

# Parameter Selection for PSO-Based Hybrid Algorithms and Its Effect on Crack Detection in Cantilever Beams

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## Abstract:

The importance of the parameters of any optimization algorithm, especially meta-heuristic algorithms that have been created to simplify the solution of optimization problems, is inevitable. The optimal values of these parameters, which generally depend on the specifics of the problem in question, have a significant impact on the performance of the mentioned algorithms and a better search of the solution space. Parameters selection will play an important role in the performance and efficiency of the algorithms. This article examines the capability of various optimization algorithms and suggests dual hybrid optimization algorithms named PSO-FA, PSO-GA, and PSO-GWO, for solving the problem of computing the depth and location of cracks in cantilever beams. The performance of Particle swarm optimization (PSO), Genetic algorithm (GA), Grey wolf optimization (GWO), Firefly algorithm (FA), and hybrid of them based on PSO optimizer to determine the location and depth of crack for cantilever beam are proposed. These suggested algorithms are optimization algorithms based on intelligent optimization. So, the performance of these algorithms is analyzed when the control parameters vary.

## 1. Introduction

One of the crucial aspects of engineering design is optimization. Metaheuristics (MHs) have become increasingly famous as a robust optimization means in numerous challenging real-world problems with various frameworks. Due to their comfort of usage, versatility, derivation-free framework, and capacity to escape local optima, MHs have received considerable attention from investigators. This has led to the development of renowned methodologies such as simulated annealing (SA) [1], Genetic Algorithm (GA) [2], Hunger Game Search (HGS) [3], Differential Evolution (DE) [4], Gradient-based Optimizer [5], (PSO) [6], Artificial Chemical Reaction Optimization Algorithm (ARCROA) [7], and Artificial Bee Colony (ABC) [8]. However, the results achieved by MHs may not be globally optimized, but several techniques can improve the performance outcome of the base algorithm

[9-12]. Metaheuristics (MHs) are optimization algorithms that have been developed based on four foundational strategies: swarm intelligence (SI), evolutionary algorithms (EA), physics-based concepts, and human interaction-based concepts. EA are inspired by the biological behaviors of various species, while SI-based algorithms are influenced by behaviors such as food foraging, mutation, territorial conflicts, and mating behavior. Furthermore, there are optimizers developed based on physics laws and fundamental hypotheses. Human behavior and social interaction have also served as sources of inspiration in the development of MHs. Figure 1 shows the different subclasses of frequently used MHs and their basic development criteria. Additionally, researchers hybridized optimizers to improve algorithm performance [11, 12]. Algorithms can be used to optimize engineering design, resulting in more promising solutions. However, according to the 'No Free Lunch' hypothesis [13], there may not be effective and efficient solutions for every problem using the same algorithm. While a meta-heuristic may yield a good result in a specific design issue, the same strategy might generate a weak result in another challenge [14, 15]. In other

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words, Metaheuristics (MH) provides optimal solutions for various problems. However, it is challenging to compare different MHs, as pointed out by Crepinsek et al. [16] MHs may have drawbacks such as slow convergence, getting trapped in a local search domain, and higher computational costs, especially while solving critical engineering problems. To overcome these limitations, hybridized, modified, and improved MHs have emerged, incorporating more beneficial attributes [17, 18]. Achieving a dynamic balance between global diversification and local intensification is crucial for MHs [11, 14]. When establishing MHs, one of the most significant factors is to strike a balance between the exploration and exploitation phases. Both these phases have their importance in the search domain to obtain quality results in the least possible time [17-19]. The quest for even more potent methods is a burning question today. Novel hybridized MHs are emerging rapidly to address this issue. In the last few centuries, various researchers have implemented thousands of hybrid MHs for engineering design optimization problems. These methods are preferred as they properly exploit global and local search strategies, but this field has not been properly addressed until now. Beams are one of the essential elements in engineering structures, with multiple uses in building industries like bridges, and offshore structures, as well as in aerospace industries such as aircraft wings and solar systems [20, 21]. It is crucial to identify sudden cracks in beam structures to prevent dangerous and costly destruction. Cracks can cause local changes in the stiffness of the structures, which can affect dynamic stability, forced vibrations, and natural vibration frequencies. It is possible to detect cracks by analyzing changes in mode shapes and natural frequencies. Various studies have explored the dynamic characteristics of systems with cracks. Sha et al. introduced a new method for determining the severity and location of a crack based on natural frequencies. This method involves examining the alterations in natural frequencies caused by the presence of the crack [22]. In their research, Gillich et al. [23] explored a new mathematical phrase aimed at detecting changes in the natural frequency of beams as a result of failure. Ghannadiasl and Ghaemifard [24] investigated the position and depth of cracks in cantilever beams using triple hybrid algorithms based on Particle Swarm Optimization (PSO). Jena and Parhi [25] proposed a modified version of the PSO algorithm. In a similar study, Jena, Thatoi, and Parhi [26] applied the Self-Adaptive Fuzzy PSO algorithm to assess its effectiveness in identifying cracks. In reference [27], the authors provided an overview of using metaheuristic algorithms and artificial neural networks for detecting damage and cracks in structures. They analyzed the performance of these algorithms by varying their control parameters and applied them to the crack detection results.

The authors compared and analyzed the results obtained with different parameters and proposed some suggestions for selecting the optimal parameters. In this article investigated the capability of various optimization algorithms and suggests dual hybrid optimization algorithms are named PSO-FA, PSO-GA, PSO-GWO, for solving the problem of computing the depth and location of cracks in cantilever beams. Also the performance of these algorithms are analyzed when the control parameters vary. In this paper, the performance of some algorithms as PSO, GA, FA, GWO, and hybrids of them is analyzed, based on the control parameters variants. And then the effect of these parameters of algorithms is applied in the hybrid algorithms for crack detection in cantilever beam, the fault diagnosis results with different parameters of algorithms are compared and analyzed. At last some suggestions for parameters selection are proposed. In other words, to optimize the hybrid algorithms, we utilized the optimal values of parameters that obtained in each single algorithms and only we optimized the population of these algorithms to know whether by increasing the population the performance of algorithms is better or no? The results showed when the population is increased, the performance of hybrid algorithms is good in crack detection in cantilever beam. The rest of the paper is structured as follows: The modelling and formulation of the problem, and the methodology (including suggested algorithms) are discussed in Sections 2 and 3, respectively. Section 4 contains the discussion of the article. Finally, the conclusion of the work is presented in Section 5.

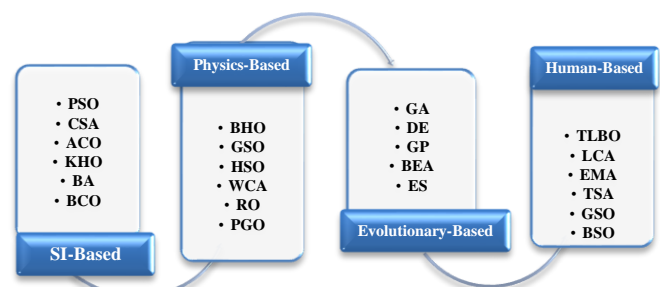


Fig. 1: The brief classification of MH algorithms

## 2. Modelling and formulation

Figure 2 depicts the geometry of a cantilever beam with a full-width open-edge crack. The crack runs perpendicular to the beam's longitudinal axis. The beam can be divided into two uniform sections, one before the crack and one after it. The dimensions of the beam include its width ( $W$ ), length ( $L$ ), crack depth ( $a$ ) which can be adjusted at position  $L$ , and thickness ( $h$ ). The flexibility of a beam can be expressed through stress severity agents. However, the presence of a

transverse surface crack can affect the beam's dynamic efficiency. The relationship between the strain energy and stress intensity factors release rate at the crack segment is further explained in [28]. Additionally, the local stiffness matrix can be obtained by taking the reverse of the flexibility matrix. The system's equation which includes the local stiffness matrix, can be shown as  $|B|=0$  [24]. This function depends on natural frequency  $\omega$ , the non-dimensional crack depth, and the relative positions of the crack  $\alpha$ .

### 2.1 Efficacies of crack on natural frequencies

This part presents the effects of cracks on the normal frequencies of an Euler-Bernoulli beam, depending on their position and depth. Table 1 summarizes the normal frequencies for various crack conditions. The method described in reference [29] was utilized to define the natural frequencies of a cracked Euler-Bernoulli beam. The geometry and mechanical properties of the cantilever beam, based on Firouzi et al.'s data [29], are taken into consideration.

### 2.2 Crack detection utilizing an inverse way

To identify the location and depth of a crack, an objective function is used. This function considers the squared difference between the measured and calculated natural frequencies, weighted appropriately (as seen in Equation (1)). The optimization design variables are taken as the crack's location and depth. The constraint equations are presented in a negative null form, as seen in Equation (2).

$$\text{Cost}(l_c, d_c) = \sum_{i=1}^3 [\varphi_i (f_i - f_i^*)] \tag{1}$$

Subject to:

$$\begin{aligned} 0 < d_c < h \\ 0 < l_c < L \end{aligned} \tag{2}$$

where  $\varphi_i$  is the  $i$ th weighting factor, and  $f_i$  and  $f_i^*$  are the  $i$ th measured natural frequency of the cracked beam and the  $i$ th natural frequency estimated from the optimization algorithm, respectively. In this paper, the inputs of the crack detection problem to measure the goal subordinate, are the first three natural frequencies of a cracked beam (FNF, SNF, and TNF). Also, the weight factors,  $\varphi_i$ 's, are considered as  $1/i$  [28].

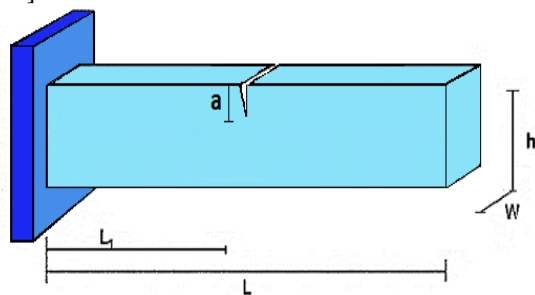


Fig. 2: Geometry of cantilever beam with an open-edge crack

Table 1: The natural frequencies for cracked beam

Crack (mm)		Natural frequencies (HZ)		
Loc.	Dep.	FNF	SNF	TNF
<b>No crack</b>	No depth	48	307	859
<b>225</b>	1	48.9967	307.0493	859.7782
<b>225</b>	2	48.9863	306.8647	859.7069
<b>225</b>	3	48.9442	306.1220	859.4204
<b>450</b>	1	48.9975	307.0620	859.7790
<b>450</b>	2	48.9975	307.0585	859.7193
<b>450</b>	3	48.9974	307.0442	859.4770

\*FNF, SNF, and TNF represent the 1st, 2nd, and 3rd natural frequency, respectively

## 3. Methodology

### 3.1 PSO algorithm

PSO is an optimization technique developed by Kennedy and Eberhart [6]. PSO uses a collective intelligence approach in which each acts like a particle in a swarm, sharing information to enhance the performance of the swarm and ultimately achieve the best possible outcome. The PSO algorithm includes several adjustment parameters such as particle number (N), inertial weight (W), maximum limited speed (v), acceleration constants ( $C_1$  and  $C_2$ ), and maximum iteration number ( $T_{max}$ ).

Among them, we mainly use W, N,  $C_1$ , and  $C_2$  as controlling parameters, meanwhile  $T_{max}$  is used as the iteration stop condition. To check these parameters, we considered 4 sets for each parameter to obtain the most optimal possible state of each parameter so that for finding the optimal value of each parameter, other parameters were fixed. The range that was chosen for finding the optimum population was [set1=125, set2=135, set3=150, and set4=175] while the W,  $C_1$ ,  $C_2$ , and  $T_{max}$  for all sets were fixed in ranges 1.22, 1, 3, and 400 respectively. For finding the optimum value of W, the range space was [set1=1.1, set2=1.15, set3=1.26, and set4=1.3] while other parameters for all sets N,  $C_1$ ,  $C_2$ , and  $T_{max}$  were fixed as 150, 1, 3, and 400 respectively. Also, for finding the optimum value of  $C_1$ , the range space was [set1=1, set2=1.5, set3=2.5, and set4= 3] while other parameters N, W,  $C_2$ , and  $T_{max}$  were fixed as 50, 0.8, 1.5, and 400 respectively for all sets. For finding the optimum value of  $C_2$ , the range space was [set1=2.75, set2=2.95, set3=3, set4=3.2] while other parameters N, W,  $C_1$ , and  $T_{max}$  were fixed as 150, 1.22, 1, and 400 respectively for all sets. Tables 2-5 show the results for each set to find the optimum value of each parameter.

### 3.2 GA Algorithm

On the other hand, GA is a heuristically probing algorithm famous in the evolutionary subjects of natural election [2]. GA is an intelligent approach to exploring a specific search area and finding solutions to problems. This algorithm uses

a population of individuals that undergo mutation and crossover, which promote diversity. To evaluate individuals and ensure that the best ones survive, a fitness function is used to measure their reproductive success. To fine-tune the algorithm, we tested four sets for each parameter to determine the most optimal state of each parameter. When finding the optimal value of each parameter, the other parameters were held constant.

The range that was chosen for finding the optimum population was [set1=50, set2=80, set3=100, and set4=110] while the Crossover, Mutation, and  $T_{max}$  were fixed in ranges 0.2, 0.2, and 400 respectively for all sets. For finding the optimum value of Crossover, the range space was [set1=0.2, set2=0.9, set3=0.72, and set4=0.3] while other parameters N, Mutation, and  $T_{max}$  were fixed as 50, 0.2, and 400 respectively for all sets. Also, for finding the optimum value of Mutation, the range space was [set1=0.2, set2=0.01, set3=0.05, and set4=0.004] while other parameters N, Crossover, and  $T_{max}$  were fixed as 50, 0.2, and 400 respectively for all sets. Tables 6-8 show the results for each set to find the optimum value of each parameter.

### 3.3 FA algorithm

The firefly Optimization (FA) algorithm is an optimization method with these features. The algorithm is inspired by the flashing behavior of fireflies. In the algorithm, randomly generated solutions will be considered as fireflies, and brightness is assigned depending on their performance on the objective function [30]. We considered 4 sets for each parameter to obtain the most optimal possible state of each parameter so that for finding the optimal value of each parameter, other parameters were fixed. The range that was chosen for finding the optimum population was [set1=20, set2=30, set3= 50, and set4=70] while the Gamma, Beta<sub>0</sub>, Alpha, and  $T_{max}$  were fixed in range 1, 1.5, 0.5, and 400 respectively for all sets. For finding the optimum value of Gamma, the range space was [set1=1, set2=0.4, set3=0.8, and set4=0.6] while other parameters N, Beta<sub>0</sub>, Alpha, and  $T_{max}$  were fixed as 20, 1.5, 0.5, and 400 respectively for all sets. Also, for finding the optimum value of Beta<sub>0</sub>, the range space was [set1=1.5, set2=2, set3=1.8, and set4=1.2] while other parameters N, Gamma, Alpha, and  $T_{max}$  were fixed as 20, 1, 0.5, and 400 respectively for all sets. At the end, to find the optimum value of Alpha, the range space was [set1=0.5, set2=0.1, set3=0.25, and set4=0.8] while other parameters N, Gamma, Beta<sub>0</sub>, and  $T_{max}$  were fixed as 20, 1, 1.5, and 400 respectively for all sets. Table 9-12 shows the results for each set to find the optimum value of each parameter.

### 3.4 GWO Algorithm

The Grey Wolf Algorithm (GWO) is a swarm intelligence technique that is widely used for optimization problems due to its superior performance compared to other similar

techniques. This algorithm models the hierarchy, leadership, and hunting behavior of grey wolves in nature. The algorithm considers four types of wolves, namely delta ( $\delta$ ), omega ( $\omega$ ), beta ( $\beta$ ), and alpha ( $\alpha$ ), to represent the leadership hierarchy [31]. In GWO, we examined two parameters, the population and the number of iteration, to find the most optimal state of each parameter so that the range for finding the N population was [set1=50, set2=100, set3=150, and set4=200] while the  $T_{max}$  was fixed as 400 for all sets, and to find the best  $T_{max}$ , the range of it was [set1=400, set2=450, set3=500, and set4=550] while the population was fixed as 100. Tables 13 and 14 show the results for each set to find the optimum value of each parameter.

### 3.5 Hybrid Algorithms functions

This section, explanations on the hybrid algorithms that combine FA, PSO, GWO, and GA algorithms are provided. For these hybrid algorithms, we utilized the optimum parameters of each algorithm that were found in the past section and only optimized the population in them to find the best answer. The pseudocode of the suggested algorithms is defined as Fig. 3.

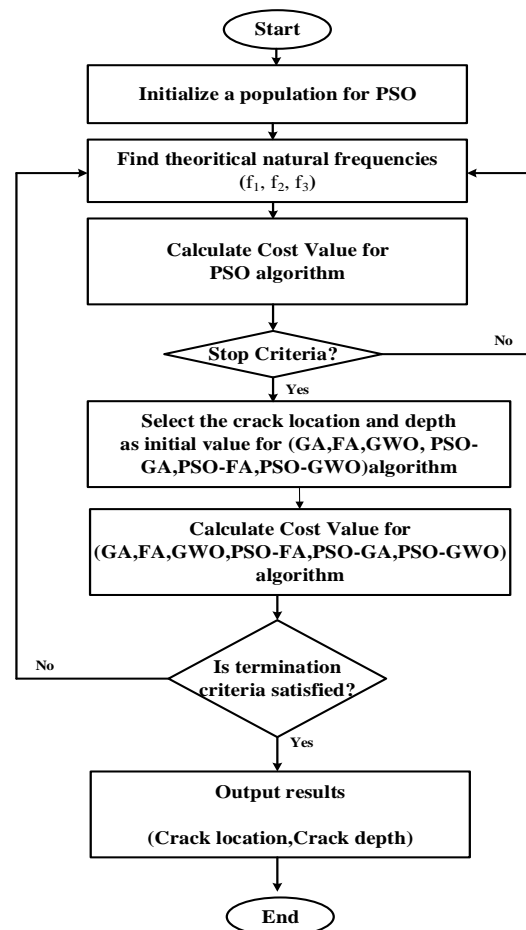


Fig 3. Pseudocode of the suggested hybrid algorithms (PSO-FA PSO-GA, PSO-GWO)

### 3.5.1 PSO-GA

The composition of the two evolutionary algorithms PSO, and GA (denoted as PSO-GA), has been derived from the concept of natural selection. Charles Darwin's theory suggests that in the PSO-GA hybrid algorithm, the offspring acquires the best genetic traits from its parents through the GA process. In this algorithm, PSO helps each organism gain a better experience, which improves their chances of survival in the symbiotic interplay. Similar to the natural selection process, the GA and PSO algorithms need to be run consecutively to simulate these actions. According to the optimum values obtained from GA and PSO algorithms. In Table 15, the results for each set to find the optimum value population were shown. In this algorithm, the range for optimizing the population was [set1=100, set2=120, set3=140, set4=150, and set5=110] while other parameters such as W, C<sub>1</sub>, C<sub>2</sub>, Crossover, Mutation, and T<sub>max</sub> were fixed as [1.3, 1.3, 0.3, 0.004 and 400] respectively in all sets. Also, the statistical results of this algorithm are presented in Table 19.

### 3.5.2 PSO-GWO

The compounding theory of GWO and PSO algorithms has proven to be effective for tackling challenging problems that individual algorithms cannot solve alone. This approach is especially useful for accurately identifying cracks in cantilever beams. Compared to PSO and GWO alone, the PSO-GWO hybrid algorithm has been shown to yield better results. The method works by continuously searching for the optimal solution until the stopping criteria are met or repeated iterations end. This is achieved by updating both velocity and position. When appraisal and repetition of PSO ended, the GWO began acting and carried on to solving optimization problems. In this algorithm, we optimize the population to know which population has good performance in crack detection, so we choose the range [set1=150, set2=170, set3=190, and set4=200] while other parameters as W, C<sub>1</sub>, C<sub>2</sub>, and T<sub>max</sub> were fixed as [1.3, 400] respectively. Table 16 shows the results of this algorithm. Also, the statistical results of this algorithm are presented in Table 20.

### 3.5.3 PSO-FA

Incorporating the FA operators within the PSO algorithm improves the balance between discovery and extraction capabilities. This optimization process updates the position and velocity to search for the optimal solution until the stopping criteria are met, or the maximum number of iterations is reached. Once the PSO assessment and iteration are complete, the FA algorithm takes over to continue solving the optimization problem. The FA algorithm starts by evaluating the fireflies' shine intensity and updating them until the maximum number of iterations is reached. In this algorithm, we optimize the population to know which population has good performance in crack detection, so we

choose the range [set1=70, set2=90, set3=110, set4=130, and set5=150] for population while other parameters such as W, C<sub>1</sub>, C<sub>2</sub>, Gamma, Beta<sub>0</sub>, Alpha and T<sub>max</sub> were fixed as [1.3, 1.3, 1.1, 1.5, 0.5 and 400] in all sets. Table 17 shows the results of this algorithm. Also, the statistical results of this algorithm are in Table 21.

## 4. Discussion

This article aims to investigate the technique for detecting cracks in cantilever beams using proposed algorithms. These algorithms are designed to determine the depth and location of cracks in beams by optimizing objective functions based on natural frequencies. The algorithms presented in this study provide results for crack detection in beams. As discussed in previous sections, seven algorithms (GWO, GA, PSO, FA, PSO-GA, PSO-FA, PSO-GWO) were utilized for crack identification in this study.

To assess the performance of hybrid algorithms, their results are compared with six general algorithms (PSO [6], GWO [31], GA[2], FA[37]) which are utilized in many engineering applications. According to the investigation of the triple hybrid algorithm based on PSO [29] that showed the PSO has good performance in detection position and depth of the crack, we decided that investigate the performance of dual hybrid algorithms based on PSO to determine whether these algorithms have a good performance like triple hybrid algorithms in crack detection or no.

To display the efficacy of the suggested hybrid algorithms, an interpretation index is described. The index calculates the variance between assessed and real parameter values. It is as follows:

$$\%ERROR = \left| \frac{D_2 - D_1}{D_2} \right| \times 100 \quad (3)$$

According to this index can say that in the PSO algorithm for optimizing the N, C<sub>1</sub>, C<sub>2</sub>, and W, set3, set1, set3, and set4 in all of them have good performance respectively. In the GA algorithm for optimizing the N, crossover, Mutation, and set 4 all of them had good performance respectively. In the FA algorithm for optimizing the N, Gamma, Beta<sub>0</sub>, Alpha, set4, set1, set1, and set1 have good performance respectively. In the GWO algorithm for optimizing the N, and T<sub>max</sub>, set 4 has good performance in all of them respectively.

The results of dual hybrid algorithms showed that in the PSO-GA algorithm, the best population was obtained in set 5, in the PSO-GWO algorithm set 4 had good results and in the PSO-FA algorithm set 5 had good results for finding the best population. Finally, Table 18 shows the best hybrid algorithm to find the optimal parameters in each set for all cases.

## 5. Conclusion and future directions

The study introduces new optimization algorithms designed to detect cracks in a cantilever beam. The PSO-FA, PSO-GWO, and PSO-GA algorithms have been improved to enhance their accuracy and convergence speed. These modifications were made to increase the effectiveness of these algorithms in identifying cracks in cantilever beams. The study focused on optimizing the parameters of these algorithms to achieve the best possible detection of crack depth and location in cantilever beams. We optimized the hybrid algorithms by using the optimal values of parameters obtained in each algorithm. The only parameter we optimized was the population of these algorithms. We wanted to determine whether increasing the population would improve the performance of the algorithms. The results showed that increasing the population improved the performance of the hybrid algorithms in detecting cracks in cantilever beams. The aim of this paper is to compare the frequencies evaluated by a proposed algorithm with the measured frequencies for a cracked beam.

The study compares the hybrid algorithms suggested in this research with other algorithms such as GWO, PSO, GA, and FA.

In summary, the comparison of these algorithms yielded the following insights:

- When considering good performance in detection in hybrid algorithms, the algorithms may be ordered as: PSO-GA > PSO-GWO > PSO-FA.
- The PSO-FA algorithm in set 2, the PSO-GA algorithm in set 1, and the PSO-GWO algorithm in sets 3, 4, and 5 have good convergence for all cases.

Consequently, it can be concluded that the PSO-GA algorithm is the most accurate in detecting cracks. The hybrid algorithms developed in this study provide better accuracy compared to other algorithms, containing those investigated in past research, in finding the crack's position and depth.

It is important to acknowledge that this article examines a select group of algorithms, omitting various advanced and hybrid variants. Moreover, the scope of the study is confined to a singular category of optimization problems. For future studies, a thorough evaluation of hybrid meta-heuristics is recommended.

To encapsulate, optimization methods—specifically algorithms—are notably more proficient when tasked with identifying the optimal solution among numerous possibilities for problems. Typically, optimization dilemmas are characterized by a multitude of potential solutions, necessitating the discovery of the most suitable one. Search and optimization techniques are inherently similar and mutually reinforcing in these scenarios. Algorithms that scrutinize a substantial portion of potential solutions to deduce the best outcome are particularly valuable.

## References

- [1] D. Bertsimas and J. Tsitsiklis, "Simulated annealing," *Statistical science*, vol. 8, no. 1, pp. 10-15, 1993.
- [2] J. H. Holland, "Genetic algorithms," *Scientific american*, vol. 267, no. 1, pp. 66-73, 1992.
- [3] P. Mehta, B. S. Yildiz, S. M. Sait, and A. R. Yildiz, "Hunger games search algorithm for global optimization of engineering design problems," *Materials Testing*, vol. 64, no. 4, pp. 524-532, 2022.
- [4] K. V. Price, "Differential evolution," in *Handbook of optimization: From classical to modern approach*: Springer, 2013, pp. 187-214.
- [5] P. Mehta, B. S. Yıldız, S. M. Sait, and A. R. Yıldız, "Gradient-based optimizer for economic optimization of engineering problems," *Materials Testing*, vol. 64, no. 5, pp. 690-696, 2022.
- [6] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proceedings of ICNN'95-international conference on neural networks*, 1995, vol. 4, pp. 1942-1948: IEEE.
- [7] B. Alatas, "ACROA: artificial chemical reaction optimization algorithm for global optimization," *Expert Systems with Applications*, vol. 38, no. 10, pp. 13170-13180, 2011.
- [8] D. Karaboga, "Artificial bee colony algorithm," *scholarpedia*, vol. 5, no. 3, p. 6915, 2010.
- [9] S. Talatahari, M. Azizi, M. Tolouei, B. Talatahari, and P. Sareh, "Crystal structure algorithm (CryStAl): a metaheuristic optimization method," *IEEE Access*, vol. 9, pp. 71244-71261, 2021.
- [10] H. R. R. Zaman and F. S. Gharehchopogh, "An improved particle swarm optimization with backtracking search optimization algorithm for solving continuous optimization problems," *Engineering with Computers*, vol. 38, no. Suppl 4, pp. 2797-2831, 2022.
- [11] S. Talatahari, M. Azizi, and A. H. Gandomi, "Material generation algorithm: a novel metaheuristic algorithm for optimization of engineering problems," *Processes*, vol. 9, no. 5, p. 859, 2021.
- [12] B. Abdollahzadeh, F. S. Gharehchopogh, and S. Mirjalili, "African vultures optimization algorithm: A new nature-inspired metaheuristic algorithm for global optimization problems," *Computers & Industrial Engineering*, vol. 158, p. 107408, 2021.
- [13] D. H. Wolpert and W. G. Macready, "No free lunch theorems for optimization," *IEEE transactions on evolutionary computation*, vol. 1, no. 1, pp. 67-82, 1997.
- [14] H. Shayanfar and F. S. Gharehchopogh, "Farmland fertility: A new metaheuristic algorithm for solving continuous optimization problems," *Applied Soft Computing*, vol. 71, pp. 728-746, 2018.
- [15] S. Kumar, G. G. Tejani, N. Pholdee, and S. Bureerat, "Performance enhancement of meta-heuristics through random mutation and simulated annealing-based selection for concurrent topology and sizing optimization of truss structures," *Soft Computing*, vol. 26, no. 12, pp. 5661-5683, 2022.

- [16] M. Črepinšek, S.-H. Liu, and M. Mernik, "Replication and comparison of computational experiments in applied evolutionary computing: common pitfalls and guidelines to avoid them," *Applied Soft Computing*, vol. 19, pp. 161-170, 2014.
- [17] H. Zamani, M. H. Nadimi-Shahraki, and A. H. Gandomi, "Starling murmuration optimizer: A novel bio-inspired algorithm for global and engineering optimization," *Computer Methods in Applied Mechanics and Engineering*, vol. 392, p. 114616, 2022.
- [18] B. S. Yildiz, P. Mehta, S. M. Sait, N. Panagant, S. Kumar, and A. R. Yildiz, "A new hybrid artificial hummingbird-simulated annealing algorithm to solve constrained mechanical engineering problems," *Materials Testing*, vol. 64, no. 7, pp. 1043-1050, 2022.
- [19] M. H. Nadimi-Shahraki, S. Taghian, and S. Mirjalili, "An improved grey wolf optimizer for solving engineering problems," *Expert Systems with Applications*, vol. 166, p. 113917, 2021.
- [20] A. H. Azimi, A. Rajabi, and S. Shabanlu, "Optimized ANFIS-Genetic Algorithm-Particle Swarm Optimization Model for Estimation of Side Orifice [21] A. Kheyroddin and F. Maleki, "Prediction of effective moment of inertia for hybrid FRP-steel reinforced concrete beams using the genetic algorithm," *Numerical Methods in Civil Engineering*, vol. 2, no. 1, pp. 15-23, 2017.
- [22] G. Sha, M. Radziński, M. Cao, and W. Ostachowicz, "A novel method for single and multiple damage detection in beams using relative natural frequency changes," *Mechanical Systems and Signal Processing*, vol. 132, pp. 335-352, 2019.
- [23] G.-R. Gillich, H. Furdui, M. A. Wahab, and Z.-I. Korca, "A robust damage detection method based on multi-modal analysis in variable temperature conditions," *Mechanical Systems and Signal Processing*, vol. 115, pp. 361-379, 2019.
- [24] A. Ghannadiasl and S. Ghaemifard, "Crack detection of the cantilever beam using new triple hybrid algorithms based on Particle Swarm Optimization," *Frontiers of Structural and Civil Engineering*, 2022/11/12 2022.
- [25] P. K. Jena and D. R. Parhi, "A modified particle swarm optimization technique for crack detection in cantilever beams," *Arabian Journal for Science and Engineering*, vol. 40, pp. 3263-3272, 2015.
- [26] P. K. Jena, D. N. Thatoi, and D. R. Parhi, "Dynamically self-adaptive fuzzy PSO technique for smart diagnosis of transverse crack," *Applied Artificial Intelligence*, vol. 29, no. 3, pp. 211-232, 2015.
- [27] A. Ghannadiasl and S. Ghaemifard, "An overview of damage and crack detection in structures using metaheuristic algorithms and artificial neural networks," *Journal of Structural and Construction Engineering*, pp. -, 2023.
- [28] S. Casciati and L. Elia, "Potential of two metaheuristic optimization tools for damage localization in civil structures," *Journal of Aerospace Engineering*, vol. 30, no. 2, p. B4016012, 2017.
- [29] B. Firouzi, A. Abbasi, and P. Sendur, "Improvement of the computational efficiency of metaheuristic algorithms for the crack detection of cantilever beams using hybrid methods," *Engineering Optimization*, vol. 54, no. 7, pp. 1236-1257, 2022.
- [30] X.-S. Yang, "Firefly algorithms for multimodal optimization," in *International symposium on stochastic algorithms*, 2009, pp. 169-178: Springer.
- [31] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey Wolf Optimizer," *Advances in Engineering Software*, vol. 69, pp. 46-61, 2014/03/01/ 2014.



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**Tables 2-20**

**Table 2:** Investigation population to find the most optimal mode (PSO)

	precise value Loc./ Dep. (mm)	Loc. (%ERROR)	Dep. (%ERROR)
<b>Set1</b>	225-1	225 (0)	1 (0)
	225-2	225 (0)	2 (0)
	225-3	223 (0.89)	3 (0)
	450-1	451 (0.22)	1.1 (9.09)
	450-2	447 (0.67)	1.93 (3.62)
	450-3	455 (1.09)	3.3 (9.09)
	<b>Set2</b>	225-1	225 (0)
225-2		225(0)	2 (0)
225-3		225 (0)	3 (0)
450-1		456 (1.31)	1.3 (23.07)
450-2		442 (1.80)	1.97 (1.52)
450-3		447 (0.67)	2.91 (3.09)
<b>Set3</b>		225-1	225 (0)
	225-2	225 (0)	2 (0)
	225-3	225 (0)	3 (0)
	450-1	450.23(0.051)	1.6 (37.5)
	450-2	454.49 (0.98)	2.35(14.89)
	450-3	449.99(0.002)	3.18 (5.66)
	<b>Set4</b>	225-1	225 (0)
225-2		225 (0)	2 (0)
225-3		226.56(0.68)	2.96 (1.35)
450-1		463 (2.80)	1.09 (8.25)
450-2		450 (0)	1.93 (3.62)
450-3		452 (0.44)	3.03 (0.99)

**Table 3:** Investigation W to find the most optimal mode (PSO)

	precise value Loc./ Dep. (mm)	Loc. (%ERROR)	Dep. (%ERROR)
<b>Set1</b>	225-1	225 (0)	1 (0)
	225-2	225 (0)	2 (0)
	225-3	225 (0)	3 (0)
	450-1	475 (5.26)	1 (0)
	450-2	447.99 (0.44)	2 (0)
	450-3	448.99 (0.22)	3.03 (0.99)
	<b>Set2</b>	225-1	225 (0)
225-2		225 (0)	2 (0)
225-3		225 (0)	3 (0)
450-1		464.9 (3.20)	1.9 (47.36)
450-2		445.99 (0.89)	2.73 (26.73)
450-3		449.99 (0.002)	3.03 (0.99)
<b>Set3</b>		225-1	225 (0)
	225-2	225 (0)	2 (0)
	225-3	225 (0)	3 (0)
	450-1	454.99 (1.09)	1.9 (47.36)
	450-2	446.99 (0.67)	2.1 (4.76)
	450-3	442 (1.80)	3.03 (0.99)
	<b>Set4</b>	225-1	225 (0)
225-2		225 (0)	2 (0)
225-3		225 (0)	3 (0)
450-1		465 (3.22)	1.03 (2.91)
450-2		455 (1.09)	2.09 (4.30)
450-3		445 (1.12)	2.9 (3.44)

**Table 4:** Investigation C<sub>1</sub> to find the most optimal mode (PSO)

	precise value Loc./ Dep. (mm)	Loc. (%ERROR)	Dep. (%ERROR)
<b>Set1</b>	225-1	225 (0)	1 (0)
	225-2	225 (0)	2 (0)
	225-3	225 (0)	3 (0)
	450-1	445.96 (0.90)	1.7 (41.17)
	450-2	454.84 (1.06)	2.20 (9.09)
	450-3	464.98 (3.20)	3.02 (0.66)
	<b>Set2</b>	225-1	225 (0)
225-2		225 (0)	2 (0)
225-3		227.61(0.011)	2.89 (3.80)
450-1		450.2 (0.044)	1.003 (0.29)
450-2		452.18 (0.48)	2.05 (2.43)
450-3		443.34 (1.50)	2.67 (12.35)
<b>Set3</b>		225-1	225 (0)
	225-2	225 (0)	2 (0)
	225-3	225 (0)	3 (0)
	450-1	454.99 (1.09)	1.03 (2.91)
	450-2	447.99 (0.44)	2.09 (4.30)
	450-3	448.98 (0.22)	3.02 (0.66)
	<b>Set4</b>	225-1	225 (0)
225-2		225 (0)	2 (0)
225-3		225 (0)	3(0)
450-1		447.21 (0.62)	1.08 (7.40)
450-2		464.99(3.22)	1.93 (3.62)
450-3		449.63(0.082)	2.98 (0.67)

**Table 5:** Investigation C<sub>2</sub> to find the most optimal mode (PSO)

	precise value Loc./ Dep. (mm)	Loc. (%ERROR)	Dep. (%ERROR)
<b>Set1</b>	225-1	227.61 (1.14)	0.96 (4.16)
	225-2	225 (0)	2 (0)
	225-3	225 (0)	3 (0)
	450-1	450.14(0.031)	1 (0)
	450-2	453.99 (0.87)	1.93 (3.62)
	450-3	449.99(0.002)	2.9 (3.44)
	<b>Set2</b>	225-1	225 (0)
225-2		225 (0)	2 (0)
225-3		225 (0)	3 (0)
450-1		464.99 (3.22)	1.13 (11.5)
450-2		452.09 (0.46)	2.17 (7.83)
450-3		444.90 (1.14)	3(0)
<b>Set3</b>		225-1	225 (0)
	225-2	225 (0)	2 (0)
	225-3	225 (0)	3 (0)
	450-1	451.99 (0.44)	1.03 (2.91)
	450-2	455 (1.09)	2.09 (4.30)
	450-3	451.9 (0.42)	2.8 (7.14)
	<b>Set4</b>	225-1	225 (0)
225-2		225 (0)	2 (0)
225-3		225 (0)	3 (0)
450-1		448.99 (0.22)	1.001(0.099)
450-2		452.26 (0.49)	2.08 (3.84)
450-3		448.9 (0.24)	2.90 (3.44)

**Table 6:** Investigation population to find the most optimal state (GA)

	precise value Loc./ Dep. (mm)	Loc. (%ERROR)	Dep. (%ERROR)
Set1	225-1	224.77 (0.1)	0.95 (5.26)
	225-2	224.96(0.004)	1.99 (0.5)
	225-3	224.98(0.008)	2.99 (0.33)
	450-1	457.73 (1.68)	0.75 (33.3)
	450-2	451.88(0.416)	1.97 (1.52)
	450-3	449.23 (0.17)	2.94 (2.04)
Set2	225-1	225 (0)	1 (0)
	225-2	227.61 (1.14)	1.93 (3.62)
	225-3	225 (0)	3 (0)
	450-1	452.7 (0.59)	0.75 (33.3)
	450-2	451.19 (0.26)	1.96 (2.04)
	450-3	455.41 (1.18)	3.3 (9.09)
Set3	225-1	225 (0)	1 (0)
	225-2	227.61 (1.14)	1.93 (3.62)
	225-3	222.61 (1.07)	2.89 (3.80)
	450-1	448.88 (0.24)	0.75 (33.3)
	450-2	450.7 (0.15)	1.94 (3.09)
	450-3	455 (1.09)	3.03 (0.99)
Set4	225-1	227.61 (1.14)	0.96 (4.16)
	225-2	225 (0)	2 (0)
	225-3	225 (0)	3 (0)
	450-1	449.41 (0.13)	0.85 (17.64)
	450-2	450.4 (0.08)	2.01 (0.49)
	450-3	449.93(0.015)	2.84 (5.63)

**Table 8:** Investigation Mutation to find the most optimal mode (GA)

	precise value Loc./ Dep. (mm)	Loc. (%ERROR)	Dep. (%ERROR)
Set1	225-1	224.98(0.008)	1(0)
	225-2	225 (0)	2 (0)
	225-3	225.6 (0.26)	2.89 (3.80)
	450-1	447.72 (0.5)	0.75 (33.33)
	450-2	445.22 (1.07)	1.85 (8.10)
	450-3	462.46 (2.69)	3.9 (23.07)
Set2	225-1	225 (0)	1 (0)
	225-2	224.99(0.004)	1.99 (0.5)
	225-3	225 (0)	3 (0)
	450-1	447.16 (0.63)	0.82 (21.95)
	450-2	453.26 (0.71)	2.23 (10.31)
	450-3	458.59 (1.87)	2.72 (10.29)
Set3	225-1	226.11 (0.49)	0.96 (4.16)
	225-2	225 (0)	2 (0)
	225-3	224.99(0.004)	2.99 (0.33)
	450-1	455.80 (1.27)	1.1 (9.09)
	450-2	449.97(0.006)	1.99 (0.5)
	450-3	453.72 (0.81)	2.72 (10.29)
Set4	225-1	227.81 (1.23)	1 (0)
	225-2	225 (0)	1.99 (0.5)
	225-3	223.61 (0.62)	2.89 (3.80)
	450-1	450.05(0.011)	1 (0)
	450-2	450.71 (0.15)	2.02 (0.99)
	450-3	449.74(0.057)	2.87 (4.52)

**Table 7:** Investigation Crossover to find the most optimal mode (GA)

	precise value Loc./ Dep. (mm)	Loc. (%ERROR)	Dep. (%ERROR)
Set1	225-1	225 (0)	1 (0)
	225-2	224.73(0.12)	1.98 (1.01)
	225-3	222.61(1.07)	2.89 (3.80)
	450-1	449.41(0.13)	0.85(17.64)
	450-2	448.89(0.24)	1.82 (9.89)
	450-3	455.3 (1.16)	3.33 (9.90)
Set2	225-1	224.84(0.07)	0.99 (1.01)
	225-2	225 (0)	2 (0)
	225-3	225 (0)	3 (0)
	450-1	445.64(0.97)	0.76(31.57)
	450-2	457.2 (1.57)	2 (0)
	450-3	451.95(0.43)	3.11 (3.53)
Set3	225-1	227.8 (1.22)	0.96 (4.16)
	225-2	225 (0)	2 (0)
	225-3	227.03(0.89)	2.88 (4.16)
	450-1	443 (1.58)	1.7 (41.17)
	450-2	453.93(0.86)	1.77(12.99)
	450-3	455 (1.09)	2.87 (4.52)
Set4	225-1	225 (0)	1 (0)
	225-2	225 (0)	2 (0)
	225-3	224.55 (0.2)	2.97 (1.01)
	450-1	451.2 (0.26)	0.77(29.87)
	450-2	451.19(0.26)	2.4 (16.66)
	450-3	447.85(0.48)	2.74 (9.48)

**Table 9:** Investigation population to find the most optimal state (FA)

	precise value Loc./ Dep. (mm)	Loc. (%ERROR)	Dep. (%ERROR)
Set1	225-1	223.88 (0.5)	0.82 (21.95)
	225-2	227.93(1.28)	1.98 (1.01)
	225-3	224.61 (0.17)	2.89 (3.80)
	450-1	450.94 (0.20)	0.76 (31.57)
	450-2	447.99 (0.44)	1.93 (3.62)
	450-3	447.99 (0.44)	3.03 (0.99)
Set2	225-1	223.86 (0.5)	1.24(19.35)
	225-2	224.99(0.004)	2(0)
	225-3	224.99(0.004)	2.99(0.33)
	450-1	465(3.22)	1.03 (2.91)
	450-2	455(1.09)	1.93 (3.62)
	450-3	462.95 (2.79)	3.01 (0.33)
Set3	225-1	227.61(1.14)	0.96 (4.16)
	225-2	223.50 (0.67)	1.92 (4.16)
	225-3	224.99(0.004)	3(0)
	450-1	448.69 (0.29)	1.5 (33.33)
	450-2	450.05(0.011)	2 (0)
	450-3	465 (3.22)	2.83 (6.007)
Set4	225-1	224.99(0.004)	1 (0)
	225-2	225(0)	1.99 (0.5)
	225-3	224.99(0.004)	2.99 (0.33)
	450-1	453.96(0.87)	1.25 (20)
	450-2	460 (2.17)	1.93 (3.62)
	450-3	455 (1.09)	3.03 (0.99)

**Table 10:** Investigation Gamma to find the most optimal state (FA)

	precise value Loc./ Dep. (mm)	Loc. (%ERROR)	Dep. (%ERROR)
Set1	225-1	222(1.35)	1.5(33.33)
	225-2	222.63(1.06)	1.93(2.04)
	225-3	226.10(0.48)	2.89(3.80)
	450-1	449(0.22)	1.93(48.18)
	450-2	455(1.09)	2.33(14.16)
	450-3	459.61(2.09)	3.11(3.53)
Set2	225-1	222(1.35)	1.5(33.33)
	225-2	222.63(1.06)	1.93(3.62)
	225-3	226.10(0.48)	2.89(3.80)
	450-1	449(0.22)	1.93(48.18)
	450-2	455(1.09)	2.33(14.16)
	450-3	459.61(2.09)	3.11(3.53)
Set3	225-1	222.97(0.91)	0.82(21.95)
	225-2	229.20(1.83)	2.13 (6.10)
	225-3	228.97(1.73)	3.24 (7.40)
	450-1	464.15(3.04)	1.86 (46.23)
	450-2	459.78(2.12)	2.25 (11.11)
	450-3	451.3 (0.28)	2.81(6.76)
Set4	225-1	225(0)	1.5(33.33)
	225-2	224.97 (0.013)	2 (0)
	225-3	228.86(1.68)	3.21 (6.54)
	450-1	475 (5.26)	1.93 (48.18)
	450-2	462.32 (2.66)	2.61 (23.37)
	450-3	475 (5.26)	3.03 (0.99)

**Table 12:** Investigation Alpha to find the most optimal state (FA)

	precise value Loc./ Dep. (mm)	Loc. (%ERROR)	Dep. (%ERROR)
Set1	225-1	225.05(0.02)	1(0)
	225-2	227.62(1.15)	1.93(3.62)
	225-3	229.80(2.08)	3.14(4.45)
	450-1	450.77(0.17)	1.65(39.39)
	450-2	454.17(0.91)	2.80(28.57)
	450-3	475(5.26)	3.03(0.99)
Set2	225-1	223.61(0.62)	0.96(4.16)
	225-2	221.70(1.48)	1.18(69.49)
	225-3	229.61(2.007)	2.89(3.80)
	450-1	464.17(3.05)	1.87(46.52)
	450-2	454.82(1.05)	2.9(31.3)
	450-3	458.36(1.82)	3.57(15.96)
Set3	225-1	227.61(1.14)	0.96(4.16)
	225-2	230.60(2.42)	1.08(85.18)
	225-3	226.63(0.71)	2.74(9.48)
	450-1	443.02(1.57)	0.88(13.63)
	450-2	445(1.12)	2.93(31.74)
	450-3	455(1.09)	3.03(0.99)
Set4	225-1	227.61(1.14)	0.96(4.16)
	225-2	230.60(2.42)	1.08(85.18)
	225-3	226.63(0.71)	2.74(9.48)
	450-1	443.02(1.57)	0.88(13.63)
	450-2	445(1.12)	2.93(31.74)
	450-3	455(1.09)	3.03(0.99)

**Table 11:** Investigation Beta<sub>0</sub> to find the most optimal state (FA)

	precise value Loc./ Dep. (mm)	Loc. (%ERROR)	Dep. (%ERROR)
Set1	225-1	225.02(0.008)	1(0)
	225-2	225(0)	1.19(68.06)
	225-3	225.02(0.008)	2.99(0.33)
	450-1	475(5.26)	1.93(48.18)
	450-2	452.26(0.49)	2.54(21.25)
	450-3	449.99(0.002)	2.99(0.33)
Set2	225-1	222.60(1.07)	0.96(4.16)
	225-2	220(2.27)	1.19(68.06)
	225-3	224.99(0.004)	3(0)
	450-1	475(5.26)	1.93(48.18)
	450-2	475(5.26)	2.93(31.74)
	450-3	446.11(0.87)	2.79(7.52)
Set3	225-1	225(0)	0.5(100)
	225-2	222.58(1.08)	1.93(3.62)
	225-3	227.61(1.14)	2.89(3.80)
	450-1	455(1.09)	1.13(11.5)
	450-2	475(5.26)	1.93(3.62)
	450-3	454.72(1.03)	2.96(1.35)
Set4	225-1	228.63(1.58)	1.34(25.37)
	225-2	223(0.89)	1.19(68.06)
	225-3	220.62(1.98)	2.89(3.80)
	450-1	465.58(3.34)	1.14(29.07)
	450-2	451.80(0.39)	2.07(3.38)
	450-3	444.12(1.32)	2.70(11.11)

**Table 13:** Investigation of the population to find the most optimal state (GWO)

	precise value Loc./ Dep. (mm)	Loc. (%ERROR)	Dep. (%ERROR)
Set1	225-1	221.63(1.52)	0.831(20.33)
	225-2	233.88(3.79)	1.87(6.95)
	225-3	226.9(0.83)	3.7(18.91)
	450-1	455(1.09)	1.9(47.36)
	450-2	450(0)	2.93(31.74)
	450-3	452.14(0.47)	3.05(1.63)
Set2	225-1	227.06(0.90)	0.823(21.50)
	225-2	224.99(0.004)	2(0)
	225-3	224.96(0.017)	2.99(0.33)
	450-1	450(0)	1.03(2.91)
	450-2	448(0.44)	1.93(3.62)
	450-3	455(1.09)	3.03(0.99)
Set3	225-1	225.01(0.004)	1(0)
	225-2	221(1.80)	1.91(4.71)
	225-3	228.98(1.73)	3.2(6.25)
	450-1	445(1.12)	1.9(47.36)
	450-2	451(0.22)	2.9(31.03)
	450-3	451(0.22)	3.03(0.99)
Set4	225-1	225(0)	1(0)
	225-2	224.99(0.004)	1.99(0.5)
	225-3	225(0)	3(0)
	450-1	451(0.22)	1.93(48.18)
	450-2	450(0)	2.9(31.03)
	450-3	455(1.09)	2.83(6.007)

**Table 14:** Investigation of the  $T_{max}$  to find the most optimal state (GWO)

	precise value Loc./ Dep. (mm)	Loc. (%ERROR)	Dep. (%ERROR)
Set1	225-1	225(0)	1(0)
	225-2	224.97(0.013)	2(0)
	225-3	225.01(0.004)	3(0)
	450-1	455(1.09)	1.09(8.25)
	450-2	455(1.09)	1.93(3.62)
	450-3	447(0.67)	3.03(0.99)
Set2	225-1	224.97(0.013)	1(0)
	225-2	225.004(0.0017)	2(0)
	225-3	224.99(0.004)	3(0)
	450-1	450(0)	1.03(2.91)
	450-2	445(1.12)	2.03(1.47)
	450-3	447(0.67)	3.03(0.99)
Set3	225-1	225.01(0.004)	1(0)
	225-2	225.004(0.0017)	2(0)
	225-3	224.99(0.004)	3(0)
	450-1	451(0.22)	1.13(11.5)
	450-2	449(0.22)	2.035(1.71)
	450-3	447(0.67)	2.93(2.38)
Set4	225-1	225.004(0.001)	1(0)
	225-2	225(0)	2(0)
	225-3	225.578(0.25)	3.10(3.22)
	450-1	448(0.44)	1.2(16.66)
	450-2	448.97(0.22)	1.93(3.62)
	450-3	449(0.22)	3.03(0.99)

**Table 16:** Investigation of the population to find the best one (PSO-GWO)

	precise value Loc./ Dep. (mm)	Loc. (%ERROR)	Dep. (%ERROR)
Set1	225-1	225(0)	1(0)
	225-2	225(0)	2(0)
	225-3	225(0)	3(0)
	450-1	474.98(5.25)	1.93(48.18)
	450-2	454.75(1.04)	2.8(28.57)
	450-3	452(0.44)	3.03(0.99)
Set2	225-1	225(0)	1(0)
	225-2	227(0.88)	1.19(68.06)
	225-3	225(0)	3(0)
	450-1	448.99(0.22)	1.33(24.81)
	450-2	453.83(0.84)	1.90(5.26)
	450-3	444.99(0.002)	2.73(9.89)
Set3	225-1	225(0)	1(0)
	225-2	223.99(0.45)	1.19(68.06)
	225-3	225(0)	3(0)
	450-1	450.98(0.21)	1.43(30.06)
	450-2	445.52(1.005)	2.86(30.06)
	450-3	450(0)	3.03(0.99)
Set4	225-1	225.97(0.42)	1.49(32.88)
	225-2	224.71(0.12)	2(0)
	225-3	225(0)	3(0)
	450-1	449.99(0.002)	1.53(34.64)
	450-2	448.99(0.22)	2.93(31.74)
	450-3	449.99(0.002)	2.63(14.06)

**Table 15:** Investigation the population to find the best one (PSO-GA)

	precise value Loc./ Dep. (mm)	Loc. (%ERROR)	Dep. (%ERROR)
Set1	225-1	225(0)	1(0)
	225-2	225(0)	2(0)
	225-3	225(0)	3(0)
	450-1	455.98(1.31)	1.13(11.5)
	450-2	451.23(0.27)	2.8(28.57)
	450-3	468.44(3.93)	2.72(10.29)
Set2	225-1	225(0)	1(0)
	225-2	225(0)	2(0)
	225-3	224.99(0.004)	3(0)
	450-1	451(0.22)	1.93(48.18)
	450-2	452.78(0.61)	2.1(4.76)
	450-3	468.26(3.89)	3.6(16.66)
Set3	225-1	225(0)	1(0)
	225-2	227.21(0.97)	1.08(85.18)
	225-3	225(0)	3(0)
	450-1	452.82(0.62)	1.78(43.82)
	450-2	450.27(0.059)	2.4(16.66)
	450-3	445(1.12)	3.03(0.99)
Set4	225-1	225(0)	1(0)
	225-2	225(0)	2(0)
	225-3	227.61(1.14)	2.98(0.67)
	450-1	450.46(0.10)	1(0)
	450-2	451.98(0.43)	2.9(31.03)
	450-3	450(0)	3(0)
Set5	225-1	225(0)	1(0)
	225-2	225(0)	2(0)
	225-3	225(0)	3(0)
	450-1	450.99(0.21)	0.99(1.01)
	450-2	450(0)	2(0)
	450-3	450.41(0.09)	3.1(3.22)

**Table 17:** Investigation of the population to find the best one (PSO-FA)

	precise value Loc./ Dep.(mm)	Loc. (%ERROR)	Dep. (%ERROR)
Set1	225-1	224.98(0.008)	0.99(1.01)
	225-2	224.98(0.008)	2(0)
	225-3	225(0)	2.99(0.33)
	450-1	455(1.09)	1.17(14.52)
	450-2	452.20(0.48)	2.08(3.84)
	450-3	449.88(0.02)	2.95(1.69)
Set2	225-1	225.36(0.15)	1(0)
	225-2	224.91(0.04)	2(0)
	225-3	224.85(0.06)	3(0)
	450-1	451(0.22)	1.23(18.69)
	450-2	455(1.09)	1.98(1.01)
	450-3	445(1.12)	3.03(0.99)
Set3	225-1	224.89(0.04)	0.99(1.01)
	225-2	225.61(0.27)	2(0)
	225-3	225.11(0.04)	2.99(0.33)
	450-1	455(1.09)	1.53(34.64)
	450-2	448.1(0.42)	1.93(3.62)
	450-3	452(0.44)	3.03(0.99)
Set4	225-1	225.11(0.04)	0.99(1.01)
	225-2	224.91(0.04)	1.99(0.5)
	225-3	224.98(0.008)	2.99(0.33)
	450-1	459(1.96)	1.22(18.03)
	450-2	461.51(2.49)	2.56(21.87)
	450-3	465.1(3.24)	3.26(7.97)
Set5	225-1	224.99(0.004)	1.99(0.5)
	225-2	224.80(0.08)	3(0)
	225-3	224.80(0.08)	3(0)
	450-1	445(1.12)	1.13(11.5)
	450-2	450(0)	1.93(3.62)
	450-3	447(0.67)	2.73(9.89)

**Table 18:** The Best hybrid algorithm to find crack detection

	precise value	Best algorithm
	Loc./ Dep.(mm)	
Set1	225-1	I, III
	225-2	I, III
	225-3	I, III
	450-1	I
	450-2	II
Set2	450-3	II
	225-1	I,II,III
	225-2	I,II,
	225-3	III
	450-1	II
Set3	450-2	II
	450-3	II
	225-1	I,III
	225-2	II
	225-3	I, III
Set4	450-1	III
	450-2	I, II
	450-3	II,III
	225-1	I,II
	225-2	I
Set5	225-3	III
	450-1	I
	450-2	I
	450-3	I
	225-1	I

Note: I = PSO-GA, II = PSO- GWO, III = PSO-FA

**Table 19:** Statistical results of the PSO-GWO algorithm

	Std	Min	Max	Mean	
Set1	225-1	4.74e-04	0	6.71e-04	3.35e-04
	225-2	0	0	0	0
	225-3	0	0	0	0
	450-1	7.99e-09	1.66e-07	1.77e-07	1.72e-07
	450-2	1.39e-07	2.48e-06	2.67e-06	2.58e-06
Set2	450-3	2.76e-07	1.14e-05	1.18e-05	1.16e-05
	225-1	1.02e-10	8.74e-13	1.45e-10	7.27e-11
	225-2	7.25e-03	3.34e-13	1.02e-02	5.12e-03
	225-3	3.45e-02	3.10e-11	4.88e-02	2.44e-02
	450-1	1.19e-08	1.46e-07	1.63e-07	1.55e-07
Set3	450-2	8.30e-09	2.45e-06	2.46e-06	2.46e-06
	450-3	1.34e-07	1.16e-05	1.18e-05	1.17e-05
	225-1	4.74e-04	2.12e-12	6.71e-04	3.35e-04
	225-2	7.25e-03	1.85e-13	1.03e-02	5.13e-03
	225-3	1.61e-13	0	2.27e-13	1.14e-13
Set4	450-1	1.44e-10	1.61e-07	1.61e-07	1.61e-07
	450-2	2.85e-08	2.42e-06	2.46e-06	2.44e-06
	450-3	4.50e-09	1.18e-05	1.18e-05	1.18e-05
	225-1	4.75e-04	6.36e-12	6.71e-04	3.36e-04
	225-2	7.10e-04	2.42e-13	1.00e-03	5.02e-04
Set5	225-3	2.01e-14	0	2.84e-14	1.42e-14
	450-1	2.67e-09	1.61e-07	1.65e-07	1.63e-07
	450-2	2.31e-09	2.46e-06	2.46e-06	2.46e-06
	450-3	2.52e-09	1.18e-05	1.18e-05	1.18e-05

**Table 20:** Statistical results of the PSO-GA algorithm

	Std	Min	Max	Mean	
Set1	225-1	2.79e-04	1.16e-10	3.95e-04	1.97e-04
	225-2	2.28e-11	2.91e-13	3.25e-11	1.64e-11
	225-3	2.05e-02	4.91e-08	2.9e-02	1.45e-02
	450-1	1.58e-07	1.98e-07	4.21e-07	3.09e-07
	450-2	6.32e-07	1.60e-06	2.49e-06	2.04e-06
Set2	450-3	2.16e-06	9.03e-06	1.21e-05	1.06e-05
	225-1	1.10e-10	1.92e-13	1.94e-10	6.61e-11
	225-2	3.05e-03	0	5.28e-03	1.76e-03
	225-3	1.30e-06	2.09e-11	2.25e-06	7.50e-07
	450-1	5.01e-04	7.89e-08	8.69e-04	2.89e-04
Set3	450-2	4.30e-07	2.49e-06	3.10e-06	2.80e-06
	450-3	1.17e-06	1.02e-05	1.19e-05	1.10e-05
	225-1	3.87e-04	7.11e-14	6.71e-04	2.24e-04
	225-2	5.91e-03	8.03e-06	1.02e-02	6.83e-03
	225-3	1.66e-02	3.17e-11	2.88e-02	9.6e-03
Set4	450-1	7.08e-08	5.25e-08	1.90e-07	1.31e-07
	450-2	1.46e-06	1.82e-06	4.42e-06	2.73e-06
	450-3	3.82e-08	1.18e-05	1.19e-05	1.18e-05
	225-1	3.87e-04	7.11e-14	6.71e-04	2.24e-04
	225-2	5.91e-03	8.03e-06	1.02e-02	6.83e-03
Set5	225-3	1.66e-02	3.17e-11	2.88e-02	9.6e-03
	450-1	7.08e-08	5.25e-08	1.90e-07	1.31e-07
	450-2	1.46e-06	1.82e-06	4.42e-06	2.73e-06
	450-3	3.82e-08	1.18e-05	1.19e-05	1.18e-05
	225-1	0	0	0	0

**Table 21:** Statistical results of the PSO-FA algorithm

	Std	Min	Max	Mean	
Set1	225-1	3.90e-06	3.54e-06	9.05e-06	6.30e-06
	225-2	4.14e-05	1.19e-04	1.77e-04	1.47e-04
	225-3	1.49e-04	1.25e-04	3.38e-04	2.31e-04
	450-1	3.38e-08	8.69e-04	8.69e-04	8.69e-04
	450-2	1.13e-07	3.77e-06	3.93e-06	3.85e-06
Set2	450-3	1.00e-06	1.47e-05	1.61e-05	1.54e-05
	225-1	3.66e-04	1.81e-04	6.98e-04	4.40e-04
	225-2	6.98e-03	4.86e-04	1.03e-02	5.42e-03
	225-3	9.6e-04	5.27e-03	6.62e-03	5.94e-03
	450-1	2.32e-06	1.64e-06	4.92e-06	3.28e-06
Set3	450-2	2.38e-03	6.77e-06	3.38e-03	1.69e-03
	450-3	1.34e-07	1.60e-05	1.62e-05	1.61e-05
	225-1	5.25e-05	5.51e-05	1.29e-04	9.22e-05
	225-2	6.88e-03	8.05e-04	1.05e-02	5.67e-03
	225-3	5.15e-03	4.68e-03	1.19e-02	8.32e-03
Set4	450-1	6.15e-04	1.10e-06	8.71e-04	4.36e-04
	450-2	8.97e-06	5.30e-06	1.80e-05	1.16e-05
	450-3	0	1.68e-05	1.68e-05	1.68e-05
	225-1	3.45e-04	1.86e-04	6.74e-04	4.30e-04
	225-2	7.19e-03	2.80e-04	1.04e-02	5.36e-03
Set5	225-3	1.07e-03	4.81e-03	6.33e-03	5.57e-03
	450-1	1.54e-07	8.69e-04	8.69e-04	8.69e-04
	450-2	5.66e-06	3.68e-06	1.17e-05	7.68e-06
	450-3	7.32e-07	1.27e-05	1.37e-05	1.32e-05
	225-1	3.90e-05	4.21e-05	9.73e-05	6.97e-05