure in addition to the risk of failure. In the developed fuzzy inference system, linguistic terms with five-point likert-scale were utilized for the triangular membership functions. Sharma and Goyal (2019) presented a fuzzy index for the evaluation of cost overrun in construction projects. They identified 55 risk factors that induce cost overrun in Indian construction projects, for instance poor site management, contractor lack of experience, frequent design change, shortage of equipment, climatic condition, etc. They applied triangular membership functions to deal with the vagueness of the input variables. Furthermore, the boundaries of the membership functions were calibrated as per feedback of experts elicited from five-point survey. Subsequently, a set of If-Then rules were established to derive the fuzzy assessment index.

Al Nahyan et al. (2018) presented a fuzzy-based decision support system to compute suitability index for project delivery methods. Fuzzy logic was employed to model the uncertainties of the technical risks, organizational risks, financial risks, economic risks and project management risks. The fuzzy membership functions were tuned based on an ordinal scale questionnaire filled by 176 professionals. Abbasianjahromi et al. (2018) introduced a fuzzy multi-attribute decision framework for subcontractor selection. They suggested 11 attributes for the evaluation of subcontractors such as resource capability, technical requirement, commitment, management capability, experience, etc. The respondents were asked to fill a questionnaire survey that was used to calibrate the fuzzy membership functions of the attributes of the fuzzy TOPSIS model.

Budayan et al. (2018) proposed a fuzzy assessment model of delay risks in construction projects. Triangular fuzzy membership functions were adopted to mimic the frequency of occurrence of delays as well as their implications. In the developed survey, the experts were asked to describe their preferences in the form of linguistic terms that ranged from 0 to 1. Maghsoodi and Khalilzadeh (2018) developed a hybrid Shannon entropy-fuzzy TOPSIS model to sort the critical success factors that influence construction projects. Shannon entropy was applied to compute the weights of the attributes. Then, fuzzy TOPSIS was performed to prioritize the factors for the purpose of successful implementation of construction products. The different factors were evaluated against time, cost, quality and safety. In the developed model, triangular fuzzy numbers were incorporated to simulate the ambiguity of the different factors. The boundaries of the triangular membership function were defined as per a survey distributed to experts and professionals in construction industry.

Noori et al. (2018) presented a fuzzy TOPSIS multi-criteria decision making model for the purpose of optimal dam site selection. A set of attributes were introduced to study and analyze the different alternatives of dam sites including: economic development, reservoir capacity, accessibility to materials and facilities, etc. The criteria and performance of alternatives were expressed in the form of triangular fuzzy numbers, whereas the fuzzy scale for evaluating the alternatives' performances was structured based on subjective judgment. Belošević et al. (2018) presented a VIKOR-based method for ranking the project alternatives at the early stages of infrastructure project developments. Triangular fuzzy numbers of five-point likert scale were assigned to describe the alternatives' ratings across the different attributes.

2.3 Research Gaps

In the view of afore-mentioned, it can be interpreted that some models focused on one of type of defects to design the bridge maintenance prioritization models. This induces incomprehensive and inefficient condition assessment models because the prioritization index doesn't reflect the actual condition of the bridge (Alsharqawi et al., 2020; Gao and Li, 2018; Dinh et al., 2017; Dinh and Zayed, 2016). Also, it is worth mentioning that most of the prioritization models capitalized on visual inspection and conventional methods to evaluate the physical condition of the bridge elements. However, these methods are subjective and deal with only the defects visible on the surface (Dromey et al., 2020; Buksh et al., 2019; Prasetyo et al., 2019; Mahdi et al., 2019; Amiri et al., 2019; Fitriani et al., 2019; Yossyafra et al., 2019; Gao et al., 2019; Contreras-Nieto et al., 2019; Markiz and Jrade, 2018; Yoon and Hastak, 2017; Rashidi et al., 2017; Nurdin et al., 2017; Suthanaya and Artamana, 2017; Nurani et al., 2017; Moufti et al., 2016; Deng et al., 2014; Bolar et al., 2013). Some models also relied on crisp or deterministic paradigms to derive the condition assessment model. Thus, they fail to capture the inherent uncertainties elicited during the inspection process, which may lead to imprecise and misleading decision-making platforms. Another issue could be observed is that some models did not consider the uncertainty of the importance weightings or correlation matrices of the different attributes that influence the decision-making process. These uncertainties arise from the vagueness and subjectivity provided by experts' judgements such that the lack of their modeling may result in inefficient intervention actions (Alsharqawi et al., 2020; Dromey et al., 2020; Buksh et al., 2019; Prasetyo et al., 2019; Mahdi et al., 2019; Amiri et al., 2019; Fitriani et al., 2019; Gao et al., 2019; Contreras-Nieto et al., 2019; Yoon and Hastak, 2017; Dinh et al., 2017; Rashidi et al., 2017; Nurdin et al., 2017; Suthanaya and Artamana, 2017; Deng et al., 2014; Bolar et al., 2013).

Some models were mainly driven by the AHP to compute the weights of the attributes of the maintenance prioritization models. AHP assumes independencies between the attributes of the model. As such, it does not model the dependencies and interaction between the different attributes, which may heavily influence the decision-making process taken by the departments of transportation (Prasetyo et al., 2019; Fitriani et al., 2019; Yossyafra et al., 2019; Contreras-Nieto et al., 2019; Gao and Li, 2018; Rashidi et al., 2017; Nurdin et al., 2017; Nurani et al., 2017; Moufti et al., 2016). Most of the developed maintenance prioritization models support network-level decision-making, whereas there is a lack of decision support system in the element-level. However, decisions at the element-level and network-level are interrelated, and dealing with one of them separately may not yield the optimum decisions for transportation agencies. Another issue of network-level decision-making models is that sometimes they provide misleading results resulting from the failure to monitor the level of deterioration of individual elements, whereas the overall bridge may be in a good condition while some building elements are experiencing high levels of deterioration. separately (Dromey et al., 2020; Buksh et al., 2019; Prasetyo et al. , 2019; Mahdi et al. , 2019; Amiri et al. , 2019; Fitriani et al. , 2019; Yossyafra et al. , 2019; Gao et al. , 2019; Contreras-Nieto et al. , 2019; Markiz and Jrade, 2018; Gao and Li, 2018; Yoon and Hastak, 2017; Rashidi et al., 2017; Nurdin et al., 2017; Suthanaya and Artamana, 2017; Nurani et al., 2017; Moufti et al., 2016; Deng et al., 2014; Bolar et al., 2013). It is also noted that there is a lack of bridge maintenance decision-making strategies in the element-level, whereas most of the conducted studies with regard to that level were basically condition assessment models. Furthermore, these models don't provide the decision-makers with the flexibility to delineate a synthesis evaluation of the extent of severities of the bridge defects separately (Alsharqawi et al., 2020; Dromey et al., 2020; Buksh et al., 2019; Prasetyo et al., 2019; Mahdi et al., 2019; Amiri et al., 2019; Fitriani et al., 2019; Yossyafra et al., 2019; Gao et al., 2019; Contreras-Nieto et al., 2019; Markiz and Jrade, 2018; Gao and Li, 2018; Yoon and Hastak, 2017; Rashidi et al., 2017; Nurdin et al., 2017; Suthanaya and Artamana, 2017; Nurani et al., 2017; Moufti et al., 2016; Dinh and Zayed, 2016; Deng et al., 2014; Bolar et al., 2013).

With respect to the fuzzy-based decision-making models, it is observed that most of them were structured on subjective methods to formulate the fuzzy expert systems. This includes the shape and spans of membership functions in addition to the fuzzy rules of the inference models. They were defined subjectively based on the engineer's expertise or intuition, which are inconsistent, time-consuming and hardly generalized to fit the case in hand. Furthermore, they are highly dependent on the size and demography of the respondents. For instance, the feedback obtained from 50 experts can be different from the feedback obtained from 100 experts. Moreover, the feedback obtained from engineers of twenty years' experience can be different from the feedback obtained from engineers of thirty years' experience (Anbari et al., 2019; Al Nahyan et al., 2018; Abbasianjahromi et al., 2018; Budayan et al., 2018; Maghsoodi and Khalilzadeh, 2018; Noori et al., 2018; Belošević et al., 2018). Another issue of concern is that with possible increase in the number of fuzzy rules in the fuzzy inference system, there is higher potential of experiencing underlying disparities among the rules that are difficult to be observed (Sharma and Goyal, 2019). Therefore, the absence of empirical objective interpretation methods for tuning the fuzzy inference systems may not provide optimal and efficient fuzzy-based decision-making models. In order to circumvent the limitations of subjective methods of fine-tuning the fuzzy inference systems, the proposed framework relies on invasive weed optimization algorithm for the purpose of automated calibration of fuzzy membership functions. In this regard, fuzzy invasive weed optimization algorithm proved its efficiency in solving complex problems in different civil engineering disciplines such as monitoring slope stability (Moayedi et al., 2019), multi-criteria route planning (Pahlavani and Delavar, 2014) and flood susceptibility modeling (Bui et al., 2018).

3. PROPOSED FRAMEWORK

The primary objective of the present study is to provide transportation agencies with an invasive weed optimization fuzzy decision-making framework that supports both element-level and network-level decisions. This is articulated through: modeling the severity levels of the bridge defects separately, designing a bridge deck maintenance prioritization model capitalizing on IBDCI, and formulating a bridge maintenance decision-making strategy. The proposed decision-making paradigm is composed of three tiers. It is worth mentioning that the first tier is tackled to improve the flexibility of the proposed framework through fitting the preferences of decision-makers, whereas in some cases they are concerned with some type of bridge defects more than the others. It is important to mention that the proposed framework deals with five types of bridge defects, namely corrosion, delamination, cracking, spalling, and scaling, and it can be tailored to map other types of bridge defects. The flowchart of the proposed framework is depicted in Figure 1. As can be seen, the proposed framework is composed of three main models, namely weight interpretation, integrated condition assessment, and bridge maintenance decision-making strategy.

In the first model, optimized fuzzy analytical network process ($\mathrm{O-FANP}$) is adopted to compute the weighting vector of the different bridge defects. Preference comparison matrices are the cornerstone of the multi-criteria decision analysis. Thus, they should be dealt with in a way that improves the consistencies of judgments through transforming inconsistent matrices to consistent ones, and minimizes the imprecisions encountered by the classical judgment assignment. Deriving the priority weighting vector is one of the principal issues in the multi-criteria decision analysis (Kou et al., 2016). Kou et al. (2014) highlighted the importance of minimizing the inconsistencies of the pairwise comparison matrices, whereas they developed a Hadamard product induced bias matrix model for the purpose of improving the consistency ratio of pairwise comparison matrices through addressing the cardinal and ordinal inconsistencies. The proposed $\mathrm{O-FANP}$ model encompasses single-objective genetic algorithm to generate more coherent judgment matrices that eventually enhances the quality of the decision-making process. In this study, five different fuzzy scales of importance with semantic ranges are experimented such that the optimum one is obtained though formulation a single-objective optimization model that minimizes the consistency ratio of the judgment matrices. Aggregation of the consistent pairwise comparison matrices plays an important role in the derivation of consensus weighting vector (Lin et al., 2020). After the selection of the optimum fuzzy scale, the consistency ratio is computed for each pair-wise comparison matrix developed by each respondent. The pair-wise comparison matrices that are considered in any further analysis stage are only the ones that exhibit a consistency ratio less than 10%. Finally, the judgments of the respondents are aggregated using the geometric mean.

Over the past years, several approaches were presented to compute the weighting priority vector such as Eigen vector method (Saaty, 1977), logarithmic least squared method (Crawford and Williams, 1985) and recently the cosine maximization method (Kou and Lin, 2014). Additionally, there are different FAHP and FANP approaches reported in the literature including: Van Laarhoven and Pedrycz (1983) fuzzy priority approach, Buckley (1985) geometric mean approach, Boender et al. (1989), Chang's (1996) extent analysis approach, Cheng's (1996) entropy-based approach, Mikhailov (2000) Fuzzy Preference Programming approach, and Zeng et al. (2007) arithmetic averaging approach, etc. The proposed $\mathrm{O-FANP}$ model capitalizes on Chang's extent analysis method that relies on the degree of possibilities of each attribute to compute the priority weights of the bridge defects. Although it allows only triangular fuzzy numbers to be utilized, it is characterized by its simplicity, lower computational requirements, capacity to deal with both qualitative and quantitative information, and efficiency in solving complex problems in broad variety of diversified fields (Yazdani et al., 2019; Phochanikorn and Tan, 2019**;** Batehi et al., 2019; Mahdiyar et al., 2019; Mavi and Standing, 2018). It is worth mentioning that the computational cost is decisive parameter in selecting the appropriate FANP approach, whereas Van Laarhoven and Pedrycz (1983) fuzzy priority method, Buckley (1985) geometric mean method, Boender et al. (1989) method, and Zeng et al. (2007) arithmetic averaging method are often criticized for being computationally expensive (Aydin and Kahraman, 2013; Büyüközkan et al., 2004).

Fuzzy analytical network process is employed to model the bridge defects importance due to its capability to simulate the dependencies between the bridge defects and the condition of the bridge deck (goal) as well as the dependencies of the bridge defects with each other. FANP is also incorporated because most of the defects are corrosion-induced failure modes. Thus, there is a dependency between the bridge defects. The importance weightings are derived based on the data elicited from the questionnaire survey distributed to the experts in the field. The developed survey is designed to sustain two levels of comparison which are: comparison of the main criteria (bridge defects) with respect to the condition of the bridge defect, and comparison of the main criteria (defects) with respect to each other. For instance, each respondent was asked to define the degree of importance of criteria X over the other criteria Y with respect to the goal. An example of the pair-wise comparison of level two is that each respondent is asked to provide the degree of importance of criteria X over criteria Y with respect to a third criteria Z.

The second phase is an invasive weed Optimization-based fuzzy model aims at formulating an IBDCI to be further used in maintenance prioritization of bridge decks. In this model, it is important to define the percentages of each condition category for the bridge defect. For instance, 40% of the cracks in bridge deck A are in a poor condition or 30% of the spalls in bridge deck B are in a very poor condition. Corrosion is evaluated using ground penetrating radar while the percentages of condition categories are extracted by the inspection reports provided by the Ministry of Transportation in Quebec (MTQ). In the inspection reports, delamination is assessed using chain drag or hammer sounding while remaining surface defects are evaluated based on the expertise and judgment of the bridge inspectors.

With regard to corrosion, the present study utilizes the model developed by Mohammed Abdelkader et al. (2019a) to compute the standardized thresholds of ground penetrating radar that are further applied to interpret the corrosion levels in concrete bridge decks. In that model, the scanned profiles of the bridge deck are exported to the GSSI RADAN7 software to extract the amplitude values of the top reinforcing rebars capitalizing on the numerical-amplitude method. Numerical amplitude method depends on the value of the amplitude of the reflected waves from the top layer of reinforcement to interpret the level of corrosion, whereas the higher the amplitude values, the better the condition of the reinforcing bars is. Subsequently, a multi-objective optimization model that accommodates both local and global search was designed to find the optimum standardized threshold values.

In the proposed invasive weed Optimization-based fuzzy model, fuzzy fuzzy-set theory is incorporated to simulate the uncertainties encountered during the evaluation of the severities of bridge defects. Establishing fuzzy inference systems require fine-tuning the membership functions and adjusting the fuzzy rules. The process of manual tuning of the parameters of the fuzzy inference systems is subjective, inconsistent, time-consuming, case dependent, which yields inferior solutions. This signifies the need for objective-based methods for tuning the membership functions. As such, the proposed framework encompasses invasive weed optimization algorithm to automatically calibrate the fuzzy membership functions. This constitutes deriving the optimum shape of fuzzy membership functions (S_D, triangular or trapezoidal), optimum boundaries for each fuzzy membership function of each bridge defect (B_{MD}), and optimum defuzzification technique (DE_FUZZ, centroid or bisector).

These optimum parameters are obtained based on structuring a single-objective invasive weed optimization model which minimizes the absolute distance between IBDCI computed from two different multi-criteria decision making methods. Invasive weed optimization (IWO) algorithm is preferred over generic algorithm because IWO is an exhaustive search engine that exemplified its capabilities in exploring complex and multi-local search spaces. Moreover, it manifested its superiority over some of the best-performing optimization algorithms such as genetic algorithm, particle swarm optimization algorithm and harmony search algorithm. Furthermore, genetic algorithm is often criticized by the low exploration and exploitation capacity, which leads to the entrapment in local minima than the true optimal solutions (Mohammed Abdelkader et al., 2019b; Asgari et al., 2016; Azizipour et al., 2016).

Group decision making has been adopted by researchers in various disciplines to establish a synchronized solution based on the individual multi-criteria decision making models such as soft consensus cost model developed by Zhang et al. (2019) and weighted-power average operator-based model developed by Li et al. (2018). In this context, the percentages of each condition category represent the degrees of the fuzzy membership functions. They are aggregated using the weighted fuzzy union approach (WFU) to obtain a severity index for each bridge defect separately capitalizing on the calibrated fuzzy membership functions. Then, using the weights fed from the weight interpretation model, the IBDCI can be computed using TOPSIS and grey relational analysis (GRA). These two multi-criteria decision making methods are selected because of their efficiency and robustness as well as their different natures (Azimifard et al., 2018; Sackey and Kim, 2018; Ma et al., 2019; Lee et al., 2019). Thus, they can provide a comprehensive and efficient representation for the physical condition of the bridge deck. It should be mentioned that the final IBDCI used for maintenance prioritization purposes, is the average of IBDCI elicited from TOPSIS and GRA.

The third model is designated for establishing a bridge maintenance decision-making strategy, which enables transportation agencies to map the appropriate intervention action as per the IBDCI. Thus, sufficient amount of inspection records should be present in order to structure an efficient bridge maintenance decision-making strategy. The percentages of condition categories of the bridge defects are assumed random variables that follow certain probability distributions. The best-fit probability distribution is selected based on the Chi-squared test. Then, Latin hypercube sampling is adopted to generate large number of scenarios. Then, these scenarios are evaluated using the integrated using the integrated condition assessment model, and appended in a database. Latin hypercube is stratified sampling scheme that enables better coverage and exploration of the domain of the variations of the input variables. It is preferred over Monte Carlo sampling because of its time-efficiency in addition to its higher capacity of establishing efficient probability distributions using less number of iterations and less sampling error (García-Alfonso and Córdova-Esparza, 2018; Gupta and Kumar, 2016). Subsequently, fuzzy C-means clustering is selected as one of the soft clustering algorithms to obtain the thresholds of the IBDCI necessitated to structure the bridge deck maintenance decision-making strategy. Fuzzy C-means clustering was preferred over other clustering algorithms due to its capability in dealing with uncertainties encountered during the bridge inspection process. Furthermore, it outperformed K-means clustering in terms of establishing more compact homogenous clusters as well as well-separated thresholds (Bhattacharjee et al., 2017; Sheshasayee and Sharmila, 2014; Goktepe et al., 2005).

INSERT FIGURE 1

4. MODEL DEVELOPMENT

This section describes the three main models presented in the "Proposed Framework" section namely, weight interpretation, integrated condition assessment, and bridge maintenance decision-making strategy.

4.1 Weight Interpretation

As mentioned earlier, the proposed framework utilizes $\mathrm{O-FANP}$ to compute the weighting vector of the bridge defects. Figure 2 describes the framework of the weight interpretation model. The input of this model is the pairwise comparison matrices while the output of this model constitutes the optimum fuzzy scale and the importance weightings of the five bridge defects. Analytical Network Process is one of the most comprehensive frameworks that can be used to analyze the governmental and corporate decisions, and to deal with complex relationship and interactions between the criteria. ANP is a widely used decision making tool that is implemented to overcome the shortcomings of the Analytical Hierarchy Process where the hierarchy is replaced by a network in the case of the ANP.

The differences between the hierarchy and network structures are described in Figure 3. ANP is considered as an extension or a more general form of the AHP. In the AHP, the hierarchy of the model is divided into several levels, where the elements of the hierarchy are assumed to be independent, which is not necessarily true because there is a dependency between the goal, criteria, and the alternatives in many cases. ANP is an effective tool in the decision making process, where interactions and feedbacks between elements of the model can be modeled. ANP allows considering both the interaction and feedback within the clusters (inner dependencies), and between the clusters (outer dependencies). Decision makers may encounter vagueness and uncertainty in the opinions and feedback of the experts in the pair-wise comparisons. Consequently, the classical ANP is incapable of reflecting the exact opinions of the experts, and the FANP will be a more efficient and realistic tool to alleviate the deficiencies of the classical ANP. The weight interpretation model is established on three main pillars, namely optimum fuzzy scale, Chang's extent analysis method, and limit supermatrix. These sub-models are discussed in the following lines.

INSERT FIGURE 2

INSERT FIGURE 3

4.1.1 Optimum fuzzy scale

Classical AHP and ANP suffer from three drawbacks, which can be summarized as follows: lack of capacity of the nine-point discrete Saaty's scale in simulating the preferences of experts with respect to the relative importance of the attributes, difficulty in identifying the appropriate overlapping between the fuzzy numbers when dealing with linguistic scales, and inferior accuracy of the AHP and ANP in the case of complex relationships among attributes demonstrated in the form of inconsistent matrices. These limitations can easily induce inconsistencies in the evaluation of experts and create misleading prioritization results (Triantaphyllou and Mann, 1990). In the light of foregoing, the $\mathrm{O-FANP}$ module aims at maximizing the overall consistency of the responses through restructuring the judgment matrices while retaining as much possible information in the original matrices.

The framework of the optimum fuzzy scale module is depicted in Figure 4. The first step is to define the goal of the problem and to decompose the problem into a network. Based on the defined goal, the criteria, and the interdependencies between the criteria are developed, the questionnaire will be developed. A questionnaire is designed based on a series of pair-wise comparisons, whereas the experts are asked to fill out the questionnaire. The pair-wise comparisons are divided into two categories: pair-wise comparisons with respect to the overall condition of the bridge deck, and pair-wise comparisons with respect to the bridge defects such as corrosion, delamination, among others. For the first level of comparisons, the experts are asked to answer some questions such as how important is the corrosion when it is compared with the delamination with respect to the overall condition of the bridge deck. For the second level of comparisons, the experts are asked to fill out some comparisons such as how important is the corrosion when it is compared with the delamination with respect to the cracking.

In the classical ANP, the experts are asked to express their judgments in terms of crisp numbers such as 1, 3, 5, etc. However, in the FANP, the experts are asked to determine the importance level of the criteria based on linguistic terms such as absolutely important, moderately important, equally important, among others, where the linguistic terms represent fuzzy numbers in the fuzzy membership functions. There are many studies that utilized either FAHP or FANP to calculate the importance weightings of the criteria (Nazari et al., 2017; Yayla and Yildiz, 2013). As such, the proposed framework investigates five different fuzzy scales to select the optimum one among them.

There are many forms of the membership functions such as triangular, trapezoidal, Gaussian, sigmoid, among others. Many studies have utilized triangular fuzzy numbers because of their simplicity, usefulness in the data processing, and efficient simulation of the fuzzy environment. A triangular fuzzy number M^{-} can be denoted as $\mathrm{M}^{-} = (\mathrm{l}, \mathrm{m}, \mathrm{u})$, whereas the fuzzy triangular membership function can be represented using Equation (1). The values of the membership functions assume values $\mu_{\mathrm{M}^{-}}(\mathrm{x})\colon \mathrm{R} \rightarrow [0, 1]$ and $\mu_{\mathrm{T}^{-}}(\mathrm{x})\colon \mathrm{R} \rightarrow [0, 1]$ (Goh et al., 2019; Darani et al., 2018; Nazari et al., 2017).

$$\mu_{\mathrm{M}^{-}}(\mathrm{x}) = \begin{cases} \dfrac{\mathrm{x}-\mathrm{l}}{\mathrm{m}-\mathrm{l}} & \text{if } \mathrm{l} \leq \mathrm{x} \leq \mathrm{m} \\ \dfrac{\mathrm{x}-\mathrm{u}}{\mathrm{m}-\mathrm{u}} & \text{if } \mathrm{m} \leq \mathrm{x} \leq \mathrm{u} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Where;

l, and u represent the lower and upper bounds of the fuzzy membership functions (least and maximum possible values of the fuzzy event). If $\mathrm{l} = \mathrm{m} = \mathrm{u}$ in the triangular membership, the pair-wise comparisons yield crisp values as in the classical ANP.

Five fuzzy triangular scales (from TFS#1 to TFS#5) are depicted in Table 1. The main operational laws for two triangular fuzzy numbers $\mathrm{M}_1^{-} = (\mathrm{l}_1, \mathrm{m}_1, \mathrm{u}_1)$, and $\mathrm{M}_2^{-} = (\mathrm{l}_2, \mathrm{m}_2, \mathrm{u}_2)$ are shown in Equations (2), (3), (4), and (5) (Nazari et al., 2017).

$$\bar{M_1} + \bar{M_2} = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \tag{2}$$

$$\bar{M_1} \otimes \bar{M_2} = (l_1 \times l_2, m_1 \times m_2, u_1 \times u_2) \tag{3}$$

$$\beta \otimes \bar{M_1} = (\beta \times l_1, \beta \times m_1, \beta \times u_1), \beta > 0, \beta \epsilon R \tag{4}$$

$$(\bar{M_1})^{-1} = (l_1, m_1, u_1)^{-1} = (\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1}) \tag{5}$$

It is necessary to defuzzify the membership function to check the pair-wise comparisons provided by the experts. Defuzzification is the process of converting the fuzzy numbers into crisp numbers. The triangular fuzzy membership function is defuzzified using Equation (6).

$$\bar{D_f} = \frac{l_f + (4 \times m_f) + u_f}{6} \tag{6}$$

Where;

$\bar{D_f}$ represents the defuzzified crisp number of the triangular fuzzy number.

After the defuzzification, the pair-wise comparison matrix (A^*) can be expressed using Equation (7), where each element of the pair-wise comparison matrix can be expressed in terms of $\bar{M_{ij}}$, which indicates the degree of importance of criteria i with respect to criteria j.

$$A^* = \begin{bmatrix} 1 & \bar{M_{12}} & \bar{M_{13}} & \dots. & \bar{M_{1r}} \\ \bar{M_{21}} & 1 & \bar{M_{23}} & \dots. & \bar{M_{2r}} \\ \bar{M_{31}} & \bar{M_{32}} & 1 & \dots. & \bar{M_{3r}} \\ \dots. & \dots. & \dots. & \dots. & \dots. \\ \bar{M_{r1}} & \dots. & \dots. & \dots & 1 \end{bmatrix} \tag{7}$$

Humans are sometimes inconsistent in answering the questions, it is very important to validate the results obtained from the decision makers. ANP is related to a group of methods that allow the identification and the check of the consistency of the pair-wise comparisons obtained from decision makers preferences. Consistency Index (CI) is calculated through Equation (8), whereas it is used to calculate the probability that the judgments of the experts are randomly generated. If the consistency index is small, this means that there is a smaller deviation from consistency and weights obtained from the ANP are accurate. If the consistency index equals zero, this will indicate perfect consistency. The Consistency Ratio is a ratio between the Consistency Index and the Random Index as shown in Equation (9).

$$\mathrm{CI} = \frac{\lambda_{\max} - \mathrm{n}}{\mathrm{n} - 1} \tag{8}$$

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{9}$$

CI, $\lambda_{\max}$ represent the consistency index and maximum Eigen value, respectively. n indicates the number of attributes. RI represents the Random Index and CR denotes the Consistency Ratio. The consistency index is compared to the random index (RI). If $\mathrm{CR} < 0.1$, this means that the degree of consistency is satisfactory and the calculation of relative importance between the attributes is acceptable. On the contrary, if $\mathrm{CR} > 0.1$, this means that ANP may lead to inconsistent results, and the judgments provided by the experts requires revision.

The optimum fuzzy scale is identified capitalizing on formulation a single-objective optimization model that minimizes the overall Consistency Ratio of the experts as shown in Equation (10). It utilizes non-dominated sorting genetic algorithm ($\mathrm{NSGA} - \mathrm{II}$) to search for the optimum solutions.

$$\mathrm{OVR\_CONST} = \min \ \frac{\sum_{\mathrm{n}=1}^{\mathrm{K}} \mathrm{CR}}{\mathrm{K}} \tag{10}$$

Where;

$\mathrm{OVR\_CONST}$ represents the overall consistency ratio. K stands for the of the pair-wise comparisons.

Genetic algorithm (GA) is one of the evolutionary algorithms. Genetic algorithm is an optimization tool developed by John Holland in 1975. Genetic algorithm is based on two main processes. The first process is the selection of individuals for the production of the next generation. The second process is the manipulation of the selected individual to form the next generation by crossover and mutation. The first step is to form a random population of solutions where the solutions are represented in the form of a string called "chromosomes". Each stage a new population of individuals is created and it is called “generation”. Chromosomes consist of genes that carry the set of values for the optimization variables (Elbeltagi et al. 2005). The second step is to calculate the fitness function for each chromosome in the population. The fitness function is used to assess the different chromosomes.

The third step is the selection of the chromosomes. The selection process determines which chromosomes will mate to form the new chromosomes. There are different types of the chromosomes selection strategies which are: roulette wheel selection, rank selection, steady-state selection, elitism, Boltzmann selection and tournament selection. The fourth step is to perform the crossover in order to generate an offspring between the two chromosomes or individuals. There are different types of crossover such as single point crossover, two-point crossover, and uniform crossover. The most common type of crossover is the single-point crossover where a random point is selected at which the remaining genes from one parent to another are swapped (Heidari and Movaghar, 2011).

The fifth step is to perform the mutation. The mutation gene is chosen randomly. The process of the mutation occurs by looping through all the genes of the individuals and if a gene is selected for mutation, the gene will be changed by a small value or it will be replaced by a new value. Mutation is performed in order to ensure the genetic diversity within the population (Heidari and Movaghar, 2011), and to avoid the stagnation around local minima. Elitism is an important strategy that is applied to preserve the higher potential solutions because there is a probability of losing best chromosomes during crossover and mutation. Finally, a population is generated in each generation and the above processes continue for a certain number of iterations.

INSERT FIGURE 4

INSERT TABLE 1

4.1.2 Chang's extent analysis method

After the calculation of the Consistency Ratio of each pair-wise comparison matrix, the pair-wise comparison matrices that are included in the calculation of the final weights stage are the ones that achieved only a Consistency Ratio less than 0.1. Saaty (2008) stated that the geometric mean is a better way than the arithmetic mean in providing a consensus aggregation of the judgment of the experts. The aggregation of the experts' opinions based on the geometric mean is shown in Equation (11).

$$A_{\bar{ij}} = \left(\Pi_{k=1}^{v} M_{\bar{ijk}}\right)^{1/v} \tag{11}$$

Where;

$A_{\bar{ij}}$ represents the aggregated relative importance. $M_{\bar{ijk}}$ represents the relative importance of criteria i with respect to criteria j by expert k. v denotes the number of the experts.

The calculation of the weights of the attributes is based on the method developed by Chang (1996). The steps of Chang's extent analysis method are described in the following lines. Assume $X = \{x_1, x_2, x_3, \dots \dots \dots \dots . x_n\}$ to be an object set, and $U = \{u_1, u_2, u_3, \dots \dots \dots \dots . u_n\}$ to be a goal set. Each object is taken and the extent analysis for each goal is performed based on this method. Accordingly, m extent analysis values for each object can be obtained with the following signs.

M_{gi}^1, M_{gi}^2, M_{gi}^3,

M_{gi}^4………..M_{gi}^m , i=1, 2, 3,……n (12)

Where;

M_{gi}^m $(j = 1, 2, 3 \dots \dots \dots m)$ are triangular fuzzy numbers.

The value of the fuzzy synthetic extent with respect to the $i - th$ object can be defined as follows.

$$S_i = \sum_{j=1}^{m} M_{gi}^j \otimes \sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^j \tag{13}$$

The fuzzy addition operation of m extent analysis values $(\sum_{j=1}^{m} M_{gi}^j)$ for a particular matrix can be performed as follows.

$$\sum_{j=1}^{m} M_{gi}^j = \left(\sum_{j=1}^{m} l_j , \sum_{j=1}^{m} m_j , \sum_{j=1}^{m} u_j \right) \tag{14}$$

In order to obtain $(\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^j)$, the fuzzy addition operation $(M_{gi}^j, j = 1, 2, 3 \dots \dots \dots m\ )$ values can be performed as follows.

$$\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^j = \left(\sum_{i=1}^{n} l_i , \sum_{i=1}^{n} m_i , \sum_{i=1}^{n} u_i \right) \tag{15}$$

The inverse of the above vector can be done using Equation (16).

$$\left(\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right)^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i}\right) \quad (16)$$

Assume M_1 and M_2 are two triangular fuzzy numbers where the degree of possibility $V(M_2 \geq M_1)$ can be defined as follows.

$$V(M_2 \geq M_1) = \sup_{y \geq x}[\min(\mu_{M1}(x), \mu_{M2}(x))] \quad (17)$$

The degree of possibility can be expressed using Equation (18).

$$V(M_2 \geq M_1) = hgt(M_1 \cap M_2) = \mu_{M2}(d) = \begin{cases} 1 & \text{if } m_2 \geq m_1 \\ 0 & \text{if } l_1 \geq u_2 \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)} & \text{otherwise} \end{cases} \quad (18)$$

Where;

d is the ordinate of the highest intersection point D between two membership functions μ_{m_1}, and μ_{m_2} as shown in Figure 5.

INSERT FIGURE 5

The degree of possibility of a convex fuzzy number to be greater than K convex fuzzy numbers M_i(i=1, 2, 3,….k) can be defined as follows.

$$V(M \geq M_1, M_2, \ldots \ldots . . M_k) = V[(M \geq M_1) \text{ and } (M \geq M_2) \text{ and } \ldots \ldots \text{ and } (M \geq M_k)] = \min V(M \geq M_i), \quad i=1, 2, 3, \ldots .k \quad (19)$$

Assume that $d'(A_i) = \min V(S_i \geq S_k), \quad k = 1, 2, 3, \ldots \ldots \ldots . n \text{ and } k \neq i$ (20)

The weight vector can be represented using the following Equation (21).

$$W' = \left(d'(A_1),\ d'(A_2), d'(A_3), \ldots \ldots \ldots \ldots \ldots \ldots \ldots, d'(A_n)\right)^T \quad (21)$$

Where;

$A_i(i = 1, 2, 3, \ldots \ldots \ldots . n)$ are n elements.

The normalized weight vectors can be obtained using Equation (22).

$$d(A_i) = \frac{d'(A_i)}{\sum_{i=1}^{n} d'(A_i)} \tag{22}$$

$$W = \left(d(A_1),\ d(A_2), d(A_3), \ldots\ldots\ldots\ldots\ldots\ldots\ldots, d(A_n)\right)^T \tag{23}$$

Where;

W is a non-fuzzy number.

4.1.3 Limit supermatrix

A synthesized supermatrix should be constructed in order to deal with the dependency between the $O-FANP$ model such as nodes and clusters. The priority weights are calculated based on the pair-wise comparisons that are performed on the element and cluster levels, and consequently, they are entered into a matrix called the “supermatrix”. The structure of the supermatrix is shown in Equation (24). If there is no relationship between the clusters, the corresponding entry is zero.

The process of mathematically structuring the supermatrix in the $O-FANP$ model involves three steps (Yazdani et al., 2019). The first step is the un-weighted supermatrix, which is constructed directly from the pair-wise comparisons. In the present study, the un-weighted supermatrix is based on the weights developed from Chang’s extent analysis method. The second step is weighted supermatrix, which is formed by multiplying the values of the elements of the un-weighted supermatrix by the affiliated cluster weights. The third step is the limit supermatrix is constructed by raising the weighted supermatrix to a power until all the columns corresponding to any node stabilizes, i.e., all the columns corresponding to any node in the supermatrix have the same values. The limit supermatrix can be obtained using Equation (25). Super Decisions 3.0 software package is used to facilitate the implementation of the previous steps.

$$
A = \begin{array}{cc}
 & \begin{array}{ccccccccccc} C_1 & \cdots & \cdots & \cdots & \cdots & C_k & \cdots & \cdots & \cdots & \cdots & C_N \end{array} \\
 & \begin{array}{ccccccccccc} e_{11} & \cdots & e_{1n_1} & \cdots & e_{k1} & \cdots & e_{kn_k} & \cdots & e_{N1} & \cdots & e_{Nn_N} \end{array} \\
\begin{array}{cc} & e_{11} \\ C_1 & \cdots \\ \cdots & e_{1n_1} \\ \cdots & \cdots \\ & e_{k1} \\ C_k & \cdots \\ \cdots & e_{kn_k} \\ \cdots & \cdots \\ \cdots & e_{N1} \\ C_N & \cdots \\ & e_{Nn_N} \end{array} &
\begin{bmatrix}
W_{11} & \cdots & \cdots & \cdots & W_{1k} & \cdots & \cdots & \cdots & W_{1N} \\
 & & & & & & & & \\
 & \cdots & \cdots & \cdots & & \cdots & \cdots & \cdots & \\
 & \cdots & \cdots & \cdots & & \cdots & \cdots & \cdots & \\
 & & & & & & & & \\
W_{K1} & & & & W_{KK} & & & & W_{KN} \\
 & & & & & & & & \\
 & \cdots & \cdots & \cdots & & \cdots & \cdots & \cdots & \\
 & \cdots & \cdots & \cdots & & \cdots & \cdots & \cdots & \\
W_{N1} & & & & W_{NK} & & & & W_{NN} \\
 & \cdots & \cdots & \cdots & & \cdots & \cdots & \cdots &
\end{bmatrix}
\end{array}
\tag{24}
$$

Where;

C_k represents the $k-$th cluster, which constitute n_k elements. e_{kn_k} denotes the elements of the cluster. W_{ij} is a matrix segment where it represents the relationship between the $i-$th, and $j-$th.

$$M_s = \lim_{x\to\infty} M^k \tag{25}$$

Where;

M_s indicates the limit supermatrix, and k represents the power that the weighted supermatrix is raised to.

4.2 Integrated Condition Assessment

The integrated condition assessment model is divided into three main sections, namely automated calibration of fuzzy membership functions, invasive weed optimization algorithm, and multi-criteria decision making. The latter one describes the basic theories of TOPSIS and GRA.

4.2.1 Automated calibration of fuzzy membership functions

The main objectives of the integrated condition assessment model are: establishing a bridge defect severity index (BDSI), and formulating a bridge maintenance prioritization platform. The latter objective is accomplished through integrating the several BDSIs into IBDCI.

The framework of the integrated bridge deck condition assessment model is shown in Figure 6. The severity levels of the bridge defects are expressed in the form of fuzzy membership functions in order to simulate the uncertainties and vagueness experienced during the inspection of the bridge deck. The proposed framework adopts invasive weed optimization algorithm to automatically calibrate the fuzzy membership functions to circumvent the limitations of subjective, tedious and case dependent manual methods of calibration. The manual tuning of fuzzy membership functions and manual adjusting fuzzy rules can induce incomprehensive and inefficient fuzzy inference systems, and maintenance prioritization models.

As shown in Figure 6, the input of the model comprises percentages of condition categories of bridge defects demonstrated in the form of degrees of fuzzy membership functions as well as the weighting vector of the bridge defects computed from the weight interpretation model. The output of the model constitutes the calibrated fuzzy membership functions, separate bridge defects severity indices, and integrated bridge deck condition index. The bridge defects severity indices for corrosion, delamination, cracking, spalling and scaling are bridge deck corrosion index (BDCI), bridge deck delamination index (BDDI), bridge deck cracking index (BDCRI), bridge deck spalling index (BDSPI), and bridge deck scaling index (BDSCI), respectively. These afore-mentioned condition indices enable the decision-makers to synthesize the severity levels of the bridge defects they are mostly concerned with.

INSERT FIGURE 6

Zadeh (1965) introduced the fuzzy set theory in 1965 to deal with the real-world problems that involve the linguistic descriptions. Fuzzy logic is used to construct the fuzzy inference system (FIS) in order to simulate human intelligence through approximate reasoning where an element can belong to a certain fuzzy set fully or partially. A fuzzy set can be defined as a set of elements that belong to the universe of discourse whose boundaries are not defined precisely. To perform the fuzzification process, it is necessary to define the universe of discourse, i.e., the input space or the set of all possible values that each input variable (bridge defect) can take. The universe of discourse of each of the condition indices (BDCI, BDDI, BDCRI, BDSPI, BDSCI, and IBDCI) are ranging from zero to one hundred. The proposed framework utilizes four condition categories to be compatible with the rating system proposed by MTQ, namely good (G), medium (M), poor (P) and very poor (VP). Each input variable in the FIS is divided into overlapping fuzzy partitions (fuzzy sets) such as Good (G), Poor (P) to be able to simulate the fuzziness elicited from the evaluation of bridge defects.

Fuzzification is the process of converting the crisp values to fuzzy values through membership functions. The fuzzy sets are described by membership functions. The membership function is a mathematical function that defines the degree of membership of an element in a fuzzy set, i.e., the membership function defines how much an element belongs to a specific fuzzy set. The degree of membership of each fuzzy is included in the interval [0, 1] where if the degree of membership of element x is close to 1, this means that element x is close to belong to the fuzzy set. The proposed model considers the triangular and trapezoidal membership functions because in practice, it is better to deal with simple form membership functions. Furthermore, they exemplified their capacities in simulating the fuzzy environment (Tran et al., 2012; Koduru et al., 2010).

The weighted fuzzy union approach is used in order to aggregate the degree of membership of the fuzzy sets to construct an overall membership function. The process of combining the fuzzy information, and integrating the membership functions through WFU is expressed through the following equation (Tee et al., 1988)

$$F^{-} = U\left(\sum_{i=1}^{n} W_i \times F_i\right) \quad (26)$$

Where;

F^{-} indicates the resultant fuzzy set. U indicates the fuzzy union operator. W_i denotes non-fuzzy weighting factors. F_i represents the fuzz set $i - th$. n indicates number of fuzzy sets.

After establishing the overall membership function, the membership function is defuzzified. Defuzzification is the process of converting the fuzzy value into a crisp value. There are some defuzzification techniques such as maximum membership principle, centroid, bisector, maximum membership, and weighted average methods. The proposed model considers the two most commonly utilized defuzzification techniques, which are: centroid and bisector methods. The centroid method finds the center of the area under the curve. The bisector method defuzzifies the overall membership function based on a vertical line that divides the membership function into two sub-regions that are equal in area. The Yager's centroid method can be performed using Equation (27) (Yager, 1980; Sadiq and Hussain, 2005; Supciller and Abali, 2015).

$$Ce = \frac{\int_x \mu_A(x) x \, dx}{\int_x \mu_A(x) \, dx} \tag{27}$$

Where;

Ce represents the center of area of the overall membership function.

A visual representation of the formulation of the optimization for the automated calibration of fuzzy membership functions is illustrated in Figure 7. As shown in Figure 7, the automated calibration of fuzzy membership functions involves: deriving the optimum shape of fuzzy membership functions (S_D), optimum boundaries of the fuzzy membership functions M for each bridge defect D (B_{MD}), and optimum defuzzification technique (DE_FUZZ). It is worth mentioning that the S_D can be either triangular or trapezoidal, B_{MD} can be a value ranging from zero to one hundred, and DE_FUZZ can be either centroid or bisector defuzzification techniques. The optimum boundaries B_{MD} are dependent on the bridge defect. Thus, they can take different values from each other in their continuum. The automated calibration of fuzzy membership functions is established on a variable-length optimization model elicited from the variability in the length of vector of decision variables when dealing with triangular and trapezoidal membership functions. As such, an efficient optimization algorithm such as invasive weed optimization is employed to search for the optimum solutions. It should be noted that the maximum length of the optimization model can be expressed as $(5 \text{ Bridge defects} \times 5 \text{ Points in 4 Membsehip fucntions}) + (1\ S_D + 1\ DE_{FUZZ}) = 27$ decision variables.

INSERT FIGURE 7

The optimum solutions are derived capitalizing on minimizing the average condition absolute distance (ACDT) obtained from TOPSIS and GRA multi-criteria decision making techniques. These two techniques are selected in order to ensure a comprehensive and reliable condition assessment model, whereas TOPSIS relies on the Euclidean distances to compare between the alternatives using the positive and negative ideal solutions as a reference. On the other hand, GRA is established on the grey theory, and it utilizes the grey relational grade to analyze the reference series and the alternative series. The single-objective optimization model is formulated using Equation (28).

$$\mathrm{ACDT} = \min \sum_{i=1}^{b} \frac{|(\mathrm{CT_i} - \mathrm{CG_i})|}{b} \tag{28}$$

Where;

$\mathrm{CT_i}$ and $\mathrm{CG_i}$ represent the integrated bridge deck condition index computed from TOPSIS and GRA, respectively. b denotes the number of considered bridges.

4.2.2 Invasive weed optimization algorithm

As mentioned earlier invasive weed optimization is utilized to automatically tune the fuzzy membership functions of the bridge defects. IWO algorithm is a meta-heuristic bio-inspired optimization algorithm that was developed by Mehrabian and Lucas in 2006. It is capitalized on simulating the invasive behaviour of weed in colonizing and finding the most suitable place for growth and reproduction. Weeds are robust and undesirable plants that grow spontaneously and they can have a harmful effect on both farms and gardens. The computational procedures of the IWO algorithm are described in the following lines (Azizipour et al., 2016; Zhou and Xidian, 2014).

The first stage is to create an initial population of weeds that are spread in the i-dimensional search space. The fitness of each weed within the population is then computed based on a predefined objective function. The production of seeds associated with each weed is calculated based on a linear function, where the number of seeds varies between the minimum and maximum number of seeds. Each weed in the population produces seeds based on its own comparative fitness value, maximum and minimum fitness values within the population, and the maximum and minimum number of seeds. The reproduction of seeds is shown in Equation (29) where the higher the fitness of the weed, the more seeds it produces.

$$\mathrm{Seed_i} = \frac{\mathrm{f_i} - \mathrm{f_{min}}}{\mathrm{f_{max - f_{min}}}} \times (\mathrm{s_{max}} - \mathrm{s_{min}}) + \mathrm{s_{min}} \tag{29}$$

Where;

$Seed_i$ represents number of seeds associated with the $i - th$ weed. f_i represents the current fitness of the weed. f_{max}, and f_{min} represent the maximum and minimum fitness of the current population, respectively. s_{max}, and s_{min} denote the maximum and minimum number of seeds, respectively.

The following stage is the spatial dispersion, where the seeds are randomly scattered in the search space based on a normal distribution of a mean equal to zero and an adaptive varying standard deviation. This step ensures that the seeds are accumulated around the weed plant, which leads to a local search around each parent weed. The standard deviation of the seed dispersion is reduced from an initial predetermined maximum value to an initial predetermined smaller value based on a non-linear function as shown in Equation (30). The probability of finding a seed far from the weed plant is high at the beginning of the optimization process and it decreases within a predefined number of iterations.

$$\sigma_i = \sigma_{min} + \left(\frac{iter_{max} - iter}{iter_{max} - iter_{min}}\right)^p \times (\sigma_{max} - \sigma_{min}) \qquad (30)$$

Where;

σ_i indicates the standard deviation of the current iteration. σ_{max}, and σ_{min} indicate the initial and final standard deviation of the optimization process, respectively. $iter_{max}$ represents the maximum number of iterations. p represents non-linear modulation index, and usually, it is a number between two and three.

Finally, competitive exclusion is performed because the number of weeds and seeds reaches the maximum population size due to the fast reproduction (exponential increase in the number of plants). The parent weeds alongside with the seeds are ranked based on the fitness value in order to eliminate the solutions with the least fitness values to keep the number of the weed plants and seeds within the maximum allowable population size. The seeds and their parent weeds with higher fitness survive, and become reproductive. The afore-mentioned procedures are iterated until the convergence criteria are met, i.e., reaching the maximum number of iterations.

4.2.3 Multi-criteria decision making

Multi-criteria decision making became one of the fastest growing areas in operation research during the second half of the twentieth century. Multi-criteria decision making is concerned with theories and methodologies that are capable to solve complex problems in management, business and construction fields. Multi-criteria decision making methods are a group of methods that enable the modeling and integration of different attributes in order to rank alternatives and choose the best alternative. Evaluation criteria in multi-criteria decision making can be divided into two main categories, namely benefit and cost criteria. In benefit criteria, the higher measure of performance the better the alternative is while in cost criteria, a lower measure of performance implies a better alternative. In the present study, TOPSIS and GRA are applied for the purpose of computing an integrated bridge deck condition index. Furthermore, the five bridge defects are cost attributes (Mulliner et al., 2013).

4.2.3.1 Computational procedures of TOPSIS

In TOPSIS, the Euclidean distances from the positive and negative ideal solutions govern the selection of the best alternative. Thus, the best alternative is the one that has the closest distance to the positive ideal solution as well as the farthest distance to the negative solution. The computational steps of TOPSIS can be expressed as follows (Azimifard et al., 2018; Sackey and Kim, 2018):

The decision matrix normalization is the first step, whereas it aims at converting the performance attributes into non-dimensional ones. The normalized decision matrix is computed using Equation (31).

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} {x^2}_{ij}} \tag{31}$$

Where;

x_{ij} represents the measure of performance of the $i-th$ alternative with respect to $j-th$ attribute.

The second step is to construct the weighted normalized matrix by multiplying the normalized decision matrix by the corresponding weighs. This is done using Equation (32).

$$v_{ij} = r_{ij} * w_j \tag{32}$$

Where;

w_j indicates the weight of the attribute.

The ideal and negative ideal solutions are determined. A^+ indicates the most preferable alternative or ideal solution. On the contrary, A^- indicates the least preferable alternative or negative ideal solution. For benefit criteria, decision maker wants to obtain the maximum value among all alternatives. On the other hand, the decision maker wants to obtain minimum value among all alternatives for cost criteria. The ideal solution and negative ideal solution can be computed using Equations (33) and (34), respectively.

$$A^+ = \{(\max v_{ij} | j \in J), (\min v_{ij} | j \in J'), i = 1,2,3, \ldots \ldots . M\} = \{v_1{}^+, v_2{}^+ \ldots \ldots \ldots . . v_N{}^+\} \tag{33}$$

$$A^- = \{(\min v_{ij} | j \in J), (\max v_{ij} | j \in J'), i = 1,2,3, \ldots \ldots . M\} = \{v_1{}^-, v_2{}^- \ldots \ldots \ldots . . v_N{}^-\} \tag{34}$$

Such that;

$$J = \{, j = 1,2,3, \ldots \ldots \ldots . N | j \text{ associated with benefit criteria}\}$$

$$J' = \{, j = 1,2,3, \ldots \ldots \ldots . N | j \text{ associated with cost criteria}\}$$

Where;

M represents the number of alternatives. N represents the number of attributes.

The fourth step is to calculate the separation distance of each alternative to the ideal and negative ideal solutions. $s^+{}_i$ represents the separation distance of each alternative in the Euclidean way from the ideal solution. On the contrary, $s^-{}_i$ represents the separation distance of each alternative in the Euclidean way from the negative ideal solution. The separation distance to the ideal solution and the separation distance to the negative ideal solution can be computed using Equations (35) and (36), respectively.

$$s^+{}_i = \left(\sum_{j=1}^{n} (v_{ij} - v^+{}_j)\right)^{\frac{1}{2}} \tag{35}$$

$$s^-{}_i = \left(\sum_{j=1}^{n} (v_{ij} - v^-{}_j)\right)^{\frac{1}{2}} \tag{36}$$

The fifth step is to calculate the relative closeness of an alternative A_i to the ideal solution A^+. The relative closeness is calculated using Equation (37). when $c^*{}_i$ is close, this means that the solution is closer to the ideal solution. Alternatives are ranked in descending order.

$$c^*{}_i = \frac{s^-{}_i}{s^+{}_i + s^-{}_i} \tag{37}$$

4.2.3.2 Computational procedures of GRA

GRA is based on Grey system theory, which was developed by Deng in 1982. Grey system theory is very useful in dealing with the uncertainty, lack of information and incomplete data. It enables to construct an adequate and reliable model, which makes grey system theory suitable for predicting the future in the presence of limited old and poor data. The process of GRA can be summarized as follows (Ma et al., 2019; Lee et al., 2019):

Grey Relational generating is normalization process for performance attributes. Equation (38) is used to normalize beneficial attributes (the higher value the better option). Equation (39) is used to normalize non-beneficial attributes (the lower value the better option). Equation (40) is used to normalize attributes with respect to a certain desired value $x^*{}_j$, whereas a closer measure of performance to the desired value, implies a better alternative.

$$y_{ij} = \frac{x_{ij} - \min\{x_{ij}, i = 1,2, \dots \dots \dots m\}}{\max\{x_{ij}, i = 1,2, \dots \dots \dots m\} - \min\{x_{ij}, i = 1,2, \dots \dots \dots m\}} \tag{38}$$

$$y_{ij} = \frac{\max\{x_{ij}, i = 1,2, \dots \dots \dots m\} - x_{ij}}{\max\{x_{ij}, i = 1,2, \dots \dots \dots m\} - \min\{x_{ij}, i = 1,2, \dots \dots \dots m\}} \tag{39}$$

$$y_{ij} = \frac{|x_{ij} - x_j *|}{\max\{x_{ij}, i = 1,2, \dots \dots \dots m\} - \min\{x_{ij}, i = 1,2, \dots \dots \dots m\}} \tag{40}$$

Reference sequence generation is the second step where the performance values are defined within the range [0, 1]. For the cost category, it is the lowest value while in the benefit category, it is the highest value. Grey Relational coefficient generation is the third step. The purpose of this step is to determine whose compatibility sequence is closest to the reference sequence. Grey relational coefficient is calculated using Equation (41).

$$\gamma(y_{0j}, y_{ij}) = \frac{\Delta_{min} + \xi\Delta_{max}}{\Delta_{ij} + \xi\Delta_{max}} \tag{41}$$

Where;

$\Delta_{ij} = |y_{0j} - y_{ij}|$

$\Delta_{min} = \min\{\Delta_{ij}, i = 1,2, \dots \dots \dots m; j = 1,2, \dots \dots \dots n\}$

$\Delta_{max} = \max\{\Delta_{ij}, i = 1,2, \dots \dots \dots m; j = 1,2, \dots \dots \dots n\}$

ξ is the distinguishing coefficient within the range [0, 1].

The grey relational grade is calculated using Equation (42). The best alternative is one associated with the highest relational grade.

$$r(y_0, y_i) = \sum_{j=1}^{n} w_j * \gamma(y_{0j}, y_{ij}) \tag{42}$$

4.3 Bridge Maintenance Decision-making Strategy

The objectives of this model constitute designing a bridge maintenance decision-making strategy, and structuring severity rating systems for the five bridge defects. The former objective enables decision-makers to determine the appropriate intervention action of the bridge deck based on its overall condition. The latter one aids in mapping the severity levels of the five bridge defects capitalizing on the bridge defects severity indices, namely BDCI, BDDI, BDCRI, BDSPI and BDSCI. The framework of the bridge maintenance decision-making strategy model is depicted in Figure 8. The input of the model comprises the importance weightings of the bridge defects and the IBDCI obtained from the previous two models in addition to the percentages of condition categories of the bridge defects. In order to structure an efficient rating system, sufficient amount of inspection records should be present. As such, the percentages of condition categories of the bridge defects are assumed random variables that follow certain probability distributions. Chi-squared is a non-parametric goodness of fit test that is applied to identify the best fit distribution and associated parameters for each condition category for each bridge defect. Latin hypercube sampling is then adopted to generate numerous representative data points capitalizing on the full exploration of the entire design space. Eventually, fuzzy C-means clustering algorithm is adopted to establish the bridge maintenance decision-making strategy and to cluster the BDSIs into very poor, poor, medium and good condition categories.

INSERT FIGURE 8

4.3.1 Chi-squared test

Chi-squared test is applied to specify whether or not a sample is drawn from a population with a specific probability distribution. The performed chi-squared test examines the null hypothesis (H_0), which implies that the data points follow a specific probability distribution. On the other contrary, the alternative hypothesis (H_1) implies that data points don't follow the probability distribution. If the $P-$value is less than the significance level (Chi-squared statistic greater than critical value), then the null hypothesis is rejected in favor of the alternative hypothesis. Nonetheless, if the $P-$value is more than the significance level, thus the null hypothesis is accepted. The Chi-squared statistic (x^2) can be expressed as follows (Love at al., 2018).

$$x^2 = \sum_{i=1}^{K} \frac{(O_i - E_i)^2}{E_i} \tag{43}$$

Such that;

$$E_i = F(X_2) - F(X_1) \tag{44}$$

Where;

O_i and E_i represent the observed frequency and expected frequency for bin i, respectively. K is a positive integer that stands for the degrees of freedom. F denotes the cumulative distribution function of the tested probability distribution. X_1 and X_2 stand for the limits of bin i. It is worth mentioning that the distribution coupled with the lowest x^2, is the best fit distribution.

4.3.2 Latin hypercube sampling

Latin hypercube sampling (LHS) was initially proposed by Mckay et al. (1979) and it was later improved by Iman and Conover (1982). It is utilized herein to generate random samples drawn from the input probability distributions of condition categories of bridge defects. LHS is a modified stratified sampling of Monte Carlo simulation that exemplified its higher capacity in simulating the variability in the design space of the input probability distributions through reducing the error of sampling. LHS provides faster convergence in estimating the parameter's uncertainties, whereas it requires less number of iterations to attain the same level of statistical accuracy of Monte Carlo simulation (MCS). As such, LHS is recommended over MCS when modeling complex problems, and when time constraint is an issue (Pan et al., 2020; Li et al., 2013).

In the Latin hypercube sampling, the whole sampling domain of the input variables is stratified into M non-overlapping and mutually exclusive bins of equal marginal probability $1/M$. Then, one of the bins is selected randomly for sampling within the first iteration, whereas the first sample is drawn from the first bin. Until the remaining M iterations, one of the bins that has not been chosen in the previous iterations is selected for sampling. This process is to ensure that all the bins are being sampled from due to the presence of M partitions and M samples. The afore-mentioned procedures are repeated for all the N input variables.

4.3.3 Fuzzy C-means clustering

Clustering is the process of partitioning the dataset into a homogenous set of clusters without having any prior information about the clusters where the points within the same cluster share similar features. Clustering algorithms are divided into two main categories, namely hard clustering and soft clustering. In hard clustering, the data points are assigned to only one cluster such as K-means clustering. Soft clustering is the process of the assignment of data points to the clusters with different membership degrees such as fuzzy C-means clustering algorithm (FCM). In the present study, FCM is applied to structure the categorization of IBDCI, BDCI, BDDI, BDCRI, BDSPI and BDSCI. FCM is an iterative clustering algorithm where each data point is assigned to one cluster or more based on the membership degrees. FCM was developed by Dunn in 1973 and improved by Bezdek in 1981. FCM is based on minimizing the following objective function (Keskin, 2015).

$$J_w = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \left\| \left(X_i - C_j \right)^2 \right\| \quad (45)$$

Where;

m is a fuzzifier constant that is greater than one. u_{ij} denotes the degree of membership of the X_i in the cluster j and it is between zero and one. X_i is a $i - th$ data point in a d-dimensional space. C_j represents the centroid of the $j - th$ cluster. $|| * ||$ is a norm distance that represents the similarity between the data point and the centroid of the cluster.

FCM starts by randomly initiating the cluster centroid. The second step is to construct the membership matrix. A membership matrix ($U_{(N \times C)}$) is composed of a group of membership degrees. The degree of membership (u_{ij}) can be calculated using Equation (46). The cluster centroids are then updated and can be calculated using Equation (47). The cluster centroids and the membership degrees are iteratively updated until the convergence criteria are satisfied. The convergence criteria is shown in Equation (48). The defuzzification process is performed using Equation (49) whereas the data point is assigned to the cluster that has the maximum degree of membership.

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\left\| (X_i - C_j) \right\|}{\left\| (X_i - C_k) \right\|} \right)^{\frac{2}{m-1}}} \quad (46)$$

$$C_j = \frac{\sum_{i=1}^{N} u_{ij}^m \times X_i}{\sum_{i=1}^{N} u_{ij}^m} \quad (47)$$

$$\max_{ij} \{ |u_{ij}^{it+1} - u_{ij}^{it}| \} < \zeta \quad (48)$$

$$D_j = \arg_i \{ \max(u_{ij}) \} \quad (49)$$

$$\sum_{j=1}^{c} u_{ij} = 1 \quad (50)$$

Where;

D_j represents the de-fuzzified value, which is calculated based on the maximum degree of membership principle. ζ is the termination constant between zero and one. it refers to the number of iteration steps.

5. SENSITIVITY ANALYSIS

One of the main objectives of the proposed framework is to perform a sensitivity analysis in order to identify the bridge defect that mostly influence IBDCI. It is conducted by changing the percentages of the weights of the bridge defect by 20%, 40%, 60%, 80% and 100% one at a time. Assume that the change in the weight of the second attribute is represented by (Δ), then the weight of this attribute (w_2') will be $w_2 + \Delta$. The weights of other attributes will be calculated using Equation (51), so that the sum of weights of the attributes will be equal to 100%.

$$w'_j = \frac{1 - w'_c}{1 - w_c} \times w_j \tag{51}$$

Where;

w_c, w'_c represent the original and modified weight of the main attribute, respectively. w_j, w'_j represent the original and modified weights of the other attributes, respectively.

6. DATA COLLECTION AND ANALYSIS

All the computations are carried out on a laptop with an Intel Core i7 CPU, 2.2 GHz and 16 GB of memory. The first stage of the proposed framework is to compute the weighting vector of the bridge defects capitalizing on $O - FANP$. A questionnaire survey is designed to get feedback from the experts based on two levels of comparison, where the experts were asked to determine how important is bridge defect A when compared with bridge defect B with respect to the condition of the bridge deck. For the second level of comparison, the experts were asked to identify how important is bridge defect A when compared to bridge defect B with respect to bridge defect C. A total of 35 responses were received from 40 experts, which implies a response rate of 87.5%. The respondents are site engineers with experience of 5-10 years. They are aware of the different construction practices of bridges as well as the different concrete defects.

In the designed survey, the experts were asked to fill out the pair-wise comparison matrices based on five linguistic terms, which are: equally important (EI), moderately important (MI), strongly important (SI), very strongly important (VSI), and absolutely important (AI). The proposed framework utilizes $\mathrm{NSGA-II}$ to determine the optimum fuzzy scale among the set of five triangular fuzzy scales. The population size and number of iterations are assumed 10 and 30, respectively. Tournament selection is the parent selection strategy. The crossover rate and the mutation rate are assumed 0.8 and 0.05, respectively. The convergence of the optimum fuzzy scale selection model is presented in Figure 9. As can be seen, the minimum $\mathrm{OVR\_CONST}$ achieved is 1.88%. Moreover, the optimization model stabilizes at iteration 8 which demonstrates the success of $\mathrm{NSGA-II}$ in searching for the optimum fuzzy scale. $\mathrm{TFS\#3}$ is selected as the optimum fuzzy scale, and it is the one used in any further computations. Table 2 and Table 3 illustrate a sample of the pair-wise comparison matrices for the first level of comparison and second level of comparison (with respect to corrosion), respectively using $\mathrm{TFS\#3}$. It should be mentioned that the optimization model provided a significant enhancement in the $\mathrm{OVR\_CONST}$ from 20.38% to 1.88%, which aids in establishing more efficient condition assessment models.

INSERT FIGURE 9

INSERT TABLE 2

INSERT TABLE 3

After the calculation of the optimum linguistic scale, the pair-wise comparison matrices that achieved a consistency ratio more than 10% are removed from any further calculations. The considered pair-wise comparison matrices are only the ones that achieved a consistency ratio less than 10%. The opinions of the experts are aggregated based on the geometric mean. The opinions of the experts are aggregated based on the geometric mean using Equation (11). The aggregated pair-wise comparison matrices are analyzed using Chang's extent analysis method to compute the weights of the five bridge defects. Table 4 presents a sample of the constructed un-weighted supermatrix, weighted supermatrix, and limit supermatrix. Based on the limit supermatrix, the weights of the corrosion, delamination, cracking, spalling and scaling are: 33.411%, 22.816%, 16.735%, 23.467%, and 3.569%, respectively. This implies that corrosion has the largest weight followed by spalling while scaling had the lowest weight of importance. The developed weight interpretation model is validated through comparison with FAHP to investigate the capability of the ANP to capture the interdependencies between the bridge defects. FAHP utilizes TFS#1 to compute the importance weightings of the bridge defects. As per the FAHP model, the weights of corrosion, delamination, cracking, spalling, and scaling are: 31.339%, 22.792%, 21.368%, 21.652%, and 2.849%, respectively. Corrosion attained the highest weight followed by delamination while scaling provided the least weight. Also, it can be inferred that the delamination, cracking and spalling had nearly equal weights. The differences in the importance weights between FAHP and $\mathrm{O-FANP}$ demonstrates the capacity of the proposed weight interpretation model to simulate the interdependencies between the bridge defects.

INSERT TABLE 4

The second model is the integrated condition assessment. The weights of the bridge defects are fed from the weight interpretation model. The first phase of the integrated condition assessment model is the automated calibration of fuzzy membership functions of the bridge defects. The percentages of severities of bridge defects alongside with their importance weightings are integrated to compute the BDSIs and IBDCI. These percentages constitute the degrees of fuzzy membership functions of bridge defects. The percentages of severities of corrosion are interpreted using the ground penetrating radar while other percentages of severities are extracted from the inspection reports. GSSI RADAN7 software is used to pick the amplitude values of the top reinforcing rebars as depicted in Figure 10. A corrosion map is developed for a bridge that is located on the Chemin Saint-Grégoire in municipality Les Cèdres that overpasses Autoroute 20, Quebec, Canada. The bridge was constructed in 1965 with a total length of 65 meters, and the width of the bridge decks is 13 meters. A corrosion map of a zone of the bridge deck is depicted in Figure 11. As can be seen, the area percentages of the “Good”, “Medium”, “Poor” and “Very Poor” categories are: 45.78%, 34.26%, 12.98%, and 6.98%, respectively.

INSERT FIGURE 10

INSERT FIGURE 11

IWO algorithm is adopted for the automated calibration of fuzzy membership functions. This comprises optimizing the shape of fuzzy membership function of bridge defects, the boundaries of fuzzy membership functions and defuzzification technique. The initial parameters of the invasive weed optimization algorithm are adopted from the literature as found in Asgari et al. (2016), Azizipour et al. (2016), and Zhou and Xidan (2014). These parameters are adapted by modifying each of them one at a time to come up with the optimum configuration of parameters capitalizing on their performance. The length of the optimization model varies within the iterations as a result of the optimization of S_D, whereas its maximum length is 27. The initial population size and maximum number of iterations are assumed 100 and 100, respectively. The minimum and maximum numbers of seeds are assumed 0 and 5, respectively. The initial and final values of the standard deviation are assumed 0.01 and 0.5, respectively. The non-linear modulation index is assumed two. The convergence curve of the invasive weed optimization model is depicted in Figure 12. The minimum ACDT achieved by the IWO algorithm is 4.878×10^{-6}. Furthermore, the optimization model stabilizes at iteration 22. This exemplifies the higher capacity of the IWO algorithm in optimizing the fuzzy membership functions of the bridge defects.

INSERT FIGURE 12

The developed automated calibration model is validated through comparison with genetic algorithm (GA) and nonlinear programming (NLP). Genetic algorithm is considered as the benchmark meta-heuristic that most of the optimization algorithms are compared with to signify their performance. Ten independent runs were carried out in order to account for the randomness of the meta-heuristic optimization algorithms and to establish a robust comparison between the optimization algorithms. The population size and number of iterations are assumed 100 for both in order to establish a fair comparison with the invasive weed optimization model. Tournament selection is the parent selection strategy. Two-point crossover is utilized such that the crossover rate is assumed 0.8 while the mutation rate is assumed 0.1. A comparative analysis between the invasive weed optimization algorithm, genetic algorithm and non-linear programming is depicted in Table 5. IWO algorithm achieved the lowest objective function value while NLP attained the highest objective function value (4.709). It can be also noticed that the IWO algorithm provided lowest maximum and mean values of the ACDT. Furthermore, IWO algorithm achieved lowest coefficient of variation than the GA. A lower coefficient of variation implies better quality and less variability in the generated optimum solutions. The convergence curve of the genetic algorithm optimization model is presented in Figure 13. It can be inferred that the minimum attained ACDT is 0.0192. Moreover, the optimization model stabilizes at iteration 53. In the light of foregoing, it can be interpreted that IWO algorithm significantly outperformed the genetic algorithm and non-linear programming. Additionally, it required more iterations to stabilize compared to the IWO algorithm.

INSERT TABLE 5

INSERT FIGURE 13

It is worth mentioning that the present optimization problem consists of discrete and continuous decision variables. Discrete optimization problems are combinatorial problems, which are subsequently considered as non-deterministic polynomial time (NP)-hard problems. Mathematical optimization algorithms often fail to deal with NP -hard problems. NLP is performed based on the active set algorithm. NLP provided the least performance compared to IWO algorithm and GA. This manifests that the NLP fails to solve the NP -hard problems with a large number of decision variables especially discrete decision variables and non-linear objective functions. NLP failed to find the global optimum solutions because, in the case of large-scale and complex problems, the exact solutions methods are inefficient to explore the design search space, and the meta-heuristic algorithms can serve as a better alternative to find the optimal solutions.

The optimized parameters of the fuzzy membership functions are presented in Table 6. As can be seen, the optimum shape of fuzzy membership function is triangular distribution. The optimum defuzzification technique is the bisector method. It can be also concluded that the optimized boundaries of the fuzzy membership functions of the bridge defects are different from each other. For instance, the distributions of the very poor, poor, good and medium categories for corrosion are (0, 25.647), (0, 25.647, 55.206), (25.647, 55.206, 100), and (25.647, 55.206, 100), respectively. On the other hand, the distributions of the very poor, poor, good and medium categories for spalling constitute (0, 37.91), (0, 37.91, 67.636), (37.91, 67.636, 100), and (67.636, 100), respectively. The calibrated membership functions of the corrosion, delamination, cracking, spalling, and scaling are illustrated in Figures 14, 15 and 16. The black, magenta, red and blue fuzzy sets denote the “Very Poor”, “Poor”, “Medium” and “Good” categories, respectively.

INSERT TABLE 6

INSERT FIGURE 14

INSERT FIGURE 15

INSERT FIGURE 16

The third model is the bridge maintenance decision-making strategy, which opts at structuring an intervention platform of bridge decks capitalizing on the IBDCI in addition to designing a severity rating system for each of the five bridge defects separately. A database is established using 10 bridges scanned using the ground penetrating radar alongside other 35 inspection records. This dataset is used to append the percentages of severities of the bridge defects for the purpose of identification the best-fit distribution. In this context, Chi-squared test is implemented to define the best-fit distribution of each condition category. The chi-squared critical value at significance level of 0.05 is 60.481. A sample of the identified best-fit distributions for some condition categories is illustrated in Table 7. The best-fit distribution is the one associated with the lowest chi-squared statistic. The chi-squared statistic for the best-fit distribution of the "Very Poor" condition category of corrosion is 2.746. Additionally, the chi-squared statistic for the best-fit distribution of the "Poor" condition category of scaling is 54.396. This indicates that the exponential distribution better fits the "Very Poor" condition category of corrosion than the uniform distribution fits "Poor" condition category of scaling.

It can be also interpreted that the best-fit distribution for the "Good" category of corrosion is uniform distribution while the best-fit distribution of the "Medium" category of spalling follows exponential distribution. Latin hypercube sampling is adopted to generate a large number of random scenarios of the severity percentages of defects based on the best-fit distribution. The histogram generated from Latin hypercube sampling is constructed based on 10,000 iterations. . Figure 17.a depicts the histogram of the IBDCI generated using Latin hypercube sampling. Figure 17.b represents the cumulative distribution of the IBDCI. The simulations of the LHS signify that there is a probability 90.37% that the IBDCI lies between 50 and 80.

INSERT TABLE 7

INSERT FIGURE 17

A comparison between Latin hypercube sampling and Monte Carlo simulation is depicted in Figure 18. The performances of the two sampling techniques are evaluated with respect to the mean convergence and standard deviation convergence. The comparison is conducted within the 10,000 iterations. However, only 500 and 5000 iterations are displayed in the mean convergence and standard deviation convergence, respectively in order to provide an in-depth evaluation for the performances of the two sampling techniques. As can be seen, it can be interpreted that Latin hypercube sampling experience less perturbations for both mean and standard deviation. The less variations during the simulation process imply a faster convergence a sampling algorithm. For instance, For instance, the cumulative mean of the Latin hypercube starts to stabilize at iteration 220 while in the case of Monte Carlo simulation, the mean of the distribution starts to stabilize at iteration 430. The cumulative standard deviation in the case of Latin hypercube sampling stabilizes at iteration 3100 while it stabilizes at iteration 4030 in Monte Carlo simulation. The mean absolute deviation (MAD) is computed in order to provide a numerical evaluation of the convergence rate, such that the MAD of the mean for the Latin hypercube sampling and Monte Carlo simulation are 0.012 and 0.056, respectively. Additionally, the MAD of the standard deviation for the Latin hypercube sampling and Monte Carlo simulation are 0.0058 and 0.0421, respectively. As such, it can be concluded that the LHS provides higher statistical accuracy and faster convergence than the MCS based on the visual and numerical analysis.

INSERT FIGURE 18

The rating systems of the BDCI, BDDI, BDCRI, BDSPI, BDSCI and IBDCI are established based on fuzzy C-means clustering algorithm. The maximum number of iterations and fuzzifier constant are assumed 9,000 and 3, respectively. A sample of the cluster memberships obtained from the FCM algorithm is depicted in Table 8. In the fuzzy C-means clustering algorithm, the data point is assigned to the cluster that has the maximum degree of membership. For instance, the data point of IBDCI 59.149 is assigned to “Cluster 2” because it has the maximum degree of membership of 0.5937. Furthermore, the data point of IBDCI 78.48 is assigned to “Cluster 4” because it is associated with the maximum degree of membership (0.8489). Table 9 describes the rating systems of the bridge defects based on their corresponding BDSI. As shown in Table 9, if the BDCRI is less than 57.223. Then, the bridge deck experience very severe cracking. It can also interpreted that if the BDSPI lies between 65.916 and 83.81. Thus, the bridge deck suffers from severe spalling. Table 9 enables the decision makers to interpret the severity levels of the bridge defects they are mostly concerned with capitalizing on the corresponding BDSI. Table 10 demonstrates the bridge deck intervention recommendations as per the IBDCI. A shown in Table 10, if the IBDCI is less than 60.318 this implies that the bridge deck needs replacement. Moreover, if the IBDCI is between 60.318 and 67.769. Thus, the bridge deck requires rehabilitation.

INSERT TABLE 8

INSERT TABLE 9

INSERT TABLE 10

7. MODEL IMPLEMENTATION

For the bridge located in the Chemin Saint-Grégoire in municipality Les Cèdres, the output of the bridge deck corrosion model, bridge deck delamination model, bridge deck cracking model, bridge deck spalling and bridge deck scaling model are depicted in Figures 19, 20 and 21, respectively. The cyan membership function represents the resultant fuzzy set of the bridge defects based on the interpreted severity levels of the bridge defects. This fuzzy set is defuzzified to obtain the bridge deck severity index for each of the defects. The degrees of membership of the resultant fuzzy set are obtained based on the percentages of condition categories of the bridge defects. As shown in Figure 19.a, the percentages of severities of corrosion are extracted from the corrosion map displayed in Figure 11. As such, the resultant fuzzy set of corrosion is established, and the BDCI is found to be equal to 70.552, which implies that the bridge deck suffers from medium corrosion. It can be also inferred from Figures 19 to 21, that the BDDI, BDCRI, BDSPI and BDSCI are equal to 57.443, 43.42, 72.923 and 41.137, respectively. This indicates the bridge deck suffers from severe delamination, very severe cracking, severe spalling and very severe scaling. Then, the IBDCI is computed capitalizing on the weights of the bridge defects and the BDSIs. The IBDCI is found to be equal to 60.844 out of 100. This implies that the bridge deck requires rehabilitation.

INSERT FIGURE 19

INSERT FIGURE 20

INSERT FIGURE 21

The developed bridge deck corrosion model using the ground penetrating radar is validated through comparison with the results obtained from the half-cell potential. Half-cell potential is a non-destructive technique that relies on the potential difference between a reference electrode and the reinforcement rebars to evaluate the corrosion in concrete structures. It is criticized by being inefficient to deal with epoxy coated reinforcement (Elsener et al., 2003). A comparison between the corrosion evaluated from both ground penetrating radar is described in Table 11. As shown in Table 11, the percentages of “Good”, “Medium”, “Poor” and “Very Poor” categories interpreted using half-cell potential are 62%, 33.6%, 3.7% and 0.14%, respectively. The BDCI obtained from ground penetrating radar and half-cell potential are 70.552 and 83.135, respectively. As such, the overall severity levels of corrosion from ground penetrating radar and half-cell potential are “Medium” and “Good”, respectively. In this context, it can be concluded that the differences in the overall corrosion assessment obtained from the models manifest the higher capacity of ground penetrating radar in detecting and evaluating corrosion. This is compatible with the recommendations provided by Gucunski et al. (2013), Barnes and Trottier (2004), and Cardimona et al. (2000) who preferred ground penetrating radar over half-cell potential with respect to modelling the deterioration in the reinforced concrete bridges.

INSERT TABLE 11

The developed integrated condition assessment model is then compared with the models established by Alsharqawi et al. (2016), and Dinh and Zayed (2016). Alsharqawi et al. (2016) introduced a quality function deployment-based model to calculate an integrated condition index. The bridge deck achieved a condition index of 22.77%, which meant that the bridge deck needs was in a poor condition and requires repair based on a three-point scale. Dinh and Zayed (2016) computed a bridge deck corrosiveness index for the same bridge deck and it was 60.26 out of 100. The bridge deck was given grade “D”, which indicated the bridge deck is very unhealthy and intervention is strongly recommended based on a five-point scale. The differences in the IBDCI obtained from the developed model with respect to the afore-mentioned models can be attributed to two main reasons. The developed model defines the bridge intervention strategy based on an evaluation of a set of defects, whereas developing a bridge intervention strategy based on a single defect often fails to provide an accurate insight about the condition of the bridge deck. Furthermore, some models don't model the uncertainties arise from the vagueness and subjectivity provided by experts' judgements, and the inherent uncertainties encountered during the evaluation of bridge defects' severities. Lack of modelling of these uncertainties sometimes induces unrobust and inefficient condition assessment models.

Sensitivity analysis is performed in order to define the most significant bridge defect through experimenting different weights of bridge defects. This is done through modifying the weights of bridge defects by 20%, 40%, 60%, 80% and 100%. The updated weights of the remaining defects are computed using Equation (51). Figure 22 describes the implications of different scenarios of weights of bridge defects on the integrated bridge deck condition index. The mean absolute deviation of the IBDCI for corrosion, delamination, cracking, spalling, and scaling are 3.28, 2.693, 1.578, 2.157 and 0.332, respectively. This implies that corrosion constitutes the highest influence on the condition of bridge deck that needs to be accurately evaluated in order to efficiently monitor the deterioration in reinforced concrete bridges. Furthermore, it can be concluded that scaling has the least influence on the condition of bridge deck.

INSERT FIGURE 22

The second case study is a bridge located in Boulevard Lévesque Est that overpasses Auto route 25 in the city of Laval. The bridge was constructed in 1966 where the length of the bridge is 55 meters while the width of the bridge is 8 meters. The corrosion map of a zone of the bridge deck is depicted in Figure 23. As shown in Figure 23, the area percentages of the "Good", "Medium", "Poor", and "Very Poor" condition categories are: 41.3%, 43.18%, 10.35%, and 5.17%, respectively. Based on the integrated condition assessment model, BDCI, BDDI, BDCRI, BDSPI and BDSCI are 80.657, 77.599, 95.171, 89.066 and 95.53, respectively, This signifies that the bridge deck experience slight corrosion, medium delamination, slight cracking, medium spalling and slight scaling. Then, IBDCI is envisioned based on the afore-mentioned bridge defects severity indices as well as the relative importance weightings of the bridge defects. The IBDCI is equal to 82.964, which manifests that the bridge deck doesn't need intervention.

INSERT FIGURE 23

A two-fold comparison is conducted between the condition ratings obtained by the proposed framework and the ones from the inspection ratings. The IBDCI is converted to a scale from one to four in order to establish a fair comparison between the two models. The first fold involves comparing the two models based on mean absolute error (MAE), which is average of the absolute differences between the two models. The MAE is equal to 1.2, which indicates there is a difference between the output of the two models. The second fold involves performing Wilcoxn test, Mann-Whitney-U test and binomial sign test to examine the statistical significant differences between the two models at a significance level (α) is set to be 0.05. The performed statistical tests investigates the null hypothesis (H_0), which means that that there is no significant difference between the two models. On the contrary, the alternative hypothesis (H_1) implies that there is a significant difference between the two models. Thus, if the $P-$value is less than the significance level, then null hypothesis is rejected in favor of the alternative hypothesis. Nonetheless, if the $P-$value is more than significance level, thus the null the null hypothesis is accepted. The $P-$values of the two models from Wilcoxn test, Mann-Whitney-U test and binomial sign are 3.84×10^{-2}, 4.86×10^{-2} and 0, respectively. Thus, the null hypothesis is rejected, which indicates that there are statistical significant differences between the two models. In the light of foregoing, it can be concluded that the developed condition assessment model significantly outperformed the condition assessment model established by the MTQ.

The developed integrated condition assessment model is implemented for the intervention prioritization of sub network of five bridge decks. Table 12 presents the BDSIs, IBDCI and prioritization rankings. It is worth mentioning that the bridge maintenance prioritization is envisioned on the IBDCI, whereas a lower IBDCI implies a more deteriorated bridge deck that needs urgent intervention. As such, it possesses a higher ranking with respect to the others. “Bridge 1” has the highest ranking while “Bridge 2” provided the lowest ranking, whereas the IBDCI of “Bridge 1” and “Bridge 2” are 60.844 and 82.964, respectively. It is expected that the developed model can provide an efficient decision-making platform that aids transportation agencies for bridge maintenance prioritization in both element and network levels.

INSERT TABLE 12

8. CONCLUSION

In the view of substantial number of worldwide bridges are reaching structural deficiency levels in addition to significant imbalance exists between the extensive needs intervention actions, and the available resources. This calls for establishing efficient Decision-making paradigms to aid transportation agencies in planning MR&R activities within squeezed budget constraints. In this context, the present study proposed an invasive weed optimization fuzzy decision support framework for the prioritization of bridge intervention actions in both element and network levels. The developed framework is composed of three fundamental tiers. The first tier encompasses designing an optimized fuzzy analytical network process model to compute the relative importance weights of corrosion, delamination, cracking, spalling and scaling. This is accomplished through formulating a genetic algorithm model that aims at maximizing the overall consistency of the responses via restructuring the judgment matrices while preserving as much possible information in the original matrices. FANP was adopted to address the vagueness and subjectivity elicited from the experts' judgements in addition to simulating the interdependencies between the bridge defects.

The second tier is the integrated condition assessment model that capitalizes on ground penetrating radar and inspection reports to evaluate the extent of severities of the bridge defects. The output of this model comprises establishing a severity index for each bridge defect separately in addition to developing a bridge intervention prioritization platform stepping on the IBDCI. The severity levels of the bridge defects are modeled in the form of fuzzy membership functions to simulate the inherent uncertainties and vagueness encountered during the inspection of the bridge deck. In this regard, a variable-length invasive weed is designed to automatically calibrate the fuzzy membership functions to circumvent the limitations of subjective, tedious and case dependent manual methods of calibration. The automated calibration constituted deriving the optimum shape of fuzzy membership functions, optimum boundaries for each fuzzy membership function of each bridge defect and optimum defuzzification technique.

The third model implicates designing a bridge maintenance decision-making strategy and structuring severity rating systems for the five bridge defects. In this model, the percentages of condition categories of the bridge defects are assumed to follow probability distribution, such that the best-fit distribution is defined according to chi-squared goodness of fit test. Then, Latin hypercube sampling is adopted to generate numerous data points necessitated for the establishment of efficient rating systems. Fuzzy C-means clustering was implemented to obtain the thresholds of the BDSIs and IBDCI.

The capabilities of the developed framework were experimented through two case studies of bridge decks in Canada. Furthermore, a six-fold comparison was conducted for its validated. In the first level, $\mathrm{O-FANP}$ outperformed classical FANP, whereas it provided a significant improvement in the $\mathrm{OVR\_CONST}$ of 90.78%. Also, $\mathrm{O-FANP}$ was compared with the FAHP to evince its capabilities to simulate the interdependencies between the bridge defects. The second level involved the validation of the automated calibration model of fuzzy membership functions through comparison with other well-performing optimization algorithms. IWO algorithm significantly outperformed the genetic algorithm and non-linear programming, whereas IWO algorithm, GA and NLP attained ACDT of 4.878×10^{-6}, 1.92×10^{-2} and 4.709, respectively. The third level involved comparing Latin hypercube sampling with Monte Carlo simulation with respect to the mean and standard deviation convergence to experiment its potential in structuring efficient rating system. Results revealed that LHS provided higher statistical accuracy and faster convergence rate than MCS for both mean and standard deviation.

The fourth level constituted appraising the BDCI obtained from ground penetrating radar and half-cell potential. Results demonstrated the higher capacity of ground penetrating radar in assessing severity levels of corrosion in reinforced concrete bridged decks. Additionally, a sensitivity analysis is performed to derive the most influential bridge defect, whereas it was concluded that corrosion and scaling experience the highest and lowest implication on the BDCI. The fifth level incorporated comparing the IBDCI with other previous condition assessment models. It was found that the developed model induces a more comprehensive and in-depth evaluation of the condition of the bridge deck.

The sixth level encompassed comparing the developed framework with the condition assessment model developed by MTQ. It was inferred that the developed framework achieved superior significant performance, whereas MAE was 1.2, which illustrated that the developed framework can better capture the deterioration experiences by bridge decks .Furthermore, the $\mathrm{P-values}$ of the two models from Wilcoxn test, Mann-Whitney-U test and binomial sign are 3.84×10^{-2}, 4.86×10^{-2} and 0, respectively. In the light of foregoing, it can be expected that the developed framework can serve as an efficient paradigm to aid transportation agencies in systematically mapping and prioritizing the bridge intervention strategies in both element and network levels.

REFERENCES

1. Abbasianjahromi, H., Sepehri, M., & Abbasi, O. (2018). “A Decision-Making Framework for Subcontractor Selection in Construction Projects.” *Engineering Management Journal*, *30*(2), 141–152.
2. Al Nahyan, M. T., Hawas, Y. E., Raza, M., Aljassmi, H., Maraqa, M. A., Basheerudeen, B., & Mohammad, M. S. (2018). “A Fuzzy-based Decision Support System for Ranking the Delivery Methods of Mega Projects.” *International Journal of Managing Projects in Business*, *11*(1), 122–143.
3. Alsharqawi, M., Zayed, T., & Shami, A. (2020). “Ground penetrating radar-based deterioration assessment of RC bridge decks.” *Construction Innovation*, *20*(1), 1–17.
4. Alsharqawi, M., Dabous, S. A., and Zayed, T. (2016). “Quality Function Deployment Based Method for Condition Assessment of Concrete Bridges.” *95th Annual Meeting of the Transportation Research Board*, Washington DC, United States of America, 10-14 January.
5. Amiri, M. J. T., Abdollahzadeh, G., & Haghighi, F. (2019). “Bridges Risk Analysis in View of Repair and Maintenance by Multi Criteria Decision Making Method (Case Study : Babolsar Bridges).” *International Journal of Transportation Engineering*, *7*(1), 91–114.
6. Anbari, M. J., Tabesh, M., & Roozbahani, A. (2017). “Risk assessment model to prioritize sewer pipes inspection in wastewater collection networks.” *Journal of Environmental Management*, *190*, 91–101.
7. Asgari, H., Haddad, O. B., Pazoki, M., and Loáiciga, H. A. (2016). “Weed Optimization Algorithm for Optimal Reservoir Operation.” *Journal of Irrigation and Drainage Engineering*, 142(2), 1-11.
8. Aydın, S., & Kahraman, C. (2013). “A New Fuzzy Analytic Hierarchy Process and Its A New Fuzzy Analytic Hierarchy Process and Its Application to Vendor Selection Problem.” *Journal of Multiple-Valued Logic and Soft Computing*, 353–371.
9. Azimifard, A., Moosavirad, S. H., & Ariafar, S. (2018). “Selecting sustainable supplier countries for Iran’s steel industry at three levels by using AHP and TOPSIS methods.”

Resources Policy, *57*, 30–44.

10. Azizipour, M., Ghalenoei, V., Afshar, M. H., & Solis, S. S. (2016). “Optimal Operation of Hydropower Reservoir Systems Using Weed Optimization Algorithm.” *Water Resources Management*, 30, 3995–4009.
11. Barnes, C. L., & Trottier, J.-F. (2004). “Effectiveness of Ground Penetrating Radar in Predicting Deck Repair Quantities.” *Journal of Infrastructure Systems*, *10*(2), 69–76.
12. Bathaei, A., Mardani, A., Baležentis, T., & Awang, S. R. (2019). “Application of Fuzzy Analytical Network Process (ANP) and VIKOR for the Assessment of Green Agility Critical Success Factors in Dairy Companies.” *Symmetry*, *11*(2), 1–22.
13. Belošević, I., Kosijer, M., Ivić, M., & Pavlović, N. (2018). “Group decision making process for early stage evaluations of infrastructure projects using extended VIKOR method under fuzzy environment”. *European Transport Research Review*, 10:43, 1-14.
14. Bhattacharjee, P. S., Fujail, A. K. M., & Begum, S. A. (2017). “A Comparison of Intrusion Detection by K-Means and Fuzzy C-Means Clustering Algorithm over the NSL-KDD Dataset.” *2017 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)*, Coimbatore, India, 14-16 December, 1-6.
15. Boender, C. G. E., Graan, J. G. d., & Lootsma, F. A. (1989). “Multi-criteria decision analysis with fuzzy pairwise comparisons.” *Fuzzy Sets and Systems*, *29*(2), 133–143.
16. Bolar, A., Tesfamariam, S., & Sadiq, R. (2013). “Condition assessment for bridges : a hierarchical evidential reasoning (HER) framework.” *Structure and Infrastructure Engineering*, 9(7), 648–666.
17. Buckley, J. J. (1985). “Fuzzy hierarchical analysis.” *Fuzzy Sets and Systems*, *17*(3), 233–247.
18. Budayan, C., Dikmen, I., Birgonul, M. T., & Ghaziani, A. (2018). “A Computerized Method for Delay Risk Assessment Based on Fuzzy Set Theory using MS Project.” *KSCE Journal of Civil Engineering*, *22*(8), 2714–2725.
19. Bui, D. T., Khosravi, K., Li, S., Shahabi, H., Panahi, M., Singh, V. P., Chapi, K., Shirzadi, A., Panahi, S., Chen, B., & Bin Ahmad, B. (2018). “New hybrids of ANFIS with several optimization algorithms for flood susceptibility modeling.” *Water*, *10*(9), 1-28
20. Bukhsh, Z. A., Stipanovic, I., Klanker, G., Connor, A. O., & Doree, A. G. (2019). “Network level bridges maintenance planning using Multi-Attribute Utility Theory.” *Structure and Infrastructure Engineering*, *15*(7), 872–885.

21. Büyüközkan, G., Kahraman, C., & Ruan, D. (2004). "A fuzzy multi-criteria decision approach for software development strategy selection." *International Journal of General Systems*, *33*, 259–280.

22. Cardimona, S., Willeford, B., Wenzlick, J., & Anderson, N. (2000). "Investigation of bridge decks utilizing ground penetrating radar." In *International Conference on the Application of Geophysical Technologies to Planning, Design, Construction, and Maintenance of Transportation Facilities*, Missouri, United States of America, 11-15 December.

23. Chang, D. (1996). "Applications of the extent analysis method on fuzzy AHP." *European Journal of Operational Research*, 95, 649–655.

24. Cheng, C. (1996). "Evaluating naval tactical missile systems by fuzzy AHP based on the grade value of membership function." *European Journal of Operational Research*, *2217*(96), 343–350.

25. Contreras-nieto, C., Shan, Y., Lewis, P., & Ann, J. (2019). "Bridge maintenance prioritization using analytic hierarchy process and fusion tables." *Automation in Construction*, *101*, 99–110.

26. Crawford, G., & Williams, C. (1985). "A note on the analysis of subjective judgment matrices." *Journal of Mathematical Psychology*, *29*(4), 387–405.

27. Darani, S. K., Eslami, A. A., Jabbari, M., & Asefi, H. (2019). "Parking Lot Site Selection Using a Fuzzy AHP-TOPSIS Framework in Tuyserkan , Iran." *Journal of Urban Planning and Development*, *144*(3), 1–12.

28. Dinh, K., Gucunski, N., Kim, J., & Duong, T. H. (2017). "Method for attenuation assessment of GPR data from concrete bridge decks." *NDT and E International*, *92*, 50–58.

29. Dinh, K., & Zayed, T. (2016). "GPR-Based Fuzzy Model for Bridge Deck Corrosiveness Index." *Journal of Performance of Constructed Facilities*, *30*(4), 1–14.

30. Deng, X., Hu, Y., & Deng, Y. (2014). "Bridge Condition Assessment Using D Numbers." *The Scientific World Journal*, Article ID 358057, 11 pages, doi: 10.1155/2014/358057. eCollection 2014.

31. Dromey, L., Ruane, K., Murphy, J. J., O'Rourke, B., & Lacey, S. (2020). "A bridge-rehabilitation strategy based on the analysis of a bridge-inspection data set." *Infrastructure Asset Management*, *7*(1), 25–35.

32. Elbeltagi, E., Hegazy, T., & Grierson, D. (2005). "Comparison Among Five Evolutionary-

based Optimization Algorithms.” *Advanced Engineering Informatics*, *19*(1): 43–53.

33. Elsener, B., Andrade, C., Gulikers, J., Polder, R., & Raupach, M. (2003). Half-cell potential measurements – Potential mapping on reinforced concrete structures. *Materials and Structures*, *36*, 1–11.
34. Farzam, A., Nollet, M.-J., & Khaled, A. (2016). “Integration of site conditions information using geographic information system for the seismic evaluation of bridges.” *Canadian Society of Civil Engineering Annual Conference: Resilient Infrastructure*, London,Canada, 1-4 June, 1-10.
35. Fitriani, H., Pratama, M. A. S., Idris, Y., & Tanzil, G. (2019). “Determination of prioritization for maintenance of the upper structure of truss bridge.” *MATEC Web of Conferences, 276,* 01036, 1-10.
36. Gao, Z., Liang, R. Y., & Xuan, T. (2019). “VIKOR method for ranking concrete bridge repair projects with target-based criteria.” *Results in Engineering, 3,* 1–9.
37. Gao, Z., & Li, J. (2018). “Fuzzy Analytic Hierarchy Process Evaluation Method in Assessing Corrosion Damage of Reinforced Concrete Bridges.” *Civil Engineering Journal*, *4*(4), 843–856.
38. García-Alfonso, H., & Córdova-Esparza, D.-M. (2018). “Comparison of uncertainty analysis of the Montecarlo and Latin Hypercube algorithms in a camera calibration model.” In *2018 IEEE 2nd Colombian Conference on Robotics and Automation (CCRA)*, Barranquilla, Colombia, 1-3 November, 1-5.
39. Goh, K. C., Goh, H. H., & Chong, H. (2019). “Integration Model of Fuzzy AHP and Life-Cycle Cost Analysis for Evaluating Highway Infrastructure Investments.” *Journal of Infrastructure Systems*, *25*(1), 1–12.
40. Goktepe, A. B., Altun, S., & Sezer, A. (2005). “Soil clustering by fuzzy c-means algorithm.” *Advances in Engineering Software, 36*, 691–698.
41. Gucunski, N., Imani, A., Romero, F., Nazarian, S., Yuan, D., Wiggenhauser, H., Wiggenhauser, H., Shokouhi, P., Taffe, A. & Kutrubes, D. (2013). *Nondestructive Testing to Identify Concrete Bridge Deck Deterioration*, Washington DC, United States of America.
42. Gupta, A., & Kumar, A. (2016). ATC calculation including wind : A probabilistic study and a comparison of MCS and LHS. In *2016 IEEE 6th International Conference on Power Systems (ICPS)*, New Delhi, India, 4-6 March, 1-6.

43. Heidari, E, & Movaghar, A. (2011). "An Efficient Method Based On Genetic Algorithm To Solve Sensor Network Optimization Problem." *International Journal on Applications of Graph Theory In Wireless Ad hoc Networks And Sensor Networks*, *3*(1): 18–33.
44. Iman, R. L., & Conover, W. J. (1982). "A distribution-free approach to inducing rank correlation among input variables." C*ommunications in Statistics-Simulation and computation*, *11*(3), 311–334.
45. Keskin, G. A. (2015). "Using integrated fuzzy DEMATEL and fuzzy C : means Algorithm for Supplier Evaluation and Selection." *International Journal of Production Research*, 53(12), 3586-3602.
46. Koduru, H. K., Xiao, F., Amirkhanian, S. N., & Juang, C. H. (2010). "Using Fuzzy Logic and Expert System Approaches in Evaluating Flexible Pavement Distress : Case Study." *Journal of Transportation Engineering*, 136(2), 149–157.
47. Kou, G., Ergu, D., Lin, C., & Chen, Y. (2016). "Pairwise comparison matrix in multiple criteria decision making." *Technological and Economic Development of Economy*, *22*(5), 738–765.
48. Kou, G., Ergu, D., & Shang, J. (2014). "Enhancing data consistency in decision matrix: Adapting Hadamard model to mitigate judgment contradiction." *European Journal of Operational Research*, *236*(1), 261–271.
49. Kou, G., & Lin, C. (2014). "A cosine maximization method for the priority vector derivation in AHP." *European Journal of Operational Research*, *235*(1), 225–232.
50. Lee, P., Wei, J., Ting, H., Lo, T., Long, D., & Chang, L. (2019). "Dynamic Analysis of Construction Safety Risk and Visual Tracking of Key Factors based on Behavior-based Safety and Building Information Modeling." *KSCE Journal of Civil Engineering*, *23*, 4155–4167.
51. Lin, C., Kou, G., Peng, Y., & Alsaadi, F. E. (2020). "Aggregation of the nearest consistency matrices with the acceptable consensus in AHP-GDM." *Annals of Operations Research*, 1–17.
52. Li, G., Kou, G., & Peng, Y. (2018). "A Group Decision Making Model for Integrating Heterogeneous Information." *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *48*(6), 982–992.

53. Li, J., Li, A., & Feng, M. Q. (2013). "Sensitivity and Reliability Analysis of a Self-Anchored Suspension Bridge." *Journal of Bridge Engineering*, *18*(8), 703–711.
54. Love, P. E. D., Ahiaga-dagbui, D. D., Smith, S. D., Sing, M. C., & Tokede, O. (2018). "Cost Profiling of Water Infrastructure Projects." *Journal of Infrastructure Systems*, *24*(4), 1–12.
55. Ma, X., Chen, H., Zhang, X., Xing, M., & Yang, P. (2019). "Effect of Asphalt Binder Characteristics on Filler–Asphalt Interactions and Asphalt Mastic Creep Properties." *Journal of Materials in Civil Engineering*, *31*(8), 1–11.
56. Maghsoodi, A. I., & Khalilzadeh, M. (2018). "Identification and Evaluation of Construction Projects ' Critical Success Factors Employing Fuzzy-TOPSIS Approach." *KSCE Journal of Civil Engineering*, *22*(5), 1593–1605.
57. Mahdi, I. M., Khalil, A. H., Mahdi, H. A., & Dina, M. M. (2019). "Decision support system for optimal bridge ' maintenance." *International Journal of Construction Management*, 1–15.
58. Mahdiyar, A., Tabatabaee, S., Durdyev, S., Ismail, S., Abdullah, A., & Rani, W. (2019). "A prototype decision support system for green roof type selection : A cybernetic fuzzy ANP method." *Sustainable Cities and Society*, *48*, 1–9.
59. Markiz, N., & Jrade, A. (2018). "Integrating Fuzzy-Logic Decision Support With A Bridge Information Management System (BRIMS) at The Conceptual Stage Of Bridge Design." *Journal of Information Technology in Construction*, *23*, 92–121.
60. Mavi, R. K., & Standing, C. (2018). "Critical success factors of sustainable project management in construction : A fuzzy DEMATEL-ANP approach." *Journal of Cleaner Production*, *194*, 751–765.
61. Mckay, M. D., Beckman, R. J., & Conover, W. J. (1979). "Comparison of Three Methods for Selecting Values of Input Variables in the Analysis of Output from a Computer Code." *Technometrics*, *21*(2), 239–245.
62. Mikhailov, L. (2000). "A fuzzy programming method for deriving priorities in the analytic hierarchy process." *Journal of the Operational Research Society*, *51*, 341–349.
63. Miyamoto, A., Kawamura, K., & Nakamura, H. (2001). "Development of a bridge management system for existing bridges." *Advances in Engineering Software*, *32*, 821–833.
64. Mohammed Abdelkader, E., Marzouk, M., & Zayed, T. (2019a). "An Optimization-Based Methodology for the Definition of Amplitude Thresholds of the Ground Penetrating". *Soft Computing*, *23*, 12063–12086.

65. Mohammed Abdelkader, E., Moselhi, O., Marzouk, M. & Zayed, T. (2019b). “A Multi-objective Invasive Weed Optimization Method for Segmentation of Distress Images.” *Intelligent automation and soft computing*, 1-20.

66. Moufti, S. A., Zayed, T., & Dabous, S. A. (2016). “Defect-Based Condition Assessment of Concrete Bridges Fuzzy Hierarchical Evidential Reasoning Approach.” *Transportation Research Record: Journal of the Transportation Research Board*, *2431* (1), 1-9.

67. Moayedi, H., Bui, D. T., & Foong, L. K. (2019). “Slope stability monitoring using novel remote sensing based fuzzy logic.” *Sensors*, *19*(21), 1–13.

68. Mulliner, E., Smallbone, K., and Maliene, V. (2013). “An assessment of sustainable housing affordability using a multiple criteria decision making method.” *Omega*, *41*(2), 270–279.

69. Nazari, A., Vandadian, S., and Abdirad, H. (2017). “Fuzzy AHP Model for Prequalification of Engineering Consultants in the Iranian Public Procurement System.” *Journal of Management in Engineering*, 32(2), 1-13.

70. Noori, A., Bonakdari, H., Morovati, K., & Gharabaghi, B. (2018). “The optimal dam site selection using a group decision-making method through fuzzy TOPSIS model.” *Environment Systems and Decisions*, *38*(4), 471–488.

71. Nurani, A. I., Pramudyaningrum, A. T., & Fadhila, S. R. (2017). “Analytical Hierarchy Process (AHP), Fuzzy AHP , and TOPSIS for Determining Bridge Maintenance Priority Scale in Banjarsari , Surakarta.” *International Journal of Science and Applied Science: Conference Series*, *2*(1), 60–71.

72. Nurdin, A., Kristiawan, S. A., & Handayani, D. (2017). “Determination of the bridge maintenance and rehabilitation priority scale in kabupaten Pinrang.” *Journal of Physics: Conference Series*, *795*, 1–7.

73. Pahlavani, P., & Delavar, M. R. (2014). “Multi-criteria route planning based on a driver’s preferences in multi-criteria route selection.” *Transportation Research Part C: Emerging Technologies*, *40*, 14–35.

74. Pan, H., Tian, L., Fu, X., & Li, H. (2020). “Sensitivities of the seismic response and fragility estimate of a transmission tower to structural and ground motion uncertainties.” *Journal of Constructional Steel Research*, *167*, 1–13.

75. Phochanikorn, P., & Tan, C. (2019). “An Integrated Multi-Criteria Decision-Making Model Based on Prospect Theory for Green Supplier Selection under Uncertain Environment : A

Case Study of the Thailand Palm Oil Products Industry." *Sustainability*, *11*(7), 1–22

76. Plebankiewicz, E., & Kubek, D. (2015). "Multicriteria Selection of the Building Material Supplier Using AHP and Fuzzy AHP." *Journal of Construction Engineering and Management*, 142(1).

77. Prasetyo, E. D. W., Handajani, M., & Ismiyati. (2019). Criteria Analysis, weight and Priority for Handling Bridges in Kudus District using AHP and Promethee II methods. *Journal of Physics: Conference Series*, *1167*(1), 012009.

78. Rashidi, M., Ghodrat, M., Samali, B., Kendall, B., & Zhang, C. (2017). "Remedial Modelling of Steel Bridges through Application of Analytical Hierarchy Process (AHP)." *Applied Sciences*, *7*(2), 1–20.

79. Saaty, T. L. (2008). "Decision making with the analytic hierarchy process." *International Journal of Services Sciences*, *1*(1), 83-98.

80. Saaty, T. L. (1977). "A scaling method for priorities in hierarchical structures." *Journal of Mathematical Psychology*, *15*(3), 234–281.

81. Sackey, S., & Kim, B. (2018). "Environmental and Economic Performance of Asphalt Shingle and Clay Tile Roofing Sheets Using Life Cycle Assessment Approach and TOPSIS." *Journal of Construction Engineering and Management*, *144*(11), 1–10.

82. Sadiq, R., & Husain, T. (2005). "A fuzzy-based methodology for an aggregative environmental risk assessment : a case study of drilling waste." *Environmental Modelling & Software*, *20*, 33-46.

83. Sennah, K., Juette, B., Witt, C., & Combar, P. M. (2011). "Vehicle Crash Testing On a GFRP-Reinforced PL-3 Concrete Bridge Barrier." *Proceedings of the 4th International Conference on Durability and Sustainability of Fibre Reinforced Polymer Composites for Construction and Rehabilitation*, Québec City, Canada, 20-22 July, 1–8.

84. Sharma, S., & Goyal, P. K. (2019). "Fuzzy assessment of the risk factors causing cost overrun in construction industry." *Evolutionary Intelligence*, 1–13.

85. Sheshasayee, A., & Sharmila, P. (2014). "Comparative Study of Fuzzy C Means and K Means Algorithm for Requirements Clustering." *Indian Journal of Science and Technology*, *7*(6), 853–857.

86. Supciller, A. A., & Abali, N. (2015). "Occupational Health and Safety Within the Scope of Risk Analysis with Fuzzy Proportional Risk Assessment Technique (Fuzzy Prat)." *Quality*

and Reliability Engineering, *31*(7), 1137–1150.

87. Suthanaya, P. A., & Artamana, I. B. (2017). "Multi-criteria Approach for Prioritizing Bridge Maintenance in Developing Country (Case Study of Bali Province, Indonesia)." *Asian Journal of Applied Sciences*, *5*(2), 410–418.
88. Tee, A. B., Bowman, M., & Sinha, K. C. (1988). "A fuzzy mathematical approach for bridge condition evaluation." *Civil Engineering Systems*, 5(1), 17–24.
89. Tran, D., Mashford, J., May, R., & Marlow, D. (2012). "Development of a Fuzzy Risk Ranking Model for Prioritizing Manhole Inspection." *Journal of Computing in Civil Engineering*, (4), 550–557.
90. Triantaphyllou, E., & Mann, S. H. (1990). "An Evaluation Of The Eigenvalue Approach For Determining The Membership Values In Fuzzy Sets." *Fuzzy Sets and Systems*, *35*, 295–301.
91. Van Laarhoven, P. J. M, & W.Pedrycz. (1983). "A fuzzy extension of Saaty's priority theory." *Fuzzy Sets and Systems*, *11*, 229–241.
92. Viami International Inc. and the Technology Strategies Group. (2013). "*Market Study for Aluminium Use in Roadway Bridges"*, Montreal, Canada.
93. YAGER, R. R. (1981). "On A General Class Of Fuzzy Connectives." *Fuzzy Sets and Systems*, *4*, 235–242.
94. Yayla, A. Y., & Yildiz, A. (2013). "Fuzzy Analytical Network Process Based Multi Criteria Decision Making." *The South African Journal Of Industrial Engineering*, *24*(2), 167–180.
95. Yazdani, M., Abdi, M. R., Kumar, N., Keshavarz-ghorabaee, M., & Chan, F. T. S. (2019). "Improved Decision Model for Evaluating Risks in Construction Projects." *Journal of Construction Engineering and Management*, *145*(5), 1–13.
96. Yossyafra, Angelia, N., Yosritzal, Meyadtri, & Mazni5, D. I. (2019). "Determining the priority criteria and ranking of provincial bridge maintenance in West Sumatra using a combination of the Fuzzy Analytical Hierarchy Process and VIKOR-Modification methods." *IOP Conference Series: Materials Science and Engineering 602* 012015**,** 8-9 November**,** Padang, Indonesia**,** 1-9.
97. Yoon, Y., & Hastak, M. (2016). "Condition Improvement Measurement Using the Condition Evaluation Criteria of Concrete Bridge Decks." *Journal of Transportation Engineering*, *142*(11), 1–8.
98. Zadeh, L. A. (1965). "Fuzzy Sets." *Information and Control*, 8, 338–353.

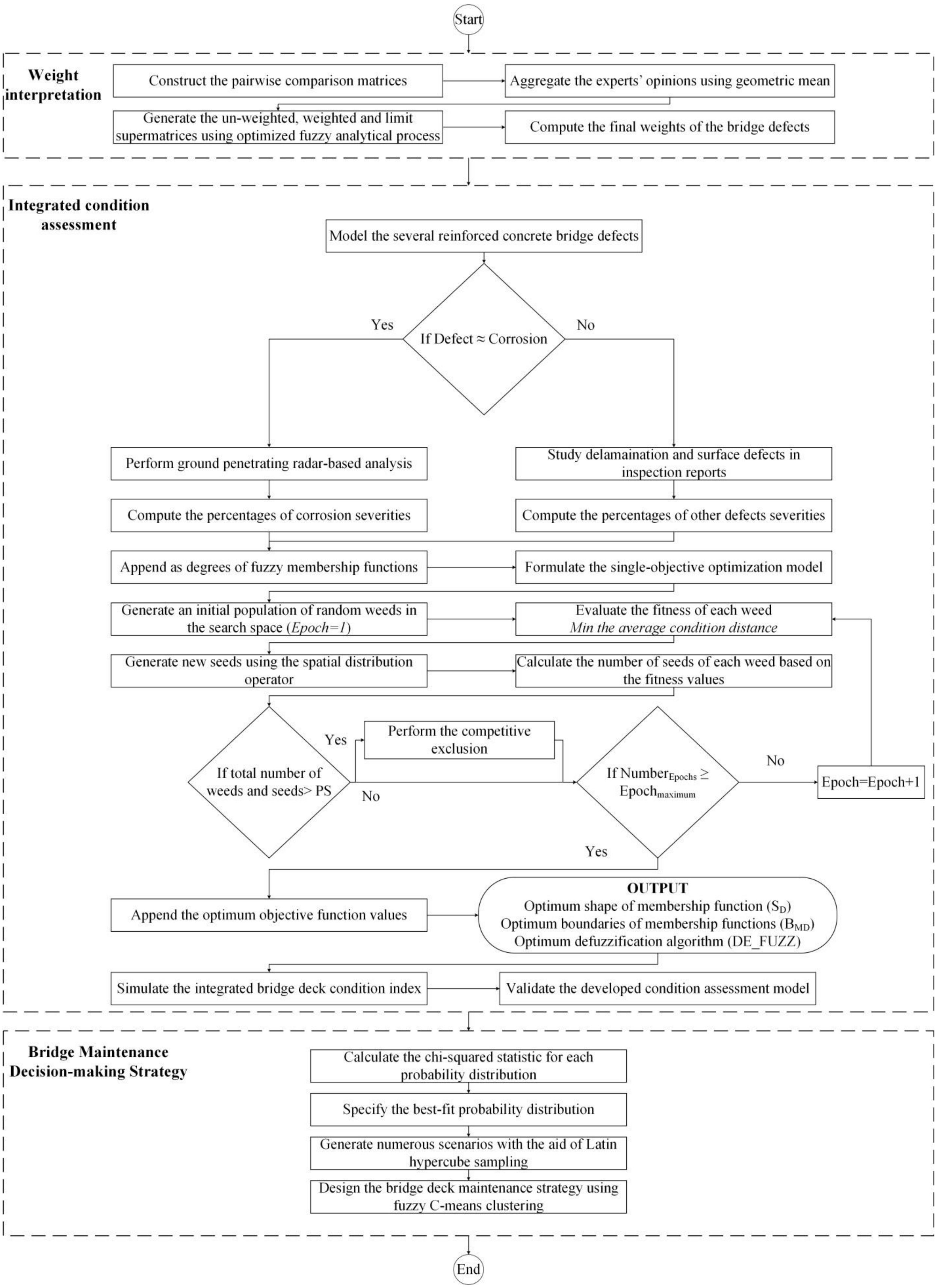
99. Zeng, J., An, M., & Smith, N. J. (2007). "Application of a fuzzy based decision making methodology to construction project risk assessment." *International Journal of Project Management*, *25,* 589–600.

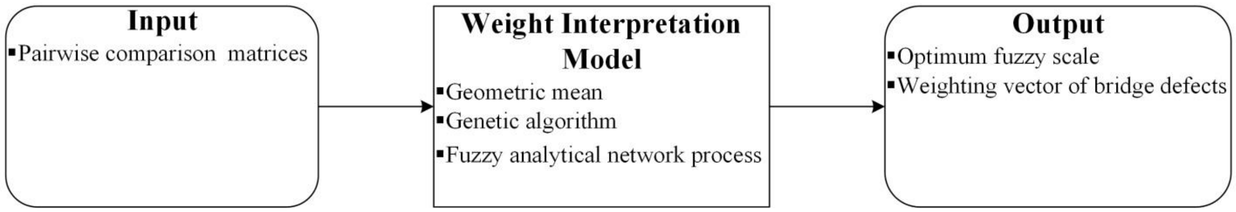
100. Zhang, H., Kou, G., & Peng, Y. (2019). "Soft consensus cost models for group decision making and economic interpretations." *European Journal of Operational Research*, *277*(3), 964–980.

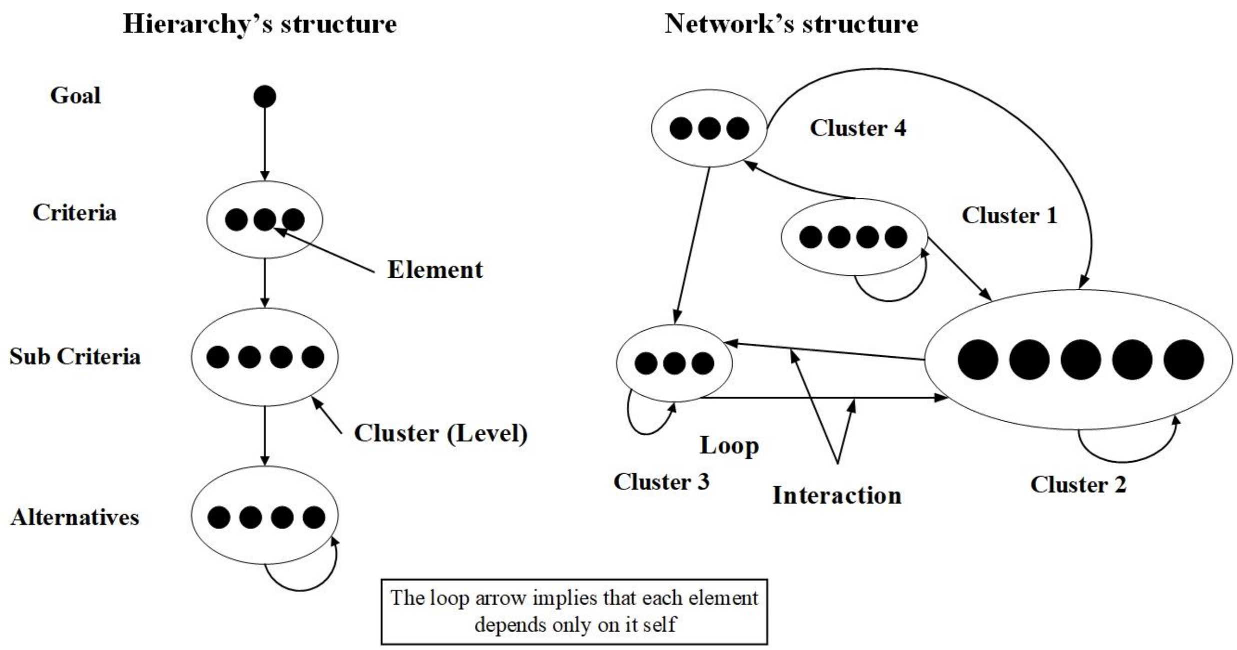
101. Zhou, Y.-Q., & Xidian, H. C. (2014). "Invasive Weed Optimization Algorithm for Optimization No-Idle Flow Shop Scheduling Problem." *Neurocomputing*, 137, 285–292.

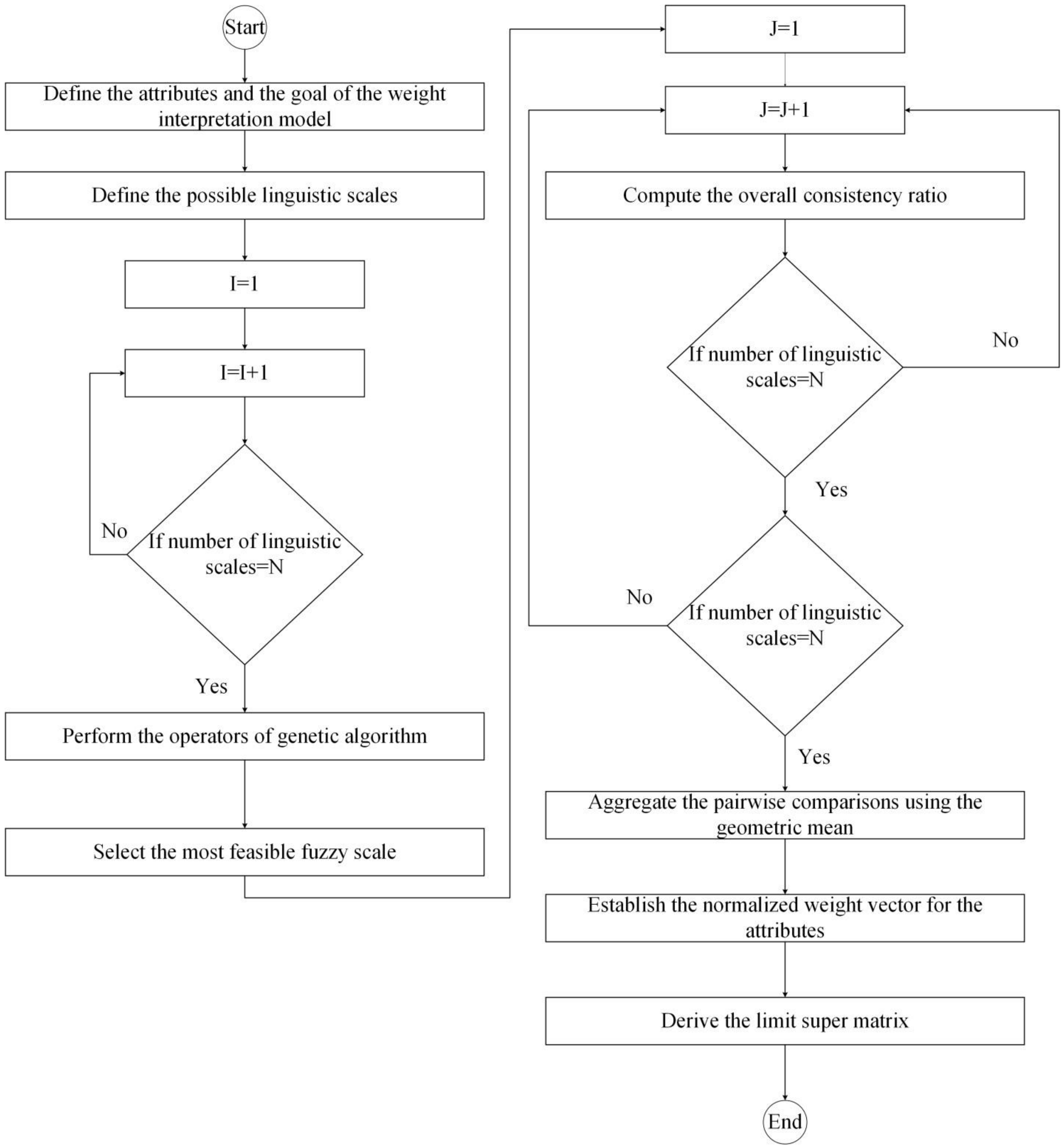
List of Figures

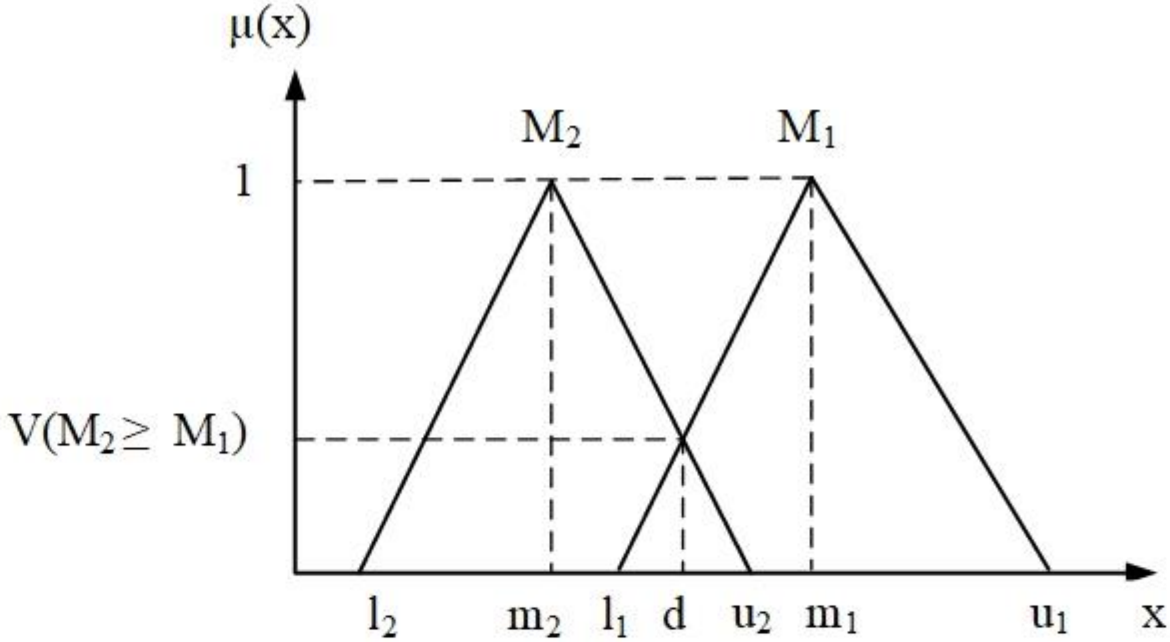
Figure 23: Corrosion map of the second bridge deck

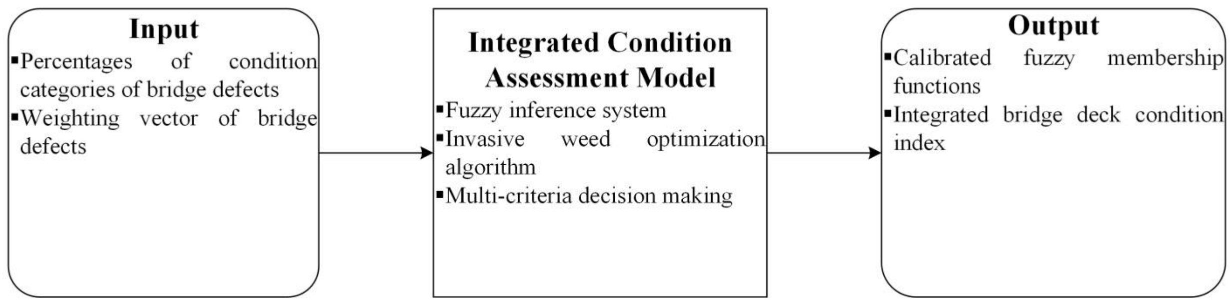

Start
Weight interpretation
Construct the pairwise comparison matrices
Aggregate the experts' opinions using geometric mean
Generate the un-weighted, weighted and limit supermatrices using optimized fuzzy analytical process
Compute the final weights of the bridge defects
Integrated condition assessment
Model the several reinforced concrete bridge defects
If Defect ≈ Corrosion
Yes
No
Perform ground penetrating radar-based analysis
Study delamaination and surface defects in inspection reports
Compute the percentages of corrosion severities
Compute the percentages of other defects severities
Append as degrees of fuzzy membership functions
Formulate the single-objective optimization model
Generate an initial population of random weeds in the search space (Epoch=1)
Evaluate the fitness of each weed
Min the average condition distance
Generate new seeds using the spatial distribution operator
Calculate the number of seeds of each weed based on the fitness values
If total number of weeds and seeds> PS
Yes
Perform the competitive exclusion
No
If Number$_{Epochs}$ ≥ Epoch$_{maximum}$
No
Epoch=Epoch+1
Yes
Append the optimum objective function values
OUTPUT
Optimum shape of membership function (S_D)
Optimum boundaries of membership functions (B_{MD})
Optimum defuzzification algorithm (DE_FUZZ)
Simulate the integrated bridge deck condition index
Validate the developed condition assessment model
Bridge Maintenance Decision-making Strategy
Calculate the chi-squared statistic for each probability distribution
Specify the best-fit probability distribution
Generate numerous scenarios with the aid of Latin hypercube sampling
Design the bridge deck maintenance strategy using fuzzy C-means clustering
End

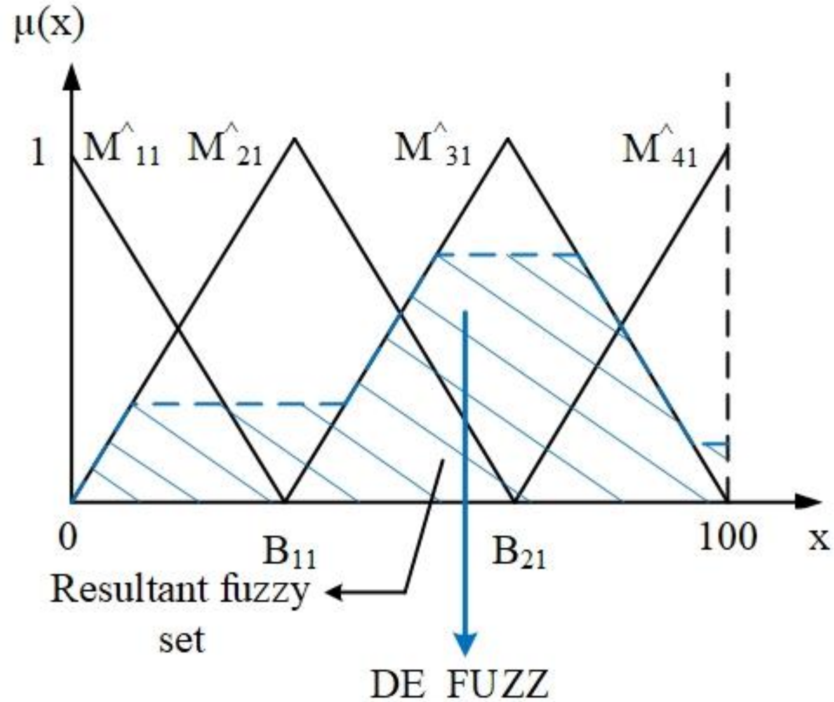

Input
▪Pairwise comparison matrices
Weight Interpretation Model
▪Geometric mean
▪Genetic algorithm
▪Fuzzy analytical network process
Output
▪Optimum fuzzy scale
▪Weighting vector of bridge defects


Hierarchy's structure
Goal
Criteria
Element
Sub Criteria
Cluster (Level)
Alternatives
Network's structure
Cluster 4
Cluster 1
Cluster 3
Loop
Interaction
Cluster 2
The loop arrow implies that each element depends only on it self

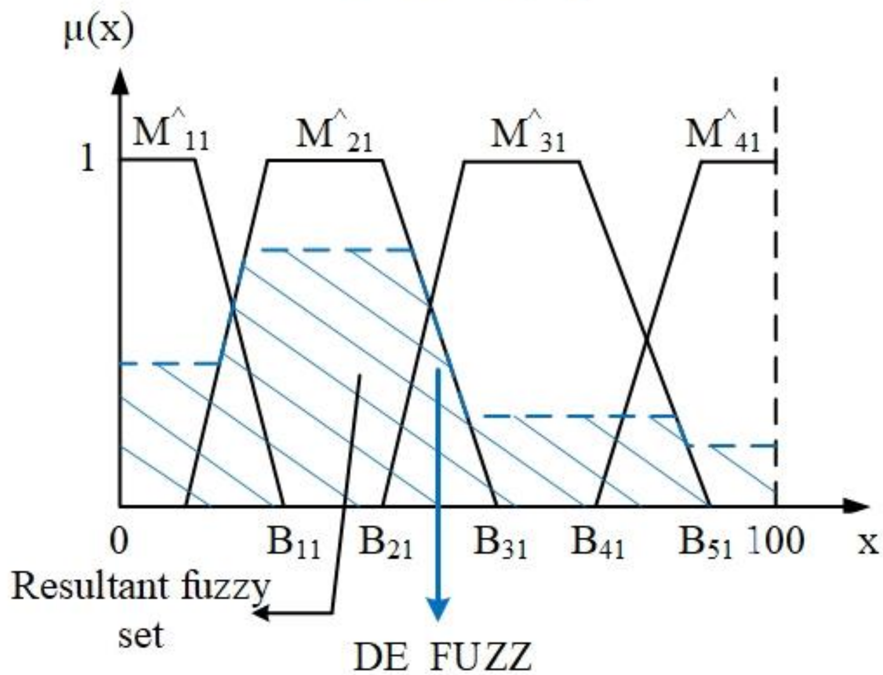

Start
Define the attributes and the goal of the weight interpretation model
Define the possible linguistic scales
I=1
I=I+1
If number of linguistic scales=N
No
Yes
Perform the operators of genetic algorithm
Select the most feasible fuzzy scale
J=1
J=J+1
Compute the overall consistency ratio
If number of linguistic scales=N
No
Yes
If number of linguistic scales=N
No
Yes
Aggregate the pairwise comparisons using the geometric mean
Establish the normalized weight vector for the attributes
Derive the limit super matrix
End


μ(x)
M2
M1
1
V(M2 ≥ M1)
l2
m2
l1
d
u2
m1
u1
x


Input
▪Percentages of condition categories of bridge defects
▪Weighting vector of bridge defects
Integrated Condition Assessment Model
▪Fuzzy inference system
▪Invasive weed optimization algorithm
▪Multi-criteria decision making
Output
▪Calibrated fuzzy membership functions
▪Integrated bridge deck condition index

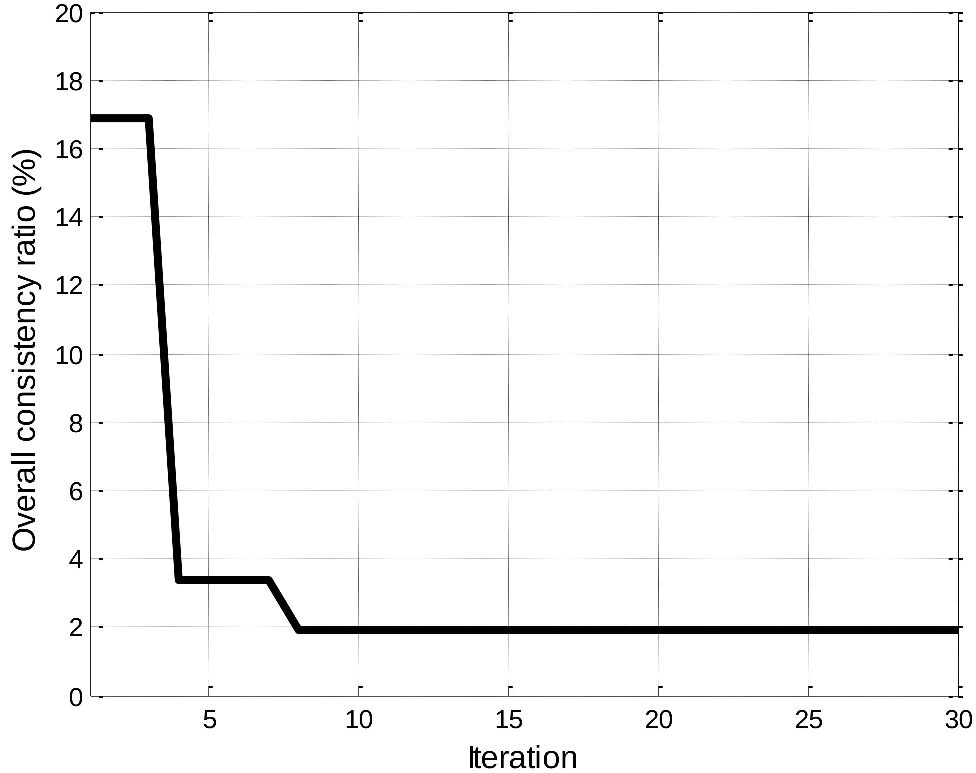


Triangular membership function (S_1)

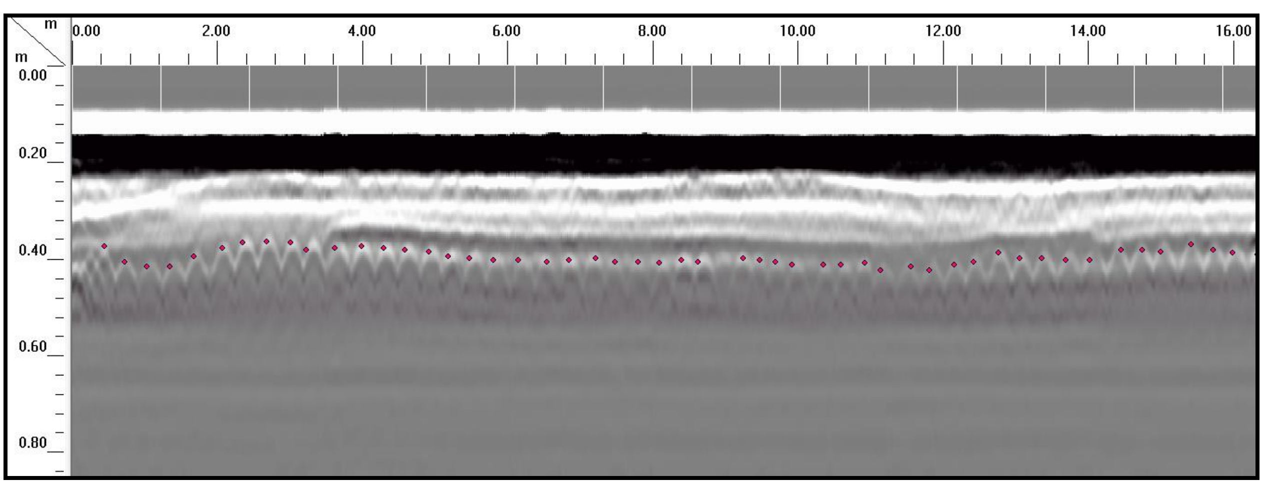


Trapezoidal membership function (S_2)

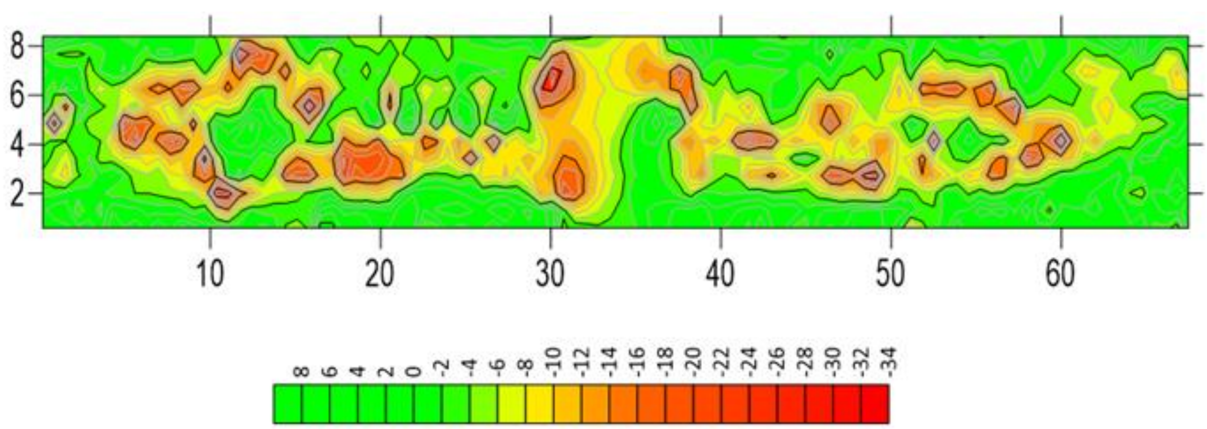

Input
▪Weighting vector of bridge defects
▪Percentages of condition categories of bridge defects
▪Integrated condition assessment model
Bridge Recommendation Decision-making Strategy
▪Chi-squared test
▪Latin hypercube sampling
▪Fuzzy C-means clustering
Output
▪Classification of the maintenance strategies based on IBDCI
▪Severity rating system of the five bridge defects



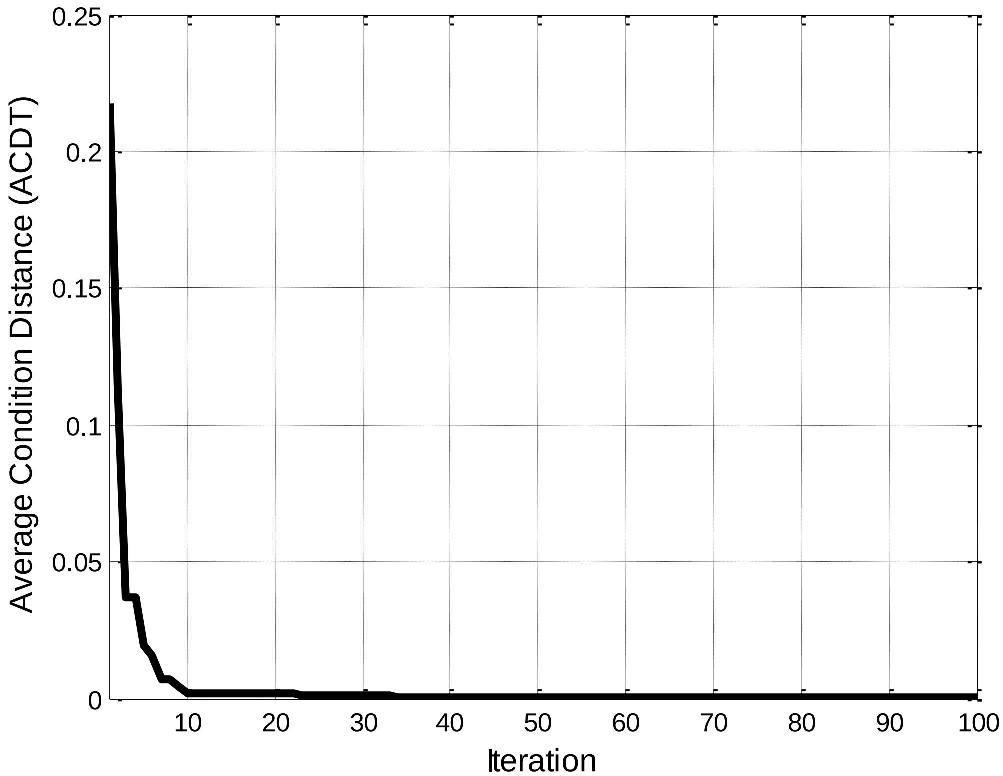
Overall consistency ratio (%)
Iteration
0
2
4
6
8
10
12
14
16
18
20
5
10
15
20
25
30



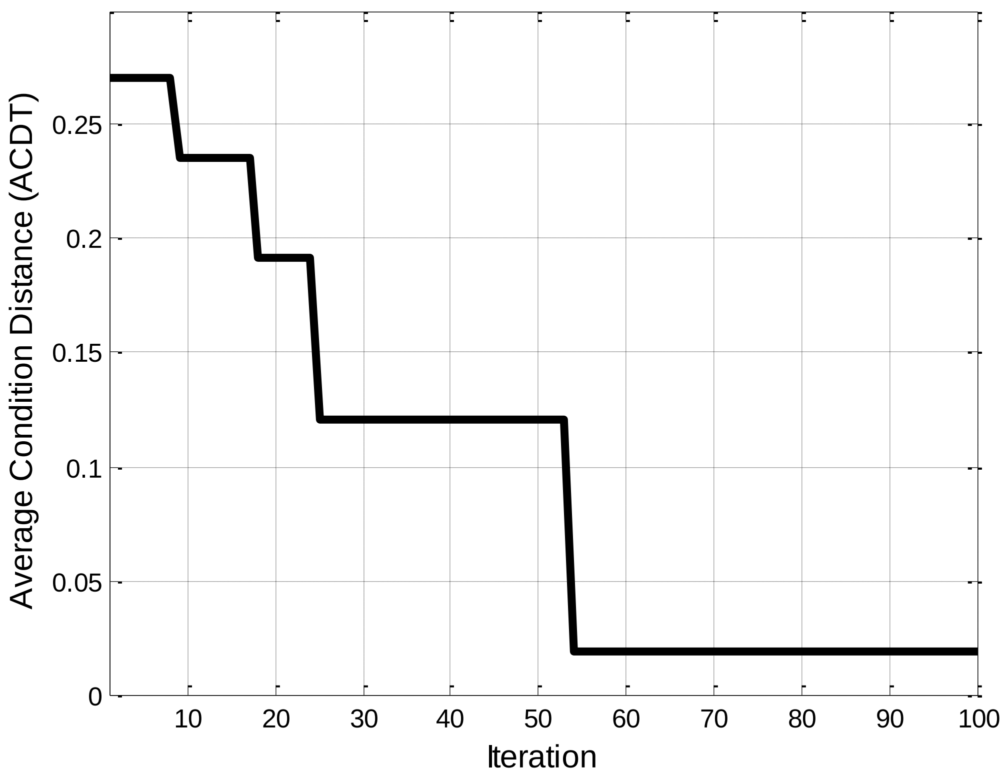
m
m
0.00
2.00
4.00
6.00
8.00
10.00
12.00
14.00
16.00
0.00
0.20
0.40
0.60
0.80



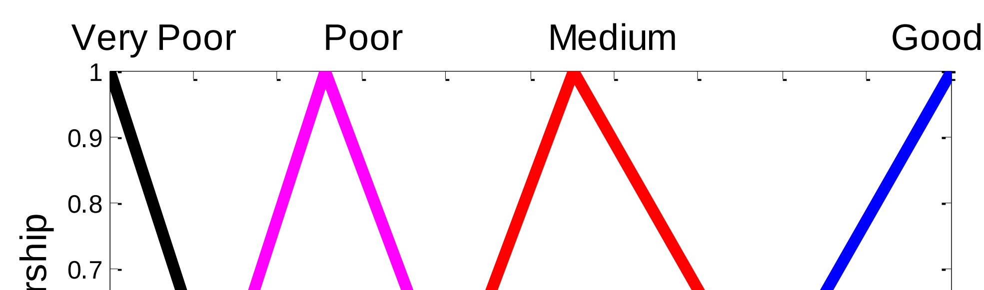
Good	Medium	Poor	Very Poor
45.78%	34.26%	12.98%	6.98%



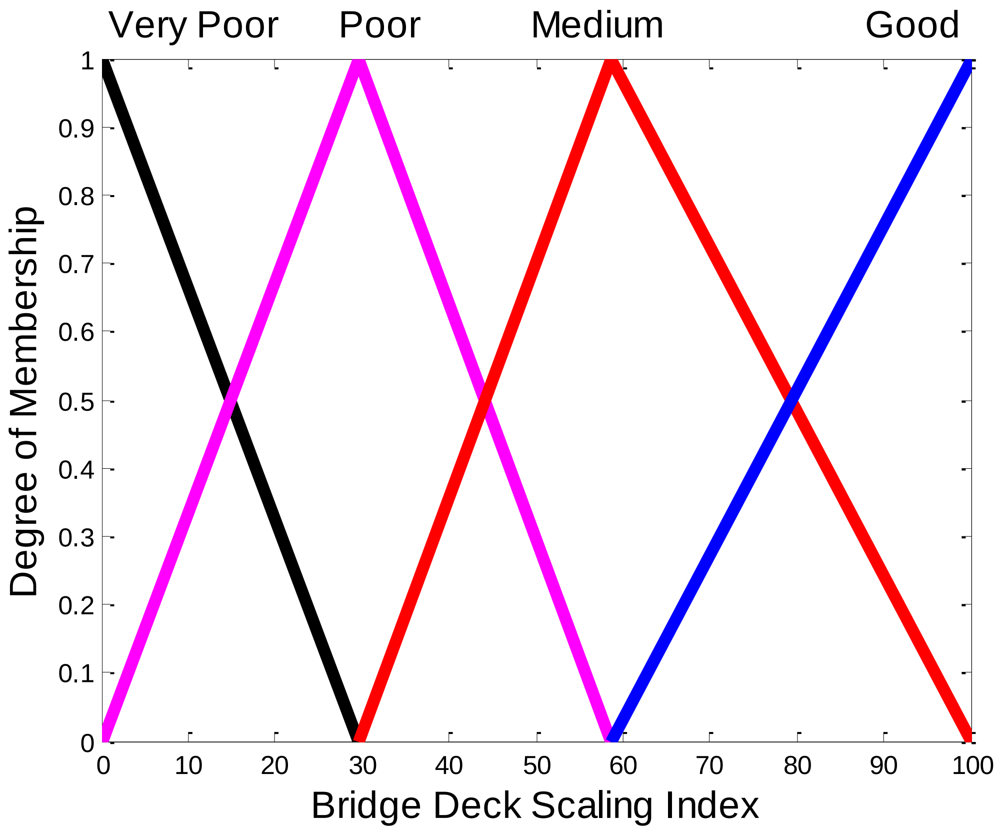
Average Condition Distance (ACDT)
0.25
0.2
0.15
0.1
0.05
0
10
20
30
40
50
60
70
80
90
100
Iteration

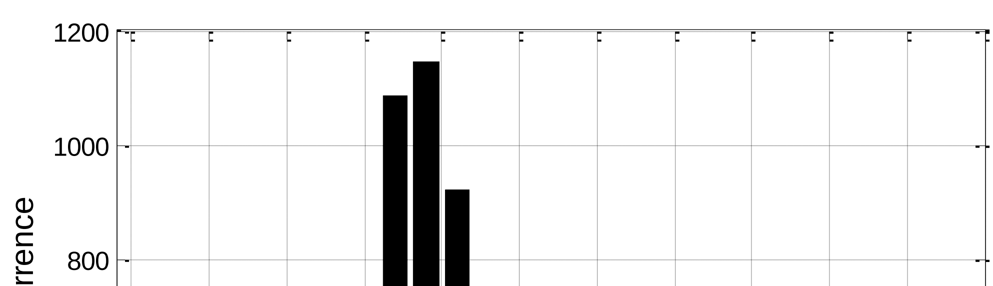


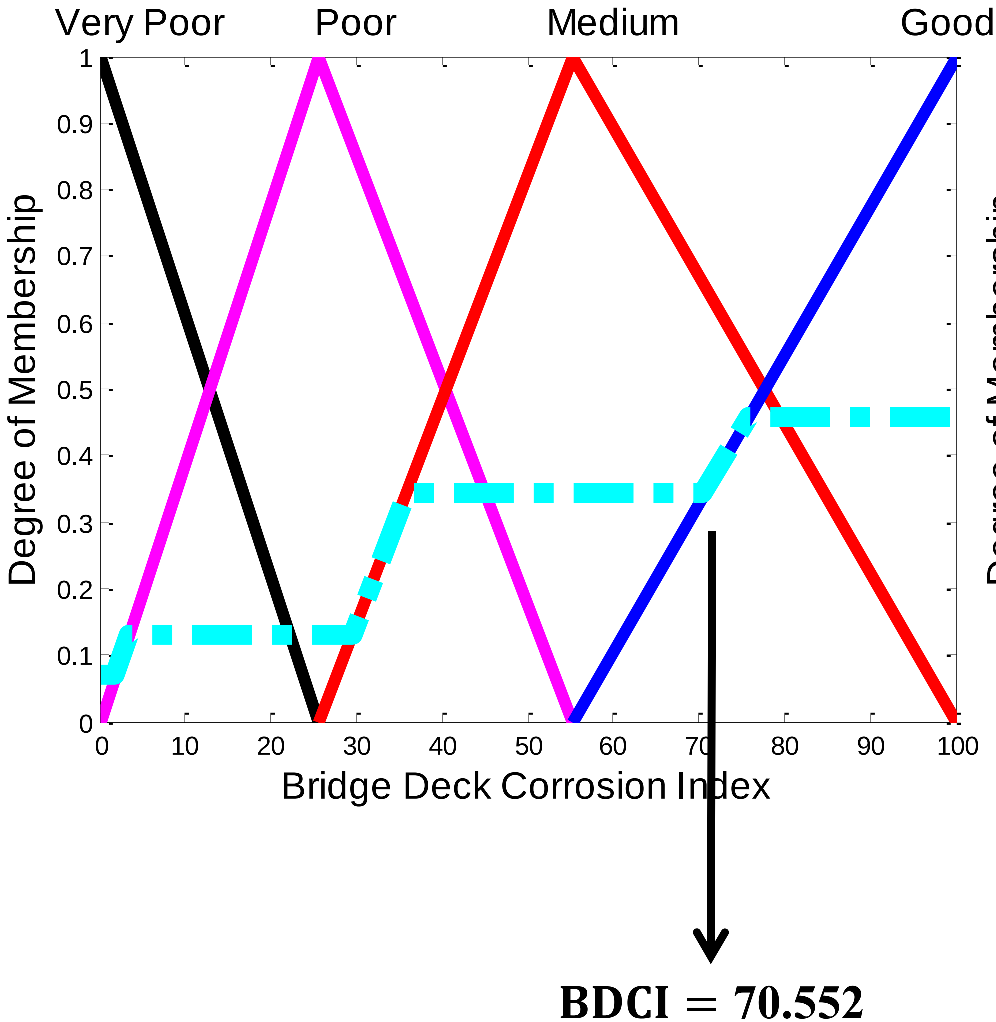
Average Condition Distance (ACDT)
0.25
0.2
0.15
0.1
0.05
0
10
20
30
40
50
60
70
80
90
100
Iteration



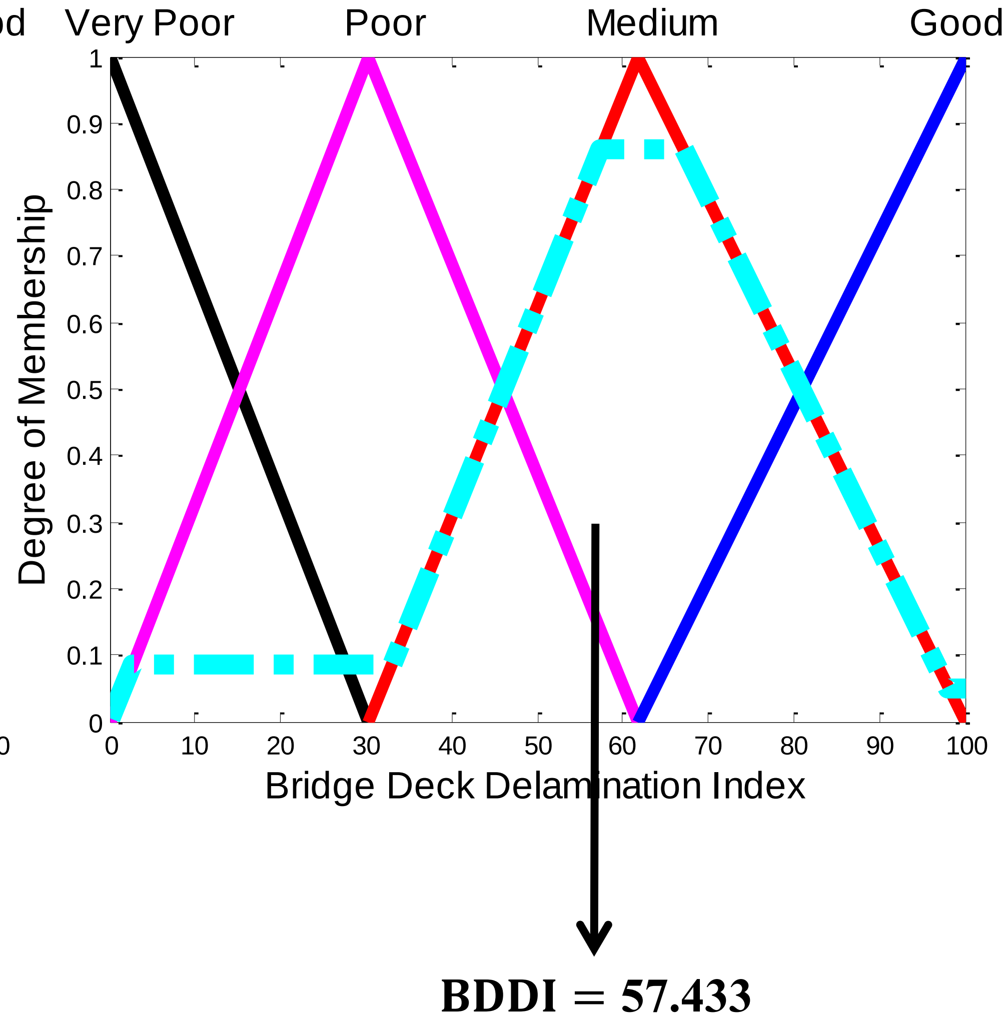
Very Poor
Poor
Medium
Good
1
0.9
0.8
0.7


Very Poor
Poor
Medium
Good
Degree of Membership
Bridge Deck Scaling Index

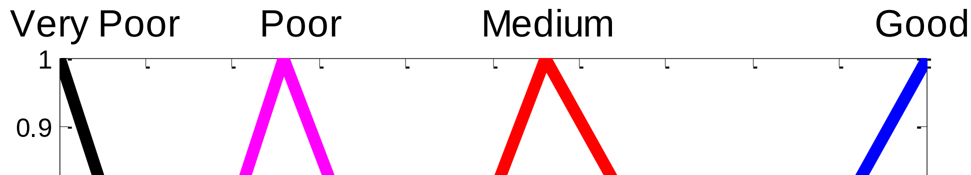

1200
1000
800

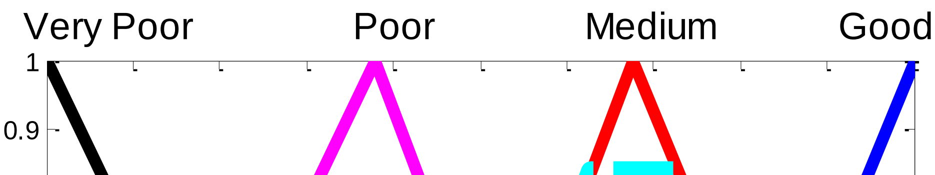


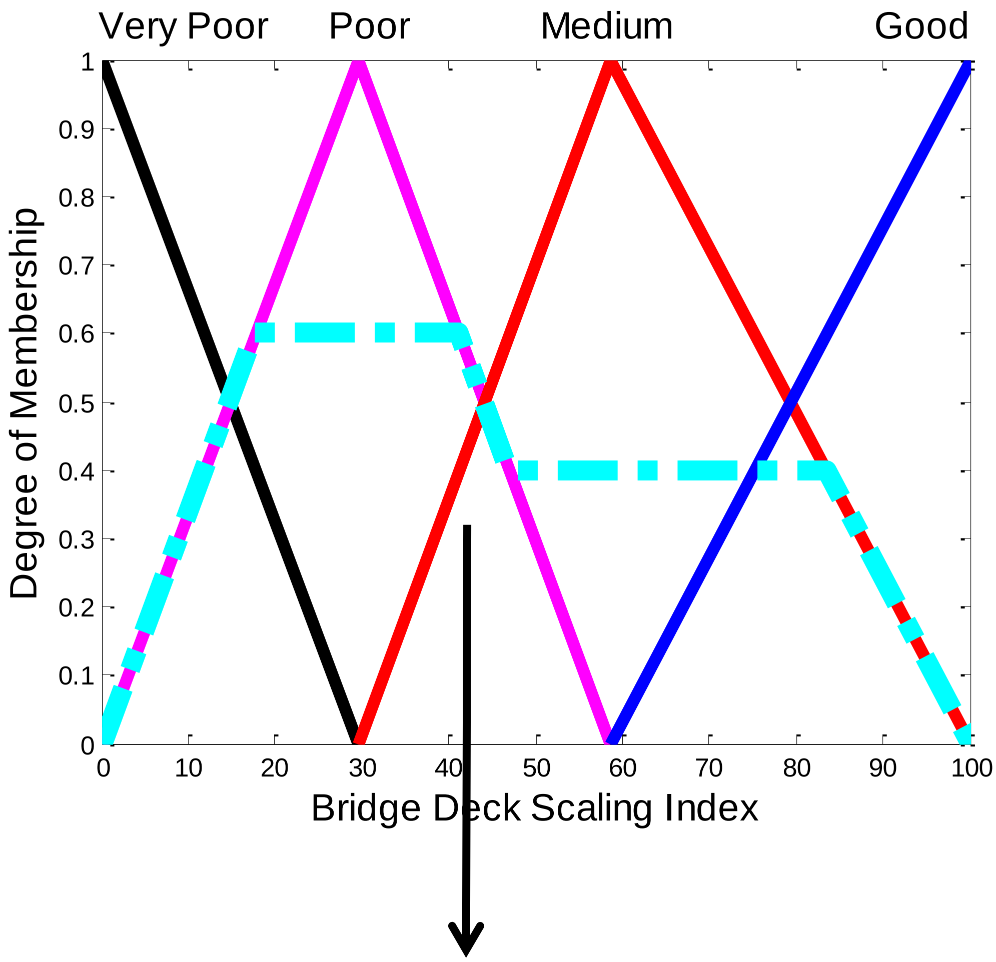
(a) Output of the bridge deck corrosion model



(b) Output of the bridge deck delamination model






Very Poor
Poor
Medium
Good
Degree of Membership
Bridge Deck Scaling Index

BDSCI = 41.137


20% Change)
40% Change

List of Tables

Table 1: Linguistic terms and five equivalent fuzzy scales (TFS#1 to TFS#5)

Linguistic term	TFS#1	**TFS#2**	**TFS#3**	**TFS#4**	**TFS#5**
Equally important (EI)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
Moderately important (MI)	(1, 3, 5)	(2, 3, 4)	(1, 1, 3/2)	(2/3, 1, 3/2)	(1/2, 1, 3/2)
Strongly important (SI)	(3, 5, 7)	(4, 5, 6)	(1, 3/2, 2)	(3/2, 2, 5/2)	(1, 3/2, 2)
Very strongly important (VSI)	(5, 7, 9)	(6, 7, 8)	(3/2, 2, 5/2)	(5/2, 3, 7/2)	(3/2, 2, 5/2)
Absolutely important (AI)	(7, 9, 9)	(9, 9, 9)	(2, 5/2, 3)	(7/2, 4, 9/2)	(2, 5/2, 6/2)

Table 2: Sample of the pair-wise comparisons with respect to the condition of the bridge deck

Bridge defects	Corrosion	Delamination	Cracking	Spalling	Scaling
Corrosion	(1, 1, 1)	(1, 1, 1)	(1, 1, 1.5)	(1, 1.5, 2)	(1, 1.5, 2)
Delamination	(1, 1, 1)	(1, 1, 1)	(1, 1, 1.5)	(1, 1, 1.5)	(1, 1, 1.5)
Cracking	(2/3, 1, 1)	(2/3, 1, 1)	(1, 1, 1)	(1, 1, 1.5)	(1, 1, 1.5)
Spalling	(1/2, 2/3, 1)	(2/3, 1, 1)	(2/3, 1, 1)	(1, 1, 1)	(1, 1, 1)
Scaling	(1/2, 2/3, 1)	(2/3, 1, 1)	(2/3, 1, 1)	(1, 1, 1)	(1, 1, 1)

Table 3: Sample of the pair-wise comparisons with respect to the corrosion

Bridge defects	Delamination	Cracking	Spalling	Scaling
Delamination	(1, 1, 1)	(1, 1, 1)	(1, 1.5, 2)	(1, 1.5, 2)
Cracking	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
Spalling	(1/2, 2/3, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)
Scaling	(1/2, 2/3, 1)	(1, 1, 1)	(1, 1, 1)	(1, 1, 1)

Table 4: Un-weighted supermatrix, weighted supermatrix, and limit supermatrix of the different affecting bridge defects

With respect to	Un-weighted supermatrix					weighted supermatrix					limit supermatrix				
	Goal	**C1**	**C2**	**…**	**C5**	**Goal**	**C1**	**C2**	**…**	**C5**	**Goal**	**C1**	**C2**	**…**	**C5**
Goal	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C1	0.306	0	0.429	…	0.392	0.306	0	0.429	…	0.392	0.334	0.334	0.334	…	0.334
C2	0.186	0.179	0	…	0.117	0.186	0.179	0	…	0.117	0.228	0.228	0.228	…	0.228
C3	0.16	0.417	0.254	…	0.058	0.16	0.417	0.254	…	0.058	0.167	0.167	0.167	…	0.167
C4	0.293	0.373	0.26	…	0.431	0.293	0.373	0.26	…	0.431	0.234	0.234	0.234	…	0.234
C5	0.053	0.029	0.056	…	0	0.053	0.029	0.056	…	0	0.035	0.035	0.035	…	0.035

Table 5: A comparative analysis between the performances of IWO, GA and NLP

Index	IWO	GA	NLP
Minimum	4.878×10^{-6}	1.92×10^{-2}	4.709
Maximum	1.6×10^{-4}	2.782×10^{-1}	.....
Mean	3.32×10^{-5}	5.93×10^{-1}	.....
Coefficient of variation	0.4756	1.2561	.....

Table 6: Optimized parameters of the fuzzy membership functions using the invasive weed optimization algorithm

Parameter	Description	Value
S_D	Shape of the membership function	Triangular
B_{11}	Very Poor fuzzy set in corrosion	(0, 25.647)
B_{21}	Poor fuzzy set in corrosion	(0, 25.647, 55.206)
B_{31}	Medium fuzzy set in corrosion	(25.647, 55.206, 100)
B_{41}	Good fuzzy set in corrosion	(55.206, 100)
B_{12}	Very Poor fuzzy set in delamination	(0, 30.364)
B_{22}	Poor fuzzy set in delamination	(0, 30.364, 61.834)
B_{23}	Medium fuzzy set in delamination	(30.364, 61.834, 100)
B_{24}	Good fuzzy set in delamination	(61.834, 100)
B_{13}	Very Poor fuzzy set in cracking	(0, 25.958)
B_{23}	Poor fuzzy set in cracking	(0, 25.958, 56.101)
B_{33}	Medium fuzzy set in cracking	(25.958, 56.101, 100)
B_{34}	Good fuzzy set in cracking	(56.101, 100)
B_{41}	Very Poor fuzzy set in spalling	(0, 37.91)
B_{42}	Poor fuzzy set in spalling	(0, 37.91, 67.636)
B_{43}	Medium fuzzy set in spalling	(37.91, 67.636, 100)
B_{44}	Good fuzzy set in spalling	(67.636, 100)
B_{51}	Very Poor fuzzy set in scaling	(0, 29.541)
B_{52}	Poor fuzzy set in scaling	(0, 29.541, 58.531)
B_{53}	Medium fuzzy set in scaling	(29.5414 58.531, 100)
B_{54}	Good fuzzy set in scaling	(58.531, 100)
DE_FUZZ	Defuzzification method	Bisector

Table 7: A sample of chi-squared test for some bridge condition categories

Condition category	Bridge defect	Chi-squared statistic	Best-fit distribution
Good	Corrosion	51.219	Uniform
Very poor	Corrosion	2.746	Exponential
Very poor	Delamination	40.289	Exponential
Medium	Cracking	12.92	Exponential
Medium	Spalling	50.54	Exponential
Poor	Scaling	54.396	Uniform

Table 8: A sample of the cluster memberships obtained from the FCM algorithm

Data point	Degree of membership				Assigned Cluster
	Cluster 1	Cluster 2	Cluster 3	Cluster 4	
59.149	0.0858	0.5937	0.2646	0.0559	Cluster 2
75.73	0.3956	0.0764	0.1141	0.4140	Cluster 4
66.768	0.2783	0.1581	0.4421	0.1215	Cluster 3
63.186	0.0193	0.0292	0.9406	0.0109	Cluster 3
70.583	0.6565	0.0780	0.1440	0.1215	Cluster 1
70.194	0.6018	0.0918	0.1738	0.1327	Cluster 1
81.586	0.1740	0.0674	0.0900	0.6687	Cluster 4
78.508	0.0845	0.0252	0.0354	0.8548	Cluster 4
57.764	0.0301	0.8724	0.0773	0.0203	Cluster 2
75.197	0.4556	0.0770	0.1168	0.3506	Cluster 1
78.48	0.0881	0.0262	0.0368	0.8489	Cluster 4
58.516	0.0649	0.7095	0.1826	0.0430	Cluster 2

63 **Table 9: Rating systems of the bridge defects based on their severity indices**

Range of the BDSI	Bridge defect	Extent of severity
Less than 42.721	Corrosion	The bridge deck suffers from very severe corrosion.
Between 42.721 and 58.29		The bridge deck suffers from severe corrosion.
Between 58.29 and 75.381		The bridge deck suffers from medium corrosion.
More than 75.381		The bridge deck suffers from slight corrosion.
Less than 55.211	Delamination	The bridge deck suffers from very severe delamination.
Between 55.211 and 69.963		The bridge deck suffers from severe delamination.
Between 69.963 and 78.073		The bridge deck suffers from medium delamination.
More than 78.073		The bridge deck suffers from slight delamination.
Less than 57.227	Cracking	The bridge deck suffers from very severe cracking.
Between 57.227 and 79.153		The bridge deck suffers from severe cracking.
Between 79.153 and 89.453		The bridge deck suffers from medium cracking.
More than 89.453		The bridge deck suffers from slight cracking.
Less than 65.916	Spalling	The bridge deck suffers from very severe spalling.
Between 65.916 and 83.81		The bridge deck suffers from severe spalling.
Between 83.81 and 91.734		The bridge deck suffers from medium spalling.
More than 91.734		The bridge suffers from slight spalling.
Less than 57.512	Scaling	The bridge deck suffers from very severe scaling.
Between 57.512 and 74.707		The bridge deck suffers from severe scaling.

Between 74.707 and 81.938		The bridge deck suffers from medium Pop-out.
More than 81.938		The bridge suffers from slight scaling.

Table 10: Bridge intervention recommendations based on the IBDCI

Range of IBDCI	Category	Corresponding Intervention action
Less than 60.318	Very Poor	Total bridge deck replacement is needed
Between 60.318 and 67.769	Poor	The bridge deck requires rehabilitation
Between 67.769 and 76.651	Medium	The bridge deck requires repair
More than 75.651	Good	The bridge deck doesn’t need intervention

Table 11: A comparison between corrosion evaluation using ground penetrating radar and half-cell potential

Method	Condition category				BDCI	Overall severity level
	Good	Medium	Poor	Very poor		
Ground penetrating radar	45.78%	34.26%	12.98%	6.98%	70.552	"Medium"
Half-cell potential	62%	33.6%	3.7%	0.14%	83.135	"Good"

Table 12: Bridge maintenance prioritization for a sub network of bridges

Bridge ID	BDCI	BDDI	BDCRI	BDSPI	BDSCI	IBDCI	Ranking
Bridge 1	70.552	57.443	43.42	72.923	41.137	60.844	1
Bridge 2	80.657	77.599	95.171	89.066	95.53	82.964	5
Bridge 3	71.023	78.033	80.092	97.404	74.241	74.339	2
Bridge 4	77.636	80.947	75.987	93.77	49.631	75.881	3
Bridge 5	83.708	74.464	90.102	93.994	80.836	79.61	4