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Life cycle assessment based environmental impact estimation model for pre-stressed concrete beam bridge in the early design phase

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ABSTRACT

The late rise in global concern for environmental issues such as global warming and air pollution is accentuating the need for environmental assessments in the construction industry. Promptly evaluating the environmental loads of the various design alternatives during the early stages of a construction project and adopting the most environmentally sustainable candidate is therefore of large importance. Yet, research on the early evaluation of a construction project's environmental load in order to aid the decision making process is hitherto lacking. In light of this dilemma, this study proposes a model for estimating the environmental load by employing only the most basic information accessible during the early design phases of a project for the pre-stressed concrete (PSC) beam bridge, the most common bridge structure. Firstly, a life cycle assessment (LCA) was conducted on the data from 99 bridges by integrating the bills of quantities (BOQ) with a life cycle inventory (LCI) database. The processed data was then utilized to construct a case based reasoning (CBR) model for estimating the environmental load. The accuracy of the estimation model was then validated using five test cases; the model's mean absolute error rates (MAER) for the total environmental load was calculated as 7.09%. Such test results were shown to be superior compared to those obtained from a multiple-regression based model and a slab area base-unit analysis model. Henceforth application of this model during the early stages of a project is expected to highly complement environmentally friendly designs and construction by facilitating the swift evaluation of the environmental load from multiple standpoints.

1. Introduction

The Paris Agreement of Conference of the Parties 21 (COP21) allotted all countries with a responsibility to reduce greenhouse gas emissions. Under this agreement, each country must decide on its Intended Nationally Determined Contributions (INDC), and report on updated goals for greenhouse gas reduction every 5 to 10 years (UNFCCC, 2016). In upholding the Paris Agreement, the Republic of Korea has set aims to reduce greenhouse gas emissions by 37% from business-as-usual (BAU) standards by 2030 (UNFCCC, 2015), and is taking actions to reduce emissions in each of its industries. In the Korean construction industry, efforts to minimize the environmental footprint has manifested in the Ministry of Land, Infrastructure and Transport's “Guide-line to Assessment of CO^2 Emission for Facilities” of 2011, for application in the detailed design phases of a construction project. This ministry is currently conducting various research in the subject matter.

In the construction industry, the processing, production and transportation of materials, along with the physical construction, gives rise not only to greenhouse gas emissions but also to a wide range of pollutants. These are hazardous to the environment and to humans, and have been causing many issues lately. For instance, asbestos had been widely used as building material, but is now banned due to reports of its toxicity to humans (Light and Wei, 1977). To this day, environmental problems have been caused during the process of deconstructing aged facilities containing asbestos. As can be seen in the example of asbestos, numerous materials used in construction can act as immediate and long lasting pollutants. Thus the need for an environmental assessment when undertaking a new construction project is evident. Hence, the Leadership in Energy and Environmental Design (LEED) v4 is advising the implementation of life cycle assessments (LCA) on construction materials in order to assess the environmental problems caused in construction (USGBC, 2010).

However, a comprehensive LCA on the entire construction business is lacking. This is due to the fact that unlike manufactured items, facilities of the exact same specifications may require different types and amounts of material and equipment inputs depending on its structure and surroundings, meaning that making an estimation on the environmental load of a structure with any significant degree of accuracy is

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very difficult. Much research is currently devoted to overcoming such difficulties and providing a means to measure or predict the environmental loads produced in construction projects. Some of these research analyze the characteristics of environmental loads unique to each type of bridge, using information from the detailed designs (Horvath and Hendrickson, 1998). Others directly measured pollutants emitted from construction equipments in order to quantify the environmental load produced in the construction phase (Ahn et al., 2013). Although much research effort is currently in the various phases of a construction project (Haapio and Viitaniemi, 2008; Jang et al., 2015; Park et al., 2016; Radhi and Sharples, 2013), those devoted to the early phases are relatively few.

As the project matures into the later phases, implementing alternatives become increasingly difficult, and the benefits of implementing alternatives dwindle. However, current LCA utilize at least semi-conclusive bills of quantity (BOQ) and construction cost data, which are only available after a basic design is completed, in order to reach an estimate on the environmental load. Thus, the current analyses are limited by the fact that an implementation of alternative designs, or parts of designs, cannot be accounted for. In order to reduce the environmental loads posed by construction projects, alternatives that take into account environmental factors must be decided on during the early phases (Díaz and Antón, 2014). If the environmental load can be taken into consideration in the early phases, the optimal design can be devised, leading to an environmentally economical design, and save the troubles of extra cost and schedule delays that would result from change orders in the construction phase.

This study targets the pre-stressed concrete (PSC) beam bridge, which is the most prevalently applied road facility, to present a method of quantifying the environmental load using limited amount of information available in the early design phases. The result of this study is expected to be of great pragmatic assistance in environmentally-friendly construction in the future, by aiding the decision of alternatives in the early design phases of a project.

2. Reviews of current literature

The construction projects usually take significant time and cost large amounts. Therefore, the decisions made in the early stages of a construction project have large effect. Fig. 1 displays the influences that have an effect on the success of a project and the expenditures required to implement changes (Gibson et al., 1995). As can be seen in the figure, the earlier into the pre-project planning phase a change is made, the larger its influence and the lower the expenditures. That is, alternative designs considered during the early design phases may have significant effects on the later stages of the project in many regards.

Despite the advantages adopting alternatives as early as possible, most existing LCA are conducted after the completion of the design phases by employing the information available from the completed design to reach a calculation. Current LCA can be categorized into those that adopt the input-output model (I-O model) to analyze energy inputs (Treloar et al., 2001; Sharrard et al., 2008; Rowley et al., 2009; Jeong et al., 2015) and those that utilize the BOQ and a life cycle inventory database (LCI DB) constructed beforehand to conduct an LCA (Cho et al., 2017; Park et al., 2016; Surawong and Soralumn, 2014; Islam et al., 2015). The former method of analysis, which provides an estimate of the environmental load based on the energy usage and the cost of a similar project using an I-O model, is simpler than the latter which employs the LCI DB. However, as the former method relies on regional and temporal economic activity data, it lacks in accuracy when considering the characteristics unique to each project. Also, while the latter methodology produces relatively accurate estimations of the environmental load by making comparisons of the actual material input of a project with a verified LCI DB.

Horvath and Hendrickson (1998) applied an input–output-based LCA method to compare the environmental loads, emissions, and characteristics thereof, for the steel bridge and steel reinforced concrete bridge. Dequidt (2012) discussed the methods of applying LCA to bridges using the LCI DB, and analyzed the characteristics of the environmental loads projected by the post-tensioned concrete box-girder bridge. Hammervold et al. (2013) presents a detailed comparative environmental life cycle assessment (LCA) case study of three built bridges- a steel box girder bridge, a concrete box girder bridge, and a wooden arch bridge- in Norway. In this research, a program named "BridgeLCA" (RAMBOLL, 2012) was used, which conducted an LCA by synchronizing the quantity of material input with the LCI DB provided by Ecoinvent (2015). Lee et al. (2017) estimated the environmental load using the LCI database and calculated the construction cost and period by using the standards of estimate and price information. Based on this data, this study proposed a selection method for paving work equipment combination considering the construction cost, construction period and environment load simultaneously. Lim et al. (2016) presented a method for calculating the daily and cumulative amount of carbon emissions for each and every activity based on the resources (i.e., material, equipment, and labor) on activities obtained from Primavera P6.

Completed research discussed above uses data from detailed designs as the input to estimate the environmental load as the output, through a rather complex calculation process. The reason that LCA research was

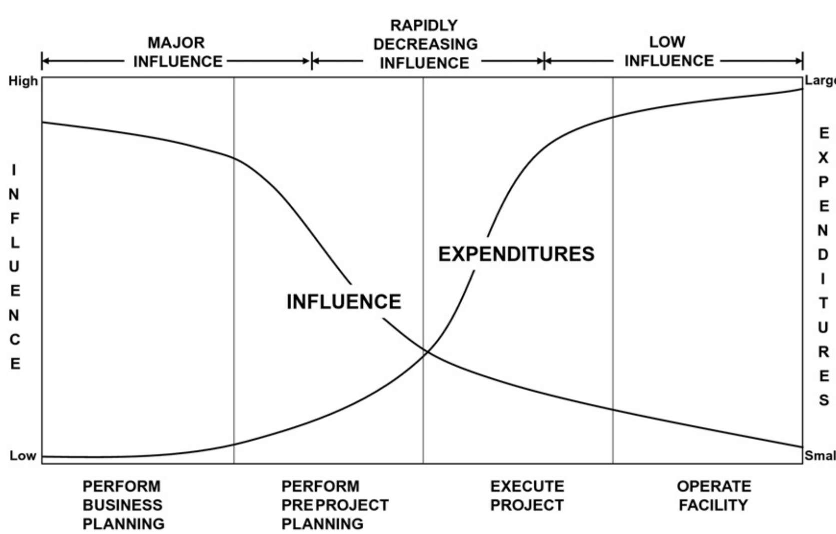

Fig. 1. Influence and expenditures curve for project life cycle (Gibson et al., 1995, pp. 312).

carried out at this detailed design phase stems from the innate differences between the manufacturing industry, which LCA is primarily utilized for, and the construction industry. That is, in the manufacturing industry, the main focus for LCA is on the final product, thereby allowing a thorough analysis to be complete before production begins. On the other hand, in the construction industry, each project's designing, manufacturing, and construction processes are executed independently, so assessments must be made on the process-level. Furthermore, structures with the same specifications may be built using different inputs, obligating the individual assessment of each project.

Due to such distinctiveness of the construction industry, research to estimate the environmental load in the early design phases and to reflect the identified environmental issues on the design has been conducted. Nam et al. (2011) has conducted research on quantifying the environmental benefits, during the feasibility study of the railroad project, based on a base-unit analysis index of air pollutants. Choi et al. (2012) presented a method of estimating the environmental load using base-unit analysis on the material input, in order to predict CO^2 emissions. Also, Lee et al. (2012) presented a method of estimating CO^2 emissions in high speed railroad construction through analysis of emissions in each work type and average base-unit analysis. Although the research so far mentioned offer handy methods of estimating the environmental load using base-unit environmental load indices, they fall short in acknowledging the distinctiveness of each case. Therefore, estimations made with such methodologies are inherent with large rates of error when applied to structures with different specifications.

To overcome such limitations, Jeong et al. (2015) has conducted research on estimating the environmental loads of educational facilities during the project planning stages. This research adopts an advanced case-based reasoning (A-CBR) model to compute energy consumption and building material quantities (direct cost), and conducts input-output (I-O) LCA based on the results of the computation. An advantage of this method is that it enables a more detailed, phase-by-phase LCA analysis. However, it is disadvantaged by the fact that the system user is required to directly employ the results of the CBR analysis to personally conduct the complex process of a LCA.

Thus, this study aims to compute the environmental load through LCA prior to applying a CBR model, and, compose a model for estimating the environmental load produced in the production of materials and in the actual construction based on the results of the earlier computation. In other words, the model in this study was built such that BOQs from completed designs were linked with the LCI DB, LCA were conducted using this linked data frame, and the data from these previous cases were used to estimate the environmental load of a new case. The advantages of this method include a higher degree of accuracy in the LCA expected from future augmentations of the LCI DB, and its real-life applicability in utilizing only the typical design variables of a structure to estimate the structure's environmental load with comparative ease.

3. Material and methods

This study was executed using the process shown in Fig. 2. The goal of this study was to estimate the environmental impact of a PSC beam bridge in the early design phases. In achieving this goal, this study first constructed a database of environmental loads of PSC beam bridges using the LCA methodology. The LCA methodology adhered to in this study is an application of the LCA methodology as per ISO 14040. This study linked the detailed design-phase data, such as the design report and the BOQ, of each bridge with the LCI database to compute the environmental load of each bridge. Secondly, a model for estimating the environmental load of a new case was constructed using CBR based on the database established in the prior phase. Lastly, based on the data from five new cases that were selected for the testing of the model constructed in this study, this study compared and analyzed the CBR, multiple regression, and base-unit analysis models.

3.1. LCA

The LCA process, as per ISO 14040, applied in this study can be seen in Fig. 3. The goal & scope definition phase aims to set the targets for the LCA and the range for analysis. In the inventory analysis phase, this study link the LCI DB with the BOQ items, and in the impact analysis phase, this study calculates the environmental load of the target installation.

3.1.1. Goal & scope definition

The objective of this study is to develop a model for estimating the environmental load of a PSC beam bridge during the early design stages. The cases selected for the case base were Korean road construction projects installed between 2001 and 2015, and to minimize the distinctiveness of the cases, this study consulted five different city councils - Seoul, Busan, Daejon, Wonju, and Iksan - for data on 99 actual projects. In this

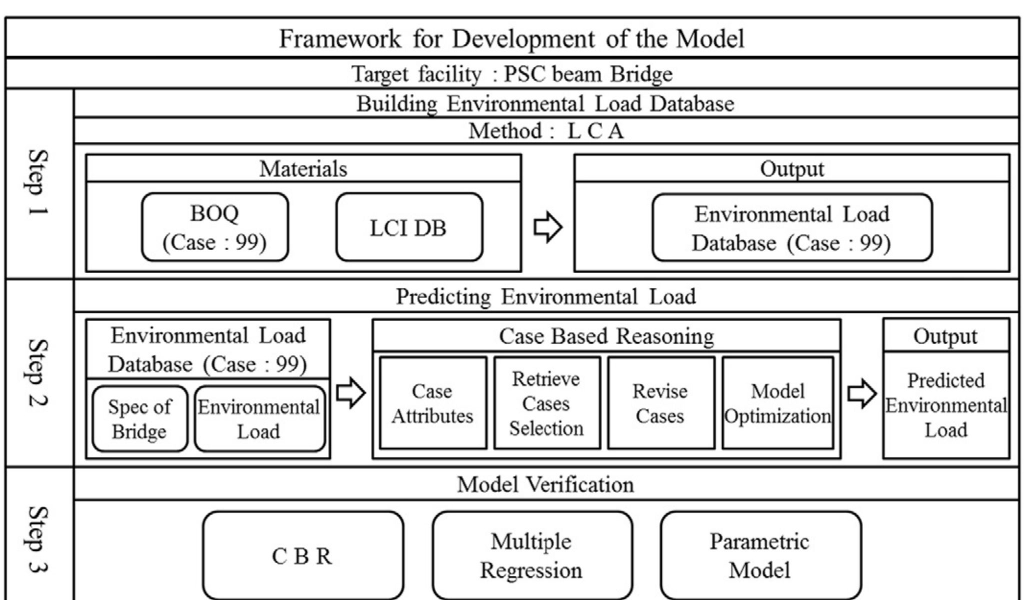

Fig. 2. Framework for estimate environmental load of PSC beam bridge.

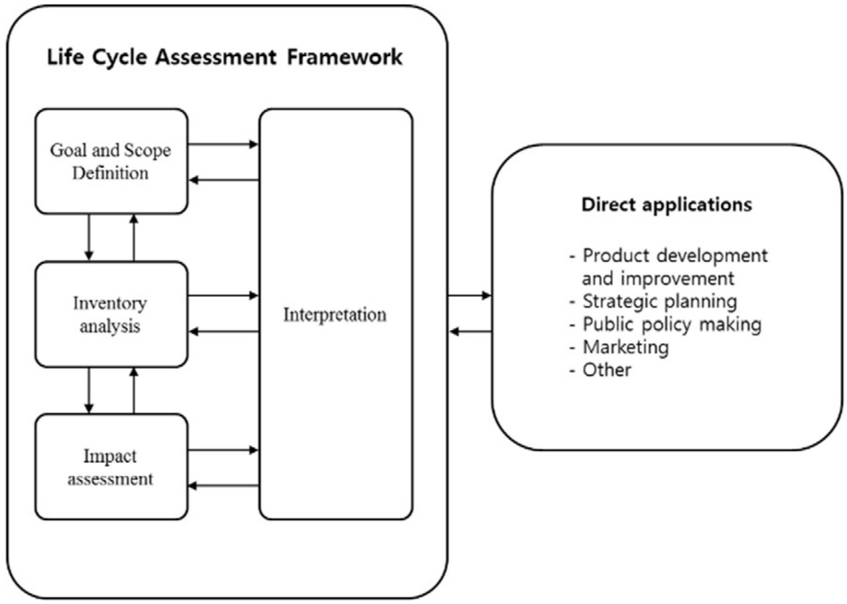

Fig. 3. Stages of an LCA (ISO, 2006, pp. 8).

study, the environmental load was computed for each case by linking the BOQ with the LCI DB. The energy used in the construction of the bridge was also calculated based on the BOQ. The installations examined in this study were bridges used for national highways, and the data from the maintenance stage was excluded. In short, the range of LCA considered in this study was the manufacturing and construction phases, and analysis of the construction phase was limited to the material input and equipment used.

3.1.2. Inventory analysis

The LCI analysis is carried out to determine the quantities of materials used in all construction activities and of fuel and engine oil for heavy machinery during the construction process (Li et al., 2010). To calculate the environmental load emitted during the life cycle of roads, the so-called LCI database of energy should be developed in each phase. This database provides individual gate-to-gate, cradle-to-gate and cradle-to grave accounting of the energy and material flows into and out of the environment that are associated with producing a material, component, or assembly in each country (NREL, 2012). In this study, the amount of input-resources (material, energy unit) is derived through the detailed analysis on the BOQ of a facility and then, the LCA based environmental load is calculated by linking the quantity of the input resources with the LCI DB considering the main purpose of each resource. The Korea Environmental Industry & Technological Institute (KEITI) manages the Korea LCI database information network that includes 416 LCI DB's according to ISO 14044 (KEITI, 2015). Thus, the majority of the inventory analysis was performed with this database, and any missing data was obtained by utilizing the LCI DB from the

Table 1
Connection list between LCI DB and resource inventory (Cho et al., 2016).

National LCI DB category	Unit	Materials	Unit	National LCI DB category	Unit	Materials	Unit
Wire Rod	kg	PC Strand	kg	Stainless Steel	kg	Stainless Pipe	m
		Wire Rope	kg			Stainless Round Bar	kg
		Welding Rod	kg			Stainless Steel Sheet	kg
		Bolt/Nail/Nut	kg			Welding Rod (Stainless)	kg
			set			Stainless Steel Sections	kg
		Steel Wire	kg	Remicon	m^3	All Type of Remicon	m^3
		Binding Wire	kg	25-240-15		Concrete Products	EA
		Ring	kg			(Hume Pipe, PC Block, etc.)	m^2
Electric Steel Sections	kg	Steel Sections	M/T	HDPE Film	kg	Grid	m^2
		Steel Pipe	m	Electric Steel Deformed Bars	kg	All Type of Rebar	kg
		Round Bar	ton	Electricity	kwh	Electricity	kwh
		Steel Rod	M/T	Portland Cement_type 1	kg	Cement	ea
		Channels	m				kg
		Sheet Piles	m	Oxygen, O2	ton	Oxygen	L
		scaffold pipes	m				bt
		Metal Cramp	kg	Epoxy Adhesive	kg	All types of Adhesive	kg
		Angles	kg	Hot Rolled Steel Coil	ton	Hot Rolled Steel	ton
		Wide Flange Beams	M/T	Steel Plates	ton	Flat Steel, Steel Plates	kg
		Steel Pipe Piles	m				ton
EPS	kg	Pattern Mold	m^2	PVC	kg	PVC Pipes	m
		Styrofoam	m^2	Aluminum Strip	kg	Aluminum Sheet	kg
Paint_Urethane Type	ton	Sealant	kg			Aluminum Powder	kg
Asphalt	kg	Blown Asphalt	kg			Aluminum Alloyed Casting	kg
		Asphalt Primer	kg	Carbon Steel	kg	Carbon Steel	kg
Diesel	kg	Diesel	L			Carbon Steel Castings	kg
Gasoline	kg	Gasoline	L			Carbon Steel Pipes	m

Table 2
Environmental load ratio for materials (unit: %).

Material item		Cost ratio	E-load ratio
Major	Remicon	26.57	56.09
	Steel	32.27	8.23
	Wire rod	3.99	7.48
	Cement	2.11	6.06
Sub-Total (1)		**64.94**	**77.85**
Minor	Plywood	5.12	5.30
	PET	0.6	4.51
	Diesel	6.06	3.84
	Section Steel	15.53	3.39
Sub-Total (2)		**27.32**	**17.04**
Total (1) + (2)		**92.25**	**94.90**

Korean Institute of Civil Engineering and Building Technology (KICT, 2015) and Ecoinvent (Ecoinvent, 2015). For instance, a wire rod is specified as its main usage for such as "manufacturing screws, nails, barbed wire, welded wire mesh, special screws, nuts, tire cords and precision machinery" in the national LCI DB. As a result, it was applied not only to pre-stressed concrete steel strand (PC strand) and steel wire but also to bolt and nail. Table 1 shows the linkage between LCI DB and materials applied in this study.

At this point, a cut-off standard exists because the LCI DBs do not encompass data on all items in the construction BOQ. The "CO^2 emission estimation guideline (Ministry of Land, Infrastructure and Transport, 2011)" lists the cut-off level as 90% of the total cost. In the case that an item for which a CO^2 emission estimate cannot be made takes up >10% of the total material cost, the ministry lists the cut-off level as 80% excluding said item. However, this study employs a cut-off level of an item as 65% of the total construction cost of the bridge. The reasoning for this, as can be seen in Table 2, is that analysis of the case base has revealed that in the construction of PSC beam bridges, items that accounted for 65% of the total cost produced 78% of the total environmental load. Due to the characteristics of the construction business, ready-mixed-concrete accounts for the vast majority of the total environmental load of the bridge, and taking into account all the major material inputs, one can assume that it encompasses the greater part of the total environmental load (Cho et al., 2016). But the incompleteness of this approach dictates the need for the revision and expansion of the existing LCI DB in the future in order to derive more persistent and accurate environmental load data.

3.1.3. Impact assessment

The impact assessment phase takes into account the environmental impact categories to deduce the environmental load. After the environmental load for each item is entered in the inventory analysis phase, one can compute the total environmental load for a case project. The main purpose of this study is to predict and compare the total environmental load of the design alternatives for facilities quickly and roughly with a small amount of input data at the early stages of a project. Therefore, the proposed model enables the estimation of the total environmental load of a facility. In addition, the model was constructed to calculate the environmental load on each of eight environmental impact categories according to the user's needs. To support this, this study computed the environmental load in eight categories: abiotic resources depletion (ARD), acidification (AD), eutrophication (EU), global warming (GW), ozone depletion (OD), photochemical oxidant creation (POC), terrestrial eco-toxicity (TET), and human toxicity (HT). Then, to compare the environmental impact among design alternatives of a facility, the units of the environmental load were standardized into eco-point units by applying the Korea eco-indicator provided by the Korean Ministry of Environment (Lee, 1999; Heo et al., 2000). The normalization factors and weight factors applied in the standardization of units are tabulated in Table 3. In other words, the environmental loads for each of the eight categories were weighted and are summed up as a single index (eco-point) and the total environmental loads of the design alternatives are compared and evaluated.

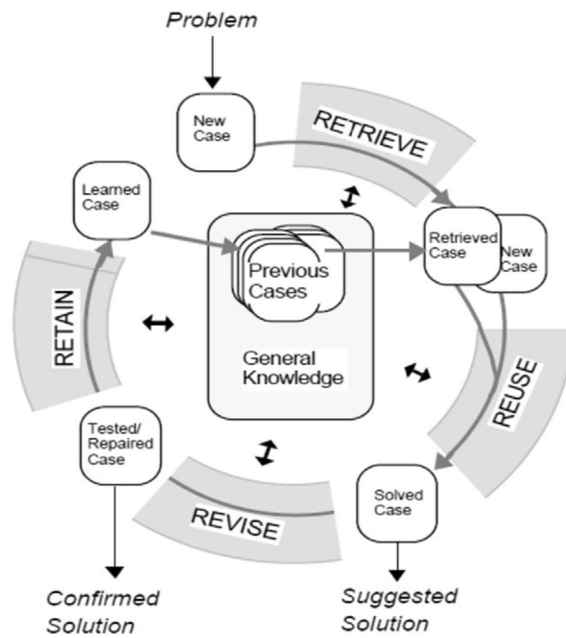

Fig. 4. The CBR cycle (Aamodt and Plaza, 1994, pp. 7).

3.2. Case-based reasoning

This study employs case-based reasoning (CBR) to construct a model for computing the projected environmental load, based on data from the LCA, in the early stages of designing. As opposed to the existing artificial intelligence (AI) technique, CBR utilizes the specific knowledge of previously experienced, concrete problem situations (cases) to solve the given problem. Compared to the parametric methodology which has typically been used as a predictive model in the planning and designing phases, CBR produces more precise results (Duverlie and Castelain, 1999), and has a higher applicability than other statistical analysis algorithms (Kim et al., 2004).

Fig. 4 depicts the CBR process used and the model that resulted in this study. The CBR model gives an estimation based on the case base. When a new "subject" case is input for predictive analysis, the "retrieval" stage is executed, in which the subject case's features are identified and searched for in the case base, and an initial match case is selected. Following is the "reuse" stage, during which the original solution is copied and modified to present a draft solution. In the "revision" stage, the

Table 3
Environmental impact categories.

Impact category	ARD	AD	EU	GW	OD	POC	TET	HT
Unit	1/yr	kg SO_2-eq	kg PO_{43}-eq	kg CO_2-eq	kg CFC_{11}-eq	kg C_2H_4-eq	kg 1,4 DCB eq	kg 1,4 DCB eq
Normalization factor	24.9	39.8	13.1	5530	0.0407	10.3	1.63	1480
Weight factor	0.231	0.036	0.038	0.288	0.292	0.065	0.216	0.105
Converted unit	Eco-point	Eco-point	Eco-point	Eco-point	Eco-point	Eco-point	Eco-point	Eco-point

Table 4
Attributes characteristics.

Features	Number of span	Span length	Total bridge length	Width	On land/over water	Number of lane	Foundation type
Data type	discrete (integer)	discrete (integer)	continuous	continuous	discrete (string)	discrete (integer)	discrete (string)

draft solution presented is evaluated and its faults are repaired into a confirmed solution, and information on the estimations made by the model are proposed to the user. In the final "retention" phase, the information is normalized and its indices are adjusted for later use, thereby continually increasing the model's reliability.

To improve the prediction accuracy of the CBR model, it is important select an "weight factors" for each attribute for the selection of relevant cases. Numerous methods, such as the analytic hierarchy process (AHP), fuzzy, genetic algorithm (GA), and neural network, have been applied in research for the selection of appropriate attribute weight factors for use in the CBR model (Morcous et al., 2002; Chua and Loh, 2006; An et al., 2007). This research adopts the GA approach, which has been previously applied in cost prediction models of PSC beam bridges (Kim and Kim, 2010), to select appropriate attribute weight factors. GA is a nonlinear heuristic method that draws on the evolutionary principle (Goldberg, 1989). It performs a learning exercise on the attribute weight factors, tailored for the characteristics of the database, to improve the accuracy of the predictions made by the CBR model, and has been tested in numerous past research as a learning tool for the attribute weight factor (Hong et al., 2011; Ji et al., 2012).

3.3. Data collection and case attribute

As detailed in Section 3.1, the data employed in this study is acquired from reports of PSC beam bridges whose detailed designs are already established and analyzed using the LCA approach. Data was harvested from a total of 99 existing bridges. From these 99 cases, five were used for training the CBR model, and five others were used to test the model. Thus, the case base comprised of data from 89 cases.

A conceptual design is prepared in the planning and feasibility study. For instance, available data to estimate the construction duration are very limited (Kim et al., 2016). This study aims to enable the estimation of the environmental load using the variables available in the early design stages of a project. Therefore, all the information accessible in the respective stage of the project was gathered by analyzing the case in design and consulting domain engineers. The variables applied in this study are detailed in Table 4. The number of spans, span length, total bridge length, width, whether on land or over water, number of lanes, and foundation type were identified as seven variables applicable in the former phase.

In order to understand the characteristics of the data from the LCA of the 99 cases, a correlation analysis was carried out. Table 5 below displays the results of the correlation analysis between the seven case attributes and the total environmental load as the dependent variable. The results indicate that the biggest factors of the total environmental load were the total bridge length and the number of spans. Analysis indicates that this is due to the characteristics of a bridge, in which the length of the bridge is one of the largest factors. Furthermore, the total bridge length, the number of spans, the width of bridge, and the number of lanes were the independent variables that displayed the highest correlation between each other. In a typical PSC beam bridge, a span can take on a length of 25 m or 30 m or 35 m, meaning that a longer bridge may require a different number of spans, so the difference that exists between the total bridge length and the number of spans in logically inevitable. Also, the width of the bridge and the number of lanes on the bridge were treated as separate variables due to the fact that various road factors such as forks and variations in road width holding different information about the bridge.

4. Case-based reasoning model

4.1. Retrieve cases selection

The case-retrieval selection phase is one in which cases similar to a new "subject case" are selected from the case base. In selecting cases from case-base similar to the subject case, the similarity scoring method can be classified into a binary similarity scoring (BSS) method and the continuous similarity scoring (CSS) method. The BSS method applies an optimal minimum similarity criterion (%) to discard the cases that did not reach a certain level of similarity. The CSS method uses the similarity score as it is. Numerical variables with order (i.e., number of span, total bridge length and width) can utilize both methods. With the BSS method, a similarity score of 100 is assigned if the deviation (refer to Eq. (1)) between the existing case and the new is less than the criterion (%), and 0 is assigned otherwise, as can be seen in Eq. (2). With the CSS method, a similarity score is assigned from 0 to 100 based on the similarity between the cases as in Eq. (3). However, in the case of four variables (i.e., span length, on land or over water, number of lines, and foundation type), categorical and discrete variables with no order, a similarity score is assigned if the inputs of the two cases match exactly, and no score is assigned otherwise.

$$Deviation(\%) = \left|\frac{Previous\ Case\ Value - New\ Case\ Value}{New\ Case\ Value}\right| \times 100 \quad (1)$$

$$\text{BSC} : Similarity\ Scores\ in\ figure = \begin{cases} deviation\ \leq criterion(\%) \rightarrow 100 \\ deviation\ > criterion(\%) \rightarrow 0 \end{cases} \quad (2)$$

$$\text{CSC} : Similarity\ Scores\ in\ figure = \begin{cases} deviation\ \leq 100(\%) \rightarrow 100 - deviation \\ deviation\ > 100(\%) \rightarrow 0 \end{cases} \quad (3)$$

Table 5
Correlations between the attributes and the total environmental load.

Attributes	Total environmental load	Number of span	Span length	Total bridge length	Width	On land or over water	Number of lane	Foundation type
Total environmental load	1							
Number of span	0.946[a]	1						
Span length	0.359[a]	0.274[a]	1					
Total bridge length	0.957[a]	0.995[a]	0.348[a]	1				
Width	0.249[b]	0.088	0.109	0.092	1			
On land or over water	−0.435[a]	−0.404[a]	−0.239[b]	−0.415[a]	−0.195	1		
Number of lane	0.249[b]	0.075	0.049	0.076	0.969[a]	−0.187	1	
Foundation type	0.358[a]	0.421[a]	0.180	0.413[a]	0.075	−0.292[a]	0.045	1

[a] Correlation is significant at the 0.01 level (2-tailed).
[b] Correlation is significant at the 0.05 level (2-tailed).

Table 6
Training case characteristics.

Case	Number of span	Span length (m)	Total bridge length (m)	Width (m)	On land or over water	Number of line	Foundation type
A	7	35	245	20.9	On water	4	Mixed
B	2	30	61.5	18.4	On water	4	Shallow
C	3	35	105	21.4	On water	4	Mixed
D	4	35	140	21.4	On water	4	Mixed
E	1	30	30	21.7	On land	4	Pile

Table 8
Test case Characteristics.

Case	Number of span	Span length (m)	Total bridge length (m)	Width (m)	On land or over water	Number of line	Foundation type
TC1	3	35	105	20.9	On water	4	Mixed
TC2	4	35	140	20.9	On water	4	Pile
TC3	11	35	385	20.9	On water	4	Mixed
TC4	7	30	210	20.9	On water	4	Mixed
TC5	1	30	30.3	20.9	On land	4	Pile

4.2. Case revision

In the case revision phase, the case selected and retrieved in the former phase is tailored to best resemble the subject case. Analysis has revealed that a bridge's length is the variable that has the largest impact on the bridge's environmental load. This is because, due to its structural characteristics, a bridge comprises mostly of its longitudinal length. Also, a bridge's width affects the width of the slabs and the foundation of the bridge. This study has therefore chosen to conform the retrieved case to the dimensions of the similar case by adjusting the slab area of the retrieved case by the ratio between the two. Eq. (4) below represents the method used to adjust the environmental load of the retrieved case to match the data for the subject case.

$$E_i = \sum_{i}^{n} (R_i \times C_i) \tag{4}$$

E_i: estimated environmental load of the subject case from retrieved case *i*.

C_i: environmental load of the retrieved case *i* with higher similarity score.

R_i: slab area ratio of the subject case to the retrieved case *i* (%).

In order to make the most similar case of the cases retrieved have the largest effect on the final environmental load calculated, this study assigned a relative "case weight" to each case according to their similarity rank. The case weight was calculated as can been seen in Eq. (5), by applying a weighted average.

$$W_i = \frac{S_i}{\sum_{i=1}^{n} S_i} \tag{5}$$

W_i: case weight of retrieved case *i*.

S_i: case similarity of retrieved case *i*.

n: number of cases retrieved.

To estimate the environmental load of the subject case, the case weight of each similar case was summed, as per Eq. (6). Hence, the total environmental load of the subject case was calculated as a weighted average of all the environmental loads of the similar cases retrieved.

$$\mathrm{F} = \sum_{i}^{n} (W_i \times E_i) \tag{6}$$

F: environmental load of the subject case.

4.3. Providing prediction result

In addition to estimating total environmental loads of a facility, in order to conduct an LCA on each specific contamination factor, the partial environmental load pertaining to each of the eight environmental impact categories needs to be calculated. Therefore, this study subdivided the total environmental load according to the relative weight of each environmental category. Eqs. (7) and (8) below represent the process used to calculate the environmental load of each of the eight environmental impact categories. Firstly, utilizing the data from the retrieved cases, the ratios of each of the eight partial environmental loads to the total environmental load are computed. Then each of these ratios is multiplied to the total environmental load of the subject case to derive an estimation of the partial environmental loads.

$$L_j = F \times ER_j \tag{7}$$

$$ER_j = \frac{\sum_{i=1}^{n} k_i}{\sum_{i=1}^{n} E_i} \tag{8}$$

j: each of the eight environmental impact categories.

k: environmental load of the retrived case *i* pertaining to each of the eight environmental impact categories.

L_j: estimated partial environmental load of subject case pertaining to environmental impact category j.

4.4. Model optimization

With the purpose of adjusting the weights of attributes for the most accurate estimation of the environmental load, this study performed optimization. The GA was applied for optimization due to its suitability in interpreting nonlinear models, and the total environmental load was defined as an objective function. The reason for the latter is twofold. Firstly, defining the total environmental load as a single objective function is more efficient than constructing a model for each partial environmental load. Secondly, as estimations on the eight partial environmental loads are drawn from cases deemed similar to the subject case, a high degree of accuracy is expected. Five cases that were deemed the most representative of the case base were selected to train the model, as can be seen in Table 6. The GA model training was conducted in such a way that the mean absolute error rates (MAER) between the estimated and the actual total environmental load was minimized.

The MAER of the optimized training cases came out to 5.33%. The calculated weights of each attribute are listed in Table 7. The attributes that played the largest roles were width (0.23), whether on land or over water (0.20), number of lane (0.18), number of Span (0.18), and total bridge length (0.10), in order.

5. Test result of the proposed model

Five cases (Test Case; TC) were selected to verify the CBR model. For the objective testing, the selection was made so that a diverse range of case-specific characteristics was reflected, as can be observed in Table 8. The first priority was length of bridge because it is most important

Table 7
Weights of attributes of the optimized training cases.

Attribute	Number of span	Span length (m)	Total bridge length (m)	Width (m)	On land or over water	Number of line	Foundation type	Sum
Weight	0.1762	0.0817	0.1015	0.2323	0.1958	0.1785	0.0340	1.0000

Table 9
Test result (%).

Case	(1)ARD	(2)AD	(3)EU	(4)GW	(5)OD	(6)POC	(7)TET	(8)HT	Total
TC1	4.27	6.38	−2.80	11.31	−20.26	0.57	−13.21	−19.67	4.77
TC2	−0.91	−11.44	16.54	−2.28	−20.19	−1.23	12.03	−17.97	−2.54
TC3	−10.36	−21.98	−7.28	−19.36	−15.63	−9.77	29.39	−11.20	−14.56
TC4	6.88	−3.33	−14.29	9.54	−3.47	10.76	18.66	2.24	7.86
TC5	26.36	−2.73	3.07	−4.68	3.18	−6.13	6.47	3.48	5.73
MAER	9.76	9.17	8.79	9.43	12.54	5.69	15.95	10.91	7.09

factor for the bridge structure. Next was the span length because it determines the type of girder and pier, and lastly the foundation type because Pile foundations need more materials than direct piles. However, most of long bridges use piles and only a few solely use direct foundations; therefore, mixed and pile foundations were chosen.

The results of testing the CBR model applied in this study are as seen in Table 9. These results indicate that the MAER for the total environmental load is 7.09%, with an error range of −14.56% ~ 7.86%. Although no standards yet exist for the estimation of environmental loads, the American Association of Cost Engineers (AACE) standards for cost estimation are −20% ~ 30% (refer to Table 10). With the latter mind, the estimation of the total environmental load produced in our model fit within the standards for cost estimation, and the model can thus be considered to have adequate reliability. In considering the errors pertaining to the eight environmental impact categories, some cases display high rates of error, seen in test case 3's (TC3) TET 29.39%, TC5's ARD 26.36%, and TC3's AD 21.98%. However, the estimation for the environmental loads fall within the error bounds, and the model is therefore deemed suitable for application.

6. Model comparison and discussion

For the purpose of verifying the advantages of the model constructed in this study, this study compared the results obtained against methodologies currently in use for the estimation of environmental loads - base-unit analysis and regression analysis. A base-unit analysis and regression analysis was conducted on each of the five test cases used earlier, and the resulting estimates for the total environmental loads were compared with those achieved using our CBR model.

6.1. Base-unit analysis

Base-unit analysis adopts the basic functional units of a bridge to estimate the environmental load. In this study, the length and the slab area of a bridge were utilized to build a base-unit analysis model. Data from 94 cases, excluding the five test cases, was used for the selection of appropriate base units.

Eqs. (9) and (10) are used to estimate an environmental load based on the slab area of a bridge. The environmental load per unit slab area for bridge i (EAi) can be calculated by dividing bridge i's total environmental load by bridge i's total slab area. This method is applied to each of the 94 bridges and a sum of EAi is computed, then divided by the total number of cases (n) to produce a comprehensive average of the environmental load per unit slab area (EAT). Using this EAT, an estimate of the environmental load for the subject case can be calculated.

$$EA_i = \frac{E_{Act\ i}}{A_i} \tag{9}$$

$$EA_T = \sum_{i=0}^{n} \frac{EA_i}{n} \tag{10}$$

$E_{Act\ i}$: environmental load of bridge i.
A_i: slab area of bridge i (m^2).
EA_i: environmental load per unit slab area for bridge i.
EA_T: base-unit environmental load per unit slab area.

Estimation of the environmental load of a bridge using the bridge length is accomplished as per Eqs. (11) and (12), similarly to the aforementioned "per slab area" calculation.

$$EL_i = \frac{E_{Act\ i}}{L_i} \tag{11}$$

$$EL_T = \sum_{i=0}^{n} \frac{EL_i}{n} \tag{12}$$

$E_{Act\ i}$: environmental load of bridge i.
L_i: bridge length of bridge i (m).
EL_i: environmental load per unit bridge length for bridge i.
EL_T: base-unit environmental load per unit bridge length.

6.2. Multiple regression analysis

For a multiple regression (MR) analysis, the same seven case attributes variables used in CBR were utilized. Two variables (i.e., on land/over water, foundation type) were substituted for dummy variables to apply to the regression equation. As a result, the significance of both variables was low, hence they were excluded, and the regression model

Table 10
AACE cost variation (Christensen and Dysert, 2005).

Estimate class	Primary characteristic	Secondary characteristic		
	Maturity level of project definition deliverablesExpressed as % of complete definition	End usage Typical purpose of estimate	Methodology Typical estimating method	Expected accuracy rangeTypical variation in low and high ranges
Class 5	0% to 2%	Concept screening	Capacity factored, parametric models, judgment, or analogy	L: −20% to −50% H: +30% to +100%
Class 4	1% to 15%	Study or feasibility	Equipment factored or parametric models	L: −15% to −30% H: +20% to +50%
Class 3	10% to 40%	Budget authorization or control	Semi-detailed unit costs with assembly level line items	L: −10% to −20% H: +10% to +30%
Class 2	30% to 75%	Control or bid/tender	Detailed unit cost with forced detailed take-off	L: −5% to −15% H: +5% to +20%
Class 1	65% to 100%	Check estimate or bid/tender	Detailed unit cost with detailed take-off	L: −3% to −10% H: +3% to +15%

Table 11
Comparison of similarity scoring method.

Similarity range (criterion, %)	Selection rank	(1) Binary similarity scoring		Similarity range (Criterion, %)	Selection rank	(2) Continuous similarity scoring	
		MAER	Standard deviation			MAER	Standard deviation
10	3	10.37%	9.78%	Max. 100%	3	9.12%	12.49%
	5	9.37%	8.56%				
15	3	11.12%	11.10%		**5**	**10.92%**	**11.76%**
	5	**7.09%**	**5.51%**				
20	3	11/87.	14.36%		7	14.72%	11.97%
	5	12.63%	10.56%				

was applied using only five variables. The data from the same 94 cases, excluding the five test cases, were employed. Results of MR analysis reveal a R^2 value of 0.947 for the model, implying a high fit. The following Eq. (13) represents the multiple-regression analysis used in this study.

$$EY = -68.363\,x_{ns} - 1.581\,x_{sl} + 4.527\,x_{tl} - 5.549\,x_w + 72.348\,x_{nl} - 56.051 \quad (13)$$

EY = Environmental load estimated using regression equation.
x_{ns}: number of span.
x_{sl}: span length.
x_{tl}: total length.
x_w: width.
x_{nl}: number of line.

6.3. Model comparison

In this study, to determine the similarity scoring method which is advantageous in terms of accuracy of the CBR model, sensitivity analysis was performed by setting the range of the minimum similarity criterion (range 10%, 15%, 20%) and selection rank of similar case (range 3, 5, 7) by the two methodologies presented above. The results are shown in Table 11.

(1) In the BSS method, the case where the minimum similarity criterion is within 15% and the selection rank is 5 has a low prediction error rate (about 7%) and a good standard deviation (about 5%). (2) In the CSS method, the case with the selection rank 5 has a low prediction error rate (about 10%) and a good standard deviation (about 11%), but the accuracy of the model is lower than the BSS method. In other words, if the continuous similarity score is applied, it was judged that cases with the low degree of similarity could be selected as a similar case. As a result, this study applied the BSS method.

CBR model has more complex analysis steps than that of other conventional models. However, those steps are processed internally in a system. Users don't need to care about the internal steps. The processing time in practice is almost zero. In the aspect of the number of input data, the base-unit model uses one, the MR model needs five, and the CBR model has seven. The CBR model needs more input variables than other conventional models. There is, however, little difference in processing the input variables because users can prepare the input data intuitively at the early phase of a project. On the other hand, the CBR model has advantages for application in terms of diversity, and accuracy as compared with the conventional models. The CBR model enables to make detailed analysis for each of the eight categories using the ratio of occupation of the environmental loads on the similar cases. MR is not capable of such a function.

In order to identify the accuracy of the CBR model constructed, a comparison of the results from the CBR model, the multiple-regression analysis model, and the base-unit analysis model are tabulated below (refer to Table 12). The average error of the CBR model, as stated earlier in Section 6.2, was calculated as 7.09%. This means that the CBR model produces more accurate estimations than the MR (10.71% average error), unit-slab area (25.15%), and the unit total length models (24.02%). Furthermore, the minimum and maximum estimation errors of the CBR model were −14.56% and 7.86% respectively, which translates to a practical applicability (class3 ~ class2) with the AACE standards in mind. However, the maximum error from the base-unit analysis was 47.95%, meaning that the results are unacceptable for practical application. Considering the MR analysis, the error bounds were computed as −17.03% ~ 16.18% (only class3), which translates to practical applicability, but still fall short of the accuracy of the CBR model.

Table 12
Model comparison.

Case	(1) CBR	(2) Multiple regression	(3) Unit	
			(3–1) Slab area	(3–2) Total length
TC1	4.77	16.18	30.22	28.49
TC2	−2.54	0.95	19.55	17.96
TC3	−14.56	−17.03	7.61	6.18
TC4	7.86	7.66	47.95	45.98
TC5	5.73	11.65	−20.43	−21.49
MAER	7.09	10.71	25.15	24.02

7. Conclusion

In this study, a CBR model has been constructed for estimating the environmental load posed by a PSC beam bridge by utilizing only the information available in the early design stages, such as the bridge's length, the number of lanes on the bridge, and width. A database has been established using LCA on BOQ's from existing bridges, and, based on this database, a CBR model that takes into account the eight environmental impact categories to produce an estimate of the environmental load has been constructed. The CBR model was then validated using five test-cases, and the MAER was calculated as 7.09%. The MAER pertaining to each of the eight impact categories were ARD 9.76%, AD 9.17%, EU 8.79%, GW 9.43%, OD, 12.54%, POC 5.69%, TET 15.95%, and HT 10.91%. Furthermore, to validate the advantages of the CBR model established in this study, the results were compared to those obtained from multiple regression and base-unit analyses. The results of the comparison showed that the 7.09% MAER of the CBR model was lower than 10.71% of the multiple regression analysis and 25.15% of the base-unit analysis on span area. Thus, the CBR model showcased a higher degree of accuracy on the estimations that it made.

If, in the future, a project planner or an engineer adopts this model during the early stages of a project, the model will enable the user to promptly estimate the environmental load; such a foresight is expected to facilitate the engineer in devising the most environmentally optimal design. In addition, this study plans to augment the model for application to a wider variety road structures, including other bridge types with the goal of developing an all-inclusive decision making system for comparing design alternatives of multiple types of structures considering various environmental loads.

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