Differential evolution algorithm: An analysis of more than two decades of application in structural damage detection (2001-2022)

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Abstract

Vibration-based structural damage detection methods using optimization techniques have been extensively increased in recent decades due to the rapid development of swarm intelligence and the introduction of robust and computationally efficient optimizers. The differential evolution algorithm (DEA) is a widely used optimization algorithm that has been successfully implemented for different engineering problems since Storn and Price released it available in 1997. This study analyzes more than two decades of application of the DEA in structural damage detection problems between 2001 and 2022. The main contribution of the present chapter is to provide detailed tabulated reviews on methodologies, objectives, and main findings of about 50 publications. This study also presents statistical analysis to investigate the contribution of objective functions, types of structures, number of publications per year, and percentage of utilized single-step and two-step methods within the recent two decades.

Keywords: Differential evolution algorithm, Damage detection, Optimization, Model updating, Inverse problem, Structural health monitoring, Objective function.

1. Introduction

As a result of earthquakes, fatigue, overloading, joint loosening, and other human-induced or nature-induced factors, structural damage may progressively expand [1, 2]. Monitoring structural conditions and making timely decisions to repair damaged elements can prevent human disasters and reduce maintenance costs [3, 4]. There are several existing techniques for localizing damaged elements and identifying their severity [5]. Some damage detection methods, such as acoustic emission [6, 7], guided wave [8-11], and electromechanical impedance [12, 13], are classified as local nondestructive testing (NDT) techniques and enable us to evaluate the condition of certain elements close to the sensors [14]. However, the global vibration characteristics of the structure, such as natural frequencies [15, 16], mode shapes [17-19], and modal flexibility [20-22], are analyzed by vibration-based methods to assess the structural health state [14]. Vibration-based methods relying on frequency-domain and time-domain responses have attracted remarkable attention [23] due to the availability of measuring signals by single or multiple accelerometers without the necessity to have a sensor adjacent to the damaged element [14]. In vibration-based methods, the inverse problem of structural damage identification can be mathematically formulated as an optimization process by defining an objective function [24, 25]. The objective function describes the discrepancy between the measured vibration characteristics and those calculated from the finite element model (FEM) [26, 27]. The optimization algorithms attempt to minimize the objective function by finding design variables, including a vector of structural elements and their damage severities between 0 and 1 [28]. The healthy and fully damaged elements are represented by 0 and 1, respectively [29]. Many optimization methods have been developed over the past several decades due to technological advancements to address challenging engineering problems [30-40]. Many researchers have evaluated the performance of classic and novel optimization algorithms using different objective functions to solve the inverse damage detection problem in structural engineering [41]. Ghannadi et al. analyzed the previously published papers on the application of different variants of particle swarm optimization (PSO) and frequently used objective functions [42]. Alkayem et al. investigated the capability of the social swarm algorithm and a novel hybrid objective function based on modal strain energy and mode shape curvature [43]. Jahangiri et al. developed a robust const function, namely holistic objective function, and employed it for damage identifcation of large-scale structures [44, 45]. Aval and Mohebian [46] proposed an efficient two-step approach for joint damage detection in frame structures. In the first step, the residual moment-based joint damage index is applied to recognize the possibly damaged connections. For identifying the severity of damaged connections in the second step, the equilibrium optimizer is utilized to minimize a hybrid objective function based on natural frequencies and modal assurance criteria (MAC). In another study, Beheshti Aval and Mohebian introduced a methodology for simultaneously detecting damaged joints and elements in skeletal structures. They have utilized the improved biology migration algorithm and a weighted hybrid objective function in their method [47]. In terms of the applicability of novel optimization algorithms in damage detection problems, several scholars have reported successful applications of different optimizers, such as slime mold algorithm [48-51], modal force information-based optimization [52], ant lion optimisation algorithm [53], visible particle series search algorithm [54], improved cuckoo search algorithm [55], YUKI algorithm [56], multiverse optimizer [57], guided water strider algorithm [58], grey wolf optimizer (GWO) [59, 60], bat algorithm [61], teaching-learning based optimization (TLBO) [62], and modified TLBO [63].

In real-world damage detection problems, measuring all degrees of freedom (DOFs) is impossible because of the limited number of sensors [64]. Therefore, several researchers have proposed practical approaches when solving a vibrations-based damage detection problem as an optimization scheme. A frequently used method to tackle incomplete modal data is condensing the FEM in the size of measured DOFs [65]. Ghannadi and Kourehli [66] compared the efficiency of different FEM reduction techniques, such as Guyan, improved reduced system (IRS), iterated improved reduced system (IIRS), and system equivalent reduction expansion process (SEREP). Kahya et al. [67] and Şimşek et al. [68] adopted Guyan's reduction method to deal with incomplete modal data for damage identification of laminated composite beams. Several optimization-based damage detection procedures have also been established based on the IRS [69], IIRS [70], and SEREP [71].

A well-known evolutionary algorithm inspired by Darwin's theory of evolution is called the differential evolution algorithm (DEA), which has been widely implemented to address various engineering problems since it was first released in 1997 [72]. This study is divided into five sections to review more than two decades of application of DEA in structural damage detection from 2001 to 2022. The opening section is the introduction, which provides a brief review of recent vibration-based damage detection methods formulated as an optimization problem. Section 2 presents an introduction to DEA and its related mathematical definition. Section 3 analyzes nearly 50 published papers to investigate methodologies, objectives, types of structures, and their findings. The most important results of this study are demonstrated graphically in Section 4 to provide a discussion. Finally, conclusions are provided in Section 5 to highlight the key points.

2. Differential Evolution Algorithm (DEA)

Differential evolution algorithm (DEA) is a straightforward but efficient heuristic method that Storn and Price [73] originally introduced for handling global optimization in continuous space. The DEA is easy to employ, requires few control variables, performs exceptionally well in parallel computation, and provides reliable results. Therefore, the DEA has grown in popularity and has been used to solve various optimization problems in practical applications [72]. The DEA is an evolutionary algorithm that includes three types of operators: mutation, crossover, and selection [74]. Figure 1 demonstrates how DEA attempts to minimize the objective function and solve the optimization problem. As depicted in Figure 1, the optimization procedure begins with the initialization phase. Then, the DE undergoes a loop that contains the processes of mutation, crossover, and selection, and this loop continues while the stop condition is satisfied [74]. The following is a description of the initialization phase and three operators [74, 75].

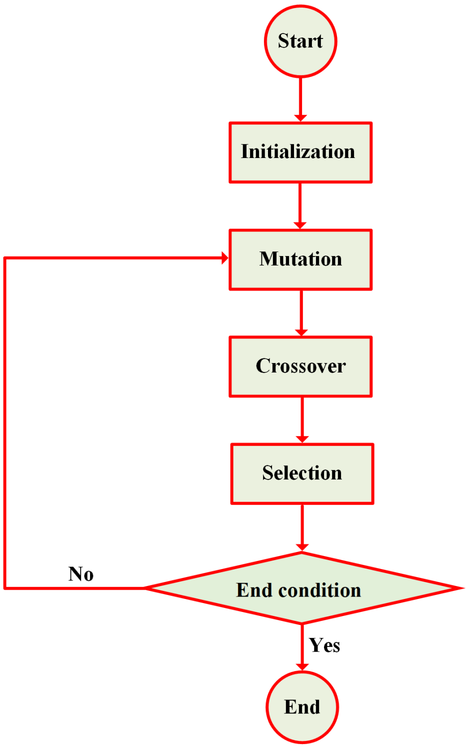

Figure 1. The flowchart of DEA [74]

2.1. Initialization

The initial population, together with the control parameters, are generated during the initialization phase. The initial population consists of *NP* solutions (vectors) with *D* variables. The following definition applies [74] to a solution (individual) of the population at generation *G*:

$$X_i^G = \left(X_{i,1}^G, X_{i,2}^G, \ldots, X_{i,D}^G\right), \qquad i = 1, 2, \ldots, NP \tag{1}$$

where D is the search space's dimension, and NP is the population's size.

By uniformly randomizing individuals inside the search space while keeping the search space constrained by the specified minimum and maximum parameter ranges, the initial population should sufficiently cover the whole search space as far as possible [75]. Individual solutions are frequently initialized using the following equation:

$$X_{i,j}^0 = X_j^{\min} + rand\,(0,1).\left(X_j^{\max} - X_j^{\min}\right) \tag{2}$$

where *rand* (0, 1) is a randomly generated number with uniform distribution that ranges between 0 and 1. The maximum and minimum bounds of the j*th* dimension of the search space are $X_j^{\max}$ and $X_j^{\min}$, respectively.

2.2. Mutation

The DEA uses the mutation procedure to generate a mutant vector V_i^G for each individual X_i^G during every generation *G*. The following list includes some of the most widespread DEA mutation techniques [74, 75]:

$$DEA\,/\,rand\,/\,1: \qquad V_i^G = X_{r1}^G + F.\left(X_{r2}^G - X_{r3}^G\right) \tag{3}$$

$$DEA\,/\,rand\,/\,2: \qquad V_i^G = X_{r1}^G + F.\left(X_{r2}^G - X_{r3}^G\right) + F.\left(X_{r4}^G - X_{r5}^G\right) \tag{4}$$

$$DEA\,/\,best\,/\,1: \qquad V_i^G = X_{best}^G + F.\left(X_{r1}^G - X_{r2}^G\right) \tag{5}$$

$$DEA\,/\,current-to-rand\,/\,1: \qquad V_i^G = X_i^G + F.\left(X_{r1}^G - X_i^G\right) + F.\left(X_{r2}^G - X_{r3}^G\right) \tag{6}$$

where *r1*, *r2*, *r3*, *r4*, and *r5* are random numbers generated from 1 to NP, neither of which are equal to index *i*. In the population at generation *G*, X_{best}^G is the best individual vector with the best fitness value. To control the differential variation's amplification [73, 74], *F* is a positive scaling factor typically ranging between [0, 1] or [0, 2].

2.3. Crossover

Following the mutation step [73-75], a trial vector $U_i^G = \left(U_{i,1}^G, U_{i,2}^G, \ldots, U_{i,D}^G\right)$ is produced for every individual using the binomial crossover operator on V_i^G and X_i^G as given in Eq. (7).

$$U_{i,j}^{G} = \begin{cases} V_{i,j}^{G} & if\ \left(rand_{i,j}\left(0,1\right) \le CR \quad or \quad j = j_{rand} \right) \\ X_{i,j}^{G} & otherwise \end{cases}, \tag{7}$$

$j = 1, 2, ..., D.$

Where j_{rand} is a uniform random number in the range [1, D] that should be computed for each individual in Eq. (7). CR is the crossover rate [73] and can be defined by users between 0 and 1.

The jth variable $U_{i,j}^{G}$ of the trial vector U_{i}^{G} will be updated as follows if it exceeds the boundary constraints [74]:

$$U_{i,j}^{G} = X_{j}^{\min} + rand\left(0,1\right).\left(X_{j}^{\max} - X_{j}^{\min}\right) \tag{8}$$

2.4. Selection

The fitness values of the target and trial vectors are assessed by the selection operator to decide which will survive and enter the following generation. During the minimization procedure, the decision vector that has the lowest fitness value would enter the upcoming generation [74], defined as follows:

$$X_{i}^{G+1} = \begin{cases} U_{i}^{G} & if\ \left(fit\left(U_{i}^{G}\right) \le fit\left(X_{i}^{G}\right)\right) \\ X_{i}^{G} & otherwise \end{cases} \tag{9}$$

3. A tabulated review on structural damage detection using the DEA (2001-2022)

This section provides a tabular approach to critically discuss different variants of DEA, characteristics of various utilized objective functions, and types of structures. The main results of the previously released publications between 2001 and 2022 are also summarized to highlight the key points. Table 1 has been organized to fulfill the role of detailed review according to the following categories:

Reference and Year: Indicate the names of the authors and the year that the work was published, respectively.

Objective: The purpose of this column is to explain the primary contribution of the work and its motivation for presentation.

Methodology: This column outlines the algorithms and methods used to address damage detection problems.

Structure: What kinds of structures are used to accomplish the structural damage detection approach is addressed in this column.

Result and Finding: The key findings of the publications are abstracted in this column.

Table 1. A review of the application of DEA for structural damage identification

Reference	**Year**	**Objective**	**Methodology**	**Structure**	**Result and Finding**
Manson and Worden [76]	2001	Several studies based on Lamb-wave propagation have promising results for damage localization in composite plates. Lamb-waves are generated by piezoceramic actuators, and the ensuing signals are measured by piezoceramic sensors located throughout the structure. The Lamb-wave will be altered if damage is applied to the structure. The Lamb-wave modification depends on the distance between the damaged area and the sensor/actuator. Therefore, this study introduced an optimization-based approach for finding the optimal location of sensors and piezoceramic actuators.	The DEA was employed to minimize an objective function relying on angles between sensor, actuator, and damage location.	Composite plate	The proposed strategy for optimal sensor placement of simple structure has provided successful results. However, this method can be applied to more complex systems in future studies.
Casciati [77]	2008	In this paper, the inverse problem of damage identification is solved by considering the stiffness of structural elements as optimization variables. Previous efforts mainly were concerned with multi-story shear buildings. In this study, a discretized model of the cantilever beam is adopted for investigation.	The DEA was applied to minimize the discrepancy between the measured and calculated modal parameters (natural frequencies and mode shapes).	Cantilever beam	The results revealed that the presented approach is sufficient for damage localization and identification when the identified stiffness matrix is compared to the initial one.
Kang et al. [78]	2012	This study compared the efficiency of an improved version of the PSO with the DEA, standard PSO, and real-coded genetic algorithm (RCGA) in structural damage detection problems.	The mode shape and natural frequency changes are used as the cost function.	Simply supported beam Planar truss	The comparison results showed that the performance of improved PSO is more efficient than the DEA, standard PSO, and RCGA.
Rao et al. [79]	2012	This paper provides a damage detection method based on the self-adaptive DEA and proper orthogonal decomposition	The three-stage procedure is presented for damage identification, localization, and quantification. In the first and second steps, the exact time instant of damage and location is	Cantilever beam Concrete slab bridge	The numerical investigations demonstrated the robustness of the proposed structural health monitoring (SHM) methodology, even under changing environmental conditions and

Reference	Year	Objective	Methodology	Structure	Result and Finding
		(POD), considering noisy data and environmental variability.	identified using POD. In the third step, the constrained optimization problem is solved by employing self-adaptive DEA to determine the damage's severity. During the optimization procedure, the objective function is formulated as the discrepancy between the proper orthogonal value of the damaged state and the calculated values from the FEM.	Plane truss	considering measurement noise. However, experimental validation is still necessary for assessing the performance of POD-based methodology in real-world applications.
Bighamian and Mirdamadi [80]	2012	Most damage assessment studies identify just stiffness reduction and assume no mass decrease. Mass reduction is a critical consideration and inevitable in aircraft composite structures. Therefore, this research outlines a novel method for simultaneously identifying the reduction of stiffness and mass in aerospace structures.	The presented algorithm to find the mass and stiffness is a signal-driven method that minimizes the differences between system digital pulse response and equivalent virtual damped SDOF using DEA as an optimizer.	Mass–spring system Bar model Shear frame Plane truss	The performance of the utilized procedure for single and multiple damage detection is satisfactory, even in noise conditions.
Kang et al. [81]	2013	This paper introduces a new variant of PSO to improve the convergence speed and accuracy of the standard PSO. The obtained results are also compared with those obtained from DEA and PSO.	The optimization algorithms minimize an objective function that has been given the dynamic (natural frequencies) and static (displacements) responses as inputs.	Clamped - Clamped beam	Compared to the standard PSO and DE, improved PSO is more successful in detecting structural damages. However, the accuracy of improved PSO is decreased with noisy inputs.
Reed et al. [82]	2013	The main contribution of this work is to improve the standard DEA to solve the structural inverse problems accurately. The proposed variant of DEA provides a reasonable convergence rate while still properly exploring the parameter space and maximizing the likelihood.	This research focuses on the maximum likelihood technique and employs a cost function based on Maximum Likelihood Estimators (MLEs). Then, an improved version of DEA is applied to minimize the suggested cost function.	Barrel vault shell	Results are shown that the presented method provides impressive performance in structural parameter estimation. Additionally, modified DEA can swiftly converge to the global minimum compared to the standard DEA.
Jena et al. [83]	2013	This paper has introduced an optimization-based inverse strategy to find the depth and location of transverse surface cracks in beam-like structures.	The damage parameters such as crack depth and crack location are formulated as a constrained optimization problem. Then, DEA is utilized to minimize the difference between calculated and measured first three natural frequencies as an objective function.	Cantilever beam	This study indicates that the proposed approach is robust in determining crack parameters and can be extended in different SHM applications.

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Vincenzi et al. [84]	2013	This study compares the damage detection in a cracked beam using the coupled local minimizers method (CLM) and DEA.	The numerical examples with error (natural frequencies and mode shapes contaminated by some error) and without error are studied to compare the performance of the DEA and CLM. During the optimization procedure, the discrepancy between the measured and calculated modal properties (natural frequencies and mode shapes) is the cost function that must be reduced.	Simply supported beam	The statistical analysis of the obtained results by optimization algorithms are demonstrated that the CLM and DEA can provide the good results. However, when the number of optimization parameters is limited, CLM performs better in accuracy and speed. When the number of parameters is increased or when pseudo-experimental data (modal properties with error) is used, DE becomes more efficient.
Villamizar et al. [85]	2014	This paper proposes an expert system based on self organizing maps (SOM) and principal component analysis (PCA) to find the simulated damage (adding a mass on the surface).	In the first step, PCA is employed to reduce the time signals and prepare a database for training SOM. The DEA is utilized to tune the training parameters in the second step.	Aircraft turbine blade	The identification error is approximately 22% when using default training parameters. The identification error is 20% by implementing DEA and training the neural network with tuned parameters.
Villalba-Morales and Laier [86]	2014	This paper compares the performance of different objective functions based on natural frequencies, modal flexibilities, mode shapes, modal strain energies, and the residual force vector when applying the adaptive DEA as an optimizer for structural damage localization and quantification.	This paper uses a simple yet efficient adaptation method to avoid utilizing the trial and error method to determine the DE parameters, and users must define only the population size. Then, cost functions based on dynamic parameters such as natural frequencies, modal flexibilities, modal strain energies, mode shapes, and the residual force vector are minimized by using adaptive DEA.	Plane truss	The objective function based on natural frequencies and mode shapes has provided the most accurate results. The cost function based on modal flexibility produced comparable results to those achieved using natural frequencies and mode shapes as an objective function. The approach does not function well when using an objective function based on natural frequencies and modal strain energies. The findings of the objective function based on the residual force vector were unreliable because several false identifications were observed.
Fu and Yu [87]	2014	The improved version of the adaptive DEA has provided better exploration ability, higher accuracy, and fast convergence. Therefore, this revised optimization algorithm is considered for structural damage identification.	The damage detection problem is converted into a constrained optimization problem. Then, minimizing the differences between measured and calculated modal parameters (natural frequencies and mode shapes) is defined as an objective function.	Space truss	The following are the significant findings of this research: I) The improved adaptive DEA is accurate for damage detection and can find the damage parameters in single and multiple damage scenarios.

Reference	Year	Objective	Methodology	Structure	Result and Finding
					II) The Improved adaptive DEA performs well when damage severity is high. III) The improved adaptive DEA is robust to noise. However, the noise level is related to the convergence rate. IV) There is still an opportunity to improve the premature convergence of the utilized optimizer. V) It is necessary to investigate how to increase accuracy and overcome the influence of structural symmetry in future studies.
Cavalini Jr et al. [88]	2015	The efficiency of the self-adaptive DEA is evaluated to reduce the discrepancies between experimental and analytical results through FEM updating. The control parameters of the algorithm, including perturbation rate, population size, crossover, and crossover parameter, are automatically adjusted by the self-adaptive DEA.	The philosophy of the self-adaptive DEA is based on the convergence rate concepts and population diversity. This technique decreases the number of objective function evaluations by defining a convergence rate to assess population homogeneity in the evolutionary process. This proposed algorithm is used to minimize the difference between the calculated and measured FRFs as an objective function. For comparison, the efficiency of the standard DEA is also evaluated to determine the optimal solution.	Rotating machine	According to the results, the self-adaptive DEA is a potential alternative for solving the inverse problems associated with FEM updating.
Jena and Parhi [89]	2015	This paper introduces a modified version of PSO to accelerate the search strategy while keeping the standard form of the PSO. The results of the modified PSO are compared with the results obtained by the DEA.	The squeezing approach was introduced into the standard PSO formulation to restrict the search domain in each iteration, resulting in a faster convergence time for reaching the best solution. Natural frequency alterations caused by the existence of a crack are beneficially utilized to identify the crack depth and crack location by employing Modified PSO and DEA through minimizing a cost function based on the differences between the measured and the calculated natural frequencies.	Cantilever beam	Based on the obtained results, the modified PSO can predict the crack parameters more accurately than those obtained by the DEA.

Reference	Year	Objective	Methodology	Structure	Result and Finding
Seyedpoor et al. [90]	2015	In this paper, the performance of DEA is investigated to handle the optimization-based damage detection problem by minimizing a frequency-based objective function. The obtained results are also compared with the PSO.	An objective function is defined using the efficient correlation-based index (ECBI). The ECBI is a hybrid cost function based on multiple damage location assurance criterion (MDLAC).	Simply supported beam Plane truss Space frame	Numerical results indicate the effectiveness of the DEA and ECBI for accurately finding the location and severity of the damage compared to those obtained result results from PSO.
Seyedpoor and Yazdanpanah [91]	2015	The performance comparison of two optimization techniques, including the DEA and PSO, is carried out to identify the robust optimization method that works properly in highly nonlinear problems such as damage detection of structures.	The hybrid objective function (ECBI) is created through the MDLAC and a weighted frequency term.	Cantilever beam Plane truss Portal frame	Compared to PSO, the DE was able to produce accurate solutions with a significantly lower number of function evaluations.
Vincenzi and Savoia [92]	2015	The surrogate-assisted DEA is presented in this study to provide higher accuracy and faster convergence in model updating procedures and dynamic parameter identification problems.	In the proposed approach based on surrogate and DEA, the response surface second-order approximation is introduced in the mutation operation of DEA. In the presented algorithm, multiple search points are employed simultaneously. Therefore, the robustness of DEA is preserved for global minimum search. Then, the surrogate-assisted DEA is applied to minimize the weighted objective function relying on natural frequencies and mode shapes.	Pontelagoscuro bridge	The proposed algorithm decreases the number of objective function evaluations. Therefore, the surrogate-assisted DEA can be efficiently implemented for optimizing the problems with computationally expensive objective functions.
Seyedpoor and Montazer [93]	2015	This paper develops a two-step procedure using a flexibility-based damage probability index (FBDPI) and DEA to find the location and severity of structural damages.	In the first step, potentially damaged elements are identified by the FBDPI. Then, the severity of damaged elements is quantified by minimizing the differences between measured and calculated mode shapes through the DEA.	Plane truss Space truss	The results indicate that the proposed FBDPI can accurately determine potentially damaged elements while only requiring a few modal data. When the damaged elements are recognized in the first step, the DEA could determine the damage severity with a few iterations during the optimization procedure.
Vo-Duy et al. [94]	2016	A two-step technique with a combination of modal strain energy-based method and an improved version of the DEA is presented in this study. The improved DEA is developed by adjusting the	The possible damaged elements are initially detected by implementing a modal strain energy-based method. In the second step, the improved DEA minimizes the error between measured and calculated mode shapes.	Laminated composite plate	The numerical study revealed that regardless of noise, the modal strain energy-based method successfully identifies damaged elements. The improved DE and DE can accurately assess damage severities even if mode shapes are

Reference	Year	Objective	Methodology	Structure	Result and Finding
		mutation and selection phases of the traditional DEA. Multiple mutation operators are employed adaptively in the mutation phase to maintain the trade-off between global exploration and local exploitation of the optimization algorithm. The elitist scheme replaces the standard section scheme of the DEA in the selection phase.			contaminated with 3% of random noise. Additionally, the improved DE needs far fewer structural analyses than the DE.
Seyedpoor and Montazer [95]	2016	This study introduces a two-stage method under the assistance of modal residual vector-based indicator (MRVBI) and DEA for correctly identifying the location and severity of damage in truss structures.	In the first stage, the MRVBI is employed to identify elements that may have been damaged. The DEA is implemented to minimize the ECBI as a cost function in the second stage to find the severity of damage for candidate elements.	Plane truss Space truss	The numerical investigations demonstrate that the utilized strategy relying on MRVBI can efficiently locate possibly damaged elements and significantly reduce the design variables. Furthermore, it has been found that the DEA can successfully handle the optimization problem in order to determine the severity of damaged elements in the narrowed search space.
Ding et al. [96]	2016	The artificial bee colony (ABC) algorithm is a swarm-based optimizer with a simple implementation. However, the ABC algorithm has some drawbacks, such as a slow convergence rate and trapping in the local optimal solutions. In this study, an improved version of ABC with the assistance of DEA is proposed to have a more effective optimization algorithm.	A new mechanism based on DEA is introduced in the employed bee phase to enhance the exploration ability of standard ABC. In the improved ABC, the tournament selection strategy is used instead of the roulette selection strategy, and simulation of the onlooker bee's behavior is performed by a novel formula. The cost function is defined only based on differences in the first few natural frequencies.	Cantilever beam Fixed–Fixed beam	Compared to the standard ABC, DEA, GA, and PSO, the improved ABC has produced more accurate damage detection results. Additionally, improved DEA converges rapidly and produces identifications with minor standard deviations.
Anh [97]	2016	This paper presents a simple but efficient modification of DEA for reducing the number of fitness evaluations in computationally expensive inverse problems.	The modified DEA employs the nearest neighbor comparison technique to evaluate a trial vector in the search population. The adopted objective function is based on the natural frequencies and mode shape components.	Two dimensional beam structure	The results show that the modified DEA has been successfully implemented to reduce the computational cost in structural damage detection problems.
Nguyen-Thoi et al. [98]	2016	This research nominates a two-step method for structural damage detection	Damage localization in structures is accomplished in the first step by utilizing the DLV technique with normalized cumulative	Space truss Portal frame	The performance and accuracy of the presented two-step method are assessed numerically, and the following results have been obtained:

Reference	Year	Objective	Methodology	Structure	Result and Finding
		that combines the damage locating vector (DLV) method and DEA.	energy. In the second step, a combined mode shape error function and MDLAC function are suggested to address the limitations of the MDLAC function, including the exclusive solution and the problem of symmetric structures.		I) The proposed two-step method can effectively determine damage locations and their severities. Additionally, robustness to noise is the other advantage of this method. II) A large number of modes are needed to provide better results.
Georgioudakis and Plevris [99]	2016	In this article, the capability of four objective functions, including the modal assurance criterion (MAC), modified total modal assurance criterion (MTMAC), co-ordinate modal assurance criterion (COMAC), and modal flexibility assurance criterion (MACFLEX) to determine structural damage in location and severity was evaluated.	The inverse problem of damage detection was formulated as an optimization problem, and the following four objective functions were taken into account: I) 1-MAC II) 1-MTMAC III) 1-MACFLEX IV) 1-COMAC The utilized optimization algorithm for minimizing the above-mentioned objective functions is the DEA.	Simply supported beam	Overall, the objective function based on MTMAC works appropriately for all damage scenarios, even though limited measurements were available.
Vo-Duy et al. [100]	2016	The research introduces a two-stage technique for damage identification in laminated composite structures, including beam and plate, employing the modal strain energy method and an improved version of the DEA. Tow improvements in the mutation phase and selection phase of standard DEA are addressed to adaptively determine the mutant factor and crossover control parameter. An adaptive mutation method with multiple mutation operators is presented in the mutation phase, while a new selection method is proposed in the selection phase.	The modal strain energy-based method is first implemented to detect potential damage elements, as well as to decrease the design variables of the optimization problem for the second stage. In the second step, the improved DEA is employed to identify the severity of damaged elements by minimizing the error function of measured and calculated mode shapes.	Laminated composite beam Laminated composite plate	The numerical studies show that regardless of noise, the modal strain energy-based method provides successful results in locating damaged elements. The improved DEA and DEA can identify damage severities accurately. However, the improved DEA needs far fewer function evaluations than the DEA.
Dinh-Cong et al. [101]	2017	A two-stage technique incorporating the DLV method and the DEA is developed	The DLV method is used to locate the damaged elements in the first stage, which uses	Laminated composite beam	Two numerical examples, a symmetric cross-ply (0/90/0) beam and an asymmetric (0/90/0/90)

Reference	Year	Objective	Methodology	Structure	Result and Finding
		for damage identification of laminated composite beams.	normalized cumulative energy. The extent of potentially damaged elements is identified in the second stage through optimizing a cost function by the DEA.		beam, are adopted to demonstrate the potential of the proposed methodology. The following outcomes have been achieved: I) The two-step procedure can accurately detect the location and severity of multiple damages at individual layers. II) In the case of a high level of random noise or a limited number of modes, the damage detection results may become erroneous.
Bureerat and Pholdee [102]	2017	This paper proposes the adaptive sine cosine algorithm integrated with DEA (ASCA-DEA) to enhance the performance of the sine cosine algorithm for solving structural damage detection problems.	The ASCA-DEA includes an adaptive strategy and the mutation operator from DEA, which increase the algorithm's performance. The ASCA-DEA is applied to minimize the root mean square error between measured and computed natural frequencies to solve the damage identification problem.	Space truss	The results show that the ASCA-DEA is a practical and dependable strategy to tackle the damage identification problems.
Dinh-Cong et al. [103]	2017	This paper compares three optimization algorithms, including Jaya, DEA, and cuckoo search (CS) for structural damage detection.	The structural damages and their severities are identified by minimizing a hybrid objective function based on the MDLAC and modal flexibility matrix.	Portal frame Plane truss Plane frame	The Jaya algorithm, DEA, and CS can provide the exact solution to damage identification problems, even in the presence of noise. However, the convergence speed of the Jaya algorithm is much more than DEA and CS.
Dinh-Cong et al. [104]	2017	For damage assessment in plate-like structures, the research provides a multi-stage optimization strategy utilizing the modified version of DEA. The modified DEA is employed as an optimizer, which can improve the balance of global and local searches.	When using the proposed multi-stage procedure, elements with a damage severity of less than 2% can be regarded as healthy and set to zero to remove them from the design variables and improve the convergence rate. The objective function in this study is the discrepancy between a measured flexibility matrix and the equivalent one from a FEM.	Square isotropic thick plate Laminated composite plate	The numerical examinations demonstrate that the presented two-stage method can accurately recognize the location and extent of damage with low computation cost.
Seyedpoor et al. [105]	2018	This paper introduces a multi-stage method for structural damage detection. First, the inverse damage identification problem is formulated as an optimization problem. Then, an improved version of	The location of identified damaged elements in each optimization step is imposed on the following step. In contrast, the impacts of undamaged elements on the subsequent step are omitted. This method eliminates undamaged	Cantilever beam Plane truss Space frame	The numerical and experimental results reveal that the presented multi-stage technique is more efficient than the single-step method relying on DEA.

Reference	Year	Objective	Methodology	Structure	Result and Finding
		DEA is employed to minimize the cost function. In the improved DEA to accelerate the convergence rate, a new mutation scheme is introduced instead of the standard mutation phase, and a random variation scheme is operated to modify the mutation constant.	elements one by one during certain stages, and the algorithm eventually converges to the actual solution (location and severity of damaged members) with a lower computational cost. This study uses the ECBI as the cost function during the multi-stage optimization procedure.		
Georgioudakis and Plevris [106]	2018	In this study, a hybrid objective function is developed as a sensitive criterion to provide a reliable optimization-based approach for finding the location and severity of structural damage.	The DEA is utilized to minimize a combined cost function, which takes into account the values of MTMAC and MACFLEX.	Simply supported beam Portal frame	When compared to MTMAC and MACFLEX, it was found that the hybrid objective function based on the MTMAC and MACFLEX performs best.
Alkayem and Cao [107]	2018	In terms of accuracy, consistency, and computational cost, the performance of five optimization methods, namely PSO, GA, DEA, Lévy flight–DEA (LFDEA), and elitist artificial bee colony–PSO (EABCPSO), is compared.	Presents a hybrid cost function that combines the residuals of the mode shape and the modal strain energy with weighting factors.	IASC-ASCE benchmark structure	The following is a summary of the findings from this study: I) GA identified many undamaged elements instead of damaged ones. II) In comparison to GA and DEA, PSO provides accurate results. However, after several tests, it was discovered that it lacked stability. III) The EABCPSO and LFDE, respectively, enhanced the accuracy and consistency of the basic version of PSO and DE. IV) The EABCPSO outperforms LFDE in terms of accuracy. Besides, the computational time of EABCPSO is lower than LFDE.
Kim et al. [108]	2018	The most significant contribution of this paper is the implementation of the modified DEA as a swift optimizer to solve the damage detection problem. Then, a comparative study is performed to assess the performance of the standard	The natural frequency and mode shape differences are considered as the cost function. A penalty function is also added to the objective function for more precise detection of damage parameters.	Plane truss Space frame	The numerical results indicate that the modified DEA can identify the location and severity of damaged elements more accurately than the standard DEA, PSO, and GA. Additionally, the convergence rate of the modified DEA is faster than the other studied algorithms.

Reference	Year	Objective	Methodology	Structure	Result and Finding
		DEA, GA, and PSO with the modified DEA.			
Seyedpoor et al. [109]	2018	This paper presents an effective method for damage identification using the time-dependent acceleration response and DEA.	The cost function is formulated using measured and calculated acceleration response vectors from a limited number of sensors. Then, the DEA was employed as a global optimization technique to address the optimization problem.	Cantilever beam Plane truss Portal frame Plane frame	According to numerical results, the combination of the acceleration response-based objective function and DEA can provide a potent tool for structural damage identification, even in a high random noise level (15%).
Fallahian et al. [110]	2018	This study introduces a practical method with the assistance of changes in acceleration response and DEA to handle the structural damage detection problem.	The proposed objective function utilizes the time-domain acceleration response as a sensitive criterion for damage occurrence.	Plane truss Portal frame	The suggested approach based on DEA and changes in acceleration response can accurately determine the location and severity of damage when the different noise level is imposed (1%, 2%, and 3%).
Bassoli et al. [111]	2018	A model updating strategy through minimization of the vibration-based objective function by employing an improved surrogate-assisted (DEA-S) for severely damaged historic masonry structures is provided in this research. The DEA-S significantly decreased the number of objective function evaluations and can be successfully implemented to optimize the highly time-consuming problems.	The weighted objective function is defined as the difference between measured natural frequencies and mode shapes from ambient vibration testing and corresponding numerical values from the CLOUD2FEM.	Historical masonry structure	Three design parameters are considered to investigate the influence of structural parameters on dynamic behaviors. The results for FEM updating are presented as follows: I) When considering the homogeneous distribution of the masonry elastic properties (E_M), the updated FEM does not represent the actual behavior of the structure. II) When elastic modulus of the portions of walls connecting the Mastio to the fortress on the west (E_{CW}) and north (E_{CN}) sides are adopted as design parameters, there is still a poor correlation between numerical and experimental models for the fourth and fifth modes. III) When masonry elastic properties for undamaged (E_U) and damaged (E_D) states are considered design parameters, the updated E_U and E_D equal 892 and

Reference	Year	Objective	Methodology	Structure	Result and Finding
					700 MPa, respectively. The updated model has a much better consistency between experimental and numerical results.
Bureerat and Pholdee [112]	2018	In this paper, the radial basis function is incorporated into the DEA (RBFDEA) to accelerate the convergence rate of the standard DEA in solving the inverse damage identification problems.	This research practices a natural frequency-based cost function for minimizing by the RBFDEA.	Space truss	The results obtained from numerical examples clearly demonstrate the advantage of the RBFDEA compared to standard DEA, whale optimization algorithm (WOA), sine cosine algorithm, moth flame optimization algorithm, real-code ant colony optimization, charged system search, league championship algorithm, simulated annealing, evolution strategies, teaching-learning-based optimization, adaptive differential evolution, evolution strategy with covariance matrix adaptation, PSO, and ABC.
Seyedpoor and Nopour [113]	2019	An efficient and swift two-step approach through a machine learning method and DEA is developed for localizing and quantifying the damaged connections in moment frames.	The possible location of damaged connections is identified in the first stage using a support vector machine (SVM), which reduces the size of the search space. The second stage employs the DEA to minimize an objective function relying on MDLAC in order to accurately detection of the severity of damage in connections.	Plane frame	The SVM exhibited high accuracy in locating probably damaged connections based on the numerical results. When implementing the DEA in the reduced search space, the severity of damaged connections can be swiftly and accurately determined.
Kim et al. [114]	2019	The main contribution of this research is to develop a practical damage detection technique for plane and space truss structures utilizing DEA and vibration data extracted from the force method.	The natural frequencies, as well as mode shapes, are taken into account to construct the objective function. In the objective function, the force mode vectors are introduced as eigenvectors.	Plane truss Space truss	The combination of the DEA with force method is significantly more efficient than GA in recognizing damaged elements, according to three numerical examples.
Sobrinho et al. [115]	2020	The structural responses of experimental simply supported beams under various loading were employed in combination with DEA to identify damaged elements.	The objective function is defined based on the least squares of the difference between experimental and numerical responses in the time domain.	Simply supported beam	The results demonstrate that using the DEA and time-domain responses as an objective function to address damage identification problems has a lot of promise.
Seyedpoor and Pahnabi [116]	2020	This paper identifies the structural damages using a sensitive damage indicator based on FRFs and DEA.	The FRFs are placed instead of natural frequencies in the ECBI formula to form the objective function.	Cantilever beam Portal frame	The results show that using the FRF-based objective function in conjunction with DEA to identify the damages elements and their severities

Reference	Year	Objective	Methodology	Structure	Result and Finding
				Plane frame	is highly effective, even when there is a lot of noise (up to 5%). However, a sensitivity analysis is necessary to determine the exact number of utilized modes because this is an important parameter that influences the accuracy of the damage identification method and varies from one example to the next.
Lieu et al. [117]	2020	An inverse two-stage technique with the assistance of modal strain energy-based index and adaptive hybrid evolutionary firefly algorithm (AHEFA) is applied to damage detection of truss structures. The AHEFA algorithm is a mixture of the DEA and the firefly algorithm, and a dynamically adapted parameter is employed to determine an optimal mutation scheme. As a result, global exploration and local exploitation capabilities are appropriately balanced [118].	In the first step, the potentially damaged elements are identified through an efficient criterion called modal strain energy-based index. The second step aims to find the exact severities of the damaged elements by addressing an optimization procedure based on AHEFA and ECBI as an objective function.	Plane truss Space truss	The performance of the AHEFA is significantly better than those obtained from the standard DEA and firefly algorithm in terms of accuracy and computational efforts.
Guedria [119]	2020	This research establishes the accelerated DEA, a modified optimizer for detecting damage in large-scale problems with a rapid convergence rate and producing accurate solutions while avoiding being entrapped into the local solutions.	The DEA algorithm is redesigned by making three modifications to the basic DEA. Firstly, a realistic choice is utilized to generate the initial population instead of producing them randomly. This kind of initialization aids the algorithm in achieving a quick convergence. Secondly, an innovative mutation operator depending on the dispersion of individuals through the search space is introduced to ensure the automatic balance between local and global searching capabilities. Lastly, a specialized exchange operator is developed and implemented to prevent premature convergence.	Isotropic plate Laminated composite plate	The following conclusions have been drawn based on the numerical examples: I) The established objective function successfully determines the location and severity of damaged elements while avoiding false identifications. II) The accelerated DEA has been shown to be a proper optimizer for recognizing locations and extents of damage while only requiring lower modes. III) For all examples investigated, accelerated DEA outperforms its competitors in terms of mean, standard deviation, and computational time.

Reference	Year	Objective	Methodology	Structure	Result and Finding
			By minimizing an objective function created by the flexibility matrix, the location and severity of damage have been determined.		
Su et al. [120]	2021	The main contribution of this paper is developing a modified version of the bat algorithm to overcome shortcomings such as lack of diversity and premature convergence. The optimization capability of the modified bat algorithm is also compared to the DEA, PSO, shuffled frog leaping algorithm (SFLA), and different versions of the bat algorithm.	The optimization algorithms attempt to minimize a hybrid objective function (combination of natural frequency, mode shape, and flexibility matrix).	Simply supported beam Plane truss	The modified bat algorithm has a higher accuracy and convergence rate than DEA, PSO, SFLA, and different variants of the bat algorithm.
Wang et al. [121]	2021	This paper proposes a damage localization method incorporating the B-spline wavelet on the interval finite element method and the optimized singular value decomposition method.	The damaged structures are modeled using a B-spline wavelet on an interval finite element method. The attractor trajectory matrix is calculated using mode shape vectors extracted by modal analysis, and the singular value decomposition-based approach is utilized to determine damage locations. For matrix trajectory decomposition, the DEA is employed to explore the optimal parameters adaptively.	Cantilever beam	Numerical and experimental investigations show that the proposed strategy based on the B-spline wavelet on the interval finite element method and optimized singular value decomposition method is robust to damage localization in beam-like structures.
Firouzi et al. [16]	2021	This paper evaluates the computational efficiency of different optimization algorithms for open-edge crack identification in Euler–Bernoulli beams. In this study, eight optimization algorithms, including the DEA, WOA, GWO, Harris hawk optimization (HHO), pathfinder algorithm (PFA), electrostatic discharge algorithm (ESDA), Henry gas solubility optimization (HGSO), and covariance matrix adaptation–evolution strategy (CMA-ES) are taken into account. Then, new hybrid versions are	Hybridized versions of studied algorithms with the Nelder-Mead algorithm (PFA-NM, ESDA-NM, HHO-NM, DE-NM, and CMA-ES-NM) are proposed to decrease the number of function evaluations. The cost function for determining the crack location and depth is the weighted squared difference between the measured and computed natural frequencies.	Cantilever beam	Regarding the obtained results, the crack location and depth can be accurately predicted with 3500 function evaluations in 150 iterations when using the ESDA. However, the PFA provides the same results with 15,000 function evaluations in 500 iterations. When implementing hybridized versions with the Nelder-Mead algorithm, the PFA-NM algorithm requires 360 function evaluations to determine the crack parameters. The ESDA-NM algorithm needs 400 function evaluations to find reliable results.

Reference	Year	Objective	Methodology	Structure	Result and Finding
		introduced to improve computational efficiency.			
Pahnabi and Seyedpoor [122]	2021	This paper introduces a method for detecting joint damage in moment frames using an improved version of DEA and time-domain responses. When employing improved DEA, a new mutated vector is operated to produce the new generation for improving the performance of standard DEA.	The objective function is assembled by substituting acceleration response vectors for natural frequencies in the ECBI equation.	Plane frame	The results reveal the effectiveness of the presented approach for determining the location and extent of joint damage with a limited number of measurements and noise effects. The influence of sensor placement on damage identification results is minor in small structures. However, increasing the number of sensors might improve the accuracy of the damage detection methodology for large-scale structures.
Aloisio et al. [123]	2022	In this paper, the indirect estimation of concrete resistance using the modulus of elasticity identified through an optimization-based FEM updating procedure is compared to the resistance directly estimated from concrete samples. To determine the optimal solution in FEM updating, two optimization techniques, including the DEA and PSO, were implemented.	For FEM updating with the DEA, the deck (E_d) and girder (E_b) modulus of elasticity are considered design parameters, and a cost function (combination of natural frequencies and mode shapes) based on changes in measured and calculated modal parameters is taken into account. The measured modal parameters are extracted through ambient vibration tests, and the numerical model is developed in Sap2000.	Corvara bridge	The resistances of the concrete specimens estimated from each span confirm the indirect results (FEM updating) for assessing concrete compressive strength. The percentage difference between the compressive strengths determined by the direct and indirect methods is about 20%. The validation is only limited to girders, and the researchers could not prepare the specimens from the deck. The utilized optimization algorithms (DEA and PSO) have provided the same results in FEM updating.

4. Analysis and Discussion

This study's central purpose is to attract readers' attention to the DEA and various modified versions for solving structural damage detection problems and other similar optimization-based problems in SHM, such as optimal sensor placement, FEM updating, and crack detection. This chapter makes an effort to give a summary of the DEA's journey over slightly more than 20 years (2001–2022). Figure 2 displays the number of reviewed articles released in the last two decades. The DEA was initially introduced in 1997. However, the first paper related to SHM was presented in 2001, according to Figure 2. Additionally, the number of published papers between 2016 and 2019 is more significant than in other periods.

The review of improved versions of the DEA revealed that the suggested improvements to the DEA's standard parameters and operators typically included modifications in the initialization mechanism, mutation, crossover, and selection operators. For example, Fu and Yu [87], Vincenzi and Savoia [92], Vo-Duy et al. [94, 100], and Bureerat and Pholdee [102] are some of them to be mentioned.

Figure 3 illustrates a pie graph of employed structures, showing beam-like structures more times used to validate the effectiveness of different vibration-based methodologies. The minor contribution is related to bridges among the other five categories.

Figure 4. depicts the percentage of papers that have been published in the fields of damage detection, FEM updating, crack detection, and optimal sensor placement. It can be seen that a large number of papers present damage detection methodologies and only a few papers focus on optimal sensor placement.

Figure 5 provides the statistical analysis of utilized objective functions over the past two decades. It is clear that the hybrid objective function based on natural frequencies and modes shapes and defined cost function using ECBI term are also popular objective functions when using the DEA as an optimizer in vibration-based damage detection problems.

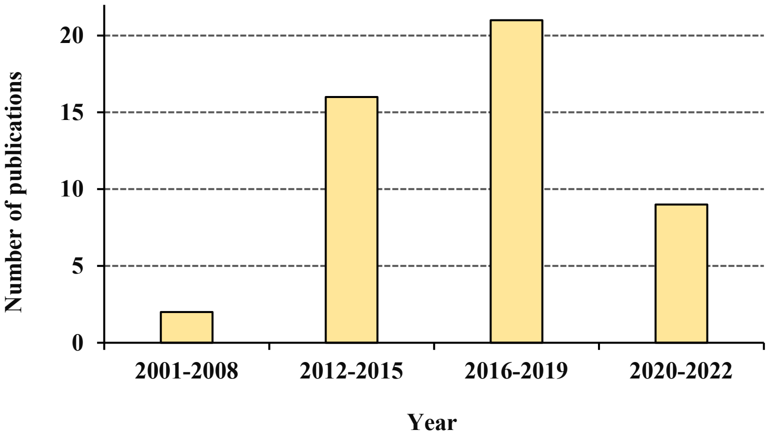

Figure 2. Number of publications in the field of structural damage detection using DEA

According to reviewed papers, several two-step and multiple-step methods have been proposed to deal with large search areas in high-dimensional optimization problems. The non-single-step methods generally attempt to reduce the number of design variables by identifying the damaged elements in the first step. Then, the DEA is implemented to minimize an objective function in the narrowed search space with lower design variables. This methodology is efficient in eliminating false alarms that are identified by single-step methods. Figure 6 demonstrates the ratio of single-step, two-step, and multiple-step procedures utilized within 20 years. According to Figure 6, 17% of methodologies have been developed based on two-step methods. The categorization of different two-step procedures is provided in Figure 7. Most researchers have applied modal strain energy to find the potentially damaged elements in the first step.

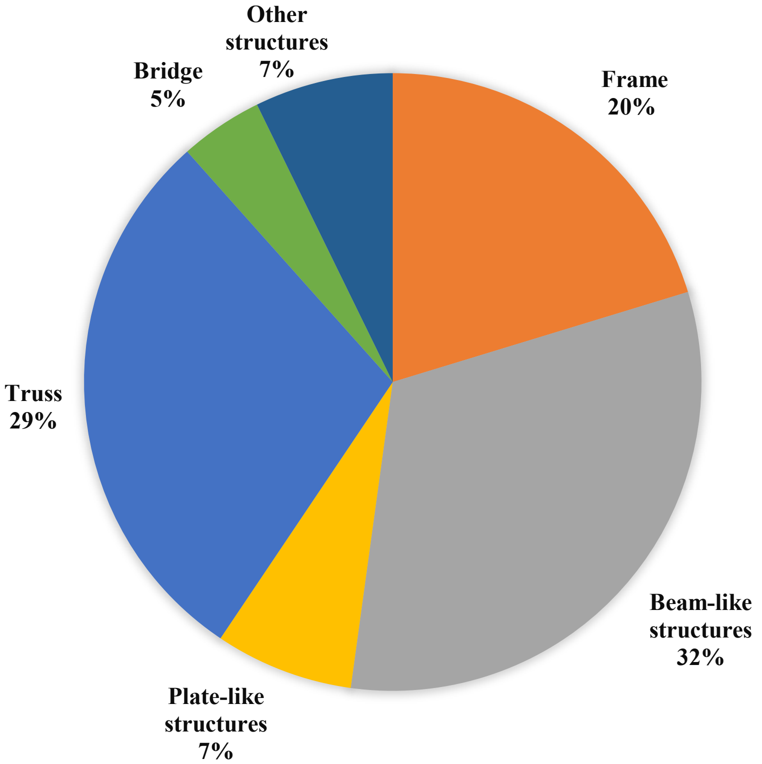

Figure 3. The distribution of structures employed in publications to show the effectiveness of suggested techniques

Figure 4. Contribution of publications in the areas of damage detection, FEM updating, crack detection, and optimal sensor placement

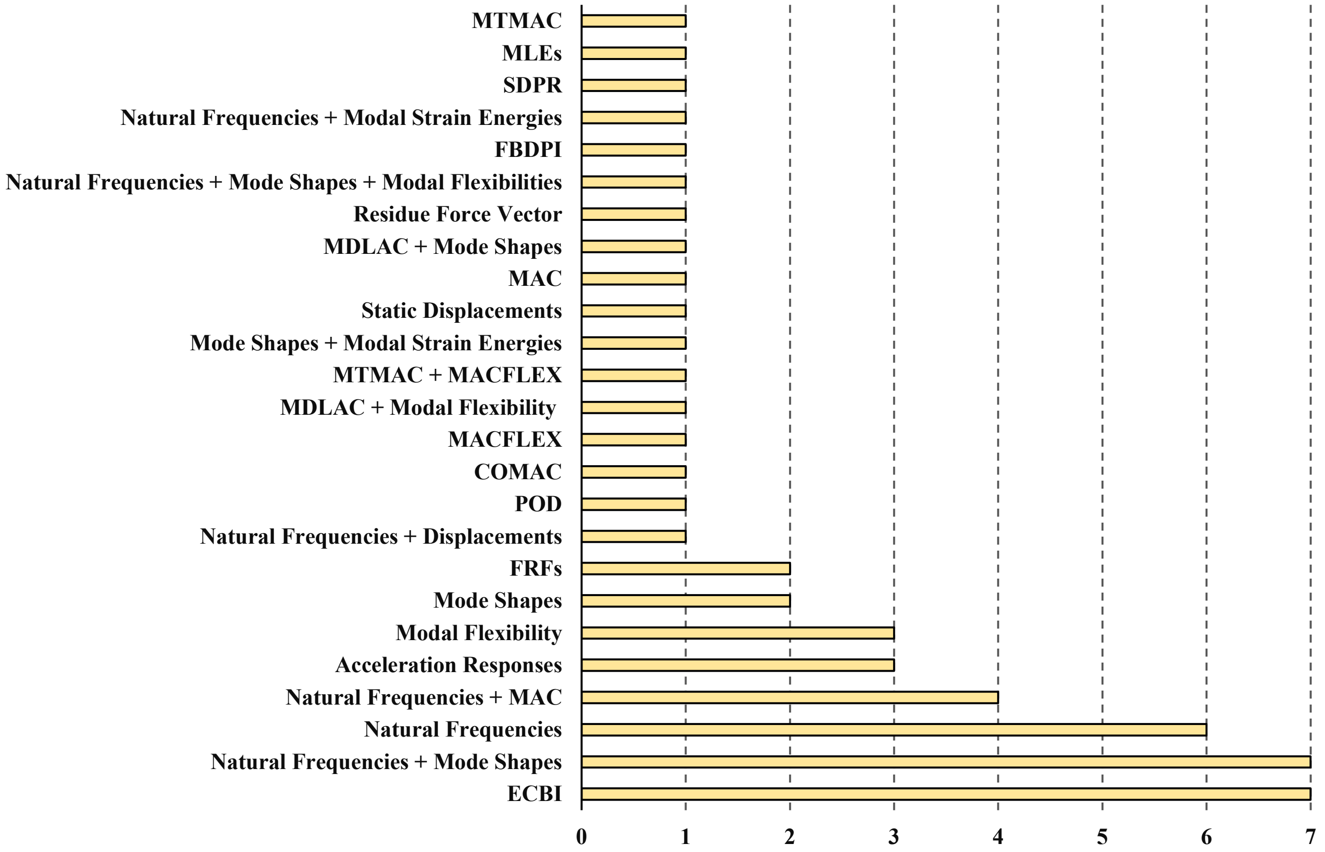

Figure 5. The categorization of implemented objective functions by the number of publications

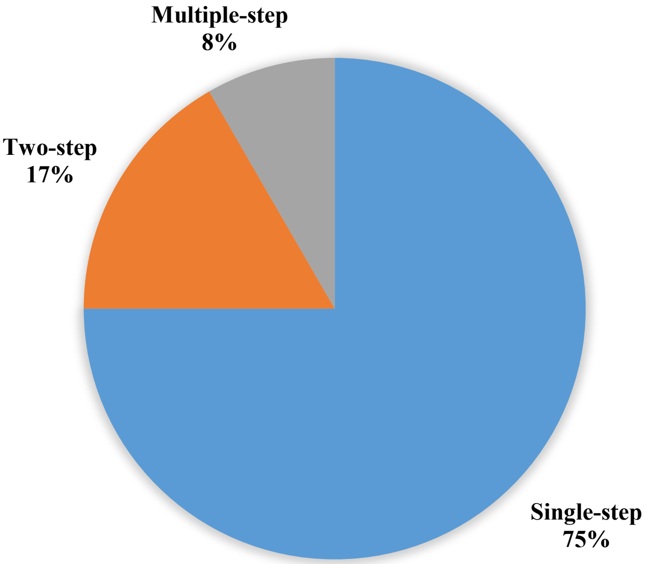

Figure 6. The ratio of single-step, two-step, and multiple-step techniques used in publications

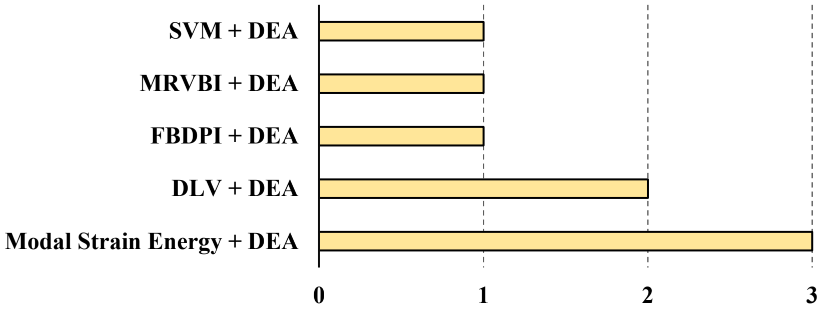

Figure 7. The categorization of various two-step techniques by the number of publications

5. Conclusions

The present chapter is conducted in two main phases. The first phase reviews the methodologies, objectives, types of structures, and results of published papers from 2001 to 2022 in tabulated form. The organization of the tabular review helps readers find the essential points of each paper and address the critical questions as well as future directions. The second phase statistically analyzes the extracted data from the tabular review and graphically quantifies the number of publications per year, the percentage of different types of structures employed to assess the damage detection methodologies, the ratio of utilized objective functions, and contribution of single-step, two-step, and multiple-step approaches with the assistance of DEA. The overall results of this review can be summarized as follows:

- The highest number of papers was published between 2016 and 2019.
- The contribution of beam-like structures is more significant than other structures. In contrast, only a few papers verify their methodology using bridge structures.
- Considerable articles propose techniques for damage detection (78.72%). The ratio of other SHM problems, such as crack detection, FEM updating, and optimal sensor placement, are 10.64%, 8.51%, and 2.13%, respectively.
- The ECBI and the combination of natural frequencies and mode shapes have been the most widespread objective functions over the past two decades.
- The percentage of utilized single-step, two-step, and multiple-step methods are 75%, 17%, and 8%, respectively. Additionally, among other methods such as DLV, FBDPI, MRVBI, and SVM
- the modal strain energy has been employed many times for detecting damaged elements in the first step.

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