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Implementation of High-Precision Life Cycle Cost Analysis (HP-LCCA) on Indonesian Bridge Management System

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Abstract: Life Cycle Cost Analysis (LCCA) is a method used to determine the preservation costs required for an object, in this case, a bridge, throughout its service life. This method has been implemented in several advanced countries, including Japan. The LCCA calculation concept in Japan differs from those in other countries, as it involves a detailed segmentation of structural elements of bridges, making the model unique and highly detailed. This model is known as High-Precision Life Cycle Cost Analysis (HP-LCCA) and will be tested for application in Bridge Management Systems (BMS) in Indonesia. Implementing this model requires several adjustments, including aligning perceptions of visual inspection results and adapting the assessment concepts for each element based on research interpretations. Additionally, the difference between non-physical and physical condition assessment models presents a challenge for adopting this calculation model. The research shows a similar pattern and positive correlation between non-physical and physical assessment models. Furthermore, factors influencing LCC calculations include bridge age and the number of segments in structural elements. This research aims to provide optimal LCC calculations and facilitate their application in BMS in Indonesia.

Keywords: bridge; asset; management; life cycle cost

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Citation: Sastrawiria, R.P.P.; Seigo, N.; Kudo, T. Implementation of High-Precision Life Cycle Cost Analysis (HP-LCCA) on Indonesian Bridge Management System. *Buildings* **2024**, *14*, 3208. https://doi.org/10.3390/buildings14103208

Academic Editor: Osama Abudayyeh

Received: 13 September 2024
Revised: 4 October 2024
Accepted: 6 October 2024
Published: 9 October 2024

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1. Introduction

Indonesia has extensive road infrastructure, the maintenance of which presents significant challenges to engineers and politicians alike. Roads and particularly bridges are key assets in supporting the national transport infrastructure. However, the management of these assets has encountered some significant issues, particularly concerning the high cost of monitoring and maintaining the bridges. According to the report from the Directorate General of Highways 2023 for the second semester, the number of bridges on national roads with a length greater than 6 m totaled 19,377 units, with a combined length of 562 km [1]. Consequently, the government requires a strategic approach to effective asset management.

Bridges, as integral components of the road network system, function to traverse various obstacles such as rivers, valleys, road intersections, and other barriers. This function necessitates that bridge structures remain in optimal condition to effectively serve road users. To maintain the condition of bridges, management strategies should be implemented even before the bridge is constructed, ideally during the selection of the bridge's superstructure type. By selecting an appropriate superstructure type, maintenance costs can be anticipated earlier.

To estimate the costs required for bridge management throughout their service life, several countries have developed Life Cycle Cost Analysis (LCCA) applications, including the United States, the Czech Republic, and Japan. Generally, LCCA is a method for calculating future maintenance costs based on the current condition data of the object under review. When considering the condition assessment structures used, Japan and Indonesia

have similarities in the range and the definitions of scores used to evaluate the condition of a bridge.

Japan has developed an application for conducting LCCA specifically for bridge structures. This application has a unique capability, as it predicts damage for each structural element that may experience physical deterioration. Physical damage includes issues such as rust on steel girders, structural cracks in concrete bridge elements, and other forms of physical damage. This approach is quite different from the concepts offered by the LCCA applications from the United States and the Czech Republic, where the calculations are intended for the entire bridge as a single unit rather than for individual elements.

To use this application, several critical data inputs are required. These include the condition values of the bridge's damaged structural elements, wherein all structural elements are divided into segments. Large, heavy elements are divided into many segments, while smaller, lighter elements are divided into fewer segments. This segmentation determines the rate of condition deterioration, which varies between segments depending on the level of damage each segment experiences. Due to its detailed analytical capabilities, this application is currently regarded as a High-Precision Life Cycle Cost Analysis tool.

This application differs from common tools used for LCCA, as it predicts the condition deterioration model for each type of structural damage found in the bridge's structural elements. Each segment of the damaged structural element has its own deterioration prediction model, which is considered to provide optimal results for bridge preservation programming.

The difference between applying condition deterioration to entire bridges versus applying it to individual bridge elements raises the question of whether this approach can effectively reduce life cycle costs (LCC). This represents a unique innovation that has not yet been addressed in other LCC studies conducted to date.

Comparisons of life cycle costs (LCC) have been conducted to optimize the required bridge span, where spans of less than 12 m with slab concrete superstructures were found to be the optimal choice [2]. In addition, the selection of material type (concrete or steel) for bridges significantly impacts LCC optimization [3]. Furthermore, in selecting maintenance types, preventive maintenance has been proven to reduce the total LCC. It is also known that optimal maintenance schemes can effectively balance safety, cost, and environmental impact, making preventive maintenance essential for the life cycle management of bridges [4]. Based on the references previously presented, prior research on the life cycle cost (LCC) of bridges has not compared results to determine the optimization across different types of bridge assessments, which may influence LCC optimization. This highlights the need to address this gap in the research.

The optimization in this model needs to be validated through in-depth research by comparing both LCC models. This comparison will help identify which optimization model provides the best value and can be adopted as the standard procedure for utilizing LCCA applications in Indonesia.

To achieve an optimized LCCA model, several questions need to be addressed in this study. First, is there a significant correlation between condition assessments in Indonesia and Japan? Second, how will this correlation affect the final LCCA calculations? Finally, what methods can be employed to optimize the LCCA results?

2. Literature Review

2.1. Life Cycle Cost

According to Sacconi et al. (2021), LCC is "a probabilistic-based approach that considers uncertainties on loads, resistances, degradation, and on the numerical modeling and structural response analysis" [5]. Several factors influence the LCC calculations for bridges, including the deterioration rate of bridge components, the discount rate, the service life of the bridge, and the uncertainty and variability of input parameters such as future traffic demand, environmental conditions, material properties, and unit costs of maintenance and repair. Additionally, Christensen (2009) states that LCC "is a method of evaluating

the total costs and benefits of a structure over its service life, taking into account the initial costs, maintenance costs, failure costs, and user costs" [6]. Furthermore, according to the Design Guide for Bridge for Service Life (2013), LCC is "an analysis methodology that assists in comparing and choosing alternative strategies for achieving long-term service life for bridge systems, subsystems, or elements" [7]. Based on this literature, it can be concluded that LCC is an approach for determining the deterioration level of structural elements, in this case, bridges, to evaluate the necessary preservation costs early.

According to the National Cooperative Highway Research Program (NCHRP) report on Bridge Life Cycle Cost Analysis, five factors influence the results of LCC: discount rate, service life and analysis period, management strategy, agency and user cost, and vulnerability cost [8]. Safi (2013) notes that the discount rate can significantly affect LCCA results, and theoretically, the discount rate tends to have a greater impact on bridge management than on bridge investment [9]. Based on these studies, the discount rate has a significant influence on LCC calculations and should therefore be a primary consideration in the analysis process.

In conducting LCC calculations, various applications have different data requirements. One such application, RealCost 3.0, developed by the Federal Highway Administration (FHWA) in 2023, requires inputs including future maintenance and rehabilitation performance, initial performance, discount rate, initial cost, and future cost, with the output being the projected life cycle cost. Additionally, the supporting data necessary for this application include free-flow capacity, queue dissipation capacity, maximum AADT (Annual Average Daily Traffic), maximum queue length, and work zone capacity [10].

On the other hand, Japan employs a different approach in conducting LCC calculations, focusing on the assessment of physical bridge conditions, particularly on structural elements. According to Kudo (2022), to improve LCC calculations, deterioration predictions must closely approximate actual deterioration in bridges. This condition is claimed to be highly effective in reducing total costs in LCC calculations [11]. Given the field conditions where each damage type has its own deterioration model, applying management strategies tailored to each type of damage can significantly reduce total maintenance costs over the bridge's service life. The application used for these calculations is the Intelligent Bridge Management System (iBMS), which requires specific input data such as physical condition values for each segment of its structural elements, material information for structural elements, general bridge information including operational year, target in-service period, and repair history.

As depicted in Figure 1, the condition assessment of damages at a specific time shows distinct values for individual condition deterioration, where 'a' represents the best condition, while 'e' represents the worst. However, after undergoing calculations using the iBMS application, the probability of condition deterioration will be presented diversely based on the application's predictive results. The probability values for each type of defect depend on the condition deterioration values obtained from visual inspections.

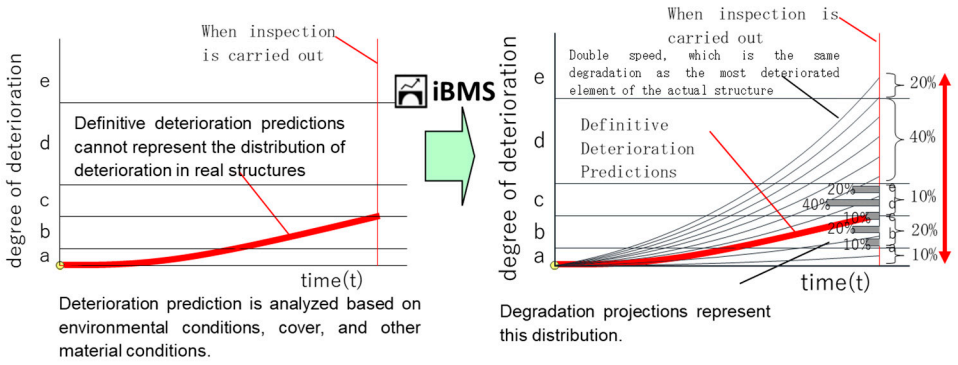


Figure 1. Example of variability in predicting deterioration.

Several predictive models are utilized in the iBMS application, including the condition deterioration model based on the Salt (potassium chloride) Penetration Model as shown in Equation (1), the Rebar Corrosion Model in Equation (2), the Cracking Model in Equation (3), and the Spalling Model in Equation (4). These four models can be expressed by the following equations:

$$\frac{\partial C}{\partial t} = \frac{\partial}{\partial x}\left(K_{Cl}\frac{\partial C}{\partial x}\right) \tag{1}$$

$$R_{corr} = \varphi S\frac{M_{Fe}\cdot i_{corr}}{z_{Fe}F} \tag{2}$$

$$W = \left(Ra\cdot\frac{\pi(\rho-1)}{\gamma} - \alpha_0\beta_0\frac{0.22\left\{(0.22+\varphi)^2+\varphi^2\right\}}{E(c+\varphi)}\cdot f_c'^{2/3}\right) / \left(\alpha_1\beta_1\frac{(c+\varphi)}{(5c+3\varphi\varphi)}\right) \tag{3}$$

$$\Delta\gamma sp = 56\left(\frac{c}{\varphi}\right)\times 10^{-3}\text{mm} \tag{4}$$

The Salt Penetration Model refers to the 2018 Standard Specification for Concrete Structures, which is intended for structural maintenance purposes [12]. In this model, $\frac{\partial C}{\partial t}$ represents the rate of change in salt concentration (C) over time (t), while $\frac{\partial}{\partial x}\left(K_{Cl}\frac{\partial C}{\partial x}\right)$ denotes the spatial diffusion of the salt concentration. Here, K_{Cl} is the diffusion coefficient for the salt (in this case, potassium chloride), and $\frac{\partial C}{\partial x}$ is the gradient of the salt concentration with respect to the spatial coordinate (x). This model is also used in various calculations for other studies, such as saltwater intrusion and saltwater penetration rate modeling [13–15].

The Rebar Corrosion Model is based on research conducted by Nozomi Someya titled Electrochemical Method for Salt Damage—Improving the Accuracy of Steel Corrosion Evaluation in Concrete Structures [16]. In this model, R_{corr} represents the corrosion rate of the rebar; φS is a factor that accounts for the surface area of the rebar; M_{Fe} is the molar mass of iron (Fe), which is a component of the rebar; i_{corr} is the corrosion current density, which measures the rate of the electrochemical reaction causing the corrosion; z_{Fe} is the valence number of iron, typically 2 in corrosion reactions; and F is the Faraday constant, which relates the amount of electric charge carried by one mole of electrons. This model is also applied in other studies, such as service life calculations, simulation processes, and condition deterioration predictions for marine environments [17–19].

The Cracking Model uses an equation from the research conducted by Lukuan Qi and Hiroshi Seki, titled Analytical Study on Crack Generation Situation and Crack Width Due to Reinforcing Steel Corrosion [20]. In this model, W represents the energy release rate or work done during crack propagation, Ra is a material constant or a factor related to the crack geometry, ρ represents a density-related parameter, and γ represents surface energy or a material property related to fracture toughness. The terms α_0, β_0, α_1, and β_1 are empirical constants or coefficients specific to the material or crack model. φ represents the crack length or a related geometric parameter, E represents the modulus of elasticity of the material, c represents an initial crack length or a characteristic length parameter, and f'_c denotes the compressive strength of the material. This model was introduced in the book Introduction to Fracture Mechanics [21] and further detailed in Fracture Mechanics of Concrete Structures [22].

The Spalling Model is based on research conducted by Seiichi Totori and Tayoaki Miyagawa, titled Deterioration Prediction of Concrete Structures Concerning Rebar Corrosion Due to Initially Induced Chlorides [23]. In this model, $\Delta\gamma sp$ represents the spalling displacement or the amount of material that has spalled off, c refers to a characteristic length or a specific parameter related to the material or crack, and φ represents another geometric parameter or material property. This model is also used in the FHWA specification titled Improved Prediction Model for PCC Pavement Performance [24].

The model used in this study is designed for reinforced concrete bridges. The potential for corrosion in the reinforcing steel is a key factor in predicting the deterioration of bridge

conditions. This is also considered due to the fact that both Japan and Indonesia face similar issues with carbonation in concrete elements, driven by environmental conditions. The total corrosion rate for each type of damage influences the deterioration prediction model, as analyzed through the iBMS application. Meanwhile, the surface condition deterioration of steel elements due to corrosion is addressed using a different formula, which is not detailed in this study and will be considered a limitation for future research.

The influence of zonation has been determined based on the provisions outlined in Japan's Standard Specifications for Concrete Structures [25], as shown in Table 1. However, in this study, the bridges selected as samples are located in Indonesia, where the chloride ion concentration levels are not yet known. Therefore, this zonation was not used in the analysis for the iBMS application calculations in this study.

Table 1. Chloride ion concentration at concrete surface (kg/m^3).

		Splash Zone	**Distance from Coast (km)**				
			Near Shoreline	**0.1**	**0.25**	**0.5**	**1.0**
Region with high airborne chloride concentration	Hokkaido, Tohoku, Hokuriku, Okinawa	13.0	9.0	4.5	3.0	2.0	1.5
Region with low airborne chloride concentration	Kanto, Tokai, Kinki, Chugoku, Shikoku, Kyusyu		4.5	2.5	2.0	1.5	1.0

Indonesia is currently in the process of developing the concept of LCC calculation for bridge structures. However, the fundamental concept used in these calculations still refers to the programming guidelines of the Bridge Management System (BMS) developed by the Directorate General of Highway in 1992. According to this document, the basics of LCC calculation are based on several key data points: condition score, traffic score, and loading score [26]. Additionally, supporting data for economic evaluation in the calculation include present value, discount rate, net present value, and internal rate of return. In addition, there is a difference in the service life between bridge designs in Indonesia, which adopt a 75-year lifespan, and in Japan, which uses a 100-year lifespan. However, this difference does not pose an issue in the iBMS application calculations, as the primary data used are the current structural condition, which may directly affect the existing deterioration rate.

Several challenges are encountered in the implementation of Life Cycle Cost (LCC) analysis, one of which is data collection and integration. Gathering accurate and comprehensive data can be quite difficult [27]. Additionally, environmental factors, traffic loads, and material degradation vary across regions [28]. The available LCC models in different countries also exhibit varying levels of complexity, with differing data requirements [29]. The final challenge lies in how LCC applications can be integrated with other modern tools, such as Building Information Modeling (BIM) and Bridge Information Modeling (BrIM), to ensure more effective use in the future [30].

Based on the concepts discussed above, there are two fundamental methods in LCC calculations: the economic principle-based method and the physical condition-based method. Both the United States and Indonesia adhere to calculating based on AADT (Annual Average Daily Traffic) and incorporate economic principles such as discount rates. In contrast, Japan's LCC calculation method focuses on the physical condition of bridges, using simulations to predict deterioration based on condition assessments. Actual condition deterioration is observed through visual inspections, validated by experts to minimize inspection errors. Furthermore, historical inspection data spanning several years can be utilized to predict future condition deterioration trends.

This research aims to focus on the unique iBMS application from Japan, specifically its method of calculating the total operational costs required for a bridge throughout its service life. iBMS distinguishes itself by determining a bridge's operational costs based

on the condition values derived from bridge inspections. Before these condition values are used in calculations, they undergo an automated correction process to ensure that the input values into the program are well calibrated. This calibration process is crucial in the analysis, as it corrects assessment errors and adjusts bridge deterioration prediction models statistically. Subsequently, the system generates several probability values for the condition, which serve as the basis for LCC calculations.

The statistical values result from a manual validation process conducted by multiple bridge experts over a development period of 10 years. This approach is claimed to be highly precise because it eliminates errors, corrects inspection outcomes, and proposes condition probability values deemed suitable for predicting deterioration rates.

In general practice, major interventions such as rehabilitation are typically undertaken when a bridge's performance falls below applicable performance standards. However, iBMS operates with predefined performance targets tailored to maintain the bridge structure within operational conditions and to reduce total maintenance costs over the long term. Additionally, iBMS provides estimated condition values for the reviewed elements over time. If assessment errors occur during bridge inspections, iBMS evaluates and corrects these errors by offering alternative condition values deemed appropriate.

This systematic approach ensures that the bridge remains operational within specified performance criteria while minimizing the overall maintenance costs. It leverages predictive maintenance strategies to anticipate condition changes, thereby optimizing resource allocation and extending the bridge's service life effectively.

With the unique features of iBMS calculations, this research is expected to provide substantial evidence of savings achievable in bridge preservation, optimizing through efficient calculation methods using the iBMS application. This is intended to serve as a guideline for LCC calculations in Indonesia.

Based on several existing studies, it can be concluded that Life Cycle Cost (LCC) calculations for bridges can be approached from both economic and condition-based perspectives, using historical data from visual inspections. This current study will adopt a deterioration model based on 10 years of historical visual inspection data collected in Japan.

2.2. Deterioration Model

In predicting deterioration, historical data and various statistical methods can be employed to enhance the accuracy of a deterioration model [31]. A deterioration model is an approach used to forecast the degradation of infrastructure over its lifespan. Several commonly used approaches for deterioration modeling include deterministic models (such as regression), stochastic models (such as Markov chains), or artificial intelligence models. Each model has its strengths and weaknesses, as illustrated in Table 2.

Table 2. Evaluation models' pros and cons.

Models	Pros	Cons
Deterministic	Easy to compute and apply, straightforward calibration with available software, and useful for predicting future conditions based on perfect knowledge of variables.	Does not account for random error in prediction, lacks flexibility, and may not be reliable due to not considering uncertainty or unobserved variables.
Stochastic	Accounts for inherent uncertainty and variation in deterioration factors, uses present condition to predict future state, and is computationally efficient for large networks.	Assumption of fixed inspection intervals may lead to inconsistent predictions, and the Markov chain approach ignores previous states of bridge condition.
Artificial Intelligence	Utilizes high processing speeds, capable of mimicking past patterns of deterioration, and can overcome some shortcomings of current models.	Still requires further research for enhancement, verification, and validation in real-world environments. May share limitations of deterministic models.

According to Malik M. and Armor B. (2024), the issues necessitate preventive, cyclic, or condition-driven maintenance measures to extend the service life of the bridge. Common types of damage in concrete bridge structures include concrete cracking, spalling, and surface deterioration due to environmental factors [32]. These types of damage can cause a significant decline in the condition of the bridge over the years. In addition to surface damage caused by environmental factors, there is also damage resulting from traffic loads on the bridge.

To obtain a good model, it is crucial to have well-validated historical bridge condition data. Additionally, selecting independent data is necessary to ensure that these elements significantly influence the deterioration of bridge conditions. It is important to note that not all data available in bridge inspection databases contribute equally to condition deterioration; thus, careful consideration is essential.

In this study, the deterioration prediction of a bridge girder element is performed using a deterministic model, where the physical deterioration model of the bridge over the years becomes the predictive model utilized in the iBMS application, specifically for the girder structural elements. The deterministic model is used because the prediction data are derived from 10 years of historical visual inspection data on concrete girder elements, which is then refined with updated inspection results in subsequent years.

For bridges that do not have historical damage or maintenance data, LCC calculations can still be performed using the iBMS application. In this case, the data used consist of the current condition of the bridge elements, which will then be directly predicted based on the level of damage observed.

However, for other elements, such as bearings, substructures, and slabs, the application employs a stochastic model using the Markov model. This is illustrated in Figure 2, which shows the soundness damage on the concrete surface due to rebar corrosion, with the probability transition of deterioration from a good condition (Condition I) to a worse condition (Condition III).

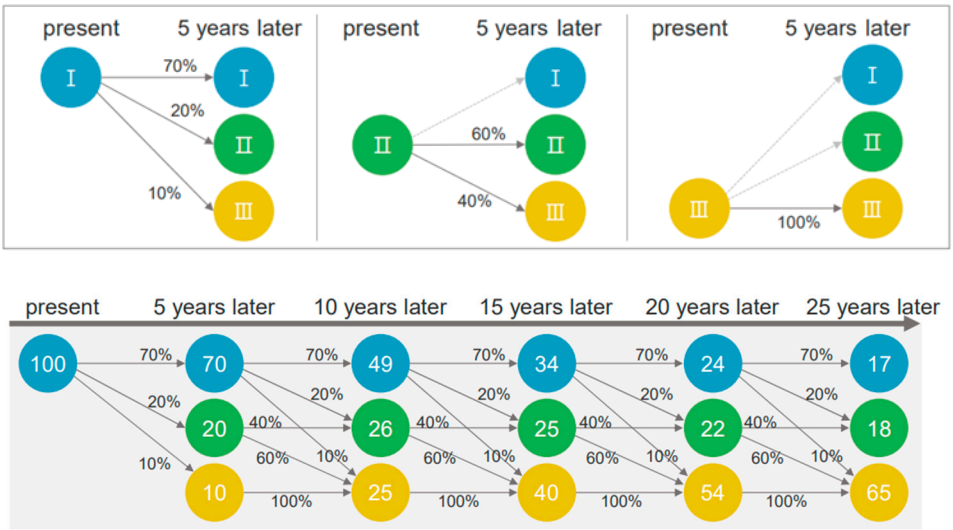


Figure 2. Example of estimating element deterioration based on Markov model.

3. Research Methodology

3.1. Methodology

This study compares the LCC analysis results using the iBMS application on several simply supported bridge types made of concrete. Bridge condition data were collected directly from the field by conducting detailed visual surveys on six selected bridges located in East Java Province, Indonesia. This location was chosen due to its favorable inspection track record, aiming to provide a low percentage error between the current inspection results and those from previous years. The focus of this study is on bridge girder structures.

Subsequently, visual inspection findings were summarized in a report, including sketches of damage observed on the reviewed elements.

Data collection for aligning perceptions of condition assessment is necessary, especially considering the iBMS application used to calculate High-Precision LCCA using criteria in the Japanese guidelines (a–e), which differ from those in Indonesia (0–5). Furthermore, this alignment process is conducted using two methods: questionnaire surveys and assessment of visual inspection results of bridges in Japan, employing correlation analysis as depicted in Figure 3.

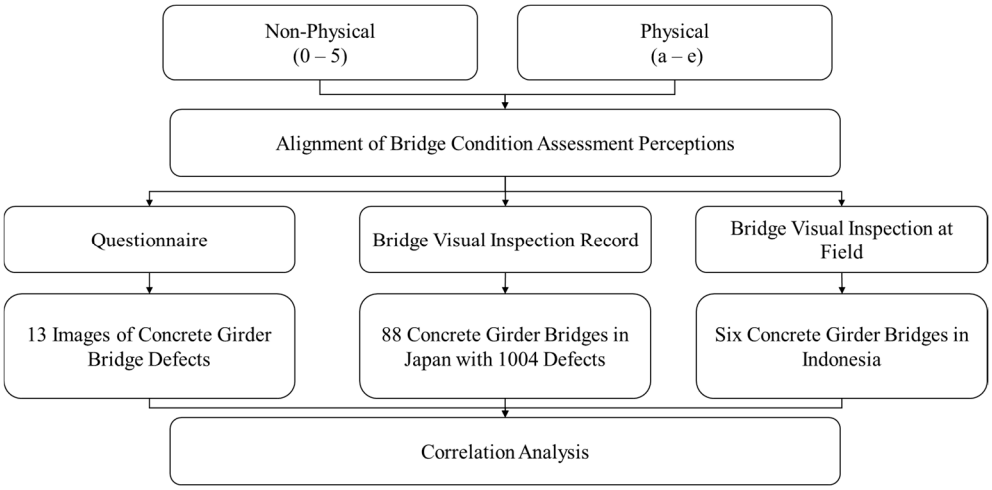


Figure 3. Method of aligning perceptions.

According to Xiangtong W. et al. (2024), Life Cycle Cost (LCC) calculations need to be conducted comprehensively, including the initial construction cost, maintenance costs, and failure costs over the bridge's service life [33]. The LCC aims to minimize costs while ensuring performance and safety. In this study, maintenance costs will be one of the results compared across models based on the visual inspection condition assessments.

The selected bridge will then be assessed using three different condition assessment methods: the Indonesian bridge inspection guidelines, the Japanese inspection guidelines, and the converted assessment results from the perception alignment between Indonesian and Japanese inspectors. By comparing these three methods, we aim to determine which assessment method provides the most optimal LCC value.

The HP-LCCA process using the iBMS application involves preparing several general data sets such as a bridge information base comprising reinforcing bar diameter, concrete strength, concrete cover, and quality information of other structural elements. Additionally, bridge inventory data such as year of service, bridge length, type of structural elements, bridge location, and visual inspection results are necessary, as can be seen in Figure 4. Therefore, visual inspections of bridge conditions are conducted in this study to provide a detailed overview of actual field damages. These inspections involve creating reports with sketches to facilitate accurate documentation of damage locations.

In the visual inspection of bridges, two assessment guidelines were employed: the Japanese and Indonesian evaluation models, as depicted in Table 3 for non-physical assessment and Table 4 for physical assessment. These methods share a similar approach but differ in their assessment models. Japan utilizes a physical model approach, focusing on specific types of damages affecting each structural element individually. In contrast, Indonesia uses a non-physical assessment that sums up five criteria: type of damage, severity of damage, damaged area, element function, and the significance of the damaged element's impact on other elements. The condition of the non-physical element is assessed by taking the worst condition among the structural elements being evaluated.

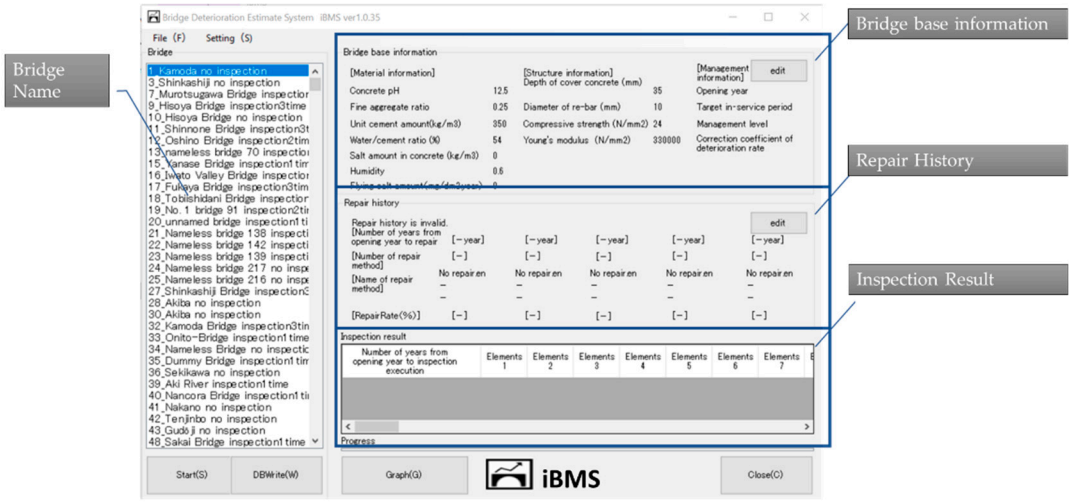


Figure 4. iBMS application for HP-LCCA calculation.

Table 3. Bridge visual condition score in Indonesia [34].

Indonesian Condition Score (Non-Physical Assessment for Each Element)	
0	No defect
1	Minor defect
2	Moderate defect
3	Major defect
4	Critical defect
5	Collapsed

Table 4. Bridge visual condition score in Japan [35].

Japanese Condition Score (Physical Assessment for Each Defect)	
a	No defect
b	Minor defect depth and minor defect area
c	Minor defect depth and major defect area
d	Major defect depth and minor defected area
e	Major defect depth and major defected area

Furthermore, as illustrated in Tables 3 and 4, there are differences in the types of treatments for each damage severity level. This condition necessitates researchers to align the final values so that they can serve as references in the LCCA process using the iBMS application, as iBMS currently only processes physical condition values based on the Japanese assessment guidelines.

Infrastructure managers typically use visual field surveys and interpret inspection reports to predict future structure states and plan maintenance [36]. According to Poli Francesca et al. (2023), regular visual inspections of bridges are subject to uncertainty due to the subjective nature of defect grading based on the inspectors' experience [37]. It also reveals that inspection reports are often overly pessimistic about structural damage, potentially leading to unnecessary rehabilitation interventions [38]. From the aforementioned references, it can be concluded that visual inspections still carry the potential for misinformation due to differences in inspectors' skill levels and errors in condition scoring, resulting in inefficient maintenance interventions.

To bridge the differences in assessment methods, a perception alignment process was conducted through a survey using a questionnaire. This questionnaire was distributed to inspectors from Indonesia and Japan. It contained 13 questions related to photographs of

concrete girder bridge damage. The assessments were conducted visually in accordance with the inspection guidelines used in both Indonesia and Japan. Each photograph was explained as objectively as possible, based on actual field conditions, to ensure that each inspector could make accurate assessments based on the provided images and descriptions. The reassessment results were then processed using simple statistical analysis to align them with the condition assessment results obtained using the Japanese method.

Additionally, a condition assessment was also conducted on sample data from bridge condition inspections in Japan, which were evaluated using the Indonesian bridge inspection guidelines. The sample size was determined based on the scope limitations of the study, focusing on concrete girder bridges with damages such as cracks, delamination, spalling, and exposed rebar. This perception alignment serves as the basis for conducting LCCA, where the application utilized has specialized algorithms tailored for condition assessments in Japan.

3.2. Theoretical Structure of Framework

High-Precision LCCA, as depicted in Figure 5, is based on a theoretical concept where the condition value of a bridge element varies among different structural elements due to varying levels of damage. These differences in damage levels automatically result in varying rates of condition deterioration. Consequently, each structural element can be handled individually, leading to more precise funding allocation and avoiding excessive burden on the overall bridge rehabilitation budget.

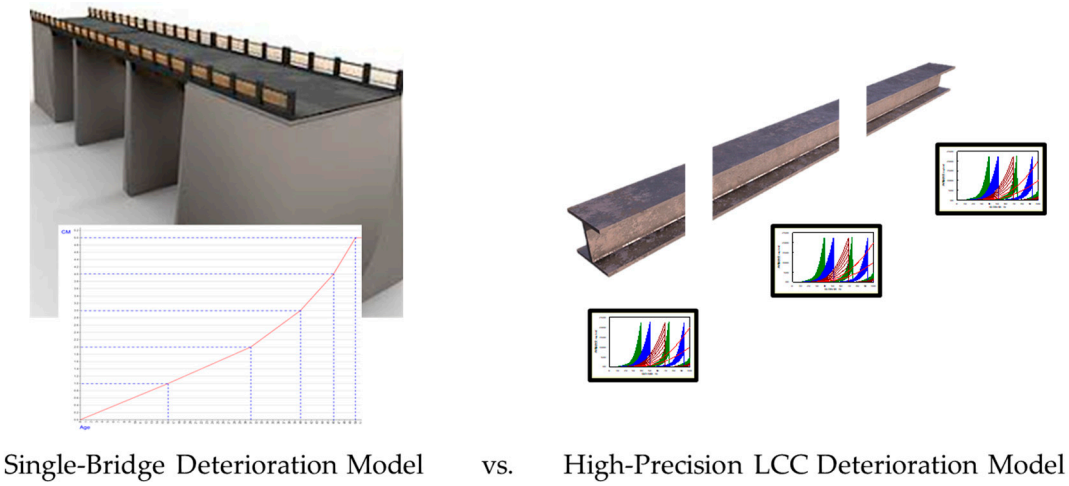


Figure 5. Single-Bridge deterioration model vs. High-Precision LCC deterioration model.

4. Result

4.1. Aligning the Perceptions

According to Gniazdowski (2023), the correlation analysis between nominal and numerical data focuses on measuring the strength of a linear correlation relationship between them [39]. Cuttler Carrie et al. (2020) emphasize that correlation analysis is a method to evaluate the strength and direction of the relationship between two variables [40]. Correlation analysis is a fundamental tool for multivariate data analysis, used to estimate the strength of the linear association between two variables [41]. However, it is important to note that correlation does not imply causation [42]. This study will analyze the relationship between the bridge condition assessment criteria in Indonesia and Japan.

Correlation analysis is a nonexperimental research method in which two variables are measured to evaluate their statistical relationship, with minimal or no control over extraneous variables. The direction of this correlation can be either positive or negative, indicating whether the variables change in the same direction or in opposite directions, respectively. The primary purpose of correlation research is to test the strength of association between variables, providing valuable insights into complex real-world relationships and aiding

in the development of theories and predictions [43]. However, this method has notable limitations, such as its assumption of a linear relationship and its sensitivity to the range of observations. Moreover, correlation analysis is not appropriate for assessing the agreement between two methods aimed at measuring the same value. In such cases, more suitable alternatives include the intraclass coefficient and Bland–Altman's limits of agreement [44].

Data collection through questionnaires for aligning perceptions serves as primary data while gathering bridge condition data from visual inspections conducted by Japanese inspectors serves as secondary data. The bridge condition assessments performed by inspectors in Japan are subsequently re-evaluated by bridge inspection experts in Indonesia to determine the correlation between these two methods of condition assessment.

The total number of inspectors participating in the questionnaire was 77 respondents, comprising 43 bridge inspectors from Indonesia and 34 from Japan, as shown in Table 4. The questionnaire was designed with two methods of condition assessment, namely Indonesian and Japanese, aiming for objective responses from representatives of each country to the questions listed in the questionnaire. It is worth noting that the questionnaire included 13 questions regarding damages to concrete girder bridge elements presented with images and descriptions, along with condition assessments based on Indonesian (0–5) and Japanese (a–e) criteria.

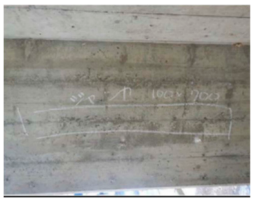
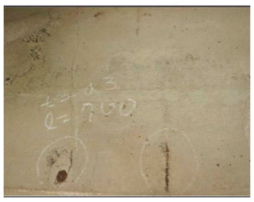
From Table 5, it can be observed that the majority of respondents are male, with the nationality of respondents being fairly balanced between Indonesia and Japan. Additionally, most respondents are under the age of 35 and have less than 5 years of experience. On the other hand, nearly half of the respondents are over the age of 35, with the majority having more than 5 years of experience.

Table 5. Respondent demographics.

Variable	Category	Frequency	Percentage (%)
Gender	Male	72	93.51
	Female	5	6.49
Nationality	Indonesia	43	55.84
	Japan	34	44.16
Age	<25	4	5.19
	25–30	24	35.06
	30–35	12	15.58
	35–40	4	5.19
	40>	30	38.96
Experience	<1 Years	6	7.79
	1–3 Years	18	23.38
	3–5 Years	23	29.87
	5–10 Years	19	24.68
	>10 Years	11	14.29
Certification	Certified	47	61
	Not Certified	30	39

The design of the questionnaire consists of a collection of images from inspections of selected bridges, deemed representative based on discussions with bridge experts in both Indonesia and Japan. Table 6 presents photos of damage to elements of concrete girder bridges, such as reinforced concrete girders and prestressed concrete girders, selected as research subjects. Each type and severity of damage has been selected to achieve a more accurate distribution of assessments. Notably, there is a difference in crack damage between concrete girders and prestressed concrete girders. Even with the same crack width, the severity of the damage will vary between these two types of girders. The questionnaire also includes explanations regarding the types and sizes of the damage depicted in the available photos.

Table 6. Pictures of damage types on concrete girder elements.

Image 1	Image 2	Image 3	Image 4	Image 5
				
Image 6	Image 7	Image 8	Image 9	Image 10
				
Image 11	Image 12	Image 13		
				

The results of the questionnaire survey presented in Table 7 show a pattern of inspection results that appear identical. This is indicated by the number of selections for good condition ratings using both non-physical and physical methods. From the table, it is evident that there is a consistent pattern in the inspection results, with ten out of thirteen types of damage (77%) exhibiting similar patterns, while the remaining three types of damage (23%) show slight differences in assessment perceptions. The values in Table 5 will be normalized for the correlation analysis in order to obtain the correlation values between the two models.

Table 7. The results of the perception alignment questionnaire.

	Non-Physical Assessment Score								Physical Assessment Score						
	CS_0	**CS_1**	**CS_2**	**CS_3**	**CS_4**	**CS_5**	**CS_VAL**	***n***	**CS_a**	**CS_b**	**CS_c**	**CS_d**	**CS_e**	**CS_VAL**	***n***
Image_1	1	9	30	1	2	0	CS_2	43	0	8	20	6	0	CS_c	34
Image_2	1	31	9	1	1	0	CS_1	43	4	9	16	0	5	CS_c	34
Image_3	0	3	36	2	2	0	CS_2	43	0	1	3	26	4	CS_d	34
Image_4	0	10	31	2	0	0	CS_2	43	0	1	6	27	0	CS_d	34
Image_5	0	3	34	5	1	0	CS_2	43	0	1	2	27	4	CS_d	34
Image_6	0	0	31	10	2	0	CS_2	43	0	0	1	25	8	CS_d	34
Image_7	0	1	31	10	1	0	CS_2	43	0	0	2	24	8	CS_d	34
Image_8	0	3	6	29	5	0	CS_3	43	0	0	0	9	25	CS_e	34
Image_9	0	0	5	32	6	0	CS_3	43	0	0	0	3	31	CS_e	34
Image_10	0	0	7	26	9	1	CS_3	43	0	0	0	11	23	CS_e	34
Image_11	0	1	13	25	4	0	CS_3	43	0	0	3	17	14	CS_e	34
Image_12	0	8	23	10	2	0	CS_3	43	0	1	13	16	4	CS_d	34
Image_13	0	14	25	4	0	0	CS_2	43	1	2	29	0	2	CS_c	34

Figure 6 shows that the level of subjectivity for each type of damage is quite varied. For condition assessment results using the non-physical inspection method, Image 3 has the highest objectivity, with a percentage of correct answers (based on expert validation ranging from 0% at worst to 100% at best) at 84%, while Image 12 has the lowest objectivity

with a percentage of correct answers of 23%. For condition assessment results according to the physical inspection method, Image 9 has the highest objectivity with a percentage of correct answers of 91%, while Image 11 has the lowest objectivity with a percentage of correct answers of 41%. The average objectivity level for both assessment methods is 66% for non-physical and 69% for physical methods. This average indicates that the assessment results of both methods have a similar level of objectivity.

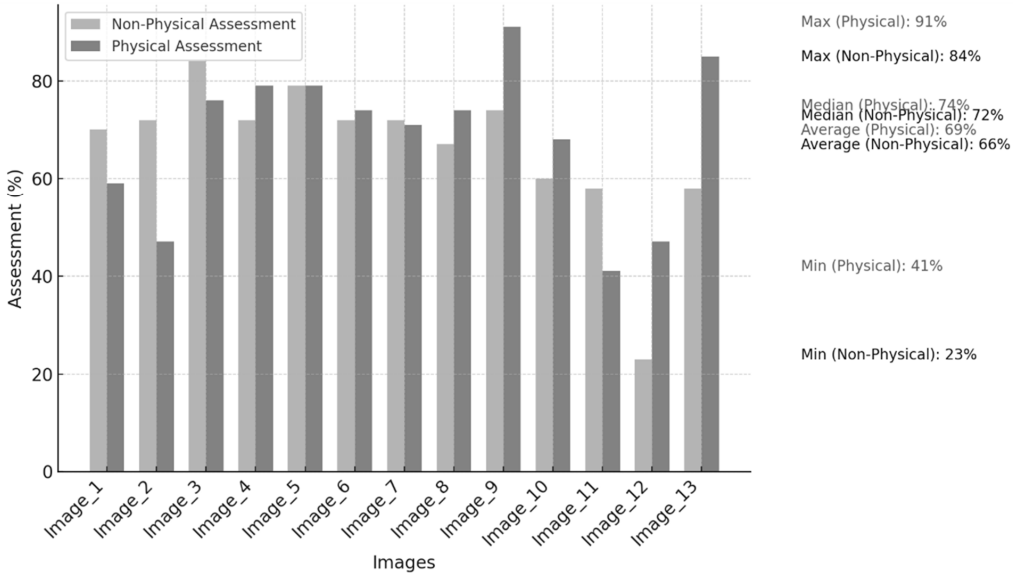


Figure 6. Percentage of objectivity of condition assessment results.

Based on the data analysis, several patterns are evident in Figure 7, illustrating the relationship between the non-physical inspection method (Indonesian) and the physical inspection method (Japanese). These results were processed using Excel's version 2409 (Build 18025.20104) correlation analysis function, yielding a range of values from −1 to 1. A value of −1 indicates that the two variables do not have a strong relationship, while a value of 1 indicates a strong relationship between the two variables [45–47].

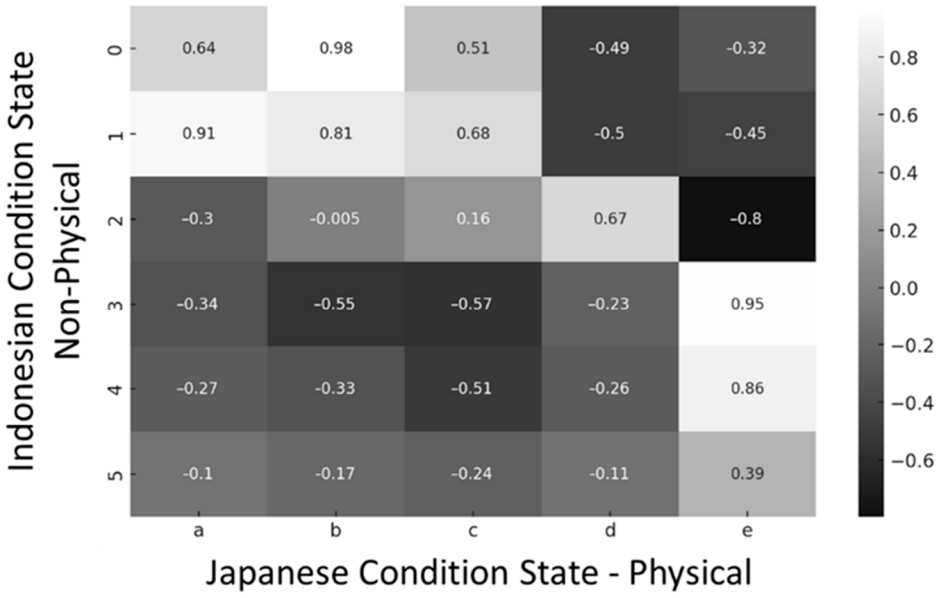


Figure 7. Correlation matrix between physical and non-physical assessment.

Figure 7 presents the results of a questionnaire that illustrates the relationship between two assessment methods, namely the non-physical and physical. The analysis reveals a strong correlation between the two sets of evaluation criteria. The non-physical criteria "0" exhibit a very strong correlation with the physical criteria "a", "b", and "c", with correlation values of 0.64, 0.98, and 0.51, respectively. Similarly, non-physical criteria "1" shows a significant correlation with the physical criteria "a", "b", and "c", with correlation values of 0.91, 0.81, and 0.68, respectively. These values indicate that non-physical criterion "1" tends to align closely with physical criteria "a", "b", and "c". Based on this analysis, it can be concluded that the non-physical assessment criteria "0" and "1" in the Indonesian method have a broad perceptual range and tend to be subjective when compared to the physical assessment criteria in the Japanese method.

Additionally, there is a positive correlation between criterion "2" and criterion "c", with a value of 0.67, indicating that the evaluation criterion "2" has a reasonably good perceptual range and objectivity. Positive correlations are also observed between criteria "3" and "4" with criterion "e", with values of 0.95 and 0.86, respectively. However, criterion "5" has a positive correlation with criterion "e" at 0.39. From these data, it can be concluded that criteria "2", "3", "4", and "5" in the non-physical assessment method have a narrow perceptual range and tend to be more objective when compared to the physical assessment criteria.

To enhance the objectivity of the assessment, an additional evaluation of bridge conditions was conducted using 88 sample data of concrete girder bridges inspected by expert bridge inspectors in Japan through the physical assessment method. These assessments were then re-evaluated by expert bridge inspectors in Indonesia using the non-physical assessment method to analyze the assessment patterns for each bridge sample. A total of 1004 defects were identified in the 88 bridge samples, with the breakdown of defects being 457 instances of concrete cracking, 105 instances of spalling, 209 instances of delamination, and 233 instances of rebar exposure, as shown in Table 8.

Table 8. Results of bridge expert perception.

Damage Sample	Type of Damage	Non-Physical Assessment Score	Physical Assessment Score
Sample 1	Delamination	2	e
Sample 2	Delamination	3	e
Sample 3	Spalling	2	c
~	~	~	~
Sample 101	Cracking	2	d
Sample 102	Cracking	2	d
Sample 103	Exposed Rebar	2	d
~	~	~	~
Sample 1001	Exposed Rebar	2	d
Sample 1002	Exposed Rebar	2	d
Sample 1003	Exposed Rebar	2	d
Sample 1004	Exposed Rebar	2	d

The data processing results, shown in Figure 8, indicate that the condition assessment is predominantly characterized by Condition "2" with a correlation to value "d". Additionally, the analysis reveals that the "0" criterion in the non-physical method tends to align with the "a" criterion in the physical method. Similarly, the "1" criterion corresponds closely with the "c" criterion, while the "2" criterion aligns with the "d" criterion. The "3" criterion shows a strong correlation with the "d" criterion. However, the "4" and "5" criteria are not represented in the sample data.

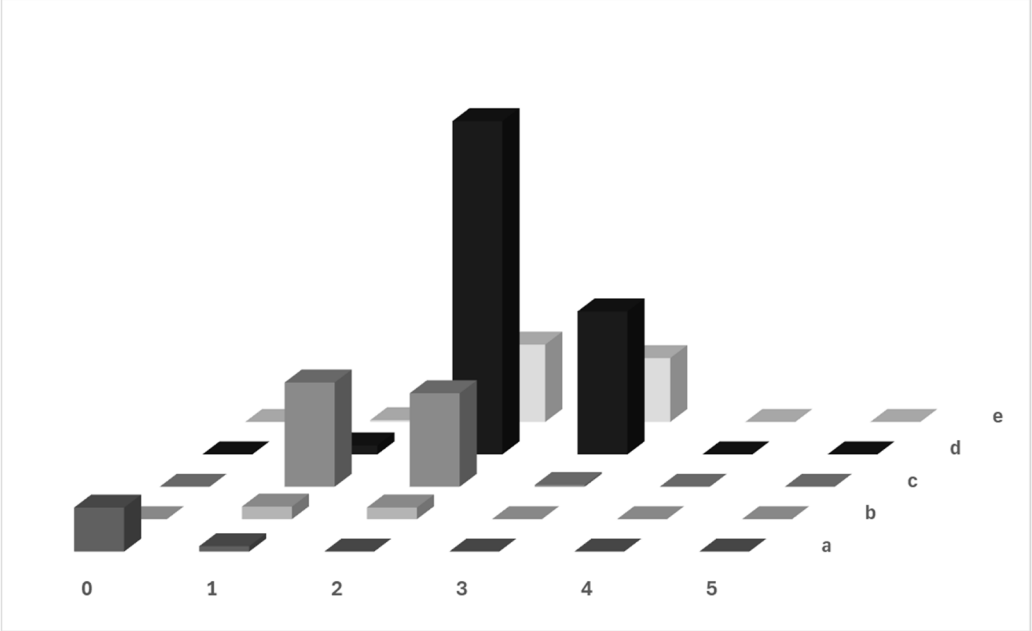


Figure 8. Bar chart depicting the relationship between the population of non-physical and physical assessments.

Based on the correlation analysis results presented in Figure 9, which depicts the correlation matrix between the non-physical and physical assessment methods, a strong correlation is evident between the two methods. The "0" criterion shows a strong positive correlation with the "a" criterion, with a value of 0.94, while the "1" criterion has a medium positive correlation with the "c" criterion, with a value of 0.56. Additionally, the "2" criterion has a positive correlation with the "d" criterion, with a value of 0.25, and the "3" criterion shows a positive correlation with the "e" criterion, with a value of 0.22. Criteria "4" and "5" were not represented in the available sample data. These results indicate a positive correlation between the non-physical and physical assessment criteria.

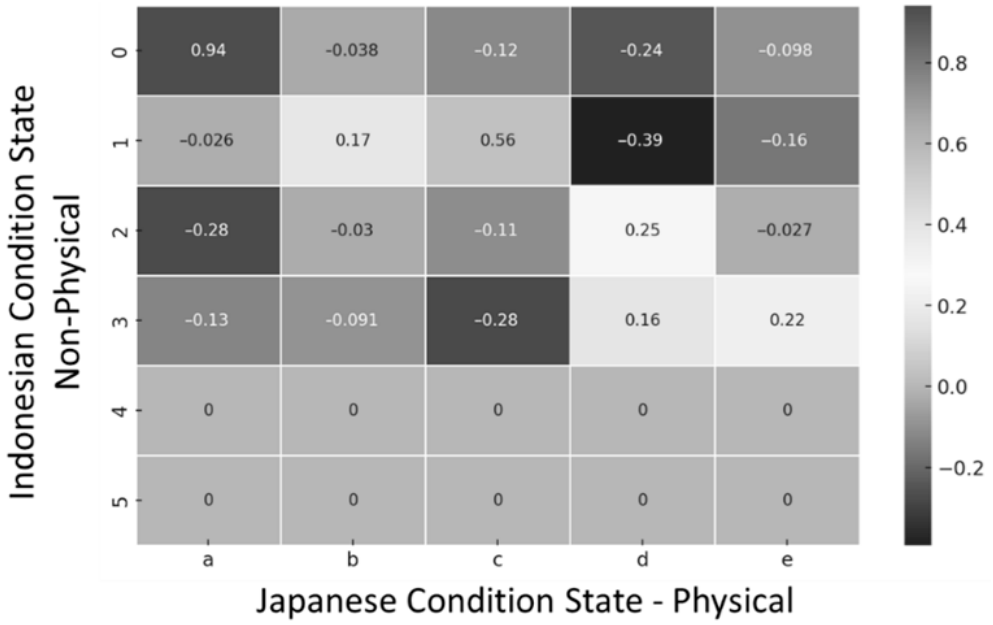


Figure 9. Correlation matrix between non-physical and physical assessment (expert).

Based on the various analysis results, the relationship between the two inspection methods (non-physical and physical) can be summarized as shown in Table 9. Subsequently, the regression analysis results from the Questionnaire and Expert assessments were compared. The values of Multiple R and Significance (F) were used as benchmarks for selecting the best correlation between non-physical and physical methods, ensuring that no negative correlations were chosen and that the significance value exceeded 0.05. According to these criteria, the most appropriate correlations selected are "0–a", "1–b", "2–d", "3–e", "4–e", and "5–e".

Table 9. Regression analysis results of the relationship between non-physical and physical assessment of questionnaire and expert results.

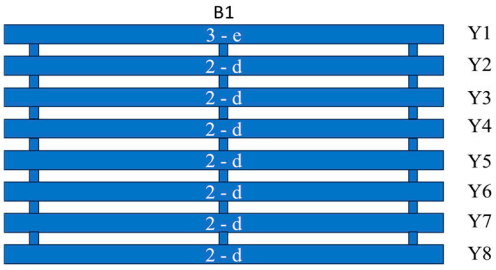
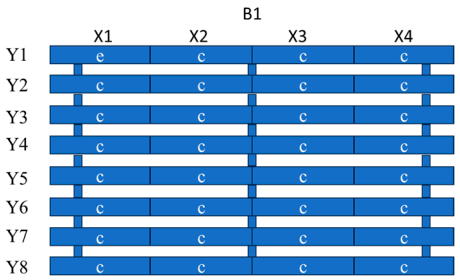
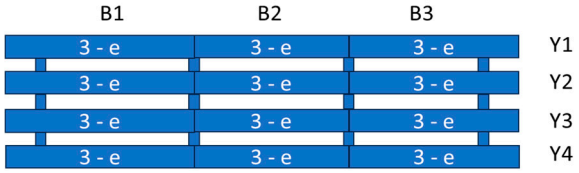
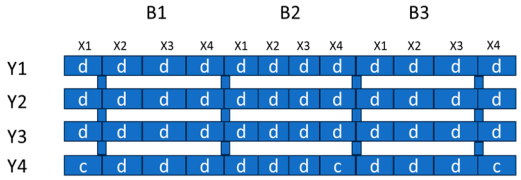
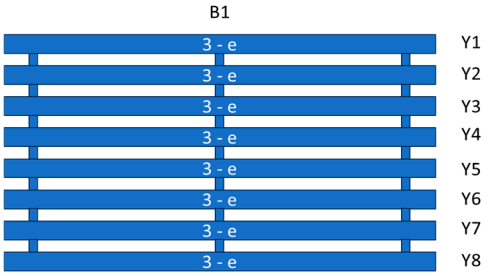
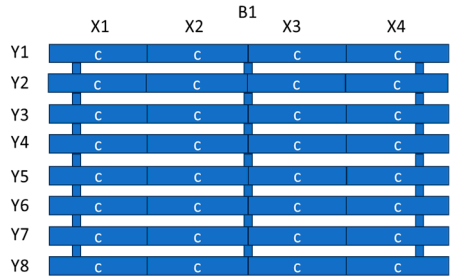
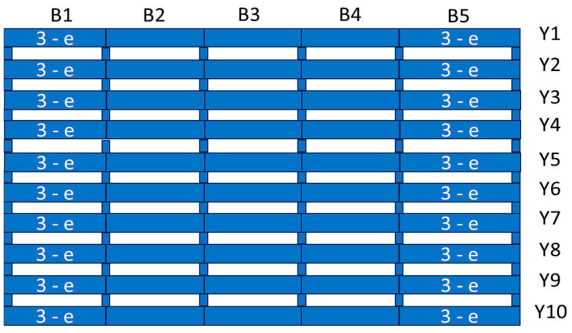
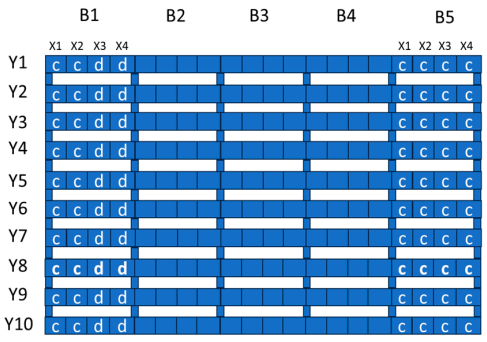
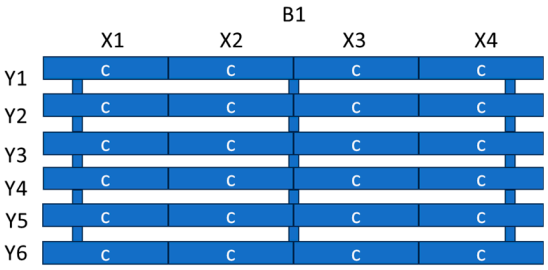
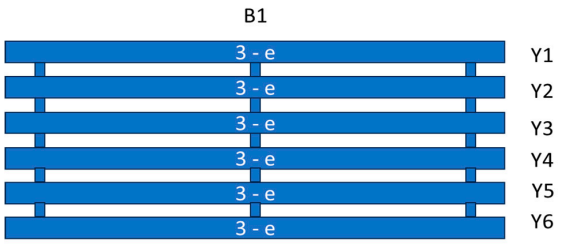
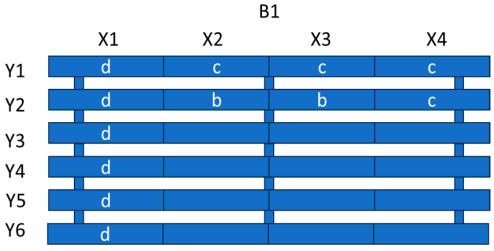
		0–a	**0–b**	**0–c**	**0–d**	**0–e**
Questionnaire	Multiple R	0.6396	0.9765	0.511	−0.4946	−0.3187
	Sig–F	0.0186	1.131×10^{-8}	0.0743	0.0857	0.2885
Expert	Multiple R	0.9409	−0.0377	−0.1207	−0.2449	−0.0983
	Sig–F	0	0.2332	0.000126	3.58×10^{-15}	0.00183
		1–a	**1–b**	**1–c**	**1–d**	**1–e**
Questionnaire	Multiple R	0.9101	0.8052	0.6829	−0.4954	−0.4524
	Sig–F	1.575×10^{-5}	0.00089	0.01008	0.0852	0.1206
Expert	Multiple R	−0.026	0.174	0.5637	−0.3931	−0.16497
	Sig–F	0.4101	2.86×10^{-8}	2.68×10^{-85}	1.902×10^{-38}	1.46×10^{-7}
		2–a	**2–b**	**2–c**	**2–d**	**2–e**
Questionnaire	Multiple R	−0.2962	−0.00496	0.1584	0.6699	−0.7969
	Sig–F	0.3257	0.9872	0.6053	0.0122	0.0011
Expert	Multiple R	−0.2781	−0.03031	−0.1112	0.2492	−0.027
	Sig–F	2.706×10^{-19}	0.3373	0.00042	1.134×10^{-15}	0.3923
		3–a	**3–b**	**3–c**	**3–d**	**3–e**
Questionnaire	Multiple R	−0.3351	−0.5479	−0.5654	−0.2335	0.9534
	Sig–F	0.2631	0.0526	0.044	0.4426	4.628×10^{-7}
Expert	Multiple R	−0.1323	−0.0913	−0.2815	0.163	0.2204
	Sig–F	2.59×10^{-5}	0.0038	9.52×10^{-20}	2.05×10^{-7}	1.652×10^{-12}
		4–a	**4–b**	**4–c**	**4–d**	**4–e**
Questionnaire	Multiple R	−0.2678	−0.3311	−0.5118	−0.2638	0.8635
	Sig–F	0.3763	0.2691	0.0738	0.3838	0.0001426
Expert	Multiple R	0	0	0	0	0
	Sig–F	0	0	0	0	0
		5–a	**5–b**	**5–c**	**5–d**	**5–e**
Questionnaire	Multiple R	−0.1031	−0.1737	−0.2365	−0.1057	0.3864
	Sig–F	0.7375	0.5702	0.4367	0.731	0.1922
Expert	Multiple R	0	0		0	0
	Sig–F	0	0	0	0	0

4.2. Bridge Visual Inspection

In this study, six simply supported concrete girder bridges located on the National Road in East Java, Indonesia, were selected. The selection was based on the type of superstructure, specifically reinforced concrete girders and prestressed concrete girders, and the types of damage observed, such as cracking, corrosion of the reinforcing steel, and spalling. Additionally, the ease of access for inspection team to the locations was considered, and the presence of heavy traffic conditions.

Visual inspections of these six bridges were conducted using the applicable bridge inspection guidelines in Indonesia. Additionally, the bridge conditions were assessed according to the assessment guidelines in Japan to determine whether there are differences between non-physical assessment methods with Indonesian inspection guidelines and the conversion between non-physical to physical assessment according to the previous perception alignment analysis results and physical assessment methods with Japanese inspection guidelines. The results of the bridge inspections can be seen in Table 10.

Table 10. Inspection results of six bridges based on non-physical and physical assessment on the National Road in East Java, Indonesia.

	Non-Physical	Physical
Bridge 1		
Bridge 2		
Bridge 3		
Bridge 4		
Bridge 5		
Bridge 6		

Based on Table 9, the LCCA results for the six bridge samples can now be calculated using the iBMS application. At first glance, the conversion from non-physical to physical assessment tends to yield worse condition ratings. However, it is important to note the differences in the detailed damage area distribution between the elements assessed by the non-physical and physical methods. Additionally, there are differences in the evaluation approach between the two methods: the non-physical method always assigns the worst condition for an element, while the physical method determines the condition based on the specific location of the damage in each segment. Subsequently, the non-physical assessment results are converted to physical assessments based on the correlation study findings.

From this damage distribution, the LCCA will be calculated using the iBMS application. This will reveal which method yields more optimal results for implementation in the Bridge Management System in Indonesia, particularly for bridges on national roads.

Based on the condition assessment results using the non-physical method, it can be seen that the condition of each individual concrete girder is evaluated, where "Y" indicates the number of girders inspected and "X" indicates the number of segments. This differs from the physical method, where the assessment is conducted for each segment, with one concrete girder divided into four inspection segments. This detailed damage assessment is a crucial part of the LCCA calculation.

High-Precision LCCA, which is a significant advantage of the iBMS application, demonstrates the extent to which an element needs to be detailed to achieve optimal results. Therefore, this study will compare the results of the non-physical and physical methods to determine the best LCCA optimization for implementation in the Bridge Management System in Indonesia.

4.3. LCCA Optimization

To determine the total Life Cycle Cost (LCC), several supporting data points are required, which serve as assumptions in calculating the total repair costs needed for the iBMS application. One of these supporting data points is the repair cost per square meter for various types of repair methods, as shown in Table 11. These costs are the figures listed in the iBMS application, corresponding to the average repair requirements in Japan, and have been manually converted using an exchange rate of 100 IRD/CNY. The use of area measurements in this calculation is based on field inspection data, as well as the maintenance planning incorporated in the iBMS application, which utilizes area-based units of measurement.

Table 11. Estimated repair cost per square meter in IDR.

No.	Repair Method	Cost IDR/m^2
1	Chloride Removal from Concrete (Electrochemical Desalination)	IDR 9,000,000
2	Sectional Repair	IDR 6,500,000
3	Surface Impregnation	IDR 1,300,000
4	Cathodic Protection	IDR 9,500,000
5	Surface Coating	IDR 1,000,000
6	Crack Injection	IDR 1,000,000
7	Replacement	IDR 40,000,000
8	Do Nothing	IDR-

The analysis results using the iBMS application reveal several LCCA outcomes that show differences between bridges inspected using the non-physical (NP) and physical (P) methods, as illustrated in Table 12. There are discrepancies in the Condition States (CS) between the NP and P methods, including the number of segments with damage such as cracking, rebar corrosion, and spalling. These differences will affect the amount of maintenance required, thereby impacting the total cost. The difference in total costs may be attributed to the varying levels of damage and the distribution of damages present. As

observed in the non-physical assessment, the evaluations tend to be worse compared to those of the physical assessment.

Table 12. Results of data analysis for six bridges with non-physical and physical methods using the iBMS application.

Name	CS_a	CS_b	CS_c	CS_d	CS_e	Age	Segment	Maintenance
Bridge 1 NP	0	0	0	7	1	24	8	3
Bridge 2 NP	0	0	0	0	12	54	12	1
Bridge 3 NP	0	0	0	0	8	33	8	2
Bridge 4 NP	30	0	0	0	20	54	50	1
Bridge 5 NP	0	0	0	6	0	79	6	1
Bridge 6 NP	0	0	0	0	6	28	6	3
Bridge 1 P	0	0	31	0	1	24	32	7
Bridge 2 P	0	0	3	45	0	54	48	2
Bridge 3 P	0	0	32	0	0	33	32	4
Bridge 4 P	60	0	20	20	0	54	100	2
Bridge 5 P	0	0	24	0	0	79	24	2
Bridge 6 P	12	2	4	6	0	28	24	8

Name	Max_Cost/Year *	Min_Cost/Year *	Avg_Cost *	Avg_100 *	Total_Cost *
Bridge 1 NP	2510.14	2333.99	2333.99	69.33	7001.96
Bridge 2 NP	1685.60	1685.60	1685.60	16.69	1685.60
Bridge 3 NP	1999.20	1999.20	1999.20	29.69	3998.40
Bridge 4 NP	2250.08	2250.08	2250.08	22.28	2250.08
Bridge 5 NP	1071.00	1071.00	1071.00	10.60	1071.00
Bridge 6 NP	1300.50	1300.50	1300.50	38.63	3901.50
Bridge 1 P	1491.40	279.28	802.76	55.64	5619.29
Bridge 2 P	1594.06	69.45	831.76	16.47	1663.52
Bridge 3 P	1069.30	36.72	700.82	27.76	2803.30
Bridge 4 P	1272.55	741.69	1007.12	19.94	2014.24
Bridge 5 P	-	-	-	-	-
Bridge 6 P	899.23	7.44	263.78	20.89	2110.25

* million Indonesian Rupiah (IDR).

Table 13 shows the correlation between bridge age, the number of segments, and maintenance frequency with the total LCC. The data indicate that as the age of the bridge increases, the total cost tends to decrease. Additionally, a greater number of segments is associated with a reduction in the total LCC. The influence of age may be attributed to the fact that as a bridge approaches its service life, the allocation for maintenance is likely to decrease. Additionally, the number of segments appears to affect the total cost, which may be due to the increasing detail in the location of damages, leading to more objective condition assessments. This, in turn, impacts the reduction in the maintenance area required.

Based on the analysis in Table 14, there is a significant difference in the total cost between the non-physical and physical methods. The total cost for the six non-physical bridges is 9% higher compared to the physical bridges. This indicates that optimization can be achieved by dividing segments into smaller parts, which may help in reducing the total life cycle cost. The difference in total costs between the non-physical and physical assessments may occur due to the varying levels of detail in the elements assessed by the two methods. As the segmentation becomes more detailed, the evaluations become more objective, resulting in a smaller treatment area that corresponds to the actual extent of the damage.

Table 13. Correlation matrix of factors affecting total LCC.

	Age	Segment	Maintenance	Max_Cost	Min_Cost	Avg_Cost	Avg_100	Total_Cost
Age	1.000							
Segment	0.161	1.000						
Crack	0.188	0.957						
Rebar	0.122	0.872						
Spalling	−0.499	−0.275						
Maintenance	−0.645	−0.052	1.000					
Max_Cost	−0.453	−0.049	−0.199	1.000				
Min_Cost	−0.131	−0.270	−0.502	0.787	1.000			
Avg_Cost	−0.250	−0.173	−0.455	0.916	0.960	1.000		
Avg_100	−0.803	−0.210	0.390	0.622	0.370	0.473	1.000	
Total_Cost	−0.819	−0.242	0.363	0.652	0.415	0.515	0.989	1.000

Table 14. Repair costs required for 100 years for bridges with non-physical and physical assessments.

Name	Max_Cost/Year *	Min_Cost/Year *	Avg_Cost *	Avg_100 *	Total_Cost *
Total NP (Bridge 1–6)	10,816.52	10,640.37	10,640.37	187.22	19,908.54
Total P (Bridge 1–6)	7627.03	2435.10	4906.74	179.33	18,112.09
Total NP–Total N	3189.49	8205.27	5733.63	7.89	1796.46
Total NP–Total N (%)	29%	77%	54%	4%	9%
Bridge 1 NP–P	1018.74	2054.70	1531.23	13.69	1382.68
Bridge 2 NP–P	91.54	1616.15	853.84	0.22	22.09
Bridge 3 NP–P	929.90	1962.48	1298.38	1.94	1195.10
Bridge 4 NP–P	977.53	1508.39	1242.96	2.34	235.84
Bridge 5 NP–P	1071.00	1071.00	1071.00	10.60	1071.00
Bridge 6 NP–P	401.27	1293.06	1036.72	17.74	1791.25
Average (Bridge 1–6)	748.33	1584.30	1172.36	7.75	949.66

* million Indonesian Rupiah (IDR).

Additionally, there are significant differences between the non-physical and physical methods in terms of maximum repair costs, which are 29% lower per year; minimal repair costs, which are 77% lower per year; and average repair costs, which are 54% lower. In this context, the physical model offers numerous advantages in cost optimization, including reductions in total life cycle cost, as well as maximum, minimum, and yearly average maintenance costs.

The average difference in repair costs between non-physical (NP) and physical (P) methods for the six bridges, as shown in Table 11, is as follows: the maximum LCC per year is IDR 748.33 million, the minimum LCC per year is IDR 1584.30 million, and the total cost is IDR 949.66 million. These values are substantial and have a significant impact on bridges younger than 50 years, as they are crucial for maintaining the bridges' condition to ensure they reach their intended service life effectively.

In some cases, age affects the outcomes of both the non-physical and physical models, where the analysis shows similar total life cycle costs, as seen with Bridge 2. This condition is likely due to the bridge being in its mid-service life, exceeding 50 years. As a result, the repair costs required for the bridge to reach its service life are not significantly high.

Similarly, a significant difference is observed with Bridge 4, where the non-physical assessment requires maintenance while the physical model does not. This discrepancy is likely due to the differing condition values between the two models. The non-physical assessment has a maximum condition value of "e", whereas the physical model has a maximum value of "c". This results in the non-physical assessment recommending maintenance, while the physical assessment considers the bridge to be still capable of functioning effectively until the end of its service life, thus not requiring maintenance.

5. Discussion

Based on the analysis of the relationship between non-physical and physical assessments, it is evident that there is a 77% similarity in the assessment patterns of the 13 concrete girder bridge damage images presented. This indicates that both assessment methods tend to evaluate concrete element damage similarly. However, 33% of the assessments show different patterns, suggesting the possibility of bias or error in either the non-physical or physical assessments. This can be attributed to the low objectivity in both types of assessments. In this study, the respondents are generally experienced bridge inspectors, which suggests that the damage images presented may have multiple interpretations, potentially leading to errors. Overall, it can be concluded that non-physical and physical assessments tend to follow similar evaluation patterns.

The assessments with multiple interpretations are particularly evident in the non-physical evaluations, especially for condition ratings of "1" and "2". These two ratings have a broad range of interpretations among inspectors in Indonesia, requiring bridge owners to closely scrutinize the condition assessments conducted by field inspectors. This also applies to the physical assessments, where there is a similarly broad range of interpretation for these condition ratings. However, statistically, it can be concluded that a rating of "1" tends to align with "c", while a rating of "2" tends to align with "d".

Conversely, in the physical assessments, the rating "c" has a broad range of interpretations, as it could shift to "b" or "d" depending on the inspector's perception. Due to this subjectivity and the potential for error in the rating range, the damage condition could be assessed as either better or worse than the actual field condition.

Between the non-physical and physical assessments, there are also instances of negative correlations, indicating a lack of a strong relationship between the two variables. This is evidenced by the minimal population of values within these negative correlations, suggesting that the relationships producing negative values do not have significant correlations.

A closer examination of the types of damage assessed reveals that cracks significantly contribute to the assessment errors made by bridge inspectors. Non-structural and structural cracks cannot be easily distinguished at a glance, even by an experienced inspector. Cracks in concrete appear similar visually, but technically, there are specific areas where high-stress concentrations lead to cracking. Additionally, cracks can result from corrosion of the reinforcing steel, causing the concrete to push outward and form distinct crack patterns. While shrinkage cracks on the concrete surface can generally be identified by their patterns, significant crack widths tend to lead inspectors to give worse condition ratings. Therefore, clearer criteria are needed to differentiate the severity of these types of damage, enabling inspectors to conduct condition assessments more objectively.

Errors in inspection results, according to the objectivity assessment study, range between 31% and 33%. This should be a point of concern for bridge managers, indicating the need for a larger sample size when validating bridge condition data in the future. This validation is crucial to anticipate assessment errors in bridge inspection reports, which can significantly impact the planning of bridge maintenance programs. To enhance the objectivity of condition assessments in the future, several measures can be implemented, including conducting regular training for bridge inspectors.

In the optimization of LCC calculations, an interesting finding emerged: several factors impact the total LCC of a bridge based on calculations performed using the iBMS software version 1.0.35 (with Visual Basic for Applications version 2.41). The analysis reveals that the age of a bridge affects the total LCC; specifically, as the bridge approaches the end of its service life, the costs required for preservation decrease. Moreover, the level of segment division correlates with a reduction in total life cycle costs, emphasizing that more detailed segment division can impact cost reduction. Also, the spalling damage in concrete has a positive contribution to the increase in total life cycle costs, indicating that spalling should be addressed promptly before it worsens.

Furthermore, the comparison results between the non-physical and physical assessments indicate a significant difference. The comparison of LCC results between each assessment indicates that a greater number of segments significantly impacts the reduction of total LCC. Specifically, the maximum LCC per year shows a 29% difference, the minimum LCC is 77% lower, and the average LCC per maintenance is reduced by 54%. These values suggest that dividing segments more extensively, as per the physical method, notably affects the LCC of a bridge. This is likely due to the more detailed condition assessment for a larger number of segments, resulting in a different deterioration model. Consequently, the non-physical assessment predicts a faster rate of condition decline (due to a worse condition assessment) compared to the physical model.

Additionally, it is noteworthy that the analysis reveals a larger discrepancy in total LCC values between non-physical and physical methods for bridges younger than 50 years compared to those older than 50 years. This condition is likely due to the fact that bridges under 50 years old may require more frequent preservation actions, whereas bridges approaching the end of their service life receive fewer maintenance interventions. This observation is logical, as bridges nearing their service life typically incur less frequent maintenance. Therefore, the physical method demonstrates more optimal results compared to the non-physical method, particularly for bridges younger than 50 years.

Based on the discussion above, there are several challenges to address in implementing HP-LCCA (High-Precision Life Cycle Cost Analysis) in Indonesia. These include the need for accurate data collection tailored to analysis requirements, with a greater segmentation of structural elements. This approach needs to be communicated to bridge inspectors in Indonesia to facilitate data integration for calculations. Additionally, ensuring the objectivity of condition assessments presents a challenge in providing more accurate and comprehensive data for LCC calculations.

6. Conclusions

The objective of the research conducted was to compare the non-physical and physical assessment methods by conducting a questionnaire survey among bridge inspectors. Correlation analysis was employed to determine the relationship between the two variables. Additionally, Life Cycle Cost (LCC) calculations were performed using the iBMS application to find the optimal values for both assessment methods.

Based on the research findings, it can be concluded that, in general, there is a similarity in the condition assessment patterns between the non-physical and physical methods. However, a small portion of the patterns remains insufficiently described due to the limitations of the available data. The strong correlation between condition assessments using both methods supports the conclusion that the non-physical method can be effectively employed for High-Precision Life Cycle Cost Analysis (HP-LCCA) using the iBMS application.

The comparison results between the non-physical and physical assessments indicate a significant difference. The physical method generally outperforms the non-physical method in Life Cycle Cost (LCC) calculations. The findings suggest that High-Precision Life Cycle Cost Analysis (HP-LCCA) can optimize the total cost required for bridge maintenance over its service life. This advantage is achieved through more detailed segmentation of structural elements, allowing for maintenance to be applied to smaller areas with varying condition predictions based on the condition state of each assessed element. Furthermore, the higher LCC associated with the non-physical method is primarily due to the application of maximum condition ratings, which contribute significantly to the overall cost.

Based on the research findings, several recommendations for implementing this application in Indonesia include the enhanced data detail to improve the detail of bridge inspection data, particularly at the individual structural element level. This enhancement can optimize the planning and scheduling of bridge preservation, helping to reduce the total repair cost according to the bridge's service life. Furthermore, the condition model needs to be updated by incorporating reference models, such as Indonesia's chloride zon-

ing, as a basis for future iBMS application development. These steps will contribute to more effective bridge management and cost optimization.

Author Contributions: Conceptualization, R.P.P.S. and N.S.; methodology, R.P.P.S. and N.S.; software, N.S. and T.K.; validation, R.P.P.S.; formal analysis, R.P.P.S. and T.K.; investigation, R.P.P.S.; resources, R.P.P.S.; data curation, R.P.P.S.; writing—original draft preparation, R.P.P.S.; writing—review and editing, R.P.P.S.; visualization, R.P.P.S.; supervision, N.S.; project administration, N.S.; funding acquisition, N.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data are contained within the article.

Acknowledgments: The authors would like to acknowledge the Generative AI tools used for grammar checking, as well as free resources such as Grammarly, Copilot, and ChatGPT 3.0, which were utilized in the preparation of this manuscript.

Conflicts of Interest: Author Tetsuro Kudo was employed by the company Oriental Consultants Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Abbreviations

AADT	Annual Average Daily Traffic
Avg_cost	Average LCC/maintenance
Avg_100	Average LCC/100-year maintenance
CS	Condition Score
FHWA	Federal Highway Administration
HP-LCCA	High-Precision Life Cycle Cost Analysis
iBMS	Intelligent Bridge Management System
LCC	Life Cycle Cost
LCCA	Life Cycle Cost Analysis
Max_cost	Maximum LCC
Min_cost	Minimum LCC
NP	non-physical
P	physical
Total_cost	Total LCC/bridge

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