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| RESEARCH ARTICLE

AI-Integrated Structural Optimization Framework for Lightweight Heavy Fabrication Systems in Smart Manufacturing Environments

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| ABSTRACT

Heavy fabrication systems, such as those used in the mining, construction, off-highway vehicle, and industrial equipment industries, are usually developed through conservative engineering practices, resulting in overdesigns in terms of structure, leading to excessive material usage. Although such practices ensure the durability and safety of the structure, they also result in increased manufacturing costs, energy consumption, and carbon emissions. The existing optimization techniques, such as topology optimization and size optimization, may not consider the manufacturability constraints of the welded structure, as well as the lack of consideration of real-world operational feedback. This paper proposes a new framework for AI-assisted structural optimization for lightweight heavy fabrication systems in a smart manufacturing paradigm. This new optimization framework includes physics-based finite element methods, machine learning-based surrogate modeling, multi-objective optimization, manufacturability-based constraint embedding, and digital twin-based feedback control in a unified architecture. The optimization process targets the minimum weight design subject to static strength, vibration, fatigue, and weld-related design constraints, while manufacturability is ensured through thickness limits, weld accessibility, and assembly feasibility. The incorporation of operational sensor information aids in the continuous improvement of predictive models, thereby allowing structural optimization to become a dynamic process rather than a static activity limited to the design phase. The proposed method improves design iterations, reduces material usage, improves vibration response, and meets sustainability goals by incorporating embedded carbon impact modeling. This proposed method moves heavy fabrication engineering into an adaptive, intelligence-based, and sustainability-focused structural system that meets Industry 4.0 and Industry 5.0 concepts.

| KEYWORDS

AI, Fabrication, Industry 4.0, Industry 5.0, AI-assisted structural optimization

| ARTICLE INFORMATION

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1. Introduction

1.1 Background and Industrial Context

Heavy fabrication systems are generally found to be the structural backbone of important industries such as mining, construction, off-road transportation, agricultural machinery, and commercial HVAC. These systems are generally large steel weldments designed to support high static and dynamic loads, impact, fatigue, and harsh environmental conditions. Due to safety considerations and uncertainties in loading conditions, structural components in heavy fabrication are traditionally over-designed, which results in material and weight penalties [1].

Conservative design practices, which emphasize reliability, often create economic and environmental issues that are noteworthy. The addition of weight to a structure has a direct relationship with the cost of raw materials, the cost of energy consumption during operation, the cost of transportation, and the environmental cost in terms of carbon emissions. For industries such as mining trucks and heavy equipment for building construction, any reduction in weight can lead to significant improvements in fuel efficiency and payload. Similarly, for HVAC systems, lightweight designs for the structure simplify the process [2].

In recent times, global sustainability demands, supply chain variability, and market competition have increased the need for lightweight yet strong structural systems. For manufacturing organizations, there is a growing need to minimize material usage without compromising structural integrity and vibration characteristics. Nevertheless, lightweighting in heavy fabrication is not only a matter of material selection; it is essentially a multi-variable optimization problem for structural systems involving load distribution, joint properties, modal response, fatigue properties, and manufacturability constraints [3].

Conventional design approaches are significantly based upon iterative finite element analysis, as well as engineering judgment and rule-based modifications. These approaches are effective; however, they are time-consuming, highly dependent upon designer skills, and often fail to take advantage of historical design information and operating experience. With changing manufacturing scenarios to increasingly digitally connected and information-rich systems, there exists a significant potential to incorporate artificial intelligence (AI) into structural optimization to develop systematic, scalable, and sustainable lightweight design solutions [4].

1.2 Research Gap

Significant research has been conducted in the field of structural optimization, which includes topology optimization, size optimization, shape optimization, and gradient-based methods for solving multi-objective problems. Recently, machine learning techniques have also been used to speed up the process of stress prediction in the context of aerospace and automotive industries. At the same time, digital twin technology has also been used to simulate the manufacturing process in real-time [5][6].

Notwithstanding these developments, there is still a gap in heavy welded fabrication systems. Firstly, many optimization methods produce geometries which are difficult to manufacture using conventional welding techniques and sheet metalworking processes. Manufacturing restrictions such as sheet thickness, accessibility for welding, bend restrictions, and tool clearance are normally considered only at a later stage in product design.

Secondly, there has been a strong focus on applying AI within lightweight industries but not to a large degree within high-mass welded heavy equipment assembly areas, which have complex load paths and high vibration sensitivities. Thirdly, there is a lack of integration between structural optimization algorithms and real-time field performance data from sensor-enabled systems. In effect, structural design is a static optimization process but not a dynamic process as might be expected from a learning mechanism [7].

Most notably, there is no unifying framework for integrating physics-based simulation, machine learning optimization, manufacturability constraints, and digital twin feedback within a closed-loop structural lightweighting system for heavy fabrication environments.

1.3 Research Objective

The main goal of this investigation is to develop an AI-aided framework for structural optimization that facilitates lightweight and structurally robust heavy fabrication systems in smart manufacturing scenarios. The proposed framework aims to bridge the gap between optimization and industrial manufacturability through the integration of:

- Physics-based finite element simulations for stress, vibration, and fatigue analysis;
- Machine learning models for surrogate-based predictions and optimization;
- Manufacturability constraints based on welding, sheet metal, and assembly considerations; and
- Digital twin feedback to leverage real-world data for optimization refinement.

By integrating these tools and techniques within a single framework, the proposed framework aims to minimize structural weight while maintaining safety, vibration, fatigue, and manufacturability performance.

2. Literature Review

2.1 Structural Optimization in Heavy Fabrication Systems

Structural optimization is widely accepted as an essential methodology in reducing material requirements without compromising the performance and safety requirements. The conventional optimization techniques include size optimization, shape optimization, and topology optimization. Size optimization focuses primarily on modifying the dimensional properties such as the thickness or cross-sectional area, while shape optimization focuses on modifying the boundaries of the shape in order to optimize the stress distribution. On the contrary, topology optimization aims at optimizing the material distribution in the given design domain in order to reduce the weight of the structure [8].

In heavy fabrication systems, such as welded steel structures found in mining trucks, off-highway equipment, and industrial frames, the primary approach for structural optimization has traditionally relied on the refinement process facilitated by finite element analysis (FEA). Engineers have often identified stress concentration points, reinforced these areas, and reduced material in low-stress areas through the simulation process. While the approach has proven effective, it is often time-consuming and relies on the experience of the engineer [4].

Topology optimization has shown promise for aerospace and automotive applications, for which additive manufacturing techniques can be used to fabricate the optimized geometries. However, the heavy fabrication industries often face geometries that are difficult to weld, bend, and assemble. In unconstrained optimization, the resulting geometries can be difficult to fabricate, with sharp internal features, irregular voids, and unsupported members. This has led to a disconnect between the optimized geometries that can be obtained with computational tools and the manufacturability of the resulting structures for the heavy fabrication industries [9].

Furthermore, the structural optimization of heavy fabrication structures must take into consideration not only the static strength properties but also dynamic properties such as vibration response, fatigue life, as well as modal frequency separation. As a result of this multi-physics consideration, the model becomes much more complex and computationally expensive. As a result, the majority of industrial lightweighting activities are based on conservative modifications rather than optimization approaches [10].

2.2 Artificial Intelligence in Structural Engineering

Recent advances in artificial intelligence (AI) and machine learning (ML) have provided new avenues for accelerating the process of structural analysis and optimization. Supervised learning algorithms, such as artificial neural networks (ANNs), support vector machines (SVMs), and ensembles, have been utilized for the prediction of stress fields, displacements, and fatigue life based on simulation data. Surrogate modeling techniques have reduced computational expenses by replacing high-fidelity finite element solutions [11].

Additionally, the introduction of Bayesian optimization techniques as well as genetic algorithms has improved multi-objective optimization capabilities, thus allowing designers to achieve weight minimization as well as maximize stiffness or durability concurrently. Reinforcement learning techniques have also been explored for generative design purposes [12].

Nevertheless, the majority of the AI-based research conducted on the optimization of structures has been focused on lightweight industries, such as aerospace, automobile, and medical devices, with minimal attention paid to heavy welded structures. This is because the behavior of heavy fabrication structures depends on the intricate behavior of the welds, residual stresses, geometrical nonlinearities, and high-mass dynamics, which are rarely addressed by the majority of the existing AI algorithms.

Furthermore, the majority of the AI algorithms that are currently available are isolated computational tools that are not integrated with the limitations that exist in the manufacturing process. This has, therefore, hindered the industrial application of the available AI algorithms, despite the immense potential that exists for the optimization of structures.

2.3 Digital Twin Technologies in Smart Manufacturing

The digital twin technology has been identified as an essential technology supporting smart manufacturing and Industry 4.0 initiatives worldwide. A digital twin is defined as a dynamic virtual representation of a physical asset that includes simulation models, real-time sensor data, and historical performance records. Digital twins are heavily used in the manufacturing industry for predictive maintenance, optimization of production processes, and monitoring of production processes [13][14].

In the context of structural systems, digital twins can help in the continuous monitoring of systems such as vibration, strain, temperature, and fatigue cycles through sensors. The data collected can then be utilized for the detection of anomalies and prediction of failures. This is particularly useful for heavy machinery under extreme conditions [15].

Despite their increasing popularity, the majority of digital twin implementations focus primarily on monitoring and enhancing operational performance, rather than actively improving structural design. The feedback loop from field performance data into redesigning the structural design is often weak or missing. While digital twins might indicate a degradation in performance or too much vibration, they are typically not utilized for automatic structural optimization [16].

Furthermore, digital twin platforms are, for the most part, distinguished from AI-driven generative design systems. As such, the scope for closed-loop learning, wherein operational data can be used to refine the algorithms used for the design of the structures, remains largely unexplored.

2.4 Identified Research Gap

The above review points out some significant gaps in the current scholarly research and industrial practice.

The first gap is that the optimization methodology for structural optimization of heavy fabrication systems is mainly based on physics-oriented techniques with limited incorporation of data-driven acceleration techniques and prediction intelligence. The second gap is that artificial intelligence techniques in structural optimization have not been extensively tailored for welded heavy structures with manufacturability constraints. The third gap is that manufacturability constraints are generally treated post-hoc rather than being inherently embedded within the optimization process. The fourth gap is that digital twin systems are generally used for monitoring purposes and not inherently utilized within the optimization process.

These gaps, collectively, point to the absence of an integrated framework that simultaneously integrates:

- Physics-based structural simulations,
- AI-aided multi-objective optimization techniques,
- Manufacturability-constrained constraint models, and
- Closed-loop digital twin feedback integration.

The solution to this gap is critical to transform heavy fabrication systems from traditional conservative structures to smart structures that are lightweight and continually improving in structure. The formulation of an integrated framework would indeed represent a significant step towards adaptive and sustainable manufacturing systems that conform to new paradigms of smart manufacturing systems.

3. Methodology

The proposed AI-integrated framework for structural optimization is envisioned as a multi-layered architecture that combines engineering physics, machine learning intelligence, manufacturability constraints, and digital twin feedback into a unified optimization process. Unlike traditional structural design processes that rely on a sequential process of simulations and design improvements, the methodology developed in the current study enables iterative, adaptive, and data-driven decision-making processes for the entire product life cycle. The proposed framework has five layers: design data, physics simulation, AI optimization, manufacturability constraint, and digital twin feedback.

This process begins with the data layer of design data, which incorporates all the necessary input variables regarding the structure or operational behavior of the welded assembly. This includes aspects such as the three-dimensional geometry of the assembly as created through a CAD program, properties of the materials used, weld joint properties, loading conditions, boundary constraints, and historical data regarding performance, including any instances of failure during operation. Geometric features are parameterized to ensure that variables such as plate thickness, dimensions of any ribs or reinforcements, placement of reinforcements, and geometry of the section are able to be altered as necessary to optimize the structure. Feature extraction is used to identify areas of loading conditions, stress concentrations, and areas of vulnerability to vibrations.

The second tier involves physics-based simulations, including high-fidelity finite element analysis. Structural analyses are carried out to evaluate static strength, displacement, modal characteristics, and fatigue performance. Static structural analysis is carried out to identify critical stress points and ensure that the stress is within allowable limits. Modal analysis is carried out to evaluate natural frequencies and modes of vibration, ensuring that resonance does not occur in the range of excitation frequency. Fatigue analysis is carried out to identify areas of potential fatigue, particularly in welded joints, where stress concentration is likely to occur. Simulations are carried out to produce validation data and training data for the next stage of optimization, in which AI is applied.

The AI optimization layer is the brain of the entire architecture. Due to the computational cost of repeatedly performing high-fidelity simulations, surrogate models based on machine learning techniques are created to estimate structural performance parameters as functions of the variables of interest. Supervised learning algorithms are used to create correlations between geometric parameters and structural responses such as stress distribution, displacement magnitude, and vibration responses. Once the machine learning models are created, optimization algorithms based on multiple objectives are used to minimize structural weight while maintaining the required structural strength, fatigue life, and vibration responses. Additionally, cost and sustainability criteria are used within the optimization process to achieve an optimal balance between performance and efficiency.

The last layer involves the incorporation of digital twin feedback to provide a closed-loop learning environment. The systems installed in the field, which are equipped with sensors, collect real-time data on various parameters such as vibration signatures, strain levels, load cycles, and temperature changes. The data is synchronized with the virtual structure to test assumptions made during the virtual environment and to identify any discrepancies between the two environments. The data is used to retrain machine learning models, update fatigue calculations, and adjust optimization constraints. The optimization of structures is thus transformed from a static exercise carried out during the design phase to a dynamic exercise that can be carried out during the lifecycle of the structure.

The entire workflow progresses in an iterative manner. A starting design structure is parameterized and evaluated through a physics-based simulation approach. Surrogate artificial intelligence models are then trained to mimic the results of the simulations, and finally, multi-objective optimization results in candidate solutions for a lightweight structure. Manufacturability constraints are applied to rule out infeasible solutions, and the results of the simulations are verified for the valid solutions. Finally, a digital twin provides real-time feedback to improve the models, thus enabling the improvement of future design iterations in a continuous manner. Lightweight, manufacturable, and performance-compliant solutions are enabled by the framework in a smart manner.

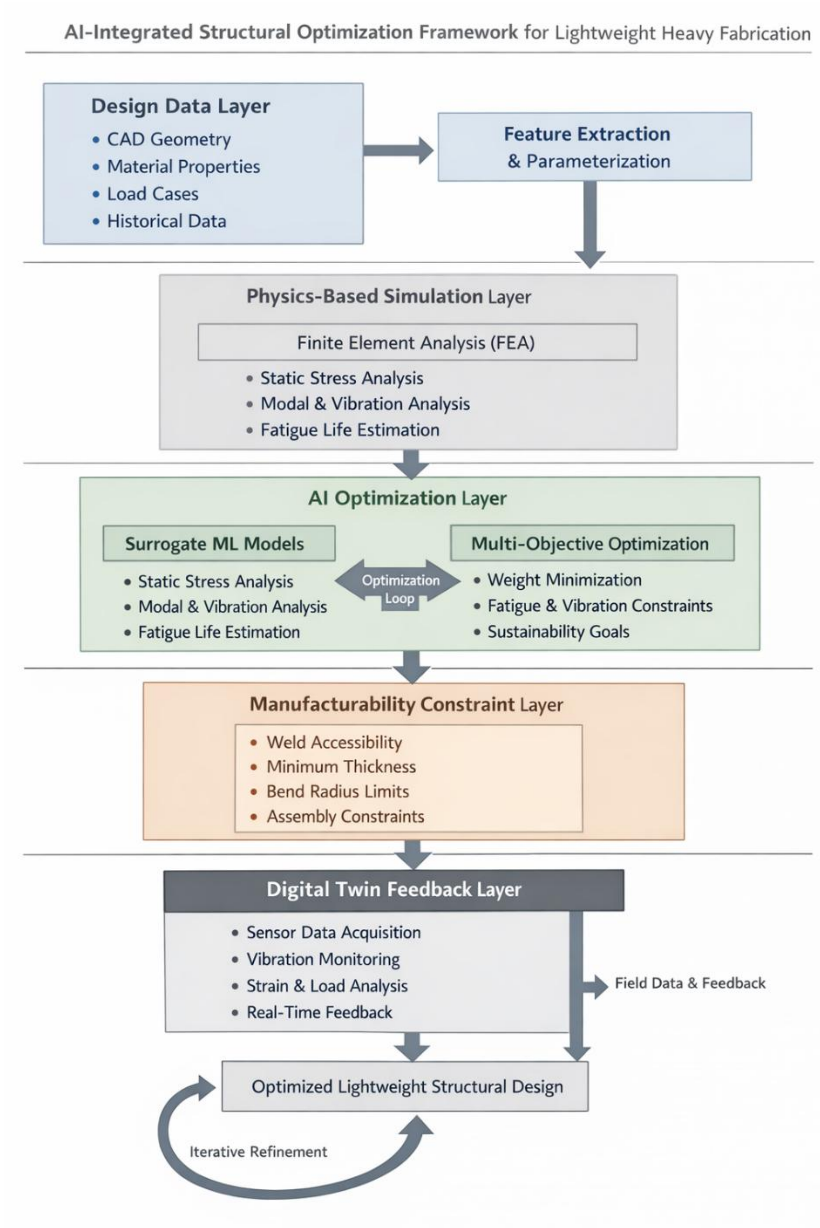

Fig 1. Framework

The figure shows a five-layer AI-integrated structure for structural optimization to produce lightweight heavy fabrication systems within a smart manufacturing environment. The optimization begins at the Design Data Layer, where data on geometry, properties of the material, loading conditions, and historical data is collected and processed through feature extraction techniques. The data is then processed through evaluation techniques within the Physics-Based Simulation Layer, where finite element analysis is performed to assess the static stress behavior of the structure, modal behavior of the structure, as well as the fatigue life of the structure. The evaluation of the structure is performed through the AI Optimization Layer, where machine learning techniques are applied to produce a lightweight structure that is optimal within a multi-objective optimization environment. The structure is further refined through the Manufacturability Constraint Layer to ensure that the structure complies with various constraints during the manufacturing phase, including weldability, minimum thickness, bend radii, as well as assembly constraints. The Digital Twin Feedback Layer is used to validate the structure through the collection of data on vibrations as well as strain within the structure.

4. Discussion

4.1 Theoretical Implications

The proposed AI-integrated structural optimization framework marks an important conceptual shift in the field of heavy fabrication engineering from a traditional deterministic and iteration-focused structural design paradigm towards an adaptive and intelligence-assisted process of structural development. Traditional structural optimization processes typically follow a structural sequence of generation, validation via simulations, modifications, and subsequent evaluation processes. While this process is effective, it is labor-intensive and heavily dependent on the expertise of engineers. The integration of artificial intelligence and digital twin feedback introduces a learning-based process that redefines structural design as an evolving process.

From a theoretical standpoint, the framework integrates traditionally distinct fields: computational mechanics, machine learning, and manufacturing engineering. The inclusion of physics-based simulation ensures that the solution meets essential structural integrity constraints, and surrogate modeling and reinforcement learning enable fast exploration of large design spaces. The inclusion of manufacturability constraints within the optimization process itself overcomes a major limitation of traditional topology optimization, which often results in designs that are difficult or impossible to manufacture via a welding process.

The incorporation of digital twin feedback provides the feedback loop for the model of structural intelligence. The proposed approach is different from static optimization techniques, which are based only on loading conditions. The proposed approach allows the use of real-world data for refining the predictive model. This approach can lead to the development of self-learning structures. Theoretically, the proposed framework positions heavy fabrication systems in the domain of cyber-physical manufacturing systems. The proposed approach is in line with the concepts of Industry 4.0 and the progression towards Industry 5.0.

4.2 Industrial Impact

The industrial consequences of the suggested framework are considerable, particularly in industries characterized by significant welded steel configurations, including mining equipment, construction equipment, agricultural equipment, and commercial HVAC structural systems. Heavy fabrication industries are often characterized by significant cost constraints and service life requirements. Even minor reductions in structural weight can have considerable economic benefits.

The AI-enhanced framework helps to achieve a systematic search for low-stress areas where the material can be removed without compromising structural integrity. Concurrent analysis of static strength, modal/vibration response, and fatigue performance reduces the risk of undesired durability degradation. Some of the expected benefits that might be achieved include:

Weight savings of 8-15% from the structure

Cost savings related to the amount of material used

Enhanced vibration performance and fatigue life

New product introduction cycle reductions by speeding up the iteration process

Reduced need for overdesigning structures conservatively

This layer of manufacturability-informed design guarantees that the optimized geometry is compatible with existing manufacturing capabilities. This reduces the risk of re-design due to infeasibility on the shop floor and fosters a collaborative relationship between the personnel in the stages of design engineering and manufacturing. Thus, the framework does not only optimize the structure for performance but also increases efficiency in operations.

4.3 Sustainability and Environmental Implications

In turn, lightweighting is fundamentally linked with the idea of sustainability in heavy manufacturing systems. This is because reducing the overall mass of the structures results in the use of fewer raw materials, the overall embodied carbon emissions associated with steel production, and fuel efficiency during transportation. Lightweighting can also improve the overall energy efficiency and emissions of greenhouse gases during the operational life of heavy equipment.

By integrating the carbon impact modeling into the framework of the proposed approach, the design decisions can be made in alignment with the environment. The reduction in the volume of the materials can be directly linked with the reduction in the carbon footprint by the use of the emission factor model. This can help the organizations comply with the requirements of the environment, social, and governance (ESG) reporting.

In addition, the digital twin feedback mechanism can help the organizations implement the predictive maintenance strategies, which can help reduce catastrophic failures and increase the life of the equipment. This can help the organizations improve the overall economic sustainability while being beneficial for the environment.

4.4 Comparison with Conventional Design Approaches

A comparative analysis reveals the potential of the proposed framework for transformation in comparison to the usual approaches to optimization of structures.

In the usual approaches, optimization is a reactive and manual process. Changes to the design are driven by the interpretation of the simulation results by engineers, and manufacturability is evaluated only after the structural feasibility of a given design is established. Feedback on field performance is seldom used as a systematic input to future design changes.

The framework, enabled by the integration of artificial intelligence, possesses a proactive and adaptive posture. Machine learning facilitates the acceleration of predictions of structural responses, thereby allowing for the exploration of a broader design space. Constraints related to manufacturability are integrated from the outset, thereby eliminating the creation of infeasible geometries. Data from the digital twin facilitates a learning environment, wherein operational learning directly influences the refinement of structural models.

The main characteristics of this advancement are as follows:

- Iteration Speed: Human iteration is replaced by autonomous multi-objective optimization.
- Learning Capability: Retraining of models, enabled by data from the field, enhances the accuracy of predictions.
- Manufacturing Integration: Constraints are integrated as integral components, as opposed to a sequential consideration of manufacturability.
- Lifecycle Perspective: Structural optimization extends beyond validation to the refinement of operations.

The progression from static, experiential design to intelligent, closed-loop optimization represents a significant advancement in the field of heavy fabrication engineering.

5. Conclusion

In the current research, an innovative framework is proposed for the application of artificial intelligence in the context of structural optimization, particularly for the operation of lightweight heavy fabrication systems under the environment of smart manufacturing. The proposed framework is designed to eliminate the persistent shortcomings of traditional approaches to the design of structures, particularly the gap that often arises between computational optimization, manufacturability, and real-world operational feedback. The proposed framework is an innovative approach towards the design of structures through the application of adaptive intelligence.

This framework enables a systematic weight reduction of the structure while preserving essential performance criteria such as static strength, vibration properties, as well as fatigue life. Contrary to common topology optimization techniques that tend to produce structures not suitable for welding processes, the consideration of manufacturing constraints within this framework increases the chances of successful implementation within heavy industries by ensuring that the obtained optimization is manufacturable through various industrial processes such as sheet metal forming, welding, as well as assembly operations.

Furthermore, the consideration of digital twin feedback changes the nature of optimization from a static activity within the design phase of a structure to a dynamic process that extends throughout the structure's lifecycle. The data collected from operational systems that incorporate sensors provides real-time validation of a digital twin, as well as predictive adjustments to a structure's performance and enhancements to long-term reliability. This closed-loop intelligence brings harmony to the practices of structural engineering with the broader context of smart manufacturing and cyber-physical production systems.

From a sustainability perspective, the framework enables a more material-efficient design, which reduces costs and minimizes carbon footprint. The lightweighting design, which is part of the multi-objective optimization, reduces raw material use and increases energy efficiency in the operation of equipment, which is beneficial for environmental and regulatory compliance.

In summary, the proposed AI-integrated structural optimization framework is a major breakthrough in the field of heavy fabrication engineering. The future directions for further research and development should be geared toward pilot implementations, incorporation with enterprise resource planning systems, and further development of reinforcement learning models for generative design. These developments will further solidify the use of artificial intelligence in the future development and evolution of the field of heavy fabrication engineering, which has the potential to be a predictive and dynamic discipline.

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