A Survey of Computational Techniques for Large-Span Steel Structures: Finite Element Analysis, Predictive Maintenance, and Deep Learning Approaches

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Abstract

This survey paper examines the interdisciplinary approach of integrating advanced computational techniques, such as finite element analysis (FEA) and deep learning, into the field of structural engineering to enhance the design, analysis, and maintenance of large-span steel structures. The increasing demand for these structures in modern infrastructure necessitates robust methodologies to ensure their safety and longevity. The paper highlights the transformative role of FEA in structural simulations, offering detailed insights into stress distribution and deformation, while recent advancements integrate machine learning to improve computational efficiency and predictive accuracy. Deep learning, particularly through neural networks, enhances predictive maintenance strategies by accurately forecasting structural health and optimizing maintenance schedules. The survey underscores the importance of data quality and model generalization, emphasizing the need for high-quality datasets and adaptable models to handle diverse operational conditions. Challenges such as computational intensity, scalability, and model interpretability are addressed, with future directions focusing on integrating emerging technologies and refining predictive models. By leveraging these advanced methodologies, the paper illustrates the potential for significant improvements in structural integrity, performance, and sustainability, ultimately contributing to the safety and reliability of large-span steel structures.

1 Introduction

1.1 Significance of Large-Span Steel Structures

Large-span steel structures are pivotal in contemporary engineering and architecture, enabling expansive areas to be covered without internal supports, thus facilitating open spaces essential for infrastructure such as sports arenas, exhibition halls, and transportation hubs [1]. The growing demand for these structures, particularly with corrugated steel designs, necessitates thorough behavioral analyses to ensure safety and performance, an area still requiring extensive research [2].

These structures are vital in specialized engineering applications, such as supporting cables and pipelines over challenging terrains like rivers, where traditional structures may fall short in terms of safety and efficiency [3]. Technological advancements in steel frame design further emphasize the importance of large-span steel structures in meeting modern architectural demands [4]. The incorporation of advanced materials, including meta-materials, significantly enhances their performance and efficiency [5].

In urban development, innovative structural solutions are crucial for addressing land scarcity, particularly in the construction of large-span underground structures [6]. Additionally, the rise of large-span concrete-filled steel tube (CFST) arch bridges is attributed to advancements in design theory and the utilization of high-strength materials [7].

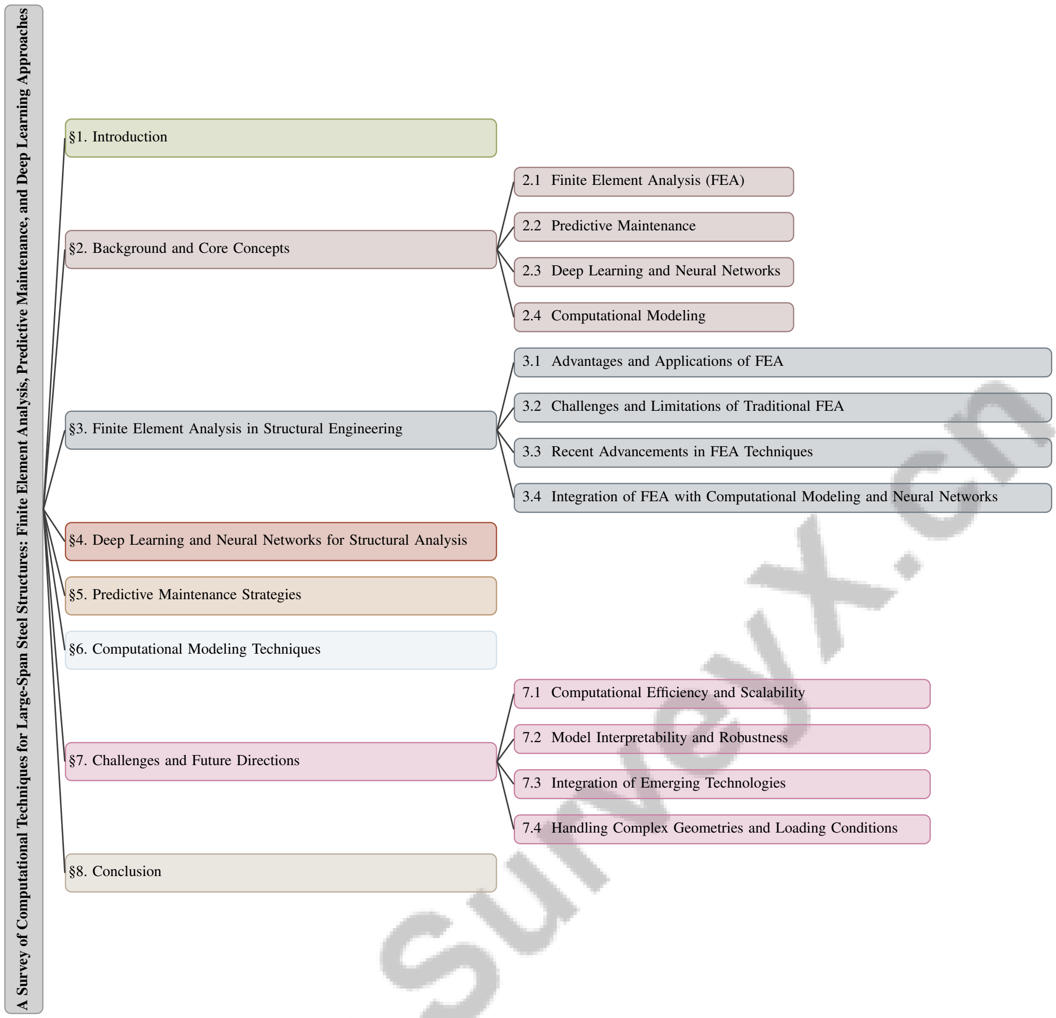

Figure 1: chapter structure

Material performance, such as that of 304L austenitic stainless steel, is critical, especially in applications prone to thermal fatigue [8]. Implementing effective quality control during manufacturing, like in hot strip steel sheets, is essential for maintaining structural integrity and longevity [9]. The necessity for high-quality datasets for accurate modeling becomes increasingly apparent, ensuring robust design and analysis based on empirical data [10].

1.2 Role of Advanced Computational Techniques

Advanced computational techniques, including finite element analysis (FEA), machine learning (ML), and deep learning (DL), are transformative in the design, analysis, and maintenance of large-span steel structures. The synergy of FEA with neural network computations has led to multiscale simulation frameworks that deepen the understanding of complex structural behaviors, as shown in bone remodeling studies [11]. These methodologies yield robust models that adapt to varying conditions, ensuring accurate predictions of structural health and performance [12].

The application of ML and DL is exemplified in optimizing control strategies for nonlinear systems, enhancing practical performance [13]. Predictive maintenance (PdM) strategies, vital for the longevity of large-span steel structures, greatly benefit from these computational techniques. For instance, model-free Deep Reinforcement Learning (DRL) algorithms learn optimal maintenance policies based on equipment health, providing actionable insights [14].

Extensive exploration of DL within predictive maintenance frameworks highlights neural networks' effectiveness in diagnostics and prognostics [15]. However, challenges persist, notably the inability of DL models to generalize across domains due to distribution discrepancies [16]. Despite these hurdles, AI's potential to enhance machine performance prediction and analysis is significant, paving new pathways for maintaining large-span steel structures [17].

Traditional computational methods, like FEA, continue to provide valuable insights into structural behaviors, as demonstrated in hyperelastic material model applications [18]. The response surface method, in conjunction with FEA, evaluates the effects of various parameters on the ultimate span of CFST arch bridges, underlining the critical role of these techniques in structural engineering [7]. These advancements highlight the importance of computational techniques in addressing the growing demands for safety, performance, and sustainability in modern engineering projects.

1.3 Interdisciplinary Nature of the Topic

The field of large-span steel structures exemplifies an interdisciplinary approach, integrating structural engineering, computational modeling, and predictive maintenance to tackle the multifaceted challenges of modern infrastructure. Structural engineering principles are fundamental for designing and analyzing large-scale frameworks, such as large-span steel pipe truss structures and prestressed concrete slabs, ensuring optimal load capacity, stiffness, and adherence to safety standards throughout the construction and operational phases. Recent studies on the construction monitoring of large-span steel roofs illustrate the necessity of systematic analysis and real-time monitoring to ensure structural integrity and compliance with design specifications, while innovative materials like prestressed and steel-reinforced concrete enhance anti-crack performance and load-bearing capabilities [6, 2, 12, 19]. FEA enhances this process by providing detailed simulations of structural behavior under various conditions, facilitating design optimization and proactive issue identification.

Predictive maintenance fosters interdisciplinary collaboration by employing advanced data-driven techniques, such as ML and DL, to forecast structural health and proactively identify maintenance needs, thus minimizing downtime and costs while enhancing system reliability in the context of the fourth industrial revolution [20, 21]. The implementation of advanced computational techniques, including deep learning and neural networks, within predictive maintenance frameworks enables complex data analysis, yielding accurate predictions of structural deterioration and lifespan, which is particularly critical for large-span steel structures where failure consequences can be severe.

Despite its interdisciplinary nature, the field faces challenges, including data privacy concerns, data complexity, and the need for collaboration among engineers, data scientists, and domain experts [20]. Overcoming these challenges necessitates a concerted effort to enhance communication and collaboration across disciplines, ensuring that insights from computational modeling and predictive maintenance are effectively integrated into structural engineering practices. This collaborative approach is vital for advancing the design, analysis, and maintenance of large-span steel structures, ultimately contributing to their safety, reliability, and longevity.

1.4 Structure of the Survey

This survey is structured into several sections, each addressing key aspects of computational techniques applied to large-span steel structures. The introduction provides an overview of the significance of these structures in modern engineering and architecture, emphasizing the transformative role of advanced computational techniques such as FEA and deep learning. The interdisciplinary nature of this field, which integrates structural engineering, computational modeling, and predictive maintenance, is highlighted to set the stage for subsequent discussions.

The second section, "Background and Core Concepts," delves into foundational concepts necessary for understanding the survey's focus, including detailed explanations of FEA, predictive maintenance, deep learning, computational modeling, and neural networks. This section equips readers with essential knowledge to appreciate the complexities of the topics discussed in later sections.

In the third section, "Finite Element Analysis in Structural Engineering," the application of FEA in designing and analyzing large-span steel structures is explored. This section covers advantages and practical applications of FEA, challenges and limitations of traditional methods, and recent advancements in FEA techniques. It also examines the integration of FEA with computational modeling and neural networks to enhance structural analysis.

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The fourth section, "Deep Learning and Neural Networks for Structural Analysis," investigates the role of deep learning in structural engineering, discussing innovative applications, the use of physics-informed neural networks (PINNs), and various architectures employed to enhance structural analysis and predictive maintenance.

The fifth section, "Predictive Maintenance Strategies," emphasizes the importance of predictive maintenance for large-span steel structures in extending lifespan and ensuring safety. This section explores the integration of ML and DL models into predictive maintenance strategies, methods for estimating remaining useful life, and challenges faced in implementing these strategies.

In the sixth section, "Computational Modeling Techniques," the survey details computational modeling techniques used in analyzing and maintaining large-span steel structures. It discusses the integration of FEA and machine learning, advanced data management, computational efficiency, and the significance of data quality and model generalization.

The seventh section, "Challenges and Future Directions," identifies current challenges in the field and discusses potential future research opportunities. Topics include computational efficiency and scalability, model interpretability and robustness, integration of emerging technologies, and managing complex geometries and loading conditions.

The conclusion encapsulates the essential themes explored, emphasizing the critical role of advanced computational techniques, such as integrating relational databases with FEA, in enhancing structural engineering practices. It underscores the importance of addressing challenges related to data size and integration in modern applications while identifying promising avenues for future research and development, particularly in improving structural performance analysis under variable force conditions and fostering modularity and adaptability in computational tools [22, 23].The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Finite Element Analysis (FEA)

Finite Element Analysis (FEA) is integral to structural engineering, enabling detailed simulations of structures under various conditions by discretizing them into finite elements. This approach is crucial for assessing responses to mechanical forces, thermal conditions, and environmental factors, especially in large-span steel structures. FEA excels in evaluating material behaviors like hyperelasticity and plasticity, with machine learning (ML) methodologies enhancing data-driven material models. For instance, Proper Orthogonal Decomposition combined with Feed Forward Neural Networks improves plasticity modeling, while artificial neural networks optimize hyperelastic material models, underscoring ML's potential to enhance predictive accuracy [24, 18].

Despite its widespread use, traditional FEA faces computational challenges, particularly with complex geometries and high-fidelity meshes required for mechanical meta-material simulations. The finite element method (FEM) demands significant computational resources, especially with spatial discretization, necessitating real-time predictive capabilities [25]. Topology optimization frameworks also require multiple FEA iterations, highlighting the need for efficient computational strategies [19].

Innovative frameworks like the Hybrid Finite Element Neural Network (FENN) Method integrate neural network predictions with FEA to enhance simulation accuracy and efficiency [11]. Advanced discretization techniques address numerical instability in hyperelastic materials [18]. The use of p-norm global stress measures for optimizing material distribution while adhering to stress constraints exemplifies advancements in FEA methodologies [26].

The integration of ML into FEA opens new avenues for optimizing structural designs and predictions. Techniques like the Physically Recurrent Neural Network (PRNN) method capture path-dependent material behaviors by embedding physics-based models, enhancing FEA capabilities [27]. Interactive geometry modification techniques allow changes in computational domains during simulations without the time costs of re-meshing [28].

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2.2 Predictive Maintenance

Predictive maintenance (PdM) is a crucial strategy in structural engineering, aiming to anticipate and prevent equipment failures, thereby minimizing unplanned downtimes and associated costs. This approach is vital for large-span steel structures, where unexpected failures pose significant safety hazards and operational disruptions [12]. Industry 4.0 has further highlighted PdM's importance, integrating it into systems management within computer-assisted manufacturing environments [29].

Advanced computational techniques, including machine learning and deep learning, have significantly enhanced PdM frameworks by facilitating complex sensor data analysis for accurate structural health and performance predictions. Traditional methods struggle with rigidity and cost, while deep learning offers flexibility and improved adaptability [14]. Leveraging historical operational data, deep learning models accurately predict the remaining useful life of structural components, enabling timely maintenance interventions [15].

In large-span steel structures, PdM is critical for monitoring stress and deformation during construction, ensuring structural integrity and longevity. Accurate real-time prediction of elastoplastic deformations remains challenging due to the path-dependent nature of material behavior [25]. Addressing this requires sophisticated modeling techniques to manage complex structural responses under diverse conditions.

PdM strategies optimize maintenance schedules, prevent failures, and enhance machine performance through comprehensive performance metric analyses. This enables tailored maintenance strategies aligned with the operational demands of large-span steel structures [17]. As PdM evolves, its role in structural engineering will become increasingly pivotal, ensuring the reliability and safety of critical infrastructure through advanced predictive capabilities.

2.3 Deep Learning and Neural Networks

Deep learning and neural networks have emerged as transformative tools in structural engineering, enhancing structural analysis and predictive maintenance precision and efficiency. These techniques model complex, high-dimensional data relationships, crucial for forecasting structural behaviors and optimizing maintenance strategies. Various neural network architectures, such as fully-connected, convolutional, and recurrent networks, effectively diagnose equipment health states and predict the remaining useful life (RUL) of structural components [15].

Physics-Informed Neural Networks (PINNs) incorporate governing physical laws into the training process, enhancing prediction accuracy in structural dynamics by integrating displacement and stress outputs [30]. The hierarchical structure of deep learning models allows automatic feature extraction, distinguishing them from traditional machine learning methods [31].

Graph neural networks (GNNs) improve predictions of deformation mechanisms in lattice architected metamaterials, showcasing deep learning's role in structural analysis [32]. Despite advancements, challenges remain in ensuring generalization capabilities across domains. Techniques like the BW-UDA method, integrating bi-weighting strategies, enhance prediction accuracy in engineering analysis problems [16]. While deep learning models excel in closed-end classification, broader applications require further development [31].

The integration of deep learning and neural networks into structural engineering revolutionizes the field by enhancing structural analysis and maintenance precision and efficiency. These techniques optimize design processes, such as topology optimization, significantly reducing computational demands and improving outcomes. Deep learning models are increasingly employed for predictive maintenance, enabling real-time monitoring and analysis to optimize maintenance tasks, addressing challenges like anomaly detection and RUL estimation [33, 19, 34]. By leveraging advanced architectures and incorporating domain-specific knowledge, these techniques are poised to play an increasingly critical role in large-span steel structures' design and upkeep.

2.4 Computational Modeling

Computational modeling is essential in structural engineering for simulating and analyzing large-span steel structures' behavior, integrating FEA with advanced deep learning techniques. This integration facilitates accurate predictions of complex structural behaviors, optimizing the design and maintenance of adaptable steel space frames crucial for large-span buildings [4].

Recent advancements have demonstrated the potential of combining statistical descriptors with feature maps from pre-trained deep learning models. Techniques like Multi-Loss Optimization Based Microstructure Reconstruction (MLO-MR) exemplify this approach, optimizing microstructure reconstruction by leveraging ML and traditional computational methods [35]. This fusion enhances structural simulations' fidelity, offering new avenues for improving predictive models' robustness and accuracy.

Innovative frameworks like Multi-Constrained 3D Topology Optimization (MC3DTO) integrate topological level-set formulations with augmented Lagrangian methods and assembly-free deflated FEA to address multi-constrained optimization problems [36]. These frameworks enable efficient exploration of design spaces, ensuring structures meet performance criteria while adhering to constraints, enhancing structural robustness.

Reduced-dimension surrogate models (RDSM) highlight computational modeling's role in characterizing damage tolerance in composite and metal structures. These models efficiently predict structural integrity by capturing individual damage mechanisms' interactions, facilitating proactive maintenance strategies [37]. Such techniques are crucial for managing complexities associated with dynamic loading conditions typical of large-span steel structures.

Neural networks' integration into computational modeling frameworks is exemplified by methods embedding physical laws into their architecture, such as the Physics-Augmented Neural Network (PANN). This approach ensures predictions are data-driven and grounded in fundamental physical principles, enhancing models' reliability and applicability in structural engineering [38].

Cohesive zone models and extended finite element methods (X-FEM), combined with experimental techniques like nanoindentation and scratch testing, provide a comprehensive methodology for failure analysis in structural components [39]. This integration of numerical simulations with empirical data offers a robust framework for understanding and mitigating potential failure mechanisms in large-span steel structures.

Deep learning architectures, such as deep convolutional autoencoders combined with modified LSTM networks, have been proposed to learn and predict fluid systems' dynamics in a low-dimensional feature space [40]. This approach exemplifies deep learning's potential to enhance predictive modeling capabilities across various domains, including structural engineering.

Computational modeling, integrating FEA and deep learning, plays a pivotal role in advancing large-span steel structures' design, analysis, and maintenance. By combining traditional maintenance practices with advanced computational techniques, including AI and Large Language Models (LLMs), engineers can create highly accurate and efficient predictive maintenance models. This innovative approach enhances critical infrastructure components' reliability and safety while significantly extending operational longevity by optimizing maintenance schedules and reducing downtime through improved failure prediction and automated analysis [41, 21, 22, 42].

3 Finite Element Analysis in Structural Engineering

The advancement of structural engineering has highlighted Finite Element Analysis (FEA) as a crucial tool for tackling complex design issues and optimizing structural performance. This section delves into the benefits and uses of FEA, emphasizing its role in analyzing stress distribution and deformation in large-span steel structures. The integration of FEA with advanced methodologies has significantly enhanced construction efficiency and safety, setting the stage for a comprehensive exploration of its advantages and practical applications in the following subsections.

3.1 Advantages and Applications of FEA

Finite Element Analysis (FEA) is indispensable in structural engineering, providing detailed insights into stress distribution and deformation of large-span steel structures. By breaking down complex geometries into finite elements, FEA facilitates precise simulations of structural responses, crucial for safety and performance. Its application extends to evaluating erection methods for steel structures, enhancing construction efficiency and safety [7].

The synergy of FEA with advanced computational techniques, such as machine learning and deep learning, has further expanded its application scope and precision. For instance, Graph Neural Networks (GNNs) outperform traditional methods by effectively modeling complex, non-linear relationships in lattice structures [32]. This demonstrates FEA's potential when combined with sophisticated computational models for more accurate structural analyses.

As illustrated in Figure 2, the key applications and advancements of FEA in structural engineering are highlighted, emphasizing its integration with artificial intelligence for enhanced modeling and predictive maintenance, as well as optimization techniques for improved material usage and construction processes. FEA optimizes construction processes by minimizing material usage and enhancing safety through accurate predictions of structural responses, identifying potential issues during design and construction [41, 43, 12]. It allows comprehensive simulations to ensure design compliance while reducing risks associated with material failure and structural integrity. Integrating deep learning-based surrogate models into FEA frameworks has achieved remarkable accuracy in structural simulations, surpassing traditional regression models through automated feature extraction and complex data pattern modeling.

Advanced discretization techniques improve the stability and accuracy of numerical simulations, particularly in dynamic scenarios, showcasing FEA's advantages in structural engineering. The integration of active learning techniques in FEA significantly enhances the efficiency of training predictive models by minimizing the number of required samples, thus conserving computational resources. A novel -weighted hybrid query strategy, for example, achieves comparable prediction accuracy to traditional sampling methods while reducing sample size by up to 58% [43, 44]. The application of Graph Convolutional Networks (GCNs) in structural analysis exemplifies the superior accuracy achievable when FEA is paired with advanced neural network models.

FEA remains essential in structural engineering, continuously evolving to meet the challenges posed by complex structural systems. The integration of machine learning and deep learning technologies significantly enhances the accuracy and efficiency of structural analyses, enabling predictive maintenance strategies that minimize downtime and extend the lifespan of structures. By leveraging industrial sensor data and employing sophisticated algorithms, these technologies facilitate real-time monitoring and analysis, contributing to more resilient and sustainable engineering practices in the steel industry [45, 12, 19, 34, 46].

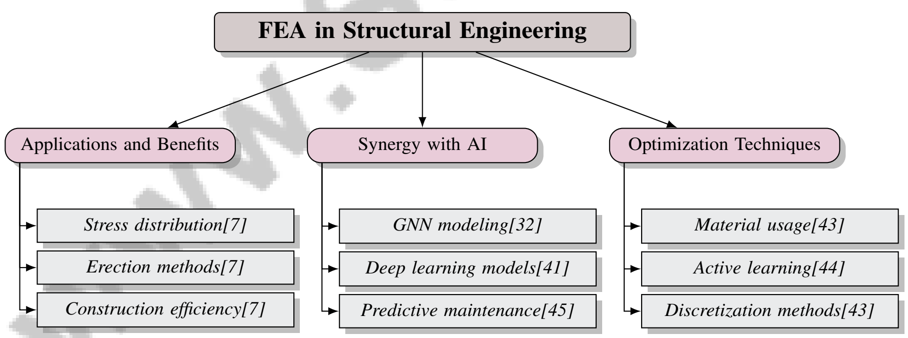

Figure 2: This figure illustrates the key applications and advancements of Finite Element Analysis (FEA) in structural engineering, highlighting its integration with artificial intelligence for enhanced modeling and predictive maintenance, as well as optimization techniques for improved material usage and construction processes.

3.2 Challenges and Limitations of Traditional FEA

Despite its foundational role, traditional Finite Element Analysis (FEA) methods face significant challenges, particularly in dynamic and complex scenarios. The computational expense becomes pronounced in nonlinear systems requiring extensive calculations across all loading paths, rendering traditional FEA impractical for real-time applications due to substantial resource demands [25]. This high computational cost is exacerbated by the complexities of nonlinear dynamics, which existing model reduction techniques often fail to address effectively [40].

Modeling damage mechanisms within high-dimensional parameter spaces presents additional challenges, as current methods struggle to provide accurate predictions due to their computational intensity [37]. This is particularly problematic for simulating material behavior under varying conditions, as traditional FEA methods often lack the flexibility to efficiently manage high-dimensional data.

Moreover, existing methods have not adequately addressed the theoretical limits of span diameter in structures like CFST arch bridges, complicating efforts to increase span diameter [7]. The computational demands of traditional FEA are heightened by the need for expensive re-meshing and simulation re-initialization when dealing with variable geometry, common in many structural engineering applications [28].

Traditional FEA also encounters limitations in managing delays and nonlinearities in complex systems, as existing benchmarks often fail to address these challenges adequately [13]. The high computational cost associated with formulations like the magnetic vector potential complicates FEA by increasing model degrees of freedom and, consequently, the demand for computational memory and time [47].

3.3 Recent Advancements in FEA Techniques

Recent advancements in Finite Element Analysis (FEA) have significantly enhanced the efficiency, accuracy, and applicability of structural simulations, particularly for large-span steel structures. Innovations include integrating advanced computational frameworks that optimize complex thin-walled structures. The MMC method effectively reduces design variables while achieving rapid convergence and clear structural boundaries, streamlining the optimization process compared to traditional methods [48].

The development of compact MATLAB implementations that combine FEA with p-norm stress sensitivity analysis has improved computational efficiency and accuracy, providing a robust tool for structural optimization [26]. This approach facilitates precise evaluations of stress distributions, critical for ensuring the safety and performance of large-span structures.

Moreover, deep learning frameworks aligned with the SIMP method for topology optimization, such as Density Sequence (DS) prediction and Coupled Density and Compliance Sequence (CDCS) prediction, enhance the learning of the optimization process, improving design accuracy and computational efficiency [19].

The application of LSTM multi-task frameworks has effectively simulated elastoplastic deformation, achieving low error rates and high predictive accuracy, particularly beneficial for capturing complex material behaviors in large-span steel structures [25]. Additionally, reduced-dimension surrogate models (RDSM) have demonstrated high accuracy in predicting total damage energy, enhancing the understanding and computational efficiency of damage mechanisms in structural analysis [37].

In bridge design, studies have successfully determined ultimate spans for CFST arch bridges, showcasing advancements in addressing complex structural challenges [7]. The integration of deep convolutional recurrent autoencoders provides accurate predictions for complex fluid dynamics, outperforming traditional model reduction methods in stability and computational efficiency [40].

Furthermore, the mixed vector-scalar formulation significantly reduces computational costs while maintaining accuracy in modeling large-scale magnetization problems, offering a promising alternative to conventional methods [47].

These advancements in FEA methodologies not only enhance the precision and efficiency of structural simulations but also broaden their applicability, meeting the increasing demands for innovative solutions in the design and maintenance of large-span steel structures. By leveraging advanced computational techniques, including machine learning and physics-guided algorithms, FEA is undergoing a significant transformation, enabling optimized structural performance while improving safety and reliability across various engineering applications. Recent innovations, such as the DeepFEA framework and FEA-Net, utilize deep learning to accelerate transient FEA predictions and develop data-driven models that leverage physical principles, addressing challenges related to computational intensity and multi-dimensional outputs while enhancing integration capabilities with relational database systems [22, 49, 43, 46].

3.4 Integration of FEA with Computational Modeling and Neural Networks

The integration of Finite Element Analysis (FEA) with computational modeling and neural networks marks a significant advancement in structural engineering, enhancing the ability to predict and analyze complex structural behaviors with improved precision and reduced computational costs. This synergy combines the detailed simulation capabilities of FEA, governed by partial differential equations, with the rapid predictive power of neural networks. Frameworks like FEA-Net and DeepFEA utilize physics-informed learning to optimize mechanical response predictions, significantly reducing computational time and enhancing accuracy in multi-physics and transient scenario simulations. Approaches such as finite element network analysis (FENA) and graph neural network-based models further streamline processes by enabling the simulation of interconnected physical systems and accelerating parameter exploration, respectively [49, 43, 46, 50].

A notable innovation in this domain is the integration of deep learning models with FEA frameworks, enabling real-time predictions of material responses under complex loading conditions while significantly reducing computational expenses. This approach leverages the ability of neural networks to model nonlinear material behaviors, such as viscoelastic and viscoplastic responses, thereby enhancing the accuracy of structural simulations [51].

In structural optimization, the Multi-Constrained 3D Topology Optimization (MC3DTO) method exemplifies the integration of FEA with computational modeling by employing assembly-free finite element analysis to manage multiple constraints efficiently. This method enhances the optimization process, allowing exploration of complex design spaces while maintaining computational efficiency [36]. Efficient load sampling techniques, combined with regression modeling, have also been utilized to identify critical force configurations, further illustrating the potential of integrating FEA with advanced computational techniques to optimize structural performance [23].

The integration of neural networks into the FEA framework is demonstrated through domain adaptation strategies, such as the BW-UDA method, which employs adversarial training to extract domain-invariant features from 3D design data. This approach enhances the prediction of engineering performance in unlabeled target domains, showcasing the potential of combining FEA with machine learning techniques to improve structural analysis [16].

Additionally, stress sensitivity analysis implemented in compact MATLAB code provides a streamlined approach for topology optimization, highlighting the efficiency gains achievable through the integration of FEA with computational modeling [26]. This integration facilitates precise evaluations of stress distributions, critical for ensuring the safety and performance of large-span structures.

The integration of Finite Element Analysis (FEA) with advanced computational modeling techniques and neural networks, such as the FEA-Net and DeepFEA frameworks, represents a significant advancement in structural engineering. This synergy enhances the accuracy and efficiency of structural analysis by leveraging physics-informed machine learning algorithms that optimize predictions of mechanical responses under various loading conditions. These methodologies facilitate rapid simulations of complex systems, effectively addressing uncertainties and improving applicability across diverse engineering scenarios, including multi-physics and multi-phase problems. As demonstrated by various case studies, these innovations reduce computational time while maintaining high fidelity in results, transforming the landscape of structural analysis [49, 43, 52, 46]. By leveraging the strengths of detailed simulations and predictive modeling, this approach contributes to the development of more robust and reliable models, ultimately ensuring the safety and longevity of large-span steel structures.

4 Deep Learning and Neural Networks for Structural Analysis

4.1 Innovative Deep Learning Applications

Deep learning applications in structural analysis have revolutionized predictive accuracy and computational efficiency. The Deep Neural Operator (DNO) model serves as a surrogate for traditional Finite Element Analysis (FEA), offering rapid mechanical response predictions essential for real-time analysis and design optimization [53]. This integration streamlines computations, providing adaptable solutions superior to conventional methods.

Neural networks, when integrated with numerical techniques, enhance modeling of complex material behaviors like hyperelasticity, as demonstrated by Franke et al., facilitating accurate simulations under varied loading conditions [54]. In structural health monitoring, Vashisht et al. illustrate deep learning's capability to manage high-dimensional data and uncertainty, crucial for predictive maintenance strategies that ensure structural longevity and safety [55].

Algorithmically consistent deep learning frameworks, such as those by Rade et al., improve optimized design predictions, aligning computations with physical constraints and accelerating structural optimization [19]. However, the robustness of these models faces challenges from adversarial attacks, necessitating robust defenses to ensure reliability in predicting the Remaining Useful Life (RUL) of structural components [56].

These applications highlight the transformative potential of computational techniques in enhancing the safety and efficiency of large-span steel structures. By harnessing deep learning, engineers develop accurate predictive models that streamline topology optimization, reducing mean squared error in compliance predictions significantly and supporting transitions to higher-resolution designs [33, 19].

4.2 Physics-Informed Neural Networks (PINNs)

Physics-Informed Neural Networks (PINNs) enhance structural engineering by embedding physical laws into neural network architectures, improving analysis accuracy and efficiency. PINNs solve partial differential equations (PDEs) governing structural dynamics without extensive labeled data, offering a robust tool for complex analysis [30]. By incorporating governing equations as constraints during training, PINNs ensure predictions adhere to physical principles, enhancing generalization [57].

The DCPINN-TO method integrates PINNs into topology optimization, efficiently computing displacement fields and strain energy, reducing computational costs while maintaining high accuracy [30]. PINNs also predict stress tensor fields using U-Net architectures, satisfying equilibrium constraints crucial for large-span steel structures [57].

In predictive maintenance, PINNs optimize Remaining Useful Life (RUL) predictions, with techniques like ECLSTM showing significant improvements, emphasizing deep learning's role in enhancing maintenance strategies [58]. However, deploying these systems in critical applications requires addressing vulnerabilities like adversarial attacks to ensure reliability [56].

PINNs' ability to learn from fewer data points and handle input variations better than existing algorithms, as demonstrated by the DDQN approach, underscores their potential in structural applications [59]. Leveraging traditional methods alongside advanced architectures, PINNs improve structural analysis accuracy and efficiency, contributing to the safety and reliability of large-span structures.

4.3 Deep Learning Architectures in Structural Analysis

Deep learning architectures have transformed structural analysis by efficiently modeling complex behaviors. These architectures use neural networks to process high-dimensional data, extracting intricate patterns essential for accurate predictions. Advanced deep operator networks, for instance, learn from multiphysics simulations, facilitating rapid inference for new input parameters and enhancing analysis efficiency [60].

Physics-informed deep learning methods improve these architectures by embedding physical laws into training, constraining learning to plausible solutions and enhancing model generalization [61]. Convolutional and recurrent neural networks, including LSTMs, model time-dependent behaviors and spatial patterns, capturing temporal dependencies and spatial hierarchies crucial for dynamic response evaluations [53, 62, 12, 63, 4].

Graph neural networks (GNNs) in structural analysis model complex interactions within lattice structures, facilitating accurate material behavior predictions under diverse conditions. Their application in stress distribution prediction in stiffened panels and deformation mechanisms in metamaterials demonstrates their ability to efficiently represent intricate designs, surpassing traditional FEA in efficiency and accuracy [32, 64].

The diverse range of deep learning architectures offers powerful tools for advancing structural analysis. By incorporating physics-guided learning and machine learning frameworks with traditional methods and domain knowledge, engineers enhance model accuracy, efficiency, and reliability for large-span structures. This multidisciplinary approach optimizes FEA through innovative tools like FEA-Net and finite element network analysis (FENA), addressing multi-physics and multi-phase problem complexities, ultimately improving structural safety and longevity [41, 22, 49, 43].

In recent years, the application of predictive maintenance strategies has gained significant attention, particularly in the context of large-span steel structures. These strategies not only enhance the longevity and safety of such structures but also optimize maintenance processes. Figure 3 illustrates the hierarchical structure of these predictive maintenance strategies, highlighting key components such as the importance of integrating machine learning and deep learning models, the estimation of remaining useful life, and the challenges and limitations associated with their implementation. This visual representation serves to clarify the multifaceted approach required for effective predictive maintenance, thereby enriching our understanding of its complexities and potential benefits.

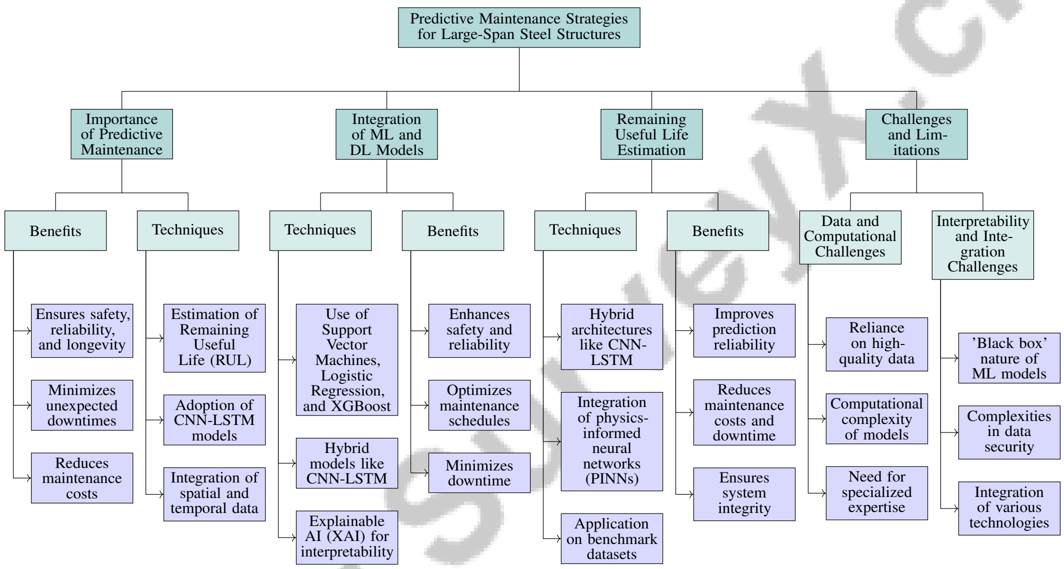

Figure 3: This figure illustrates the hierarchical structure of predictive maintenance strategies for large-span steel structures, focusing on the importance, integration of machine learning and deep learning models, remaining useful life estimation, and associated challenges and limitations.

5 Predictive Maintenance Strategies

5.1 Importance of Predictive Maintenance for Large-Span Steel Structures

Predictive maintenance (PdM) is essential for ensuring the safety, reliability, and longevity of large-span steel structures. These infrastructures require proactive strategies to detect and prevent potential failures, thereby minimizing unexpected downtimes and reducing maintenance costs compared to traditional manual methods [65]. A critical component of PdM is the estimation of Remaining Useful Life (RUL), which informs timely maintenance actions. Traditional regression techniques often fall short in RUL prediction accuracy, leading to the adoption of advanced hybrid deep learning models like CNN-LSTM, which enhance predictive capabilities by integrating spatial and temporal data [66, 67].

Incorporating machine learning into PdM frameworks significantly improves maintenance prediction accuracy. Various classification methods enhance PdM precision, facilitating effective maintenance planning, particularly in scenarios with unbalanced datasets common in the manufacturing sector [17, 59]. For large-span steel structures, PdM leverages intelligent sensors and real-time analytics to evaluate stress states, ensuring safety during construction and operation. This data-driven approach enhances structural integrity, prolongs operational lifespan, and aligns with the sustainability demands of the fourth industrial revolution [68, 20].

5.2 Integration of Machine Learning and Deep Learning Models

The integration of machine learning (ML) and deep learning (DL) models into PdM strategies has revolutionized the management of large-span steel structures by enhancing safety, reliability, and operational efficiency. These advanced techniques enable the development of predictive models that accurately forecast equipment failures, optimizing maintenance schedules and minimizing downtime [17]. ML algorithms such as Support Vector Machines, Logistic Regression, and XGBoost effectively analyze complex, multimodal sensor data, crucial for maintaining structural integrity [17].

Hybrid deep learning models, such as CNN-LSTM, combine CNNs for feature extraction with LSTMs for sequential learning, leveraging both spatial and temporal information to improve RUL estimation [66, 40]. Integrating Explainable AI (XAI) techniques within PdM frameworks enhances interpretability, allowing engineers to understand predictive models' decision-making processes and align maintenance strategies with operational goals [67].

Moreover, deep reinforcement learning in PdM strategies allows adaptive learning from limited data, enhancing predictive accuracy and robustness, particularly in data-constrained scenarios [59]. These integrations hold significant potential for improving the safety, reliability, and efficiency of large-span steel structures, paving the way for future advancements in engineering and infrastructure management [41, 42].

5.3 Remaining Useful Life Estimation and Uncertainty Quantification

Estimating the Remaining Useful Life (RUL) of large-span steel structures is crucial for operational efficiency and safety. Advanced computational models, including hybrid architectures like CNN-LSTM, effectively capture spatial and temporal patterns from sensor data, enhancing RUL prediction accuracy [66]. The integration of physics-informed neural networks (PINNs) with data-driven models, such as those developed by Nascimento et al., incorporates physics-based constraints into modeling cumulative damage, improving prediction reliability [69].

Uncertainty quantification is vital in RUL estimation, providing insights into variability and confidence levels associated with predictions. The MLMRGP framework, integrating high and low-fidelity data, robustly quantifies mode shape variations under uncertainty [58]. Machine learning models have demonstrated significant reductions in maintenance costs and downtime through accurate failure predictions, as seen in methods like PDDQN-PN, which enhance learning efficiency and consistency [68, 14].

Applying deep learning models to benchmark datasets, such as NASA's turbofan engine dataset, validates their effectiveness in prognostics and health management, ensuring robustness across different scenarios [56]. These advancements facilitate sophisticated maintenance strategies for large-span steel structures, optimizing schedules, minimizing downtime, and ensuring system integrity [42, 12, 45].

5.4 Challenges and Limitations in Predictive Maintenance

Implementing predictive maintenance (PdM) for large-span steel structures involves challenges that can affect their effectiveness. A primary challenge is the reliance on high-quality data, which is crucial for accurate predictions and model performance. Variability in data quality across operational conditions can significantly impact PdM model efficacy, necessitating extensive and reliable datasets [17]. Managing large datasets from numerous monitoring points is complicated by environmental factors affecting sensor accuracy [12].

The computational complexity of PdM models poses challenges, especially for real-time applications on low-power systems, where high computational demands limit practicality [66]. Implementing these models requires specialized expertise, which may not be readily available, complicating PdM strategy deployment [17].

The 'black box' nature of many machine learning models used in PdM can hinder interpretation and understanding, potentially impeding adoption due to non-transparent decision-making processes [70].

Ensuring interpretability and transparency is vital for gaining trust and successful implementation. Additionally, integrating various technologies within PdM frameworks introduces complexities in data security and real-time processing [71].

Addressing these challenges is essential for advancing PdM practices and ensuring the safety and longevity of large-span steel structures. By integrating Explainable AI (XAI) and advanced machine learning techniques, engineers can develop more robust predictive models, enhancing prediction accuracy, optimizing maintenance schedules, and fostering trust among operators [72, 22, 41, 42].

6 Computational Modeling Techniques

6.1 Integration of Finite Element Analysis and Machine Learning

Integrating Finite Element Analysis (FEA) with machine learning (ML) methodologies significantly enhances structural engineering by improving the accuracy and efficiency of structural analysis. This fusion enables the creation of advanced predictive models that simulate complex structural behaviors, optimizing the design and maintenance of large-span steel structures. Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are particularly effective in extracting features from multivariate time series data, crucial for predicting the Remaining Useful Life (RUL) of structural components [66]. This hybrid approach leverages CNNs' spatial feature extraction with LSTMs' temporal learning, producing robust predictions vital for predictive maintenance.

Deep learning algorithms excel at learning intricate patterns from extensive datasets, facilitating precise equipment health and RUL predictions [15]. The integration of traditional ML algorithms, such as Random Forest and Support Vector Machines (SVM), with neural networks further refines prediction accuracy, as demonstrated by frameworks utilizing classical ML techniques alongside neural network architectures [67].

Innovative methodologies like the Deep Active Learning Regression framework employ a student-teacher neural network architecture to predict failure probabilities and guide design space sampling, enhancing FEA's predictive capabilities. Additionally, graph neural networks (GNNs) effectively represent complex relationships within lattice structures, highlighting the potential of combining FEA with ML for improved structural analysis [32].

The integration of physics-informed neural networks (PINNs) with data-driven models advances cumulative damage modeling by embedding physics-based constraints into ML methods, ensuring predictions are grounded in fundamental physical principles [69].

Furthermore, deep reinforcement learning algorithms, such as DDQN, illustrate the potential of merging traditional Q-learning with deep learning to predict device failures based on sensor data [59]. This integration not only enhances the accuracy and efficiency of structural analyses but also fosters innovative solutions in structural design and maintenance, contributing to the safety and longevity of large-span steel structures.

6.2 Advanced Data Management and Computational Efficiency

Method Name	Data Management	Computational Efficiency	Integration Techniques
PMML[73]	Data Collection Sources	Real-time Telemetry	Combines Machine Learning
NP-ODE[52]	Data-driven Surrogate	Reduces Computational Costs	Neural Ordinary Differential
RDBMS-FEA[22]	Relational Database Management	-	Rdbms Into Fea
ASMF[74]	Online Data Collection	Adaptive Surrogate Modeling	Online Learning Integration

Table 1: Comparison of advanced data management and computational efficiency methods used in modeling large-span steel structures, highlighting their data management approaches, computational efficiency, and integration techniques. The table includes methods such as PMML, NP-ODE, RDBMS-FEA, and ASMF, each contributing uniquely to enhancing predictive maintenance and structural analysis.

Advanced data management and computational efficiency are pivotal in modeling and analyzing large-span steel structures, especially when integrating FEA with ML techniques. Effective data management is crucial for handling vast data from telemetry, error logs, and maintenance histories, which are essential for developing accurate predictive models [73]. Efficient processing of these complex datasets enables the extraction of meaningful insights that inform structural analysis and maintenance strategies. Table 1 provides a comprehensive comparison of various methods employed to enhance data management and computational efficiency in the context of large-span steel structures, illustrating their distinct approaches and integration techniques.

The NP-ODE (Neural Process-Ordinary Differential Equation) method exemplifies advancements in computational efficiency by reducing costs while providing robust uncertainty quantification and improved interpretability compared to existing surrogate models [52]. This method combines neural networks' strengths with ordinary differential equations, facilitating more accurate and efficient simulations of structural behaviors.

In FEA, supporting data management systems are essential for structuring and scaling environments that handle complex relationships and large data volumes [22]. These systems enable efficient data organization and retrieval, crucial for high-fidelity simulations and analyses. By leveraging advanced data management techniques, engineers can ensure computational models are grounded in reliable datasets, thereby enhancing the accuracy of structural predictions.

The on-the-fly construction of surrogate models further illustrates potential improvements in computational efficiency for structural analysis. This approach allows for adaptive refinement of surrogate models without offline training, significantly reducing computational time [74]. Streamlining the modeling process enables real-time analysis and decision-making, essential for maintaining the safety and performance of large-span steel structures.

The integration of advanced data management and computational efficiency techniques plays a pivotal role in enhancing structural analysis and predictive maintenance. By leveraging these innovations, predictive maintenance (PdM) can optimize maintenance schedules and improve prediction accuracy for system failures, ensuring the reliability and longevity of critical infrastructure components in complex environments like the steel industry and sectors undergoing the fourth industrial revolution. Organizations can minimize downtime and operational costs while maximizing system availability and performance [20, 21, 45, 42].

6.3 Data Quality and Model Generalization

Data quality is fundamental to developing reliable predictive maintenance models for large-span steel structures. High-quality data ensures models accurately reflect operational conditions and structural behaviors, which is vital for informed maintenance decisions. Poor data quality can undermine predictive maintenance models' accuracy, leading to misguided maintenance decisions that may incur financial losses and safety risks. Thus, robust data integrity and effective feature selection methodologies are crucial in predictive maintenance strategies. Leveraging advanced algorithms and artificial intelligence can enhance prediction accuracy, optimize maintenance schedules, and improve operational performance while mitigating risks associated with equipment downtime and system failures [75, 73, 76, 42].

Model generalization across different scenarios is equally important. Models must be robust enough to perform well under varying conditions and diverse data distributions. This capability is essential for ensuring effective predictive maintenance strategies in various operational environments. One promising approach to improving generalization is federated learning, which trains models across multiple decentralized datasets without direct data sharing, enhancing privacy and security. However, further development is needed to effectively handle heterogeneous data distributions and improve generalizability [77].

Future research should focus on advancing federated learning methodologies to accommodate the diverse datasets typical of large-span steel structures. By enhancing the generalization capabilities of predictive maintenance models and ensuring high-quality data inputs, engineers can create more reliable frameworks for predictive maintenance. This advancement is crucial for improving safety and extending the operational lifespan of critical infrastructure, particularly in increasingly complex computing systems. The integration of AI technologies, such as ML and deep learning, plays a vital role in optimizing maintenance schedules and improving prediction accuracy for system failures, thereby reducing unplanned downtime and associated costs. As industries transition towards the fourth industrial revolution, the shift to predictive maintenance signifies a significant evolution in maintenance strategies, underscoring the need for continued research and innovation to meet modern infrastructure demands [21, 42].

7 Challenges and Future Directions

7.1 Computational Efficiency and Scalability

Enhancing computational efficiency and scalability in the structural analysis of large-span steel structures is a persistent challenge. Traditional finite element methods (FEM) require substantial computational resources, especially with complex geometries and high-dimensional data, limiting real-time applications [47]. Deep learning models, such as CNN-LSTM frameworks, offer promising alternatives by utilizing spatial and temporal data for improved predictions, with ongoing research aimed at optimizing these models for computational efficiency and robustness across various RUL estimation datasets [66].

Advanced neural network architectures, including deep convolutional recurrent autoencoders, enhance computational efficiency by simplifying training processes and accommodating systems with variable parameters [40]. However, scalability remains a challenge due to high variability in connectivity and geometry [31]. Future research should focus on improving data quality, exploring hybrid models, and integrating predictive maintenance with emerging technologies to enhance computational efficiency and scalability [17]. The development of reduced-dimension surrogate models (RDSMs) could enhance predictive capabilities, although data quality remains crucial [37].

Incorporating explainable AI techniques into predictive models can clarify predictions, enabling stakeholders to understand machine degradation causes and improving model interpretability [67]. However, challenges persist with rare failure events where insufficiently diverse input data may compromise model robustness [59]. Addressing computational efficiency and scalability challenges requires integrating advanced modeling techniques, efficient data management, and scalable computational frameworks. Overcoming these challenges will enhance the development of sophisticated predictive models, improving structural assessments' accuracy and ensuring large-span steel structures' safety and longevity [2, 45, 3, 12, 4].

7.2 Model Interpretability and Robustness

Interpretability and robustness are critical for predictive models in structural engineering, particularly for large-span steel structures. Explainable AI techniques enhance prediction transparency by clarifying machine degradation causes, fostering stakeholder trust and informed decision-making [67]. However, a trade-off exists between the performance of classical machine learning algorithms and their explainability compared to more complex neural network models, which may offer superior predictive capabilities but lack transparency.

Robustness is equally essential, as predictive models must perform reliably across diverse conditions and data distributions. Graph Neural Networks (GNNs) offer advanced capabilities for modeling intricate structural interactions but introduce computational challenges in large-scale applications [78]. Ensuring model robustness requires addressing computational demands and scalability issues for real-world deployment.

Recent advancements in adaptive degradation process modeling have improved RUL prediction accuracy, facilitating real-time updates and effective uncertainty quantification [79]. These advancements suggest the potential for developing more robust predictive models that adapt to changing conditions and deliver reliable predictions across varying operational contexts.

Exploring digital twins (DTs) in predictive maintenance has highlighted the need for unified standards and ethical considerations related to data privacy and security [80]. Addressing these gaps is crucial for advancing predictive models' interpretability and robustness, ensuring accurate predictions while adhering to ethical standards and maintaining data integrity.

Enhancing interpretability and robustness requires integrating advanced computational techniques, addressing computational challenges, and considering ethical implications. By focusing on construction monitoring, stress analysis, and innovative design approaches, structural engineering can improve predictive models' reliability and accuracy for large-span steel structures, enhancing safety measures and extending these structures' lifespan [2, 3, 4, 12].

7.3 Integration of Emerging Technologies

Integrating emerging technologies into structural analysis and maintenance offers significant opportunities to enhance predictive models' efficiency, accuracy, and reliability for large-span steel structures. Hybrid models combining Physics-guided Neural Networks (PgNNs), Physics-informed Neural Networks (PiNNs), and Physics-encoded Neural Networks (PeNNs) address data scarcity by utilizing data-driven insights and domain-specific knowledge, improving predictive maintenance strategies' robustness and applicability [81].

Advancements in database capabilities for Finite Element Analysis (FEA) are crucial for supporting technology integration. Future research should focus on enhancing automated data integration methods and addressing database implementation limitations, essential for managing complex datasets [22]. Exploring a strictly neural network version of the finite element method and applying the FEIH()-GNN framework in other continuum mechanics areas presents further innovation opportunities in structural analysis [82].

Incorporating transformer-based models into predictive frameworks can enhance modeling of longer sequences and complex dependencies, improving predictive capabilities [83]. Integrating deep learning with symbolic reasoning, as suggested by Marcus, can address current limitations by enabling models to leverage data-driven and knowledge-based approaches [84].

Explainable AI (XAI) methods that are inherently interpretable, along with hybrid approaches combining data-driven and physics-based models, should be further developed to enhance transparency and reliability [85]. Extending reachability analysis to three-dimensional time series data and incorporating real-time data processing capabilities can bolster predictive models' robustness and applicability in dynamic environments [86].

Future research should prioritize practical hardware solutions for neural networks in predictive maintenance and creating standardized datasets for evaluation, vital for advancing the field and ensuring predictive model reliability [87]. Enhancing neural network robustness during training and extending verification techniques to ensure global stability are critical steps toward improving model resilience and performance [88].

Identifying modular components within monolithic networks and developing methods for learning more complex task representations can further enhance predictive models' adaptability and efficiency, contributing to advancements in structural engineering practices [89]. By integrating these emerging technologies, the field can develop more robust and reliable models, ensuring large-span steel structures' safety and longevity. Future research should explore optimizing computational efficiency in areas like image processing and natural language processing, yielding insights applicable to structural analysis [90]. Additionally, sector-specific predictive maintenance applications and sensor technology advancements should be investigated to enhance machine learning models' interpretability and adoption [70]. Integrated models accommodating system-level predictive maintenance complexities and emerging trends in machine learning and data analytics warrant further exploration [75].

7.4 Handling Complex Geometries and Loading Conditions

Analyzing complex geometries and varying loading conditions in large-span steel structures presents significant challenges, requiring advanced computational techniques and innovative modeling approaches. These structures experience diverse and dynamic loading scenarios, necessitating robust models for accurate structural response predictions. The surrogate matrix methodology efficiently handles complex geometries and nonlinear problems, reducing memory usage and computation time [91].

High-quality labeled datasets are crucial for predictive maintenance models' effectiveness, yet obtaining such data in real-world applications poses challenges impacting model reliability [92]. Future research should leverage IoT for real-time data collection and analysis, explore advanced deep learning architectures, and address current model limitations to enhance predictive maintenance strategies [93]. Integrating scalable hierarchical parallel methods can improve non-symmetric systems' handling and communication efficiency, essential for processing complex structural data [94].

Interactive geometry modification techniques show promise in modifying computational domains during simulations without re-meshing and restarting analyses, enhancing mesh deformation algorithms' robustness [28]. Future research will focus on expanding these methods to address dynamics, acoustics, and thermal issues in structural optimization [48].

Graph Neural Networks (GNNs) have emerged as powerful tools for surrogate modeling in complex simulations, yet improving their adaptability to various scenarios and performance with limited training data remains essential [50]. Extending Physics-Informed Neural Networks (PINNs) to address more complex partial differential equation systems offers a promising direction for future research, facilitating advancements in complex structural analyses [61].

Utilizing multigrid preconditioners in topology optimization has shown potential for optimizing hybrid approaches and exploring adaptive strategies for switching between GMG and AMG preconditioning based on specific problem characteristics [95]. Additionally, adapting models to new boundary conditions not represented in training data underscores the need for further advancements in model robustness and adaptability [96].

Addressing challenges in large-span steel structures and investigating innovative solutions—such as advanced construction monitoring, optimal steel mesh layouts, and steel space frames—can enhance robust and reliable model development. These advancements will significantly contribute to large-span steel structures' safety, durability, and longevity, as evidenced by recent studies demonstrating simulation analyses and stress monitoring effectiveness in ensuring structural integrity during construction phases [2, 3, 4, 12]. Future research should continue enhancing computational techniques' robustness and exploring additional applications in complex simulation scenarios, ensuring predictive models remain accurate and efficient across various structural contexts.

8 Conclusion

This survey explores how advanced computational methods, particularly finite element analysis (FEA), deep learning, and predictive maintenance, are revolutionizing the design, analysis, and upkeep of large-span steel structures. These methods have greatly improved the precision and efficiency of capturing complex material behaviors, surpassing traditional approaches. The integration of machine learning has been pivotal in enhancing load capacity and crack resistance, underscoring the need for sophisticated computational strategies in structural engineering.

The interdisciplinary fusion of structural engineering, computational modeling, and neural networks has been instrumental in optimizing structural performance and integrity. This synergy has resulted in predictive models that not only boost accuracy but also offer fresh insights into material behavior, as evidenced by their superior performance in engineering contexts. The ability of these models to adapt across various scenarios highlights their promising potential for future advancements.

As computational techniques continue to evolve, they hold the promise of significantly advancing structural engineering practices. Future research should focus on refining these models to enhance their scalability, interpretability, and robustness, ensuring they effectively address the complexities of modern infrastructure. By driving innovation in computational methodologies, the field can develop more reliable and efficient solutions, ultimately improving the safety and durability of large-span steel structures.

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