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DATA ENVELOPMENT ANALYSIS FOR EFFICIENCY MEASUREMENT OF BRIDGE RESILIENCE

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Abstract. The resilience of a bridge is computed using different quantitative and qualitative assessment methodologies. However, the resilience score obtained by these assessment approaches is insufficient for the decision-makers for setting a priority level for bridges in need of resilience improvement. To address this issue, the present study develops a methodology using the data envelopment analysis (DEA) approach. A total of 12 bridges are selected as the decision-making units in the DEA model. This study considers the variables such as age, area, design high flood level, and finish road level of the bridge as inputs, and bridge resilience index as the output variable. Based on these variables, three frameworks are developed to compute the efficiency of bridge resilience. A variable return to scale with the output-oriented formulation of DEA is selected to compute the efficiency of bridge resilience in all three frameworks. Thus, the proposed methodology enables bridge owners to set a priority level for bridges in need of resilience improvement based on the scores of the assessment methodology.

Keywords: bridge, data envelopment analysis, efficiency, prioritise, resilience, sensitivity analysis.

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Introduction

Bridges form an integral part of the ground transportation infrastructure. They minimize travel costs by providing the transportation amenities across inaccessible terrains, high-altitude areas, above the water bodies, and traffic intersections. Thus, bridges integrate the social and economic aspects of any nation. Over the past few decades, several bridges around the globe have suffered different levels of dysfunctionality due to earthquakes, floods, cyclones, and tsunamis (Banerjee et al., 2019). Although such dysfunctionality does not always result in immediate collapse, time-based deterioration over a period of time may lead to bridge collapse. Thus, the natural disasters and time-based deterioration have drawn a good deal of attention of the bridge engineering and management community toward working on the concept of improvement of resilience (Giunta, 2017; Nezhad et al., 2022). Bridge resilience can be defined as a bridge ability to maintain its functionality, social, and economic value against the disaster; and to plan the recovery activities to regain its original functionality, social, and economic values within the shortest time (Patel et al., 2020). Extensive research has been carried out by researchers and professionals on the concept of bridge resilience (Banerjee et al., 2019). As a consequence, a resilience matrix or a single-measure index is developed to determine the priority level for improvement of resilience of different bridges. Bocchini & Frangopol (2012a,b) and Karamlou & Bocchini (2014, 2016) introduced a framework to evaluate the resilience of damaged bridges on highway networks. Further, Karamlou & Bocchini (2015) proposed a simulation-based methodology to improve the accuracy of evaluation of resilience and life-cycle assessment of highway bridges. Decò et al. (2013) illustrated a methodology for evaluating the probabilistic resilience of bridges against multiple hazards. Biondini et al. (2015), Dong & Frangopol (2015, 2016), Zheng et al. (2018), and Vishwanath & Banerjee (2019) presented a framework to evaluate the life-cycle resilience of a corroded reinforced-concrete bridge under seismic conditions. Ikpong & Bagchi (2015) and Stevens & Tuchscherer (2020) developed an index to evaluate bridge resilience against climate-change-related extreme events using weight factors. Domaneschi & Martinelli (2016) presented a framework using a decision-making process to evaluate the resilience of cable-stayed bridges. Andrić & Lu (2017) used a fuzzy logic application to predict the seismic resilience of multiple bridges. Minaie & Moon (2017) proposed an approach using historic and heuristic data to evaluate the resilience of bridges. Patel et al. (2020) developed an index using multi-criteria-decision-making techniques to compute the resilience of bridges against floods. Ghasemi & Lee (2021) proposed an instantaneous bridge resilience metric by combining the robustness and structural redundancy measures.

Thus, the above-mentioned literature discusses various quantitative or qualitative approaches that have been developed to evaluate the resilience of multiple bridges. However, three questions remain unanswered in regard to prioritising resilience improvement of different bridges based on these quantitative or qualitative approaches: (1) whether prioritising resilience improvement of different bridges using indices and measure-matrix is an effective means of improving bridge resilience index (BRI) score, (2) whether some alternative method using a similar approach of prioritising can be developed; and (3) how the new method compares with the existing method of prioritising resilience improvement of different bridges. Addressing these questions is essential, especially while setting the priority level for bridges having the same resilience index or a single measure-matrix score. Therefore, this study aims at developing a methodology that addresses the aforementioned unresolved issues.

To this effect, the present study applies the data envelopment analysis (DEA) method. In Section 1, the reason behind utilizing DEA and an overview of different methodologies, applications, and approaches used within this methodology are discussed. Section 2 demonstrates the formulation of the research methodology. Section 3 presents the data collection. Section 4 discusses the results. Validation and sensitivity analysis of the study are performed in Section 5 and conclusions drawn from this study are presented in Section 6.

1. Data envelopment analysis (DEA)

DEA was first introduced by Charnes et al. (1978), and it is an extension of Farrell's (1957) work on efficiency measures. Farrell (1957) described an efficiency measure as the ratio of single output to single input, and Charnes et al. (1978) explored the efficiency measure of a multiple outputs-to-multiple inputs case. Since then, DEA has undergone extensive development as an efficiency measurement technique (Emrouznejad, 2018). The basic principle of DEA is to assess efficient frontiers that can be employed to improve the performance of organisation/peer units (Ozbek et al., 2009; Zhu, 2104, 2015). These organisation/peer units are called decision-making units (DMUs) in DEA. Therefore, efficient DMUs obtained from the multiple DMUs create an efficient frontier. DMUs with an efficiency score equal to 1 are called efficient DMUs. In contrast, DMUs with an efficiency score between 0 and 1 (i.e., $0 \leq$ efficiency score < 1) are inefficient DMUs. However, an efficient frontier incorporates the given input and output data. Further, the efficiency measure quantifies the distance to the efficient frontier in one way or another. The efficient frontier DMUs act as a benchmark or peer for the other DMUs (Ozbek et al., 2009).

For evaluating these efficient frontier DMUs, the DEA model is generally classified into two formulations: (1) CRS, also known as the CCR model (Charnes et al., 1978), and (2) VRS, also known as the BCC model (Banker et al., 1984). In the CRS formulation, the proportional change to the output variable is the same as in the input variable. However, in the VRS formulation, a proportional change in the output variable is not the same as in the input variable (Ozbek et al., 2009; Zhu, 2015). Moreover, Ozbek et al. (2009) and Zhu (2015) express two types of orientations in the DEA model: (1) input-orientation and (2) output-orientation, and it lies on the evaluator to choose the orientation of the model. An input-oriented model evaluates the necessary reduction to input variables when the output variables remain constant. In contrast, an output-oriented model evaluates the necessary increment to output variables when the input variable remains constant. Therefore, if the evaluator is more flexible with changing the input, then the input-oriented models should be selected or vice versa. Ozbek et al. (2009) and Vyas & Jha (2017) presented the advantages and limitations of using DEA. The main advantages are as follows: (1) DEA allows for the efficient use of multiple input and output variables, (2) the weights of inputs and outputs are not required, and (3) the efficiency compares the best operating organisation/peer units rather than evaluating average performance. The main limitation of DEA is that the standard formulation of DEA formulates a different linear program for each DMU. Therefore, the evaluation process is extensive when the number of DMUs is large. However, this limitation can be overcome by enhancing the utility of the software used to develop and run the DEA model.

DEA is a widely used technique for efficiency measurement in research areas such as healthcare, agriculture, food processing, and selection of new technologies, among others (Ozbek et al., 2009; Zhu, 2104). Some studies (Wang et al., 2008; Ozbek et al., 2010; Wakchaure & Jha, 2011) have applied DEA in the bridge engineering and management domain. Wang et al. (2008) used DEA along with the analytical hierarchy process and proposed a methodology to assess the bridge risk and decide the priority level for maintenance. Ozbek et al. (2010) applied DEA to measure the efficiency of several bridges in Virginia counties that need maintenance. Wakchaure & Jha (2011) presented a method using the DEA, which would help to select those bridges in need of maintenance management and to enhance the efficiency of the bridge management system. Therefore, all these studies showcase the implementation of the

DEA concept in bridge engineering and management domains, such as bridge risk assessment and maintenance management. Further, a review of the above-mentioned studies indicates that researchers, professionals, and managers have used DEA as a decision-making tool in the bridge engineering and management domain. Therefore, the current study utilises DEA in prioritising resiliency improvement of different bridges based on the resilience score.

2. Research methodology

To achieve the study objective, a research methodology is developed and illustrated in this section. The research methodology is accomplished in four steps, as shown in Figure 1. These four steps are briefly described as follows.

2.1. Step 1: Determination of the decision-making units

The DMUs are compared to each other to ensure similar operating conditions. Two things that influence the selection of DMUs are homogeneity and the number of DMUs (Ozbek et al., 2009). In this regard, a homogeneous set of units (DMUs) should perform the same task under the same geographic conditions and have a similar objective. Therefore, the present study selects 12 bridges as DMUs. All bridges are homogeneous in nature because they operate under the same geographic conditions. These bridges are built across the river Tapi in Surat city (Gujarat state) in India. They connect two almost equal parts of Surat city and are maintained by SMC (SMC, 2022). These 12 bridges also perform a common task of channelizing the traffic and helping communities cross the river easily.

A large number of DMUs should be selected to facilitate the identification of efficient and inefficient DMUs. The number of DMUs should be higher than the product of the number of input and output variables (Tyagi et al., 2009). In short, as mentioned in the previous paragraph, 12 bridges are selected as DMUs for this study followed by the identification of input and output variables for DEA.

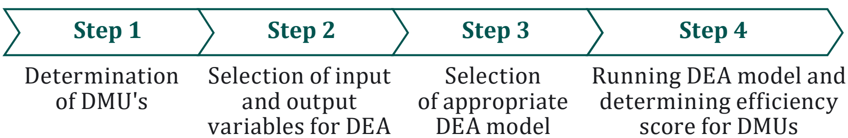

Figure 1. Research Methodology

2.2. Step 2: Selection of input and output variables for DEA

The selection of input and output variables influences the performance of DMUs (Ozbek et al., 2009). Either a quantitative or a qualitative approach is used to screen input and output variables as it helps to reduce the number of inputs and outputs to a practical level. In this regard, variables like age, area, design high flood level (HFL), finish road level (FRL), and resilience score of the bridge are selected for this study. The reason for their selection is the easy availability of the information. However, there are several other variables that are not

Table 1. List of excluded variables

Sr. No.	Excluded variable for this study	Reason/Remark for exclusion
1	Load-carrying capacity	Lack of information
2	Deterioration rate	Lack of information
3	Corrosion rate	Lack of information
4	Scouring	Lack of information
5	Accessible to material and equipment	Already used in the evaluation of bridge resilience score*
6	Availability of backup contractor	Already used in the evaluation of bridge resilience score*
7	Diversion length	Already used in the evaluation of bridge resilience score*
8	Availability/Arrangement of funds	Already used in the evaluation of bridge resilience score*
9	Planning and Scheduling	Already used in the evaluation of bridge resilience score*
10	Inspection techniques	Already used in the evaluation of bridge resilience score*
11	Restoration time	Already used in the evaluation of bridge resilience score*
12	Disaster preparedness	Already used in the evaluation of bridge resilience score*
13	Area and region affected	Already used in the evaluation of bridge resilience score*
14	Tendering	Already used in the evaluation of bridge resilience score*
15	Emergency response management	Already used in the evaluation of bridge resilience score*
16	Traffic volume	Already used in the evaluation of bridge resilience score*
17	Severity of hazard	Already used in the evaluation of bridge resilience score*
18	Bridge condition	Already used in the evaluation of bridge resilience score*
19	Restoration cost	Already used in the evaluation of bridge resilience score*
21	Political condition	Not possible to quantify
22	Life cycle cost	Lack of information

Note: *Bridge resilience score is taken from Patel et al. (2020)

considered for this study, and the reason for their exclusion is shown in Table 1.

Thus, the age, area, design HFL, and FRL are considered as the input variables. However, these input variables do not satisfy the isotonicity principle of DEA because an increase in the age of bridge can reduce BRI score (Dong & Frangopol, 2016). Similarly, a decrease in the area of bridge due to dysfunction or maintenance work can reduce BRI score. Also, if the high flood level increases and comes parallel to the design HFL or FRL, the bridge might be closed for the traffic, affecting the bridge resilience score. However, according to Tanassoulis (2001), Ozbek et al. (2010), and Wakchaure & Jha (2011) such variables could be used either by deducting from large values, taking the inverse, or treating them as the output variables. Therefore, this study uses inverse values of the bridge age, area, design HFL, and FRL as the input variables for the final evaluation process in DEA. The BRI score is considered as the output variable and obtained via the methodology developed by Patel et al. (2020). However, for this study, it is assumed that a bridge attains an excellent BRI after the evaluation, so the corresponding BRI is taken as 1. In this study, the change in the overall BRI is measured by subtracting the actual BRI obtained via Patel et al. (2020) methodology from 1. The change in the overall bridge resilience in terms of BRI is used as an output variable for the final evaluation process in DEA.

Further, Tyagi et al. (2009) assert that if there are multiple input or output variables, then they should be divided into different frameworks to achieve better results and perceptions from the DEA model. In this connection, the selected input variables in the present study are first divided into two frameworks. In Framework 1, the age and area of bridge, which represent the bridge general characteristics, are considered input variables. In Framework 2, the remaining two input variables, design HLF and FRL of bridge, representing the bridge hydraulic design characteristics, are considered. Bridge BRI score is considered the output variable in both frameworks. Therefore, the diversification of input variables into the two aforementioned frameworks can help in easily building perceptions of the efficiency and effectiveness of the resilience score against the two different characteristics of the bridge. Moreover, it can also provide the relationship between different characteristics and bridge resilience. There is one more framework, that is, Framework 3, which considers all these four input variables (age, area, design HFL, and FRL of the bridge) in order to achieve a comprehensive analysis and obtain the efficiency of BRI. Framework 3 also considers the BRI score of the bridge as the output variable. Figure 2 represents the input and output variables selected in the three frameworks.

2.3. Step 3: Selection of DEA model

As discussed in the previous section, two different formulations (CRS and VRS) and two types of orientations (input-oriented and output-oriented) are available in DEA models. The choice of formulation and orientation depends on the objective of the study. In this study, the output variable (BRI) does not increase or decrease in proportion with an increase in input variables (age, area, design HFL, and FRL of the bridge). Patel et al. (2020) have mentioned that the BRI of the bridge (the output variable in this study) can be improved with regular maintenance, proper coordination with the owner of other infrastructure, and considering other criteria. In this regard, the input variables have a non-constant return to scale with respect to the BRI scores. Therefore, the present study selects the VRS with an output-oriented BCC formulation. The formulation is then applied to all the three frameworks proposed in Step 3. Equations (1) to (5) express the mathematical form of the VRS output-oriented BCC formulation (Banker et al., 1984; Zhu, 2014).

$$\phi^* = \max \phi \qquad \text{subjected to} \tag{1}$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} \le x_{i0} \qquad i = 1, 2, 3, \ldots, m; \tag{2}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} = \phi\, y_{r0} \qquad r = 1, 2, 3, \ldots, s; \tag{3}$$

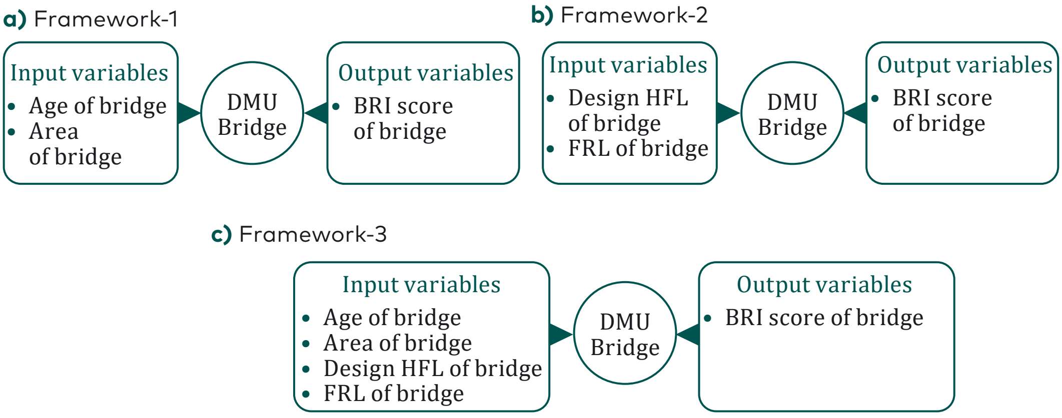

Figure 2. Input and output variables for DEA

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{4}$$

$$\lambda_j \geq 0 \qquad j = 1, 2, 3, \ldots, n \tag{5}$$

where ϕ^* = efficiency for j^{th} DMU; j = number of DMUs in the data set; y_{rj} = number of outputs for j^{th} DMU; x_{ij} = number of inputs for j^{th} DMU; λ_j = peers for j^{th} DMU.

A computer program known as DEAP version 2.1 is utilized to efficiently and quickly resolve these aforementioned linear programming problems. A detailed illustration of DEAP 2.1 is given in the next step.

2.4. Step 4: Running DEA model and determining efficiency scores for DMUs

DEAP 2.1 was developed by Tim Coelli using a freeware program FORTRAN (programming language) (Coelli, 1996). This computer program uses four methods to evaluate the efficiency score: (1) standard CRS formulation, (2) standard VRS formulation, (3) cost-DEA method, and (4) Malmquist DEA method. CRS formulation evaluates technical efficiency, whereas VRS evaluates pure technical efficiency. The cost-DEA method is the extension of both the CRS and VRS methods, which evaluates cost-efficiency. The Malmquist DEA method requires panel data to evaluate the total factor productivity change, technological change, technical efficiency change, and scale efficiency change. Further, these four methods involve either input- or output-orientation formulation. Out of these four methods, the cost-DEA method and Malmquist DEA method are not applicable for this study because no cost and panel-related data are available as the input or output variables. However, as mentioned in Step 3, the study has already preferred VRS with output-oriented formulation to CRS and input-orientation formulation.

Further, there are three options available in this DEAP 2.1: (1) one-stage DEA model, (2) two-stage DEA model, and (3) multi-stage DEA model (Coelli, 1996). These three options are regarding the treatment of slacks. The slacks represent a substantial numerical value of inefficiency for the inefficient DMUs and are often introduced after the radial efficiency score improvement (Morita et al., 2005). However, Coelli (1996) suggests using the multi-stage DEA model rather than the remaining two options to identify efficient projected points with mixed inputs and outputs. With regard to this statement, the current study uses the multi-stage DEA model option.

3. Data collection

The DEAP 2.1 accepts variables in text format (Coelli, 1996). The variable sheet is shown in Table 2. Out of these selected variables, data of the BRI scores (output variable) were considered from the study of Patel et al. (2020). Further, the values of the age, area, design HFL, and FRL of bridges (input variables) were obtained from the SMC website (SMC, 2022). Then, the values of these variables were discussed with engineers working at the bridge cell department of SMC. These engineers are involved in constructing, repairing, and maintaining bridges in Surat city. The discussion with engineers was conducted on phone using an open-ended, unstructured questionnaire. The reason for preferring telephonic interviews over personal face-to-face interviews was the COVID-19 situation. In this questionnaire, five questions were asked to validate the data available from the website. These five questions were as follows. (1) What is the year of bridge construction? (2) What is the length of bridge? (3) What is the carriage-way width of bridge? (4) What is the design HFL of bridge? (5) What is the FRL of bridge? Herein, the age of bridges was measured from the year the bridge was constructed up to 2019. The year of construction was made available by the bridge

Table 2. Details of input and output variables

DMU	Age, years	Inverse of age[a]	Area, m^2	Inverse of area[a]	Design HFL, m	Inverse of design HFL[a]	FRL, m	Inverse of FRL[a]	BRI score	Change in resilience in terms of BRI[b]
DMU 1	18	0.0556	8169	0.000122	15	0.0667	19.66	0.0509	0.60	0.40
DMU 2	7	0.1429	10575	0.000095	16.51	0.0606	22.08	0.0453	0.65	0.35
DMU 3	37	0.0270	4251	0.000235	15	0.0667	20.58	0.0486	0.52	0.48
DMU 4	8	0.1250	4914	0.000204	16.25	0.0615	21.05	0.0475	0.69	0.31
DMU 5	7	0.1429	16136	0.000062	15.75	0.0635	20.66	0.0484	0.61	0.39
DMU 6	2	0.5000	15750	0.000063	15.56	0.0643	20.26	0.0494	0.71	0.29
DMU 7	43	0.0233	4043	0.000247	11.52	0.0868	15.71	0.0637	0.53	0.47
DMU 8	23	0.0435	9375	0.000107	13.90	0.0719	10.08	0.0992	0.64	0.36
DMU 9	2	0.5000	5697	0.000176	12	0.0833	16.36	0.0611	0.69	0.31
DMU 10	27	0.0370	10500	0.000095	11.40	0.0877	16.50	0.0606	0.58	0.42
DMU 11	1	1.0000	5792	0.000173	12	0.0833	16.36	0.0611	0.69	0.31
DMU 12	1	1.0000	13773	0.000073	9.2	0.1087	15.50	0.0645	0.62	0.38

Note: [a]Input variable; [b]Output variable for DEA model owner. The reason for calculating the age of bridge until the year 2019 was the BRI scores were evaluated by Patel et al. (2020) in the year 2019. The variable area of bridge is considered to be the product of the bridge length and carriageway width. As mentioned in Step 2 of the research methodology section, the inverse of input variables and change in BRI are evaluated and shown in Table 2. Thus, these inverse input variables and BRI change are considered for the final computation process in DEAP 2.1.

4. Result and discussion

As mentioned in Sections 2.3 and 2.4, a VRS output-oriented BCC formulation and a computer program DEAP 2.1 are used to evaluate efficiency scores. The outcome of the model is obtained and depicted in Tables 3–5 for Frameworks 1, 2, and 3, respectively. These three tables represent the DMUs (bridges) with their efficiency scores and peers (benchmarking). The DMUs whose scores are equal to 1 are termed efficient DMUs and the rest – inefficient. Further, the peers obtained in outcomes indicate efficient DMUs with their corresponding weights (presented in bracket). For example, DMUs 3 and 10 appear as peers to DMU 1 (Table 3). The corresponding peer weights of DMUs 3 and 10 to DMU 1 are 0.193 and 0.807, respectively. These efficiency scores and peers are then used to rank DMUs. The obtained ranks in the first, second, and third frameworks are depicted in the last column of Tables 3, 4, and 5, respectively.

Thus, the results of Framework 1 (Table 3) indicate that DMUs 3, 5, 7, and 10 have an efficiency score equal to 1, so they are designated as efficient DMUs. These four DMUs show better efficiency against the variable age and area of bridge. Then, as mentioned previously, peers, along with their corresponding weights, are used to rank the efficient DMUs. Therefore, out of four efficient DMUs, DMU 10 is referred as a peer by eight other DMUs. These DMUs are DMUs 1, 2, 4, 6, 8, 9, 11, and 12 with their corresponding peer weight 0.807, 1.000, 0.221, 0.030, 0.914, 0.421, 0.443, and 0.667, respectively (refer to column 3 of Table 3). The summation of DMU 10 peer weights (i.e., 0.807 + 1.000 + 0.221 + 0.030 + 0.914 + 0.421 + 0.443 + 0.667) is 4.503. Thus, DMU 10 is ranked as the first DMU based on the summation of the peer weight. Similarly, the ranking of the remaining efficient DMUs is also carried out. Herein, if two DMUs are efficient and referred to by the same number of DMUs as peers, then the DMU, which has a larger value after the summation of peer weights, should be given a better rank. Further, the result of Framework 1 also indicates that eight DMUs are inefficient as their efficiency score is not equal to 1. These eight DMUs are DMU 1, DMU 2, DMU 4, DMU 6, DMU 8, DMU 9, DMU 11, and DMU 12. To rank these inefficient DMUs, efficiency scores are used. In this regard, the efficiency score of DMUs 1, 2, 3, 4, 6, 8, 9, 11, and 12 are 0.927, 0.833, 0.664, 0.742, 0.847, 0.682, 0.684, and 0.950, respectively (column 2 of Table 3). Based on these efficiency scores, DMUs 1, 2, 3, 4, 6, 8, 9, 11, and 12 are ranked fifth, eighth, twelfth, ninth, seventh, eleventh, tenth, and sixth, respectively. Furthermore, the mean and standard deviation of the efficiency score for all the DMUs in Framework 1 are 0.861 and 0.137, respectively.

Similarly, results for Frameworks 2 and 3 are interpreted and presented in Tables 4 and 5, respectively. However, in Framework 2 (Table 4), the inefficient DMUs 9 and 11 have the same efficiency score. Moreover, DMUs 9 and 11 have the same BRI score (Table 2). Therefore, in this case, DMUs 9 and 11 are given the eleventh rank (column 3 of Table 4). The mean and standard deviation of efficiency scores for all the DMUs in Framework 2 are 0.837 and 0.135, respectively. Further, in Framework 3 (Table 5), DMUs 1 and 7 are found efficient, but still, they are not referred to by any other DMUs. In this case, the BRI score (Table 2) is considered for ranking DMUs 1 and 7, where the BRI of DMU 1 is 0.600, so it is ranked sixth. In contrast, the BRI of DMU 7 is 0.530, so it is ranked fifth. Thus, the DMU with the smaller BRI should be given priority. The mean and standard deviation of the efficiency score for all the DMUs in Framework 3 are 0.908 and 0.133, respectively.

Overall, it is observed that DMU 3 is common in all three frameworks as an efficient DMU. Furthermore, DMUs 3, 5, 7, and 10 are proven efficient in Frameworks 1 and 3 but not in Framework 2. DMU 2 is found efficient in Frameworks 2 and 3 and inefficient in Framework 1. Furthermore, the results of the five DMUs, DMUs 4, 6, 9, 11, and 12, prove them to be inefficient DMUs in all three frameworks.

So far, the results obtained in all three frameworks from the DEA model are presented. Further, z-values of the efficiency scores are evaluated to establish the efficiency/inefficiency of different DMUs and accordingly prioritise DMUs to enhance their BRI score. The z-value is generally known as the z-score or standard score and is used to describe the distance of the raw score from its mean when measured in the standard deviation unit (McLeod, 2019). Therefore, the z-value of Frameworks 1 and 2 (Tables 3 and 4) are computed and compared with Framework 3 (Table 5) efficiency scores. The reason for computing z-values for only Frameworks 1 and 2 is that the input variables of both frameworks represent different characteristics of the bridge. At the same time, Framework 3 assumes all four variables as the input

Table 3. Result of DEA for Framework 1

DMU	Efficiency score	Peers/ Benchmarking	Rank
DMU 1	0.927	3 (0.193), 10 (0.807)	5
DMU 2	0.833	10 (1.000)	8
DMU 3	1.000	3	2
DMU 4	0.664	3 (0.779), 10 (0.221)	12
DMU 5	1.000	5	3
DMU 6	0.742	10 (0.030), 5 (0.970)	9
DMU 7	1.000	7	4
DMU 8	0.847	3 (0.086), 10 (0.914)	7
DMU 9	0.682	3 (0.579), 10 (0.421)	11
DMU 10	1.000	10	1
DMU 11	0.684	3 (0.557), 10 (0.443)	10
DMU 12	0.950	10 (0.333), 5 (0.667)	6

Table 4. Results of DEA for Framework 2

DMU	Efficiency score	Peers/ Benchmarking	Rank
DMU 1	0.833	3 (1)	7
DMU 2	1.000	2	2
DMU 3	1.000	3	1
DMU 4	0.834	2 (0.833), 3 (0.167)	6
DMU 5	0.992	2 (0.667), 3 (0.333)	3
DMU 6	0.699	2 (0.500), 3 (0.500)	10
DMU 7	0.979	3 (1.000)	4
DMU 8	0.750	3 (1.000)	9
DMU 9	0.646	3 (1.000)	11
DMU 10	0.875	3 (1.000)	5
DMU 11	0.646	3 (1.000)	11
DMU 12	0.792	3 (1.000)	8

Table 5. Results of DEA for Framework 3

DMU	Efficiency score	Peers/ Benchmarking	Rank
DMU 1	1.000	1	6
DMU 2	1.000	2	4
DMU 3	1.000	3	3
DMU 4	0.834	3 (0.167), 2 (0.833)	9
DMU 5	1.000	5	2
DMU 6	0.742	10 (0.030), 5 (0.970)	10
DMU 7	1.000	7	5
DMU 8	1.000	8	7
DMU 9	0.682	10 (0.421), 3 (0.579)	12
DMU 10	1.000	10	1
DMU 11	0.684	10 (0.443), 3 (0.557)	11
DMU 12	0.950	10 (0.333), 5 (0.667)	8

variables. Equation (6) presents the mathematical formulation of evaluating the z-value (McLeod, 2019).

$$A = \frac{X_{ni} - \mu_i}{\sigma_i}, \tag{6}$$

where A = z-value; x_{ni} = n^{th} efficiency score of i^{th} framework; μ_i = mean of i^{th} framework; σ_i = standard deviation of i^{th} framework.

Based on Equation (6), the z-values for Frameworks 1 and 2 are evaluated. The efficiency score of DMU 1 in Framework 1 is found to be 0.927 (Table 3), while the mean and standard deviation for Framework 1are obtained as 0.861 and 0.137, respectively. Inserting these values of DMU 1 in Equation (6), the z-value is found to be −0.481. In Framework 2, the efficiency score of DMU 1 is observed as 0.833 (Table 4), and the mean and standard deviation of Framework 2 are 0.837 and 0.135, respectively. Based on these values, the z-value of DMU 1 in Framework 2 is observed as −0.030. Similarly, z-values for the remaining DMUs from Frameworks 1 and 2 are evaluated, and then they are plotted in the quadrilateral graph shown in Figure 3.

The X-axis of Figure 3 represents the z-values from Framework 1, while Y-axis represents the z-values from Framework 2. Therefore, the output of this quadrilateral graph is presented in four quadrants, where the first quadrant presents the positive z-values of Framework 1 (X-axis) as well as from Framework 2 (Y-axis). DMUs 3, 5, 7, and 10 are found in the first quadrant of Figure 3. A comparison with the ranks obtained in Framework 3 (Table 5) reveals that DMUs 3, 5, 7, and 10 are efficient DMUs obtaining the third, second, fifth, and first ranks, respectively, which implies that DMUs 3, 5, 7, and 10 have the effectual BRI score for all input variables (age, area, design HFL, and FRL of the bridge). In this regard, DMUs 3, 5, 7, and 10 should have the first priority for improving the BRI and have better efficiency considering the selected input variables (age, area, design HFL, and FRL of the bridge). In the second quadrant (Figure 3), Framework 1 (X-axis) represents a positive z-value, while Framework 2 (Y-axis) represents a negative z-value. DMUs 1 and 12 are found in this second quadrant. However, in Framework 3 (Table 5), DMU 1 is an efficient DMU with the sixth rank, while DMU 12 is an inefficient DMU with the eighth rank. Thus, this study recommends to improve the BRI of DMUs 1 and 12 to have better resilience considering the design HFL and FRL of the bridge. DMUs 1 and 12 are in the second quadrant due to a higher design HFL than the FRL of bridge (Table 2). Therefore, there are chances that the bridge (DMU 1 and 12) might get submerged under the severe flooding condition, thus affecting the BRI score of the bridge. At the same time, DMUs 1 and 12 have a low BRI score of the bridge and, in contrast, have less bridge age. In the third quadrant

(Figure 3), both the values of Framework 1 (X-axis) and Framework 2 (Y-axis) represent negative z-values. DMUs 4, 6, 8, 9, and 11 are found in this third quadrant. Out of these, DMUs 4, 6, 9, and 11 are also observed as inefficient DMUs, while DMU 8 is found efficient in Framework 3 (Table 5). Thus, this study recommends that the BRI of all these five DMUs should be given least priority for enhancing the BRI score. At last, in the fourth quadrant (Figure 3), Framework 1 represents a negative z-value (X-axis), while Framework 2 represents a positive z-value (Y-axis). DMU 2 is found in the fourth quadrant, whereas it is observed as an efficient DMU in Framework 3 with the fourth rank (Table 5). Still, the study suggests enhancing the BRI score of DMU 2 to have an appropriate efficiency considering the age and area of bridge because it has less age and a larger bridge area while having a low BRI. Overall, the results recommend that DMUs in the first quadrant should be prioritised for improving their BRI. Therefore, DMUs 3, 5, 7, and 10 should be given first priority to improve their BRI, while DMUs 1, 2, and 12 should be given second priority to improve the BRI. On the contrary, DMUs 4, 6, 8, 9, and 11 should be given low priority for improving BRI scores based on the study by Patel et al. (2020). Table 6 shows the rank comparison between the current study and the BRI score obtained by Patel et al. (2020).

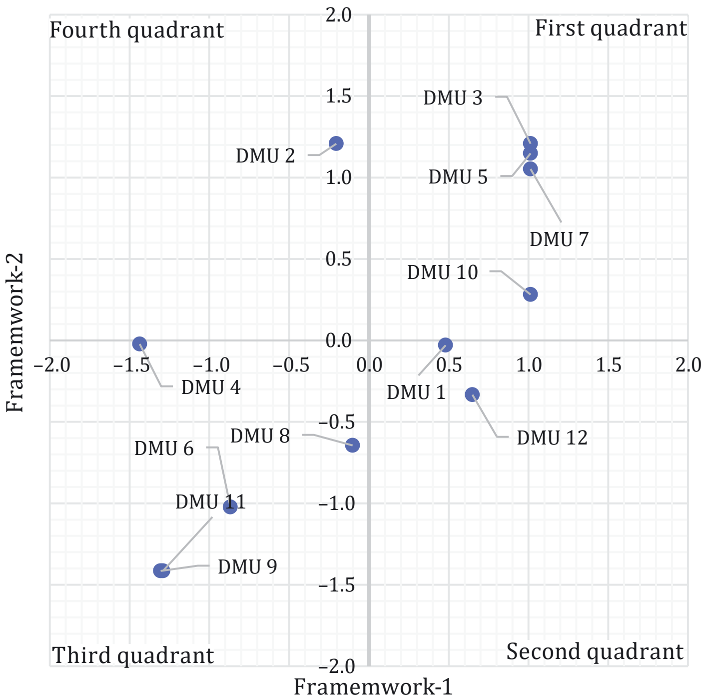

Figure 3. Result of z-value for Framework-1 and 2

Table 6. Rank comparison between the current study and BRI score

DMU	Rank based on BRI obtained by Patel et al. (2020)	Rank as per this study
DMU 1	4	2
DMU 2	8	2
DMU 3	1	1
DMU 4	9	9
DMU 5	5	1
DMU 6	12	10
DMU 7	2	1
DMU 8	7	8
DMU 9	9	12
DMU 10	3	1
DMU 11	9	11
DMU 12	6	2

To enhance this BRI, Patel et al. (2020) explain that those bridge owners should utilise advanced resources, develop preparedness of disaster management planning, and coordinate with other concerned infrastructure owners, disaster management teams, and transportation agencies. Disaster management preparedness can prompt the bridge recovery functions (Andrić & Lu, 2017). Along with this disaster management planning, bridge owners should use advanced resources such as building information modelling (BIM), finite modelling, and wireless sensing techniques to analyse and improve the bridge structural health condition. The finite-element modelling and wireless sensing techniques can be applied to collect real-time damage detection data of the bridge's structural components (Nassif et al., 2017; Bhowmik et al., 2019, 2020). Then, this real-time damage detection data can be collaborated with BIM to track and schedule the maintenance work of bridges (McGuire et al., 2016). Lastly, Freckleton et al. (2012) stated that intelligent transportation and advanced traveller information systems could be used to ensure more effective, efficient, and standardised operation of transportation networks during the recovery process of the bridge.

5. Validation and sensitivity analysis

Validation is a process that ensures the quality of the proposed methodology (Luko & Rojas, 2010). Therefore, in this study, two methods, (1) Spearman's rank correlation test and (2) reliability, are used to validate the proposed research methodology. As mentioned previously, Framework 1 and Framework 2 assume two different input variables of the bridges, both of which are considered in Framework 3. Therefore, the Spearman rank correlation test is employed to compute the relationship between the rankings of only Framework 1 and 2. The Spearman test value is found to be +0.64, which indicates an excellent direct relationship between the ranking of Frameworks 1 and 2. Then, the reliability of efficiency scores is examined by using sensitivity analysis. In sensitivity analysis, the robustness of DEA results is checked by eliminating an input or output variable from the DEA model and then computing the DEA result again (Ramanathan, 2003). Some researchers, e.g., Lin & Hong (2006), Tyagi et al. (2009), and Yang et al. (2016) adopted the procedure of Ramanathan (2003) to conduct sensitivity analysis (SA) and suggested that it was a suitable method to test the result of DEA. Thus, the current study employs sensitivity analysis on Framework 3, as it has four input variables and one output variable. The reason for not applying sensitivity analysis on Frameworks 1 and 2 is that they have only two input variables and one output variable. Therefore, if one input variable is eliminated from Frameworks 1 and 2, both the frameworks are left with a single input variable and single output variable, which does not fulfil the property of the DEA model in DEAP 2.1.

Therefore, all the input variables in Framework 3 are eliminated one by one, and then the DEA model selected in the research methodology (Steps 3 and 4) is rerun. Considering this fact, the study performs four experiments to conduct SA, where the variable of age of the bridge is removed from the analysis in experiment 1. Similarly, experiments 2, 3, and 4 remove the variables of area, design HFL, and FRL of the bridge variables from the analysis. Table 7 displays the results of all the experiments. The second column of Table 7 lists the original efficiency score for each DMU of Framework 3. Meanwhile, the third to sixth columns of Table 7 represent the efficiency scores for experiments 1–4.

The result of sensitivity analysis shows no change in experiments 1, 3, and 4, so the variables age, design HFL, and FRL are less sensitive to the resilience of the bridges. However, a significant change in the efficiency scores is observed by removing the variable of area of the bridge from the DEA model. Based on the results of experiment 2, there is a change in the efficiency score (column 4 of Table 7) of DMUs 4, 5, 6, 9, 11, and 12. Therefore, the input variable of area of the bridge represents high sensitivity to the BRI score of these DMUs.

Thus, the DEA application has been used for a group of 12 bridges. The same method can be applied in the case of bridges across various divisions/regions/states/owners. The research methodology proposed in this study has two prime benefits. First, selected and presented variables such as age, area, design HFL, and FRL along with BRI can be used for setting a priority level for bridges in need of resilience improvement. These data are easy to maintain and are available with bridge owners. These variables can be replaced with other variables as per the requirements of bridge owners, and the efficiency score can be computed by using the same proposed methodology. Second, this study helps prioritise resilience improvement of bridges based on their efficiency score computed using the DEA. Thus, the proposed evaluation process is easy to follow and logical for bridge owners to justify and allocate the budget for the maintenance of the bridge. The research is in progress to develop an online web-based tool that can evaluate the BRI score and help prioritise resilience improvement. The bridge owners can directly use this online system to measure the bridge's resilience. Moreover, this tool can also be used for bridge asset management, as it can save data and keep records of resilience for multiple bridges.

Table 7. Results of sensitivity analysis

DMU	Original efficiency score	Experiment 1 efficiency score	Experiment 2 efficiency score	Experiment 3 efficiency score	Experiment 4 efficiency score
DMU 1	1.000	0.947	0.833	1.000	1.000
DMU 2	1.000	1.000	1.000	1.000	1.000
DMU 3	1.000	1.000	1.000	1.000	1.000
DMU 4	0.834	0.834	0.834	0.693	0.834
DMU 5	1.000	1.000	0.992	1.000	1.000
DMU 6	0.742	0.742	0.699	0.742	0.742
DMU 7	1.000	0.979	1.000	1.000	1.000
DMU 8	1.000	0.862	0.750	0.847	1.000
DMU 9	0.682	0.682	0.646	0.682	0.682
DMU 10	1.000	1.000	0.875	1.000	1.000
DMU 11	0.684	0.684	0.646	0.684	0.684
DMU 12	0.950	0.950	0.792	0.950	0.950

Conclusions

The present study proposes a novel methodology to prioritise bridges for improving their resilience. To achieve this objective, first, a nonparametric approach known as DEA is used to measure the efficiency score of bridges. In the DEA model, variables like age, area, design HFL, FRL, and BRI score of the bridges are selected as input and output variables to assess the efficiency score. Then, using these variables, three different frameworks are developed. In Framework 1, age and area of bridge are considered as input variables, while in Framework 2, design HFL and FRL of bridge are considered as input variables. Lastly, in Framework 3, all four variables are considered input variables. The BRI score of the bridge is considered as the output variable in all three frameworks. A total of 12 bridges located in India are selected as the DMUs. Then, the efficiency scores of these three frameworks are evaluated by the VRS output-oriented formulation.

Subsequently, the z-values of efficiency scores from Frameworks 1 and 2 are evaluated. Then, these z-values are compared with Framework 3 to have a better insight of efficiency scores. The methodology is then validated using the Spearman rank correlation and sensitivity analysis. Spearman rank correlation test is performed on Frameworks 1 and 2, thus obtaining a value of +0.64, which indicates an excellent direct relationship between the ranks of Frameworks 1 and 2. While sensitivity analysis is performed on Framework 3, it is used to test the impact of removing input variables on efficiency scores. The results of sensitivity analysis indicate that the input variable area of the bridge has high sensitivity in DMUs 4, 5, 6, 9, 11, and 12. The study suggests prioritising DMUs 3, 5, 7, and 10 first to improve their BRI score.

The present study concludes that it is not enough to consider only the resilience score for setting a priority level for bridges in need of resilience improvement, but the proposed prioritisation exercise should also be performed holistically. The exercise should consider various other variables that are not preferred during the bridge resilience assessment process. This methodology can also identify a bridge with a high resilience score but not efficient considering the variables like the bridge age, area, design HFL, and FRL. Future studies could include more input variables, such as load-carrying capacity, deterioration rate, etc. These variables are not considered in the present study due to the unavailability of the data. Future studies can also use fuzzy DEA to evaluate the variables whose data are unavailable. In brief, the proposed methodology is logical and practical in setting a priority level for bridges in need of resilience improvement.

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Notations

Variables and functions

DMU 1 – Savijibhai Korat Bridge
DMU 2 – Swami Dayanand Saraswati Bridge
DMU 3 – Pandit Shyamji Krishna Varma Bridge (Old)
DMU 4 – Pandit Shyamji Krishna Varma Bridge (New)
DMU 5 – Dr. Shyama Prasad Mukherjee Bridge
DMU 6 – Chandra Shekhar Azad Bridge
DMU 7 – Nehru Bridge
DMU 8 – Swami Vivekanand Bridge (Makkai Pool)
DMU 9 – Sardar Patel Bridge [(New) Adajan to Athwa lines]

DMU 10 – Sardar Patel Bridge (Old)
DMU 11 – Sardar Patel Bridge [(New) Athwa lines to Adajan]
DMU 12 – Pandit Dindayal Upadhyay Cable Stay Bridge

Abbreviations

BCC – Banker Charnes Cooper
BRI – Bridge Resilience Index
CCR – Charnes Cooper Rhodes
CRS – Constant Return to Scale
DEA – Data Envelopment Analysis
DEAP – Data Envelopment Analysis Program
Design HFL – Design High Flood Level
DMU – Decision Making Unit
FRL – Finish Road Level
SMC – Surat Municipal Corporation
VRS – Variable Return to Scale