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Decision-Making Based on Multi-Dimensional Quality Control for Bridges

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Featured Application: Railway bridge interventions often requires significant resources. This work proposes a decision-making procedure where optimization of intervention costs and inspections is made through use of Principal Component Analysis (PCA) together with analysis on value of information (VOI) for data filtering.

Abstract: Quality control (QC) may be applied as a framework for maintenance planning when assigning different intervention measures to single structural elements or systems. This work proposes a reliability-based maintenance decision-making process for planning visual inspections on bridges based on the value of information and prior inspection data, and also promotes updating and improvement cycles for subsequent planning. To that aim, an integration between SHM (Structural Health Monitoring) data with a multidisciplinary approach is proposed to obtain a reliability index attending to QC. The data analysis was mainly carried out with respect to an existing measurement database and structural assessments, which were combined to obtain weighted importance coefficients for each component according to their significance in the structure. The Iranian railway network has a built stock of nearly 28,200 bridges from which a database obtained from 104 bridges was studied in this work, considering the data obtained from technical identification checklists. The results were then calibrated and validated with a dataset of seven bridges, which were inspected onsite. The inspection comprised the identification and grading of damages and defects on each element. Observed defects were considered as input for the risk analysis of each component of the network by considering the probability of detection, occurrence and its likely consequences. Decision making with inspection and intervention costs optimization was then performed, for a specific case study, using Principal Component Analysis (PCA) together with the value of information (VOI) for data filtering. With this approach, several parameters with lower values reduced from inspection and other valuable data remain for bridge quality assessment with optimum maintenance cost.

Keywords: quality control; decision making; visual inspection; principal component analysis

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1. Introduction

1.1. Quality Management

Quality management based on result-oriented performance is being used by maintenance managers regarding business analytical approaches [1]. 'Result-oriented' is a term used to express a process and activity plan that focuses on the outcome rather than the process used to deliver a service, such as maintenance services during the operation process. While focusing on the results, it also maintains the required process orientation for quality results and, in particular cases, even contributes to improving the process itself [2]. Integrated quality systems are considering the optimized process for inspections and maintenance activities in terms of quality assurance connected with quality control, which is a gap in maintenance decision-making and research [3,4]. On the other hand, cost quality trade-offs are required when decision-makers seek to reduce maintenance cost and maximize quality or safety [5]. Meanwhile, in recent research, the inspection strategies are founded on the relevant failure probability [6]. For example, objects that have a low probability of a defect may use a sample inspected or without inspection as an appropriate inspection strategy [7], but a high uncertainty after the pre-inspection should be checked [8–11]. Therefore, the classification of structural elements and their defects is vital since risky zones exist in bridges and inspectors must not miss them in favor of safe elements in their visual tests and maintenance activity.

Consequently, safety enhancement for risk mitigation in operation procedures based on structural element prioritization is one of the most important results and objectives for inspection planning and maintenance management. For this manner, finding the intervention action priority, as well as the inspection and maintenance method, is of significant importance. Meanwhile, the degradation model and life cycle cost based on durability prepare a row database for decision making based on the priority of elements to planning the maintenance activities [12–14]. According to recent research results, risk analysis and the value of information can be applied using decision trees together with Bayesian inference for optimization and updating [15]. Regarding the database measurements, data noise and outliers may be reduced using the Principal Component Analysis (PCA) to obtain valuable parameters for the decision support system [16]. The PCA is important for maintenance decision-makers because the parameter weights will modify and correct according to reality. To that aim, a visual inspection may provide the raw data for the first step of multi-quality control and complement it with an accurate structural investigation based on structural health monitoring (SHM) tools [17]. In addition to PCA, other outlier classification methods have been noted in recent research for SHM data analysis such as anomaly detection, the Bayesian dynamic linear model, and the Bayesian dynamic linear model [18].

1.2. Reliability Centered Maintenance (RCM)

Decision making based on Reliability Centered Maintenance (RCM) may be considered by the use of a quality level to find and select optimized maintenance activities [19]. Hence, by comparing measured quality levels, it is possible to determine and attribute an index value to each section of a route in service that will allow the production of a comprehensive idea on how, where and when this system might fail during its life cycle. On the other hand, there is a complementary relationship between reliability and risk [20,21]. Calculation methods with health monitoring tools have also been considered in risk analysis and combined with other measures to calculate reliability, as detailed in [22].

On one hand, traditional maintenance procedures based on routine visual inspections with consideration of the complexity of the interrelations between design stress and environment for failure analysis are not beneficial [23]. On the other hand, a major threat to the safe operation of a railway system is the existence of visible defects, such as cracks on railway track components that lead to track geometric irregularities; loosen fasteners; railhead surface cracks; traverse failures; and ballast pollution, among others. To find these defects, it is necessary to use a visual inspection or appropriate sensors for data collecting. To this end, there are several checklists that many railways use to track irregularities, which are clustered in checklists based on UIC code e712 [21].

1.3. Bridge Inspection

The American Association of State Highway and Transportation Officials (AASHTO) Manual for Condition Evaluation of Bridges, 1994 describes five types of bridge inspection [24]. These are: (i) initial inspection, (ii) routine inspection, (iii) in-depth inspection, (iv) damage inspection and (v) special inspection. Initial inspection with lower cost support by visual inspection can be performed at several levels of detail, from rapid ones to very detailed ones when all the elements of the structure are analyzed [25,26]. For the first step in this research, input data were obtained by initial inspections and visual tests, as well as questionnaire forms. The results were obtained after analyzing the raw dataset feeding posterior decision support system for planning routine, in-depth and special inspections. Categorizing the defects of bridge concrete elements after inspection remains a subjective and laborious task. This is important in light of over-aging bridge stock for avoiding destructive bridge collapses, as happened in 2018 in Genoa, Italy [27].

For routine inspection, the frequency of inspection depends on the condition state and local features and defects. This study aims at providing a framework for decision-making to find adequate inspection intervals and valuable data. For in-depth inspection, it is necessary to plan and perform non-destructive tests (NDT). Therefore, this process will monitor, probe and measure the material performance based on these tests. The measured response relies on the analyzed material property and the test object itself. Examples of the NDT method for bridges are visual inspection, ultrasound tests, thermography, and electrical resistivity, among others. In this sense, the proposed framework is a tool for optimizing the planning of inspections and tests that are considered important in attending to the property or element to be analyzed.

Condition monitoring is used as a framework to derive information for reliability calculation. In this case, irregularities and damage detection are variables to take into account within the RCM concept. For instance, recent research has attempted to detect structural features and analysis of their behavior to measure asset performance during operation [28–30]. According to the type of material and the consequences of certain damage, the type of inspection is selected for each element [31]. For instance, damages make a change in the structural behavior of the element (e.g., change in stiffness) that can only be analyzed by specific types of inspections. Based on this, measuring the change in the performance of a given parameter (e.g., loss of stiffness) indicates that the structure may be affected by specific damage and with that knowledge it is possible to prepare a database for RCM [32]. In recent research, an attempt to evaluate the relationship between track damages and stiffness changes was made in [33]. Numerical simulation is another method that is being used for sensitivity analysis in railway track stiffness and structural behavior prediction [34,35]. Rail surface damage detection is another subject that is considered in recent research for RCM based on their damage type [36–38]. After monitoring and damage detection, the process of RCM is updated with information that has been extracted within the SHM. Therefore, to obtain the reliability index, it is necessary to consider the probability of occurrence and the defect consequences based on their location and other technical features of the structure. Additionally, FEM (Finite Element Method) has been applied for finding models which are useful for predicting exposures and consequences of a defect in the future. This model has to be calibrated and validated by experimental data through a comparison of the real situation (onsite testing and inspection) and the FEM model.

Prioritization is one of the most important tools for optimizing decision making. To make a decision without wasting resources, it is necessary to act based on the conditions. Using the rigid technical limit states according to the standards and manuals without considering the statistical database and conditions leads to waste of resources. Contingent decisions with mathematical tools provide the possibility of optimization in the direction of managing limited resources. This research makes an attempt to represent a framework for infrastructure maintenance decision-making with regard to resources limitation and passenger demands for safe operation through the railway network, and avoiding destructive crises such as catastrophic bridge collapses in the past. This contingent decision-making optimizes technical standards for inspection planning, with consideration of local parameters that will affect operation risk. The local situation of the environment, the age of equipment, and several other local parameters have to be considered in maintenance activities such as inspection planning to operate safely. The rigid time base maintenance (TBM), or attaching sensors to elements for condition base maintenance (CBM), are not the optimum approach for maintenance. With this approach, pre-posterior analysis based on statistical tools prepares the priority of equipment according to operation risk by keeping an important equipment database and reducing some elements with useless data from routine checks to keep the value of data during the inspections.

2. Methodology

The present work proposes the development of a decision-making framework based on a quality index for railway network assets. Decision makers use the quality index and their impact to prepare an effective ranking list of components for maintenance activities. These structural elements work together in series or parallel in a network and it is desirable to analyze the impact of each element's risk on the operation interruption due to probable failures. In this section, the fundamental conceptions related to continuous improvement are investigated, the developed algorithm reliability is presented and the required mathematical tools, such as PCA, are introduced.

To that aim, the Deming cycle process concept was considered for the continuous improvement of the decision-making process framework. This process, also known as the PDCA cycle (Plan, Do, Check, Act) is a continuous quality improvement model [23]. Each activity of this research is denoted by each part of the PDCA framework. Meanwhile, this research method attempts to prepare a decision support system for optimizing these activities based on mathematical tools and statistical methods. Therefore, the overview of the research method based on the PDCA framework was divided into the main contribution with subsections, as presented in Figure 1.

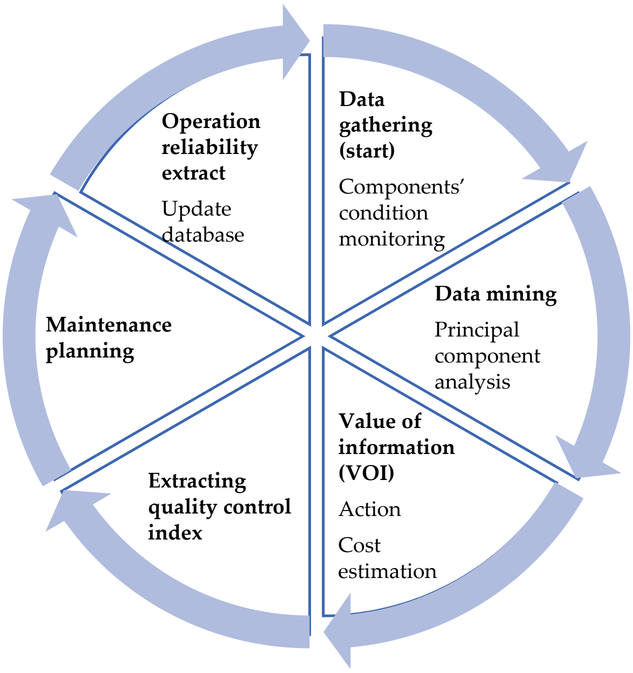

Figure 1. Maintenance planning with continuous improvement.

According to Figure 1, the result of this method would be extracting the reliability at the end stage, which will be updated during each cycle based on the new condition (i.e., new information). This dynamic index will update with the new input data to improve inspection effectiveness for the next cycle of maintenance.

2.1. Overview of the Case Study

Based on structural features and material type, a clustering process has been made for a dataset of bridges from the Iranian railway network in order to obtain a prioritization system. There are several types of bridge in the Iranian railway network, and they are clustered and defined in Table 1. For this clustering analysis, 104 bridges were considered from the Iranian railway network, considering Line 5 of the Tehran transportation network. The frequency distribution of bridge types in that case is shown in Figure 2. After the clustering analysis, the most frequent type of bridge FB (Fer béton) has been selected for the further analysis process. Bridges were selected specifically from the Tehran suburban railway network due to the availability of inspection data. Within that cluster, a dataset consisting of seven Reinforced Concrete (RC) bridges were selected due to their location near critical intersections and due to their heavy traffic flow.

Table 1. Bridge types.

Type	Name	Description
D	Daloot	This type of bridge is made of concrete with a rectangular shape and width of fewer than 4 m.
FB	Fer béton	Deck and column in these bridges are made of reinforced concrete.
AV	Aqueduc voûte (masonry and concrete)	Arch bridge with one span constructed by concrete and masonry.
Avs	Aqueduc voûte Surbaissé	Arch bridge with a single span constructed with concrete and masonry with low height arch.
Viaduct	Viaduct	This type is constructed with the several spans with arch shape on a deep valley.
PV	Poly voûte	These bridges are constructed with steel arch, truss, arch, steel beam, and plate as well as beam and plate.

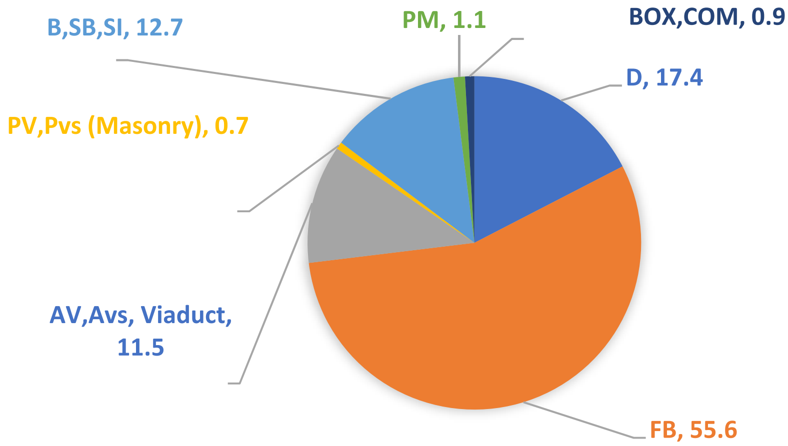

Figure 2. Relative frequency distribution (%) of bridges in the case study sample.

2.2. Initial Input Data

The initial data gathering, along with the empirical study, has been performed, taking into account the available dataset (FB bridges), with both macro (global) and micro (local) approaches. The micro approach was focused on the components' condition state within each bridge, whereas the macro level corresponds to the quality index as an indicator for the condition state of each bridge in an overall view. This is an adequate tool for the comparison of the bridges in terms of quality in a railway network. The quality feature measurement method based on the Mahalanobis distance is used to evaluate the reliability of data samples [36]. The standard deviation concept is capable of calculating the highest valuable variable for comparison and maintenance decision making. Obtaining the quality index for condition rating of the bridge requires analyzing raw data with regard to valuable variables.

Two types of raw datasets have been considered to define the quality level of the bridge and its operation risk estimation, namely structural identification (SI) and probable defects (PD).

2.2.1. Structural Identification

SI datasets are here considered as information that may define a structure since its design, such as construction location and global geometry features of the structure. This database is of importance for a risk assessment in terms of structural features that may impact on the failure type and its effects (consequences of failure, CoF). As they depict the overall features of the structure itself, they do not change significantly over time and during the operation. This dataset is prepared through questionnaire forms filled out by expert inspectors based on designer documents [39].

2.2.2. Probable Defects

The PD dataset was obtained through calculations based on visual inspection results. Visual inspection is a traditional condition monitoring method that is still considered as a main source of information for asset management. In this case, this method applies as a double—check alongside the mechanized method. This paper focused on visual inspection as an ordinary method for pre-analysis, and then the results develop a decision process for finding the frequency of inspections for each element, not only for the traditional inspection method but also for modern inspection tools and NDT methods. Since the structure degrades throughout its lifespan, this dataset should be updated during the operation time for each structural element. The structural elements' state was evaluated between 0 and 5, with 0 being the best condition and 5 representing damaged components, with the defect severity being based on handbooks and standards [29,40]. For this specific purpose, failure is considered as the loss of structural function for the specific structural element based on probable defects. If failure extends to the overall structure it will overcome the structure limit state and lead to structural failure. Therefore, the PD database (extracted from defects) is extended to failure when the defect is critical, thus allowing us to also infer the Probability of Failure (PoF).

2.3. Output Data

Often, carrying out specific maintenance activities and their management is strongly related to the usage of limited resources. Thus, it is crucial to consider the existing resources during the operation and maintenance as an output parameter. This framework prepares a database for implementing RCM to choose the best interventions attending to those needs.

2.4. Updating Input Data

After the first QC based on the initial input database using visual inspection data, it is desirable to update the input database and related costs for considering its consequences for further steps. Analysis of variance simultaneous component analysis (ASCA) was made by combining analysis of the variance (ANOVA) and PCA tools. This method was used to update the initial input database for further steps according to the result of a statistical analysis process.

The new priority of components after remedial actions and the new condition status was assigned to each element. There may be several critical elements monitored by the NDT method according to the initial QC plan.

2.5. Components

The risk assessment must take into account the consequences of a given element leading to the stopping of other elements. A defect in a given element may affect other elements' performance and, thus, the outcome depends on all dependent elements' status in the structure. To trace that dependency, Figure 3 presents a hierarchic chart relating elements of a bridge.

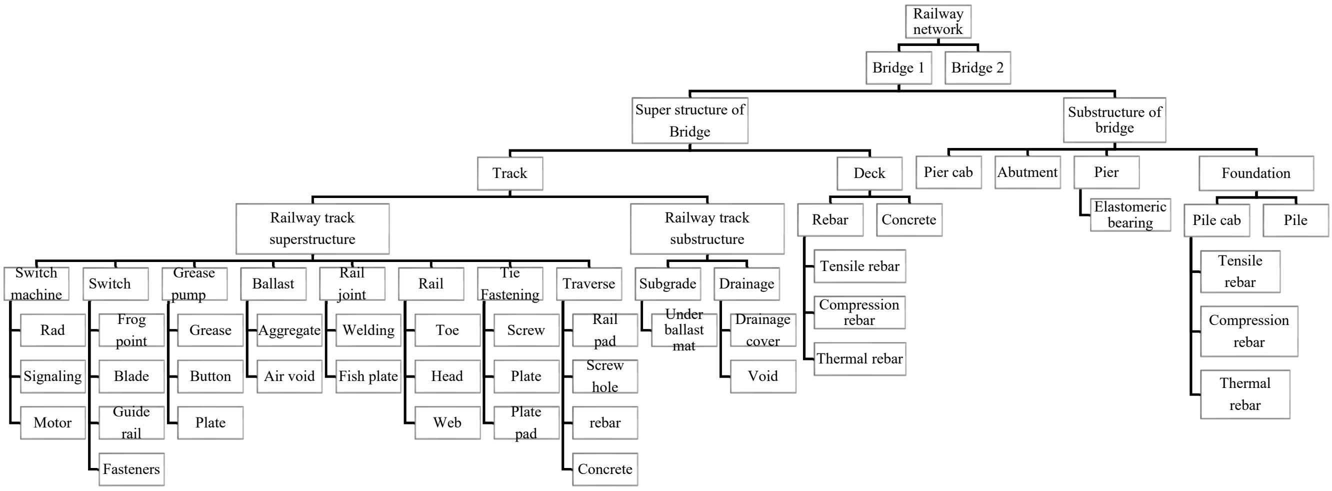

Figure 3. Bridge components within a railway network.

2.6. Quality Control Process

Unreliable conditions interpret risk for each component. Indeed, in a simple description, reliability may be connected with risk according to the following equations if they are considered for structural elements [41].

$$Reliability = 1 - Risk \tag{1}$$

$$Risk = PoF \times CoF \tag{2}$$

$$PD\ database \overset{Defect\ density\ estimation}{\Rightarrow} PoF \tag{3}$$

$$SI\ data\ base \overset{PCA\ Analysis}{\Rightarrow} CoF \tag{4}$$

The *PD* database has been processed according to a multivariate Kernel estimation to extract *PoF* [42]. Meanwhile, this method may easily be applied to multivariate situations based on the volume of material and its damages. Based on this method, the density distribution of *PoF* has been calculated. For *CoF*, it is necessary to extract the weighted index based on the *SI* database and the PCA analysis method.

The reliability index was then extracted based on structural risk as considered in Equation (1). For the next step, it is necessary to extract the overall risk for the bridges in the macro approach, according to the local information obtained at the micro level (based on the components detailed in Figure 3).

3. Results and Outputs

The presented framework, applied to the case study, is presented in the Figure 4 and following topics step by step.

3.1. Data Gathering and Pre-Posterior Analysis (Step 1)

Creating a comprehensive database is the first step of a multi-dimensional QC. For this purpose, an analysis was made to assess a bridge using questionnaire forms and inspection checklists, which were filled by an expert inspector according to the existing technical standards [43,44], and to prioritize the elements considering their structural performance and dependency on other elements [45,46].

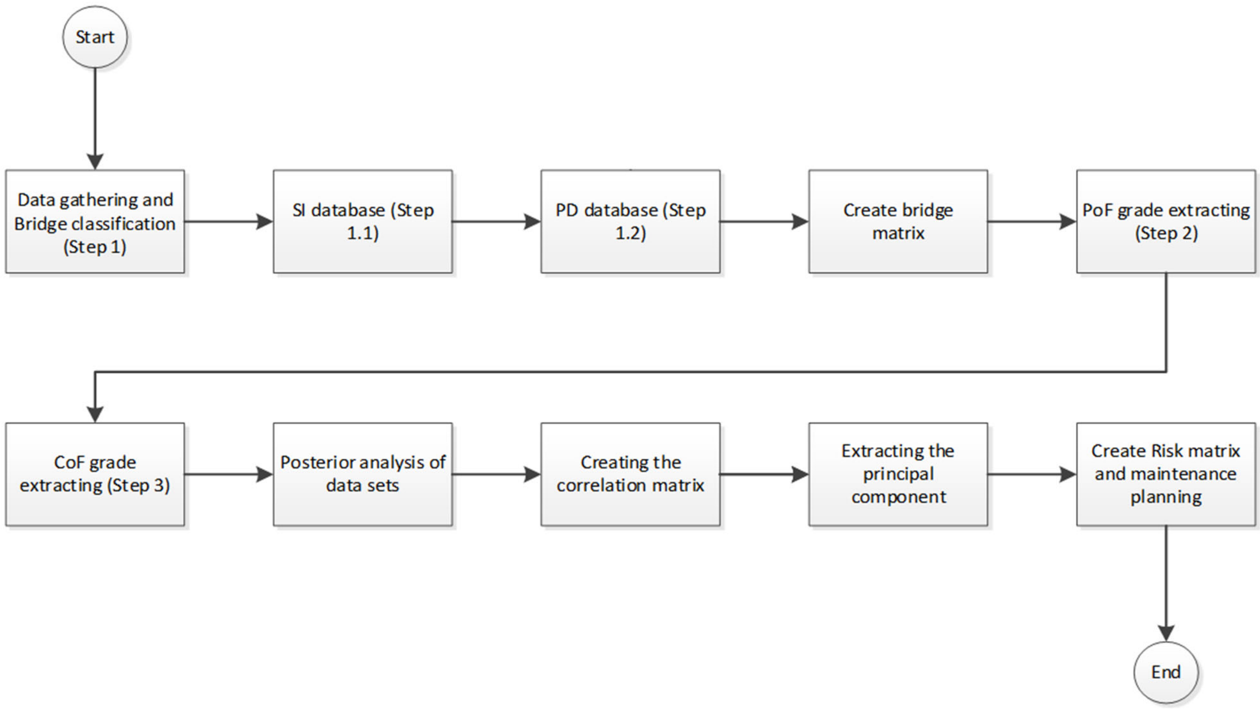

Figure 4. Data analysis process.

3.1.1. SI Database

These qualitative data comprise the SI dataset based on the Section 2.2.1 explanation and will prepare CoF, which has been obtained based on inspector observation and their checklist items. This qualitative dataset has been organized by a matrix, which has 35 parameters (reduced to 23 due to local reasons) for comprising SI for seven RC bridges and extracting the weight based on the CoF extraction step. Therefore, this framework for other cases may differ. These 23 parameters are comprised of items, which are then clustered into the following items: location, construction process, elements interaction quality, environmental features and geometrical features. Additionally, seven rows illustrate seven case studies corresponding to bridges in the railway network.

3.1.2. PD Database

The PD database was prepared to obtain the PoF based on defect density probability in elements. To this end, the damages on each RC element have been detected and registered, distinguishing those related to environmental conditions (e.g., carbonation, corrosion, concrete layer detachment) and structural reasons (e.g., cracks due to overload or fatigue) [47]. Therefore, it is necessary to analyze surface damages to assess defect exposure. Meanwhile, the durability feature directly links surface defects [12]. However, the traditional method relies on subjective interpretation based on visual inspection. Consequently, image-processing software monitors the rate of defect expansion without any human error disorder [14]. Through this tool, it is possible to assess structures in terms of quality in their lifetime based on quantitative measurements of the defect.

Eventually, the geometry of all elements was considered by their approximate volume to estimate the defect density. To separate segments with and without defects, a value of 0 was given to intact RC material and for a defect segment the value was 1. Meanwhile, for segments with a high level of defects, a value of 2 was assigned. For this research case, according to Eurocode 2 and ACI 224R-01 [48], the limit state of crack width was considered to be 0.3 mm. Hence, 0.3 mm for cracks was the limit state for these RC elements. Moreover, the coefficient of these defects was 1 until the rebar was exposed through that type of crack, leading to a value of 2 if higher. This grading is summarized in Table 2.

Table 2. Defect exposure for RC elements.

Damage Type	Component State	
Cracks	**Exposure Factor**	**Rating**
Intact element [1]	0	Nothing
Crack without exposed rebar or other RC damage	1	Moderate
Crack with exposed rebar	2	High

[1] Crack width limit state = 0.3 mm.

The exposure factor is a subjective value that the inspector assessing risk must define based on Table 2 in pre-posterior analysis. After data gathering (PD and SI), the dataset was analyzed based on the following step by calculating two types of grades for bridge comparison and their quality index. These grades have been calculated in steps 2 and 3 based on the case study database.

3.2. PoF Grade Extracting (Step 2)

After dataset preparation, the first step for bridge comparison is extracting the probability of failure (PoF). Since defects have been detected by inspection in each element of the bridge, it is necessary to convert these data from micro to macro vision for data analysis. Macro vision is an approach for comparison of the bridges in a network as a whole rather than only focusing on their components. Therefore, it is necessary to apply the PD database for extracting PoF and then extracting the quality index in each case. Then, it is possible to compare the bridges based on the final extracted index. There are seven cases of RC bridges that have been studied in this research.

The process to obtain the defect density is given in Table 3, and a detailed explanation is given as follows:

A-Table 3: in this column, the total of the observed defects in each case has been illustrated by considering their exposure factor based on Table 2 and structural limitations.

B-Table 3: the fourth column consists of defect density, calculated according to Equation (5), where F denotes the failure observed of each element over the approximate volume V of these elements.

$$F_d = \frac{\Sigma F}{\int V dv} \tag{5}$$

$$V = \text{Volume},\ F = \text{Failure},\ F_d = \text{Failure density}$$

C-Table 3: defect density was then normalized using Equation (6). This column shows the results of this step for finding the PoF grade. This process would be completed after all bridge comparisons, based on calculating the quality index to reach the research aims.

$$F_{d_n} = \frac{F_d}{\frac{\Sigma F_d}{n}} \tag{6}$$

$$F = \text{Failure},\ F_d = \text{Failure density},\ F_{d_n} = \text{Overall failure density for ``}n\text{'' elements},\ n = \text{number of observed elements}$$

Table 3. Normalization of defect density.

Bridge Number	Failure = Defect × Exposure Factor (A)	Approximate Volume of Material	Defect Density (B)	Normalized Defect Density (C)
1	6	748.8	0.008	0.28
2	4	712.92	0.005	0.2
3	12	5653.44	0.002	0.07
4	4	709.8	0.006	0.2
5	5	6652.8	0.0007	0.03
6	4	854.568	0.005	0.16
7	1	684.936	0.001	0.05

3.3. CoF Grade Extracting (Step 3)

After data gathering, it is necessary to analyze the SI dataset. SI has 35 parameters for seven bridges in the case study. Therefore, all these 35 items have been measured for seven bridges and then the CoF grade was extracted based on statistical analysis and their weight according to the principal component, as follows.

3.3.1. Posterior Analysis of Datasets

Analysis of variance (ANOVA) is a standard method for describing and estimating heterogeneity among the means of a response variable [49]. Datasets and extracted variables based on environment and structural features, with higher variance, have more value of information. According to the national standard [47], 35 items are important for quality assessment. In this case study, several items have been eliminated as follows tables due to posterior analysis where it was found that their importance compared to the other variables was low. Moreover, the reasons for selection and elimination are provided as follows Tables 4 and 5.

Table 4. Selected items for quality index.

Valuable Items	Selection Reason
Importance in network	There are three different levels of importance imaginable for cases of bridges [40].
Expansion Joint, Drainage, RCC surface, Curing quality	Differences in quality level leading to different states for RCC bridges as a case study in this research.
Liquefaction, land slide, rockfall, the density of soil	According to the various soil material and features, this event probability is valuable for the comparison bridges in this research case study.
Thunderstorm, flood, climate	Since these bridges are located in a suburban area and pass over from a city, geographical parameters effect the environment's features.
Span number, abutment height and others.	Bridge length and their structural system designing are defining the geometrical items which are important for the quality index.

Table 5. Removed items for quality index.

Non-Significant Items for Comparison	Elimination Reason
Approximate million gross tons (MGT)	This item is the same for all cases because the operation period is the same for all cases.
Probability of earthquake	Since the bridges are located in the same area in terms of earthquake classification, the probability of earthquake for these bridges is the same.

3.3.2. Creating the Correlation Matrix

In this case, 23 items are mentioned as a sample in Table 4, remaining after normalization and elimination of useless data. Therefore, it is necessary to create a matrix 23∗23 for calculating the covariance, as given in Equation (7).

$$\sum_{23*23} = \left(\frac{1}{n}\right)x^T x \tag{7}$$

n = 7 = Number of observed bridges

x = Matrix of the indexes, with 23 items for seven bridges in this case study

In this research, "n" is equal to the number of bridge cases for this study and raw data, with 23 parameters. Therefore, the matrix for this step has seven cases and 23 parameters.

3.3.3. Extracting the Principal Component

The weighted criteria matrix is a valuable decision-making tool that relies on the variance of items. Since the variance is dependent on the value of information, it is necessary to calculate the variance for datasets in each item. Meanwhile, the dataset has a big dimension that comprises items based on Tables 4 and 5, and therefore filtering the dataset is vital for decision-makers. If the amount of variance is low, this item would be neglected for the final quality index. Large eigenvalues correspond to large variances and good value of information. In this step, finding the best combination of items based on their weight in each index is important for extracting the quality index. In this manner, the matrix was rotated to extract the weight of items in several attempts. Here, after 10 iterations, the results converged to maximize the value of information. Consequently, six components were extracted with an eigenvalue higher than one. These components will reduce the items for inspection and, therefore, the cost of inspection will optimize. Since the rotation of variable items in this matrix is necessary for determining their weight, Promax was chosen with Kappa equal to four. Promax is an oblique rotation method that begins with Varimax (orthogonal) rotation and then uses the Kappa measure. Kappa is the multicollinearity measure which is defined as the square root of the ratio for the largest eigenvalue divided by the smallest eigenvalue. Figure 5 illustrates the results of the software after analyzing the data. Based on this figure, six components were extracted by the PCA method. The weight of each parameter illustrates its value in bridge comparison after index extraction. In this extracted quality index, the contribution of the item from the data in each principal component is shown in Table 6.

The distance parameter has been estimated by measuring the kilometers between the bridge and the closest central station (Gare). For the other qualitative parameters, values were given between [0, 5], [0, 4] or [0, 3] according to specific standard ranges [50] and were defined by expert judgment during the initial field studies.

The matrix represented in Table 7, with symmetrical shape, is proper for the comparison of all available components based on the main diagonal which contains the variances. In the next table (Table 8), the variance of each principal component has been compared.

Based on Table 8, if the first principal component is chosen for the quality index, 31.6% has been considered for the value of information. Moreover, if six principal components are considered for the quality index, 100% value of information has been taken into account.

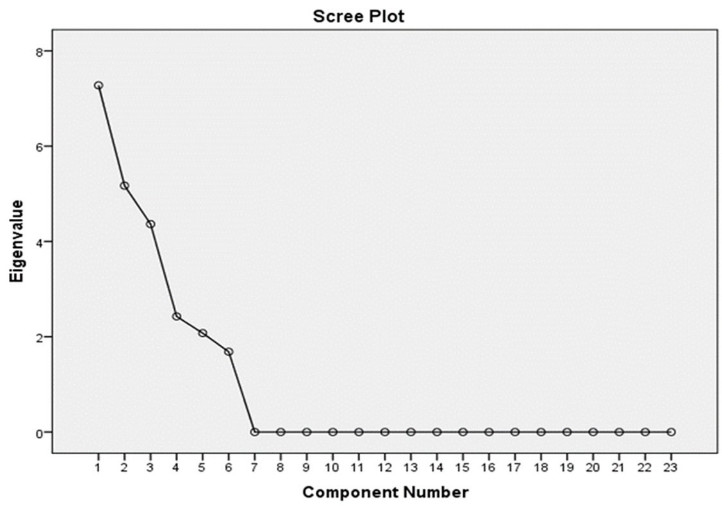

Figure 5. PCA elbow method and principal components.

Table 6. Coefficient of Quality index items and CoF grades.

No	Topic	Name	Parameter	1	2	3	4	5	6
1	Location	Distance from the main station	A	0.014	0.001	−0.007	0.301	−0.012	0.008
2		Importance in network	B	0.014	0.001	−0.007	0.301	−0.012	0.008
3	Construction process	RCC surface quality	C	−0.007	−0.005	0.206	0.011	0.001	−0.001
4		Curing quality	D	0.118	−0.083	0.037	−0.108	0.080	0.227
5		Overall quality before an operation	E	−0.007	−0.005	0.206	0.011	0.001	−0.001
6	Elements' interaction quality	Drainage	F	0.002	0.209	0.002	0.001	−0.010	−0.002
7		Expansion Joint	G	−0.042	−0.041	−0.075	−0.083	0.285	0.115
8		Foundation Isolation	H	0.002	0.209	0.002	0.001	−0.010	−0.002
9	Geotechnical features	Liquefaction	I	0.002	0.209	0.002	0.001	−0.010	−0.002
10		Land slide	J	0.013	−0.013	0.021	0.034	0.006	−0.417
11		Rock fall	K	0.031	−0.131	0.056	0.063	−0.214	−0.088
15		Density of soil	L	−0.138	−0.023	0.095	0.185	0.140	−0.117
16		Distance from an underground void	M	−0.177	−0.003	−0.011	−0.021	−0.037	0.057
12	Environmental features	Thunderstorm	N	−0.128	−0.016	−0.172	0.171	0.140	−0.115
13		Flood	O	0.007	0.005	−0.206	−0.011	−0.001	0.001
14		Climate	P	0.002	0.209	0.002	0.001	−0.010	−0.002
17	Geometrical features	Span number	Q	0.138	0.023	−0.095	−0.185	−0.140	0.117
18		Span length	R	0.043	−0.030	0.046	0.108	0.300	−0.086
19		Abutment height	S	0.012	−0.010	0.052	0.085	0.014	0.300
20		Pier height	T	0.208	−0.017	−0.029	0.038	−0.117	0.104
21		Bridge width	U	−0.030	0.113	0.166	−0.025	0.223	−0.233
22		Bridge length	V	0.171	0.007	0.014	0.013	0.053	−0.059
23		Deck area	W	0.157	0.011	0.046	0.051	0.098	−0.104

Table 7. Component score covariance matrix.

Component	1	2	3	4	5	6
1	1.246	0.050	1.740	−0.986	0.207	2.286
2	0.050	1.221	0.209	0.012	2.098	0.109
3	1.740	0.209	2.892	−0.949	0.928	2.156
4	−0.986	0.012	−0.949	1.016	−0.317	0.587
5	0.207	2.098	0.928	−0.317	4.119	−0.686
6	2.286	0.109	2.156	0.587	−0.686	4.543

Table 8. Total Variance Explained.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.277	31.638	31.638	7.277	31.638	31.638	4.851	21.091	21.091
2	5.171	22.48	54.122	5.171	22.48	54.122	4.776	20.766	41.85
3	4.364	18.97	73.096	4.364	18.97	73.096	4.530	19.695	61.55
4	2.426	10.549	83.645	2.426	10.549	83.645	3.274	14.235	75.787
5	2.076	9.028	92.673	2.076	9.028	92.673	3.128	13.599	89.38
6	1.685	7.327	100.00	1.685	7.327	100.00	2.441	10.614	100.0
7	1.012×10^{-5}	4.398×10^{-15}	100.00						
8	5.881×10^{-16}	2.557×10^{-15}	100.00						
9	4.575×10^{-16}	1.989×10^{-15}	100.00						
10	3.096×10^{-16}	1.346×10^{-15}	100.00						

Based on the recent method and the importance level of a bridge it is necessary to keep the value of information during the operation and inspections. Additionally, based on Table 8, items' contribution in each principal component has been shown by their weight. It is desirable to choose an optimized principal component and also items in each principal component by their weight. These weighted grades will apply to the CoF index in multi-dimensional QC. Therefore, based on Table 6, the CoF index is as follows:

$$\begin{aligned}\mathrm{CoF} = 0.01(A+B+S+J+D) + 0.04(\mathrm{G}) + 0.13(\mathrm{J}) + 0.31(\mathrm{K}) + 0.14(\mathrm{L}+\mathrm{Q}) \\ + 0.18(\mathrm{M}) + 0.13(\mathrm{N}) + 0.04(\mathrm{R}) + 0.2(\mathrm{T}) + 0.03(\mathrm{U}) + 0.17(\mathrm{V}) \\ + 0.16(\mathrm{W})\end{aligned} \tag{8}$$

It is necessary to mention that items in Equation (9) with a coefficient weight lower than 0.009 have been eliminated when being selected from Table 6. According to the obtained CoF index, it is necessary to focus on geotechnical features, especially on bridges' elements that relate to rockfall, and to monitor the soil behavior concerning to these parameters. Rockfall has the highest weight compared to the remaining items, taking into account their consequences.

Meanwhile, the quality ranking of the bridges demands an index for prioritization based on their probability and the consequences of failure.

Moreover, this extracted reliability index and QC approach will apply for future bridge design located in this area.

For example, for calculating PoF in the worst condition, it is necessary to suppose the minimum length and lowest width of the bridge to increase the failure density and calculate the highest PoF among other existing cases.

$$\begin{gathered}0.01(0.8+2.2+1.5+2.2+1.7) + 0.04(2.3) + 0.13(2.2) + 0.31(2.2) + 0.14 \\ (2.2+1.6) + 0.18(1.5) + 0.13(1.6) + 0.04(1.5) + 0.2(1.3) + 0.03(1.2) + \\ 0.17(1.2) + 0.16(1.4) = 2.9 = \mathrm{CoF};\ \mathrm{PoF} = 0.4\end{gathered} \tag{9}$$

On the other hand, the best conditions would be considered for this dataset of case studies, and based on the highest and lowest level of quality it is necessary to apply the K-means for clustering them in the risk matrix as follows. The K-means method will prepare the thresholds for risk management and QC index interpretation [51,52].

If the estimated risk comprises PoF and CoF located in the green area or red cells based on Figure 6, the decision maker may act differently. The green cells show the best quality in bridges assuming their structural nodes [53], based on lower expected risk accounting for their CoF and PoF. The bridge with a quality index that has been clustered in this area may continue with ordinary and preventive maintenance. The yellow cell illustrates that the bridge is near to high-risk area and it is necessary to focus on its preventive maintenance, emphasizing frequent inspections to avoid entering the emergency state. The red area relates to damaged bridges, thus those in an emergency state. If the operation of a bridge, which its quality index, is located in this area, is not safe and emergency intervention is necessary. These thresholds for bridge quality index and the colored areas are determined by the K-mean method and experiments of inspectors during the operation, which are provided by multivariate statistical process monitoring [52].

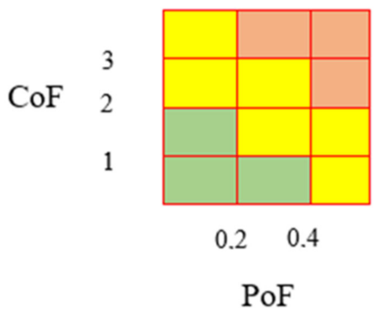

Figure 6. Risk matrix.

4. Conclusions

This research proposed the application of the estimation output based on probable risk concerning input data (SI and PD) to assign maintenance or intervention actions for bridges associated with different condition levels. This process, clustering bridges in different groups by asset and element, has increased the optimization process for gathering data when variance analysis supports the filtering of useless data. Meanwhile, the traditional maintenance method did not consider the output of inspection and maintenance activities to evaluate the consequence of decision making during the operation. Maintenance activity comprises inspection, remedial actions and data analysis to extract the QC index. Based on this research, it was possible to review the maintenance planning based on outputs through the comparison according to the inspection by input datasets, diagnosis and assessment results.

With this approach, several parameters were reduced for inspection and six components remain as valuable items in terms of technical aspect for bridges' quality assessment. Data gathering is a costly action in maintenance activities, and this study attempts to prepare a framework to rely on the quality index for clustering and prioritization, as well as noise reduction for inspection objects. In this framework, the reduction of worthless data in ordinary routine inspection and NDT for other types of inspection is considered. Decision-making with the proposed framework is applicable to improve the precision and efficiency of inspection, because reducing irrelevant data related to structural components during maintenance will save the required project resources, such as time, cost, and human labor. Meanwhile, risky elements and their related index with the higher variance have more value of information for operators, among the others. Focusing on important elements leads to increasing the safety of structures. The proposed framework was validated and considered a specific dataset of railway bridges, but may be extended and applicable to other studies if prior information on inspections is given.

Applying Bayes' rule for developing statistical investigation is notable for future research work. This tool will provide the possibility of risk assessment for all network components and prepare a decision-making framework in geographic priorities with the combination of PCA. Additionally, the use of artificial intelligence algorithms to collect and record structural information and compare experimental test results with numerical models to extract quality indicators is a valuable database for developing decision support system databases in future research.

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