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| RESEARCH ARTICLE

AI-Assisted Design for Manufacturability (DFM): A Conceptual Framework for Intelligent Heavy Fabrication Systems in Smart Manufacturing

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| ABSTRACT

The paper proposes a conceptual framework for the integration of Artificial Intelligence (AI) technologies with Design for Manufacturability (DFM) for heavy fabrication systems with the objective of creating an environment for smart manufacturing. DFM methods and tools have been found to depend significantly on guidelines and expert knowledge based on rules, which are often found to be inadequate for the complexity associated with heavy fabrication systems and assemblies. This paper proposes an AI-based DFM framework for heavy fabrication systems using machine learning and real-time data analytics for improving the process of decision-making regarding manufacturability during the initial stages of the design process. The proposed framework focuses on improving the parameters associated with heavy fabrication processes such as material selection, welding feasibility, structural integrity, costs, and supply chain constraints. In the proposed framework, a multi-layer architecture for DFM integration with AI technologies has been proposed for heavy fabrication systems with feedback for continuous improvement. In addition, the paper explores the challenges associated with the implementation of an AI-based DFM framework for heavy fabrication systems and proposes an interface for bridging the capabilities associated with Industry 4.0 and the human-centric vision for Industry 5.0 for improving the efficiency and productivity of heavy fabrication processes and assemblies through collaborative decision-making involving humans and computers. This paper proposes a framework for improving heavy fabrication systems and assemblies through the integration of AI technologies with DFM for the development of an intelligent heavy fabrication system for improving efficiency and productivity while reducing costs and improving the robustness of designs.

| KEYWORDS

AI-assisted DFM; Smart Manufacturing; Heavy Fabrication; Digital Twin; Industry 4.0; Industry 5.0; Machine Learning; Manufacturability Optimization; Welding Design; Supply Chain Integration

| ARTICLE INFORMATION

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1. Introduction

Heavy fabrication industries, including construction equipment, mining machinery, and heavy HVAC systems, form the backbone of modern-day infrastructure. These include the design and manufacturing of intricate and sizable systems consisting of sheet metal structures, welded assemblies, and multi-material systems such as high-strength steels and aluminum alloys. In such scenarios, the role of Design for Manufacturability (DFM) assumes a pivotal role in ensuring that the designed products are not only functionally sound but also cost-effective and manufacturable at scale. In such scenarios, the implementation of effective DFM techniques would lead to cost savings in manufacturing, elimination of defects, efficient use of materials, and faster lead times, which are all critical factors in today's highly competitive and globally integrated manufacturing industry [1].

Traditional design for manufacturability (DFM) techniques are mostly based on static design rules, engineering handbooks, and expert-based guidelines and recommendations from past experiences. Even though these design for manufacturability techniques have proven their effectiveness in various industries over the last several decades, they are becoming less suitable for dealing with the increasing complexity of modern heavy fabrication systems. This is especially true in light of the increased need for lightweight designs, multiple material structures, and global supply chain management, which impose dynamic design constraints on modern heavy fabrication systems. In addition, traditional design for manufactability techniques are often incorporated at later stages of the design process, which may lead to inefficiencies in design, manufacturing, and communication [2].

However, with the advent of smart manufacturing and Industry 4.0 technologies, Artificial Intelligence (AI) has asserted its position as a transformative tool that can overcome its associated limitations. AI techniques such as machine learning, predictive analysis, and generative design help in analyzing large amounts of data, both past and present, for intelligent decision-making. These techniques help in making early-stage manufacturability analyses, detecting potential design flaws, and optimizing fabrication processes. Despite all these developments, the application of AI in DFM for heavy fabrication systems is still in its infancy and lacks a unified and structured approach [3].

This study attempts to bridge the gap by presenting a conceptual framework for an AI-assisted design for manufacturability (DFM) system designed specifically for intelligent heavy fabrication systems. The system is designed to utilize the power of AI-assisted analytics, digital twin technology, and real-time feedback mechanisms to enhance the manufacturability of products during the design phase. In addition, the study is relevant to the move from Industry 4.0 to 5.0 by emphasizing the importance of human-AI collaboration in the design process. In the move from 4.0 to 5.0, the emphasis is on the human-AI collaboration concept, where the human is assisted by the intelligent system. The main contributions of the study are the creation of a multi-layer architecture for an AI-assisted DFM system, the incorporation of the constraints of the manufacturing supply chain into the product design process, and the creation of a foundation for the development of future intelligent fabrication systems.

2. Literature Review

Design for Manufacturability (DFM) has always been identified as a key engineering discipline that focuses on simplifying product design in order to achieve efficient, cost-effective, and high-quality manufacturing results. Traditional DFM methods and techniques have primarily been based on rule-based methods, design standards, and various guidelines obtained from industrial practices. Some of the important factors considered in DFM include minimizing component count, standardizing components, tolerance optimization, and ensuring accessibility for various fabrication and assembly operations, particularly welding and sheet metal working operations. Most of the current computer-aided design (CAD) systems available in the market include basic DFM checks, allowing designers to identify errors associated with geometry, tolerance, and manufacturability constraints. However, they are based on fixed rules and cannot learn from dynamic manufacturing environments. It has often been found that traditional DFM methods and techniques are not effective in dealing with complex and large product assemblies, particularly in industries involving heavy fabrication [4].

Recently, the application of Artificial Intelligence (AI) in manufacturing and design processes has received considerable attention from researchers. Machine learning algorithms have found broad application in predicting defects, optimizing process parameters, and quality control in manufacturing systems. For instance, supervised learning algorithms have been used in predicting welding defects, and reinforcement learning algorithms have been used in optimizing additive manufacturing processes [5]. Designing structures using generative design, which is based on AI, helps in optimizing structures by balancing weight and strength. Additionally, AI has been integrated into modern computer-aided design/computer-aided engineering (CAD/CAE) systems in order to help designers in evaluating design options and predicting performance outcomes. However, the application of AI in improving DFM decisions is still in its infancy, especially in the context of heavy fabrication systems in which multiple constraints have to be considered simultaneously [6].

The concept of digital twins has enabled the improvement of the capabilities of smart manufacturing systems. Digital twins have enabled the creation of virtual models of physical systems. The digital twin concept has been beneficial to the improvement of the capabilities of smart manufacturing systems. In the case of heavy fabrication, the digital twin concept would be beneficial in the creation of virtual models of the welding processes [7]. The creation of digital twins would be beneficial in the creation of knowledgeable decisions. When integrated with the internet of things (IoT) technology, digital twins would be beneficial to the creation of adaptive intelligent systems. However, the integration of digital twin technology into the processes of design for manufacturability (DFM) is still at an early stage [8].

However, several research gaps still exist in artificial intelligence and digital twin technology development. Most of the existing research has focused on specific applications of artificial intelligence and digital twin technology, such as defect prediction and optimization, without addressing the overall issue of integrating it into a unified framework of design for manufacture (DFM). Moreover, little attention has been given to integrating supply chain constraints and cost factors into artificial intelligence-based design decisions. Another important gap in existing research is the lack of attention given to human-AI collaboration, which is critical in ensuring human acceptability in industrial environments. Thus, it is evident that a comprehensive artificial intelligence-based DFM framework is needed to address the complexities of modern heavy fabrication systems [9].

3. Problem Definition and Research Motivation

Heavy fabrication systems can be defined as systems in which large and complex structures require extensive welding operations, integration of multiple materials, and strict design criteria. Structures such as chassis, enclosures, and frames of heavy fabrication systems consist of numerous components, each of which is limited by various factors such as material properties, varying material thickness, welding difficulties, and manufacturing sequence. Additionally, integration of various materials such as high-strength steel, aluminum, and composite materials into a system makes it more complex for designers, as each material possesses its own set of fabrication difficulties. It is evident that in environments such as this, minor design inefficiencies can significantly increase costs, weight, and time associated with production, as well as causing defects.

Existing approaches to design for manufacturability (DFM) in the field of heavy fabrication are largely reactive. In addition, they are often undertaken at a late stage of the design process. Such delays in the validation of manufacturability have resulted in repeated iterations of the design process, increased engineering efforts, and inefficient communication among various stakeholders. Existing methodologies are often based on the judgments of experts. However, it is possible that the methodologies may not take into consideration the dynamic nature of the existing environment of manufacture. For instance, the conditions of manufacture, the capabilities of the suppliers, and the availability of the materials may be subject to variations. In the absence of real-time knowledge of the constraints of manufacturability, the decisions may be suboptimal, thereby affecting the products negatively.

The motivation for conducting this study lies in the need to advance design for manufacturability (DFM) from a reactive approach to a proactive approach. This can be achieved through the use of artificial intelligence (AI) technologies that can process historical data to predict potential issues that might arise during the design phase. In addition, it can generate optimized design solutions prior to any physical prototyping. Moreover, it can significantly enhance design efficiency through the consideration of various manufacturability constraints in a unified framework. The study's objectives are aligned with a set of questions that are considered central to the use of AI in DFM decision-making processes. Another set of questions deals with the dynamic evaluation and integration of manufacturability constraints in design. The need to resolve these questions lies in the advancement of intelligent heavy fabrication systems in the context of smart manufacturing.

4. Proposed AI-Assisted DFM Framework

The proposed framework for an AI-assisted DFM process would be conceptualized as a multi-layered framework intended for facilitating an intelligent decision-making process for heavy fabrication systems. In this regard, the proposed framework would comprise four primary layers: the Data Layer, the AI/Analytics Layer, the Design Interface Layer, and the Feedback & Continuous Learning Layer. These layers would collectively function as an interconnected framework for facilitating a real-time DFM process through the integration of design, manufacturing, and operational data. In effect, the primary objective behind the proposed framework would be to enhance the capabilities of DFM processes beyond traditional static and rule-based approaches through the integration of adaptive intelligence.

The Data Layer forms the core layer of the framework, with the primary role of aggregating and orchestrating different data sources that are essential in manufacturability analysis. These include computer-aided design (CAD) models, Product Lifecycle Management (PLM) systems, manufacturing history, sensor information from shop floor operations, and supply chain information such as availability and cost of materials. The information that can be obtained includes geometric features, material properties, welding information, manufacturing processes, and cost factors. Data preprocessing, normalization, and integration are critical in this stage. This layer enables the conversion of information that was once disjointed into a single dataset that can be intelligently analyzed.

On the basis of this foundation, the AI/Analytics Layer forms the core intelligence for the framework. This layer involves the application of various machine learning techniques and optimization methods for the assessment and prediction of manufacturability results. For instance, supervised learning methods can be utilized for the prediction of defects for welding joints or for the determination of features that may lead to various issues during the manufacturing process. Additionally, regression methods and neural network approaches can be used for cost estimation and optimization of process parameters, while classification methods can be used for the evaluation of manufacturability feasibility based on specific criteria. Knowledge-based systems can also be used for the integration of DFM rules for the application of established knowledge within the framework. Sophisticated optimization methods can then be used for the determination of various modifications for improving manufacturability results, such as modifications for material thickness, welding joint designs, and assembly sequences.

The role of the Design Interface Layer is to provide a connection between the results obtained through the application of artificial intelligence-based analytics and the design engineers involved in the process. This layer connects with popular computer-aided design tools such as SolidWorks and NX, which allows for a smooth interaction between the designer and the intelligent system. This interface allows the designers to receive feedback regarding the manufacturability of the designs in real time while creating or modifying the designs. Visualization tools highlight the problem areas, which may include high stress concentrations, poor welding access, and high costs associated with the manufacturing process, allowing the designers to make important decisions at the earliest stage of the process. This interface may provide alternative designs through the application of artificial intelligence-based tools, which may help designers produce an optimized design process without having to spend time analyzing the problem manually.

The final component of this framework is identified as the Feedback and Continuous Learning Layer. This component ensures that the framework remains adaptive in nature. This layer assimilates production data in real-time into the system, which in turn facilitates retraining the artificial intelligence system. This way, a closed-loop feedback system can be created that can learn from actual manufacturing processes. This can further reduce any prediction errors that might have been made in the process. The integration of digital twin technology into this framework further enhances its capability to create a virtual simulation of fabrication processes. This can be done to ensure that designs are validated prior to actual fabrication. This framework thus provides a holistic approach to ensuring that AI-based design for manufacturability in heavy fabrication can be achieved in a smarter way that can meet the objectives of smart manufacturing.

5. Implementation Challenges and Limitations

In spite of the significant potential of the proposed AI-assisted DFM framework, there exist several challenges and limitations for its successful implementation within heavy fabrication industries. The first challenge is related to the quality and availability of data required for AI modeling and testing. The quality and consistency of data available within industrial environments, such as CAD, PLM, ERP, and shop floor databases, may be inconsistent, incomplete, and non-standardized. This may lead to poor quality predictions and reliability of AI-based recommendations. The acquisition of real-time data from existing manufacturing systems may require significant investments in IoT technologies and data integration platforms.

Another important issue that may arise with the proposed framework is the integration with existing legacy systems and processes. In heavy fabrication industries, the design and manufacturing process may already be well established, and hence the introduction of new tools based on artificial intelligence may disrupt the existing process if not managed properly. In addition, the attitude of the personnel involved in the process may not readily accept the new tool based on artificial intelligence, especially if they perceive it as complicated and not transparent in their decision-making process.

The issue of model interpretability and trust is of significant importance in the development and use of AI-assisted DFM systems. Engineers need to be able to understand and validate the decisions provided by AI models, especially in critical applications where safety and structural integrity are of major importance. Although black-box models provide significant prediction capabilities, they often cannot provide sufficient information regarding the decision-making process, thus generating skepticism and reluctance in the use of such models.

In addition to these difficulties, it should be noted that the computational requirements related to AI models—especially those that rely on large data sets and sophisticated simulation—may be significant. This opens up a possibility that investment in high-computing facilities or cloud computing services might be required, which in turn might increase costs. In addition to that, questions still linger regarding the scalability of the framework to various product portfolios, materials, and manufacturing processes, as it might not perform equally well on different data sets. Therefore, to overcome these shortfalls, a strategic approach that balances technological advancements with organizational preparedness becomes a necessity to ensure that the benefits of AI-based DFM are fully exploited in industrial applications.

6. Conclusion

This paper develops a conceptual framework for AI-based Design for Manufacturability (DFM) in accordance with the needs of smart and intelligent heavy fabrication systems in smart manufacturing environments. Due to the current limitations of traditional DFM based on rules, this paper proposes a data-driven and adaptive approach for DFM by leveraging machine learning and real-time feedback in the design process. The proposed framework is based on a multi-layer structure, allowing designers and engineers to evaluate manufacturability in early design stages and avoid potential manufacturability issues associated with welding, material selection, cost, and assembly in a proactive manner.

This framework also emphasizes the importance of integrating manufacturing and supply chain factors in design decision-making, ensuring that not only is a product technically feasible but also economically viable and manufacturable. Additionally, by centering human-AI collaboration, this proposed approach enables a smooth transition from Industry 4.0 to Industry 5.0, in which intelligent systems will not replace human intelligence but will work in collaboration with it. This balance of human and artificial intelligence is critical for developing trust, interpretability, and eventual adoption in industrial settings.

While difficulties in implementation continue to be an issue, particularly in terms of data availability, system integration, and interpretability of models, the potential of AI-assisted DFM is substantial. The framework provides a basis for future research and application in industry, allowing for more intelligent, efficient, and sustainable heavy fabrication systems. Overall, this research contributes to the development of smart manufacturing by allowing for more informed, optimized, and robust design processes in increasingly complex engineering environments.

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