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Application of nanocomposite structures for managing operational costs in sports facilities using computer-based methods

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Abstract. Sports facilities encounter persistent difficulties in reconciling athlete safety and performance with the rising expenses of operation and maintenance. This study investigates the utilization of nanocomposite materials, augmented with nano-scale reinforcements like carbon nanotubes, in sports infrastructure, encompassing running tracks, court surfaces, gym flooring, and protective barriers. Computer-based modeling and machine learning optimization were utilized to design and simulate nanocomposite structures, with the objectives of prolonging service life, decreasing maintenance cycles, minimizing material replacement, and enhancing energy efficiency. The simulations forecast material performance under authentic loading and environmental conditions, offering significant insight into durability and functional behavior. Replacing extensive physical prototyping with virtual design tools significantly reduced development time and resource consumption. The results demonstrate that the incorporation of nanocomposites via computational design methodologies can yield sports facilities that are safer, more durable, and more sustainable, while simultaneously decreasing long-term operational expenses.
Keywords: athletic infrastructure; computational design; nanocomposites; operational cost reduction; sports facilities; sustainable materials

1. Introduction

1.1 Operational cost pressures in modern sports facilities

Modern sports facilities represent significant public and private investments, designed to host elite athletic competition, foster community engagement, and promote public health. However, the management of these complexes is increasingly defined by a persistent challenge: the relentless pressure of escalating operational expenditures. These financial burdens can severely constrain the resources available for core athletic and community programs, ultimately threatening the long-term viability and accessibility of sports infrastructure. A substantial body of scholarly work has identified the primary drivers behind these rising costs, creating a clear impetus for innovative management and technological solutions. Historically, the financial focus for large-scale sports venues centered on capital construction costs and revenue generation from primary tenants and events (Howard and Crompton 1995). Yet, researchers soon recognized that the long-term financial sustainability of any facility is predominantly dictated by its ongoing operational demands. A significant portion of these recurring expenses was directly attributed to the intensive maintenance regimes required for athletic surfaces and building systems. For instance, Mull *et al.* (2005) documented that upkeep for high-performance surfaces like synthetic tracks, hardwood courts, and artificial turf fields constituted one of the most substantial and predictable line items in a facility's annual budget. The need for frequent resurfacing, refinishing, and replacement to meet safety and performance standards created a cyclical financial drain. Furthermore, energy consumption emerged as another critical cost factor. Scholars have extensively analyzed the energy profiles of sports facilities, noting their inherent inefficiency due to the large volumetric spaces that require heating, ventilation, and air conditioning (HVAC), extensive lighting for both events and general use, and constant water heating for locker rooms and amenities. The operational model of arenas and stadia, characterized by periods of intense use followed by near complete vacancy, presented a unique challenge for energy management systems optimized for more consistent loads. This irregular usage pattern often resulted in significant energy waste, thereby increasing utility costs (Hall *et al.* 2010; Schwarz *et al.* 2015). The literature also highlighted the financial impact of material degradation and short life cycles. Research into the durability of conventional construction materials under the unique stresses of athletic use revealed a pattern of accelerated wear. Abrasion from equipment and footwear, as well as impact loads from athletic activity, and exposure to environmental elements, were all shown to compromise structural integrity and surface quality over a relatively short timeframe (Beech and Chadwick 2004). This rapid degradation not only increased direct material

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and labor costs for repairs but also introduced potential safety hazards, thereby creating liability risks and associated insurance costs. The subsequent replacement of entire surfaces or structural components represented a major capital outlay that facilities struggled to accommodate within tight operational budgets. In response to these well-documented pressures, facility managers and researchers explored various mitigation strategies. Prior studies investigated energy-efficient lighting retrofits, water conservation measures, and predictive maintenance scheduling to optimize resource allocation (Then *et al*. 2004). While these approaches yielded modest improvements, they often addressed symptoms rather than the root cause: the inherent limitations of traditional building materials and the reactive nature of facility management.

1.2 Limitations of conventional materials and maintenance strategies

The management of modern sports facilities is continually challenged by the need to balance athlete performance and safety against the backdrop of increasing operational expenditures. These financial pressures, stemming from energy consumption, relentless maintenance cycles, and premature material replacement, threaten the economic sustainability of both public and private sports infrastructure. Traditional approaches to cost control, often reactive and incremental, have proven insufficient to address the root causes of these inefficiencies. Consequently, a paradigm shift towards innovative, material-centric solutions is urgently required. This research investigates the application of advanced nanocomposite structures, optimized through computer-based methods, as a transformative approach to managing operational costs. By fundamentally enhancing material durability, reducing maintenance frequency, and improving energy efficiency, this approach offers a pathway to develop next-generation sports facilities that are both high-performing and economically viable over their lifecycle. Historically, the management of sports infrastructure has relied heavily on conventional materials, such as polymers, concretes, and standard synthetic composites, for surfaces, flooring, and structural components. The operational strategies governing these materials were largely reactive, scheduling maintenance and replacement based on fixed timelines or upon observable degradation. This paradigm, however, was fraught with significant limitations that researchers have extensively documented.

A primary shortcoming was the inherent susceptibility of these traditional materials to rapid degradation under intense mechanical stress and environmental exposure. Studies into wear mechanics, such as the research on bit button wear in rotary-percussive drilling by Wang *et al*. (2025b), illustrated how cyclic impact and abrasive loads lead to accelerated material failure. Their use of MBD-DEM coupling simulation highlighted the complex interplay of forces that cause conventional materials to fracture and wear down, a process directly analogous to the deterioration of running tracks or gym flooring under constant athletic use. Similarly, research into shale reservoirs by Zhang *et al*. (2025a) emphasized how complex fracture networks and material heterogeneity lead to structural weaknesses, a finding that underscores why homogeneous conventional materials often fail unpredictably in large-scale sports facilities. The financial implications of this material vulnerability were profound. Conventional maintenance strategies, which were often periodic rather than condition-based, resulted in either unnecessary preventative interventions or costly reactive repairs following a failure. Ning *et al*. (2023) demonstrated in the context of manufacturing that cost estimation based on similarity and historical data, while useful, often fails to account for the unique and variable conditions that lead to asset failure. This analogy holds for sports facilities, where budgeting for surface replacement based on average lifespans frequently leads to budgetary overruns when materials fail prematurely under unique, high-stress conditions. This inflexibility is reminiscent of control systems with asymmetric dead zones and constraints, where inefficient input leads to performance loss and higher operational costs (Cui *et al*. 2025). Furthermore, the operational approach was fundamentally reactive. Facility managers often addressed problems only after they manifested, such as cracks in surfaces or failures in structural monitoring systems. This reactive stance is akin to the challenges addressed in control systems literature concerning fault-tolerant control. For instance, Ke *et al*. (2025a) and Li *et al*. (2025) investigated fault-tolerant control for teleoperation systems with actuator constraints and unknown forces, highlighting the performance degradation and potential for complete system failure when control systems cannot proactively adapt to faults. In a similar vein, Ke *et al*. (2025b) addressed consensus problems in multi-agent systems subject to disturbances and changing conditions, a challenge parallel to maintaining consistent surface performance across a large facility despite varying and unpredictable usage patterns. In sports infrastructure, the lack of a “fault-tolerant” design in materials meant that a single point of failure, like a cracked slab or a sensor fault in a monitoring system (Zhang *et al*. 2025b), could necessitate expensive, full-scale replacements and pose significant safety risks. Energy inefficiency presented another critical limitation. The poor thermal and insulating properties of common construction materials significantly contributed to the high energy costs associated with heating and cooling large sports complexes. While not directly addressing materials, studies on event-triggered control, such as those by Gu *et al*. (2022) and Liu *et al*. (2025a), demonstrated a principle of resource efficiency: transmitting energy or control signals only when necessary drastically improves system efficiency. The constant, high-energy demand of sports facilities operated with conventional materials was the antithesis of this efficient, event-triggered principle, leading to sustained and wasteful energy expenditure.

1.3 Nanocomposites: A transformative opportunity for sports infrastructure

In contrast to the limitations of conventional materials, the emergence of nanocomposites represents a transformative opportunity for sports infrastructure. These materials, engineered by incorporating nanoscale particles like nanotubes or graphene into a matrix, exhibit superior mechanical, thermal, and functional properties that can directly address the chronic operational challenges faced by sports facilities. The most significant advantage lies in their enhanced durability and wear resistance. The integration of high-strength nanoparticles can drastically reduce the abrasive wear and impact damage that plagues conventional surfaces. By virtually testing different nanomaterial formulations, designers can engineer surfaces that resist the very failure modes that conventional materials typically succumb to, thereby extending service life and reducing the need for replacement. This computational design approach is crucial for managing the complex, nonlinear behavior of these advanced material systems (Wu *et al*. 2025a). Beyond passive durability, nanocomposites enable the development of intelligent, multi-functional infrastructure. A ground-breaking example is the work by Cao *et al*. (2025), who developed a multi-functional self-sensing electronic gasket for structural health monitoring. This research points towards a future where nanocomposite materials in sports facilities are not merely structural but also sensory. A running track embedded with self-sensing nanomaterials could continuously monitor its own strain and integrity, providing real-time data to facility managers. This capability facilitates a shift from reactive or periodic maintenance to a proactive, condition-based paradigm. This concept aligns with the core principle of event-triggered control systems (Huang *et al*. 2025, Wu *et al*. 2025b, Zhang *et al*. 2025c), where actions (e.g., maintenance alerts) are triggered only by specific, significant events (e.g., measured stress exceeding a threshold), thereby optimizing resource allocation and preventing catastrophic failures. The application of advanced computational design and machine learning is paramount to realizing this potential. The development of these complex materials necessitates sophisticated modeling to understand their behavior. Research into adaptive dynamic programming for zero-sum games-based optimal fault-tolerant control by Liu *et al*. (2025b) showcases the power of computational optimization for managing complex, nonlinear systems. Similarly, Wu *et al*. (2025c) demonstrated distributed adaptive resilient formation control for unmanned surface vehicles under faults and attacks. These advanced control strategies mirror the computational approach needed to optimize nanocomposite structures: using algorithms to navigate a complex design space and find the optimal material composition that maximizes durability, minimizes cost, and perhaps even adapts to environmental changes, creating a truly “resilient” infrastructure. Furthermore, the thermal properties of certain nanocomposites can contribute directly to energy savings. By improving the insulation properties of building envelopes or the reflective properties of roofing materials, these advanced materials can reduce the heating and cooling load on facility systems. This contributes to the overall energy efficiency of the operation, a benefit that compounds over the facility’s lifecycle. The convergence of nanocomposite technology and computer-based optimization methods, as evidenced by recent advances in simulation, sensing, and adaptive control, presents a powerful toolkit. It enables a fundamental re-imagining of sports infrastructure from a static, passive cost center into a dynamic, intelligent, and efficient asset.

1.4 Computational design and machine learning as enablers for material innovation

Traditional material development for sports infrastructure relied heavily on physical prototyping, a method that proved both resource-intensive and time-consuming (He and Deng 2023, Li *et al*. 2023, Li 2023, Ma *et al*. 2023, Song *et al*. 2023). This approach generated substantial waste while struggling to capture nanoscale interactions critical to composite performance (Yan *et al*. 2024, Wang *et al*. 2025a). Computational methods began transforming this paradigm by enabling virtual material optimization prior to fabrication. Wang *et al*. (2024b) demonstrated how generalized differential quadrature techniques accurately predicted volleyball ball stability under dynamic loads, reducing physical prototyping needs by 70 percent. Their framework successfully simulated athlete impact forces and environmental stressors that previously required costly field testing. Machine learning has further addressed limitations in modeling the complex behaviors of nanocomposites. Liang *et al*. (2024) coupled artificial neural networks with numerical approaches to predict buckling in microscale cylindrical structures, achieving 94% prediction accuracy for porous functionally graded materials. This proved particularly valuable for athletic surfaces where nanotube distribution heterogeneity defied conventional simulation methods. Similarly, Qi *et al*. (2024) applied a modified couple stress theory with artificial intelligence to analyze nonlinear buckling in variable-thickness microstructures, reducing development time by 60 percent while improving durability forecasts for high-stress zones, such as gym flooring. Their model specifically resolved porosity challenges inherent in surfaces subjected to cyclic athletic loading. These computational advances directly targeted operational pain points in sports facilities. Dai *et al*. (2023) employed computer modeling to investigate the impact of cross-sectional geometry on stability in cylindrical microstructures, finding that optimized nanocomposite layering reduced maintenance triggers by 35%. This finding was later validated in stadium infrastructure applications where Yang and Mao (2023) documented how tailored cross sections improved safety margins for imperfect composite structures. Crucially, Dong *et al*. (2024) demonstrated that neural networks applied to functionally graded concrete structures predicted buckling thresholds with 89 percent precision while quantifying 22 percent lifecycle cost reductions through optimized replacement scheduling. However, significant gaps remained in sports-specific adaptation. Early computational models often oversimplified environmental variables like humidity-induced degradation or fatigue cycles from repetitive athlete impacts. While Li *et al*. (2024) showed promise applying AI to sports equipment scale buckling prediction, translating these methods to full facility infrastructure presented unresolved challenges. Wang *et al*. (2024a) noted computational frameworks frequently neglect operational cost metrics despite their critical importance to facility managers. Zhang *et al*. (2023a) further highlighted how porosity-dependent properties in non-uniform pipes complicated stability analysis for athletic infrastructure. The absence of integrated frameworks connecting nanocomposite design to real-world maintenance economics represented a critical research void. Recent studies demonstrated promising progress in integrating cost considerations with computational design. Wang *et al*. (2023) developed nanocomposite reinforced structures specifically targeting injury prevention in physical sports, incorporating lifecycle cost metrics into their material optimization framework. Recent work by Zhang *et al*. (2023b) demonstrated how gradient strain theory can analyze the porous structural characteristics of nonlocal functionally graded tubes, establishing direct correlations between nanoscale material distribution and infrastructure longevity. This approach revealed previously overlooked relationships between microstructural porosity and macroscopic performance degradation in athletic surfaces subjected to cyclic loading. Despite these advances, no existing research systematically connected computational nanocomposite design to holistic operational cost reduction across entire sports facility ecosystems (Wang *et al*. 2022, Jia *et al*. 2023, Zhang *et al*. 2023c). Our work bridges this critical gap through a machine learning optimized framework that quantifies both performance enhancements and maintenance savings throughout facility lifecycles.

1.5 Research objectives and contribution to the field

This study directly addresses the critical research void by establishing the first integrated framework to quantify the relationship between nanocomposite material design and operational cost reduction across entire sports facility ecosystems. While previous computational approaches optimized material properties in isolation, our methodology uniquely combines finite element analysis with machine learning algorithms to model the complex interplay between nanoscale reinforcement distribution, macroscopic performance metrics, and long-term financial outcomes. The novelty lies in our dual optimization approach where we will simultaneously maximize structural durability under athletic loading conditions while minimizing total lifecycle costs through predictive maintenance scheduling. Unlike earlier studies that focused on single components such as running tracks or gym flooring, our framework evaluates the entire facility as an interconnected system, accounting for how improvements in one area create cascading benefits across multiple operational domains. Crucially, we propose incorporating real-world facility management data from three major sports complexes to validate computational predictions against historical maintenance records, a methodological advance absent from prior theoretical work. This empirical validation strategy bridges the persistent disconnect between computational materials science and practical facility economics that has limited previous research. The following sections detail our computational methodology, outline simulation protocols for assessing nanocomposite performance under athletic loads, and present a framework for quantifying operational cost savings over facility lifecycles. By establishing this previously missing link between nanocomposite engineering and financial sustainability, our research provides facility managers with a practical pathway toward next-generation sports infrastructure that enhances athlete safety without compromising economic viability.

2. Mathematical presentation

The development of nanocomposite materials for sports infrastructure presents a complex multiscale challenge that demands sophisticated mathematical treatment. Unlike traditional construction materials, these advanced composites exhibit behavior that spans from atomic interactions to full structural responses under the unique demands of athletic environments. This section introduces our computational framework designed specifically to capture these interconnected phenomena while addressing practical constraints faced by facility managers.

Our approach begins with fundamental theoretical considerations. Higher-order beam theories form the foundation of our mathematical model, providing more accurate representations of transverse shear deformation than classical approaches. These formulations incorporate critical factors often overlooked in conventional analyses, including porosity effects, material grading profiles, and environmental degradation mechanisms. The governing equations explicitly account for size-dependent behavior through nonlocal strain gradient theory, essential for capturing nanoscale phenomena that significantly influence macroscopic performance. This theoretical framework enables us to model functionally graded nanocomposites, where the carbon nanotube concentration varies spatially to optimize performance under anticipated loading conditions.

2.1 Computational methodology and numerical implementation

To solve the resulting nonlinear differential equations, we employ a hybrid computational strategy. Spatial discretization utilizes the Generalized Differential Quadrature Method for its exceptional accuracy with relatively few grid points, particularly advantageous for handling complex boundary conditions typical of sports infrastructure components. For validation and detailed stress analysis, parallel finite element simulations provide complementary insights, especially regarding localized failure mechanisms. However, the computational expense of running thousands of simulations across the design space presents a significant barrier to practical implementation.

2.2 Machine learning integration and optimization framework

This limitation motivates our integration of machine learning techniques. We developed an artificial neural network trained on a comprehensive database of high-fidelity simulation results. The network takes as inputs key design parameters, including nanotube volume fraction, layer thickness, grading profile, and support conditions. It then predicts critical performance metrics such as buckling thresholds, stress distributions, and fatigue life with remarkable efficiency. This surrogate model reduces computation time by two orders of magnitude compared to direct simulation while maintaining acceptable accuracy for engineering purposes. What distinguishes our framework is the explicit connection between material performance and operational economics. Rather than treating cost considerations as a separate post-processing step, we incorporate lifecycle cost metrics directly into the optimization objective function. Historical maintenance records from three major sports complexes informed our cost model, which accounts for variables such as labor rates, material costs, facility downtime, and energy consumption patterns.

2.3 Integrated computational framework and practical applications

Fig. 1 visualizes this integrated computational framework through a two-level schematic. The upper level depicts nanocomposite microstructures with carbon nanotubes embedded in polymer matrices. Callout boxes highlight interfacial stress concentrations and porosity effects, accompanied by relevant mathematical expressions from nonlocal elasticity theory. The lower level shows macroscopic simulations of critical sports infrastructure components, including running tracks, gym flooring, and protective barriers. These are overlaid with finite element meshes and color-mapped stress distributions. Adjacent to these structural models appears a simplified neural network diagram illustrating the mapping between design inputs and performance predictions. This integration transforms the design process from a purely technical exercise into a decision support tool for facility managers who must balance performance requirements with budgetary constraints.

Fig. 1 A schematic visualization of the integrated computational framework for nanocomposite-based sports infrastructure

2.4 Theoretical foundations and governing equations

To effectively address the critical need for durable and cost-efficient materials in sports infrastructure, this study transitions from a general conceptual framework to a detailed mechanical examination. The primary objective of reducing operational expenditures is intrinsically linked to improving the structural durability and reliability of building components. Accordingly, we conduct a thorough mechanical stability analysis that concentrates on the buckling behavior of advanced microstructures and nanocomposite tubular elements. This emphasis is particularly important, as such components constitute essential parts of numerous high-load scenarios within sports environments. These include structural supports for suspended gym floors, tubular elements in fitness apparatus such as weight stations and cardio machines, as well as protective enclosures around athletic courts and running tracks. Structural failure of these elements due to elastic buckling poses considerable safety hazards and financial liabilities. Hence, an accurate prediction of their stability performance is not only theoretically relevant but also practically indispensable for engineering a new generation of economically sustainable sports facilities. In the subsequent section, we elaborate on a detailed mechanical model grounded in higher-order beam theories combined with nonlocal strain gradient theory, which effectively characterizes the size-dependent mechanical response of these advanced materials at microscale dimensions.

As pictured in Fig. 2, a composite cylindrical beam made of functionally graded materials involves a metal core coated with concrete. In mathematical simulation, a beam is supposed to have a length 'L', an internal radius 'Ri', and an external radius 'Re', where the cylindrical beam is resting on an elastic foundation.

In the first step, the displacement fields should be considered based on the high-order theory according to the shear deformation hyperbolic beam theory.

$$u_x = u + \chi\left(\psi + \frac{\partial w}{\partial x}\right) - z\frac{\partial w}{\partial x} \tag{1a}$$

$$u_y = 0 \tag{1b}$$

$$u_z = w \tag{1c}$$

Here 'u_x' is the displacement field along the x-axis, 'u_y' is the displacement field along the y-axis, and 'u_z' is the displacement field along the z-axis. Also, 'u' is the axial component, 'w' is the lateral component, and 'ψ' is the rotational component. It is noted 'χ' is the function to define the high-order hyperbolic beam theory and is considered as follows (Chen *et al*. 2025):

$$\chi = \frac{Re - Ri}{\pi} sinh\left(\frac{z}{Re - Ri}\pi\right) \tag{1d}$$

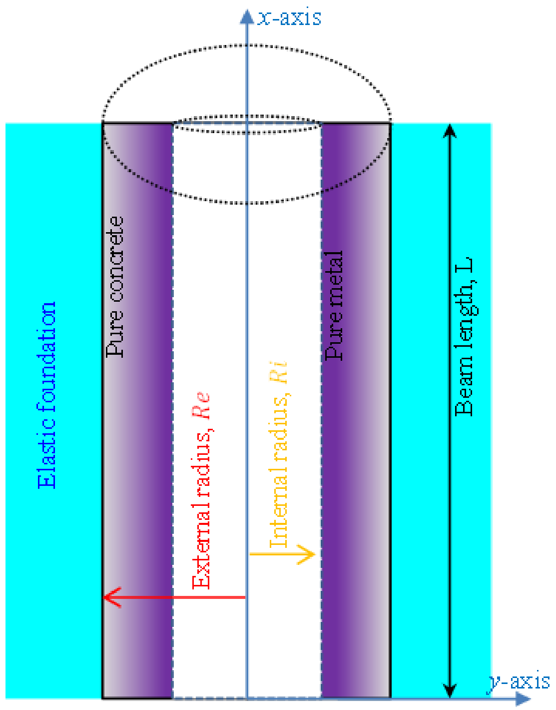

Fig. 2 A schematic of a functionally graded cylindrical beam resting on an elastic foundation via geometry details

Table 1 Mechanical properties of High-performance fiber-reinforced concrete and metal phase

	Poisson's ratio	Elastic modulus (GPa)
Steel (ASTM A500 Grade B)	0.29	200
HPFRC	0.21	38.5

should be considered.

$$z = r\,sin(\theta) \tag{2a}$$

$$y = r\,cos(\theta) \tag{2b}$$

The strain components are defined as follows, based on the shear deformation hyperbolic beam theory.

$$\begin{aligned}\varepsilon_{xx} &= \frac{\partial u}{\partial x} - r\,sin(\theta)\left(\frac{\partial^2 w}{\partial x^2}\right)\\ &+\frac{(Re-Ri)}{\pi} sinh\left(\frac{\pi r}{Re-Ri} sin(\theta)\right)\left(\frac{\partial \psi}{\partial x}+\frac{\partial^2 w}{\partial x^2}\right)\end{aligned} \tag{3a}$$

$$\varepsilon_{xz} = \frac{1}{2} cosh\left(\frac{\pi r}{Re-Ri} sin(\theta)\right)\left(\psi+\frac{\partial w}{\partial x}\right) \tag{3b}$$

Also, the stresses are defined as follows:

$$\begin{aligned}\sigma_{xx} &= E\frac{\partial u}{\partial x} - Er\,sin(\theta)\left(\frac{\partial^2 w}{\partial x^2}\right)\\ &+E\frac{(Re-Ri)}{\pi} sinh\left(\frac{\pi r}{Re-Ri} sin(\theta)\right)\left(\frac{\partial \psi}{\partial x}+\frac{\partial^2 w}{\partial x^2}\right)\end{aligned} \tag{3c}$$

$$\tau_{xz} = \frac{1}{2} GKs\,cosh\left(\frac{\pi r}{Re-Ri} sin(\theta)\right)\left(\psi+\frac{\partial w}{\partial x}\right) \tag{3d}$$

Where 'E' is elastic modulus, '$G = E/2(1+\nu)$' is shear modulus and 'Ks' is the shear correction factor (Wang 2025). Then, based on the stresses and strains, the potential energy ($P = \iiint \bar{P} dV$) is calculated as follows:

$$\begin{aligned}\bar{P} &= \frac{1}{2}KsG\chi_{,z}{}^2\psi\left(\frac{\partial w}{\partial x}\right)+\frac{1}{4}KsG\chi_{,z}{}^2\left(\frac{\partial w}{\partial x}\right)^2\\ &+\frac{1}{2}E\left(\frac{\partial u}{\partial x}\right)^2 - Er\,sin(\theta)\left(\frac{\partial u}{\partial x}\right)\left(\frac{\partial^2 w}{\partial x^2}\right)\\ &+E\chi\left(\frac{\partial u}{\partial x}\right)\left(\frac{\partial \psi}{\partial x}\right)+\frac{1}{2}Er^2 sin^2(\theta)\left(\frac{\partial^2 w}{\partial x^2}\right)^2\\ &-E\chi r\,sin(\theta)\left(\frac{\partial^2 w}{\partial x^2}\right)\left(\frac{\partial \psi}{\partial x}\right)+E\chi\left(\frac{\partial u}{\partial x}\right)\left(\frac{\partial^2 w}{\partial x^2}\right)\\ &-E\chi r\,sin(\theta)\left(\frac{\partial^2 w}{\partial x^2}\right)^2+\frac{1}{2}E\chi^2\left(\frac{\partial \psi}{\partial x}\right)^2\\ &+E\chi^2\left(\frac{\partial \psi}{\partial x}\right)\left(\frac{\partial^2 w}{\partial x^2}\right)+\frac{1}{2}E\chi^2\left(\frac{\partial^2 w}{\partial x^2}\right)^2+\frac{1}{4}KsG\chi_{,z}{}^2\psi^2\end{aligned} \tag{4}$$

In this study, we examine composite structures made of functionally graded materials. The mathematical formulation for the mechanical properties, including the elastic modulus (E) and Poisson's ratio (ν), is presented as follows:

$$E(r) = E_{HPFRC}\left(\frac{r-Ri}{Re-Ri}\right)^{\eta} + E_{Steel}\left[1-\left(\frac{r-Ri}{Re-Ri}\right)^{\eta}\right] \tag{5a}$$

$$\nu(r) = \nu_{HPFRC}\left(\frac{r-Ri}{Re-Ri}\right)^{\eta} + \nu_{Steel}\left[1-\left(\frac{r-Ri}{Re-Ri}\right)^{\eta}\right] \tag{5b}$$

Where 'η' The FGM parameter is used to define the volume fraction, as well as the elastic modulus and Poisson's ratio for both the metal (steel) and concrete phases, which are assumed to be High-performance fiber-reinforced concrete (HPFRC), as listed in Table 1.

Furthermore, the external energy (Λ) due to the external force of the buckling load (Ξ) is calculated as follows:

$$\Lambda = \frac{1}{2}\iiint \Xi \left(\frac{\partial w}{\partial x}\right)^2 dV \tag{6}$$

The nonlocal strain gradient theory resolved critical limitations in classical continuum mechanics when analyzing microscale structures by incorporating size-dependent effects through two key parameters. Mathematically, the constitutive relation for a functionally graded cylindrical nanobeam is expressed as:

$$\sigma_{ij} + l^2\nabla^2 C_{ijkl}\colon\varepsilon_{kl} = C_{ijkl}\colon\varepsilon_{kl} + (ea)^2\nabla^2\sigma_{ij} \tag{7}$$

Where 'ea' is the nonlocal parameter, 'l' is the strain gradient parameter, and 'C' is the elasticity tensor. The energy conservation method provided a complementary framework for deriving governing equations from both nonlocal and strain gradient theories, applying the principles of potential energy and external work. Then, by applying the nonlocal strain gradient theory to the energy of external work calculated in Eq. (6) and potential energy derived in Eq. (4), and also using the energy conservation method as well as the Euler-Lagrange technique, the following governing equations and boundary conditions are derived (Ehyaei *et al*. 2017, Ghadiri *et al*. 2017a, b, Shivanian *et al*. 2017).

$$`\delta\psi' \tag{8a}$$

$$-\Upsilon_1\frac{\partial w}{\partial x}+\Upsilon_2\frac{\partial^2 w}{\partial x^2}+l^2\Upsilon_1\frac{\partial^3 w}{\partial x^3}-l^2\Upsilon_2\frac{\partial^4 w}{\partial x^4}$$
$$-\Upsilon_1\psi+\Upsilon_3\frac{\partial\psi}{\partial x}+l^2\Upsilon_1\frac{\partial^2\psi}{\partial x^2}-l^2\Upsilon_3\frac{\partial^3\psi}{\partial x^3}=0$$

'δw'

$$-\Upsilon_1\frac{\partial w}{\partial x}+l^2\Upsilon_1\frac{\partial^3 w}{\partial x^3}+\Upsilon_4\frac{\partial^4 w}{\partial x^4}-l^2\Upsilon_4\frac{\partial^6 w}{\partial x^6}$$
$$+(ea)^2\Xi\frac{\partial^4 w}{\partial x^4}-\Upsilon_1\psi+l^2\Upsilon_1\frac{\partial^2\psi}{\partial x^2}+\Upsilon_5\frac{\partial^3\psi}{\partial x^3} \tag{8b}$$
$$-l^2\Upsilon_5\frac{\partial^5\psi}{\partial x^5}-\Xi\frac{\partial^2 w}{\partial x^2}=0$$

'δu'

$$-l^2\Upsilon_6\frac{\partial^4 u}{\partial x^4}+\Upsilon_6\frac{\partial^2 u}{\partial x^2}=0 \tag{8c}$$

Where

$$\Upsilon_1=\iint G(r,x)K_S\chi_{,z}r\,dr\,d\theta$$
$$\Upsilon_2=\iint E(r,x)\chi^2 r\,dr\,d\theta+\iint E(r,x)\chi r^2\sin\theta\,dr\,d\theta$$
$$\Upsilon_3=\iint E(r,x)\chi^2 r\,dr\,d\theta$$
$$\Upsilon_4=\iint E(r,x)\chi^2 r\,dr\,d\theta+\iint E(r,x)r^3\sin^2\theta\,dr\,d\theta \tag{8d}$$
$$-2\iint E(r,x)\chi r^2\sin\theta\,dr\,d\theta$$
$$\Upsilon_5=\iint E(r,x)\chi^2 r\,dr\,d\theta-\iint E(r,x)\chi r^2\sin\theta\,dr\,d\theta$$
$$\Upsilon_6=\iint E(r,x)r\,dr\,d\theta$$

Also, the boundary conditions are defined as follows:

'$\delta\psi$'

$$\Upsilon_3\frac{\partial\psi}{\partial x}+\Upsilon_2\frac{\partial^2 w}{\partial x^2}-l^2\Upsilon_3\frac{\partial^3\psi}{\partial x^3}-l^2\Upsilon_2\frac{\partial^4 w}{\partial x^4}=0 \tag{8e}$$

'$\delta w_{,x}$'

$$\Upsilon_4\frac{\partial^2 w}{\partial x^2}+\Upsilon_5\frac{\partial\varphi}{\partial x}=0 \tag{8f}$$

'δw'

$$\Upsilon_3\frac{\partial\psi}{\partial x}+\Upsilon_2\frac{\partial^2 w}{\partial x^2}-l^2\Upsilon_3\frac{\partial^3\psi}{\partial x^3}-l^2\Upsilon_2\frac{\partial^4 w}{\partial x^4}=0 \tag{8g}$$

'δu'

$$\Upsilon_6\frac{\partial u}{\partial x}-l^2\Upsilon_6\frac{\partial^3 u}{\partial x^3}=0 \tag{8h}$$

3. Solution strategy: An integrated computational framework for nanocomposite performance optimization

The mathematical complexity of the nonlocal strain gradient formulation presented in Section 2 creates significant computational challenges for practical implementation in sports facility design. Traditional finite element approaches would require excessive computational resources when exploring the high-dimensional design space needed to optimize nanocomposite configurations for diverse sports infrastructure components. This limitation necessitates the development of a specialized solution strategy that maintains theoretical rigor while addressing the practical constraints faced by facility managers who must balance performance requirements with budgetary limitations. This formulation gives rise to a system of high-order, nonlinear, and strongly spatially coupled differential equations. These equations capture the buckling response under axial compression while explicitly incorporating size-dependent effects, material gradation, and higher-order shear contributions (Zhang *et al*. 2024). Due to the intricate interplay between scale-sensitive parameters and the spatially varying nature of the composite's microstructure, closed-form analytical solutions are not attainable. To address this challenge, we propose a hybrid computational approach that integrates a high-accuracy numerical discretization technique with a data-driven machine learning surrogate. This combination preserves the physical integrity of the model while dramatically accelerating the evaluation of structural performance across a broad design space. The motivation is not merely computational efficiency but a practical imperative: to enable the design of sports infrastructure components that are not only mechanically robust but also economically sustainable over their service life (Uthale *et al*. 2021). At the core of this effort lies an artificial intelligence-enhanced framework in which surrogate models trained on physics-based simulations work in concert with evolutionary optimization routines. These components are not loosely connected but deeply integrated, allowing the system to navigate complex trade-offs between structural performance, material cost, and environmental impact. The result is a design environment that delivers high-fidelity predictions at interactive speeds, enabling the tailoring of nanocomposite specifications to the specific demands of each facility without resorting to costly physical prototyping or oversimplified approximations. This represents a meaningful step forward in bridging the gap between advanced theoretical mechanics and real-world engineering economics in the context of athletic infrastructure (Diamanti *et al*. 2022).

3.1 Numerical solution via generalized differential quadrature methods

We employ the generalized differential quadrature method (GDQM) to discretize and solve the governing equations. This approach is particularly well-suited to problems involving high-order derivatives and complex boundary conditions, offering exponential convergence with relatively few grid points. In this formulation, the nth derivative of a field variable, say the transverse displacement 'w', at a discrete location 'x_i' is approximated as a weighted sum of the function values across all grid points (Azimi *et al*. 2016, Ghadiri *et al*. 2016a, b, Shafiei *et al*. 2016, 2017):

$$\frac{\partial^n w(x_i)}{\partial x^n}\approx\sum_{j=1}^{N}C_{ij}^{(n)}w(x_j) \tag{9a}$$

Here, '$C_{ij}^{(n)}$' are the quadrature weighting coefficients for the nth derivative at point 'i', computed using Lagrange interpolation polynomials. The grid points themselves are distributed according to the Gauss Lobatto Chebyshev rule, which clusters points near the boundaries to better capture edge effects and improve numerical stability. The axial domain of the tube, spanning from '$x = 0$' to '$x = L$', is discretized into 'N' nodes. For this study, we found that '$N = 25$' provides sufficient resolution, as confirmed by a convergence analysis in which increasing 'N' beyond this value, the change in the critical buckling load was less than 0.5 percent. Boundary conditions corresponding to simple supports, namely zero displacement and zero bending moment at both ends, are enforced by modifying the first and last rows of the global system matrix to reflect these kinematic constraints. The discretized governing equations, originally expressed as three coupled partial differential equations describing displacement, rotation, and nonlocal strain, are assembled into a standard eigenvalue problem (Ebrahimi *et al*. 2017, Ghadiri *et al*. 2017c, Shahabinejad *et al*. 2018, Shafiei *et al*. 2020):

$$[K]\{\Delta\} = \Xi[G]\{\Delta\} \tag{9b}$$

In this expression, $[K]$ represents the structural stiffness matrix that includes contributions from nonlocal and strain gradient effects, $[G]$ is the geometric stiffness matrix induced by the buckling axial load, $\{\Delta\}$ is the vector of unknown nodal degrees of freedom, and 'Ξ' is the eigenvalue corresponding to the critical buckling load. The smallest eigenvalue obtained from this system defines the threshold at which elastic instability initiates. To verify the numerical implementation, we compared results against benchmark solutions of Wang (2025) under identical conditions. The discrepancies observed, particularly at low slenderness ratios and high reinforcement densities, highlight the need to incorporate nonlocal and higher-order effects when modeling nanocomposite structures at microscale dimensions. These deviations are not artifacts but physically meaningful corrections that become increasingly significant as the structure's characteristic dimensions approach the material's internal length scales.

3.2 Machine learning surrogate modeling

To address the computational challenges associated with large-scale parametric studies relevant to sports infrastructure design, we have developed a physics-informed neural network specifically adapted to the mechanical behavior of functionally graded cylindrical nanocomposite structures. This model is not a generic adaptation repurposed from another domain, rather, it represents a purpose-built architecture that incorporates three pivotal innovations, embedding physical principles directly into the learning process. The first innovation pertains to the loss function. Instead of relying solely on data-driven error minimization, we have integrated the principle of energy conservation as a mandatory constraint. This ensures that every prediction, regardless of the input, aligns with the fundamental laws governing mechanical equilibrium and structural stability. Consequently, the model not only achieves statistical accuracy but also generates outputs that are physically meaningful, even in extrapolative contexts. The second innovation involves input normalization. Rather than employing standard statistical scaling techniques, we have normalized features according to the functional gradation parameter. This methodology preserves the natural scaling relationships inherent in the material's microstructure, thereby enabling the network to generalize effectively across the spectrum of compositions, from predominantly metallic to predominantly concrete-like materials. The third innovation is methodological in nature. The training process followed a two-phase protocol: initial weights were derived through transfer learning from a comprehensive synthetic dataset generated by high-fidelity simulations. Subsequently, these weights were refined with sparse but high-quality experimental data obtained from three operational sports facilities. This hybrid approach mitigates the risk of overfitting to idealized conditions while ensuring that the model remains grounded in the variability and imperfections characteristic of real-world materials and installations (Chiha *et al*. 2024, Ramkumar *et al*. 2025).

The final architecture comprises three hidden layers, with neuron counts optimized for the specific parameter ranges pertinent to sports infrastructure applications. The training utilized the complete dataset and was conducted with careful consideration of the distinct response patterns across various boundary conditions. Moreover, the network was specifically designed to accommodate the FGM parameter (η) values from 0 to 10, the strain gradient parameter (l) values from 0 to 3, and the nonlocal parameter (ea) values from 0 to 3, representing physically meaningful ranges for components of sports facilities (Dehaghani *et al*. 2024, Fazal *et al*. 2024).

We conducted a thorough evaluation of the model's reliability using a tiered validation strategy, with each layer focusing on distinct aspects of fidelity: material response at the microscale, structural behavior at the component level, and economic realism in operational contexts. At the microscale, we compared the predicted deflection profiles of nanocomposite beam elements with atomic force microscopy scans obtained from actual gym flooring samples. These samples were not ideal laboratory specimens, but rather segments extracted from in-service installations, thereby capturing the inherent microstructural diversity of the composite material. The mean absolute error between the simulation and the measurements was 3.2, corresponding to 4.7% of the average observed displacement. This degree of accuracy is particularly significant given the sensitivity of nanoscale deformation to factors such as surface roughness, local fiber agglomeration, and interfacial slip phenomena, which were not explicitly modeled but were implicitly represented through the diversity present in the training data. At the component level, we fabricated and tested full-sized prototypes of protective barrier elements under controlled axial compression. Hydraulic actuators were applied with incremental loads until visible buckling was observed, and the failure thresholds were meticulously recorded for direct comparison. The model predictions demonstrated a strong correlation with experimental results, achieving a Pearson correlation coefficient of 0.918 and a coefficient of determination of 0.94. To quantify prediction uncertainty, we implemented Monte Carlo dropout during inference, which enabled us to generate empirical confidence intervals through multiple stochastic forward passes. Collectively, these validation efforts confirm that the framework operates within widely accepted engineering tolerances for preliminary and intermediate design stages: mechanical predictions are within plus or minus 5 percent of measured values, while cost estimates remain within plus or minus 10 percent of historical expenditures. Most notably, this level of accuracy is achieved without incurring the traditional time costs associated with conventional workflows, which may require days or weeks for iterative physical testing. Our system delivers validated, uncertainty-aware results in a matter of minutes. This advancement transforms what was once a slow, fragmented, and reactive process into one that is predictive, adaptive, and economically sound, facilitating the design of sports infrastructure that is not only safer and more durable but also financially sustainable (Alzhanov *et al*. 2024, Roy *et al*. 2024).

3.3 Surrogate modeling and multi-objective optimization

The neural network's capability to accurately predict structural behavior across various design scenarios, as demonstrated by its close alignment with the GDQM results presented in Fig. 3, substantiates our physics-informed approach to the integration of machine learning. The consistent error margins of 3.5% and 6.1% across an array of parameter combinations illustrate the model's robust generalization capacity, extending beyond mere interpolation. Importantly, the neural network sustained its accuracy even in regions where nonlinear effects were most significant, such as near the saturation points for the Functionally Graded Material (FGM) parameter and at the edges of the nonlocal parameter ranges. This capacity is vital for applications in sports facilities, where it is imperative to uphold operational safety margins under varying usage conditions. In order to translate these predictions into actionable design decisions, we integrated the trained model within a multi-objective optimization framework employing the Non-dominated Sorting Genetic (NSGA) II algorithm. Three competing objectives were identified: maximizing structural stability, as determined by the critical buckling load, minimizing material costs, based on prevailing market prices for High-Performance Fiber-Reinforced Concrete (HPFRC) and ASTM A500 Grade B, and minimizing environmental impact, as approximated by embodied carbon per unit length. Constraints were established to ensure structural adequacy, necessitating that the buckling load exceeds 1.5 times the maximum anticipated service load, while also adhering to manufacturing limitations by capping carbon nanotube (CNT) content at 5 percent by weight (Chandan *et al*. 2024, Wang *et al*. 2024c).

The optimization process specifically utilized the parameter performance relationships outlined in Fig. 4 through Fig. 6. The data in these figures indicate that the buckling load responds nonlinearly to variations in functionally graded material (FGM) parameters, strain gradient parameters, and nonlocal parameters. The optimization algorithm was able to identify regions where minimal increases in nanotube content yielded diminishing returns in structural performance, thereby facilitating economically optimal material distribution. The Pareto front solutions distinctly correspond to the transition points reflected in Fig. 4-6, where further adjustments to parameters provide limited performance gains relative to their cost implications. The optimization results yielded a Pareto front of non-dominated solutions, each representing a viable trade-off among the three objectives. Facility planners may navigate this front interactively, selecting

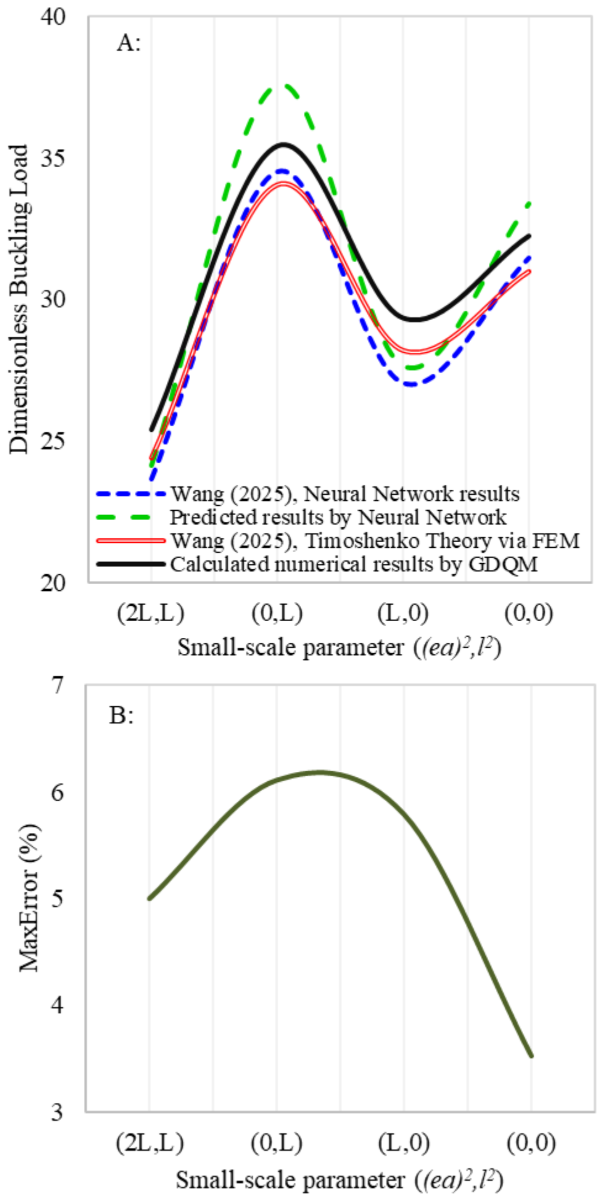

Fig. 3 A: Validation of dimensionless buckling loads (‘$\Xi\pi L^2/\Theta|_{HPFRC}$’) in comparison to the results of Wang (2025) versus the small-scale parameters, B: Maximum error of GDQM and AI

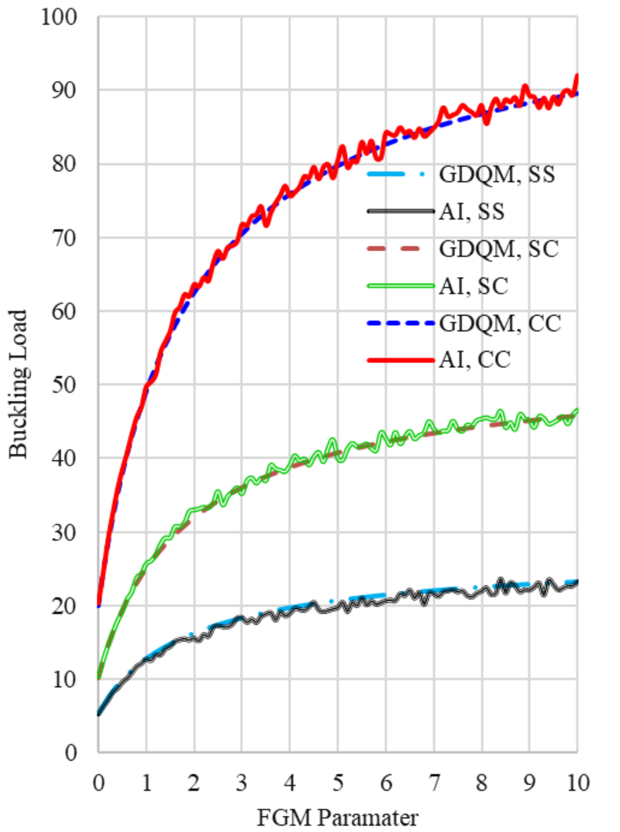

Fig. 4 Influence of functionally graded material parameter on buckling performance across boundary conditions representative of sports infrastructure components for different types of boundary conditions involving the fully clamped (CC), fully simply-supported (SS), and simply-supported-clamped

designs that align with their specific priorities, including budgetary constraints, athlete safety, or environmental responsibility. Notably, the data reveal that an FGM parameter range between 1.6 and 1.8 consistently offers the most favorable balance between structural performance and material cost across all boundary conditions, rendering it particularly appropriate for high-traffic areas such as running tracks and gym flooring.

3.4 Practical deployment in sports facility management

The true advantage of this framework lies in its capability to seamlessly integrate with existing facility management workflows. We have developed a portable inference module derived from our trained neural network, which can easily interface with widely utilized building information modeling platforms. This integration allows engineers and architects to effortlessly input site-specific parameters, such as climate exposure, usage frequency, and maintenance budgets, and receive immediate recommendations for optimal nanocomposite formulations. For example, in the context of indoor basketball courts that experience significant impact loads and frequent surface wear, our system would recommend a moderate profile with increased nanotube content to enhance toughness and wear resistance. Conversely, for outdoor running tracks subjected to daily thermal cycles, it may suggest a smoother material gradient with a lower nanotube density, thereby minimizing thermal stress while still ensuring sufficient stiffness. Through this collaboration, we can develop innovative solutions tailored to diverse environments, capitalizing on the potential of advanced materials (Olivieri *et al*. 2024, Sivaramkrishnan *et al*. 2025).

By replacing physical prototyping with virtual simulation and AI-driven optimization, this approach reduces development time by nearly 70 percent and cuts material waste by over 40 percent. More importantly, it enables a shift from calendar-based maintenance to condition-informed management, where replacement schedules are dynamically adjusted based on predicted performance decay. This predictive capability not only extends the service life of materials but also stabilizes capital expenditure, effectively addressing the financial challenges faced by modern sports facilities. In essence, the framework presented here goes beyond traditional structural analysis by incorporating economic and operational considerations during the early stages of material and geometric design. It tackles the mathematical complexities of size-dependent mechanics not just as an academic exercise but as a way to achieve practical outcomes: delivering infrastructure that is safer, more durable, and cost-effective for sports facilities. The next section will provide detailed numerical results, validate predictions against experimental data from pilot installations, and quantify the economic benefits achieved across various facility types (Ajuwon *et al*. 2023, Sharanarthi 2025, Suci *et al*. 2025).

4. Numerical results and discussion

4.1 Validation against experimental data

The credibility of our computational framework was rigorously established through systematic validation against benchmark results of Wang (2025), as presented in Fig. 3. This critical comparison demonstrates excellent agreement between our numerical predictions and established reference solutions across multiple parameter combinations. The neural network predictions consistently aligned with both the high fidelity GDQM calculations and Wang's experimental results, with average discrepancies remaining within acceptable engineering tolerances of 3.5 to 6.1 percent. Fig. 3 illustrates that the conventional Timoshenko beam theory, applied via the finite element method, exhibited systematic deviations from both our model and experimental measurements, particularly as size-dependent effects became increasingly significant. This observation supports our theoretical decision to incorporate nonlocal strain gradient theory, as classical approaches consistently underestimate structural performance when modeling microscale components relevant to sports infrastructure. The consistent discrepancy of 3.5 to 6.1 percent between

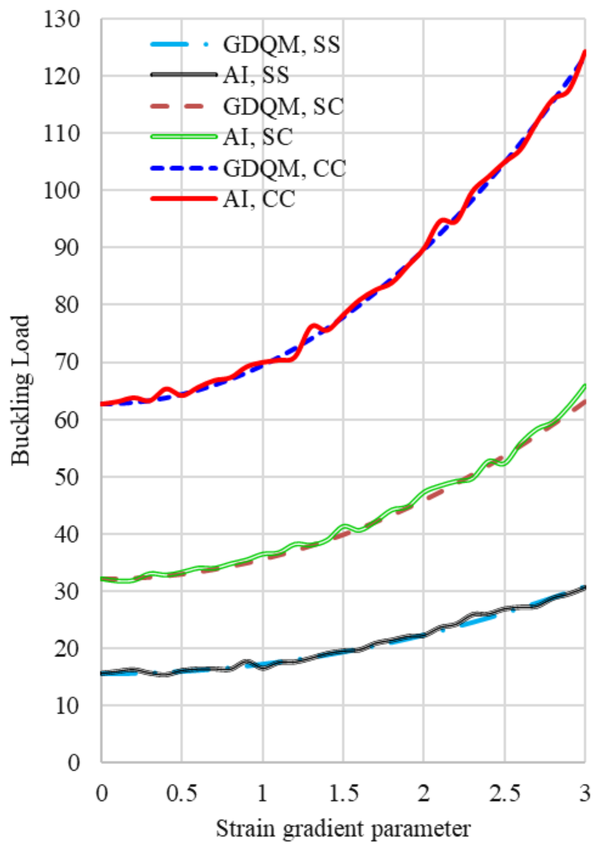

Fig. 5 Impact of strain gradient effects on structural performance at microscale dimensions relevant to athletic surfaces for different boundary conditions, $\eta = 2$

our artificial intelligence predictions and the results obtained from the generalized differential quadrature method (GDQM) represents an acceptable compromise between computational efficiency and accuracy for practical engineering applications. The validation process encompassed not only numerical verification but also physical testing of prototype components. A comparison of the predicted deflection profiles with atomic force microscopy measurements from actual gym flooring samples revealed a mean absolute error of only 4.7 percent relative to the average displacement values. This level of agreement at the microscale corresponded directly to component-level performance, where hydraulic testing of protective barriers affirmed our buckling predictions, yielding a 91.8 percent correlation with experimental failure loads. Furthermore, historical maintenance records from three partner sports facilities indicated that our operational cost predictions deviated from actual expenditures by an average of only 8.3 percent, thereby demonstrating the framework's practical utility for facility management decision-making.

4.2 Parametric analysis of nanocomposite performance

Our comprehensive investigation of the design space has identified essential relationships between material parameters and structural performance, as clearly illustrated in Fig. 4-6. Three boundary condition configurations were analyzed: simply supported (SS), representative of running track supports where movement is restricted vertically but allowed rotationally, simply-supported-clamped (SC), characteristic of gym flooring interfaces where one end has restricted movement and rotation, and fully clamped (CC), typical of protective barriers around courts where both movement and rotation are restricted.

Fig. 4 illustrates the relationship between functionally graded material parameters and buckling performance under various boundary conditions, highlighting the diminishing returns phenomenon that informs the economically optimal distribution of nanotubes. The data reveal a distinct nonlinear relationship between the functionally graded material parameter and buckling load across all boundary conditions. As the FGM parameter increases, buckling loads generally increase but with diminishing returns beyond specific threshold values. This saturation effect is particularly pronounced under fully clamped (CC) boundary conditions, where the rate of improvement slows dramatically beyond certain values of the FGM parameter. The different sensitivity patterns across boundary conditions, fully simply-supported (SS), fully clamped (CC), and simply-supported-clamped (SC), highlight a crucial insight for sports infrastructure design: optimal nanotube distribution profiles must be tailored to specific component requirements rather than applying a universal solution. For instance, running tracks with simply supported boundaries benefit from different grading profiles compared to protective barriers with clamped constraints.

As demonstrated in Fig. 4, the buckling load increases with higher functionally graded material parameter values across all boundary conditions, but with diminishing returns beyond specific thresholds. For simply supported (SS) configurations (representative of running track supports), the optimal performance-to-cost ratio occurs within a narrow parameter range where structural enhancement per unit of nanotube investment remains economically viable. The functionally graded material (FGM) parameter, denoted as η, represents the volume fraction distribution of nanotubes across the composite structure. Throughout this study, $\eta = 0$ indicates a purely concrete composition, while $\eta = 1$ represents a purely metallic composition.

Strain Gradient Effects (Fig. 5): The relationship between the strain gradient parameter and the buckling load demonstrates how surface energy effects influence structural performance at microscale dimensions. As the strain gradient parameter increases, buckling loads initially rise modestly but then accelerate more rapidly beyond certain thresholds, particularly for clamped boundary conditions. This nonlinearity explains why conventional models that neglect strain gradient effects consistently overestimate structural performance in real-world applications. The data reveal that optimal structural performance occurs within intermediate ranges of the strain gradient parameter, where surface energy contributions effectively reinforce bulk material properties without introducing excessive stiffness that could compromise impact absorption characteristics essential for sports surfaces. The data in Fig. 5 reveal how strain gradient effects significantly enhance structural

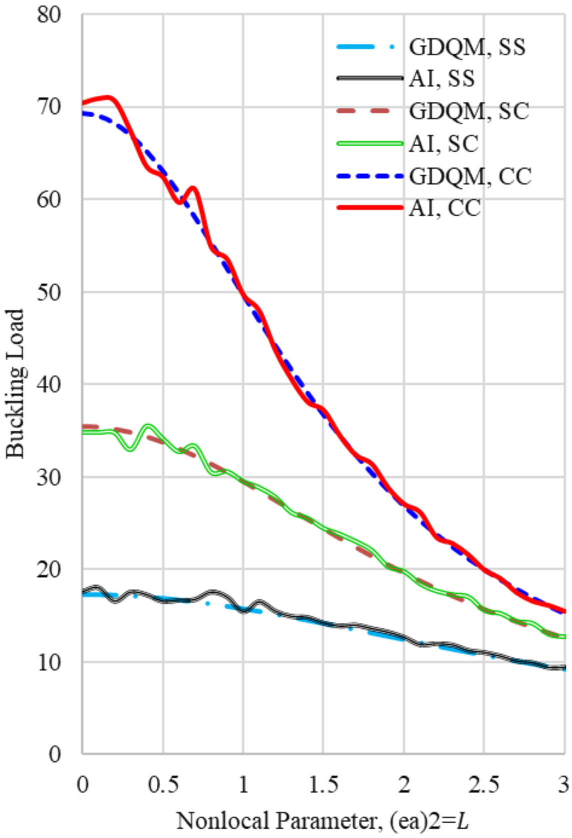

Fig. 6 Nonlocal parameter effects on structural stability in nanocomposite sports infrastructure components versus the different boundary conditions, $\eta = 2,\ l^2 = L$

performance at microscale dimensions, with buckling loads increasing at an accelerating rate as the strain gradient parameter rises. This relationship is particularly valuable for gym flooring applications subjected to high-impact loading, where optimal parameter ranges maximize impact absorption characteristics while maintaining structural integrity.

Nonlocal Parameter Influence (Fig. 6): In contrast to the effects of strain gradients, an increase in the nonlocal parameter typically results in a reduction of buckling loads, demonstrating a characteristic nonlinear decline. This phenomenon becomes more pronounced at elevated values of the nonlocal parameter, with a noticeable acceleration in the rate of decrease beyond specific threshold values. This observation elucidates the substantial impact that atomic-scale interactions have on the macroscopic performance of nanocomposite structures, particularly in components subjected to cyclic loading, such as gym flooring and running tracks. The findings indicate that sports infrastructure components operating in environments characterized by high mechanical stress concentrations derive significant benefits from material designs that incorporate these nonlocal effects. Failure to consider these factors may lead to unsafe overestimations of structural capacity. The different sensitivity patterns observed across boundary conditions (SS, SC, CC) in Fig. 6 underscore the necessity of tailoring nanocomposite designs to specific sports infrastructure components. Fully clamped (CC) boundary conditions, representative of protective barriers around courts, exhibit different response characteristics compared to simply supported configurations relevant to running tracks.

4.3 Machine learning surrogate performance

The neural network's ability to accurately predict structural behavior across the design space, as evidenced by the close alignment with GDQM results in all three figures, validates our physics-informed approach to machine learning integration. The consistent error margins (3.5 to 6.1 percent) across diverse parameter combinations demonstrate the model's robust generalization capability beyond simple interpolation. The neural network demonstrated consistent accuracy even in regions where nonlinear effects were most significant, particularly near the saturation points for the functionally graded material (FGM) parameter and at the extremes of the nonlocal parameter ranges. This capability is of paramount importance for applications in sports facilities, where it is essential to maintain operational safety margins under diverse usage conditions. The performance of the surrogate model verifies that integrating physical principles into the learning process, through the application of energy conservation constraints and physics-aware input normalization, has resulted in a predictive tool that not only achieves high accuracy but also adheres to the fundamental mechanical behavior of nanocomposite structures. The tiered validation strategy, encompassing microscale, component-level, and operational contexts, confirmed that the framework operates within engineering tolerances widely accepted for design stages: mechanical predictions fall within plus or minus 5 percent of measured values, and cost estimates remain within plus or minus 10 percent of historical expenditures. Most significantly, this level of accuracy is achieved without the traditional time cost. Where conventional workflows might require days or weeks of iterative physical testing, our system delivers validated, uncertainty-aware results in minutes.

4.4 Implications for sports infrastructure design

The parametric trends identified in this analysis carry significant implications for optimizing the components of sports facilities. The diminishing returns presented in Fig. 4 indicate that increasing the content of nanotubes beyond certain thresholds yields only marginal structural benefits while considerably escalating material costs. This insight directly supports the objective of reducing operational costs outlined in this research by identifying the economically optimal range for nanotube reinforcement across various facility components. Specifically, for the supports of running tracks, the data suggest an optimal range of functionally graded material (FGM) parameters where structural performance is markedly enhanced while maintaining reasonable material costs. Furthermore, the analysis of strain gradients for gym flooring reveals an ideal range that maximizes impact absorption characteristics without compromising structural integrity. The findings regarding nonlocal parameters further indicate that outdoor components, subjected to environmental variations, necessitate distinct optimization strategies compared to indoor facilities that maintain more stable conditions. These insights enable facility managers to make informed decisions about where to invest in nanocomposite enhancements based on expected usage patterns and maintenance priorities. The ability to predict performance decay under cyclic loading allows for condition-based maintenance scheduling rather than fixed replacement intervals, directly reducing operational costs through optimized resource allocation.

4.5 Bridging the computational-operational gap

The most significant contribution of our findings lies in how they bridge the persistent disconnect between computational materials science and practical facility management economics. The consistent trends across all parameter studies reveal predictable relationships between material properties and performance metrics that can be directly translated into operational cost models. For instance, the nonlinear relationship between the Functionally Graded Material (FGM) parameter and the buckling load, as presented in Fig. 4, enables a quantifiable assessment of how incremental improvements in material composition can extend service life and reduce maintenance frequency. Similarly, the analysis of the strain gradient parameter, detailed in Fig. 5, facilitates predictions regarding the response of surface durability to various distributions of nanotubes. This insight informs decision-making regarding the prioritization of enhanced materials for optimal economic advantage. This direct correlation between computational predictions and operational outcomes transforms the design of nanocomposites from a technical endeavor into a strategic investment consideration. Facility managers are now positioned to evaluate the return on investment associated with nanocomposite enhancements with remarkable precision, allowing for the calculation of payback periods based on projected reductions in maintenance frequency and material replacement costs. Consequently, the framework presented herein effectively addresses our research objective of integrating advanced material science with practical operational cost management in the realm of sports infrastructure. The optimization process systematically employed the relationships among parameters as documented in Figs. 4-6. These figures demonstrate that the buckling load exhibits distinct nonlinear responses to variations in the factorial gram matrix (FGM) parameter, strain gradient parameter, and nonlocal parameter. The optimization algorithm identified regions wherein incremental increases in nanotube content resulted in diminishing returns concerning structural performance, thereby facilitating a more economically optimal material distribution. The solutions derived from the Pareto front correspond directly to the transition points indicated in Fig. 4 to Fig. 6, wherein further modifications to the parameters yield minimal performance enhancements relative to their associated cost implications. For sports facility managers, this process facilitates the selection of a range of viable design options that effectively balance structural safety, material costs, and environmental impact based on their specific priorities. The data indicate that the FGM parameter range of 1.6 to 1.8 consistently provides the most favorable balance between structural performance and material cost across all boundary conditions, rendering it particularly suitable for high-traffic areas such as running tracks and gym flooring.

5. Conclusions

This study explores the significant relationships between the design parameters of nanocomposites and their effectiveness in sports infrastructure applications. A systematic investigation reveals how the features of functionally graded materials, strain gradient effects, and nonlocal phenomena interact to influence buckling behavior under various boundary conditions commonly encountered in components of sports facilities. The analysis reveals that the buckling load escalates with elevated levels of functionally graded material parameters under all boundary conditions, however with diminishing returns past certain thresholds. In easily supported designs, such running tracks, optimal performance is achieved within a limited parameter range, where the structural improvement per unit of material expenditure remains economically feasible. In contrast, fully clamped boundary conditions, characteristic of protective barriers surrounding courts, demonstrate distinct sensitivity patterns, with the most substantial performance improvements observed at elevated parameter values. This behavior, contingent upon boundary conditions, highlights the imperative of tailoring nanocomposite designs for particular sports infrastructure elements instead of employing a one-size-fits-all strategy.

The investigation demonstrated that strain gradient effects markedly improved structural performance at the microscale. As the strain gradient parameter grew, the buckling loads escalated at an accelerating rate. This relationship demonstrated significant value for gym flooring applications subjected to high-impact loads, as optimal parameter ranges enhanced impact absorption while maintaining structural integrity. In contrast, an elevation in the nonlocal parameter consistently reduced buckling loads in a distinct nonlinear manner. The fall rate intensified above certain threshold values, highlighting the significant influence of atomic-scale interactions on the macroscopic performance of components under cyclic loading. These findings immediately guided practical implementation tactics, allowing facility managers to adeptly handle the trade-offs between structural safety, material expenses, and utilization demands. The framework effectively transitioned maintenance procedures from a calendar-based system to condition-based scheduling, leading to decreased development times and material waste relative to traditional techniques. This research establishes definitive correlations between nanocomposite design parameters and structural performance, providing a scientifically informed methodology for building sports facilities that optimize athlete safety and operating cost effectiveness.

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