Visual Abstract

The application of PSO in structural damage detection: an analysis of the previously released publications (2005–2020)

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ABSTRACT. The structural health monitoring (SHM) approach plays a key role not only in structural engineering but also in other various engineering disciplines by evaluating the safety and performance monitoring of the structures. The structural damage detection methods could be regarded as the core of SHM strategies. That is because the early detection of the damages and measures to be taken to repair and replace the damaged members with healthy ones could lead to economic advantages and would prevent human disasters. The optimization-based methods are one of the most popular techniques for damage detection. Using these methods, an objective function is minimized by an optimization algorithm during an iterative procedure. The performance of optimization algorithms has a significant impact on the accuracy of damage identification methodology. Hence, a wide variety of algorithms are employed to address optimization-based damage detection problems. Among different algorithms, the particle swarm optimization (PSO) approach has been of the most popular ones. PSO was initially proposed by Kennedy and Eberhart in 1995, and different variants were developed to improve its performance. This work investigates the objectives, methodologies, and results obtained by over 50 studies (2005-2020) in the context of the structural damage detection using PSO and its variants. Then, several important open research questions are highlighted. The paper also provides insights on the frequently used methodologies based on PSO, the computational time, and the accuracy of the existing methodologies.

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INTRODUCTION

The existing civil structures including buildings, dams, bridges, tunnels, towers, and different types of other structures hold an important role in today's world [1]. As technology advances, infrastructures play a more significant role than the past as they handle extensive human activities [2]. Civil structures experience a wide variety of deteriorating factors during their service life cycle, and the subsequent destructions may impact the normal performance of structures [3]. The structural deterioration could be caused by natural incidents such as strong earthquakes, high winds, tsunamis, tornadoes, etc. The structural damages may also cause by man-made events such as extreme loading, explosions, terrorist attacks, traffic loads, etc. [4]. In recent years, the structural health monitoring (SHM) strategies have become a fast-spreading topic not only in civil engineering but also across various engineering disciplines such as aerospace and mechanics [5]. It is essential to implement SHM for its swift localization and repair capability to prevent the expansion of the secondary damages and even more severe ones [6]. Therefore, it is an undeniable fact that the SHM strategies play a vital role in providing life-safety and economic advantages [7].

SHM strategies can be mainly categorized based on two methods: I) vibration-based methods II) vision-based methods [8]. The main sense behind the vibration-based methods is the alternation of such physical properties as stiffness, mass, and damping after the deterioration of the structure members. The dynamic characteristics such as natural frequencies and mode shapes are highly change-sensitive in physical properties. Therefore, the analysis of the discrepancy between the dynamic characteristics before and after the occurrence of the damage could be accomplished as a suitable damage detection tool. The vibration-based methods could fall under two classifications: I) the response-based methods II) the model-based methods. The response-based methods are often capable of localizing the damaged members by experimental response data such as natural frequencies, mode shapes, and accelerations. In addition to the experimental response data, FEM of the structures is required for damage detection and the quantification of its severity through the model-based methods. As mentioned earlier, the response-based methods are only capable of detecting the damaged members. However, the model-based methods come with some constraints and require further advancement. For instance, the numerical model analysis is a time-consuming process; therefore, the model-based methods are not practical in establishing a real-time SHM system [9]. Due to the limitations of sensors installed in real-world projects, only incomplete mode shapes are accessible. To handle the challenge of the limited measurements, either mode shapes have to be expanded, or FEM is to be reduced. In this regard, some helpful studies have been presented [10–18]. Moreover, developing an accurate model of complex structures which could represent the real structural performance is a challenging problem, and requires more efforts. For example, Mashayekhi and Santini-Bell have addressed the complexity of the Memorial bridge using a three-dimensional multi-scale FEM [19,20]. In addition to the problem of the complexity in large-scale structures, there are some differences between the experimental achievements and numerical models. These disagreements between FEM and real models can be justified by different factors including uncertainties in the properties of the materials, and the boundary and connectivity conditions [21]. Hence, a large number of model updating techniques have been presented to makes a correlation between the experimental and numerical models [22]. In this regard, some fundamental publications are presented by Friswell and Mottershead [23], Mottershead and Friswell [24], and Mottershead et al. [25]. Besides, FEM updating is an active track in terms of SHM, and the novel methodologies are subsequently expanded by some researchers.

For instance, the innovative FEM updating techniques were implemented to large-scale structures by Tran-Ngoc et al. [26], Ho et al. [27], Hoa et al. [28], Rezaiee-Pajand et al. [29], Pan et al. [30], and Zhu et al. [31]. According to the literature review, the FEM-updating methods are mainly divided into two categories: I) direct methods II) iterative methods. A type of the conventional approaches for FEM updating is the direct methods. Such techniques attempt to reproduce the measured modal data in a single step; therefore, these methods are computationally efficient. However, there are some drawbacks such as a lack of node connectivity as well as the demand for a large amount of data [32]. Direct methods have been frequently employed to date, and some researchers have tried to present modified versions [22,33–35].

In iterative methods, an objective function is minimized by adjusting several design variables during the iterative procedure. The objective functions are often established upon modal parameters such as natural frequencies and mode shapes [32].

Considering the concept behind the iterative methods, FEM updating problems could be formulated as an optimization scheme [36]. Thereby, the optimization algorithms have been applied to minimize the objective functions. During the past years, a significant number of optimization algorithms are proposed for FEM updating, including conventional methods such as GA and PSO [37] as well as some novel types such as grey wolf optimizer (GWO) [38], multiverse optimizer (MVO) [39], salp swarm algorithm (SSA) [40], and Jaya algorithm [41].

Reference	Year	Title
Poli [53]	2008	Analysis of publications on particle swarm optimisation applications
Mahor et al. [54]	2009	Economic dispatch using particle swarm optimization: A review
Rana et al. [55]	2011	A review on particle swarm optimization algorithms and their applications to data clustering
Yusup et al. [56]	2012	Overview of PSO for optimizing process parameters of machining
Sarkar et al. [57]	2013	Application of particle swarm optimization in data clustering: A survey
Esmin et al. [58]	2013	A review on particle swarm optimization algorithm and its variants to clustering high-dimensional data
Lalwani et al. [59]	2013	A comprehensive survey: Applications of multi-objective particle swarm optimization (MOPSO) algorithm
Gopalakrishnan [60]	2013	Particle swarm optimization in civil infrastructure systems: state-of-the-art review
Ghorpade-Aher and Bagdiya [61]	2014	A review on clustering web data using PSO
Saini et al. [62]	2014	A review on particle swarm optimization algorithm and its variants to human motion tracking
Alam et al. [63]	2014	Research on particle swarm optimization based clustering: A systematic review of literature and techniques
Kulkarni et al. [64]	2015	Particle swarm optimization applications to mechanical engineering-A review
Zhang et al. [65]	2015	A comprehensive survey on particle swarm optimization algorithm and its applications
Zhou et al. [66]	2016	The application of PSO in the power grid: A review
Andrab et al. [67]	2017	A review: evolutionary computations (GA and PSO) in geotechnical engineering
Pluhacek et al. [68]	2017	A review of real-world applications of particle swarm optimization algorithm
Elsheikh and Abd Elaziz [69]	2018	Review on applications of particle swarm optimization in solar energy systems
Hajihassani et al. [70]	2018	Applications of particle swarm optimization in geotechnical engineering: a comprehensive review
Elbes et al. [71]	2019	A survey on particle swarm optimization with emphasis on engineering and network applications
Sibalija [72]	2019	Particle swarm optimisation in designing parameters of manufacturing processes: A review (2008–2018)
Jahandideh-Tehrani et al. [73]	2020	Application of particle swarm optimization to water management: an introduction and overview
Kashani et al. [74]	2020	Particle swarm optimization variants for solving geotechnical problems: Review and comparative analysis

Table 1: Various review papers on different applications of PSO.

Following the establishment of an agreement between the experimental and numerical models through the FEM updating methods, the damage identification procedure could be organized similar to the concept utilized for the iterative FEM updating. The structural damages are often defined by the reduction of the members' stiffness. In this regard, the optimization algorithms attempt to minimize the objective functions during an iterative process and find those design variables that would include stiffness for each member. For further discussion, the damage modal characteristics are usually inserted in the objective functions. Then, the optimization algorithms evaluate the objective functions, and they iteratively minimize the discrepancy between the measured modal data (for the damaged members) and the calculated ones.

For the model-based damage detection problems solved by the optimization frameworks, the performance of the identified damages mainly depends on two subject. The first is the objective function, and the second one is the optimization algorithm [42]. Some studies have been conducted to make a comparison between the different objective functions in terms of

structural damage detection [43–46]. As mentioned above, the optimization algorithms play an important role for an accurate damage detection. Therefore, numerous researchers have employed a wide variety of optimization algorithms in the context of SHM. Earlier attempts were also related to the traditional algorithms, mostly GA. Friswell et al. [47,48], Ruotolo et al. [49], and Mares and Surace [50] have pioneered in the 1990s in this area.
Another algorithm that has become popular and has been applied constantly in different engineering problems is PSO. PSO simulates the social behavior of a flock of birds seeking food [51] suggested by Kennedy and Eberhart in 1995 [52]. PSO is efficiently reflected for the structural damage detection problems, and a large number of methodologies have also been developed. Like other algorithms, PSO has some drawbacks, with a persisting chance of generalization of the modified versions. To address some of these drawbacks such as the premature convergence, and to lower the computational time, different variants of PSO have been developed and implemented on damage detection problems.
Several review studies have been published focusing on the application of PSO for different engineering disciplines. In this regard, a list of review studies between 2008 and 2020 is presented in Tab. 1. Fig. 1 illustrates the number of review papers by different disciplines. It is evident in this figure that no work was done to analyze the publications on structural damage detection using PSO as well as its existing variations. This paper has reviewed over 50 studies conducted from 2005 to 2020 and constitutes the first of this kind that investigates the objectives, methodologies, and presents the main results of the PSO-based damage identification methods by the year of publication and the types of structures. The rest of the paper is organized as follows:
Section 2 presents the mathematical relations and flow chart of PSO. Section 3 comprehensively investigates the application of PSO on structural damage detection. Section 4 discusses the investigated papers in the manner of questions and answers. Finally, Section 5 concludes the work and Section 6 suggests future directions.

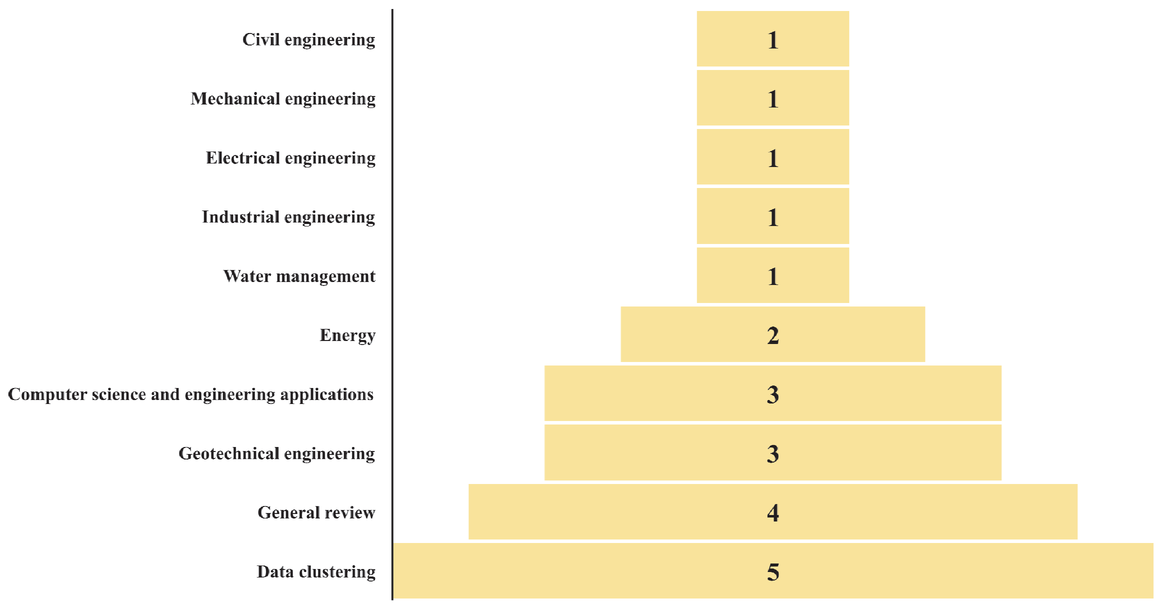

Figure 1: Number of review papers on different applications of PSO.

Particle Swarm Optimization (PSO)

PSO is a population-based optimization algorithm introduced by Kennedy and Eberhart [52]. The PSO mimics the swarm behavior of birds in nature. The PSO algorithm consists of two vectors: velocity and position. The position vector (x_i) represents the value of each variable in the optimization problem. The velocity vector (v_i) is utilized to update the position of particles. Fig. 2 shows the swarm behavior of birds and updating procedure of the position [69].
In this algorithm, each candidate solution is named a "particle" and indicates a coordinate in a D-dimensional space, where D is the number of the parameters to be optimized [75]. Therefore, the position of the ith particle can be defined by x_i vector:

$$x_i = \left[x_{i1} x_{i2} x_{i3} \dots x_{iD} \right] \tag{1}$$

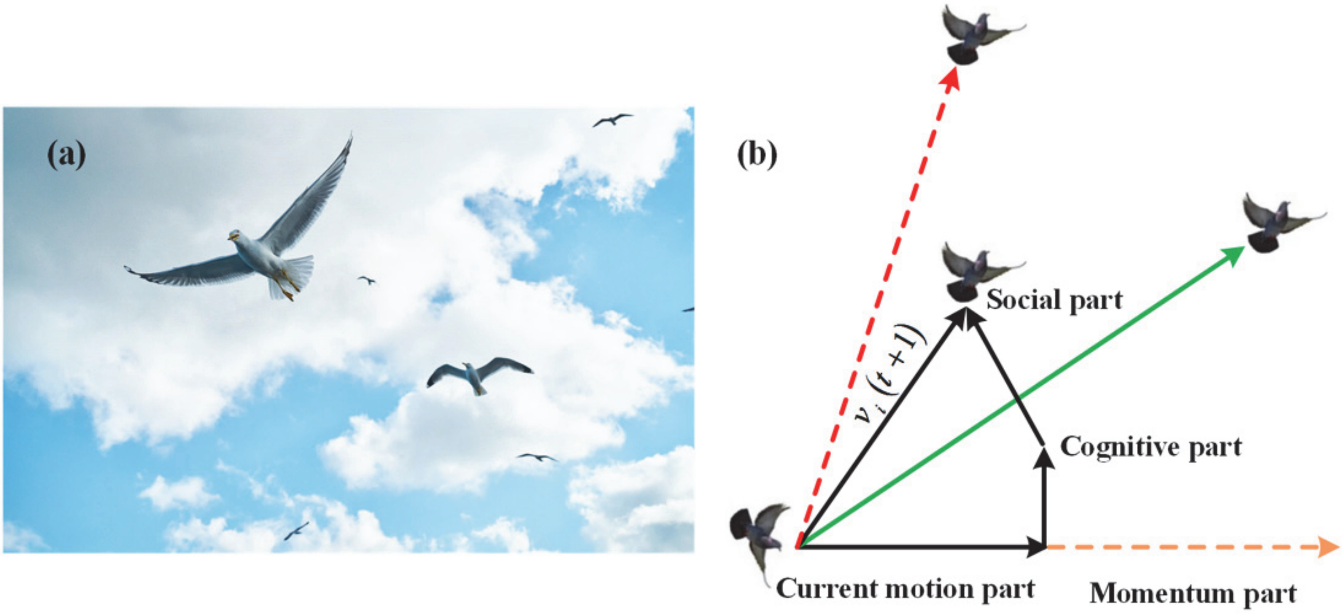

Figure 2: (a) Swarm behavior of birds in nature, (b) Updating the position and velocity of birds in PSO.

The population of N candidate solutions organizes the swarm:

$$X = \{x_1, x_2, ..., x_N\} \tag{2}$$

To find the optimal solution to the problem, the particles define trajectories in the parameter space based on the following equation of motion:

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{3}$$

In Eqn. (3), t and $t+1$ represent two sequential iterations of the algorithm, and v_i is the vector collecting the velocity components of the ith particle along the D dimensions.
The velocity of the ith particle is calculated as follows:

$$v_i(t+1) = v_i(t) + c_1\left(p_i - x_i(t)\right)R_1 + c_2\left(g - x_i(t)\right)R_2 \tag{4}$$

In Eqn. (4), p_i is the "personal best" of the particle, g is the "global best", and c_1 and c_2 are acceleration constants usually in $0 \ll c_1, c_2 \ll 4$ range, which are called "cognitive coefficient" and "social coefficient", respectively.
R_1 and R_2 are two diagonal matrices of random numbers generated through a uniform distribution in [0,1]. The flow chart of PSO is illustrated in Fig. 3.
Standard PSO has been successfully applied to different optimization problems. However, there are still some drawbacks. To address the different demands, the original PSO has experienced a wide variety of improvements from 1995 to date, and researchers constantly attempt to develop new variants [76]. The various variants of PSO can be summarized as follows:
I) Combination of PSO with different optimization algorithms such as GA, colonial competitive algorithm (CCA), elitist artificial bee colony, sine-cosine algorithm (SCA), cuckoo search (CS). II) Developing modified versions based on Nelder–Mead algorithm III) Introducing unified versions IV) Improving PSO by implementing immunity strategies
Tab. 2 presents comprehensive information on different varients of PSO and their applications in structural damage identification problems. Each modified version can be addressed single or multiple challenges such as premature convergence, poor accuracy, slow convergence, or high computational complexity.

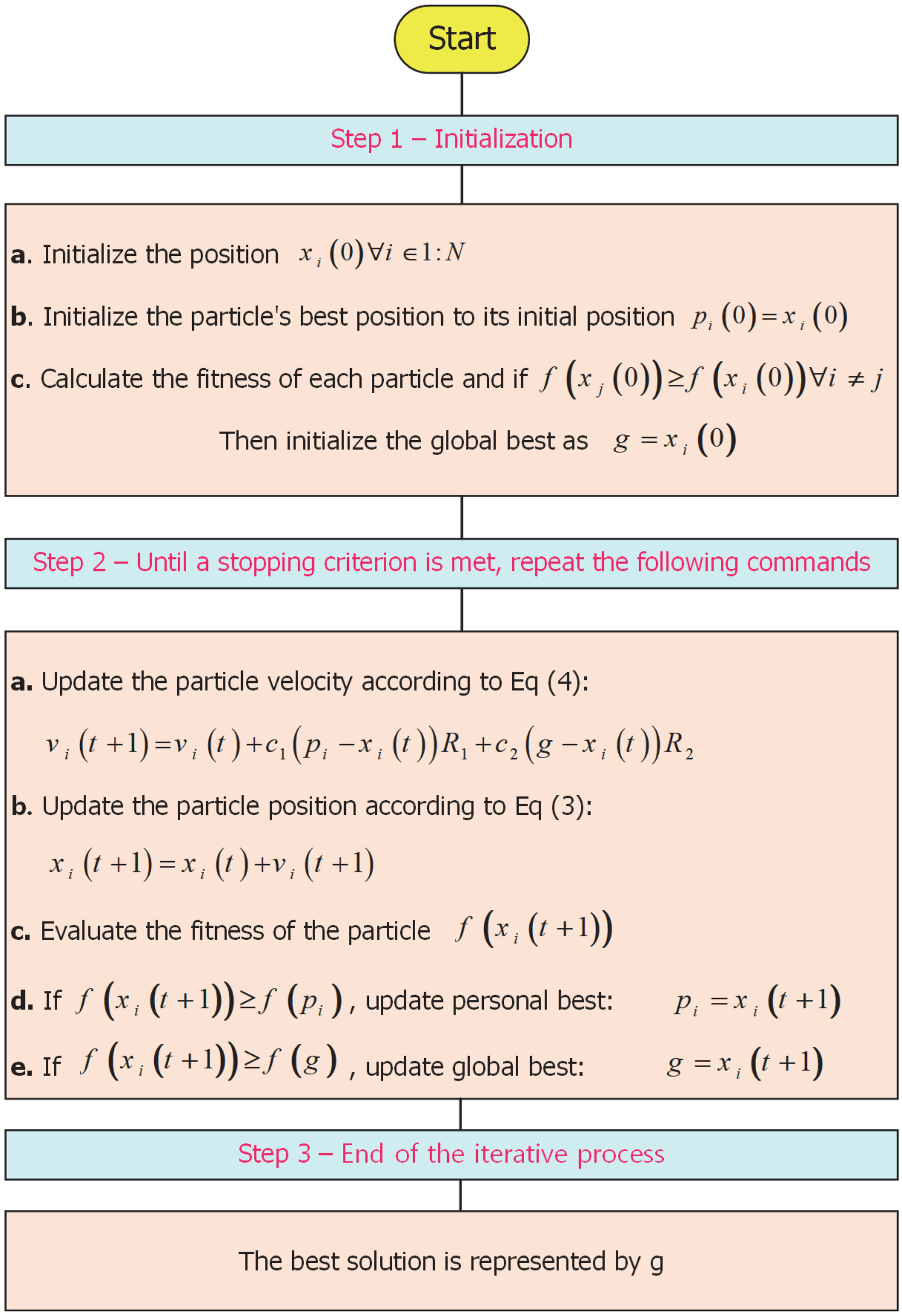

Figure 3: The flow chart of PSO.

AN ANALYSIS OF DIFFERENT STUDIES ON STRUCTURAL DAMAGE DETECTION USING PSO (2005-2020)

A tabulated scheme is utilized to make a desirable accessibility possible for the application of PSO in the structural damage detection methods, and to analyze the cons and pros of the different variants of PSO. Tab. 2 summarizes the application of PSO in detecting structural damages by some categorizations including the following:

- **Reference and Year**: Represent the authors' names and the publication date, respectively.
- **Objective**: This section answers the question of why the paper is presented and what the main contribution is.
- **Methodology:** The algorithms, tools, and techniques employed in solving damage detection problems are presented i n this section.
- **Structure**: This section answers the question of what type of structures are utilized for implementing the structural

damage detection methodology.

- **Result and Finding**: This section is a summary of the main outcomes of the papers.

Reference	Year	Objective	Methodology	Structure	Result and Finding
Mouser and Dunn [77]	2005	Comparing the performance of GA and PSO in updating mass, stiffness, and damping through an inverse solution.	Optimization algorithms were applied to minimize the difference between the measured frequency response functions (FRFs) and the calculated ones.	Mass – spring – damper system	PSO is configured easily and yielded much better results compared to GA.
Saada et al. [78]	2008	This study discusses the difficulty of damage detection by only using natural frequencies and the optimization problem is solved via a modified version of PSO.	Firstly, a model parameter modification is conducted to organize an acceptable agreement between the experimental and numerical models. Then, the first three natural frequencies are inserted into the objective function to recognize the damage properties.	Free-Free beam	Generally, the method introduced in this paper is capable of detecting the single damages and its accuracy declines when facing multiple damages.
Yu and Wan [79]	2008	An improved version based on the sigmoid function has been developed to address the convergence drawback of PSO and is subsequently employed for the damage detection problems.	An objective function is defined through the differences between the healthy and damaged dynamic characteristics to discover the damaged member and the extent of the damage.	Plane frame	The results of this paper have revealed that the improved PSO can effectively modify the convergence rate of the standard PSO and provides a better solution to detect single and multiple damages.
Begambre and Laier [80]	2009	A simple procedure based on Nelder–Mead algorithm is proposed to control the parameters of PSO.	An objective function is formulated using FRFs.	Planar truss Free–Free beam	The proposed version of PSO can accurately detect the location and severity of the damage even when inserting incomplete and noisy data. Additionally, this algorithm has outperformed the standard PSO and simulated annealing (SA) when solving benchmark functions.
Yu and Chen [81]	2010	The standard PSO has been improved by macroeconomic strategies to solve the multi-objective optimization problems on damage detection.	Two objective functions are employed to minimize the discrepancy between the modal data under healthy and damaged conditions. The first objective function is based on MAC and natural frequency. The second one includes modal flexibility.	Simply supported beam Continuously supported beam	The comparative results of damage detection illustrate the efficiency of the second objective function and the modified PSO with macroeconomic strategies.
Sandesh and Shankar [82]	2010	Developing an accurate hybrid optimization algorithm combining GA and PSO to address the inverse problem of crack detection in the time domain.	Minimizing the sum of the square of deviations between the measured and estimated accelerations as an objective function.	Aluminum plate	The hybrid PSO-GA provided a more accurate tool for damage detection. PSO is a fast algorithm, and

					GA is a slow one with poor accuracy.
Liu et al. [83]	2011	PSO is used to optimize the parameters of the support vector machine (SVM) to improve the classification and regression accuracy.	The accuracy of damage detection and quantification are used as objective functions.	Simply supported bridge	The proposed algorithm based on PSO and SVM was effectively capable of identifying the damage parameters.
Gökdağ and Yildiz [84]	2012	Presenting a comparative study to identify the best objective function for the damage detection problems while using PSO as an optimizer.	The objective functions based on natural frequencies, multiple damage location assurance criterion (MDLAC), modal flexibility, and strain energy residual are investigated.	Cantilever beam	This study illustrated that the objective function based on the modal flexibility is the best among other functions.
Seyedpoor [85]	2012	The damage detection problems with large numbers of design variables exert high computational costs. Therefore, a useful method is applied to reduce the dimensions of the search domain and decreases the computational effort of PSO.	A two-stage approach is introduced for damage detection. In the first stage, a modal strain energy-based index (MSEBI) is used to locate the potentially damaged members. In the second stage, PSO minimizes MDLAC in the downsized search area.	Cantilever beam Planar truss	This study concluded that the combination of MSEBI and MDLAC could be practical for multiple damages detection.
Baghmisheh et al. [86]	2012	Proposing the hybrid PSO–Nelder–Mead (PSO–NM) algorithm to predict the depth and location of the crack. The results of PSO–NM is compared with those obtained by the standard PSO, hybrid GA–Nelder–Mead algorithm (GA–NM), and Nelder–Mead algorithm (NM) in terms of accuracy and speed.	In this study, the cracked elements are simulated by a torsion spring. The parameters of the crack are determined through minimizing the difference between the calculated natural frequency (obtained from FEM) and the measured natural frequency (obtained through modal analysis).	Cantilever beam	Both numerical and experimental investigations showed that PSO–NM is the fastest and the most accurate algorithm among other methods.
Xiang and Liang [87]	2012	A two-step procedure is reported based-on 2-D wavelet transform and PSO for multiple damages detection and localization.	In the first step, the 2-D wavelet transform is used to decompose the mode shapes and predict the damage locations. In the second step, the severity of the damage is identified through inverse analysis and the reduction of the discrepancy between the measured and calculated natural frequencies.	Thin plates	The results of this study revealed that the use of higher natural frequencies could lead to accurate outcomes in identifying the severity of the damages.
Kang et al. [88]	2012	This study proposed the immunity enhanced PSO (IEPSO) algorithm to improve the efficiency and convergence rate of the basic PSO, and implemented it for structural damage identification problems.	An objective function consisting of mode shape and natural frequency changes is adopted.	Simply supported beam Planar truss	IEPSO is robust for damage identification problems and also provides reliable results when compared with the standard PSO, real-coded genetic algorithm (RCGA), and

					differential evolution (DE).
Nanda et al. [89]	2012	In order to make a better convergence for the standard PSO, a new version called the incremental PSO is implemented to solve the crack detection problem.	This study practices a natural frequency-based damage indicator as an objective function for minimization during an optimization procedure.	Cantilever beam	The convergence rate of the new PSO is more desirable than the basic version. Consequently, the outcomes achieved by the incremental PSO have a reasonable level of accuracy.
Saada et al. [90]	2013	Damage identification methods relying only on natural frequency indicators encounter several shortcomings. Therefore, this paper tries to overcome the existing challenges of damage detection techniques established on the natural frequency changes.	Some modifications are applied to one-dimensional Euler–Bernoulli beam elements. Then, a modified version of PSO is employed to solve an objective function defined only by natural frequency characteristics.	Free-Free beam	The results of the experimental example confirmed that the proposed method could identify the location and extent of the small damages.
Kang et al. [91]	2013	In this study, damage detection problems are solved using IEPSO because of its accuracy and convergence speed.	Presents an objective function, which has received the dynamic responses (natural frequencies) and the static response (displacements) as inputs.	Clamped-Clamped beam	IEPSO is more effective in structural damage identification when compared with the standard PSO and DE. The accuracy of IEPSO declines when inputs are contaminated with a certain level of noise.
Guo et al. [92]	2014	PSO cannot provide satisfactory results for multiple damage identification in complex structures. Hence, this paper proposes a two-stage procedure based on evidence fusion and some strategies to improve the standard PSO.	In the first stage, evidence fusion modal strain energy and frequency is used to locate the damaged elements. In the second stage, the improved PSO is employed to determine damage severities by minimizing an objective function based on mode shapes and natural frequencies.	Planar truss	The suggested technique has an acceptable accuracy to predict the location and severity of the damage in lightly damped structures.
Mohan et al. [93]	2014	This paper presents a comparative study of PSO and GA for crack detection.	An objective function related to natural frequency has been minimized to find the location and depth of the crack.	Cantilever beam Space truss	The performance of PSO in recognizing the location and depth of the crack is significantly superior to GA.
Nanda et al. [94]	2014	The exploration and exploitation capability of PSO is increased by the unified PSO (UPSO). Hence, this modified version was adopted for crack detection in the study.	The damage indicators are defined as an objective function based on the changes of the natural frequencies, mode shapes, and a combination of both.	Cantilever beam Plane frame	The utilized scheme can simultaneously detect the site and depth of the crack.
Nanda et al. [95]	2014	This study experimentally and numerically showed the capability of an optimization-based scheme for joint damage identification through UPSO.	The joint damage is simulated as the reduction of the joint fixity factor at each connection. An objective function combination of the mode shapes and natural	Plane frame	This damage detection procedure holds acceptable accuracy for the experimental examples. The accuracy of this methodology is still reasonable after

			frequencies is considered for minimizing by the optimization algorithm.		applying 5% and 10% noise.
Ma et al. [96]	2014	The revised PSO has been applied for structural damage detection problems to overcome the premature convergence and a time-consuming procedure in searching for optimum solutions by the standard PSO.	The potentially damaged members are located through MSEBI at the beginning to limit the dimension of variables in damage identification problems formulated as an optimization framework. Then, the exact location and severity of the damages are identified by integrating RPSO and an objective function.	Simply supported beam Shear frame	The results of this study demonstrated that the hybrid method on MSEBI and RPSO can provide precise outcomes. When comparing PSO and RPSO, RPSO is more useful than PSO in terms of computational speed and accuracy.
Jiang et al. [97]	2014	The basic PSO is simply entrapped into the local optimum and has the drawback of premature convergence. The same disadvantage has not been completely addressed in the multiparticle swarm coevolution optimization (MPSCO). Therefore, the improved MPSCO is introduced and implemented as an optimization algorithm in some damage detection problems.	An objective function between the simulated and measured time-series responses has been maximized to localize and quantify the structural damages.	Shear frame	Not only the improved MPSCO is more efficient than GA, but it is also robust to noise and provides reliable results for the structural damage detection in both numerical and experimental studies.
Shabbir and Omenzetter [98]	2014	This study presents an innovative method consisting of PSO and sequential niche technique (SNT) to systematically explore the search domain for FEM updating of the complex problems.	SNT adjusts the objective function after every solution without modifications to the PSO search strategy.	Cable-stayed footbridge	The results demonstrate that the proposed methodology is promising for the model updating, and it could be practiced for large-scale structures.
Liu et al. [99]	2014	The optimum values of bias and weight are regulated by PSO to accomplish the organization between the instructive search of the artificial neural networks (ANNs) and the global optimization of PSO.	A Two-stage damage detection approach has been generalized in this study. The damaged elements are initially localized by the modal flexibility index. Then, optimized ANNs by PSO are used to estimate the extent of the damage.	Simply supported beam	This study concludes that the combination of the modal flexibility index and ANNs with optimized characteristics (bias and weight) is more favorable when compared with those obtained by integrating the modal flexibility index and the conventional backpropagation networks.
Rasouli et al. [100]	2014	In general, there are limited numbers of sensors to measure the structural response in real-world problems. Therefore, the number of DOFs in FEM is extensively greater than the measured locations. In order to react to the challenge of the	In this study, mode shapes are condensed by the Guyan's method, and the downsized model is utilized to formulate the objective function through mode shape orthogonality.	Simply supported beam Plane frame Spring-mass system	Results revealed that the presented approach is sensitive to the damaged elements when the noise level is increased to 8%, and incomplete modal data are used.

		incomplete measurements, DOFs were reduced by the Guyan's method in FEM. Then, the damage detection problem was solved through the inverse analysis procedure established by PSO and the reduced model.			
Pal and Banerjee [101]	2015	To bypass the noise effect and to achieve accurate detection, a new method was developed on MSEBI in the wavelet domain and an optimization-based model updating mechanism through PSO.	As a first assessment, the MSEBI in the wavelet domain is considered for detecting the damaged locations. Then, the severity and location of the damages are accurately determined during the optimization procedure through the minimization of the objective function with the modal curvature components.	Plane frame	The experimental and numerical results are encouraging, and the proposed methodology can be applied to full-scale structures.
Kaveh and Maniat [102]	2015	Each optimization problem has some local optimums. Therefore, seeking the global optimum encounters difficulties. This study makes a comparison between PSO and the magnetic charged system search (MCSS) to search for the global optimum in the damage detection problems.	To form the objective function, modal characteristics such as mode shapes and natural frequencies are utilized.	Planar truss Space truss Plane frame Multi-span beams	The MCSS has a greater exploration capacity in finding the global optimum. Therefore, MCSS provides robust and efficient results for damage detection problems even when incomplete dynamic characteristics are contaminated by a certain level of noise.
Chen and Yu [103]	2015	This study proposes an intelligent two-step approach combining PSO, NM algorithm, and MSEBI to establish an adequate balance between accuracy and computational cost.	Through a two-step procedure, the damaged members and the severities of these damages are recognized by MSEBI and the minimization of the objective function with mode shape components, respectively. It should be noted that the optimization algorithm is the PSO–NM.	Simply supported beam	The presented method is not only able to determine the location of the damages, but it is also robust to noise and precisely quantifies the damage severity.
Chen and Yu [104]	2015	In this study, an improved version of the PSO–NM algorithm is introduced to solve the damage evaluation problems with a low computational cost through the two-step methodology.	The damaged members are primarily located with the assistance of MSEBI. The extent of the damage is evaluated during its second phase by minimizing 1-MAC through the improved PSO–NM algorithm.	Plane frame	The used techniques can determine the damage site and its severity in multiple and single damage scenarios. This method also has high tolerance against noisy inputs.
Khatir et al. [105]	2015	This study compares PSO and GA for damage detection in beam-like structures reduced by the proper orthogonal decomposition (POD) method with radial basis function (RBF).	An objective function only with frequency components is formulated. PSO and GA are initially applied to minimize the objective function and	Composite beams	The results of the comparison between GA and PSO show a better performance of PSO in terms of accuracy and

			recognition of the damage parameters. Then, POD and RBF are used to construct a reduced model.		computational effort. Besides, using POD and RBF can reduce the computational time of the optimization process.
Hosseinzadeh et al. [106]	2016	In order to perform a fast and reliable algorithm to minimize the objective functions in the damage detection problems, a hybrid algorithm based on PSO and the CCA is employed.	The main contribution of this study is that it focuses on structural damage detection when the completed measurements are unavailable. The Neumann series expansion-based model reduction (NSEMR) is applied to mimic the sparse sensor installation at master DOFs. Then, the generalized flexibility matrix is generated to form the objective function complying with the reduced mass and stiffness matrices.	Planar truss Plane frame Shear frame	PSO-CCA has a high convergence speed compared to PSO and CCA. The results of this study confirm the practicality of the suggested methodology relying on a reduced model by NSEMR and the hybridization of PSO and CCA. Hence, for future works, it is possible to allocate this method for damage quantification as well as damage detection in large-scale structures.
Hosseinzadeh et al. [107]	2016	Democratic PSO (DPSO) is used for solving the inverse problems of damage detection because of its swift and accurate technique in exploring the solution domain in complex problems.	The flexibility matrix components are considered to formulate a novel objective function by the concept of MAC. Subsequently, NSEMR is implemented to FEM to put the limited measurements condition using sparse sensors installation.	Planar truss Plane frame Shear frame	The results obtained from numerical and experimental examples demonstrated that the introduced technique could detect the damaged members with slight errors (less than 5%) in the identified severities.
Gerist and Maheri [108]	2016	This study presents a three-stage technique for damage localization and quantification, under the assistance of PSO, to address the high computation cost of the optimization problems due to the large search space.	Firstly, the damaged members are found through basis pursuit (BP). Then, the initial estimation of the damage locations and their extents are determined by minimizing 1-MDLAC. Subsequently, the dimension of the search area is downsized by removing the damaged members with low severities through the micro search (MS) operator embedded in the PSO. Basis pursuit denoising (BPDN) is also applied to decrease the noise effects.	Cantilever beam Planar truss Plane portal frame	The main results of this study can be summarized as follows: I) The standard PSO and PSO-MS are not enough to detect the damaged parameters. II) For all scenarios, damaged members are detected using the BP method. But this method cannot estimate the correct extent of the damage for most scenarios. III) The suggested three-stage BP-PSO-MS strategy has the fastest convergence and obtains accurate results compared with other well-known algorithms.

Khatir et al. [109]	2017	The main contribution of this study is to perform a comparison between PSO and GA to evaluate single and multiple damages in graphite-epoxy composite beams.	An objective function based on natural frequencies and MAC is defined.	Composite beams	Results clearly show the superiority of PSO in terms of the computational cost and the accuracy of the identified values.
Jebieshia et al. [110]	2017	This study compares the efficiency of two variants of PSO, namely UPSO and IPSO, for damage detection in composite elements.	An 8-noded curved isoparametric serendipity quadratic member is used to establish the FEM of the laminated composite shells. The damage detection problem is solved by optimizing an objective function based on natural frequencies and MAC.	Laminated composite shells	Results of a comparative study between PSO, UPSO, and PSO confirmed the superiority of UPSO.
Chen and Yu [111]	2017	To explore a more accurate solution in damage detection problems, this paper introduces a new hybrid methodology by integrating the recently published method (the improved PSO–NM) in Ref. [103] and a novel objective function relying on the Bayesian inference.	The Bayesian inferences are added to the objective function to eliminate the noise effect and uncertainty quantification. Then, the objective functions (defined by natural frequencies and mode shapes) with and without Bayesian terms are minimized by the improved PSO–NM.	Plane portal frame IASC-ASCE benchmark structure	The statistical comparison shows that the utilized objective function with the Bayesian term is more reliable for damage detection. Additionally, the effectiveness of the improved PSO–NM as a robust optimizer is also reconfirmed.
Luo and Yu [112]	2017	To develop a damage detection approach with high tolerance against noise, $l_{1/2}$-norm regularization is applied to create the objective function in the PSO-based two-step method.	The regularized objective function as a combination of eigenvalues and mode shapes is minimized to determine the damaged member in the first step. Subsequently, only those members detected in the first step are considered as the optimization values.	Cantilever beam	The proposed two-step method could accurately diagnose the damaged members while the noise level increases to 15%.
Khatir et al. [113]	2018	In this study, the location and depth of the open cracks are determined through frequency measurements and PSO as an optimization algorithm.	The location and depth of the cracks are introduced in an exponential function for the calculation of the equal stiffness reduction. The frequency-based objective function is defined and minimized via PSO.	Cantilever beam Plane frame Free-Free beam	The results obtained for the numerical examples (cantilever beam and plane frame) and experimental free-free beam demonstrate the feasibility of this method for the detection of the location and depth of the cracks.
Alkayem and Cao [114]	2018	The comparison of the performances of five optimization algorithms, namely PSO, GA, DE, Lévy flight–DE (LFDE), and elitist artificial bee colony–PSO (EABCPSO), is conducted in terms of accuracy, consistency, and computational cost.	This paper introduces a hybrid objective function consisting of the modal strain energy and the mode shape residuals with the weighting factors.	IASC-ASCE benchmark structure	The results of this study could be summarized as follows: I) Numerous false members were detected by GA. II) PSO provides an accurate detection compared to GA and

					DE. However, PSO is not reliable for several runs. III) The consistency and accuracy of the standard version of PSO and DE were improved by EABCPSO and LFDE, respectively. IV) EABCPSO is more accurate than LFDE. Additionally, LFDE is more time-consuming than EABCPSO.
Chen and Yu [115]	2018	NM is embedded into PSO to enhance the global searching ability of the standard PSO in damage detection problems.	Natural frequencies and mode shapes are adopted to organize the objective function. Monte Carlo simulations are initially used to find useful control parameters for PSO. Then, the proposed objective function is minimized by PSO-NM in order to obtain optimal solutions.	Simply supported beam	The experimental and numerical investigations prove the efficiency of Monte Carlo simulations in determining the control parameters of PSO. Moreover, the effectiveness of NM in combination with PSO was confirmed once more by this study.
Xu et al. [116]	2018	PSO is only able to minimize the single objective functions. Hence, the multi-objective PSO (MOPSO) is employed to minimize the discrepancy between the dynamic characteristics in the two objective functions simultaneously.	An iterative two-stage methodology combination of MSEBI and MOPSO is suggested for the structural damage assessment. In the first stage, only the damaged members are located. The second stage attempts to predict the severity of the damaged elements.	3-D offshore platform	The main novelty of this approach is the use of the iterative MSEBI to localize the damage, which can detect the damaged members more accurately than those obtained by the noniterative MSEBI. In conclusion, the introduced method consists of MSEBI, and MOPSO effectively detects the damage and its severity under noisy conditions and incomplete measurements.
Alkayem et al. [117]	2019	This study proposes a hybrid optimization techniques namely, SCA and PSO (SCAPSO) to produce a new and reliable algorithm with better searching capabilities.	An objective function containing the mode shape curvature (MSC) and modal strain energy (MSTEN) is considered to formulate the damage detection problem as an optimization paradigm.	Irregular-shape structures	The numerical assessments illustrate the capability of this method in detecting the damages with a relatively low computational cost.
Jebieshia et al. [118]	2019	As a result of balancing the influence of both global and	The weighted sum of the squared errors between the	Laminated composite beam	This methodology successfully detected

		local search directions, both exploitation and exploration capabilities have been improved by UPSO. Therefore, this paper applies this algorithm to handle the optimization problem of damage detection.	calculated and measured natural frequencies (only for the first few modes) is considered to form the objective function.	Laminated composite plate	and quantified the single and multiple damages with acceptable accuracy. However, the objective function can be enriched by additional modal properties such as mode shapes or FRF for precise damage recognition.
Huang et al. [119]	2019	The previous studies have come along with drawbacks such as slow convergence rate, easily entrapped in the local optimum, and relatively low tolerance to noise when the PSO and cuckoo search are applied as an optimizer. Consequently, the said drawbacks and the impact of the temperature variations are addressed by introducing PSO-CS algorithms.	The objective function based on natural frequency, modal strain energy, and MAC is minimized through PSO, CS, and PSO-CS.	Simply supported beam IASC-ASCE benchmark structure	The PSO–CS could identify the damage characteristics more robustly than CS and PSO while exposed to noisy inputs and temperature variations.
Huang et al. [120]	2019	The bare-bones PSO (BBPSO) is a simple yet robust variant of PSO. However, BBPSO is easily entrapped into the local optimum like other variants of PSO. Hence, BBPSO with double jump (BBPSODJ) is presented to address this weakness.	An objective function is established by considering l_1-norm regularization and integrating the widely used dynamic characteristics, natural frequencies, and mode shapes.	Planar truss Shear frame	The numerical and experimental evaluations on a 31-bar plane truss and a three-story shear frame report the superiority of BBPSODJ compared to PSO, BBPSO, and GA.
Ghannadi and Kourehli [121]	2019	This study formulates the damage detection problems as an optimization paradigm via PSO and moth-flame optimization (MFO).	The hybridization of MAC flexibility and natural frequencies has been adopted as an objective function.	Planar truss Shear frame	The results obtained by MFO are more promising than those obtained by PSO, while only the first few modes are introduced to the objective function, and the modal characteristics are contaminated by a certain percentage of the noise level.
Ghannadi and Kourehli [40]	2019	This study compares the capability of PSO and salp swarm algorithm (SSA) for FEM updating and subsequent damage detection.	The FEM updating and damage detection have been conducted using the minimization of an objective function based on the natural frequency vector assurance criterion (NFVAC) and natural frequencies.	Shear frames	In this study, the advantages of SSA have been concluded in terms of FEM updating and damage detection for multi-story shear buildings.
Mishra et al. [122]	2019	This study evaluates the effectiveness of UPSO and ant lion optimization (ALO) in detecting the damages exerted on the structural members.	Two objective functions are employed in this article. The first one only minimizes the differences between the measured and calculated natural	Cantilever beam Planar truss Shear frame	The benchmarking studies for numerical and experimental examples indicate the efficiency of ALO. ALO provides reliable

			frequencies. Then, the first objective function is extended with the mode shape components.	Space truss	results with less standard deviation in convergence curves.
Mishra et al. [123]	2019	This study makes a comparison between ten optimization algorithms, including UPSO, artificial bee colony (ABC), scout UPSO (SUPSO), ant colony optimization (ACO), cultural algorithm (CA), grasshopper optimization algorithm (GOA), multiverse optimizer (MVO), gray wolf optimizer (GWO), SSA, teaching-learning-based optimization (TLBO) considering the accuracy of the identified damages, convergence rate, success rates and the computation time.	The objective function is established by combining natural frequencies and their corresponding mode shapes.	Large-scale space trusses	The only optimization algorithm that could provide satisfactory outcomes in terms of accuracy, success rates, computation time, and convergence rate is TLBO.
Huang et al. [124]	2019	The applicability of the recently published PSO-CS algorithm [119] is benchmarked by classical functions such as Sphere, Rosenbrock, Rastrigin, and Schaffer. Afterward, the same methodology proposed by Huang et al. [119] is used for damage detection of the I-40 bridge with field measurements and considering the temperature variations.	In order to address the impact of the temperature variations on the dynamic responses, the temperature changes are modeled by alterations in the elastic modulus of steel and concrete. The same objective function designed by Huang et al. [119] is employed once more (containing natural frequency, modal strain energy, and MAC).	Simply supported I-40 bridge	The hybrid PSO-CS can minimize the benchmark functions and finding the optimal solutions. Besides, for damage detection under the temperature variations, the performance of hybrid PSO-CS and hybrid objective function is validated when exposed to the field measurements.
Khatir et al. [125]	2019	This study presents a multi-step approach combined with the isogeometric analysis (IGA), Cornwell indicator (CI), ANNs, and PSO to accurately detect the location and extent of the damage with low computational time when numerical models are assembled with a large number of DOFs.	In the first step, a three-layer composite plate is modeled by IGA, and CI is applied to detect the damaged locations. In the second step, and following the elimination of the healthy members detected in the previous step, an objective function is defined using CI, and damage severities are identified during an iterative optimization procedure through PSO. In the third step, ANNs are employed to reduce computational time in identifying the damage severities. To train ANNs, CI is considered the input, whereas damage severities and locations are considered the targets.	Laminated composite plate	In the first step, where CI and IGA are used, the damaged members are recognized quickly and accurately. In the second step, following the elimination of the healthy members detected in the first step, the combination of PSO and CI estimates the severity of the damages. The computational time for the second step is about 6 hours. In the third step, ANNs are successfully applied to address the challenge of the long computational time of the second step and decrease the computational time to about 25 seconds.

Wang et al. [126]	2020	The optimization algorithms often function properly to find the optimal solutions when the search area is small. In this study, an iterative two-stage strategy is introduced. Firstly, the potentially damaged members are detected. Then, three optimization algorithms, including PSO, GA, and beetle antenna search (BAS), are organized in the narrow search area to find the damage's exact severity.	A new damage localization index called the modal energy-based index (MEBI) is utilized to classify the damaged members. Afterward, three objective functions based on the modal flexibility, the integration of natural frequencies and mode shapes, and also MSEBI are solved by PSO, GA, and BAS to determine the exact severity of the damaged elements.	3-D offshore platform Cantilever beam	To detect the damaged members, the new damage localization index (MEBI) performs better than the conventional damage localization index (MSEBI). MSEBI is selected as the best objective function. BAS is more efficient than GA and PSO in terms of the computational time.
Zenzen et al. [127]	2020	The main contribution of this article is implementing the transmissibility concept into the objective function and developing a new index. PSO is also used to minimize the objective function as the optimization algorithm.	A new objective function is formulated by replacing the transmissibility with the mode shape vectors in the MAC formulation.	Planar truss	The methodology used for solving the inverse problem of detecting the damage in a plane truss with 25 members is efficient for single and multiple damage scenarios.
Tran-Ngoc et al. [128]	2020	In order to handle the premature convergence as a fundamental challenge of standard PSO, an improved version of PSO combined with the orthogonal diagonalization (OD) is utilized.	Young's modulus of truss members and the stiffness of 8 springs under bearings are updated through the newly developed hybrid PSO and an objective function with natural frequencies and mode shapes as inputs.	Guadalquivir railway bridge	The upgraded version of PSO not only accurately updates FEM but also significantly decreases computational costs.
Guo et al. [129]	2020	This study presents a two-step process of damage detection and quantification based on IPSO and wavelet transform. A comparative study of IPSO, standard PSO, GA, and bat algorithm (BA) is also conducted to identify the severity of the damaged members.	In the first step, the damaged members are detected by wavelet transform. Then, to estimate the extent of the structural damage, the optimization algorithms are applied to minimize the discrepancy between the measured and calculated modal characteristics (natural frequencies and mode shapes).	Clamped-Clamped beam Plane portal frame	The Damaged location can be accurately detected by wavelet transform under different noise levels. IPSO is not entrapped into the local optimums and can accurately predict the severities of the damaged members. Hence, the combination of wavelet transform and IPSO could provide a practical tool for structural health monitoring purposes.
Fathnejat and Ahmadi-Nedushan [130]	2020	The damage location and its severity are detected through the two-stage approach. The first stage is designed for the localization of the damaged members, whereas the second stage is outlined to estimate the extent of the damage.	The damaged members are classified by MSEBI at the first stage. In the second stage, ANNs (cascade feed-forward neural network (CFNN) and the group method of data handling network (GMDHN)) are used in combination with the optimization procedure	Space truss Double layer grid	Similar to the previous studies, MSEBI is an efficient criterion for damage localization. To identify the damage severity, PSO outperforms CBO and BA. To identify the damage severity, an integration of PSO with both

			(PSO, BA, and colliding bodies optimization (CBO)) to generate a surrogate of the FEM and reach a short computational time.		CFNN and GMDHN provides the same level of accuracy. However, where GMDHN is used, the computational time is significantly less than that of CFNN.
Barman et al. [131]	2020	To improve UPSO in terms of accuracy and convergence rate, a new version of the combination of the standard continuous UPSO and binary UPSO (mixed UPSO) is introduced to be employed in a two-stage method for the delamination assessment in composite structures.	The locations of the delamination cases are initially detected through the MSC index. Then, the interface of the delamination cases is estimated by minimizing an objective function relying on the changes in natural frequencies and mode shapes.	Laminate composite beam Laminate composite plate	The overall results of this paper demonstrate a superior accuracy for the localization of the single and multiple delamination cases and their interface, while the modal components are contaminated by a certain level of noise.

Table 2: A review on the application of PSO on the structural damage detection.

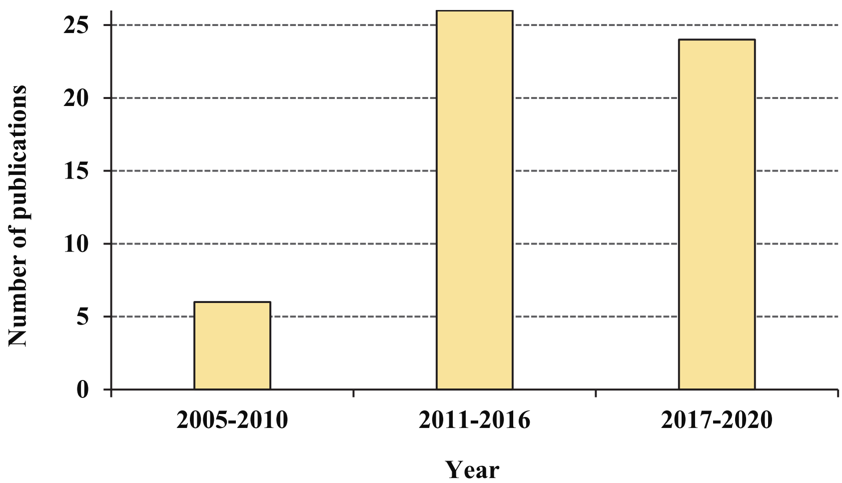

Figure 4: Number of publications in the area of structural damage detection based on PSO - A classification by year.

The number of publications on structural damage identification using PSO is shown in Fig. 4. It can be observed that the considerable developments in optimization-based damage detection methodologies have been conducted in the last decade. Fig. 5 presents the contribution of the publications in the fields of crack detection, FEM updating, damage detection, FEM updating and subsequent damage detection. It can be easily realized that the main contribution of recently published papers is damage detection. Then, the combination of FEM updating and damage detection is the frequently used methodology.

Figure 5: Contribution of the publications in the fields of crack detection, damage detection, FEM updating, and FEM updating+damage detection

The percentage of utilized structures to illustrate the performance of proposed methodologies in the publications is shown in Fig. 6. As given in Fig. 6, beam-like structures are the most utilized example in order to verify the different methodologies in the area of structural damage identification.

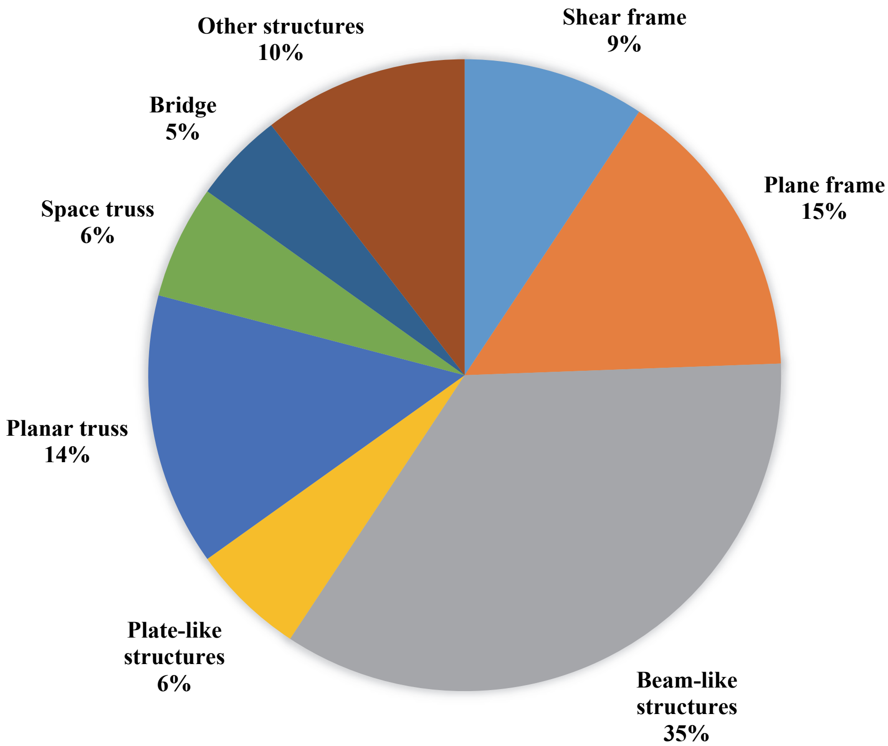

Figure 6: The percentage of utilized structures to demonstrate the efficiency of proposed methodologies in the publications

In recent years, single-step, two-step, and multiple-step methods have been proposed by different researchers.
Fig. 7 shows the percentage of each method. It is clear that the single-step methods are the most utilized techniques. However, two-step and multiple-step methods have been developed to provide better accuracy for damage identification.

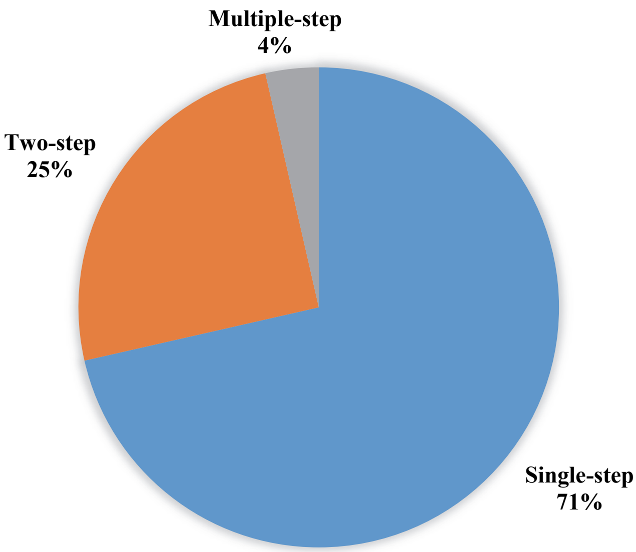

Figure 7: The percentage of employed single-step, two-step, and multiple-step methods in the publications

The utilized two-step methods are classified in Fig. 8. A large number of two-step methods are related to the combination of modal strain energy-based methods and PSO.

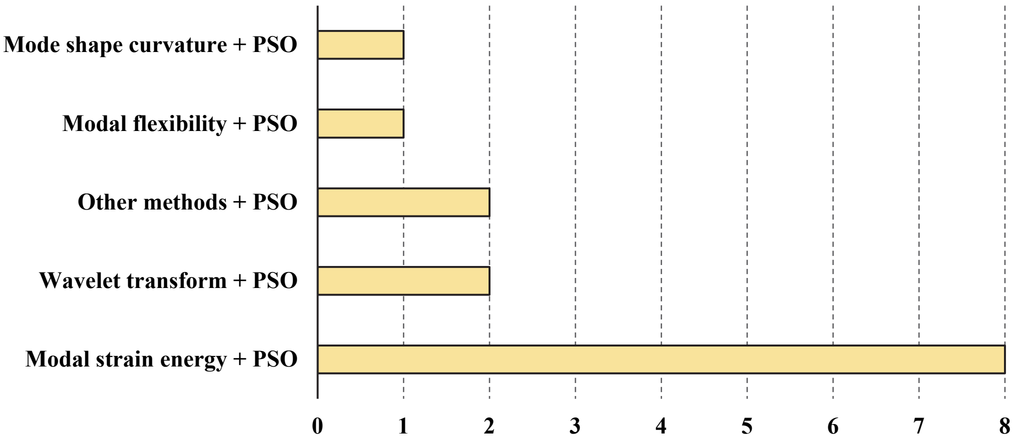

Figure 8: The classification of different two-step methods by number of publications

As mentioned earlier, objective functions and optimization algorithms play a crucial role in identifying accurate results in structural damage detection problems. Fig. 9 and Fig. 10 illustrate the classification of utilized objective functions and different variants of PSO by the number of publications. As shown in Fig. 9, the most utilized objective functions are based on natural frequencies, natural frequencies + MAC, and natural frequencies + mode shapes, respectively.
Fig. 10 presents four algorithms, including PSO, UPSO, IPSO, and PSO-NM, which have repeatedly been applied to detect structural damages.

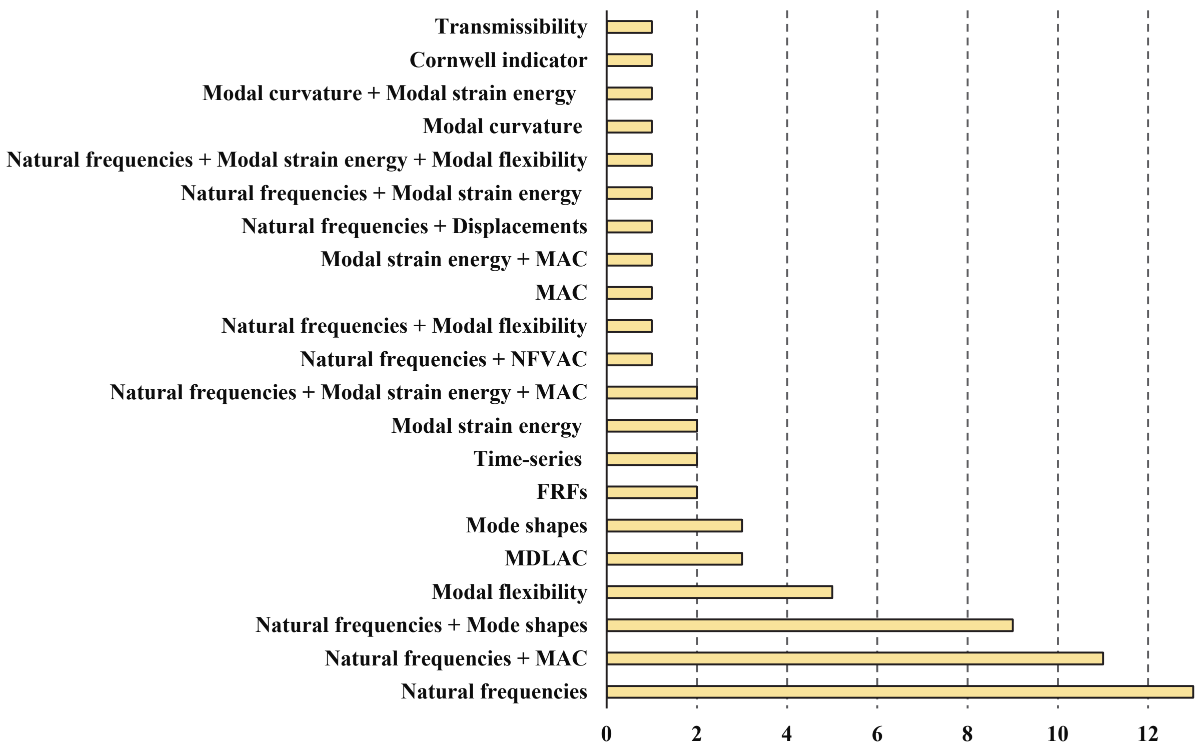

Figure 9: The classification of utilized objective functions by the number of publications.

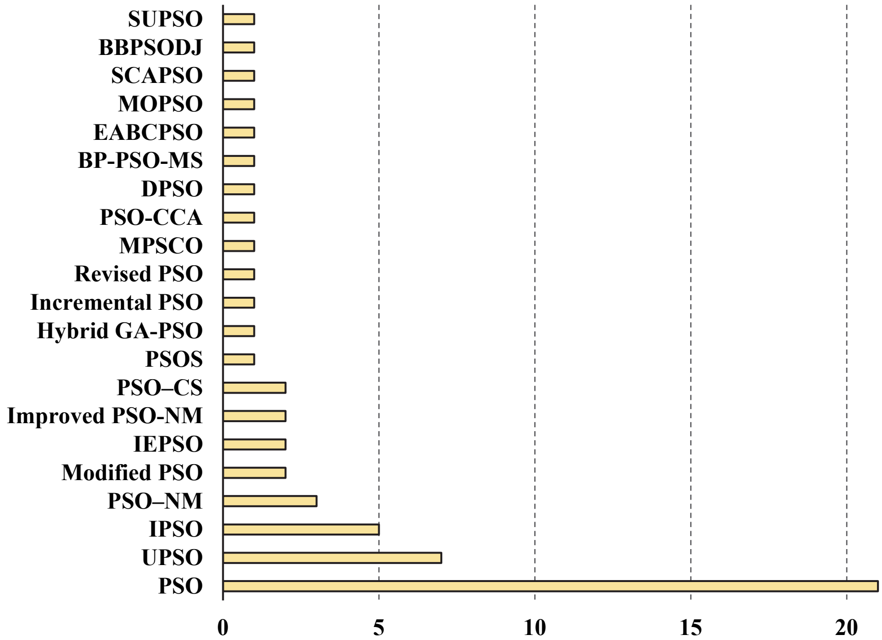

Figure 10: The classification of different variants of PSO by the number of publications

Discussion

To quickly and suitably provide the possibility of understanding the main points put forward by the existing studies conducted between 2005 and 2020, this section provides various questions and answers.

a) *Why are the different variants of PSO developed?*

After investigating more than 50 studies, it could be claimed that the standard PSO has some drawbacks in terms of solving damage detection problems. For instance, the basic PSO is easily entrapped in local optimum, and the premature convergence is a fundamental problem of the standard PSO. Therefore, some modified versions are proposed to improve the performance of the standard PSO. Additionally, some modified versions try to lower the computational time.

b) *Why are the two-step methods frequently implemented for damage detection methodologies?*

For the large-scale damage detection problems formulated as an optimization scheme, there is an enormous search area to detect the optimal design variables. Most optimization algorithms cannot function properly when exposed to a large number of variables. Therefore, several two-step methods are proposed to enhance the performance of the optimization algorithms by narrowing the search area. For example, the damage localization methods such as MSEBI, MSC, and wavelet transform are practiced in some studies. Hence, the number of design variables drops by eliminating the healthy members. In the second step, the optimization algorithms are employed to measure the severity of the damage by minimizing the objective functions. In conclusion, the damage localization methods are efficient for improving the performance of the optimization algorithms and the accuracy of the damage evaluation.

c) *Which one of the damage localization methods are frequently used in two-step methods?*

Among various damage localization methods, MSEBI is the most popular. It should be noted that the new damage localization index called MEBI was introduced by Wang et al [126]. MEBI is similar to MSEBI, yet it provides accurate outcomes.

d) *Can robust results be achieved without improving the PSO algorithm?*

In a study conducted by Shabbir and Omenzetter [98] , the combination of SNT with objective function could present robust results for FEM of the large-scale structures. It should be emphasized that the main contribution of this paper is adjusting the objective function after every solution without any improvement in PSO search strategy.

e) *Based on the analysis performed on the previous studies, does PSO always provide more accurate results compared to GA? How about the computational time?*

GA is one of the earliest optimization algorithms, and according to the analysis of the studies conducted between 2005 and 2020, it has been extensively applied to structural damage detection problems. Some studies have compared the efficiency of PSO with that of GA in terms of accuracy and computational time. Based on the analysis made in the previous studies, it could be concluded that PSO is capable of determining the damage characteristics with high accuracy and short computational time compared to GA.

f) *Based on the analysis made in the previous studies, do frequency-based objective functions suffice for accurate damage detection? Can you elaborate more on the popular and extensively used objective functions?*

According to the analysis made in the previous studies, some methodologies use a frequency-based objective function. Generally, it can be summarized that natural frequencies do not fully suffice for damage detection. Especially, the damage detection accuracy declines in complex structures such as laminated composites, as well as the multiple damage scenarios. Several objective functions are defined by the combination of natural frequencies and mode shapes, modal flexibility, MDLAC, MAC, NFVAC, strain energy, etc. Among the aforementioned objective functions, the combination of the natural frequencies and the mode shapes (or MAC) is a frequently used objective function with acceptable accuracy in complex structures.

g) *What is the perspective of PSO considering the novel and robust nature-inspired optimization algorithms?*

As Nikola Tesla said: "the key to innovation is combining old ideas in new ways". Today, numerous novel optimization algorithms have been developed, improved, and enhanced by the inspiration of the swarm behavior of PSO. Since 2014 to date, new generations of optimization algorithms such as GWO [132], MFO [133], SSA [134], MVO [135], ALO [136], water strider algorithm (WSA) [137], plasma generation optimization (PGO) [138], vibrating particles system (VPS) [139], thermal exchange optimization (TEO) [140] have been introduced. For structural damage identification, successful applications of GWO [38,141], MFO [121,142], SSA [40], MVO [39], ALO [122], WSA [143,144], PGO [145], VPS [146], and TEO [147] have been reported during the past years. These algorithms have some major advantages as follows:

i) The possibility of easy practice for different problems

ii) There are few control parameters to begin the optimization procedure and have powerful exploration and exploitation capabilities.

Alongside the new nature-inspired optimization algorithms, different versions of PSO are constantly being released and are still effective in structural damage detection problems.

h) *How many control parameters are there for PSO? How could the best values be determined for them?*

Generally, to begin the optimization process complying (see Fig. 3), four control parameters, including the number of particles (N), the maximum number of iterations (t_{max}), cognitive coefficient (c_1), and social coefficient (c_2) are required. To avoid the velocity explosion [148], an inertia weight is introduced, and Eq (4) can be rewritten as follows [75]:

$$v_i(t+1) = \omega(t+1)v_i(t) + c_1\big(p_i - x_i(t)\big)R_1 + c_2\big(g - x_i(t)\big)R_2 \tag{5}$$

where $\omega(t+1)$ represents the inertia weight at the $(t + 1)^{th}$ iteration of the algorithm. The inertia weight can be defined by dynamic adjustment strategies or considered as a constant value. The definition of a linearly decreasing inertia weight, according to Eq (6), can provide reliable results in most engineering cases [75].

$$\omega(t) = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{t_{max}} t \tag{6}$$

Several authors [87,88] inserted $\omega_{min} = 0.4$ and $\omega_{max} = 0.9$ in Eq (6). These are the uncertain parameters with a significant influence on the convergence rate.

Most of the papers published in the context of damage identification, update the particle velocity by Eq (5) and implement the linearly decreasing inertia weight. Hence, the basic or standard PSO is known by considering this modification, and a flexible MATLAB code can be found in Ref. [149].

In summary, the control parameters for the optimization algorithms are usually selected empirically and through trial-and-error methods. However, Chen and Yu determined the optimal values for the inertia weight, cognitive coefficient, and social coefficient by Monte Carlo simulation [115].

i) *According to the analyzed studies, how could the computation time of PSO be lowered when optimizing a large number of variables?*

As mentioned earlier, the two-step methods have initially detected the potentially damaged members. Then, the optimization algorithms could swiftly determine the accurate severity of the damaged elements.
FEM of the composite structures includes a large number of DOFs. Hence, Khatir et al. [105] employed POD and RBF to construct a short model which lowers the computation time consumed by the optimization procedure.
The results obtained by some of the studies show that the combination of ANNs and optimization algorithms can significantly decrease the computational time. For example, Khatir et al. [125], Fathnejat and Ahmadi-Nedushan [130] have suggested hybrid methodologies.

CONCLUSIONS

One of the important tools for SHM systems is damage detection techniques. The model-based damage detection methods have received extensive attention among other types of vibration-based methods. Because model-based methods could identify the severity and the location of the damage. In iterative model-based methods, the vector of the design variables, including both severity and location of the damages, is achieved through minimizing an objective function by the optimization algorithms. Similar to other optimization based-problems, the accuracy of the detected damages is also significantly influenced by the capability of the optimization algorithm. It should be noted that the utilized objective function is another important matter. In recent years, PSO and its modified versions have been widely applied to optimization-based damage detection problems as a pioneering optimization approach. This paper analyses available publications released between 2005 and 2020 and discusses them in terms of methodologies, objectives, and results. Finally, the following conclusions can be drawn:

(i) In general, premature convergence is a fundamental problem of the basic PSO, and this drawback deteriorates the accuracy of the damage detection, especially in complex structures with multiple damage scenarios. Hence, several variants of PSO have been developed to address this disadvantage. Tab. 2 presents more information about the di fferent modified versions of PSO.

(ii) According to Tab. 2, many publications have proposed two-step damage detection methodologies. The first step d etects the damaged members using damage localization techniques such as wavelet transform, MSEBI, and MSC. After eliminating the undamaged members, the extent of the damage is estimated through an optimization operati on. In summary, the two-step method lowers the number of the design variables since PSO cannot function prop erly to tackle the optimization problems in a large search space.

(iii) Based on the analyzed publications (2005-2020), PSO yields accurate results with low computational time compared with those obtained by GA.

(iv) As mentioned before, the utilized objective functions play a vital role in optimization problems. Shabbir and Omenzetter [98] have adjusted the objective function with SNT and presented enhanced results without modifying the standard PSO. The overall investigations show that frequency-based objective functions are not suf ficient for damage detection in complex structures. The most popular objective function with adequate accuracy is the combination of natural frequencies and mode shapes (or MAC).

(v) To start the optimization procedure with the standard PSO, the number of particles (N), the maximum number of iterations (t_{max}), cognitive coefficient (c_1), social coefficient (c_2), and the inertia weight (ω_{min} and ω_{max}) should be determined. Considering six uncertain parameters, establishing a desirable combination of the control parameters may be challenging.

(vi) Regarding the computational time, where the two-step methods are used, the elapsed time dramatically lowers because optimizing a low number of variables requires short computational time. The combination of ANNs and optimization algorithms, as well as the use of the reduced models by POD and RBF, are other methods could reduce the computational time.

FUTURE DIRECTIONS

I) Recently some hybrid algorithms based on PSO and GWO have been developed [150–152]. Due to the successful application of both PSO and GWO, a hybrid algorithm maybe provides more efficient results for structural damage detection problems. There are also hybrid algorithms based on PSO and other nature-inspired optimization techniques such as MFO [153], MVO [154], and SSA [155].

II) As recently mentioned, objective functions play a significant role in accurate damage detection. Therefore, it is necessary to present a comparative study between different objective functions based on natural frequencies, mode shapes, modal strain energy, MAC, MTMAC, NFVAC, etc.

III) According to Tab. 2, many studies focused on damage detection of small-scale structures. Complexity is a fundamental challenge in SHM. Therefore, researchers should be addressed real-world damage detection problems and provide practical methodologies.

IV) To overcome the incomplete modal data in damage detection problems, FEM reduction techniques have been applied by most studies. Presenting a comparative study between FEM reduction and mode shape expansion methods can be an attractive topic for future works.

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