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# Artificial Intelligent in Optimization of Steel Moment Frame Structures: A Review

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***Abstract*—**The integration of Artificial Intelligence (AI) techniques in the optimization of steel moment frame structures represents a transformative approach to enhance the design, analysis, and performance of these critical engineering systems. The review encompasses a wide spectrum of AI methods, including machine learning algorithms, evolutionary algorithms, neural networks, and optimization techniques, applied to address various challenges in the field. The synthesis of research findings highlights the interdisciplinary nature of AI applications in structural engineering, emphasizing the synergy between domain expertise and advanced computational methodologies. This synthesis aims to serve as a valuable resource for researchers, practitioners, and policymakers seeking a comprehensive understanding of the state-of-the-art in AI-driven optimization for steel moment frame structures. The paper commences with an overview of the fundamental principles governing steel moment frame structures and identifies the key optimization objectives, such as efficiency of structures. Subsequently, it delves into the application of AI in the conceptual design phase, where algorithms aid in generating innovative structural configurations and optimizing material utilization. The review also explores the use of AI for real-time structural health monitoring and predictive maintenance, contributing to the long-term sustainability and reliability of steel moment frame structures. Furthermore, the paper investigates how AI-driven algorithms facilitate the calibration of structural models, enabling accurate prediction of dynamic responses and seismic performance. Thus, by reviewing and analyzing the recent achievements in applications artificial intelligent in optimization of steel moment frame structures, the process of designing, analysis, and performance of the structures can be analyzed and modified.

***Keywords*—**Artificial Intelligent, optimization process, steel moment frame, structural engineering.

## I. Introduction

THE integration of AI in the optimization of steel moment frame structures marks a paradigm shift in structural engineering, promising enhanced efficiency and performance. AI can play a significant role in the optimization of steel moment frame structures, offering advanced methods for design, analysis, and decision-making [1]. Recent years have witnessed a surge in the utilization of AI techniques for optimizing steel moment frame structures. Machine learning algorithms, particularly genetic algorithms, neural networks, and swarm intelligence, have proven to be powerful tools in efficiently exploring the vast design space and identifying and optimal solutions [2]. These methods enable structural engineers to consider a multitude of design parameters, leading to structures that are not only cost-effective but also robust in the face of dynamic loads and uncertainties [3]. Implementing AI in the optimization of steel moment frame structures requires collaboration between structural engineers, data scientists, and domain experts [4]. Additionally, it is crucial to validate AI models with real-world data and adhere to industry standards and codes for structural design and safety [5].

Over the past year, the advancements in AI have played a pivotal role in enhancing the efficiency, reliability, and sustainability of designing these critical structural elements [6]. Through the utilization of machine learning algorithms, optimization processes have become more dynamic, allowing for the consideration of a myriad of variables and parameters that were once challenging to incorporate [7].

Meta-heuristic algorithms for assessing the collapse risk of steel moment frame mid-rise buildings are presented by Jough and Şensoy [8] in order to provide a better risk management strategy in steel moment frames. Steel Moment-Resisting Frame Dependability via Interval Analysis using the FCM-PSO Method is studied by Jough and Şensoy [9] to enhance accuracy and decrease execution time in calculation of seismic fragility curves. Assessment of out-of-plane behavior of non-structural masonry walls using FE simulations is presented by Jough and Golhashem [10] in order to reduce self-weight axial compression of the walls with modern lightweight masonry units. To analyze variability via the creation of a tectonic fragility curved for an SMRF construction, an adaptive neuro-fuzzy method dependent on the fuzzy C-means techniques is implemented by Jough and Aval [11] to incorporate epistemic uncertainty and increasing calculation accuracy. Road map to BIM applications for identifying and contextualizing variables of infrastructure projects is presented by Ghasemzadeh et al. [12] to identify and prove the existing lack of using BIM for infrastructure projects. Epistemic Uncertainty Treatment Using Group Method of Data Handling Algorithm in Seismic Collapse Fragility is presented by Jough et al. [13] to increase precision, and reliability of the outcomes results. Uncertainty interval analysis of steel moment frame by development of 3d-fragility curves towards optimized fuzzy method is presented by Jough and Ghasemzadeh [14] to enhance accuracy and reduce execution time in driving the 3D-fragility curves. The contribution of steel wall posts to out-of-plane behavior of non-structural masonry walls is investigated by Jough [15] to provide smaller modification factors in masonry walls with wall post.

Soori et al. [16]-[19] proposed virtual machining methods for

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improving and assessing Computer Numerical Control (CNC) machining in virtual settings. Soori et al. [20] investigated the use of AI and machine learning to CNC machine tools in order to increase efficiency and profitability in component production processes. In order to enhance the functionality of machined parts, Soori and Arezoo [21] examined the subject of residual stress measurement and reduction in machining operations. To enhance the integrity of the surface and reduce residual stress while grinding Inconel 718, Soori and Arezoo [22] recommended employing the Taguchi optimization approach to determine the ideal machining settings. Dastres and Soori [23] examined how to utilize advancements in web-based decision support systems to provide solutions for data warehouse administration through support for decision-making. Dastres and Soori [24] examined uses of artificial neural networks to investigate methods to implement them to increase the efficacy of products. Dastres and Soori [25] suggested using communication systems in environmental issues to reduce the detrimental impacts of technology development on natural disasters.

Dimensional, geometrical, tool deflection, and thermal defects have been modified by Soori and Arezoo [26] to improve accuracy in 5-axis CNC milling processes. Recent developments in published articles are examined by Soori et al. [27] in order to evaluate and enhance deep learning, machine learning, and AI's effects on advanced robots. Soori and Arezoo [28] created a virtual machining system application to investigate if the tool life and cutting temperature throughout milling operations are influenced by the cutting parameters. Soori and Arezoo [29] investigated how coolant affected the cutting temperature, surface roughness, and tool wear when turning Ti6Al4V alloy. Soori et al. [30] studied how to improve quality control and streamline part production operations in industry 4.0 smart factories by utilizing the Internet of Things. To reduce the amount of wear on cutting tools while drilling, Soori and Arezoo [31] proposed a virtual machining system. Soori and Arezoo [32] reduced surface roughness and residual stress to raise the overall quality of products made with abrasive water jet cutting. In order to improve the precision of five-axis milling operations for turbine blades, Soori [33] calculated and compensated for deformation errors. Soori and Arezoo [34] studied the application of the finite element approach in CNC machine tool modification in order to assess and improve accuracy in CNC machining processes and components. Soori et al. [35] studied several energy use optimization techniques in order to assess and optimize energy consumption in industrial robots. Soori et al. [36] examined the negative and positive aspects of virtual manufacturing systems in order to assess and improve the part production process in Industry 4.0. In order to develop the supply chain management in advanced manufacturing, artificial neural networks are studied by Soori et al. [37].

This review aims to critically evaluate the role of AI in risk assessment and optimization processes for steel moment frame structures, exploring the advantages, challenges, and potential avenues for future research. Therefore, it is possible to review and assess the latest developments in AI applications for the optimization of steel moment frame structures, allowing for the examination and modification of the structural design, analysis, and performance processes.

## II. Generative Design by Topology Optimization

Topology optimization is a specific area where AI has made an impact. This approach involves determining the optimal layout of materials within a given design space to achieve the best structural performance. AI algorithms, especially generative design algorithms, can explore a wide range of design possibilities for steel moment frame structures [38]. They can optimize the distribution of material, shape, and connections to achieve the best structural performance while meeting specified constraints [6]. AI algorithms can assist in generating and analyzing complex topologies, helping engineers to discover innovative and efficient structural forms [39]. Here's how these technologies can be integrated into the design process:

1. Topology optimization: This is a computational design method which iteratively optimizes the material distribution within a given design space to achieve the best structural performance under specified constraints [40]. In the context of steel moment frame structures, topology optimization can help determine the optimal placement and configuration of structural elements such as beams and columns to maximize structural efficiency and minimize material usage [41]. This process typically involves defining design objectives (e.g., minimizing weight, maximizing stiffness) and constraints (e.g., displacement limits, stress limitations) [42], [43].
2. Generative design: Generative design, often powered by AI algorithms, explores a range of design possibilities by generating numerous design iterations based on specified input parameters and constraints. In the context of steel moment frame structures, generative design can explore various configurations and geometries, providing a broader design space for optimization [44]. Through the analysis and learning of previous successful ideas, AI can assist the generative design system in order to suggest more creative and effective solutions for problems [45].
3. AI in optimization: Machine learning algorithms can be employed to analyze historical data, simulation results, and real-world performance data to identify patterns and correlations. AI can assist in predicting the structural performance of different design configurations, helping designers make informed decisions during the generative design process [46]. Optimization algorithms, driven by AI, can efficiently navigate the complex design space and converge towards optimal or near-optimal solutions [47].
4. Integration and Iteration: The generative design and topology optimization processes should be iterative, allowing designers to refine and improve the design over multiple cycles [48]. AI algorithms can continuously learn from the results of previous design iterations, providing insights that contribute to better-informed decision-making in subsequent iterations [49].
5. Sensitivity analysis: AI can be used to perform sensitivity

analyses, helping designers understand how changes in design parameters impact structural performance [50]. This information is valuable for making trade-offs between conflicting objectives and refining the design to meet specific requirements.

6. Collaboration and visualization: AI-powered tools can facilitate collaboration among multidisciplinary teams by providing intuitive visualizations of design alternatives and their associated performance metrics [49]. Virtual and augmented reality technologies can enhance the visualization of design solutions, aiding in better communication and decision-making [51].

The intelligent generation method of innovative structures using machine learning is shown in Fig. 1 [52].

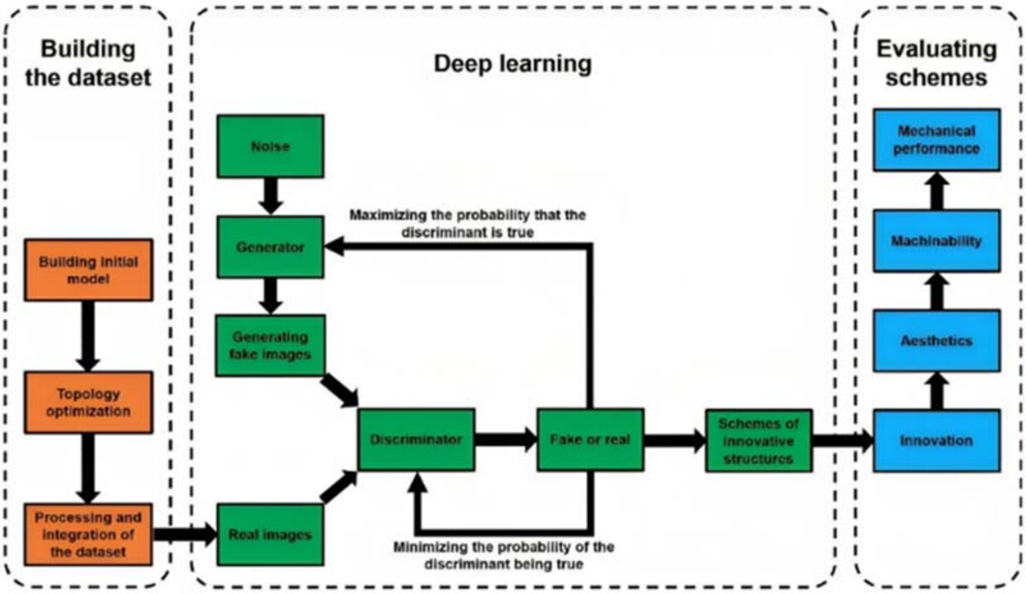


Fig. 1 The intelligent generation method of innovative structures using machine learning [52].

By combining generative design, topology optimization, and AI, engineers and architects can leverage computational tools to explore innovative and efficient steel moment frame structures, ultimately leading to optimized designs with improved performance and reduced material usage [53].

## III. Performance Prediction by Material Behavior Modeling

The use of AI in predicting the performance of steel moment frame structures through material behavior modeling and optimization is an innovative approach which can enhance the design and performance of such structures. AI can be used to model the behavior of steel materials under different conditions [54]. This includes predicting how steel moment frames will respond to various loads and environmental factors, aiding in the selection of optimal materials [55]. AI techniques, particularly machine learning models, can be trained to predict the performance of steel moment frame structures under different loading conditions [56]. This can aid in the early stages of design by providing quick and accurate assessments of the structural response. Here's a general outline of how AI can be applied in this context:

1. Data collection and preprocessing: gather data on material properties, historical performance of steel moment frame structures, and relevant environmental conditions. Preprocess the data to remove noise, outliers, and ensure consistency [57].
2. Material behavior modeling: develop a material behavior model that captures the complex interactions within the steel moment frame structure. Use AI techniques, such as machine learning algorithms, to model the material behavior based on the collected data [58]. Consider incorporating nonlinear material models that better represent the behavior of steel under various loading conditions [59].
3. Performance prediction: train the AI model to predict the performance of steel moment frame structures under different scenarios, including varying loads, environmental conditions, and material properties. Validate the model using a separate set of data to ensure its accuracy and reliability [60].
4. Optimization: utilize optimization algorithms within the AI framework to enhance the design of steel moment frame structures. Optimize parameters such as member sizes, connections, and material specifications to improve overall performance, considering factors like cost, safety, and sustainability [61].
5. Uncertainty and sensitivity analysis: incorporate uncertainty analysis to account for variations in material properties, external loads, and other factors that may affect performance. Conduct sensitivity analysis to identify critical parameters that significantly influence the behavior of the steel moment frame structures.
6. Real-Time monitoring and adaptation: implement real-

time monitoring systems to collect data on the actual performance of structures in the field. Use this real-time data to continuously update and improve the AI model, allowing for adaptive optimization over the lifespan of the structures [62].

7. Interdisciplinary collaboration: foster collaboration between structural engineers, material scientists, and AI experts to ensure a comprehensive understanding of the interactions between material behavior and structural performance.
8. Regulatory compliance: ensure that any proposed optimizations and designs comply with relevant building codes and safety standards [63].

An advanced machine-learning method for deriving state-dependent fragility curves of existing steel moment frames is presented in Fig. 2 [64].

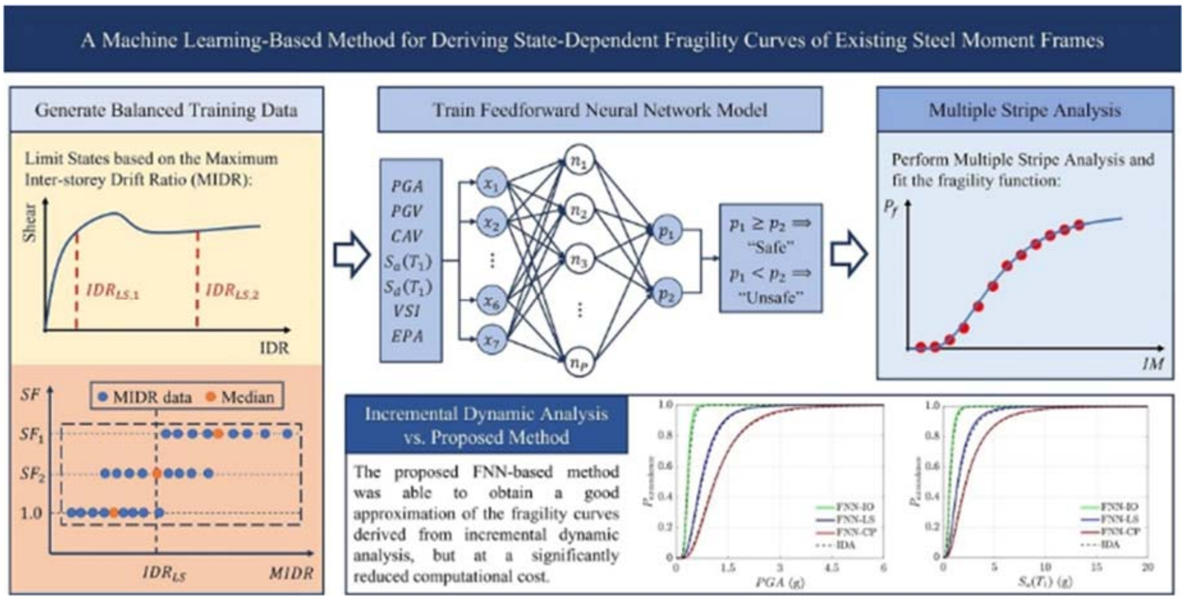


Fig. 2 An advanced machine-learning method for deriving state-dependent fragility curves of existing steel moment frames [64]

By integrating AI into the prediction and optimization processes, more robust and efficient steel moment frame structures can be created which are better tailored to specific conditions and requirements. This approach has the potential to revolutionize the field of structural engineering, making designs more adaptive, cost-effective, and resilient [65].

## IV. Structural Analysis using Finite Element Analysis

Use AI can enhance FEA by automating the analysis process, reducing computational time, and improving accuracy. Machine learning algorithms can learn from past simulations to predict structural behavior under different scenarios [66]. Integrating FEA with AI optimization in the design of steel moment frame structures provides a powerful tool for engineers to create efficient, cost-effective, and high-performance designs [67]. This approach enables the exploration of a vast design space, leading to innovative solutions that may not be apparent through traditional design processes [68]. There are three steps in applications of finite element analysis using structural analysis.

- Modeling: Create a detailed 3D model of the steel moment frame structure using FEA software. Define the geometry, material properties, and boundary conditions accurately.
- Loading: Apply appropriate loads and constraints to simulate real-world conditions. Consider various load cases, such as gravity loads, lateral loads, and seismic loads [69].
- Analysis: Perform FEA to obtain the structural response, including stresses, strains, and deformations. Evaluate the structure's performance under different loading scenarios.

The applications of AI in Structural Analysis and optimizations can be defined as

- Objective function definition: Define the optimization goals, such as minimizing material usage, reducing weight, or maximizing structural performance under certain criteria (e.g., minimizing deflections or stresses).
- Parameterization: Identify design parameters that can be adjusted to achieve the optimization goals. These parameters may include member sizes, connection details, and material properties [70].
- AI Algorithms: Utilize AI algorithms, such as genetic algorithms, particle swarm optimization, or machine learning techniques, to iteratively adjust the design parameters and improve the structure's performance [56].
- Integration with FEA: Adapt the AI optimization process to the FEA software to provide accurate evaluation of the structural performance [71].

As a result, the benefits of structural analysis using Finite Element Analysis can be explained as,

1. Efficiency: Speed up the design process by automating the exploration of a vast design space.
2. Improved Performance: Identify innovative and optimized solutions that may not be apparent through traditional

design approaches [72].

3. Adaptability: Easily adapt to changes in design requirements or loading conditions through rapid optimization iterations.
4. Cost-Effective: Optimize designs for efficiency, potentially reducing material usage and construction costs [39], [73].
5. Data-Driven Decision Making: Use data from simulations and optimizations to inform decision-making in the design and construction phases [74].

The von Mises stress progressive contour for the designed beam–column connection structures is presented in Fig. 3 [75].

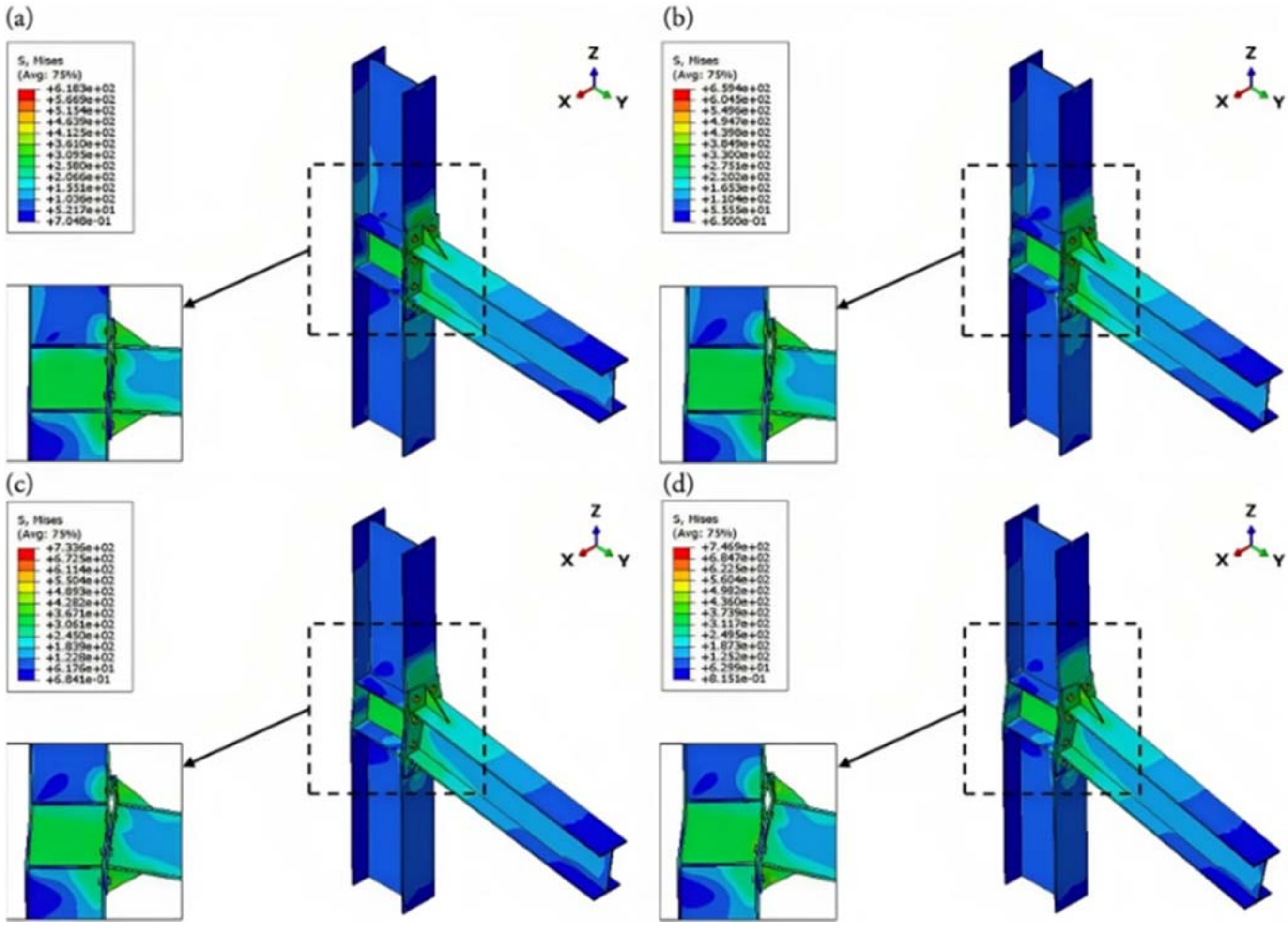


Fig. 3 The von Mises stress progressive contour for the designed beam–column connection structures [75]

The integration of FEA and AI in the optimization of steel moment frame structures holds the potential to revolutionize the way engineers approach structural design, leading to more efficient, cost-effective, and high-performance solutions.

## V. Data-Driven Design

Data-driven design and the integration of AI in the optimization of steel moment frame structures represent a promising approach for enhancing the efficiency and performance of structural design processes [76]. AI can leverage data from past projects and simulations to inform the design process. Historical data on structural performance, failures, and maintenance can be valuable in improving the reliability and efficiency of steel moment frame designs [77]. Here's how these concepts can be applied in the context of steel moment frame structures:

### *A. Data-Driven Design*

Data Collection: Gather historical data on the performance of steel moment frame structures. This can include data on material properties, structural configurations, loading conditions, and performance under various events (e.g., earthquakes) [78].

Database Creation: Build a comprehensive database that catalogs the collected data. This database serves as the foundation for training and validating machine learning models [79].

### *B. AI in Optimization*

Machine Learning Algorithms: Implement machine learning algorithms in order to analyze the collected data and identify patterns, correlations, and trends that may not be apparent through traditional methods. Supervised learning can be employed to predict structural responses based on input parameters, while unsupervised learning can help in discovering hidden patterns [80].

Optimization Algorithms: Utilize optimization algorithms, such as genetic algorithms or particle swarm optimization, in conjunction with AI to iteratively search for the best design parameters. These algorithms can consider multiple design variables, such as member sizes, connection details, and material properties, to find the optimal configuration [56], [81].

### *C. Integration of DDD and AI in Structural Design*

Performance Prediction: Develop AI models that can predict the performance of steel moment frame structures under different loading conditions. This can assist designers in making informed decisions during the early stages of the design process [82].

Design Parameter Optimization: Implement AI-driven optimization algorithms to search for the most efficient and cost-effective design parameters, considering factors like structural safety, material usage, and construction costs [83].

Real-Time Decision Support: Incorporate AI into the design process to provide real-time decision support. Designers can interact with the system, receive suggestions, and explore design alternatives based on the AI's analysis of the input parameters.

### *D. Benefits of the Approach*

Efficiency: DDD with AI can significantly reduce the time required for design iterations by automating the analysis and optimization processes [84].

Performance Improvement: The integration of AI allows for a more comprehensive exploration of the design space, potentially leading to superior structural performance.

Cost Optimization: By considering various design parameters and their impact on structural behavior, AI can contribute to the optimization of material usage and construction costs [85].

### *E. Challenges and Considerations*

Data Quality: The success of DDD and AI hinges on the quality and quantity of available data. Incomplete or inaccurate data may lead to unreliable predictions and optimizations.

Interpretability: Ensuring that the AI models provide interpretable results is crucial for the acceptance and understanding of the design decisions made by the system.

Ethical Considerations: As with any AI application, ethical considerations must be taken into account, particularly when it comes to safety-critical structures like buildings.

Implementing data-driven design with AI in the optimization of steel moment frame structures requires a multidisciplinary approach involving structural engineering, data science, and computer science. Additionally, collaboration with domain experts and continuous validation against real-world data is essential to ensure the reliability and effectiveness of the developed models.

## VI. Risk Assessment

The AI plays a pivotal role in risk assessment, providing a comprehensive understanding of potential vulnerabilities and failure modes in steel moment frame structures. By leveraging probabilistic models and advanced data analytics, AI facilitates a more nuanced evaluation of uncertainties associated with material properties, loading conditions, and seismic events [86]. This enables engineers to make informed decisions, optimizing designs to mitigate potential risks and enhance the overall safety and reliability of structures. AI can analyze historical data and current conditions to assess risks associated with steel moment frame structures [87]. This includes predicting potential failure modes, identifying vulnerabilities, and recommending measures to mitigate risks. Risk assessment in the context of utilizing AI in the optimization of steel moment frame structures involves identifying, evaluating, and mitigating potential risks associated with the application of AI in structural engineering [88]. Here are some key aspects to consider:

### *A. Data Quality and Integrity*

Risk: Inaccurate or incomplete data used for training AI models can lead to suboptimal or unsafe structural designs.

Mitigation: High-quality data collection, cleaning, and validation processes can be presented [89].

### *B. Model Accuracy and Reliability*

Risk: AI models may not accurately predict the behavior of steel moment frame structures, leading to design errors.

Mitigation: AI models using independent datasets and real-world case studies can be validated. So, feedback loops for continuous model improvement can be provided [90].

### *C. Interpretability of AI Models*

Risk: Lack of interpretability in AI models can make it challenging to understand how decisions are made, potentially leading to distrust.

Mitigation: Advanced AI models and explanations for model decisions can be used. Engineers can understand and trust the optimization recommendations in terms of process optimization [55].

### *D. Uncertainty and Sensitivity Analysis*

Risk: AI models may not adequately account for uncertainties in material properties, loading conditions, or other variables.

Mitigation: Analyses can be implemented in order to assess the impact of variations in input parameters on the structural optimization results [91].

### *E. Ethical Considerations*

Risk: Unintended biases in the data or model may result in unfair or unsafe design recommendations.

Mitigation: AI models for biases can be reviewed to follow ethical guidelines and standards in AI development [92].

### *F. Cybersecurity*

Risk: AI systems may be vulnerable to cyberattacks, potentially compromising the integrity of the structural optimization process.

Mitigation: Robust cybersecurity measures, including encryption, secure data storage, and regular security audits can be implemented [93].

### *G. Regulatory Compliance*

Risk: Failure to comply with industry regulations and standards may lead to legal and safety issues [94].

Mitigation: Relevant regulations in structural engineering can be used in order to provide AI-based optimizations based on established codes and standards.

### *H. Human-In-The-Loop Integration*

Risk: Overreliance on AI without human oversight may result in missed engineering considerations.

Mitigation: AI technology can be integrated by Implementing HITL approaches to combine AI insights with human expertise [95].

### *I. Long-Term Performance and Adaptability*

Risk: AI models may become outdated or less effective over time as structural design practices evolve.

Mitigation: Strategies for continuous monitoring, updating, and adapting AI models can be developed to ensure they remain relevant and effective [96].

### *J. Communication and Collaboration*

Risk: Lack of communication and collaboration between AI specialists and structural engineers may hinder successful implementation.

Mitigation: Advanced collaboration between AI experts and structural engineers can be implemented. So, the process can facilitate effective communication to ensure that the optimization process aligns with engineering requirements [97].

Utilizing energy-based approximation analysis, the incremental collapse durability of momentary steel frameworks constructed with various connecting details is evaluated which is shown in Fig. 4 [98].

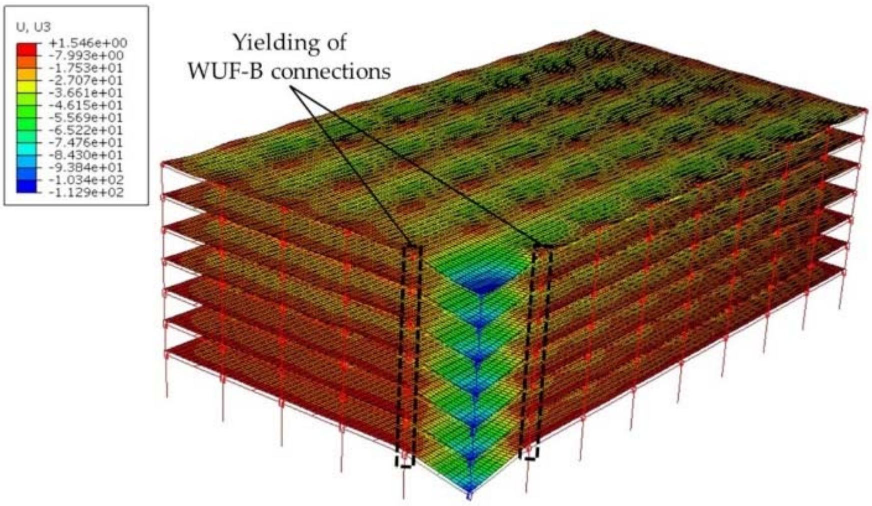


Fig. 4 Evaluation of progressive collapse resistance of steel moment frames designed with different connection details using energy-based approximate analysis [98]

By addressing these considerations, engineers can enhance the robustness and reliability of AI-based optimization in steel moment frame structures, minimizing potential risks and ensuring safer and more efficient designs.

## VII. Construction Optimization

Optimizing the construction of steel moment frame structures using AI involves leveraging AI algorithms and technologies to enhance various aspects of the construction process. Optimizing the design and construction of steel moment frame structures using AI involves leveraging advanced computational techniques to enhance efficiency, reduce costs, and improve overall performance [6]. AI can optimize construction processes by analyzing project schedules, resource allocation, and cost estimations. This can lead to more efficient construction timelines and cost-effective strategies for erecting steel moment frame structures. Implementing AI in the optimization of steel moment frame structures requires collaboration between structural engineers, construction professionals, and AI experts [56], [99]. It is essential to ensure that the AI applications align with industry standards and regulations while addressing the specific challenges of steel frame construction [100]. Here are some ways AI can be applied to optimize the construction of steel moment frame structures:

### *A. Design Optimization*

Generative Design: AI algorithms can be used to explore multiple design possibilities and identify the most efficient and cost-effective steel moment frame configurations.

Parametric Design: Parametric modeling can be implemented to enable quick adjustments to the design based on various parameters, allowing for optimization in real-time [101].

### *B. Material Selection*

AI-driven Material Analysis: AI can be utilized for analyzing the properties of different materials, helping to select the most suitable and cost-effective materials for the steel moment frame construction.

*C. Construction Planning and Scheduling*

Predictive Analytics: Predictive analytics can be used to forecast potential delays, resource constraints, and other project risks, enabling proactive adjustments to the construction schedule.

Resource Allocation: AI algorithms can be used to optimize the allocation of construction resources, such as labor, equipment, and materials, to maximize efficiency [102].

*D. Project Management*

Risk Management: AI-powered risk management systems can be implemented to identify and mitigate potential risks in the construction process, minimizing the likelihood of delays or cost overruns.

Real-time Monitoring: IoT sensors and AI to monitor construction activities can be utilized in real-time to provide immediate feedback and enabling quick responses to deviations from the plan [103].

*E. Quality Control*

Computer Vision and Image Analysis: Computer vision technologies can be employed to assess the quality of welds, connections, and other critical components during the construction process.

Machine Learning for Defect Detection: Machine learning models can be used to detect potential defects in steel components, ensuring the quality and safety of the final structure.

*F. Cost Estimation*

AI-driven Cost Models: AI models can be developed which can accurately estimate the costs associated with different phases of the steel moment frame construction, helping project managers plan budgets more effectively [7].

*G. Energy Efficiency and Sustainability*

Optimization for Sustainability: AI can be used to optimize the design and construction processes with a focus on sustainability, incorporating energy-efficient materials and practices.

*H. Supply Chain Optimization*

AI-driven Supply Chain Management: AI can be applied to optimize the supply chain by predicting material requirements, managing inventory, and identifying potential bottlenecks [104].

*I. Post-Construction Performance Monitoring*

Sensor Data Analysis: AI algorithms can be implemented to analyze sensor data from the constructed steel moment frame structure to monitor its performance over time and identify any maintenance or retrofitting needs [105].

*J. Collaborative Platforms*

AI-enhanced Collaboration: AI-powered collaborative platforms can be utilized to facilitate communication and coordination among various stakeholders involved in the construction project [106].

Fig. 5 presents a grouping technique for optimizing steel skeleton structures using a combinatorial search algorithm based on a fully stressed design [107].

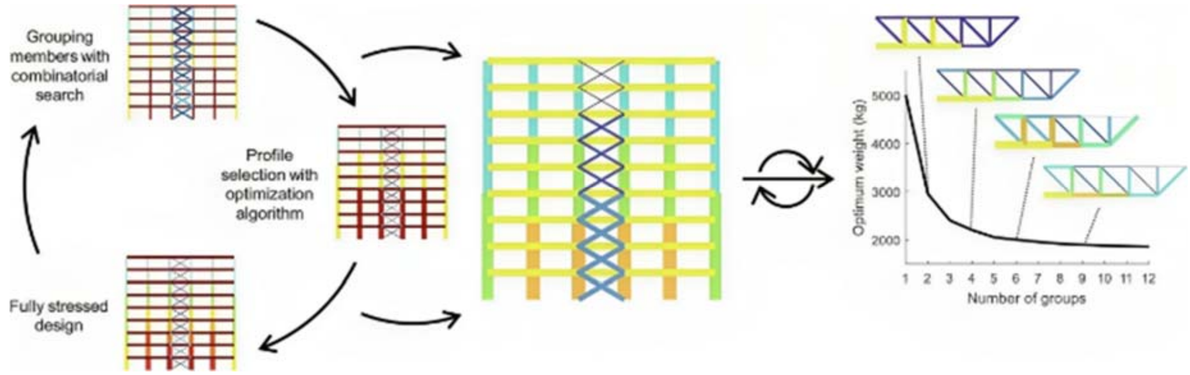


Fig. 5 A grouping technique for optimizing steel skeleton structures using a combinatorial search algorithm based on a fully stressed design [107]

By integrating these AI-driven approaches, construction processes for steel moment frame structures can be optimized for efficiency, cost-effectiveness, sustainability, and overall project success. Collaboration among architects, engineers, contractors, and AI specialists is crucial for the successful implementation of these technologies.

## VIII. Sensor Data Integration

Integrating sensor data with AI can significantly enhance the optimization of steel moment frame structures in various ways. Steel moment frame structures are commonly used in buildings and other infrastructure to resist lateral loads such as wind or seismic forces [108]. The integration of sensor data and AI in the optimization process can lead to improved performance, increased safety, and more efficient designs [109]. Incorporating data from sensors embedded in the structure allows for real-time monitoring [110]. AI algorithms can analyze these data to detect structural anomalies, predict potential issues, and recommend maintenance or intervention strategies [111]. Here's how this integration can be beneficial:

*A. Real-Time Structural Health Monitoring*

Sensors placed on the structure can continuously monitor various parameters such as strain, displacement, acceleration, and temperature.

AI algorithms can process this real-time sensor data to assess the structural health of the moment frame. Any anomalies or deviations from expected behavior can be quickly identified [112].

*B. Predictive Maintenance*

AI models can analyze historical sensor data to predict potential issues or failures before they occur. This allows for proactive maintenance and reduces the risk of unexpected structural failures, ensuring the long-term reliability of the steel moment frame [113].

*C. Optimization of Design Parameters*

AI algorithms can analyze large datasets, including sensor data and historical performance records, to optimize design parameters for steel moment frame structures.

The optimization process may consider factors such as material properties, cross-sectional dimensions, and connection details to enhance structural performance while minimizing costs [108].

*D. Adaptive Structural Control*

AI can be applied to develop adaptive control systems that adjust in real-time based on sensor feedback. This adaptive control can optimize the stiffness and damping characteristics of the moment frame, improving its ability to withstand dynamic loads [114].

*E. Energy Efficiency*

Sensor data, combined with AI, can be used to optimize energy consumption in buildings with steel moment frame structures.

AI algorithms can control heating, ventilation, and air conditioning systems based on real-time occupancy and environmental conditions, leading to energy savings [115].

*F. Seismic Performance Enhancement*

AI can be employed to develop advanced seismic retrofitting strategies based on real-time seismic sensor data.

The system can adjust damping devices or implement other measures to enhance the structure's resilience during seismic events [116].

*G. Data-Driven Decision Making*

AI-driven analytics can provide insights into structural behavior, helping engineers and decision-makers make informed choices during the design, construction, and maintenance phases.

*H. Integration with Building Information Modeling*

Sensor data can be integrated with BIM to create a comprehensive digital twin of the structure.

AI algorithms can then simulate various scenarios, enabling more accurate predictions of structural behavior under different conditions.

Dynamic reaction of a multi-story structure is shown in Fig. 6 [117].

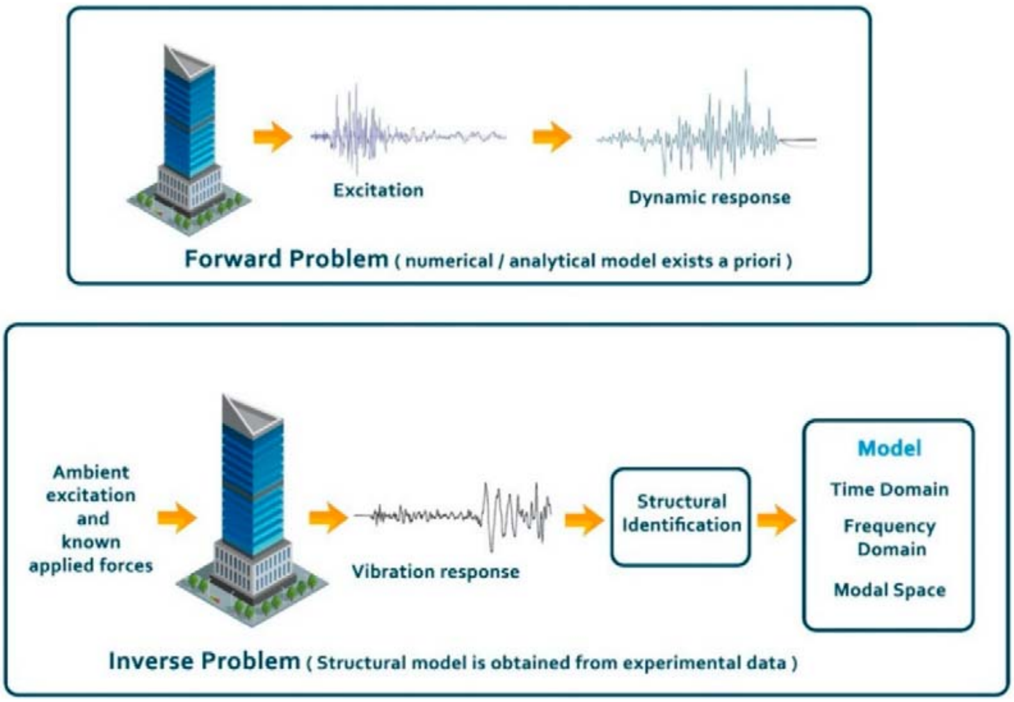


Fig. 6 Practical implementation of structural health monitoring in multi-story buildings [117]

In summary, integrating sensor data with AI in the optimization of steel moment frame structures enhances their performance, safety, and efficiency throughout their lifecycle. This approach allows for data-driven decision-making, predictive maintenance, and the development of adaptive strategies to ensure the resilience of these structures in the face of changing conditions.

## IX. Adaptive Structural Systems

Adaptive structural systems refer to systems that can adjust their properties or behavior in response to changing external conditions. When applied to the optimization of steel moment frame structures using AI, it involves leveraging AI techniques to enhance the design, analysis, and performance of these structures [56], [118]. AI can be used to develop adaptive structural systems that can adjust in real-time to changing conditions [119]. This includes dynamic control of damping systems, shape-changing elements, or other features to optimize performance under varying loads [120]. Here's a breakdown of how adaptive structural systems and AI can be integrated for optimizing steel moment frame structures:

### *A. Design Optimization*

Generative Design: AI algorithms can be employed to generate multiple design alternatives based on specified criteria and constraints. This helps in exploring a wide design space to identify optimal configurations for steel moment frame structures [121].

Topology Optimization: AI-driven topology optimization algorithms can optimize the layout and distribution of material within the structure to achieve maximum strength and stiffness while minimizing weight [122].

### *B. Structural Analysis*

Machine Learning for Analysis: Machine learning algorithms can be trained on large datasets of structural analyses to predict the behavior of steel moment frame structures under various loading conditions. This can lead to faster and more efficient analysis processes [123].

### *C. Performance Monitoring and Control*

Sensor Integration: Adaptive systems often involve the integration of sensors to monitor real-time structural performance [124]. AI algorithms can process the data from these sensors to detect anomalies, assess structural health, and make informed decisions about necessary adjustments [125].

Active Damping Systems: AI can be applied to control active damping systems within the structure. These systems adjust the stiffness or damping characteristics of the frame dynamically to mitigate vibrations or respond to changing environmental conditions [126].

### *D. Material Selection*

Material Behavior Prediction: AI can assist in predicting the behavior of different materials under varying conditions, aiding in the selection of optimal materials for specific components of steel moment frame structures [127].

### *E. Energy Efficiency*

Optimal Control Strategies: AI algorithms can optimize control strategies for energy-efficient operation of adaptive components within the structure, such as adjusting the stiffness of dampers to minimize energy dissipation during seismic events [128].

### *F. Learning from Performance Data*

Feedback Loops: Performance data from the actual operation of the structure can be fed back into the AI system to continuously improve its predictions and decision-making processes. This creates a feedback loop that enhances the adaptive capabilities over time [129].

### *G. Safety and Reliability*

Risk Assessment: AI can contribute to risk assessment by considering uncertainties in design parameters, construction variations, and environmental conditions [130]. This can improve the safety and reliability of steel moment frame structures [131].

Actuation concepts for adaptive high-rise structures subjected to static wind loading are shown in Fig. 7 [132].

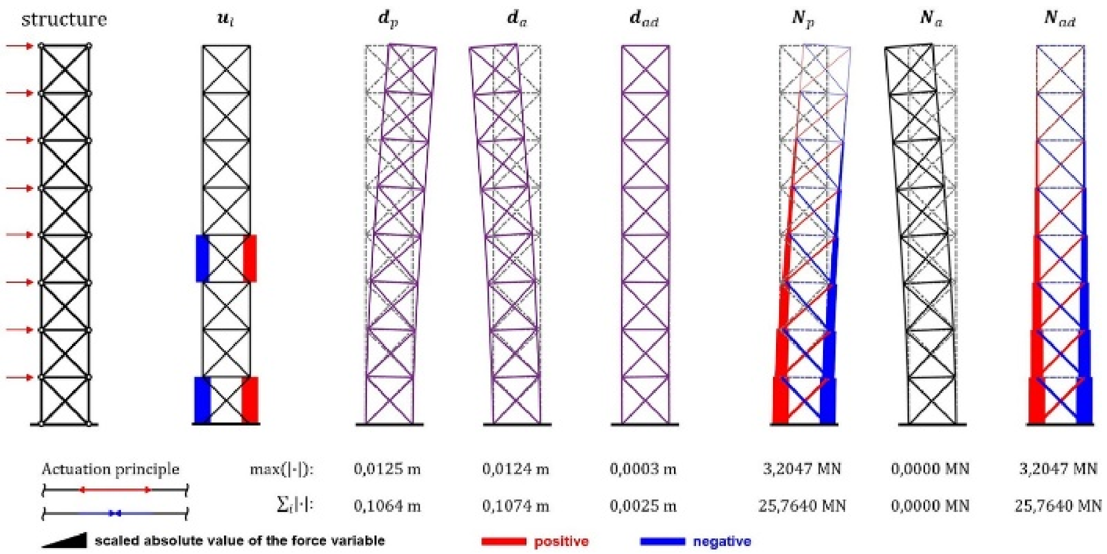


Fig. 7 Actuation concepts for adaptive high-rise structures subjected to static wind loading [132]

The integration of adaptive structural systems with AI in the optimization of steel moment frame structures represents a holistic approach to design and operation [118]. It considers not only the initial design phase but also the dynamic and changing conditions throughout the structure's lifespan. This synergy holds the potential to create more resilient, efficient, and safer structures.

## X. Energy Efficiency

Improving energy efficiency in the optimization of steel moment frame structures using AI involves integrating advanced algorithms and models to enhance the design, construction, and operation phases [56], [133]. AI can optimize the energy performance of steel moment frame structures by analyzing environmental conditions, occupancy patterns, and energy consumption data. This can inform decisions about heating, ventilation, air conditioning (HVAC) systems, lighting, and other energy-related components [134]. Here are several ways AI can contribute to energy-efficient optimization in steel moment frame structures:

### A. Design Optimization

Generative Design: AI algorithms can explore a vast design space, generating numerous design alternatives for steel moment frame structures. These algorithms can consider energy-efficient parameters, such as material usage, structural integrity, and thermal performance [135].

Topology Optimization: AI can assist in optimizing the layout of structural elements to minimize material usage while maintaining structural integrity, consequently reducing energy requirements for both fabrication and transportation of materials [136].

### B. Performance Prediction

Machine Learning Models: Machine learning models can be developed in order to predict the energy performance of steel moment frame structures based on various factors like geometry, materials, and environmental conditions [137]. These models can guide designers to choose the most energy-efficient options [138].

Simulation and Analysis: AI-powered simulations can predict the behavior of structures under different conditions, allowing for the selection of designs that optimize energy efficiency over the lifetime of the structure [139].

### C. Material Selection

Data-Driven Material Choices: AI can analyze extensive databases of material properties, considering factors like strength, durability, and thermal conductivity. This analysis helps in choosing materials that contribute to the energy efficiency of the structure.

Recyclability and Sustainability: AI can assess the environmental impact of materials, promoting the use of sustainable and recyclable materials, thereby reducing the overall energy footprint of the structure [140].

### D. Construction Optimization

Project Management: AI can optimize construction schedules, resource allocation, and logistics to minimize energy consumption during the construction phase.

Robotics and Automation: AI-driven robotics and automation in construction processes can be implemented to improve efficiency and reduce energy-intensive manual labor [141].

### E. Operational Efficiency

Smart Building Systems: AI for smart building management systems can be utilized which can optimize energy consumption during the operational phase. This includes intelligent HVAC systems, lighting control, and predictive maintenance.

Occupancy and Usage Monitoring: AI-driven sensors can be implemented to monitor occupancy patterns and usage, enabling the adjustment of building systems in real-time to minimize energy wastage [142].

#### 1. Life Cycle Assessment

AI-Based Life Cycle Analysis: Life cycle assessments using AI can be implemented to evaluate the environmental and energy impact of steel moment frame structures from raw material extraction to end-of-life considerations [143].

#### 2. Regulatory Compliance

AI for Compliance Monitoring: AI can be used to ensure that the constructed steel moment frame structures comply with energy efficiency regulations and standards [144].

Development of optimum cold-formed steel sections for maximum energy dissipation in uniaxial bending is shown in Fig. 8 [145].

Implementing AI in the optimization of steel moment frame structures for energy efficiency requires a multidisciplinary approach involving structural engineering, materials science, machine learning, and sustainability practices [146]. Collaboration between experts in these fields can lead to innovative solutions that significantly reduce the environmental impact of construction projects [147].

In order to obtain the optimized results in the optimization process of steel moment frame structures involving AI requires a comprehensive approach, code compliance and safety should be considered [148]. AI can assist in ensuring that the designed steel moment frame structures comply with relevant building codes and safety standards [149]. Automated checks can help identify potential issues and ensure that the final design meets regulatory requirements. Here are several key considerations and steps you might take:

1. Regulatory Compliance:
   - National, and international building codes and standards relevant to steel moment frame structures can be checked [87].
   - AI-driven optimization adheres to these codes and standards can be implemented. For example, in the United States, the American Institute of Steel Construction (AISC) standards are crucial [148].
2. Risk Assessment:
   - Risk assessment can be conducted to identify potential safety hazards associated with the use of AI in optimizing

steel structures.
- Identified risks can be mitigated to ensure the safety and reliability of the structures [65].

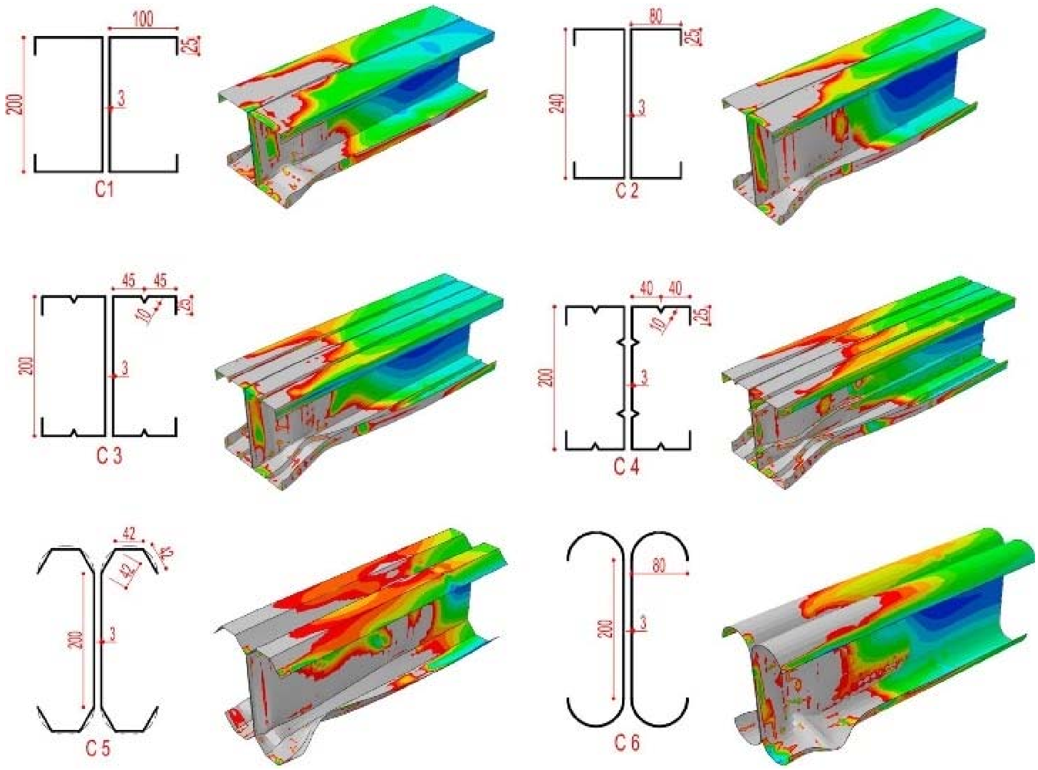


Fig. 8 Development of optimum cold-formed steel sections for maximum energy dissipation in uniaxial bending [145]

3. Certification and Approval:
- Structural engineers, architects, and relevant authorities can work together to obtain certifications and approvals for the AI-driven optimization methods.
- Optimization process aligns with industry-accepted practices can be implemented. So, the process does not compromise the structural integrity or safety of the moment frame structures [150].
4. Quality Assurance:
- Robust quality assurance procedures can be implemented to validate the accuracy and reliability of AI algorithms used in the optimization process [151].
- The AI models can be updated and validated to account for changes in codes, standards, or design requirements [152].
5. Data Quality and Security:
- The quality and integrity of the data used can be tested to train and test the AI models.
- Security measures can be implemented to protect sensitive structural data from unauthorized access or manipulation.
6. Explainability and Transparency:
- The AI optimization process should be transparent and explainable during optimization process to allow engineers and stakeholders to understand the decision-making process [139]. This is crucial for gaining trust in the AI-driven optimization and for meeting regulatory requirements [153].
7. Human-in-the-Loop (HITL):
- A human-in-the-loop approach can be implemented to review and validate AI-driven design decisions. This helps in catching any potential oversights or errors that may arise during the optimization process [154].
8. Documentation:
- Comprehensive documentation of the AI models, algorithms, and the optimization process can be implemented.
- Standards, and safety regulations can be considered regarding the relevant codes.
9. Continuous Monitoring and Maintenance:
- A system for continuous monitoring of the optimized structures can be established [155].
- Maintenance protocols can be implemented to address any issues that may arise over time [156].
10. Stakeholder Communication:
- Stakeholders, including clients, regulators, and project teams can be considered.
- Safety and compliance should be checked throughout the project lifecycle. Configurations of strain gauges and movement transducers is shown in Fig. 9 [157].

By addressing these considerations, one can help ensure that AI-driven optimization of steel moment frame structures complies with safety standards and regulatory requirements [3]. Collaboration with domain experts, transparent processes, and ongoing monitoring are key elements in achieving this goal.

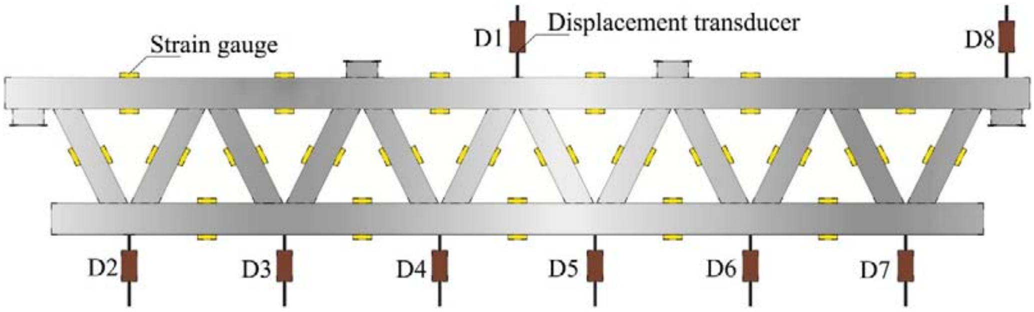


Fig. 9 Experimental study on square hollow stainless steel tube trusses with three joint types and different brace widths under vertical loads [157]

## XI. Conclusion

The application of AI in the optimization of steel moment frame structures can provide a significant advancement in the field of structural engineering. The integration of AI technologies has demonstrated the potential to enhance the efficiency, performance, and sustainability of steel moment frame structures through various optimization processes. AI algorithms, such as machine learning and optimization techniques, offer the capability to analyze vast amounts of data, consider complex design variables, and identify optimal solutions for steel moment frame structures. This results in structures that not only meet safety and regulatory requirements but also achieve superior performance in terms of load-carrying capacity, cost-effectiveness, and resilience.

The integration of AI in the optimization of steel moment frame structures marks a significant milestone in the field of structural engineering. By considering various interconnected factors and parameters simultaneously, AI-driven optimization processes can lead to innovative and resource-efficient designs that align with sustainability goals. Over the past year, we have witnessed the transformative impact of AI on enhancing the efficiency, reliability, and sustainability of these critical infrastructures. Moreover, AI enables real-time monitoring and adaptive control of steel moment frame structures, allowing for continuous optimization throughout their lifecycle. This dynamic responsiveness to changing conditions, such as environmental loads or structural deterioration, contributes to increased safety and longevity.

AI algorithms have proven instrumental in streamlining the design process, considering a multitude of variables and constraints to arrive at optimal solutions. The ability of AI to swiftly analyze vast datasets, predict structural behaviors, and iterate through numerous design alternatives has not only accelerated the optimization process but has also led to structures with improved performance and resilience. Furthermore, AI has demonstrated its prowess in adapting to dynamic environmental conditions, ensuring that steel moment frame structures are not only optimized for current demands but are also future-proofed against potential changes and uncertainties. The self-learning capabilities of AI systems contribute to continuous improvement and refinement of design strategies, making them increasingly adept at addressing evolving challenges in structural engineering. The ability of AI to analyze vast datasets and simulate various scenarios has empowered engineers to achieve unprecedented levels of precision in optimizing steel moment frame structures. This not only contributes to the overall safety and resilience of these structures but also enables a more cost-effective and resource-efficient approach to design and construction.

While the adoption of AI in structural engineering is promising, challenges such as data reliability, model interpretability, and ethical considerations must be carefully addressed. The need for large datasets, accurate modeling of complex structural behaviors, and the interpretability of AI-driven decisions are areas that demand attention. Additionally, the ethical considerations surrounding AI applications in structural engineering, such as bias in data and decision-making algorithms, warrant careful consideration to ensure the responsible use of these technologies. As the field continues to evolve, collaboration between structural engineers, data scientists, and other stakeholders will be crucial to harness the full potential of AI for optimizing steel moment frame structures.

In summary, the integration of AI has the potential to revolutionize the design, analysis, and maintenance of steel moment frame structures, paving the way for safer, more efficient, and environmentally conscious infrastructure in the future.

## XII. Future Research Works Directions

The integration of AI in the optimization of steel moment frame structures represents a transformative leap in structural engineering. As the field continues to evolve, the collaboration between structural engineers, data scientists, and AI researchers becomes paramount. The evolution of AI in structural optimization opens avenues for further research and innovation. Integration with Building Information Modeling (BIM), real-time monitoring systems, and the development of hybrid optimization methods are potential directions for future exploration. Additionally, addressing the challenges related to interpretability and ethical considerations will be crucial for establishing trust in AI-driven decision-making processes. AI can continue to revolutionize the optimization process of steel moment frame structures, fostering a new era of smart, adaptive, and resilient infrastructure. This journey exemplifies the transformative potential of AI in addressing complex engineering challenges, and as we look forward, the collaboration between human ingenuity and AI promises to redefine the possibilities in structural design and optimization. Future research in this area can explore various directions to enhance the efficiency, safety, and cost-effectiveness of structural design. Here are some potential research directions:

1. *Integration of Machine Learning Algorithms:* Explore the integration of machine learning algorithms for predicting structural performance under different loading conditions. Develop models that can learn from historical data, structural behavior, and failure modes to improve design predictions.
2. *Multi-Objective Optimization:* Extend optimization models to consider multiple objectives, such as minimizing cost, maximizing structural performance, and reducing environmental impact. Investigate techniques to balance conflicting objectives in the optimization process.
3. *Uncertainty Quantification:* Incorporate uncertainty quantification methods to account for variations in material properties, construction processes, and loading conditions. Develop AI-driven approaches for robust optimization considering uncertainties.
4. *Generative Design and Topology Optimization:* Explore generative design techniques to automatically generate and refine structural layouts and configurations. Investigate topology optimization methods that leverage AI to improve the efficiency of the design process.
5. *Advanced Structural Health Monitoring (SHM):* Integrate AI for real-time structural health monitoring to assess the in-service performance of steel moment frame structures. Develop algorithms for anomaly detection and predictive maintenance based on continuous monitoring data.
6. *Human-in-the-Loop Optimization:* Investigate the integration of human expertise with AI algorithms in the optimization process. Develop interactive tools that allow structural engineers to guide and validate AI-driven design decisions.
7. *Lifecycle Performance Optimization:* Extend optimization beyond the design phase to consider the entire lifecycle of structures. Incorporate AI models for predicting long-term durability, maintenance requirements, and end-of-life considerations.
8. *Sustainability Optimization:* Integrate AI to optimize structures for sustainability, considering factors such as carbon footprint, energy efficiency, and recyclability. Develop tools that support decision-making processes aligned with sustainable design principles.
9. *Ethical Considerations and Safety:* Address ethical considerations related to AI in structural optimization, including transparency, accountability, and bias. Prioritize safety by ensuring that AI-driven designs comply with relevant codes and standards.
10. *Interdisciplinary Collaboration:* Foster collaboration between structural engineers, computer scientists, and domain experts to advance the field through a multidisciplinary approach. Encourage the development of AI tools that are user-friendly and accessible to professionals with varying expertise.

As technology evolves, these research directions can contribute to the ongoing development of AI-driven optimization methods for steel moment frame structures, ultimately leading to more robust, efficient, and sustainable designs.

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