# Comparative study of meta-heuristic algorithms for damage detection problem

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**Abstract.** This study presents a comprehensive comparative analysis of several meta-heuristic optimization algorithms for solving the damage detection problem in concrete plate structures. The problem is formulated as a bounded single objective optimization problem. The performance and efficiency of the algorithms are compared under various scenarios using noise-contaminated data. The results show that these meta-heuristics are powerful methods for global optimization and are suitable for solving the damage detection problem. The study compares the performance of these algorithms in: (1) identifying the location and extent of damaged elements, and (2) robustness to noisy data. The proposed meta-heuristic algorithms show promise for solving the damage detection problem. Particularly, the GSK-ALI, MRFO, and Jaya algorithms demonstrate superior performance compared to the other algorithms in identifying damaged elements within concrete plate structures.

**Keywords:** Structure Health Monitoring (SHM), Damage detection, Plates, Meta-Heuristic, Flexibility matrix.

## 1 Introduction

The safety of structures can be threatened by damage, which is a significant concern for maintaining their integrity. To address this issue, structural health monitoring (SHM) is commonly employed to gather vast amounts of data using wireless sensors, signal processing technology, and artificial intelligence. However, analysing and assessing the condition of a structure based on this data can be a complex task. Damage detection is crucial in structural condition assessment, as it helps to identify damage, determine its severity, and estimate the remaining life of a structure [1]–[3]. It is important to note that structural damage may not always be predictable, which is why early detection of damage is crucial for fast and efficient repairs, and to ensure the

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safety and serviceability of the structure [4]. Non-destructive vibration studies that display structural dynamic characteristics behaviour, such as frequency response functions (FRFs) and modal properties, are typically used to identify structural damage. Since these features are related to physical structural properties, changes in these properties can be used to infer damage, under the assumption that changes in physical structural properties lead to modifications in dynamic structural properties [5]. Damage detection in structures typically relies on analysing the vibrational responses of the structure [6]. However, small differences in these responses can be difficult to detect due to variations in environmental conditions such as temperature, wind, and rain [6]. Many methods have been proposed in the literature to address this issue and improve the practical applicability of damage detection techniques. These methods can be used for both structural health monitoring and early detection of damage [7]–[12]. An extensive review of methods for the detection of damage is available in [3], [13].

Numerous approaches have been put forward to tackle the problem of identifying damage in structures, employing a wide range of techniques. Several of these methods are associated with particular characteristics of the structure, such as its modal strain energy [14], mode shape derivative [15], [16], natural frequency response [17], wavelet transform [18], [19], and residual force vector [20], [21]. These features are typically employed as indicators of damage in the structure and furnish valuable insights into the site and the magnitude of the damage.

The presented study aims to evaluate the effectiveness of several meta-heuristic methods for solving the damage detection problem in structures. The problem is modelled as a bounded single objective optimization problem, and the performance and the efficiency of the algorithms are compared under various scenarios using noisy data. The meta-heuristic algorithms studied in this research are inspired by the collective intelligence of social animals or insects, such as herds, birds, or fish, and include well-known algorithms such as Particle Swarm Optimization (PSO) [22], Artificial Bee Colony (ABC) [23], Differential Evolution (DE) [24], and Teaching-Learning-Based Optimization (TLBO) [25].

In recent years, there has been a sustained interest in swarm-based methods, and several advanced swarm intelligence methods have been developed. These methods are known for their excellent computing performance and have been applied in a wide range of fields such as Mechanical Engineering [26], Aerospace Engineering [27], Structural Design [28], Automotive Industry [29], Civil Engineering [30], to examine the performance of these algorithms, a numerical simulation of different scenarios with noisy data in a concrete plate structure is performed. The results of this study will be of interest to researchers in the field of structural health monitoring, as they will help identify the most effective and efficient meta-heuristic algorithms for solving the damage detection problem.

The article is organized as follows: In Section II, the problem of damage detection is explained theoretically. The algorithmic concepts used in the study are briefly outlined in Section III. The results are then presented and discussed in Section IV. Finally, the findings are presented in Section V, as well as prospective research interests.

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# 2 Structure of Damage Detection problem

## 2.1 Damage detection modelling

The simplest expression of the damage detection problem is by applying a linear equation of motion representing the undamped free vibration [31].

$$[M][\ddot{x}]+[K][x]=0 \tag{1}$$

Where [x] is the displacement vector, [K] and [M] represent respectively the stiffness and the mass matrix. In this case, the equation of motion can be expressed as follows:

$$\begin{aligned} x(t) &= \phi_i u_i(t), \\ u_i(t) &= A_i \cos\left(\omega_i t - \theta_i\right), \end{aligned} \tag{2}$$

Where $\phi_i$ and $\omega_i$ represent the *ith* mode shape and modal frequency, respectively, $u_i$ is a displacement time variation given by the harmonic excitation, $\theta_i$ stands for the *ith* angle of phase, $A_i$ denotes the *ith* constant associated with the *ith* mode shape. Replacing equation (2) into (1), this gives:

$$u_i(t)\left(-\omega_i^2[M]\phi_i+[K]\phi_i\right)=0 \tag{3}$$

However, the eigenvalue formula used to represent the vibrational mode characteristic of a healthy plate structure is expressed as follow:

$$\left([K]-\omega_i^2[M]\right)\phi_i=0 \tag{4}$$

In the literature, there are several methods for modeling a damaged plate structure, such as a cracked model [32]. However, these methods can increase the complexity of the simulation and may not be effective for studying the structural performance response in optimization analyses. As a result, a commonly used method for modeling damage to structural elements in optimization problems is to reduce the stiffness of element. The global stiffness matrix of the structure is the sum of the intact and affected stiffness matrices, and can be represented mathematically as follows:

$$\mathrm{K}=\sum_{e=1}^{nele}(1-a_e)\mathrm{K}_e \tag{5}$$

Where $\mathrm{K}_e$ corresponds to the stiffness matrix of the element *eth*, *nele* indicates the number of elements and $a_e$ corresponds to the damage ratio $\in [0, 1]$ representing the degree of damage of the elements, where 0 means a healthy element and 1 meaning that the element is fully damaged.

## 2.2 The objective function based on modal flexibility.

According to [33], structural damage leads to a reduction in stiffness and an increase in flexibility of a structure. This means that any changes to the flexibility matrix can be

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considered as an indication of structural damage and can provide further information about the damage's site and severity. However, previous research as cited in [34] has shown that using the flexibility matrix is more effective for identifying damage compared to other methods. In the current study, the objective function for evaluating damage in concrete structures is based on the difference between the flexibility matrix calculated from a numerical model and the one obtained from a measured model, which is used to compare the two flexibility matrices and assess the damage.

$$f(x) = \frac{\left\| F^{\exp} - F^{ana}(\mathrm{x}) \right\|_{Fro}}{\left\| F_j^{\exp} \right\|_{Fro}}, \qquad \mathrm{x} = (x_1, ..., x_n) \in [0,1]^n \tag{6}$$

$F^*$ is the flexibility matrix expressed as follows:

$$F^* = \sum_{i=1}^{n\mathrm{mod}} \frac{1}{(\omega_i^*)^2} \, \phi_i^* (\phi_i^*)^T \tag{7}$$

Where $\omega_i{}^*$and $\phi_i{}^*$represent the *ith* natural frequency and its associated mode shape, the superscripts exp and ana refer to the damaged model and the analytic model, the number of modes is *nmod*, the design vector of variable for the damage extent of *n* elements is x, and $\|.\|_{Fro}$ present the Frobenius norm of a matrix. However, in this study, we use generated data which were obtained by numerical simulations of damage scenarios on a structural model. To improve the generalizability of our results, we also applied data augmentation techniques, such as adding noise and changing the location of the damage, on the generated data.

## 3 INSTRUCTION TO THE OPTIMIZATION METHOD

Real-world engineering problems often present a wide range of complex optimization challenges. To address these issues, metaheuristic algorithms can be employed as they are user-friendly and do not rely on gradient information. This study delves into various techniques for addressing the problem of damage detection, and a comparisons of different algorithms are also presented.

### 3.1 Differential Evolution DE

The differential evolutionary algorithm (DE) [24] utilizes a combination of individuals from the same population, including the parent, to generate new candidates. The DE algorithm only selects candidates that are superior to their parents. Due to its straightforward design and minimal number of control settings, the DE has been successful in many real-world applications and has been used to find optimal solutions in various complex optimization problems.

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### 3.2 Particle Swarm Optimization PSO

This method is a type of stochastic optimization technique and evolutionary algorithm that was developed by James Kennedy and Russ Eberhart in 1995 [22], to solve difficult computational optimization problems. It has been widely used in various optimization problems and research projects since its introduction. The approach is based on the concept of swarm theory, which is inspired by the behaviour of swarms of birds, fish, etc. The swarm theory is a population-based evolution algorithm where each swarm or particle represents a specific decision. The position of the particle is updated through its velocity vector and aims to reach the optimal solution.

### 3.3 Teaching Learning based Optimization TLBO

The TLBO method, introduced by Rao et al. in 2011 [25], is a population-based optimization algorithm that is based on the teaching-learning methodology. It relies on a population of learners, where the optimization procedure is carried out through two distinct phases. The initial phase, also known as the "teaching stage", involves learners acquiring knowledge from a teacher. Subsequently, the "learning phase" takes place, during which learners interact to optimize problem-solving. In this approach, the group of learners represents diverse variable configurations employed to tackle optimization issues. These different configurations are handled as different subjects available for the learners, and their performance is evaluated through a fitness estimation value. The best solution among the entire population is the "teacher" in this algorithm. The TLBO approach uses the concept of a population of learners, where the different configurations of variables are considered as individuals in the population, and the optimization is carried out through the interactions among the learners, using the teaching and learning methodology. The optimization process is divided into two phases, teacher phase and learner phase, where the best solution in the population is considered to be the teacher.

### 3.4 Artificial Bee Colony ABC

The ABC algorithm was introduced by Karaboga (2005) [23] as a Swarm Intelligent Metaheuristic method to solve optimization problems. The inspiration for this algorithm comes from the neighbourhood honeybee behaviour while searching for food sources in the wild in a colony. The artificial bees present is classified into three basic categories: worker bees, observer bees and scout bees. There are an equal number of worker bees and scout bees as there are food sources, and each individual bee is related and associated to each source of food. The worker bees look up the food sources in memory. Then, they exchange their data with the spectator bees. The spectator bees will be waiting inside the hive and decide which of the food sources to choose. As a result, the most favourable food sources tend to be more likely to be chosen. Scout bees are changed from few worker bees that abandoned food sources and looked for new sources.

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### 3.5 Harmony search HS

Harmony Search (HS) [35] is a metaheuristic optimization algorithm that was first proposed by Zong Woo Geem in 2001. It is inspired by the process of improvisation in music, where a musician searches for a perfect harmony by adjusting the pitch and playing time of musical notes. In the HS algorithm, a set of potential solutions (referred to as "harmonies") is represented as a set of decision variables. The algorithm uses a set of heuristic rules to generate new harmonies and to update existing ones. The objective function, which represents the desired harmony, is used to evaluate the quality of each harmony. The algorithm continues to iterate and update the harmonies until a satisfactory solution is found or a stopping criterion is met. HS has been shown to be effective in finding global optimal solutions and is relatively easy to implement.

### 3.6 Sparrow Search algorithm SSA

The Sparrow Search Algorithm SSA [36] is an optimization algorithm that employs swarm-based techniques, drawing inspiration from the hunting behaviour of sparrows. It models the behaviour of birds in a flock, where specific members, known as "generators," lead the search for food while others, referred to as "followers," trail behind. To find the best solution to a problem, the algorithm mimics this process by utilizing a group of individuals that search for the optimal solution. The SSA algorithm uses a mechanism called "detection and early alert" to identify and avoid suboptimal solutions. This is done by selecting certain individuals from the population to act as "scouts" and explore different parts of the search space. If a scout detects a suboptimal solution, it "flies away" and searches for a new solution.

### 3.7 Gaining Sharing Knowledge-based Algorithm GSK-Ali

The GSK algorithm (Gaining Sharing Knowledge-based Algorithm) is an optimization algorithm that is based on the human process of acquiring and sharing knowledge. The algorithm consists of two phases: the junior phase and the senior phase. In the junior phase, initial solutions are generated by using different methods such as randomization or heuristics. Then, in the senior phase, the solutions are transferred and interoperate with other solutions generated by the algorithm. This allows the algorithm to explore different parts of the search space and identify a global optimal solution. Several variations of the GSK algorithm have been developed to adapt it to specific types of problems and to enhance its performance [37], [38].

### 3.8 Manta ray foraging optimization MRFO.

The Manta Ray Foraging Optimization (MRFO) [39] algorithm is a metaheuristic optimization algorithm that is inspired by the foraging behaviour of manta rays. Manta rays are known for their ability to efficiently search for food in their environment, by using a combination of random exploration and directed search. The MRFO algorithm simulates this behaviour by using a population of individuals, called "manta rays", to

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explore the search space and identify an optimal solution. Each manta ray is characterized by its own search strategy and step-size, which are updated during the optimization process. The algorithm uses a combination of random exploration and directed search, to efficiently explore the search space and identify the global optimal solution.

### 3.9 Pathfinder algorithm PFA

The Pathfinder algorithm is a novel metaheuristic optimization algorithm that is inspired by the survival strategies employed by animal groups in nature. It was first proposed by Yapici and Cetinkaya in 2019 [40]. The algorithm is based on the division of group members into two distinct roles: leaders and followers. Leaders are responsible for exploring new territories in the search space and identifying potential solutions. Followers rely on the guidance of the leaders to locate these solutions. As the search progresses, individuals may switch roles based on their relative proficiency in each. This allows for a greater degree of adaptability in the search process, as individuals can switch between exploring and exploiting the search space. Unlike other swarm intelligence algorithms, the PFA algorithm does not impose any specific limitations on the population size or the number of leaders and followers. This allows the algorithm to adapt to different optimization problems and search spaces.

## 4 Experimental results

### 4.1 Test Setup

This section is dedicated to evaluating the efficiency of all the methods for identifying damage through a numerical simulation of a concrete plate. The assessment of the algorithm's ability to accurately detect and quantify damaged elements will be displayed by testing it on finite element models (FEM) of a concrete plate exposed to three different damage cases. The resilience of these methods is also examined by incorporating noisy data. Noise levels of 3% on frequencies and 0.15% on mode shapes are incorporated in the simulation, as outlined in [41].

$$f_i^{noise} = (1 + \eta_f(2.rand[0.1] - 1))f_i \tag{10}$$

$$\varphi_{ij}^{noise} = (1 + \eta_m(2.rand[0.1] - 1))\left|\varphi_{ij}\right| \tag{11}$$

It's important to keep in mind that the matrices used to determine the flexibility are resolute through the use of numerical models and experimental data simulations. Only the displacement of the plate degrees of freedom in the transverse direction are considered. Additionally, the process of identifying damage is repeated 20 times per case and the averages are calculated. Table 1 provides the settings parameters for the listed algorithms, corresponding to the optimal parameter values determined in their original research papers. The optimization algorithms are designed to stop under two specific conditions. First, the process stops when the maximum number of iteration *($I_{max}$)* is reached, second, the process can also be stopped if the value of the objective function of the best individual reaches an extremely weak or 0 value (threshold = $10^{-8}$). Both

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above-mentioned conditions will indicate the end of this process. The FEM for the plate and all algorithms were developed using the MATLAB programming software. The simulation and numerical solutions were carried out on a powerful personal computer featuring an Intel(R) Core (TM) i7-8750H CPU @ 2.20 GHz, 12GB of Random-Access Memory (RAM), and running on a 64-bit version of Windows 10.

**Table 1** Parameter setting of the algorithms.

| Algorithm | *Np* | $Max_{ietr}$ | Parameters Setting |
|---|---|---|---|
| MDE | 30 | 500 | F<br>Cr |
| TLBO | 30 | 500 | Teaching Factors 1 or 2. |
| ABC | 30 | 500 | Food number 15<br>Inertia weight 0.7 |
| JAYA | 30 | 500 | $r_1$, $r_2$ random number between [0, 1] |
| GSK-ALI | 30 | 500 | $K_r = 0.9$, $K_f = 0.5$<br>$P = 0.1$, $K = 10$ |
| HS | 30 | 500 | Par = 0.4<br>HMCR = 0.8 |
| MRFO | 30 | 500 | α, β random generated and subject to iteration number |
| PFA | 30 | 500 | α, β random number in the range of [1,2]<br>possibility of switch 0.8 |

## 4.2 Numerical result

An examination of a concrete plate is conducted in this example, which was first used in [42]. The geometric and material properties of the plate outlined in table 3. The plate is rigidly fixed along its four edges and discretized using quadrilateral finite elements with four nodal points, as depicted in figure 1. Three damage cases are evaluated with different site, as outlined in figure 2. The specifics of the damaged elements and the corresponding damage ratios are presented in table 4. The identification of damage is carried out utilizing only the initial three frequencies and their associated mode shapes for all cases.

**Table 3** The Concrete plate parameters

| Settings / Unit | Value |
|---|---|
| Length (Lx, Ly) / m | 2 |
| Thickness (t) / m | 0.15 |
| Young's modulus (E) / GPa | $2e^{10}$ |
| Poisson ratio (*v*) | 0.20 |
| Mass density (ρ) | 2400 |

**Table 4** Damaged Elements Cases

| Cases | Element No. | Damage rate |
|---|---|---|
| 1 | 27 | 0.20 |
| 2 | 43 | 0.20 |
| 3 | 67 | 0.20 |

As part of this study, a Kruskal-Wallis test was performed at the 0.05 level of significance, a non-parametric statistical test, followed by a Mann-Whitney test to compare the results of the algorithms. Table 2 shows the *p-values* obtained from this

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statistical analysis, and utilized to specify whether there is a significant difference between the algorithms, respectively, with a 95% confidence level.

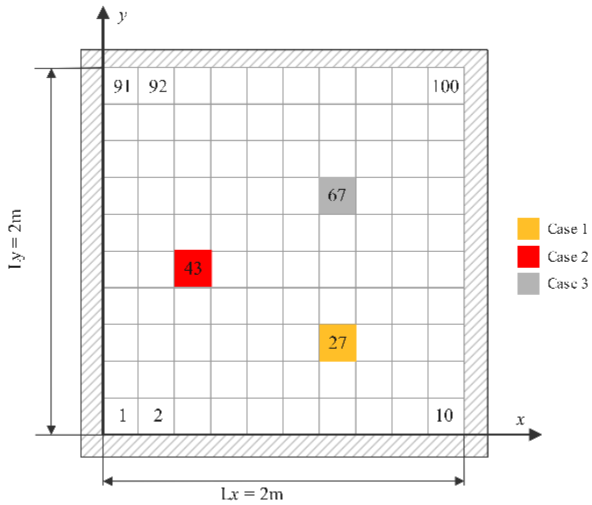


**Figure 1** Discretised a plate with three damage cases.

The statistical result compares the performance of several algorithms, identified by their acronyms (ABC, GSK-ALI, HS, JAYA, MDE, MRFO, PFA, and TLBO). Table 5 provides information on the dimension of the problem (Dim), as well as the best value, worst, average, the standard deviation, while the errors refer to the discrepancies between the average damage ratios obtained by the algorithms and the actual damage ratio. The table is divided into three cases with different site of the damage, each representing the results for a 10 dimension of the problem. It appears that the table is comparing the performance of these algorithms across three different experiments, represented by the three cases, it is also comparing the effectiveness of different algorithms and how they perform in several scenarios of damage in presence of noisy data.

Comparing these algorithms, the performance of the algorithms varies depending on the detection of damage taking into consideration the presence of noise. The best results for each algorithm are not always consistent across the location of the damage. As an illustration, the ABC algorithm records a best result of 2.09E-01 in the initial case, while it is 1.85E-01 in the second set of findings and 1.97E-01 in the third case of damage. Additionally, the majority of algorithms display a low standard deviation, indicating that the outcomes remain consistent during multiple iterations. Furthermore, GSK-ALI and TLBO exhibit superior performance in the first two scenarios with best values of 1.98E-01, 2.01E-01, 2.02E-01, and 2.29E-01 respectively. In the third case, it seems that GSK-ALI is performing better with the best value of 2.00E-01 compared to the actual damage ratio. Overall, it can be seen that ABC and MRFO have similar performance with an average of 2.153e-01 and 2.044e-01 respectively.

The GSK-ALI technique displays a commendable performance, recording a slightly elevated mean score of 1.965e-01 and a standard deviation of 1.044e-02. Conversely, the HS algorithm yields the poorest results, with an average value of 2.708e-01, while

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the MDE has the highest standard deviation of 3.706e-02. However, some algorithms such as ABC, MDE, and JAYA have a relatively high standard deviation, which indicates that their results may be less consistent across multiple runs.

**Table 5** Experimental results of test of the three cases

| Algorithms | Dim | Case | Best | Worst | average | Std | Error% |
|---|---|---|---|---|---|---|---|
| ABC | 10 | 1 | 2,09E-01 | 2,40E-01 | 2.153e-01 | 3.614e-02 | 7.65 |
| GSK-ALI | | | **1,98E-01** | **1,87E-01** | **1.965e-01** | **1.044e-02** | **1.75** |
| HS | | | 2,32E-01 | 2,95E-01 | 2.708e-01 | 2.729e-02 | 15 |
| JAYA | | | 2,54E-01 | 2,40E-01 | 2.218e-01 | 1.926e-02 | 27 |
| MDE | | | 2,43E-01 | 3,02E-01 | 2.501e-01 | 3.706e-02 | 35.4 |
| MRFO | | | 2,09E-01 | 2,40E-01 | 2.044e-01 | 1.979e-02 | 2.2 |
| PFA | | | 2,09E-01 | 2,40E-01 | 2.095e-01 | 2.772e-02 | 4.75 |
| TLBO | | | 2,02E-01 | 2,24E-01 | 2.055e-01 | 2.808e-02 | 2.75 |
| ABC | 10 | 2 | 1,85E-01 | 3,03E-01 | 2.244e-01 | 3.724e-02 | 22 |
| GSK-ALI | | | **2,01E-01** | 1,90E-01 | **1.999e-01** | 1.625e-02 | **0.05** |
| HS | | | 2,23E-01 | 2,58E-01 | 2.418e-01 | 2.013e-02 | 20.9 |
| JAYA | | | 2,02E-01 | 2,23E-01 | 2.257e-01 | **1.249e-02** | 28.5 |
| MDE | | | 1,90E-01 | 2,97E-01 | 2.271e-01 | 2.780e-02 | 35.5 |
| MRFO | | | 2,04E-01 | **2,01E-01** | 2.044e-01 | 2.601e-02 | 2.2 |
| PFA | | | 2,04E-01 | 1,76E-01 | 2.014e-01 | 1.597e-02 | 0.7 |
| TLBO | | | 2,29E-01 | 2,21E-01 | 2.078e-01 | 1.509e-02 | 3.9 |
| ABC | 10 | 3 | 1,97E-01 | 2,79E-01 | 2.233e-01 | 3.102e-02 | 11.65 |
| GSK-ALI | | | **2,00E-01** | **2,09E-01** | 2.053e-01 | **1.221e-02** | 2.65 |
| HS | | | 2,54E-01 | 2,21E-01 | **2.039e-01** | 2.748e-02 | **1.95** |
| JAYA | | | 2,54E-01 | 2,21E-01 | 2.422e-01 | 1.730e-02 | 21.1 |
| MDE | | | 2,49E-01 | 2,93E-01 | 2.225e-01 | 3.076e-02 | 12.5 |
| MRFO | | | 2,56E-01 | 2,83E-01 | 2.593e-01 | 2.072e-02 | 29.65 |
| PFA | | | 2,48E-01 | **2,09E-01** | 2.469e-01 | 2.150e-02 | 23.45 |
| TLBO | | | 2,48E-01 | 2,54E-01 | 2.524e-01 | 1.907e-02 | 26.2 |

Based on the comparison criteria of the best values, mean, standard deviation, and the error, it can be concluded that GSK-ALI outperforms its competitors. It is noteworthy, that in real-world applications, where the damage detection problem involves high complexity and dimensionality, there are time constraints. Therefore, GSK-ALI is preferred due to its efficient in detection of the damaged elements in a concrete plate structure.

## 5 Conclusions

In this study, a comprehensive evaluation of seven meta-heuristic algorithms is presented in order to determine the optimal detection of damage in a concrete plate structure. The algorithms were applied to three different scenarios of damage site, and a thorough comparison of the experimental results was conducted. The results indicate that GSK-ALI, MRFO, and Jaya algorithms exhibit superior performance when compared to the other algorithms. Notably, GSK-ALI demonstrates the best performance in most of cases, as evidenced by the highest best, mean, and standard deviation values and the errors refer to the discrepancies between the average damage ratios obtained by

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the algorithms and the actual damage ratio. These findings can be utilized by researchers to generalize these selected approaches to other classes of damage detection problems. Future research will focus on the implementation of an improved version of the GSK-ALI algorithm to solve damage detection issues in different types of structures under complex scenario and the investigation of the performance of GSK-ALI for multi-objective functions in the context of optimal sensor placement OSP for damage detection in structure health monitoring.

**Table 2** The p-values obtained by the comparison of the Kruskal-Wallis test followed by Mann-Whitney test

| Algorithms | *p-value* | analysis |
|---|---|---|
| ABC VS GSK-ALI | 2.068e-02 | Algorithms differ significantly |
| ABC VS HS | 3.846e-02 | Algorithms differ significantly |
| ABC VS JAYA | 1.413e-01 | Algorithms differ significantly |
| ABC VS MDE | 1.393e-01 | Algorithms differ significantly |
| ABC VS MRFO | 7.958e-01 | No significant difference |
| ABC VS PFA | 9.705e-01 | No significant difference |
| ABC VS SSA | 9.411e-01 | No significant difference |
| ABC VS TLBO | 8.187e-01 | No significant difference |
| GSK-ALI VS HS | 1.491e-06 | Algorithms differ significantly |
| GSK-ALI VS JAYA | 4.489e-08 | Algorithms differ significantly |
| GSK-ALI VS MDE | 4.636e-05 | Algorithms differ significantly |
| GSK-ALI VS MRFO | 7.958e-03 | Algorithms differ significantly |
| GSK-ALI VS PFA | 7.957e-03 | Algorithms differ significantly |
| GSK-ALI VS SSA | 2.052e-03 | Algorithms differ significantly |
| GSK-ALI VS TLBO | 4.636e-03 | Algorithms differ significantly |
| HS VS JAYA | 2.311e-01 | Algorithms differ significantly |
| HS VS MDE | 6.897e-01 | No significant difference |
| HS VS MRFO | 5.942e-02 | Algorithms differ significantly |
| HS VS PFA | 2.975e-02 | Algorithms differ significantly |
| HS VS SSA | 2.150e-02 | Algorithms differ significantly |
| HS VS TLBO | 4.513e-02 | Algorithms differ significantly |
| JAYA VS MDE | 6.952e-01 | No significant difference |
| JAYA VS MRFO | 2.398e-01 | Algorithms differ significantly |
| JAYA VS PFA | 8.235e-02 | Algorithms differ significantly |
| JAYA VS SSA | 5.942e-02 | Algorithms differ significantly |
| JAYA VS TLBO | 1.646e-01 | Algorithms differ significantly |
| MDE VS MRFO | 2.226e-01 | Algorithms differ significantly |
| MDE VS PFA | 1.023e-01 | Algorithms differ significantly |
| MDE VS SSA | 9.049e-02 | Algorithms differ significantly |
| MDE VS TLBO | 2.282e-01 | Algorithms differ significantly |
| MRFO VS PFA | 7.172e-01 | No significant difference |
| MRFO VS SSA | 7.788e-01 | No significant difference |
| MRFO VS TLBO | 9.941e-01 | No significant difference |
| PFA VS SSA | 9.528e-01 | No significant difference |
| PFA VS TLBO | 7.618e-01 | No significant difference |
| SSA VS TLBO | 8.130e-01 | No significant difference |

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