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A mini review on machine learning technique for bending and buckling behaviors of different composite structures

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A B S T R A C T

This paper examines recent developments in machine learning (ML) techniques for optimizing and predicting the flexural and buckling behavior of composite structures, including those made from concrete, fiber-reinforced polymers (FRP), wood, and metals. To enhance the understanding of structural system performance and data-driven modeling, various ML techniques are demonstrated and reviewed throughout the paper, including artificial neural networks (ANN), deep learning, and support vector machines (SVM). The paper also provides examples of how ML applications can reduce testing costs while improving design accuracy and fostering innovation in civil, materials, and mechanical engineering.

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1. Introduction

Increasing speed in manufacturing has led to an increased demand for materials with lower density, higher durability, stiffness, and strength, as well as reduced costs. As a versatile option, composite materials have emerged, which have the potential to offer these improvements in a variety of applications [1, 2]. Composites consist of a matrix phase combined with dispersed reinforcement, which may be in particle or fiber form. the use of synthetic or natural fibers has had widespread applications in mechanical engineering, aerospace, construction, biomedical, marine, and automotive sectors [2]. Computational analysis of composites faces challenges due to (i) the need to accurately model dissimilar material interfaces (e.g., metal/ceramic, metal/polymer, ceramic/polymer) and their interfacial interactions, and (ii) the virtually infinite design space of possible material combinations, which requires reliable material parameters to yield meaningful insights [3]. Artificial intelligence (AI), using machine learning (ML) and deep learning (DL) algorithms, enhances the aforementioned processes by analyzing large data sets [4]. Recent advances in ML enable data-driven damage detection and identification in structural systems. This

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study proposes a novel method for three-dimensional (3D) delamination identification in sandwich composite structures, where damage is often difficult to detect and requires efficient inspection. The methodology integrates automated structural health monitoring (SHM) using ML, parameterizing damage as two- and three-dimensional ellipses and categorizing it into core, interface, and skin regions [5]. Sheet metal forming has long supported diverse manufacturing needs. Among forming techniques, sheet bending and stamping are particularly important. Springback, the elastic recovery after tooling removal due to residual stresses, must be predicted to achieve accurate forming. Recently, ML has been increasingly applied to sheet metal forming to improve decision-making, reduce defects, and enhance manufacturing quality. ML operations are usually categorized into supervised learning, unsupervised learning, or reinforcement learning.

2. Types of composite structures

Composite materials are created by combining two or more different materials to take advantage of their individual best properties. The complex failure modes of composites stem from their heterogeneity, which cannot always be detected through ordinary inspection. Types of composites include carbon-fiber reinforced composites, polymer-matrix composites, metal-matrix composites, and natural composites. Examples of natural composites include wood, sandwich panels, and ceramic-matrix composites [6, 7].

2.1. Concrete

Concrete is one of the most widely used construction materials due to its high compressive strength and low tensile strength. However, due to this property, it is prone to cracking, which reduces the durability and lifespan of structures [8]. To mitigate this issue, innovative self-healing concrete technologies have been introduced as solutions that improve stability and reduce maintenance costs through the automatic repair of cracks. These technologies enhance the longevity and durability of concrete structures. In addition, an advanced strategy involving the incorporation of nanoparticles into fiber-reinforced polymers (FRP), combined with self-healing concrete systems, can further enhance structural resistance to environmental factors and improve durability [8].

2.2. Fiber-reinforced polymers (FRP)

Nanoparticles can serve as effective additives in composite FRP materials (Fig. 1).

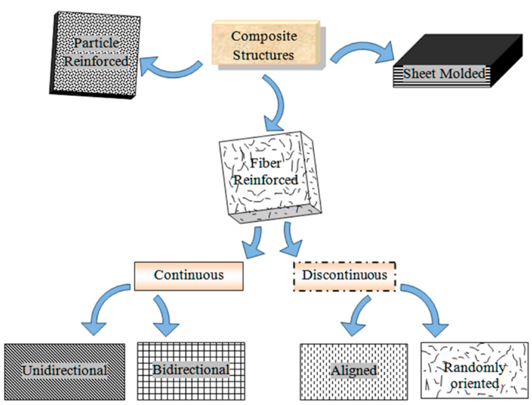

Fig. 1. Types of composites [10].

They improve the bond between the fibers and the FRP matrix through effective chemical interactions (better adhesion), increased surface dryness, and enhanced mechanical bonding. Therefore, it is important to evaluate the performance of these nanoparticles under environmental conditions, such as humidity and ultraviolet (UV) radiation, to accurately assess the durability of the materials. The outcomes of this work will assist in the development of FRP materials with improved environmental stability and erosion resistance [9].

2.3. Composite wood products

Engineered wood products (EWPs) are sustainable, high-performance building materials made from the renewable resource of wood. these products offer increased durability and strength by improving undesirable natural properties such as knots, as well as dimensional stability and more consistent mechanical properties. These improvements result from controlled modifications of natural wood, which form the basis of engineered composite products. As a result, EWPs offer improved structural performance for high-demand applications where plain wood is not sufficient. Also, the increased use of EWPs has generated significant economic growth in the wood industry and is enabling a new marketing process [11].

2.4. Metal matrix composites (MMCs)

Metal matrix composites (MMCs) are widely used in the aerospace, automotive, and sports industries due to their advanced mechanical properties [12]. These materials, especially particle-reinforced ones, offer several advantages, including high strength, high tensile modulus, scalable production, and low cost. However, while stiff reinforcements increase strength, they may reduce resilience elements such as the stiffener, resulting in unstable strength-to-stiffness interactions (Fig. 2). Recent developments in nanocomposites (MMNCs), structurally modified foams, and self-similar metals based on the stiffening method have led to improved stiffness, tensile strength, and rocket-like strength. These exceptional innovations have paved the way for a new generation of functional foams with adjustable and tunable structural performance properties [13].

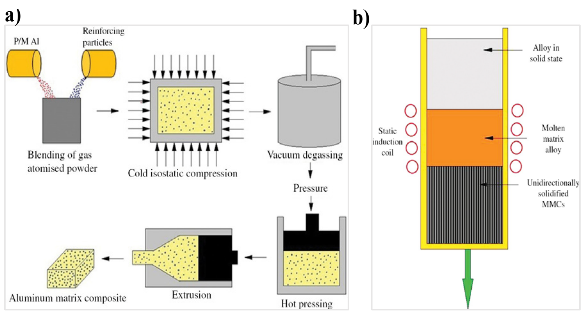

Fig. 2. The schematic of MMC with different modern methods, a) hot-pressed billets, b) *in situ* process [14].

2.5. Ceramic matrix composites (CMCs)

ML plays a critical role in improving the performance of ceramic matrix composites (CMCs) in extreme environments. Machine-based predictive models allow for accurate prediction of strength and properties such as strain under extreme conditions such as high stress and significant motion loss. Algorithms such as random forest, neural network, and support vector machine reduce the time-consuming design and testing of materials and analyze the complex relationships among material structure, properties such as metal volume or color, and operating conditions. In addition, ML will help to ultimately detect damage effects and improve product design, key factors in maintaining the mechanical and thermal resistance of ceramic materials in harsh conditions. Finally, ML has increased the precision and energy of research and technological development in the world of modern materials [15].

2.6. Sandwich structures

Fiber sandwich structures with high corrosion resistance and high strength-to-weight ratio are suitable for applications in marine and industrial industries. In this design, thin layers are used on the surface of a lightweight core, the types of which are shown in Fig. 3, with thermal insulation properties with two different thermal and insulation properties, with the main goal of reducing weight and strength being the main part of the engineering program.

Using ML algorithms, it is possible to predict the nonlinear relationship between multi-component elements, including different materials and shapes, and loading, and reduce the analysis time. These methods help to increase the regularity of the structure's health during damage (such as impact) in FRP structures. Ultimately, combining the sandwich structure with ML provides a path to designing safer, lighter, and stronger structures [16].

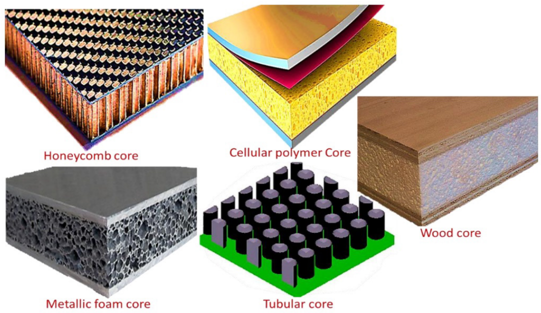

Fig. 3. Sandwich composites with various core models [16].

2.7. Asphalt concrete

The addition of industrial waste materials like limestone dust, silica ash, clay and fly ash to dry asphalt composites has improved their mechanical strength and strength properties. Various tests such as corrosion resistance, moisture sensitivity and internal strength have been well used to increase the productivity of these composites. In this area, ML through big data analysis has shown great skill in predicting the effects of materials on improving material performance and has enabled more suitable material formulations. These approaches not only reduce environmental problems associated with failure to prevent waste transfer but also increase the durability of asphalt. For example, the use of limestone powder and fly ash has been well documented to increase the paving quality of asphalt [17].

2.8. Syntactic foams

Synthetic foams are composite materials consisting of hollow microspheres in metallic, nucleophilic, and ceramic matrices. These foams have low density, high strength-to-weight ratios, and closed-cell structures that provide excellent hydrostatic pressure strength, impact resistance, and buoyancy. Glass microspheres are commonly added to the matrix to provide a lighter structure. Specifically, the addition of glass microspheres (3M, K20; ~60µm, $0.2g / cm^3$) helps improve resin fluid adhesion, viscosity, and shape retention during material processing [7].

3. Composite structure

3.1. Effective composites in civil engineering

FRP bars are greatly used in civil engineering due to their high compressive strength, low weight, and corrosion resistance. The common types of fiber-reinforced polymers include AFRP, BFRP, HFRP, GFRP, SFCB, and CFRP. While carbon fiber-reinforced polymers (CFRP) are more costly compared to the others, their strong performance in strengthening critical structures is well established. Glass fiber-reinforced polymers (GFRP) are also widely used due to large-scale production, variable costs, and efficient handling processes. BFRP bars made from silt soil are similarly strong to GFRP and represent a more sustainable option. Hybrid fiber-reinforced polymer bars (HFRP) combine carbon fibers with either silt or glass fibers, making them robust for use in hot and humid conditions. AFRP bars have limited applications due to their susceptibility to moisture and reduced durability [18].

3.2. Machine learning in composite structures

Machine learning is increasingly being used in materials development and manufacturing to improve accuracy and efficiency while reducing the cost of modeling complex material behaviors. Machine learning algorithms can be categorized into three main types based on learning objectives and data: reinforcement learning, unsupervised learning, and supervised learning each with its own advantages. Among these, artificial neural network (ANN)-based modeling plays a critical role in forecasting material performance based on experimental or simulated data. combining ANNs with other ML techniques can help overcome their limitations and increase the overall reliability of modeling, as ANNs effectively capture nonlinear relationships [19].

4. Machine learning techniques for bending and buckling behaviors of composite structures

Recent advances in ML have addressed the limitations of traditional design approaches for FRP-strengthened RC members, enabling accurate prediction of mechanical behavior using models such as neural networks (NNs), support vector machines (SVM), and ensemble learning algorithms including random forest (RF) and XGBoost. In laminated and fiber-reinforced composites, the buckling stability improves with layer stacking, while antisymmetric and thermally nonuniform laminates show higher critical buckling loads [18, 25]. Analytical frameworks such as Hamilton's principle remain effective for beam buckling problems [26]. Graphene platelet (GPL) and carbon nanotube (CNT)-reinforced nanocomposites have also been analyzed for buckling and vibration behavior, demonstrating the influence of reinforcement patterns and material gradation [27]. Supervised ML algorithms including ANNs, SVM, K-nearest neighbors (KNN), and decision trees have shown promising accuracy in modeling bending, springback, and buckling responses. Among these, multilayer perceptron NNs offer superior prediction capability in complex nonlinear problems such as sheet metal air bending and punch displacement estimation. The result of these technologies is the integration of neural network-based predictions with finite element analysis (FEA) simulations, which provides a data-driven and efficient path to evaluate and optimize the flexural performance and stability of advanced composite structures [19]. Table 1 compares various applications and performance characteristics in machine learning.

Table 1
Comparison of several applications and behaviors in ML.

Application	Description	Ref.
Buckling Prediction	Development of machine learning models Accurate prediction of buckling behavior Composite plates with different types of cuts and fiber orientations Advances in ANNs	[20]
Flexural Strength Assessment	Machine learning techniques Accurate prediction of critical buckling load Thin-wall composite structures with diverse hole shapes Thin layers under mechanical and thermal loads Enable efficient assessment of structural resilience	[21]
Data-Driven Design Optimization	Machine Learning Accelerates Civil Engineering ML Enables Data-Driven Prediction Structural Health Monitoring and Efficient Decision Making in Various Subdomains Reduces Experimental Needs and Increases Project Sustainability	[22]
Real-Time Monitoring and Maintenance	ML with Internet of Things (IoT) sensor data analysis Structural health monitoring of civil engineering infrastructure Damage detection Material strength prediction structural integrity assessment under different conditions	[23]
Functionally Graded Composites	Porous functionally graded composites Nature-inspired porosity Structural structures with improved mechanical properties and lightness Modeling with the help of artificial intelligence and machine learning Support for mechanical analysis and design Improved buckling, vibration and bending performance	[24]

5. Conclusion

In the presented set of studies, ML has well demonstrated the role of world-building in improving the accuracy of predicting the performance of composite structures in the face of compression and flexural cracking problems.

Various algorithms like ANN, random forests and SVM have increased the predictive power in areas such as fracture behavior, critical force and stiffness to about 90%. Also, multi-stage ML models reduce computational time from hours to milliseconds, while maintaining an accuracy comparable to full finite element simulation (FEA).

In other areas, ML has enabled immediate safety assessment as an advanced technology in defect detection and health monitoring of composite structures. In particular, incorporating ML into structural optimization and architectural design processes will enable the construction of stronger, more economical, and lighter structures.

Based on the above, improving ML models based on physical concepts and creating standardized datasets can help increase the reliability of predictions and industrial application of composite materials and related technologies in construction.

Overall, future research should focus on strengthening the link between data-driven ML results and empirical physical concepts so that sustainable materials and structures, which are of great concern to the world today, can meet global construction needs.

Author contributions

Sogand Jalili: Conceptualization, Writing – original draft, Writing – review & editing; **Iman Jalili:** Conceptualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare no conflict of interest.

Data availability

No data is available.

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