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Bridge Maintenance Prioritization and Condition Rating Based on Fermatean Fuzzy AHP Approach

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Abstract

Bridges are considered critical components of transportation infrastructure and play an integral role in public welfare and economic development. Bridge authorities in Iraq face multiple challenges in maintaining the efficiency and serviceability of the bridge network while developing a maintenance plan within limited budgets. Thus, this study aims to develop a systematic condition assessment methodology as a tool to prioritize maintenance projects and optimize available budgets to enhance the management of bridge networks. For this purpose, the bridge structure is broken down into four components: deck, superstructure, substructure, and accessories, and each component is divided into a number of elements. Bridge maintenance experts were surveyed to assign weights for the identified components and elements using the Fermatean fuzzy Analytic Hierarchy Process (FF-AHP). The weighted averaging approach was then used to aggregate components' condition ratings with expert-determined weights to obtain the overall Bridge Condition Index (BCI) of each bridge. Bridges with the lowest BCI get higher priority for maintenance. The proposed methodology was applied to thirteen bridges in Baghdad to demonstrate its practicality. The results indicate its reliability and capability to evaluate and rank bridges based on their urgency for maintenance. The proposed method would help bridge engineers and policymakers to make informed maintenance investment decisions during the budget allocation process.

Keywords: Bridge Maintenance; Condition Rating; Maintenance Planning; Maintenance Prioritization; Fermatean Fuzzy AHP.

1. Introduction

Bridges are a key element of transportation infrastructure and an essential component of a nation's socioeconomic development. Due to their long service life, bridges are subjected to aging, fatigue stresses, natural and man-made hazards, and increased traffic volumes [1, 2]. This places significant pressure on infrastructure managers to improve the availability and serviceability of bridges and to reconsider maintenance planning strategies [3]. In Iraq, bridges have not been adequately maintained to prevent their deterioration. Many of the bridges were constructed between the 1940s and the 1980s and are approaching or already have exceeded their design service life and need considerable investments to maintain sustainable operation and long-term serviceability. Furthermore, the increase in traffic loads beyond the predicted levels during the design phase, combined with exposure to aggressive environmental conditions, has significantly increased their deterioration [4]. It is therefore necessary to maintain bridges at a desirable level of conditions for public safety and the nation's economy. Maintaining bridges requires clearly defined condition ratings, standards for structural assessment, global and local damage descriptions corresponding to rates of deterioration, maintenance work procedures, and prediction of future deterioration.

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Condition rating can be defined as the evaluation of the bridge's current state in comparison with its as-built condition to obtain a bridge condition index [5]. A bridge condition or health index is widely employed by transportation authorities as the most common performance indicator for preserving structural condition or prioritizing maintenance projects for their bridge stock [6-8]. Such indices support decision-makers to make informed maintenance decisions by allocating budget to the most deserving bridge. This is extremely important from the viewpoint of developing countries where funds are scarce [9]. Additionally, the condition rating module is considered the most important part of any Bridge Management System (BMS), as it directly reflects structural safety and serviceability [1, 10]. Many countries worldwide have developed BMS frameworks that employ numerical condition indices for the inspected bridge to help decision-makers in deciding appropriate maintenance, rehabilitation, and replacement strategies [5]. Given that Iraqi transportation authorities have not adopted a systematic and rational methodology for bridge condition rating, developing such a methodology is considered a vital step for establishing a comprehensive BMS.

Several studies aimed to develop bridge condition rating methods. For example, Rashidi et al. [8] developed a priority index for ranking the bridges in the network using AHP model. This index combines three factors, including structural efficiency, functional efficiency, and client impact factor. They concluded that the presented model could enable the decision-makers to compare the overall condition of a number of bridges in the network. Wakchaure & Jha [11] employed AHP to determine the weight of bridge components and subcomponents. The study defined five condition states to assess the condition of bridge components. The study then identifies the Bridge Health Index (BHI) of bridges under consideration using the AHP weights and the condition states of bridge components to help stakeholders in India decide the priority of bridges for maintenance. Sasmal & Ramanjaneyulu [12] employed the fuzzy hierarchical analysis process (FAHP) for priority ranking of existing reinforced concrete bridges. Alsharqawi et al. [5] developed a condition rating index using the quality function deployment (QFD) and the k-means clustering technique for rating bridge decks. Omar et al. [13] developed a systematic condition rating method for concrete bridge decks utilizing infrared thermography (IRT), ground-penetrating radar (GPR), and visual inspection. Lallam et al. [14] utilized the FAHP approach to assess the condition of masonry arch bridges in order to support decision-making during maintenance planning. Additionally, Contreras-Nieto et al. [15] proposed a geographic information system (GIS), based on Multi Criteria Decision-Making (MCDM) methodology, to visualize bridges for maintenance priorities, hence enhancing the decision-making process. The AHP was employed for computing the weights of assessment factors (such as resiliency, travel comfort, safety, and serviceability) that influence maintenance prioritization strategies.

Despite the significant effort to establish condition rating methods, further research is still needed. Some of the above studies focus primarily on bridge decks, as their poor conditions can immediately cause discomfort to road users. However, bridge structure also includes other components such as superstructure and substructure, which significantly influence the overall bridge condition. Therefore, these components must be incorporated to develop an integrated bridge management system. In addition, some studies focused on utilizing the traditional AHP to develop bridge condition rating models. AHP is widely used for determining attribute weights for its ability to represent complex decision problems in structured hierarchical formats [16, 17]. However, using AHP alone is inadequate to handle the uncertainty and ambiguity inherent in expert judgments. To address this limitation, various fuzzy sets (FSs) are integrated with AHP as excellent tools for overcoming such uncertainty [18]. Although several scholars have utilized the triangular fuzzy number logic in bridge condition evaluation [12, 14], the integration of Fermatean fuzzy sets (FFSs) into bridge condition assessment has not yet been explored. In comparison with other FSs, the FFSs can better describe the uncertainty of complex uncertain problems [19].

Moreover, only a few systematic studies have been conducted to develop a bridge condition index for maintenance planning and decision-making. To address these gaps, this study aims to develop a BCI for bridge maintenance prioritization and condition rating using the Fermatean Fuzzy AHP (FF-AHP) approach. A weighted averaging approach is adopted in this study to compute the BCI since it offers a comprehensive view of the overall bridge condition and assists in planning maintenance activities [7, 11, 20]. The developed BCI takes into consideration both the weight and the condition state of various bridge elements. An FF-AHP-based questionnaire was developed to determine the weights of bridge elements and components based on experts' opinions. The proposed approach was then applied to thirteen bridges in Baghdad to test its practicality. To the best of the authors' knowledge, this study is the first to incorporate the AHP approach with FFSs for evaluating bridge conditions. Furthermore, no previous studies have investigated bridge condition in Iraq. Consequently, this study represents the first attempt to fill this gap and thus develops a methodology to evaluate and prioritize bridges in Iraq. The proposed method will help Iraqi bridge engineers and policymakers to evaluate and prioritize bridge maintenance projects more efficiently.

This research is structured in the following order. Section 2 includes a literature review. The research methodology is discussed in section 3. The subsequent part, section 4, is devoted to results analysis and discussion. The last section presents the conclusions of the study.

2. Literature Review

2.1. Condition Rating Systems

Condition ratings are necessary for successful BMSs. They enable transportation departments to evaluate and predict bridge condition, diagnose deterioration mechanisms, and identify appropriate maintenance and preservation measures accordingly [21]. The availability of element-level inspection data has led to the redevelopment of bridge condition indices used worldwide. Currently, a large number of BMSs depend on element-level data to compute BCIs [22]. According to the computational methodology employed, currently used methods for formulating condition indices can be categorized into four approaches [20, 22], as follows:

- The ratio-based method evaluates the current condition of a structure with respect to its original value. The aim of this method is to determine the remaining value of the bridge. The California Bridge Health Index (BHI) is an example of this method.
- The weighted averaging approach is appropriate for bridge maintenance planning. This approach assesses the overall condition of the structure by integrating the condition ratings of all individual bridge elements with their corresponding weights assigned based on their impact on the bridge's structural integrity. Examples of this method include the United Kingdom (BCI), Australia's bridge condition number (BCN), Austria (BCI), and South Africa (BCI).
- The worst-conditioned component approach only considers the structural elements that represent the weakest or the most critical parts of the bridge for computing the overall numerical index. This approach is beneficial for evaluating structural vulnerability in case of a disaster and for recognizing high-risk bridges since the condition of the whole bridge is based on its weakest parts [20]. However, the main limitation is that it does not provide a complete picture of the deterioration of the bridge, because only the condition of the most critical elements is assessed. The Japanese and German BCIs are examples of this approach.
- Qualitative methods characterize a bridge structure as "Poor," "Fair," or "Good," according to the condition state of elements under evaluation and their importance instead of using a numerical scale. As a result, this method is used to identify bridges that need to be maintained and not for prioritization because it lacks the numerical scale necessary for classifying bridges within the same network. The Bridge Health Indicator developed by Roads and Maritime Services in Sydney, Australia, is an example of qualitative methods.

Among these approaches, the weighted averaging is considered the most commonly adopted method [7]. It assesses the overall bridge condition by aggregating the condition ratings of its components. For example, in the United Kingdom, the BCI is calculated by classifying defects based on their degree of severity and extent. Both bridge component weights and their condition ratings are aggregated to compute the BCI [22]. The South African BCI is computed using routine condition assessments data and the bridge importance factor derived from the bridge's average daily traffic (ADT) [7]. In Austria, the BCI is computed using bridge element inspection data, where every element is given five ratings according to the following attributes: the type, extent, severity of the damage, urgency of intervention and the importance of a bridge component [22]. Several researchers have also adopted the weighted averaging approach for bridge condition assessment. For instance, Xu et al. [23] developed a framework to assess structural condition efficiency for suspension bridges in China using expert surveys and structural characteristic analysis to determine the health index of bridges and support stakeholders making maintenance decisions.

Abiona & Head [24] utilized the random forest algorithm, which consists of multiple decision trees, for evaluating the importance of bridge elements to the bridge's overall condition. Patel et al. [25] proposed a fuzzy-based framework for condition rating of railway bridges. The method handled the uncertainty in human judgment through triangular fuzzy membership functions and computed component significance by using the Fuzzy Weighted Geometric Mean (FWGM) technique. Rashidi et al. [26] developed a comprehensive methodology for structural assessment and strengthening of steel-concrete composite bridges. The proposed methodology integrated three phases: detailed structural assessment, optimized Carbon Fiber-Reinforced Polymer (CFRP) systems, and clear implementation protocols. Tabor et al. [7] developed a maintenance prioritization framework for pedestrian bridges in Taiwan. Bridge experts were interviewed through the Delphi method to calculate the weight factors indicating the importance of the structural safety and serviceability components to the identified bridge. Then, the weighted averaging approach was used to compute pedestrian BCI. Bukhsh et al. [3] utilized the Multiple Attribute Utility Theory (MAUT) model for bridge maintenance planning. The proposed method prioritized twenty-two bridges from the Netherlands road network based on multiple performance indicators, including condition index, maintenance cost, user delay cost, and environmental impact.

2.2. Applications of AHP in Bridge Maintenance

AHP is considered one of the most widely adopted and most popular MCDM methods. The AHP, proposed by Saaty [27], is used to compute attribute weights in MCDM research. These weights are determined through analyzing the subjective judgments of experts obtained from pairwise comparisons [28]. In situations when precise numerical values are not feasible, fuzzy logic can be utilized [29]. This provides a computational framework to capture and model the inherent uncertainties of human judgment. Therefore, various fuzzy set extensions have been incorporated with the traditional AHP approach that has been proposed. For example, the hesitant fuzzy AHP [30], intuitionistic fuzzy AHP [31], spherical fuzzy AHP [32] and Fermatean fuzzy AHP [29].

In the bridge maintenance field, there are a number of studies employing AHP. For instance, Al Hawarneh et al. [33] proposed a bridge screening framework to prioritize deficient bridges. Taguchi Design of Experiment was employed to identify the key performance indicators (KPIs), while the FAHP assigned weights to the identified KPIs. The aggregation of five KPIs (condition index, importance index, social impact index, economic impact index, and impact on Aboriginals index) led to the development of the Bridge Screening Index (BSI) that is used to determine the bridges that are in greater need of maintenance. Yue et al. [34] developed a model based on game theory for the condition evaluation of concrete continuous girder bridges. The AHP approach and the entropy weight method were utilized for constructing a combined weighting-fuzzy hierarchical comprehensive evaluation model. Yau et al. [35] proposed a model to assist bridge authorities in determining the post-disaster maintenance action priority order of bridges using the AHP method. Bridges have been ranked and classified based on their vulnerability to disaster-induced damage and the bridge's strategic importance by evaluating twelve decision factors.

Another study by Darban et al. [6] employed AHP for determining the BCI of bridges in Iran, enabling the evaluation and prioritization of bridges for maintenance based on eight indices: structural index, safety index, hydrology and climate, geotechnical and seismic, performance index, facilities index, strategic importance, and traffic and pavement index, which are rated based on experts' judgment and weighted using AHP. Alshibani et al. [36] utilized AHP and MAUT models to develop a decision support system for prioritizing bridges for maintenance. Several criteria were included in their study to determine bridge priority, such as condition status, bridge age, location, previous records for maintenance, and traffic volume. Rogulj et al. [37] proposed a knowledge-based expert system for condition rating of historical road bridges using fuzzy logic and sets of α-cuts. For this purpose, data collected from visual inspection were used to obtain the ratings of bridge components (superstructure, substructure, and equipment), which were then weighted by employing AHP. The aggregation of weighted component ratings resulted in the final rating of the bridge, represented as the Historic Road Bridge Condition Assessment Index (HRBCAI). Rashidi et al. [38] develop a decision support framework for evaluating remediation strategies of concrete bridges using the simplified analytical hierarchy process (S-AHP).

3. Research Methodology

This study employs a six-step methodology for the development of BCI. In the first step, the various bridge components and elements are identified. In the second step, the FF-AHP method is used to determine the weights of bridge components and elements. In the third step, Element Condition Indices (ECIs) are calculated based on field inspection reports and drawings. Then, both the ECIs and their weights are used to obtain the component condition indices, which are aggregated to compute the overall BCI. Lastly, bridges are prioritized for repair and maintenance based on their BCI. The framework of the study is presented in Figure 1.

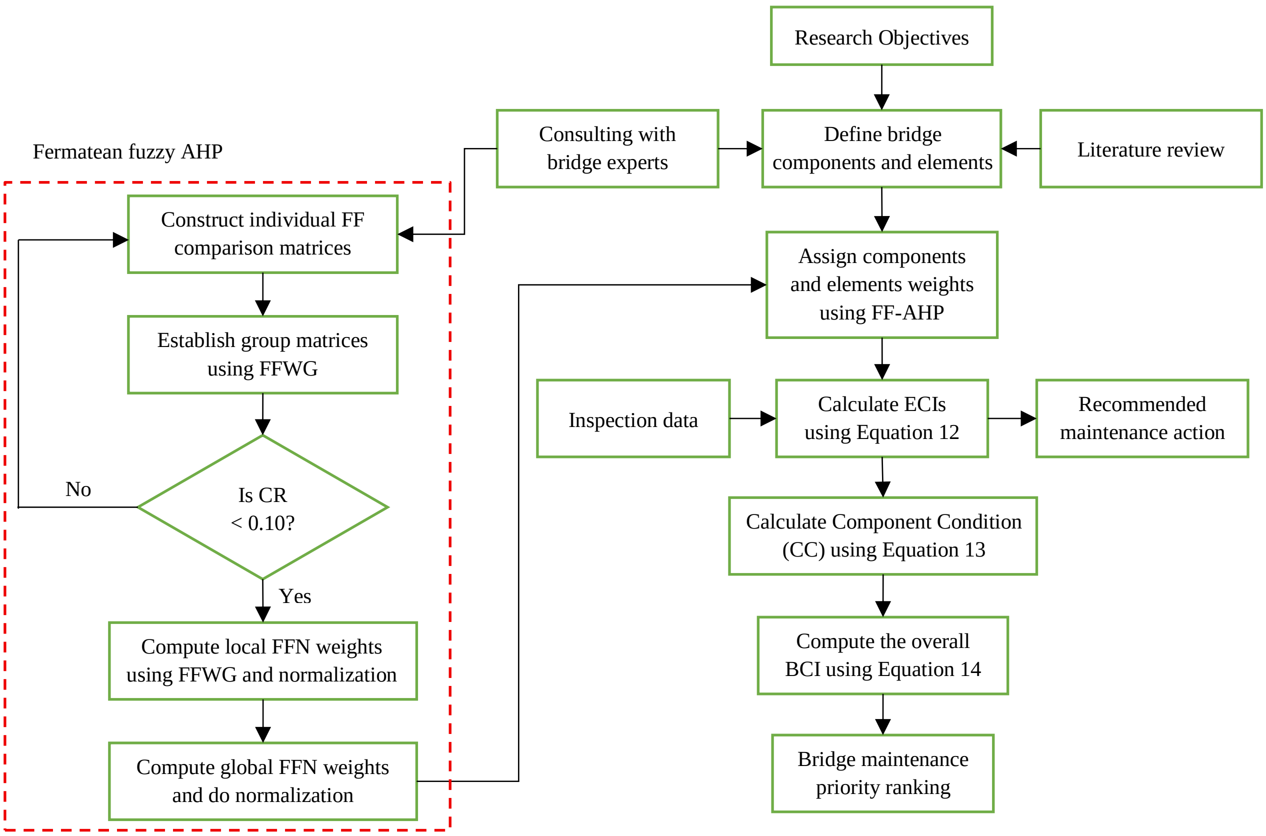


Figure 1. Proposed BCI methodology flowchart

3.1. Identification of Bridge Components and Elements

Bridge management practices around the world differ in how they identify the bridge elements to be inspected as well as in the weighting assigned to these elements. For example, the New York BMS divides bridges into 13 elements [1]. Inspecting a large number of bridge elements can become costly and is not always feasible due to limitations in resources and accessibility issues.

The approach proposed in this paper focuses on four major components: deck, superstructure, substructure, and accessories. Each component is further divided into a number of elements. The adopted classification was determined based on a literature review, the AASHTO Manual for Bridge Element Inspection [39], and discussions with bridge maintenance experts in Iraq. The selected elements are intended to capture all the necessary components required for managing the needs of the transportation departments while maintaining practicality in implementation. Figure 2 displays the hierarchy of various bridge components and elements adopted in this study.

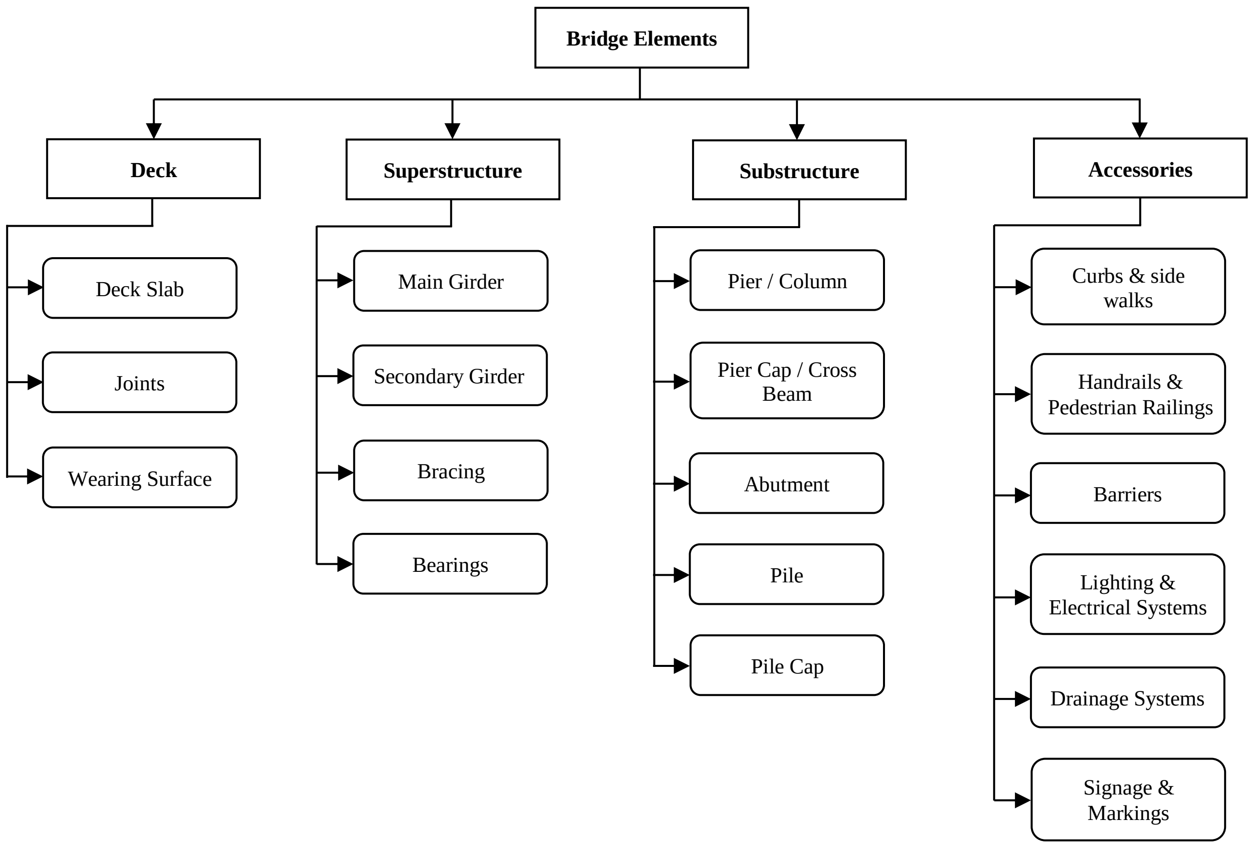


Figure 2. Bridge components and elements used in the study

3.2. Assignment of Bridge Components and Elements Weights

The relative importance weights of bridge components and elements are computed to represent their contributions to the structural integrity of the bridge. The FF-AHP is employed for this task. Six experts involved in bridge maintenance were invited to obtain their insights on the proposed problem. Conducting interviews with six experts is considered adequate for obtaining reliable feedback, which aligns with previous studies that employed sample sizes ranging from four to nine in pairwise comparison-based questionnaires [36]. The main advantage of AHP compared to other MCDM approaches is that it does not necessitate a statistically significant (large) sample size to yield reliable and robust results [40]. Moreover, the decision to consult a larger group may not maintain the consistency ratio (CR) of the group comparison matrix within its range ($CR < 0.1$), which can affect the accuracy of FF-AHP results [19]. The expertise of the participating panelists is the critical factor in AHP analysis [41]. Some researchers argue that because AHP is based on expert judgments, judgments from even a single qualified expert are usually representative [42]. In addition, Boje & Murnighan [43] compared the effectiveness of employing groups of three, seven, or eleven experts and found that there are no significant differences among participants, particularly when the experts are carefully selected and are confident in their assessments.

For this purpose, a purposive sampling technique was employed to select experts based on predefined criteria. Purposive sampling is considered a non-probability sampling approach that is most effective when selecting knowledgeable experts based on the objective of the study [44]. These included being professionals in the area of bridge maintenance and having more than 20 years of experience and knowledge of bridge design, construction, or maintenance. Under these considerations, six experts in these fields were invited to participate in the questionnaire survey.

A questionnaire based on FF-AHP is designed to evaluate the perceptions of experts on the relative importance of bridge elements. The questionnaire is structured into two parts. The first part addresses participants' demographic information, such as the academic certificate, years of experience, and organization type. The second part aims to assign weights for bridge components and elements by conducting pairwise comparisons. Experts are asked to compare each corresponding pair of elements and to determine the more important one. The following subsections provide some preliminaries of the FFSs and the Fermatean fuzzy AHP adopted in this study.

3.2.1. Preliminaries

A fuzzy set was developed in 1965 by Zadeh [45]. Since their introduction, many fuzzy set extensions have developed to handle uncertainty in complex systems, such as intuitionistic fuzzy sets [46], Pythagorean fuzzy sets [47], spherical fuzzy sets [48], and Fermatean fuzzy sets (FFSs) [49]. The FFS concept is built on the intuitionistic fuzzy sets (IFSs) and Pythagorean fuzzy sets (PFSs) concepts. When compared with IFSs and PFSs, Fermatean fuzzy set theory is a more advanced and innovative approach in dealing with vague and uncertain data since it provides a broader range of membership and non-membership degrees [50]. Furthermore, in conflicting decision-making situations, IFSs and PFSs showed weaknesses, as the membership degree and non-membership degree given by the decision makers can exceed 1 [18].

Senapati & Yager [49] provided an example to demonstrate the reasonability of the FFS: Consider an expert's evaluation that a particular alternative satisfies the overall expectations with a probability of 0.9, yet the same alternative fails to satisfy the expectations with a probability of 0.6. This voter judgment cannot follow the condition of IFS given that $0.9 + 0.6 = 1.5 > 1$. Also, it cannot follow the condition of PFS since $0.9^2+0.6^2 = 1.17 > 1$. However, the FFS can capture this evaluation effectively, given that $0.9^3 + 0.6^3 = 0.945 \leq 1$. This is to mention that FFSs are capable of handling higher levels of uncertainties.

The Fermatean membership grades are capable of representing a larger set of membership grades than PFSs and IFSs [49], as illustrated in Figure 3. Here it can be noticed that intuitionistic membership grades are all points beneath the line $a + b \leq 1$, the Pythagorean membership grades are all points with $a^2+b^2 \leq 1$ and the Fermatean membership grades are all points with $a^3 + b^3 \leq 1$. FFS theory is a remarkable approach in modelling complex human preferences during decision-making processes [19]. That is the reason for adopting FFS in this study. It is particularly suitable in addressing complex MCDM problems since it can capture the nuance and complex nature of real-world evaluations. This section presents some basic concepts of FFS that have been utilized in the proposed methodology.

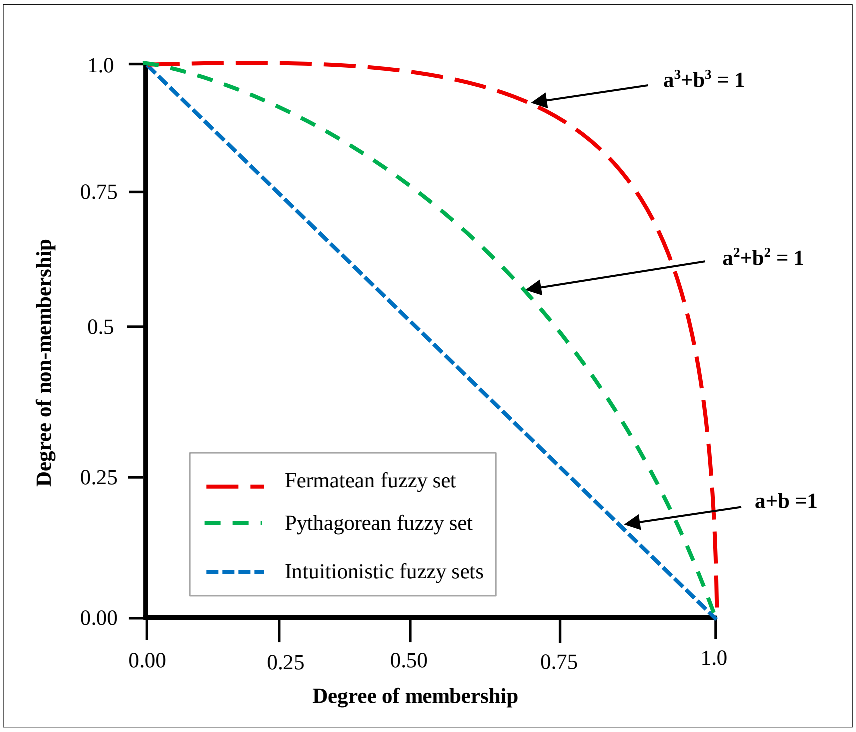


Figure 3. Comparation of intuitionistic fuzzy sets, Pythagorean fuzzy sets, and Fermatean fuzzy sets

Definition 1 [49]. $\bar{\bar{F}}$ is a Fermatean fuzzy set within a universe X can be presented in Equation 1:

$$\bar{\bar{F}} = \{\langle x, \alpha_{\bar{\bar{F}}}(x), \beta_{\bar{\bar{F}}}(x) \rangle \mid x \in X\} \tag{1}$$

where, $\alpha_{\bar{\bar{F}}}(x) \in [0,1]$ and $\beta_{\bar{\bar{F}}}(x) \in [0,1]$ reflects the degree of membership and the degree of non-membership of element x in $\bar{\bar{F}}$ set respectively, and $\alpha_{\bar{\bar{F}}}(x)$ and $\beta_{\bar{\bar{F}}}(x)$ meet the condition in Equation 2

$$0 \le (\alpha_{\bar{\bar{F}}}(x))^3 + (\beta_{\bar{\bar{F}}}(x))^3 \le 1, \forall x \in X \tag{2}$$

The degree of indeterminacy (hesitancy) of element x in $\bar{\bar{F}}$ set is:

$$\pi_{\bar{\bar{F}}}(x) = \sqrt[3]{1 - (\alpha_{\bar{\bar{F}}}(x))^3 - (\beta_{\bar{\bar{F}}}(x))^3}, \forall x \in X \tag{3}$$

Definition 2 [49]. Assume $\bar{\bar{F}}_1 = (\alpha_{\bar{\bar{F}}1}, \beta_{\bar{\bar{F}}1})$ and $\bar{\bar{F}}_2 = (\alpha_{\bar{\bar{F}}2}, \beta_{\bar{\bar{F}}2})$ are two FFSs, then some FFS operations are given as follows:

$$\bar{\bar{F}}_1 + \bar{\bar{F}}_2 = \left(\sqrt[3]{\alpha_{\bar{\bar{F}}1}^3 + \alpha_{\bar{\bar{F}}2}^3 - \alpha_{\bar{\bar{F}}1}^3\alpha_{\bar{\bar{F}}2}^3}, \beta_{\bar{\bar{F}}1}\beta_{\bar{\bar{F}}2}\right) \tag{4}$$

$$\bar{\bar{F}}_1 \, x \, \bar{\bar{F}}_2 = \left(\alpha_{\bar{\bar{F}}1}\alpha_{\bar{\bar{F}}2}, \sqrt[3]{\beta_{\bar{\bar{F}}1}^3 + \beta_{\bar{\bar{F}}2}^3 - \beta_{\bar{\bar{F}}1}^3\beta_{\bar{\bar{F}}2}^3}\right) \tag{5}$$

Definition 3 [49]. Assume $\bar{\bar{F}}_i = (\alpha_{\bar{\bar{F}}_i}, \beta_{\bar{\bar{F}}_i})(i = 1,2,\dots,n)$ is a number of FFNs and $w = (w_1, w_2, \dots, w_n)^T$ is a weight vector of $\bar{\bar{F}}_i$ with $\sum_{i=1}^{n} w_i = 1$, then a Fermatean fuzzy weighted geometric (FFWG) operator is a function FFWG: $\bar{\bar{F}}^n \to \bar{\bar{F}}$, where

$$FFWG(\bar{\bar{F}}_1, \bar{\bar{F}}_2, \dots, \bar{\bar{F}}_n) = \left(\prod_{i=1}^{n} \alpha_{\bar{\bar{F}}_i}{}^{w_i}, \prod_{i=1}^{n} \beta_{\bar{\bar{F}}_i}{}^{w_i}\right) \tag{6}$$

Definition 4 [29]. Assume T = $(\alpha_{\bar{\bar{F}}}, \beta_{\bar{\bar{F}}})$ is any Fermatean fuzzy set (FFS), the definitions of score function (SF) is as follows:

$$SC(T) = \left(\alpha_{\bar{\bar{F}}}{}^3 - \beta_{\bar{\bar{F}}}{}^3\right) \tag{7}$$

3.2.2. Fermatean Fuzzy AHP

AHP is commonly employed in the literature to compute the weights of factors. The AHP method is not enough to be used alone in case of uncertainty. Various fuzzy extensions have been developed and integrated with AHP to address the uncertainty inherent in expert judgments. FF-AHP provides greater flexibility, consistency, and accuracy in capturing uncertain information. In this study, FF-AHP steps can be expressed as follows:

Step 1: Build the decision hierarchy of bridge components and elements (Figure 2).

Step 2: The Fermatean fuzzy number (FFN) linguistic scales shown in Table 1 are used to establish individual pairwise comparison matrices. Equation 8 is employed to calculate the score indices (SI) in Table 1.

$$SI\,(\bar{\bar{F}}) = \left|10\left(\alpha_{\bar{\bar{F}}}{}^3 - \beta_{\bar{\bar{F}}}{}^3\right)\right| \tag{8}$$

Table 1. Linguistic scale used for FF-AHP comparison matrix

Linguistic Variable	Label	FFN		Score Index (SI)
Extremely high importance	EHI	0.970	0.233	9
Very high importance	VHI	0.900	0.307	7
high importance	HI	0.794	0.083	5
Slightly high importance	SHI	0.670	0.091	3
Equal importance	EI	0.465	0.082	1
Slightly low importance	SLI	0.322	0.038	1/3
Low importance	LI	0.272	0.050	1/5
Very low importance	VLI	0.243	0.040	1/7
Extremely low importance	ELI	0.224	0.050	1/9

Step 3: To generate FF group comparison matrices, the Fermatean fuzzy weighted geometric mean (FFWG) operator given in Equation 6 is applied to aggregate the individual comparison matrices.

Step 4: To perform consistency analysis, all the FF comparison matrices are defuzzified using Equation 8, and then the classical calculation of the consistency ratio for AHP is used. The consistency of pairwise comparisons is evaluated using Equation 9:

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

where CR is the consistency ratio, RI is the Random Index presented in Table 2, and CI is the Consistency Index computed using Equation 10:

$$\mathrm{CI} = \frac{\lambda\ \mathrm{max} - \mathrm{n}}{\mathrm{n}-1} \tag{10}$$

where, λ max stands for the maximum eigenvalue of the pairwise comparison matrix, and n represents the number of elements being compared. A comparison matrix can be considered consistent when the consistency ratio is less than 0.1. If the consistency ratio exceeds 0.10, it is necessary to revise their judgments to locate and correct the cause of the inconsistency.

Table 2. Values of consistency indices

n	3	4	5	6	7	8	9
RI	0.525	0.882	1.109	1.248	1.342	1.406	1.450

Step 5: To compute the local FFN weights, the FFGW operator (Equation 6) is applied for each row of the group comparison matrix to get the FF weights. It has been assumed that all of the w values in the equation are equivalent to the average, with their sum equal to 1. For instance, in a 3 × 3 comparison matrix, all weights will be equivalent to 1/3. The FF weights are further defuzzified using Equation 7 and then normalized via Equation 11 for obtaining the local weights (LW_i).

$$LW_i = \frac{\mathrm{sc}(\bar{\bar{F}}_\mathrm{i})}{\sum_{i=1}^{n} \mathrm{sc}(\bar{\bar{F}}_\mathrm{i})} \tag{11}$$

The global weights of sub-attributes are calculated by multiplying the local weights of sub-attributes with the weight of the corresponding main attributes.

3.3. Determination of Element Condition Index (ECI)

In practice, several assessment grades and standards have been employed to evaluate the condition of bridge components and elements. For example, numerical rating scales (e.g., 0 to 5 or 1 to 9) and linguistic expressions (e.g., good, fair, and poor). In this study, four condition states—condition state 1 (CS1), condition state 2 (CS2), condition state 3 (CS3), and condition state 4 (CS4), which represent good, fair, poor and severe conditions, respectively—are adopted. The number of condition states and their descriptions is based on the AASHTO Manual for Bridge Element Inspection [39], as presented in Table 3. These condition states are required to determine the condition index of each element, where a weighted coefficient is assigned to each of them.

Different weight coefficients have been adopted in practice for computing the elements' condition index under four condition states. Inkoom et al. [51] considered three approaches for the assignment of the condition state weights. In all approaches, the CS1 has the greatest effect on the element condition index and is assigned a factor of 1, while the CS4 has no impact on the condition index and is assigned a factor of 0. The first approach, which represents the commonly adopted default approach, has a linear distribution for the weights, between 1 for CS1 and 0 for the worst state. It is assumed that material degradation represents an estimate of the economic value of the particular bridge element. Under this approach, an element with four condition states has 100% of its economic value in CS1, while in CS2 and CS3, the element has 67% or 33%, respectively, of its economic value and has minimal economic value in CS4. The second approach, referred to as the "optimistic approach," assumes that CS2 is almost as good as new, with a weight of 0.80, and that CS3 has a weight of 0.40. The third approach assumes that CS2 and CS3 are really bad and have weights of 0.50 and 0.25, respectively. This approach can be termed the "pessimistic approach." Inkoom et al. [51] demonstrated that the linear and pessimistic trends result in lower bridge health index values compared to the optimistic trends and were more conservative. Accordingly, the adopted condition index weight coefficients can influence the resulting ECIs and BCIs.

In this study, the condition index of the bridge elements will be computed using the default approach, in which the weight coefficients assigned to the four condition states (CS 1 to CS 4) are 1, 0.67, 0.33, and 0, respectively. These condition states and weight coefficients are presented to the same bridge experts consulted during the element weighting process to verify their consistency with the institutional bridge management practices in Iraq, and they confirmed the selection of these values. However, the decision maker can select different weights based on their maintenance management policies.

Table 3. Element condition states description

Element Condition State	Element State Level	Description
CS1	Good	That portion of the element is in good condition with no deterioration, or the deterioration is insignificant to the function of the element. Preventive maintenance may be needed.
CS2	Fair	That portion of the element is in fair condition with minor defects that indicate the progression of the deterioration process. Preventive or corrective maintenance may be needed.
CS3	Poor	That portion of the element is in poor condition with advanced deterioration but does not require structural review. Corrective maintenance or other remedial action may be needed.
CS4	Severe	That portion of the element is in severe condition with serious defects that warrant a review of the structure to identify their effect on the strength or serviceability of the element or bridge. Major rehabilitation or replacement is generally required.

In the proposed method, the condition state of a bridge element (i.e., the element quantity that is distributed across the four condition states, CS1 to CS4) is identified by quantifying each defect and assigning it to the proper condition state based on its extent and severity. These condition state quantities (CS1 to CS4) are then converted into a percentage value to represent the percent of element in each of these four conditions. To determine the overall health of the element, the ECI is calculated using Equation 12, where the percentages of element in each condition state are multiplied by their corresponding weight coefficients as follows:

$$ECI = 100 \times CS1\% + 67 \times CS2\% + 33 \times CS3\% + 0 \times CS4\% \quad (12)$$

The ECI values range from 0 to 100, where 100 represents an excellent condition and 0 represents a failed condition. ECI values can be classified into condition categories based on predefined index ranges. For instance, the element is rated in very good condition if its ECI is between 71 and 90; if the ECI is between 21 and 50, then it is rated in poor condition; meanwhile, between 61 and 70 is good condition, and fair condition is between 51 and 60. ECI values can also be used to determine the recommended maintenance action for each bridge element. Table 4 presents the recommended maintenance action for each ECI range.

Table 4. Recommended Maintenance actions for bridge elements based on ECI values

Element Condition Index (ECI)	Condition Description	Recommended Maintenance Action	Description
≥ 91	Excellent Condition	Do Nothing	No intervention required
71–90	Very Good Condition	Monitoring and Preventive Maintenance	Regular monitoring and light preventive measures
61–70	Good Condition	Minor Preventive and Corrective Maintenance	Localized minor repairs and preventive treatments
51–60	Fair Condition	Moderate Preventive and Corrective Maintenance	Broader corrective actions to restore functionality
21–50	Poor Condition	Major Maintenance	Extensive repair work to address significant deterioration
0–20	Very Poor Condition	Replacement	Element has failed or is near failure; replacement is required

3.4. Determination of Bridge Condition Index (BCI)

To obtain the BCI, the component condition (CC) is calculated using Equation 13 by weighting and aggregating the ECIs of all elements belonging to that same component. Each ECI is multiplied by the element local weight derived from FF-AHP, and the weighted values are summed to compute the overall CC. Then, the components' condition indices are weighted and aggregated to compute the BCI using Equation 14, as follows:

$$CC_i = \sum_{k=1}^{m} ELW_k \times ECI_k \quad (13)$$

$$BCI = \sum_{i=1}^{n} CW_i \times CC_i \quad (14)$$

where: ELW_k= local weight of element ‘k’ obtained from FF-AHP; ECI_k= element condition index of element ‘k’ ; m = number of elements in bridge component i; CW_i = weight of component ‘i’ obtained from FF-AHP; CC_i = condition index of component ‘i’; n = number of bridge components. Bridges are assigned a condition index ranging from 0 to 100, as shown in Table 5, where 0 indicates a failed condition, while 100 indicates that the bridge is in excellent condition.

Table 5. BCI ranges and their corresponding condition description

BCI Range	Description
91-100	Excellent Condition
81-90	Very Good Condition
71-80	Good Condition
51-70	Fair Condition
21-50	Poor Condition
0-20	Very Poor Condition

4. Results Analysis and Discussion

4.1. Case Study Description

The application of the developed methodology is demonstrated with real case study bridges. The considered bridges inventory includes thirteen bridges crossing the Tigris River in Baghdad, the capital of Iraq. Their primary features are as listed in Table 6. The latest field inspection reports (2022) conducted by the Iraqi Public Authority for Roads and Bridges were used to obtain the data on these bridges. The gathered data cover geometrical and structural characteristics, as well as defects of all bridge elements above ground. The bridges were built between 1941 and 1991, which means that the newest bridge is more than 30 years old. Some of the selected bridges are steel bridges, while the others are reinforced concrete (RC) bridges. Three bridges have special features (cable-stayed bridge, suspension bridge and truss bridge) while the remaining are girder bridges. The bridges are placed in a road network that has an average daily traffic volume of more than 35,000 vehicles per day.

Table 6. Bridge inventory data for the 13 case study bridges over the Tigris River in Baghdad

Bridge ID	Width (m)	Length (m)	Bridge Type	Material of Construction	Construction Date	Bridge Image
A1	26.1	600	Prestressed Concrete Box Girder	RC	1982	
A2	9	800	Steel Plate Girder	Steel	1957	
A3	9	330	Steel Plate Girder	Steel	1940	
A4	9.5	312	Steel Plate Girder	Steel	1941	
A5	20	2950	Concrete Girders-RC Slab	RC	1992	
A6	24.8	2950	Concrete Girders-RC Slab	RC	1982	

A7	19	270	RC Girder	RC	1977	
A8	24.8	610	Prestressed Concrete Girders-RC Slab	RC	1979	
A9	14.9	600	Prestressed Concrete Girders & Box Girder	RC	1985	
A10	12.2	850	Steel Plate Girder	Steel	1957	
A11	9	1050	Steel Truss Bridge	Steel	1952	
A12	31	750	Cable Stayed Steel Bridge	Steel/RC	1979	
A13	15	320	Suspension Bridge	Steel Suspension Cable	1991	

To rank the thirteen bridges based on their priority for maintenance, it is necessary to determine the condition of each of them. The acquisition of information about the structural condition through inspections plays a pivotal role in examining the integrity and stability of the bridge and its safety for vehicles and pedestrians. During visual inspection, each bridge is evaluated and assigned a predefined condition rating, providing a condition assessment of the selected stock of bridges. However, the main limitation of condition assessment through visual inspection is the uncertainty inherent in bridge inspectors' subjective ratings while using linguistic expression to quantify defects associated with the various bridge elements [1]. In addition, visual inspection provides limited defect-detection capabilities. This can significantly affect the reliability of the condition assessment process. Therefore, nondestructive evaluation (NDE) techniques, such as impact echo, ultrasonic surface wave, half-cell potential, ground-penetrating radar, infrared thermography, and image-based techniques, have been used in the inspection processes to tackle such limitations. Incorporating the NDE technologies in the inspection process can help in detecting a wide range of subsurface defects [5].

Accordingly, the inspection reports adopted in this study incorporated in-situ testing in addition to visual inspection to make the inspection process more objective and reliable. The assessment started with the elements, where accessible elements were hands-on inspected and their defects were documented. By the completion of the site inspection phase, a testing campaign (i.e., non-destructive testing NDT as well as semi-destructive methods such as concrete core extractions) is planned based on the identified defect locations. Figure 4 presents a statistical representation of defects and damages classified by their type observed in the 13 case study bridges. The four most common defect types are corrosion, damage, connection, and delamination. Corrosion has the highest frequency (31.3%). Damage comes after that with 26.63%. In the third place are connection-related defects (13.74%), and in the fourth place is delamination (13.2%). Meanwhile, defects such as distortion, scour, exposed rebar, and settlement each contribute less than 2% of the total defects.

The proposed procedure outlined in the preceding section was applied to all thirteen bridges in the considered stock to compute BCI and priority rankings. The following subsections present and discuss the results and main findings in terms of element weights, element condition index, and priority ranking of bridges.

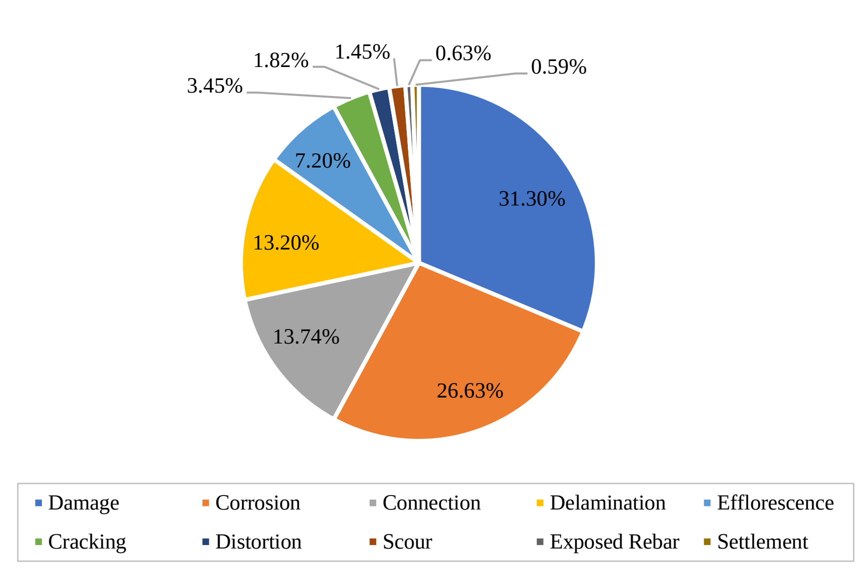


Figure 4. Distribution of defects and damages identified across all case-study bridges

4.2. Methodology Implementation

To obtain the relative importance weights for bridge components and elements based on the decision hierarchy illustrated in Figure 2, experts' opinions are first gathered and converted into a decision matrix by using linguistic values given in Table 1. The linguistic values are translated into the Fermatean fuzzy numbers to build individual comparison matrices. To establish the group comparison matrices, the FFWG operator (Equation 6) is used for aggregating the individual comparison matrices.

Since AHP allows subjective judgments by decision makers, consistency of the judgments is not automatically guaranteed. Saaty [27] mentioned that to control the consistency of pairwise comparisons, a computation of consistency ratio should be performed. When the CR value exceeds the threshold of 0.1, decision-makers are required to revise their initial judgments and locate and correct the cause of the inconsistency [27]. Accordingly, follow-up communications were conducted with the experts to clarify each question and ensure consistency in their responses. The consistency ratios of all comparison matrices are computed using Equation (8), and all satisfy the requirements of CR < 0.1.

For example, the consistency ratios of the six individual FF comparison matrices of bridge components are 0.083, 0.086, 0.001, 0.095, 0.086, and 0.088. Meanwhile, the consistency ratio of the FF group comparison matrix of the bridge components (Table 7) is 0.013. Given that the consistency ratio of the group comparison matrix is < 0.1, the analysis can move to the next phase.

Table 7. Group comparison matrix of bridge components

Components	Deck		Superstructure		Substructure		Accessories		FF-Weight		Defuzzified Weights	Weight	Rank
Deck	0.465	0.082	0.366	0.052	0.400	0.059	0.630	0.089	0.455	0.069	0.094	0.208	3
Superstructure	0.590	0.076	0.465	0.082	0.525	0.085	0.689	0.090	0.561	0.083	0.176	0.391	1
Substructure	0.540	0.075	0.411	0.063	0.465	0.082	0.689	0.090	0.517	0.077	0.137	0.304	2
Accessories	0.342	0.043	0.313	0.040	0.313	0.040	0.465	0.082	0.353	0.049	0.044	0.097	4

The FF-weights of bridge components are obtained by performing the FFWG operator for each row in Table 7. The FF-weights are then defuzzified using Equation 7 and normalized via Equation 11 to determine bridge components' final weights. This process is repeated for all bridge element groups to obtain their local weights, as presented in Tables A1–A4 in Appendix I. The global weight of elements is calculated via multiplying their local weights by their components' weight. The weights of bridge components and elements are listed in Table 8.

As shown in Table 8, the superstructure gained the greatest importance (39.1%), followed by the substructure (30.4%) and the deck (20.8%), while accessories were of the least importance (9.7%). This indicates that experts prioritized structural elements that contribute to the structural capacity of the bridge over non-structural elements like accessories. This finding is consistent with the study done by Tabor et al. [7], where experts prioritized structural safety components (e.g., piers/abutments and floor system members) over serviceability components (e.g., railing, deck walkway, stairs, and drainage).

Table 8. Weights of bridge components and elements using FF-AHP

Components	Weight	Elements	Local Weight	Global Weight
Deck	0.208	Deck Slab	0.576	0.120
		Joints	0.212	0.044
		Wearing Surfaces	0.212	0.044
Superstructure	0.391	Main Girder	0.402	0.157
		Secondary Girder	0.269	0.105
		Bracing	0.104	0.041
		Bearings	0.224	0.088
Substructure	0.304	Pier / Column	0.316	0.096
		Pier Cap / Cross Beam	0.105	0.032
		Abutment	0.316	0.096
		Pile	0.164	0.050
		Pile Cap	0.098	0.030
Accessories	0.097	Curbs & Side Walks	0.124	0.012
		Handrails & Pedestrian Railings	0.195	0.019
		Barriers	0.201	0.020
		Lighting & Electrical Systems	0.168	0.016
		Drainage Systems	0.195	0.019
		Signage & Markings	0.116	0.011

For the deck component, the results show that the deck slab is identified as the most important element to the condition rating of the deck (57.6%), while the joints (21.2%) and wearing surfaces (21.2%) are the second most important elements. This result can be attributed to the fact that the deck slab gets direct traffic loads from the vehicles and it has a large surface area that is subjected to extreme weather conditions. Similar findings have been reported in previous studies [1, 24], where the deck slab was also identified as the dominant element of the deck component. However, Alshibani et al. [36], pointed out that the bearing pad is the most influential element in maintaining the bridge structure because its service life is shorter than that of other components, and it has impacts on the bridge and traffic flow in case of any sudden failure. They consider that other structural elements, such as abutments, pier columns, and foundations, are designed to withstand loads for longer periods.

In the superstructure, the main girder has the highest structural importance value, with 40.2% of the total superstructure weight and 15.7% of the overall bridge elements' weight. This result makes sense since most of the bridges in Iraq are girder bridges, where girders are considered their base design elements and therefore have influence on the superstructure condition rating. This research finding has been widely supported by the literature [1, 3, 6, 11, 24].

For the substructure, both the pier/column and the abutment are identified as the most significant elements influencing the substructure condition, each contributing 31.6% to the total substructure weight. This result reflects the fact that the pier is one of the bridge's key components that transfers superstructure vertical loads to the foundations and resists horizontal forces acting on the bridge, such as seismic events.

Similarly, the abutment is an important part of the bridge, as it transfers the loads from the superstructure to the earth, and it is subjected to earth pressure, hydrostatic forces, and traffic loads. This result is similar to the work done by Dabous & Al-Khayyat [1], who considered both the abutment and pier to be the most important elements in the substructure.

The accessories were considered the least important (9.7%), as they are non-structural elements and do not contribute to the structural integrity of the bridge, which is consistent with the findings reported in studies [1, 8, 11]. However, accessories play a significant role in traffic safety, durability, movement and ride quality, and their condition can influence the efficiency of the structural elements. Inadequate or deteriorated accessories can significantly increase the likelihood of accidents. For instance, bridge barriers (20.1%) and railings (19.5%) are considered critical elements of a bridge safety system and essential for preventing and minimizing collisions and impact damage. Other bridge characteristics, such as the drainage system, are also considered influential accessory elements (19.5%), since poor drainage systems can negatively impact the safety of traveling vehicles [10].

After computing the relative importance weights of bridge components and elements, the next step is determining the ECIs. First, the element-level defects are quantified from inspection reports and classified into four condition states to determine the percentage of the element in each state. Table 9 presents an example of the condition assessment of the steel cross girders and diaphragms, illustrating how each defect was quantified and classified across the four condition states.

The steel cross girders and diaphragms, with a total area of 5,000 m², are affected by five types of defects, namely, corrosion, cracking, damage, connection, and distortion, which are classified under condition states CS2, CS3, and CS4. The results show that 73.56% of the element remains in good condition, 5% in fair condition, 5% in poor condition, and 16.44% in severe condition.

Table 9. Example of element-level condition state assessment for the steel cross girders and diaphragms

<table>
<tr><th rowspan="2">Defect Number</th><th>Element / Defect Description</th><th>Unit of Measure</th><th>Total Quantity</th><th>CS1 (Good)</th><th>CS2 (Fair)</th><th>CS3 (Poor)</th><th>CS4 (Severe)</th></tr>
<tr><th>Steel Cross Girders & Diaphragms</th><th>m^2</th><th>5,000</th><th>3,678 (73.56%)</th><th>250 (5%)</th><th>250 (5%)</th><th>822 (16.44%)</th></tr>
<tr><td>Corrosion (1000)</td><td>Localized corrosion, especially at cantilevers and near drainage outlets and loss of protective coating and paint.</td><td>m^2</td><td>354</td><td>0</td><td>45</td><td>65</td><td>244</td></tr>
<tr><td>Cracking (1010)</td><td rowspan="2">A local area that was damaged in the 1990 war and poorly repaired has been observed. The cantilever at the repair jacket is found with a complete loss of the compression flange end section, indicating a critical condition.</td><td>m^2</td><td>312</td><td>0</td><td>63</td><td>43</td><td>206</td></tr>
<tr><td>Damage (7000)</td><td>m^2</td><td>134</td><td>0</td><td>25</td><td>27</td><td>82</td></tr>
<tr><td rowspan="2">Connection (1020)</td><td rowspan="2">Connection damage and loss between the cross girder/cantilever and the main girder at the repair location.</td><td>m^2</td><td>262</td><td>0</td><td>56</td><td>41</td><td>165</td></tr>
<tr><td>each</td><td>149</td><td>0</td><td>25</td><td>43</td><td>81</td></tr>
<tr><td>Distortion (1900)</td><td>Significant distortion is observed at a local area that was damaged in the 1990 war and poorly repaired.</td><td>m^2</td><td>111</td><td>0</td><td>36</td><td>31</td><td>44</td></tr>
</table>

Using Equation 12, the ECI for the steel cross girders and diaphragms is calculated as follows:

$$ECI = 100 \times 73.56\ \% + 67 \times 5\% + 33 \times 5\% + 0 \times 16.44\% = 78.56$$

According to Table 4, an ECI value of 78.56 indicates that the steel cross girders and diaphragms are in a very good condition state and only monitoring and preventive maintenance are required. The same process is applied for all elements to compute their ECIs. The analysis and assessment using the ECI metric establishes a clear and measurable basis for prioritizing maintenance interventions for the bridge's elements within the transportation network.

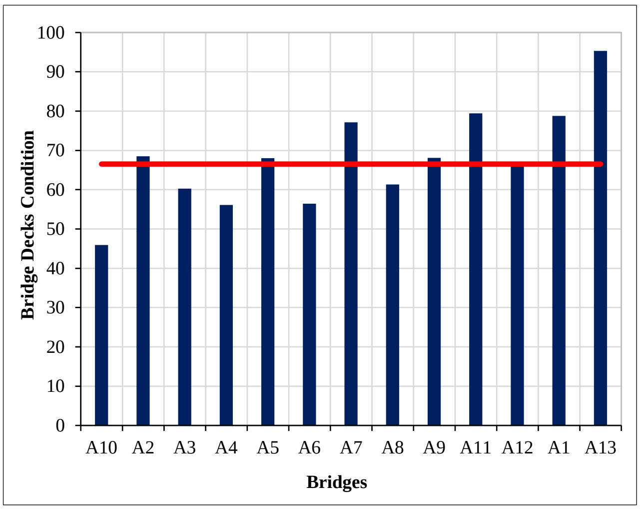
Using Equation 13, the weight of each element (derived from the FF-AHP model and presented in Table 8) is multiplied by its ECI value and then aggregated for all elements that belong to the same component to determine the condition index of each bridge component.

Subsequently, the condition ratings of the four components were multiplied by their weights and summed to compute the overall BCI using Equation 14. All bridges are then ranked based on their BCIs values to determine bridge priority for maintenance. Table 10 presents the results of applying the proposed BCI methodology for the thirteen case study bridges.

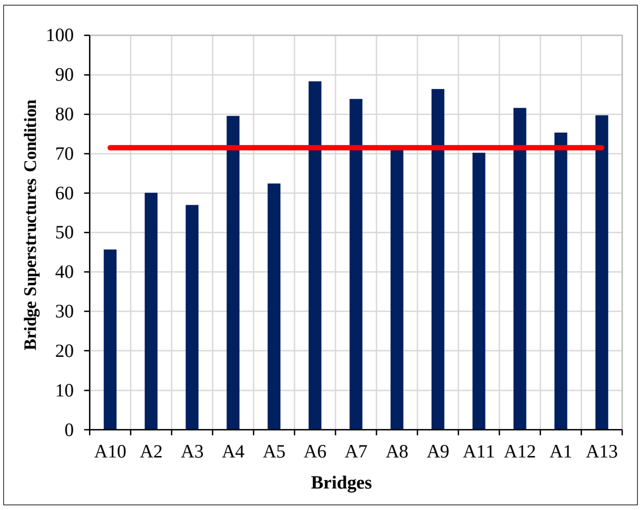
Table 10. Results of applying the proposed BCI for the thirteen case study bridges

Bridge ID	Components	Component Weight (CW)	Component Condition (CC)	CW×CC	BCI=∑ (CW×CC)	Condition Description
A10	Deck	0.208	45.901	9.547	54.21	Fair Condition
	Superstructure	0.391	45.680	17.861		
	Substructure	0.304	72.590	22.067		
	Accessories	0.097	48.758	4.729		
A2	Deck	0.208	68.464	14.240	60.52	Fair Condition
	Superstructure	0.391	60.053	23.481		
	Substructure	0.304	60.395	18.360		
	Accessories	0.097	45.756	4.438		
A3	Deck	0.208	60.232	12.528	62.79	Fair Condition
	Superstructure	0.391	56.998	22.286		
	Substructure	0.304	72.683	22.096		
	Accessories	0.097	60.680	5.886		
A8	Deck	0.208	61.289	12.748	64.34	Fair Condition
	Super Structure	0.391	71.638	28.011		
	Substructure	0.304	60.715	18.457		
	Accessories	0.097	52.774	5.119		
A5	Deck	0.208	67.989	14.142	65.18	Fair Condition
	Superstructure	0.391	62.424	24.408		
	Substructure	0.304	68.634	20.865		
	Accessories	0.097	59.466	5.768		
A4	Deck	0.208	56.100	11.669	69.49	Fair Condition
	Superstructure	0.391	79.576	31.114		
	Substructure	0.304	64.668	19.659		
	Accessories	0.097	72.701	7.052		
A11	Deck	0.208	79.453	16.526	71.127	Good Condition
	Superstructure	0.391	70.254	27.469		
	Substructure	0.304	67.864	20.631		
	Accessories	0.097	67.020	6.501		
A6	Deck	0.208	56.441	11.740	71.22	Good Condition
	Superstructure	0.391	88.370	34.553		
	Substructure	0.304	66.344	20.168		
	Accessories	0.097	49.064	4.759		
A9	Deck	0.208	68.123	14.170	73.82	Good Condition
	Superstructure	0.391	86.383	33.776		
	Substructure	0.304	63.649	19.349		
	Accessories	0.097	67.284	6.527		
A7	Deck	0.208	77.159	16.049	74.89	Good Condition
	Superstructure	0.391	83.874	32.795		
	Substructure	0.304	64.290	19.544		
	Accessories	0.097	67.000	6.499		
A12	Deck	0.208	66.805	13.895	75.42	Good Condition
	Superstructure	0.391	81.585	31.900		
	Substructure	0.304	78.273	23.795		
	Accessories	0.097	60.137	5.833		
A1	Deck	0.208	78.764	16.383	75.96	Good Condition
	Superstructure	0.391	75.322	29.451		
	Substructure	0.304	77.989	23.709		
	Accessories	0.097	66.131	6.415		
A13	Deck	0.208	95.288	19.820	83.53	Very Good Condition
	Superstructure	0.391	79.724	31.172		
	Substructure	0.304	76.642	23.299		
	Accessories	0.097	95.226	9.237		

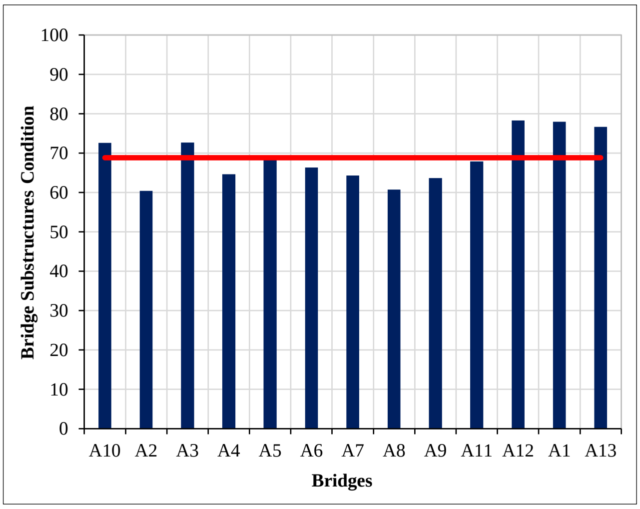
The condition rating results for the four bridge components for the case study bridges show that, on average, the superstructure components have the best condition (mean= 72.45), followed by substructure (mean= 68.83) and deck (mean= 67.85), while the accessories record the lowest condition ratings (mean= 62.46). The lower ratings for the decks and accessories are mainly due to inadequate maintenance, heavy traffic loads, leakage and sealing condition, and failure of the drainage system. Bridges demonstrating low condition scores for the deck and accessories will significantly lower the overall BCI and should be prioritized for maintenance intervention. Recommended actions include replacement of expansion joints, waterproofing protection of the deck, reinstatement of the deck drainage system and repair of the spalled concrete and reinforcement corrosion to prevent further deterioration, extend the service life of the structure, and ensure user safety. Figure 5 presents the condition ratings of the four components (deck, superstructure, substructure, and accessories) for all thirteen bridges.



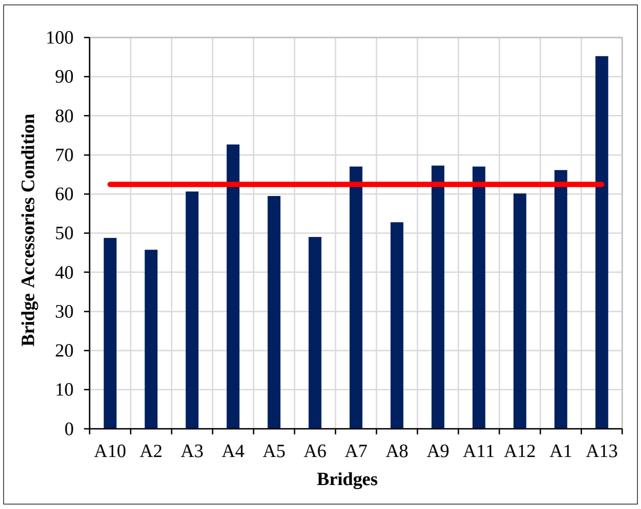
(a) Deck



(b) Superstructure



(c) Substructure



(d) Accessories

Figure 5. Condition rating of the four bridge components for the 13 case study bridges

The results shown in Table 10 revealed that Bridge A10 gets the highest priority for maintenance since it has the lowest condition rating (BCI = 54.21). The deck, superstructure and accessories of Bridge A10 were rated in poor condition, which individually lowers its overall condition, indicating the need for extensive repair work to address significant deterioration.

Bridge A4, Bridge A5, Bridge A8, Bridge A3 and Bridge A2 are rated in fair condition (BCI 51-70), indicating that those bridges require moderate preventive and corrective maintenance. Bridge A1, Bridge A12, Bridge A7, Bridge A9, Bridge A6 and Bridge A11 are rated in good condition with BCI ranging between 71 and 80. Meanwhile, Bridge A13 has the best condition rating (BCI=83.52), indicating a very good condition that requires only regular monitoring and light preventive measures. Figure 6 shows the BCIs for the 13 bridges, ranked from highest to lowest.

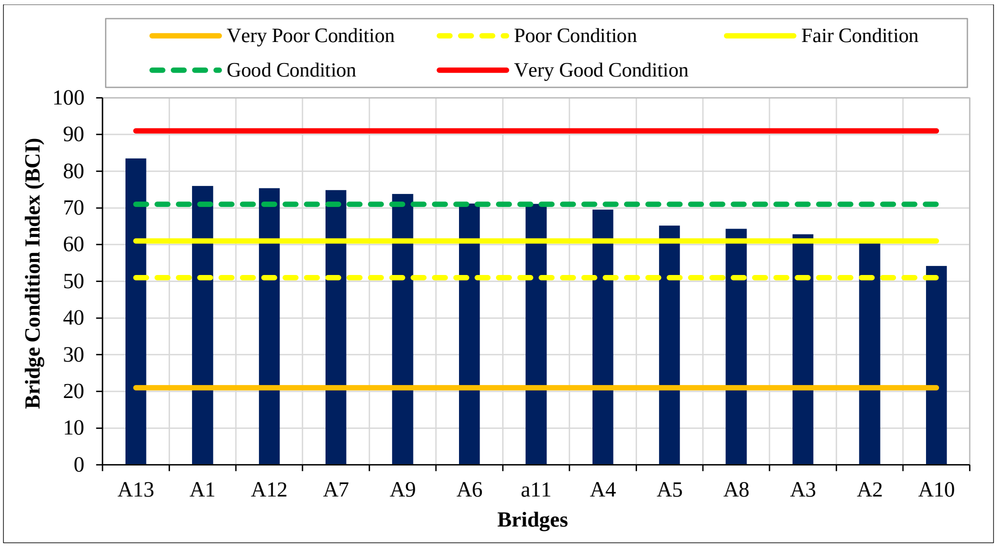


Figure 6. Bridge condition indices of the 13 case study bridges

The evaluation of the case study bridges confirmed the feasibility and applicability of the proposed methodology. The developed BCI approach simplifies the inspection and condition assessment process while offering proper maintenance recommendations for decision-makers. It enables bridge authorities to capture both the severity and extent (quantity) of defects affecting structural integrity. In addition, it facilitates the assessment of individual bridges and their components, helping to identify those in urgent need of maintenance. This methodology can also assist in determining element treatment, as well as the scope and frequency of future maintenance inspections. Such information is vital for establishing optimal maintenance strategies and for effectively allocating funds for a network of bridges.

The proposed methodology is simple and easy to implement, saving time and costs in bridge network monitoring. Furthermore, its high flexibility allows for easy adaptation and application to other regions. This research helps fill another gap in the field of bridge condition monitoring in Iraq: the lack of efficient and comprehensive condition rating methods or systems. By providing an accurate and comprehensive condition assessment framework, the study contributes to improving the quality of bridge management practices.

5. Conclusions

Since a significant number of bridges are suffering from deterioration with limited financial resources allocated for maintenance projects, bridge authorities must use their budget efficiently. This calls for establishing a priority approach to evaluate and select bridges for maintenance treatments and support decision-makers in identifying the critical structures when dealing with a large number of bridges at the time of the assessment. Thus, this study presents a bridge condition index for bridges in Iraq that considers both the weights and the condition ratings of various bridge components. As a simplified representation of the structure, the bridge was divided into four components, and each of the components was further divided into a number of elements. A questionnaire was developed for surveying the views of experts about the weight of various elements using FF-AHP. The integration of AHP with Fermatean fuzzy sets enhanced the flexibility in representing uncertainty in expert judgments and allowed for more reliable decision-making in comparison with traditional fuzzy sets. The weighted averaging approach was then used to aggregate component condition indices with the weights obtained from FF-AHP to obtain the BCIs of all bridges. Bridges can be ranked and classified according to their BCIs. Bridges with the lowest BCI get higher priority for maintenance. The proposed methodology was applied to thirteen bridges in Baghdad to confirm its ability to prioritize a large bridge inventory.

The need for this approach can be justified due to the absence of a comprehensive model or index for assessing the bridge conditions in Iraq. Thus, this paper is considered innovative since it represents the first attempt to fill this gap and develop a BCI to evaluate and prioritize bridges in Iraq. The proposed model can help Iraqi engineers evaluate bridges and prioritize maintenance work more effectively. It can improve the decision-making process to ensure a fully transparent and comprehensive evaluation and achieve better results in terms of distributing the available funds to bridges that are in urgent need of maintenance and thus enhance the safety and functionality. Furthermore, this study is the first to apply a hybrid Fermatean fuzzy decision-making method for bridge condition evaluation, reducing dependence on rigid numerical scales and minimizing subjective bias.

Although the proposed index is tailored for bridges in Iraq since it was developed using insights from Iraqi bridge maintenance experts, it can be easily adjusted to suit other countries. As part of future research, the authors are interested in combining the FF-AHP model with other MCDM methods to create a more comprehensive decision support model for bridge maintenance prioritization that takes into account other factors (e.g., economic, social, strategic importance, and political factors) in addition to the bridge condition index during bridge maintenance planning.

6. Declarations

6.1. Author Contributions

Conceptualization, S.S.J. and S.R.M.; methodology, S.S.J.; formal analysis, S.S.J.; investigation, S.S.J.; resources, S.S.J.; data curation, S.S.J.; writing—original draft preparation, S.S.J.; writing—review and editing, S.S.J.; supervision, S.R.M. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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6.5. Conflicts of Interest

The authors declare no conflict of interest.

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Appendix I

Table A1. Group comparison matrix of deck elements

Element	Deck Slab		Joints		Wearing Surfaces		FF-Weight		Defuzzified Weights	Weight
Deck Slab	0.465	0.082	0.630	0.089	0.558	0.086	0.547	0.086	0.163	0.508
Joints	0.342	0.043	0.465	0.082	0.437	0.072	0.411	0.063	0.069	0.216
Wearing Surfaces	0.387	0.056	0.494	0.083	0.465	0.082	0.446	0.073	0.089	0.276

Table A2. Group comparison matrix of superstructure elements

Element	Main Girder		Secondary Girder		Bracing		Bearings		FF-Weight		Defuzzified Weights	Weight
Main Girder	0.465	0.082	0.525	0.085	0.745	0.108	0.558	0.086	0.564	0.090	0.179	0.402
Secondary Girder	0.411	0.063	0.465	0.082	0.630	0.089	0.494	0.083	0.494	0.079	0.120	0.269
Bracing	0.290	0.042	0.342	0.043	0.465	0.082	0.364	0.049	0.360	0.052	0.047	0.104
Bearings	0.387	0.056	0.437	0.072	0.593	0.088	0.465	0.082	0.465	0.073	0.100	0.224

Table A3. Group comparison matrix of substructure elements

Element	Pier		Pier Cap / Cross Beam		Abutment		Pile		Pile Cap		FF-Weight		Defuzzified Weights	Weight
Pier	0.465	0.082	0.670	0.091	0.465	0.082	0.593	0.088	0.670	0.091	0.565	0.087	0.180	0.313
Pier Cap / Cross Beam	0.322	0.038	0.465	0.082	0.322	0.038	0.364	0.044	0.593	0.088	0.401	0.054	0.064	0.112
Abutment	0.465	0.082	0.670	0.091	0.465	0.082	0.558	0.086	0.670	0.091	0.558	0.086	0.173	0.302
Pile	0.364	0.049	0.593	0.079	0.387	0.056	0.465	0.082	0.670	0.091	0.482	0.069	0.112	0.195
Pile Cap	0.322	0.038	0.364	0.049	0.322	0.038	0.322	0.038	0.465	0.082	0.355	0.047	0.045	0.078

Table A4. Group comparison matrix of accessories elements

Element	Curbs & Side Walks		Handrails & Pedestrian Railings		Barriers		Lighting & Electrical Systems		Drainage Systems		Signage & Markings		FF-Weight		Defuzzified Weights	Weight
Curbs & Side Walks	0.465	0.082	0.411	0.063	0.387	0.056	0.465	0.082	0.387	0.056	0.437	0.072	0.424	0.068	0.076	0.124
Handrails & Pedestrian Railings	0.525	0.085	0.465	0.082	0.465	0.082	0.494	0.083	0.437	0.072	0.593	0.088	0.494	0.082	0.120	0.195
Barriers	0.558	0.086	0.465	0.082	0.465	0.082	0.494	0.083	0.465	0.082	0.558	0.086	0.499	0.084	0.124	0.201
Lighting & Electrical Systems	0.465	0.082	0.437	0.072	0.437	0.072	0.465	0.082	0.465	0.082	0.558	0.086	0.470	0.079	0.103	0.168
Drainage Systems	0.558	0.086	0.494	0.083	0.465	0.082	0.465	0.082	0.465	0.082	0.525	0.085	0.494	0.083	0.120	0.195
Signage & Markings	0.494	0.083	0.364	0.049	0.387	0.056	0.387	0.056	0.411	0.063	0.465	0.082	0.416	0.064	0.072	0.116