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OPTIMAL DESIGN OF LAMINATED COMPOSITE AND NANOCOMPOSITE STRUCTURES USING EVOLUTIONARY OPTIMIZATION TECHNIQUES: A SURVEY

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ABSTRACT

The optimal design of laminated composite and nanocomposite (LCNC) structures stands at the forefront of materials engineering, offering the potential to revolutionize the development of advanced materials with superior mechanical, thermal, and electrical properties. By tailoring LCNC structures to meet specific performance requirements, optimizing material usage, and exploring innovative design approaches, engineers can create lighter, more efficient, and environmentally friendly structures that excel in diverse applications. Many industries such as automotive, aerospace, and construction are already using composite and nanocomposite materials to develop high-strength and lightweight structures. Thus, this survey delves into evolutionary optimization techniques as powerful tools for achieving optimal configurations in LCNC structures, highlighting the importance of selecting the appropriate technique for a given optimization problem. A strict selection method was employed to come up with this review paper, and only reputable literary sources were used. The research articles used in this survey were searched from top research databases such as ScienceDirect, IEEE Xplore, Scopus, and Google Scholar. The articles published in the period, 2015 to 2024 were considered. Common design optimization problems such as buckling load, vibration, and weight and cost minimization were covered.

Index words: LCNC structures; Evolutionary optimization; Optimal design; Advanced materials.

I. INTRODUCTION

Advancements in material technologies have accelerated the use of many new materials in diverse applications. Among the available options, fibre-reinforced composite materials, especially laminated composites, are recognized to have the potential to bring about a future material revolution, especially because of their flexible functionalities and related advantages [1]. Laminated composite materials are well known for their high stiffness, strength, lightweight, longer fatigue life, and corrosion resistance. Their key benefit is that they can be tailored to suit the intended application and for this reason, the demand and growth for these materials are on the rise [2]. More recently, the field of composite design witnessed the

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advent of nanocomposite materials, and these materials have since attracted much attention due to their significant improvement in their mechanical, chemical, and thermal properties. Nanocomposites can be defined as materials that incorporate nanofillers into a matrix of a standard composite material [3]. Figure 1 shows the schematic diagram for the formation of a laminated nanocomposite structure.

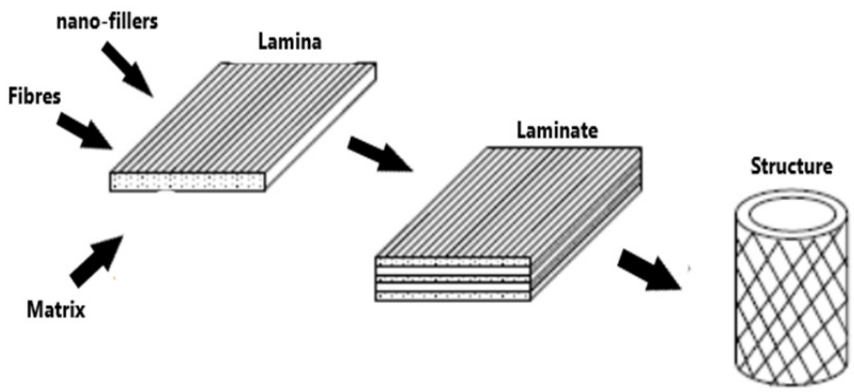

Fig. 1. Schematic diagram showing the formation of laminated nanocomposite structure

Nanofillers in nanocomposites represent a cutting-edge area of materials science where integrating nanoscale materials into a standard composite leads to enhanced properties and novel functionalities. Commonly used nanofillers in composite materials include nano-clay, carbon nanotubes (CNTs), carbon nanofibers (CNFs), and graphene nanoplatelets (GNPs) [4]. Both laminated composite and nanocomposite (LCNC) materials are advanced materials, and they are well-suited to applications that require lightweight and versatile structural designs. Figure 2 demonstrates that LCNC materials are slowly replacing traditional materials as far as weight and cost minimization are concerned.

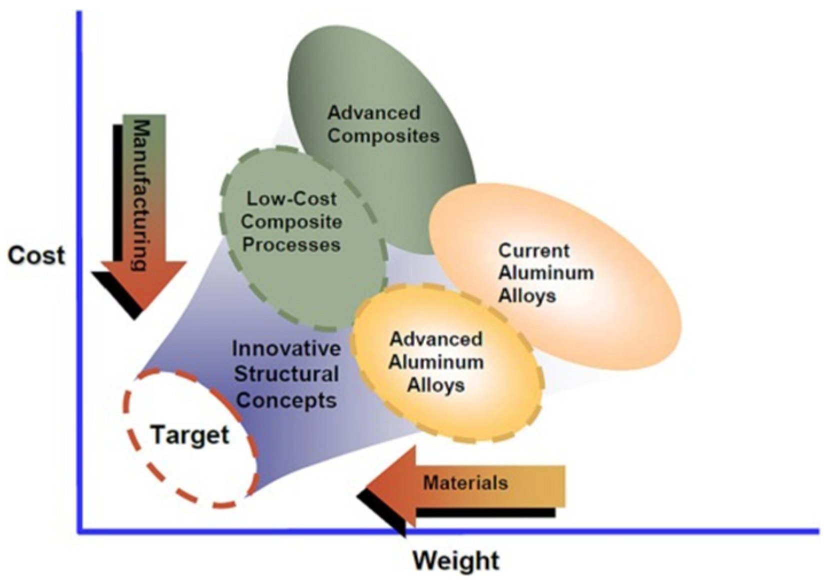

Fig. 2. Weight and cost consideration for different materials selection [5]

Many industries such as automotive, aerospace, and construction are already using LCNC materials to develop high strength and lightweight structures to minimize the cost of materials. However, the complex behavior of these materials creates a need

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to first validate the performances of the structures before use [6]. Thus, a process of optimization is crucially required when designing LCNC structures. Over several years, numerous techniques have been developed and suggested for the optimal design of LCNC structures. Most of these optimization techniques are experimental, analytical, and classical numerical methods. The designs based on physical experimentation are expensive and consume much time to reach the desired outcome [7]. Analytical and classical numerical optimization methods are limited when it comes to non-linear and multi-objective optimization problems, which is mostly the case when designing LCNC structures [8]. Such methods suffer from the lack of robustness, and they are hampered by inauspicious features in the multi-dimensional space like "ridges", "canyons", "flat spots" and multiple extremes. Besides, they are local in scope; the optima they seek are the best in the neighbourhoods of the current point. With the advent of evolutionary computation, many new optimization algorithms have been developed as an alternative to analytical and classical numerical techniques for the design of LCNC structures. These evolutionary algorithms have since proved to be effective in various applications because of their ability to handle complex, multi-dimensional, and non-linear optimization problems commonly found in structural design. In [9-11], the genetic algorithm (GA) was successfully utilized for the optimal design of different types of LCNC structures. The particle swarm optimization (PSO) technique was also implemented to design LCNC structures in [12, 13]. Some other evolutionary algorithms that have been applied for the design optimization of LCNC structures include differential evolution (DE) [14], simulated annealing (SA) [15], and ant colony optimization (ACO) [16]. These examples and many more confirm the supremacy of evolutionary computation for the optimal design of LCNC structures.

Although evolutionary algorithms prove to be superior to conventional optimization techniques, their applicability depends on the nature of the design problem at hand, and selecting the appropriate algorithm for a given application is of prime importance. Thus, this paper provides a review of the available studies related to the design optimization of LCNC structures using evolutionary algorithms highlighting the importance of selecting the appropriate technique for a given design problem. Moreover, it should be noted that many review papers on this topic, concentrate solely on composite structures without considering nanocomposite structures and this paper aims to fill that gap by exploring the optimization of both LCNC structures. Moreover, the survey is limited to the study of LCNC beams, plates, panels, and shells.

II. COMPOSITE AND NANOCOMPOSITE STRUCTURES

LCNC structures have been useful in various applications such as automotive, aerospace, construction, maritime, and energy. They offer a remarkable strength-to-weight ratio which makes them significantly lighter than traditional materials while maintaining high levels of strength and stiffness, making them advantageous in weight-sensitive applications. The next sections cover different types of LCNC structures which include beams, plates, panels, and shells.

A. BEAMS

Different types of LCNC beams, straight and curved, have been developed and employed in numerous engineering applications such as for constructing bridges and buildings. With superior strength-to-weight ratios, they excel in applications where weight reduction is of prime importance. Figure 3 shows the microscopic geometry of a typical laminated composite beam.

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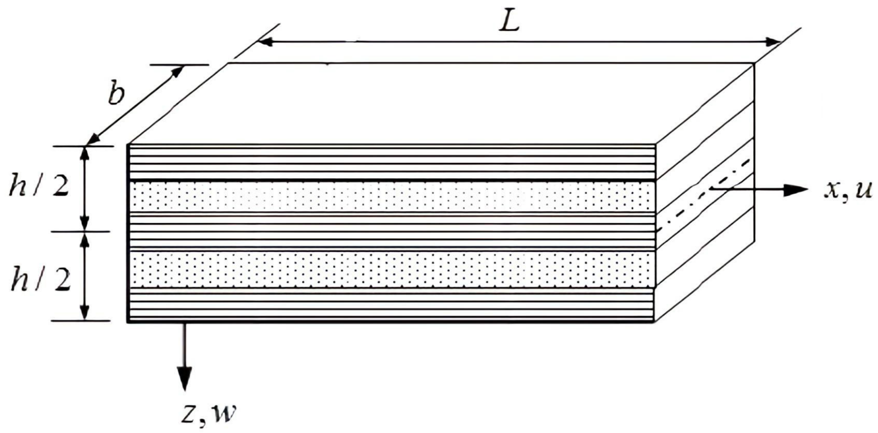

Fig. 3. Typical geometry of a laminated composite beam

In a study by Lotfy et al. [17], composite straight beams were used to develop railroad crossties and they proved to be reliable and durable compared to traditional wooden counterparts. LCNC materials can be also utilized to produce bumper beams. Bumper beams are structural components used in the automotive industry as part of the vehicle's bumper system. The main objective of the bumper system is to absorb the kinetic energy in accidents by deflection or deformation during crashes. Zhu et al. [18] designed and optimized a composite bumper beam with variable cross-sections for automotive vehicles. Their design demonstrated superiority to conventional metallic bumper beams in terms of lightweight and crashworthiness. Another type of LCNC beam is the box beam, which is the most useful structural element used for turbine and aircraft designs. A study by Qin et al. [19] presented the design and nonlinear analysis of a multi-bolted joint composite box-beam for sectional wind turbine blades. Their design performed better than the conventional box-beams studied.

B. PLATES

Plates in composite science are described as structures with one of the dimensions noticeably smaller than the other two [20]. These structures are employed in several industries because of their high strength and lightweight functionalities. Common applications of composite plates include aircraft components (such as wings and fuselage panels), automotive parts (like body panels and structural components), boat hulls, sporting goods (such as tennis rackets and bicycle frames), and civil engineering structures (such as bridges and building facades). The inclusion of nanofillers in composite plates has significantly improved their performance and increased their applications. The most common and used composite plate is the conventional laminated plate. To improve their performance, conventional laminated composite plates have been designed and optimized in several studies. The studies [21-23] showed the vibration analysis and frequency optimization of composite plates, and the buckling analysis was tackled in [24-27] and the articles [28, 29] which explored damage detection on laminated composite plates. Laminated nanocomposite plates were also designed and optimized in [30, 31]. Some others that frequently used composite and nanocomposite plates include perforated plates [32, 33], skew plates [34, 35] and stiffened plates [36, 37].

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C. SHELLS

Composite shells, crafted from materials like fiberglass or carbon fiber embedded in an epoxy resin matrix, represent a versatile solution employed across diverse industries. Renowned for their lightweight nature, composite shells find extensive use in aerospace for components like fuselage sections and wings, in marine applications for boat hulls due to their corrosion resistance, and in automotive sectors for body panels, all contributing to enhanced efficiency and performance. Figure 4 gives the schematic diagram of the composite laminated cylindrical shell.

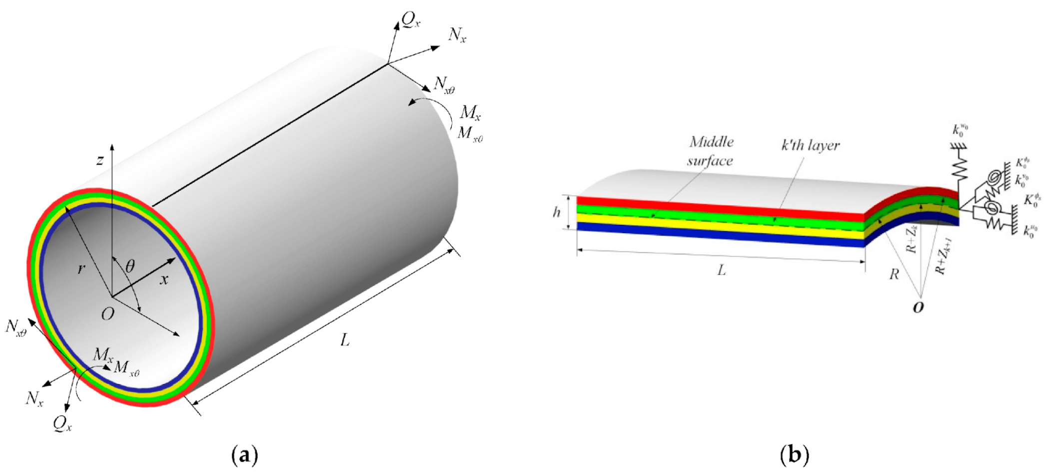

Fig. 4. A schematic diagram of the composite laminated cylindrical shell with elastic boundary conditions (a) whole cylindrical shell (b) the cross-sectional view showing different layers [38]

The addition of nanomaterials in composite shells further improves the versatility and performance of these structures. There are three main types of LCNC shells namely conical, cylindrical, and spherical shells. A typical example of the application of composite cylindrical and spherical shells is manufacturing pressure vessels for storing gases or liquids under high pressure in industries such as oil and gas, chemical processing, and alternative energy. Architectural structures employ composite conical shells for domes and canopies, offering both aesthetic appeal and structural efficiency. The design and optimization of conical shells can be found in studies [39, 40], cylindrical shells were investigated in [39, 41] and spherical shells were analyzed in [42, 43].

D. PANELS

LCNC panels are versatile structural elements typically comprised of a core material sandwiched between two outer layers. With advantages including being light in weight, enhanced strength, and corrosion resistance, LCNC panels find wide applications in construction, manufacturing, and industrial settings. Panels are commonly used for wall cladding, roofing, insulation, partitions, and other architectural and structural elements. Imbalzano et al. [44] designed and studied auxetic composite panels under blast loadings. The designed panels were able to absorb double amount of the impulsive energy. The maximum velocity of the back facet was reduced by 70% as compared to monolithic ones. Nanocomposite panels were optimized in the study by Al-Furjan et al. [45].

III. OVERVIEW OF COMMONLY USED EVOLUTIONARY COMPUTATION TECHNIQUES

Evolutionary computation encompasses various computational paradigms inspired by principles from biological evolution to solve complex problems [46]. These techniques employ algorithms that mimic evolutionary processes like mutation, selection, recombination, and adaptation to generate solutions. Some commonly utilized evolutionary computation methods include:

A. GENETIC ALGORITHM

A genetic algorithm (GA) is a computational optimization technique inspired by the process of natural selection and evolutionary biology. The fundamental theory of the use of the GA to solve problems was first developed by John Holland [47]. Holland pioneered the use of the selection, crossover, and mutation processes and these genetic operators form an essential part of the GA as a problem-solving method. Figure 5 shows the flowchart of a standard GA.

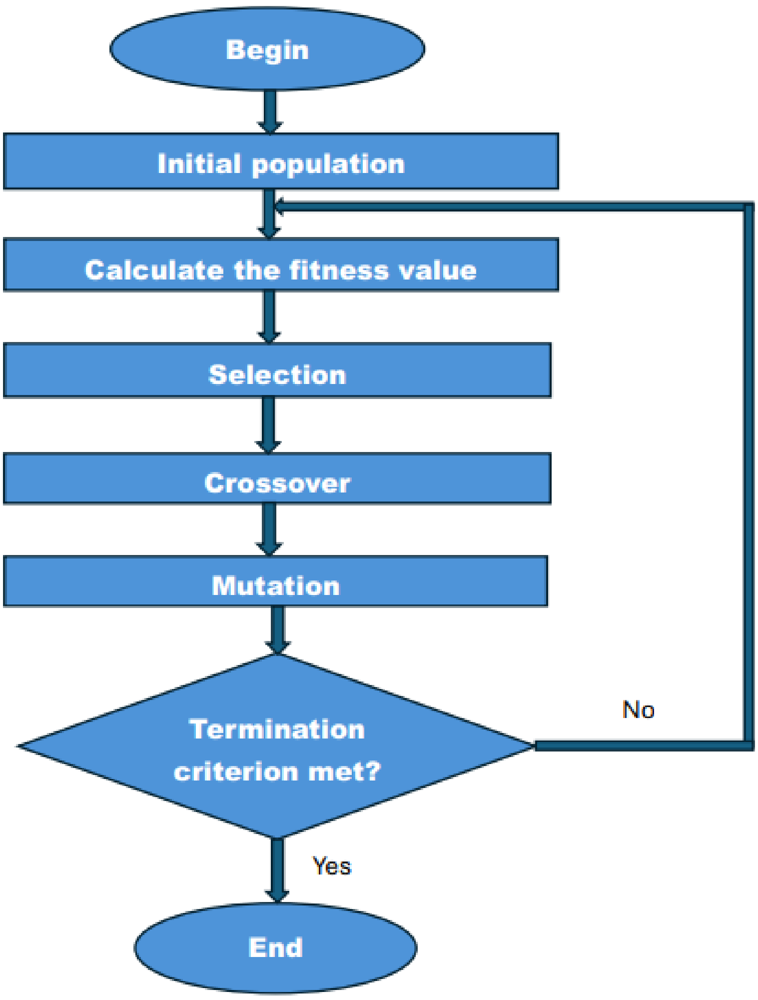

Fig. 5. A flowchart of a standard GA.

Since then, numerous variants of the GA have been developed and implemented in various optimization problems. When implementing the GA, the first step is to select the genes for the initial generation. After that, the best genes in the population

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are extracted through fitness function calculations. Then genes that have the best fitness function values are selected to produce offspring using the crossover and mutation operators. The crossover operator, which is also known as recombination, involves combining the genetic material from selected two parents to create new offspring. The mutation operator involves introducing random changes in the genetic material of individuals within the population. The mutation process helps to maintain genetic diversity and prevents premature convergence of the algorithm. A wide range of GA variants have been developed and employed to solve optimization problems for example the elitism genetic algorithm [48], adaptive genetic algorithms [49], and hybrid genetic algorithms [50] to mention a few. Genetic algorithms offer various advantages including their ability to handle complex, non-linear optimization problems with large solution search spaces, where traditional techniques normally struggle. Their population-based approach promotes diversity, which aids in avoiding local optima and finding globally optimal solutions. Additionally, genetic algorithms are highly adaptable and can accommodate several types of optimization problems, encoding schemes, and fitness functions. However, it should be noted that the performance of a GA highly depends on the choice of parameters such as population size, mutation rate, and crossover rate, which can be challenging to tune effectively. Therefore, the selection of these parameters is of prime importance.

B. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization (PSO) is a metaheuristic optimization technique that exploits the concepts of animals' social behaviors such as birds flocking or fish schooling. It was first developed by Eberhart and Kennedy [51]. Using the flocking analogy, the PSO algorithm maintains a swarm of individuals known as particles, where each particle represents a potential solution. The particles in the swarm have fitness values mapped using the objective function, and each particle has a velocity that determines its direction and range. Each particle adjusts its position and velocity based on its own experience (p_{best}) and the collective experience of the swarm (g_{best}), aiming to converge toward the optimal solution. The PSO algorithm iteratively updates the particles' positions and velocities, influenced by the particles' historical knowledge and the best-performing solutions encountered by the swarm, until a termination condition is met. Several variants of the PSO have been suggested by different researchers and these include generalized particle swarm optimization (GEPSO) [52], pyramid particle swarm optimization (PPSO) [53], and species-based particle swarm optimization [54]. PSO has several advantages, including its simplicity, efficiency, and versatility in solving a wide range of optimization problems. PSO algorithms' straightforward implementation approach and fewer parameters to tune make them accessible to users with varying levels of expertise. Additionally, PSO strikes a balance between exploration and exploitation, robustly navigating through noisy or uncertain objective functions to find optimal or near-optimal solutions. On the other hand, one of the PSO drawbacks include its susceptibility to premature convergence, particularly towards local optima in complex optimization problems, and its sensitivity to parameter settings. Therefore, selecting the best settings is crucial for the optimal performance of this algorithm.

C. DIFFERENTIAL EVOLUTION

Differential evolution (DE) is a population-based algorithm first introduced by Storm and Price [55] for solving complex optimization problems. When implementing the DE algorithm, the first step is to randomly initialize a population of candidate solutions in the search space where each solution is given as a vector of real-

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valued parameters. After that, the algorithm iteratively improves the population by implementing the mutation operator to generate new candidate solutions. The mutation process is performed by creating a trial vector for all candidate solutions in the population. After the mutation, the crossover operator is applied to combine the trial vector with the original individual, producing potentially improved offspring. These offspring solutions replace their parents in the population based on the selection criterion given by the objective functions of the optimization problem. The mutation and selection stages are repeated until a termination condition is met. It should be noted that, although the DE algorithm and the GA utilize similar operators, the usage of these operators is different. For example, the GA is crossover based and the mutation is only applied to about 1-2% of the population. In the DE algorithm, the mutation operator is applied to each individual while being transferred to the next generation. The crossover operator is not the dominant operator in DE as it is for the GA. The ordinary DE has been modified by several researchers creating new variants such as mixed variable differential evolution (MDE) [56], multiple sub-populations-based DE (MPADE) [57], sinusoidal differential evolution (SinDE) [58], and adaptive guided differential evolution algorithm (AGDE) [59]. The DE algorithm presents several advantages such as its simplicity in implementation, computational efficiency for multi-objective optimization problems, and robustness to parameter settings. Despite being less sensitive to parameter settings compared to other evolutionary algorithms, DE's performance can still be impacted by suboptimal parameter values which can lead to a slower convergence rate.

D. OTHER ALGORITHMS AND HYBRIDIZATION

In addition to the above-mentioned techniques, some other evolutionary algorithms have been successfully implemented for tackling complex optimization problems. One of them is simulated annealing (SA) based on metallurgical annealing. The other one is the grey wolf optimization (GWO) inspired by the leadership and hunting processes of grey wolves. The whale optimization algorithm (WOA), which mimics the hunting mechanism of humpback whales has been also applied to several optimization problems. Some other interesting evolutionary algorithms include the ant colony optimization (ACO), bee colony optimization (BCO), JAYA optimization algorithm, and salp swarm optimization (SSO) algorithm. To improve the performance of evolutionary algorithms some researchers made recourse to hybridization of the algorithms. For example, the PSO can be combined with the GA to give the PSO-GA hybrid algorithm. In most cases, one of the algorithms is used to fine-tune the optimization parameters whereas the other is utilized for the actual optimization process. Machine learning techniques such as artificial neural networks (ANN) can also be combined with evolutionary algorithms to form a hybrid system. For instance, Li et al. [60] combined ANN with the GA (ANN-GA) for the optimization of engine efficiency and emissions. Fuzzy systems such as Fuzzy Logic (FL) can also be hybridized with evolutionary algorithms for optimization [61]. Lastly, traditional, or gradient-based optimization techniques can also be merged with evolutionary algorithms to produce a powerful optimization tool. For example, D'Angelo and Palmieri [62] proposed a hybrid GA that combines the gradient-descent technique with a classical genetic algorithm to solve constrained optimization problems.

IV. APPLICATIONS OF EVOLUTIONARY ALGORITHMS FOR THE OPTIMAL DESIGN OF CNC STRUCTURES

This survey aims to provide an insightful overview of the current state of research, methodologies, and applications of evolutionary algorithms for the optimal design of

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LCNC structures. Evolutionary algorithms have been utilized for the optimal design of composite and nanocomposite structures in various design problems such as buckling load, vibration, and weight and cost minimization. Evolutionary computation techniques present a potent solution for the design of LCNC structures due to their prowess in global optimization, adept handling of non-linearity and multimodality, and capability in multi-objective optimization, enabling designers to balance conflicting objectives effectively.

A strict selection method was employed to come up with this comprehensive review paper. The research articles used in this survey were searched from top research databases such as ScienceDirect, IEEE Xplore, Scopus, and Google Scholar. The articles published in the period, 2015 to 2024 were selected. Additionally, the research articles with the most citations were selected to make sure that the used material is relevant and credible. To narrow down the scope of this survey, the article focuses on the application of evolutionary algorithms to tackle (a) buckling problems (b) vibration problems, and (c) optimum weight and cost problems, for the optimal design of LCNC structures. Additionally, the survey is limited to the study of LCNC beams, plates, panels, and shells.

A. BUCKLING PROBLEMS

In engineering and structural design, it is essential to prevent buckling, as it can lead to catastrophic failure of a component or structure. Buckling optimization involves finding the optimal design parameters, such as dimensions, material properties, and support conditions, to minimize the risk of buckling under given loading conditions. Several evolutionary algorithms have been suggested for the buckling optimization of LCNC structures.

Karakaya and Soykasap [63] proposed a genetic algorithm and a generalized pattern search algorithm for the optimal design of a composite panel. The composite panel was defined as simply supported on four sides and subjected to biaxial in-plane compressive loads. A 64-ply laminate made of graphite/epoxy was considered and the laminate was regarded as symmetric and balanced with discrete fiber angles $0_2, \pm 45, 90_2$ in the laminate sequence. Several combinations of loading conditions and plate aspect ratio were tested to maximize the critical buckling load. The results were compared with other published research work, and it was found that the genetic algorithm is efficient when it comes to problems that require searching of global optima.

In [64], a challenging multimodal optimization design problem of composite panels was tackled by the use of emergent niching particle swarm optimization (PSO). The adopted algorithms in their study comprised of the species-based PSO (SPSO), the fitness Euclidean-distance ratio-based PSO (FER-PSO), the ring topology-based PSO, and the Euclidean distance-based locally informed particle swarm (LIPS) optimizer. The algorithms were applied to a multimodal buckling maximization problem of composite panels. The results showed that the ring topology-based PSO with no niching parameters was more reliable as compared to the other algorithms and these findings can serve as benchmark solutions for future work.

Ghasemi et al. [65] implemented a new multi-step optimization technique to predict the optimal fiber orientation in glass fiber-reinforced polymer (GFRP) composite shells. The proposed method contained a genetic algorithm coupled with an analytical approach. They considered two critical parameters namely, ultimate buckling load and weight of the shells. Other factors such as shell thickness, number of layers, and angle were also considered. To evaluate the critical buckling pressure in GFRP specimens, the obtained results were compared with experimental results. It was concluded that the application of the genetic algorithm caused a decrease of 21% and 28% in the optimum local mass of stiffened unsymmetrical angle-ply and unstiffened symmetrical angle-ply laminated composite shells, respectively.

The improved grey wolf optimization (GWO) technique was utilized for studying the dynamic buckling of laminated truncated nanocomposite conical aircraft shells in moisture and temperature environments as well as in magnetic fields [66]. The laminates of the hybrid nanocomposite were made up of a polymer, carbon fibers, and carbon nanotubes (CNT) based on the Halpin-Tsai model. The improved GWO algorithm was used to optimize the instability and frequency of the structure thereby defining the subjective and objective functions. The main contribution of the study was to maximize the inequality and frequency constraints to control the instability. Moisture, the cone semi-vertex angle, and the number of layers were optimized whilst factors like carbon fiber volume content, temperature influence, CNT radius, and magnetic field were also considered. The results proved that the improved GWO algorithm has better capabilities of searching the global optima compared to the traditional GWO. This is because the proposed algorithm was flexible and able to study the optimum conditions of every problem considered.

Ho-Huu et al. [67] proposed a numerical optimization technique comprised of mixed integer and continuous design variables to optimize the design of laminated composite plates under buckling loads. The thickness of layers and fiber orientation angles were taken as design variables. To analyze the buckling behavior of laminated composite plates, the finite element method was employed. The improved differential evolution algorithm called mixed-variable differential evolution (MDE) was then used to solve the optimization problems. The efficacy of the proposed optimization technique was evaluated using numerical examples. The results concluded that the MDE is effective for solving problems that involve maximization of the buckling load factor.

Liu [68] employed the finite element method and NSGA-II genetic algorithm to determine the maximum buckling load capacity of cylindrical composite shells under axial loading. The parameters such as fiber angle, number of layers, and layer thickness were considered. ABACUS software was utilized to perform the finite element analysis of the composite cylindrical shells for determining the buckling load. The NSGA-II genetic algorithm was then used to modify the layout and thickness of the composite layers to optimize the buckling strength and weight of the structure. The genetic algorithm was successfully able to optimize all geometric characteristics studied.

In [69], the buckling behavior of functionally graded nanocomposite beams reinforced with nano clay was investigated. The specimens were first prepared accordingly and the tensile and buckling tests were also conducted. The GA was then utilized to estimate the Young's modulus of functionally graded nanocomposite beams. The first-order shear deformation beam theory was applied to simply supported beams and the Hamilton principle was then used to derive the governing equations. In addition, the effect of the nano clay on the buckling load was also studied. To evaluate the effectiveness of their technique, a comparison of the theoretical analysis and experimental results was conducted. The results demonstrated high accuracy of the GA for the scenarios presented.

A hybrid optimization technique based on the adaptive Kriging model and an improved particle swarm optimization algorithm (IPSO) was developed to maximize the buckling load of laminated composite plates [70]. The Kriging model was used for directly predicting the buckling load of laminated plates thereby improving the optimization process. The IPSO algorithm was then utilized to maximize the buckling load. Different factors such as the number of layers, aspect ratios, load type (uniaxial and biaxial), and boundary conditions were considered. The results of the proposed method were then compared to the results in the literature, and it was concluded that the proposed technique was able to achieve optimum results with less computational burden.

Moradi et al. [71] presented a strategy for finding the optimal stacking sequence of stiffened laminated composite panels to achieve their maximum buckling load. The ABAQUS software was used to perform the buckling analysis of the composite panels. An algorithm based on the combination of the PSO and GA was then introduced for the optimization process. The traditional PSO technique was enhanced by introducing a new inertia weight of velocity. The efficiency of the proposed modeling method was evaluated by comparing the modeling results with experimental results and published models. The results proved that the proposed optimization procedure has better performance than existing techniques in terms of accuracy and convergence speed.

A method based on artificial neural networks (ANN) and GA for the optimization of composite laminates was presented in [72]. The buckling loads were predicted using ANN and these ANN models proved to be cost-effective and consumed less computational time as compared to other models. To create the data sets for training and testing the ANN models, the finite element analysis (FEA) and the Latin hypercube sampling (LHS) methods were employed. The genetic algorithm was then utilized for the optimization of the stacking sequences and structural dimensions for maximizing the weight of the laminates. The efficiency of the proposed optimization method was tested by comparing it with other machine learning techniques. The proposed optimization method provided satisfactory results for the problems studied. Table I gives summarized applications of evolutionary algorithms in buckling problems.

TABLE I
A SUMMARY OF EVOLUTIONARY ALGORITHMS IN BUCKLING PROBLEMS

Reference	Evolutionary algorithm	Keynotes
[63]	GA	• The GA was found efficient for finding the global optima. The critical buckling loads were maximized for different plate aspect ratios.
[64]	PSO	• The ring topology-based PSO without any niching parameter was found to be the best compared to other PSO variants for buckling optimization of composite plates.
[65]	GA	• A regenerated GA coupled with an analytical approach was implemented for the ultimate buckling load. The results presented a maximum decrease of 28% in the optimum local mass of the laminates.

[66]	GWO	• The improved GWO was utilized for dynamic buckling optimization of laminated shells. It provided better abilities compared to the standard GWO for searching the global optima.
[67]	MDE	• The MDE was proposed for the numerical design optimization of laminated composite plates. It was able to effectively deal with both the integer and continuous design variables and provided better results compared to a standard DE algorithm.
[68]	NSGA-II	• The NSGA-II was used to find the maximum buckling load of composite shells. The algorithm was able to optimize all the geometric configurations studied.
[69]	GA	• The GA was used for studying the buckling behavior of composite beams. A high accuracy percentage was achieved in identifying Young's modulus after comparing it with experimental results.
[70]	IPSO	• The A-Kriging-IPSO method was utilized to maximize the buckling load of laminated composite plates. The obtained results were in good agreement with the literature results and with minimum computational problems.
[71]	PSO-GA	• A hybrid PSO-GA was proposed for maximum buckling optimization of composite panels. The proposed method had better performance compared to previously published models.
[72]	GA	• The GA was used to predict the buckling load of composite laminates. The proposed method was found efficient for the scenarios studied.

B. VIBRATION PROBLEMS

Understanding the vibrational behavior of composite and nanocomposite structures helps engineers detect potential weaknesses or damage, optimize the designs, predict fatigue life, and ultimately reduce costs by preventing rework and failures. By analyzing natural frequencies, mode shapes, and damping ratios, engineers can tailor LCNC structures to meet operational requirements while maximizing safety, reliability, and efficiency in their applications.

Savran and Aydin [73] employed the differential evolution, Nelder Mead method, and simulated annealing algorithms were utilized for optimizing the fundamental frequency, buckling resistance, and weight of hybrid graphite/epoxy-sitka spruce and graphite-flax/epoxy laminated composite plates. The main motivation of their research was to test the usage of the Sitka spruce as an alternative to synthetic E-glass and natural flax fiber. The authors considered single-objective and multi-objective approaches to acquire optimum design for the hybrid and non-hybrid structures. Then evolutionary algorithms were employed to solve the optimization design problem. Their results showed that the plates designed from hybrid graphite/epoxy-sitka spruce were lighter and had higher frequency and buckling resistance as compared to those designed from glass/epoxy, flax/epoxy, and hybrid graphite-flax/epoxy.

Vosoughi et al. [74] maximized the fundamental frequency of thick laminate with respect to fiber orientations. The governing equations were based on higher-order shear deformation theory and the optimization involved a combination of PSO and genetic algorithms. In the numerical results, authors investigated the effect

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of problem parameters on the optimal design including layer numbers, thickness ratio, and boundary conditions employing the finite element method for numerical solutions of the problems. Their method proved to be robust and accurate for the scenarios studied.

The nondominated sorting genetic algorithm II (NSGA-II) was suggested by Vo-Duy et al. [11] for the multi-objective optimization of laminated composite beam structures. The main objective was to maximize the natural frequency whilst minimizing the weight of the beam. Fiber volume fractions, fiber orientation angles, and thickness are considered as the design variables. The beam was subjected to a constraint where the natural frequency should be equal to or greater than a predetermined frequency. To carry out free vibrational analysis, the finite element (FE) method with a two-node Bernoulli-Euler beam element was used. The NSGA-II was then employed to solve the multi-objective optimization problem. After comparing their results with published results in the literature, their approach proved to be reliable and effective.

Kalita et al. [75] used a combination of optimization algorithms, namely, GA, repulsive particle swarm optimization with local search and chaotic perturbation (RPSOLS), and co-evolutionary host-parasite (CHP) algorithm for designing skew laminates under varying operational conditions. The FE approach based on the first-order deformation theory was used to measure the natural frequencies of the composite panels. Their research work was based on maximizing the first two modes of the natural frequency by optimizing the stacking sequence of the composite laminates. Their results concluded that the CHP algorithm outperformed both the GA and RPSOLS algorithms in terms of computational speed, accuracy, and reliability.

A global optimization framework based on GA and FE methods was developed by Pal et al. [76] to optimize frequency and avoid resonance in composite shells. For objective function formulation, the first-order shear deformation theory was used. The ply angles were taken as the design variables where only discrete ply angles with 5^0 increments in the ± 90 design space were considered. Various numerical studies were conducted to validate the proposed approach and rectangular and cylindrical shell panels of different radius of curvature and boundary conditions were considered. The obtained results showed an excellent agreement with the published results in the literature.

Peng et al. [77] proposed an optimization procedure that used a combination of GA and PSO to obtain the resonance frequency of the cylindrical composite structure. The nonlocal strain gradient theory (NSGT), zigzag theory, and Hamilton's principle were used for the shear deformable shell displacement field problem formulation. The modal equations of motion were solved by the general differential quadrature element method (GDQEM). The GA-PSO was then utilized to optimize the frequency by varying the angle of composite layers. Their results revealed that after reaching a certain number of layers composite layers (30), increasing the number of layers had no effect on the resonance frequency of the cylinder for all the boundary conditions considered.

Le-Anh et al. [78] proposed a numerical method for the static and fundamental frequency optimization of folded laminated composite plates using an adjusted differential evolution (aDE) algorithm. In their optimization procedure, the objective function was to maximize the fundamental frequency and minimize the strain energy. The fiber orientation was considered as the design variable. For the analysis of the behavior of the folded laminated composite plates, the cell-based smoothed

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discrete shear gap method (CS-DSG3) was used. To search for the optimal solutions, the aDE was utilized. The aDE was designed by integrating the conventional DE for handling discrete integer variables. To check the validity of their study, they compared their results and the results of other algorithms presented in the literature such as GA and PSO. Their optimization procedure proved to be efficient, especially for integer-based design variables.

A multi-objective optimization procedure based on the NSGA-II was proposed to provide optimal natural frequency and cost for graphene/fiber-reinforced nanocomposite laminates [8]. The vibrational analysis was solved by the FE method and the first-order shear deformation theory. To get the effective material properties, micromechanical equations were utilized. The NSGA-II was then used to search for the optimal solutions for different scenarios. For the optimization, four types of design variables which include fiber angles, graphene and fiber distribution, and layer thickness were considered. In their results, they deduced that increasing the graphene nanoplatelets content whilst minimizing fiber content gives cost-effective designs.

Vo-Duy et al. [79] presented a numerical optimization technique for maximizing the fundamental frequency of laminated functional graded carbon nanotube-reinforced composite quadrilateral plates. Their approach was a combination of the CS-DSG3 method for first frequency analysis and the adaptive elitist differential evolution algorithm (aeDE), for solving the optimization problem. The carbon nanotube orientation in the layers was considered as the design variable. In their findings, the obtained frequencies were better than those from existing studies.

Duc et al. [80] proposed a non-linear vibration analysis of laminated composite cylindrical shells using meta-heuristic optimization algorithms. The equations for the analysis were given by the classical shell theory combined with von Karman's nonlinearity and those equations were solved using the Galerkin method. Their optimization procedure involved the minimization of the vibration amplitude and the maximization of the natural frequency. The PSO algorithm and the whale optimization algorithm (WOA) were implemented to solve the optimization problem. Their results showed that the WOA yielded more suitable results for three- and four-layer cases whilst the PSO algorithm performed better for five-layer cases.

An optimization technique for vibration analysis of rotating cross-ply laminated nanocomposite blades was proposed by Xiang et al. [81]. In their study, the vibration analysis and lay-up optimization were done on rotating pre-twisted laminated functional graded CNTs reinforced composite shallow conical shells. The governing equations of the rotating blades were derived and solved by the kp-Ritz method. The GA was then employed to optimize the nondimensional frequency parameter for searching the optimal layering sequence of the rotating shallow conical shells. Their results demonstrated that the GA is a useful tool for sequence optimization of rotating blades in terms of enhancing the vibration characteristics. Table II gives summarized applications of evolutionary algorithms in vibration problems.

TABLE II
A SUMMARY OF EVOLUTIONARY ALGORITHMS IN VIBRATION PROBLEMS

Reference	Evolutionary algorithm	Keynotes
[73]	DE	• DE was utilized to find the fundamental frequency of laminated composite plates. The algorithm was able to obtain a lightweight structure with a higher frequency & buckling resistance.
[74]	PSO-GA	• A PSO-GA method was used to obtain the maximum fundamental frequency of thick laminated composite plates. The applicability and usability of the proposed technique were tested by solving different problems and the results were satisfactory.
[75]	CHP	• GA, RPSOLC, and CHP algorithms were compared for natural frequency optimization in the design of skew composite laminates. The CHP algorithm outperformed other algorithms in terms of accuracy and computational speed.
[76]	GA	• The GA was employed for the fundamental frequency optimization of composite shells. The GA approach proved reliable compared to other algorithms such as sine cosine algorithms, salp swarm optimization, and ant lion optimizer.
[77]	GA-PSO	• A GA-PSO optimization technique was used to obtain the optimum frequency of laminated rotary nanostructures. The method was able to determine stacking sequences that give the highest frequencies.
[78]	aDE	• The aDE algorithm was proposed for static and frequency optimization of laminated composite plates. The proposed technique outperformed the GA and PSO in terms of reliability and effectiveness.
[8]		• NSGA-II was utilized to find the maximum fundamental frequency of graphene/fiber-reinforced nanocomposite laminates. By employing this technique, an increase in fundamental frequency was noted for the laminates studied.
[79]	aeDE	• The aeDE algorithm was used for the fundamental frequency maximization of laminated composite plates. The algorithm was able to maximize any desirable higher-order frequencies.
[80]	PSO-WOA	• The PSO and WOA algorithms were compared for maximization of natural frequencies of laminated composite shells. The results confirmed that the WOA gave suitable results for cases with 3 & 4 laminate layers while the PSO performed better in five or more-layer cases.
[81]	GA	• The GA was proposed for the optimization of the nondimensional frequency of laminated composite blades. The results proved that the GA is useful for multi-objective optimization problems.

C. OPTIMUM WEIGHT AND COST PROBLEMS

LCNC materials are essential in modern engineering. However, their cost can be very high, and many efforts must be made to reduce it. Therefore, weight and cost optimization in LCNC materials is crucial for enhancing performance, reducing costs, improving efficiency, and ultimately maintaining competitiveness in the marketplace.

De Munck et al. [82] optimized hybrid composite concrete beams for minimization of both the cost and mass. For finding the optimal solutions, the NSGA-II coupled with a meta-model was utilized. Their optimization procedure gave insights into the influence of different parameters such as the concrete class and span on the cost and weight of composite-concrete beams.

Composite sandwich panels with honeycomb core structures were optimized by Gholami et al. [83] using the PSO method. The panels were subjected to a uniformly distributed load and the Navier-type solution was used to predict the deflection of the panels. To optimize the weight of the panels, the niching memetic PSO (NMPSO) and locally informed particle swarm (LIPS) variants of PSO were implemented. Their results confirmed the effectiveness of the NMPSO in finding optimal solutions for constrained and unconstrained objective functions.

Shrivastava et al. [84] employed a classical GA interfaced with a CAE solver for weight minimization of a carbon fiber composite wing torsion box. Their main objective was minimizing the structural weight. The optimization procedure was characterized by an intelligent laminate selection which was based on static strength, ply orientations, and thickness of the laminates. Their results showed a 29% weight reduction on the aircraft wing torsion box and a 54% reduction in terms of the metallic structure.

Albanesi et al. [85] presented a meta-modal optimization procedure for designing the composite laminate of wind turbine blades. Their methodology combined GA and artificial neural networks (ANN) to minimize the mass and computational cost of the optimization procedure. The proposed method was applied to redesign a 40-kW wind turbine blade to minimize its mass while the structural and manufacturing constraints are fulfilled. The obtained results showed a mass reduction of 20% as well as a 40% reduction in computational cost as compared to the reference design. Table III gives summarized applications of evolutionary algorithms in weight and cost problems.

TABLE III
A SUMMARY OF EVOLUTIONARY ALGORITHMS IN WEIGHT AND COST PROBLEMS

Reference	Evolutionary algorithm	Keynotes
[82]	NSGA-II	• The NSGA-II was utilized for weight and cost minimization of composite beams. The optimization algorithm was able to show the dominance of certain design variables in the design space.
[83]	NMPSO	• Several variants of PSO were employed for the minimization of weight in the design of composite sandwich panels. The results confirmed the superiority and effectiveness of the NMPSO algorithm for finding optimal solutions.

[84]	GA	• The classical GA was utilized for weight minimization of a carbon fiber composite wing torsion box. The results showed that the proposed technique achieved 54% weight reduction concerning the metallic structure.
[85]	GA	• A GA was used for mass minimization in the design of composite laminated wind turbine blades. The proposed procedure was able to save up to 20% of mass compared to the reference design.

V. CHALLENGES AND FUTURE DIRECTIONS

Navigating the intricate design landscapes inherent in LCNC structures represents a formidable challenge for researchers in the domain of evolutionary optimization. The multidimensional nature of these design spaces, influenced by a myriad of parameters including material composition, fiber orientation, and interface properties, demands sophisticated optimization methodologies capable of efficiently exploring and exploiting such complexities. Moreover, the uncertainty in material properties, stemming from factors such as manufacturing variability and environmental degradation, adds another layer of complexity to the optimization process. Addressing these challenges requires the integration of robustness and reliability considerations into the optimization framework to ensure the validity and applicability of the optimized designs under real-world conditions. In addition to addressing these challenges, future research directions in the field of optimal design of CNC structures using evolutionary optimization techniques hold immense promise for advancing the state-of-the-art. One avenue of exploration involves leveraging machine learning and surrogate modeling techniques to accelerate the optimization process by constructing efficient approximations of complex material behaviors. By training neural networks, these surrogate models can capture the underlying relationships between design parameters and performance metrics, allowing for rapid evaluation of candidate designs without the need for computationally expensive simulations. Furthermore, adaptive and hybrid optimization algorithms offer exciting opportunities for enhancing the convergence speed and solution quality of evolutionary optimization techniques. Adaptive algorithms dynamically adjust their parameters and operators based on problem characteristics and solution progress, allowing for more efficient exploration of the design space and faster convergence to optimal solutions. Hybridizing evolutionary algorithms with other optimization techniques, such as gradient-based methods or local search heuristics, can further exploit their complementary strengths, leading to more robust and versatile optimization frameworks.

Moreover, integrating manufacturing constraints into the optimization process early on is crucial for ensuring the practical feasibility and cost-effectiveness of the optimized designs. By incorporating process simulation models and design for manufacturability (DFM) principles into the optimization framework, researchers can account for manufacturing constraints such as material availability, processing limitations, and production costs during the design optimization process. This holistic approach not only ensures that the optimized designs meet performance requirements but also facilitates a seamless transition from design to manufacturing, thereby reducing time-to-market and enhancing product competitiveness. Additionally, advancing material characterization techniques, such as in-situ microscopy, spectroscopy, and imaging, hold tremendous potential for gaining deeper insights into the structure-property relationships of composite and nanocomposite materials. By clarifying the complex interactions between constituent materials at

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the micro- and nano-scale, these advanced characterization techniques enable the development of more accurate material models and optimization objectives, leading to the design of superior-performing structures with tailored properties.

Furthermore, extending topology optimization techniques to the design of nanocomposite structures represents a promising avenue for unlocking novel material architectures with unparalleled performance characteristics. Topology optimization, which seeks to determine the optimal distribution of material within a given design domain to achieve specified performance objectives, has traditionally been applied to macroscopic structures composed of homogeneous materials. However, by extending this approach to the micro- and nano-scale, researchers can explore a vast array of material architectures and morphologies at the atomic and molecular levels, leading to the discovery of innovative designs with enhanced mechanical, thermal, and electrical properties. By tailoring the distribution and arrangement of nanoparticles or nanofillers within the polymer matrix, researchers can engineer nanocomposite materials with unprecedented combinations of strength, stiffness, toughness, and conductivity, opening new possibilities for applications in aerospace, automotive, biomedical, and renewable energy sectors.

VI. CONCLUDING REMARKS

The authors reviewed over 300 articles, and they did not seek to cite as many sources as possible but adhered to the principle of less but better. The main emphasis was to provide relevant achievements on the application of evolutionary algorithms for the optimal design of LCNC structures. In general, the design optimization of LCNC structures involves systematically improving the performance and efficiency of these materials through exploration and refinement of their design parameters. This process typically begins with defining the objectives (e.g., minimizing weight, maximizing stiffness) and constraints (e.g., material properties, manufacturing limitations) of the structure. Next, the LCNC structure is represented using suitable mathematical models, often involving discretization of design variables such as ply orientations, thicknesses, and stacking sequences. Various optimization techniques are then employed to search for the optimum combination of the design parameters. Thus, through iterative analysis and evaluation, the optimal design structure is identified, balancing performance requirements with practical constraints.

In general, most research work focuses on the utilization of evolutionary algorithms for the design optimization of composite structures, and just a few studies were conducted on nanocomposite structures. It was also found that the GA, particularly the NSGA-II was the most common and efficient evolutionary algorithm for buckling optimization. Different variants of PSO were also considered useful for tackling buckling problems. For vibration analysis and frequency optimization of LCNC structures, three optimization techniques, namely, the GA, PSO, and DE were the best. Hybrid optimization techniques such as GA-PSO were also found to be instrumental in tackling vibration problems. For weight and cost optimization problems, it was found that there were few studies where weight or cost was used for objective function formulation, it was rather considered as a constraint in most cases. Again, the GA was the most common and effective evolutionary algorithm to solve weight and cost optimization problems.

The conclusion that can be drawn from this work is that evolutionary optimization techniques are powerful tools for achieving optimal configuration in LCNC structures. They can easily handle non-linear and multi-objective optimization problems, enabling designers to balance conflicting objectives effectively. The best evolutionary algorithms for the optimal design of LCNC structures were found to be the GA and PSO. However, the development and optimization of nanocomposite structures is still lacking, and a lot of work should be done on utilizing these materials. Lastly, this survey should serve as a reference for the researchers interested in studying the application of evolutionary computation for design optimization of LCNC structures.

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CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

LIST OF ABBREVIATIONS

LCNC	Laminated Composite and Nanocomposite
CNTs	Carbon Nanotubes
CNFs	Carbon Nanofibers
GNPs	Graphene Nanoplatelets
GA	Genetic Algorithm
PSO	Particle Swarm Optimization
DE	Differential Evolution
SA	Simulated Annealing
ACO	Ant Colony Optimization
GEPSO	Generalized Particle Swarm Optimization
PPSO	Pyramid Particle Swarm Optimization
MDE	Mixed Variable Differential Evolution
MPADE	Multiple Sub-Population-Based Differential Evolution
SinDE	Sinusoidal Differential Evolution
AGDE	Adaptive Guided Differential Evolution
GWO	Grey Wolf Optimization
WOA	Whale Optimization Algorithm
BCO	Bee Colony Optimization
SSO	Salp Swarm Optimization
ANN	Artificial Neural Networks
FL	Fuzzy Logic

SPSO	Species-Based Particle Swarm Optimization
FER-PSO	Fitness Euclidean-Distance-Ratio-Based Particle Swarm Optimization.
LIPS	Locally Informed Particle Swarm Optimizer
GFRP	Glass Fiber-Reinforced Polymer
NSGA-II	Non-Dominated Sorting Genetic Algorithm-II
IPSO	Improved Particle Swarm Optimization
FEA	Finite Element Analysis
LHS	Latin Hypercube Sampling
RPSOLS	Repulsive Particle Swarm Optimization with Local Search and Chaotic Perturbation
CHP	Co-Evolutionary Host-Parasite
NSGT	Nonlocal Strain Gradient Theory
GDQEM	General Differential Quadrature Element Method
aDE	Adjusted Differential Evolution
CS-DSG3	Cell-Based Smoothed Discrete Shear Gap Method
aeDE	Adaptive Elitist Differential Evolution
NMPSO	Niching Memetic Particle Swarm Optimization

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