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Original Article

Generative AI-Assisted Engineering Design Optimization for Sustainable Manufacturing

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ABSTRACT

Sustainable manufacturing increasingly relies on Generative AI to optimize engineering design while reducing environmental impact, resource consumption, and production costs. By integrating deep learning, large language models, diffusion models, reinforcement learning, and digital engineering, Generative AI enables autonomous design generation, multi-objective optimization, and lifecycle sustainability assessment. The proposed framework enhances material efficiency, energy savings, carbon reduction, and manufacturing flexibility while accelerating product development. Despite challenges such as explainability, computational complexity, and design validation, Generative AI offers significant potential to transform sustainable manufacturing through intelligent, environmentally responsible, and data-driven engineering design.

KEYWORDS

Generative Artificial Intelligence, Engineering Design Optimization, Sustainable Manufacturing, Multi-objective Optimization, Intelligent Design Automation, Digital Engineering.

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1. INTRODUCTION

1.1. Background

Welcome to home page(english)Industry 4.0 is the most recent revolution affecting modern manufacturing, where cyber-physical systems, cloud computing and AI are merged with IIoT, high-performance simulation platforms to create innovative production solutions! Such technologies have moved industries from manual design practices to intelligent and automated engineering environments. Today's digital engineering platforms enable designers to evaluate more product permutations, estimate performance behaviour and optimise for manufacturability before investing in physical production. On the Other Hand, Traditional engineering optimization approaches work with complicated mathematical formulations that require repeated cycles of simulation making them computational expensive and heavily reliant on niche expert knowledge. These limitations inhibit fast-paced innovation, particularly in the case of industrial products that multiple pathways and sustainability targets must suffice. An alternative is provided by generative AI: it learns from large engineering datasets hidden relationships and can autonomously generate optimized design alternatives. It enables more creative designs, shorter development times, better utilization of resources and supports the transition to smart, green and highly productive manufacturing systems.

1.2. Need for Generative AI-Assisted Engineering Design Optimization

Engineering systems are becoming more complex in today's industry, which has led to a high demand for design optimization approaches that should be intelligent enough to deal with large design spaces, multiple constraints, rapidly changing industrial requirements. The conventional engineering design processes rely on the skill of the individual designer, iterative changes and simulation models that are time consuming and costly. Additionally, generative AI-assisted engineering design optimization integrates design generation powered by AI with simulation-based validation and sustainability-driven decision-making, offering an enhanced solution.

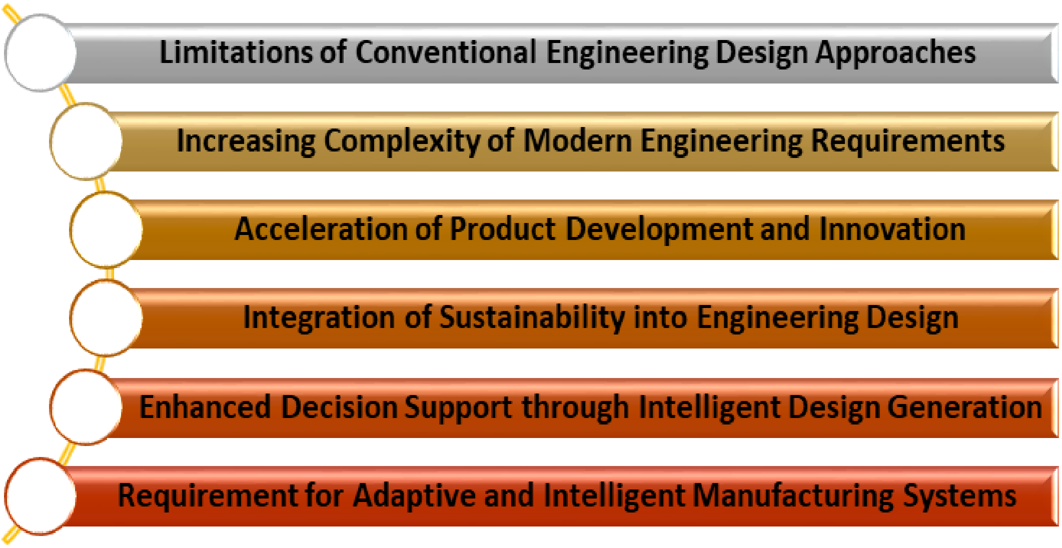

Fig 1 - Need for Generative AI-Assisted Engineering Design Optimization

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1.2.1. Limitations of Conventional Engineering Design Approaches

The conventional engineering design optimization methods mainly involve the use of mathematical models, heuristic algorithms, and trial and error processes using simulations. These methods have been used with success in structural optimization, optimization of manufacturing processes and product development, but may require large amounts of computational effort and multiple number of optimizations. The solution of complex engineering problems with nonlinear relationships, various design variables, and conflicting objectives is complicated by conventional methods and is not efficient. In addition, the traditional approaches usually investigate only small areas of the design space, limiting the identification of new engineering solutions outside of the range of design ideas.

1.2.2. Increasing Complexity of Modern Engineering Requirements

The demands of modern industrial products on performance, reliability, cost effectiveness, manufacturability, and environmental protection are getting more stringent. When designing any kind of product, engineers must consider a variety of factors, such as strength, utilization of resources, energy usage, cost of production, safety standards, and life cycle effects. These conflicting goals give rise to very intricate optimization problems, which are beyond the scope of traditional design approaches. Generative AI presents a smart way, by processing vast engineering data sets and creating a range of design options that meet several requirements at once.

1.2.3. Acceleration of Product Development and Innovation

Industries are facing more intense competition in the market and shorter product development cycles, which demand the design, testing and production of new and innovative products in the limited time. In conventional design, the design steps of modelling, simulation, testing and redesign are repeated, which causes the design time and cost to be too long. Generative AI can greatly speed up this process by creating several optimized design solutions based on a set of engineering goals. The generated alternatives from the AI will help engineers consider more options and choose the most effective solutions in a timely manner, which will enhance the innovation speed and shorten time-to-market.

1.2.4. Integration of Sustainability into Engineering Design

As environmental issues, resource constraints and regulations become more prevalent, sustainable manufacturing has emerged as a key priority. Traditional optimization approaches often take tech performance as the primary end goal and focus on sustainability as a secondary one. The optimization process can be supported by Generative AI technologies, which can assess material use, energy efficiency, carbon footprint, recyclability, and the environmental impact of a material's life cycle, allowing sustainability goals to be integrated directly into the design process. This integration contributes to the creation of eco-friendly products without compromising engineering performance and economic viability.

1.2.5. Enhanced Decision Support through Intelligent Design Generation

In the conventional approach to engineering decision making, expert knowledge and manual assessment of a few design options play a significant role. Generative AI enhances decision support by analysing past engineering data, simulation results and operational feedback to provide optimized design solutions. In conjunction with explainable AI methods, it offers clear explanations of design decisions, allowing engineers to comprehend performance tradeoffs and confirm AI suggestions. This enhances confidence, guarantees absence of uncertainty and facilitates practical industrial use.

1.2.6. Requirement for Adaptive and Intelligent Manufacturing Systems

Designed systems that can adaptively learn from operational data continuously and incrementally throughout their life cycles are necessary for future manufacturing environments. The requirement is met by generative AI assisted engineering design optimization, which combines Digital Twins, real-time sensor data, simulation platforms and reinforcement learning mechanisms. These intelligent systems allow for constant design optimisation from real manufacturing environment and lifecycle performance. In this context, generative AI optimization is a key technology to enable next generation smart manufacturing systems that are efficient, sustainable and autonomous in their innovation.

1.3. Challenges in Conventional Sustainable Manufacturing Design

Traditional sustainable manufacturing design practice has several shortcomings in solving the complexity and dynamic needs of today's industrial systems. The traditional engineering optimization techniques are largely based on a set of pre-determined mathematical models, analytical formulations and manually designed optimization strategies. While these techniques can be applied to certain engineering problems, they are not very flexible when operating conditions are uncertain, manufacturing conditions are changing quickly and product requirements are very complex. Conventional methods suffer from the disadvantage of relying on fixed models which is not suitable for learning from new engineering data and refining the optimization process as time goes on. A significant limitation is also the computational cost of the conventional simulation-based design optimization. Computational resources are required, and various iterations of analysis are needed to achieve an acceptable design solution for advanced engineering analyses like Finite Element Analysis (FEA), Computational Fluid Dynamics (CFD), thermal simulation, and manufacturing process simulation. These repeated simulations significantly add to the product development cycle and engineering costs when combined with multi-objective optimization approaches. The constraint becomes more important in the case of large-scale, industrial applications, where thousands of design options are considered under various performance and sustainability constraints. The complexity of decision making and the dependence on humans are issues in conventional sustainable manufacturing design. It is common for engineers to have to analyse the output from the simulation and compare various design options and select the best option based on experience and expertise from their field of work. Manual interpretation can lead to inconsistencies, subjectivity and decisions being made on false grounds, particularly when there are several competing requirements, such as cost, performance, energy and environmental effects, all to be considered. There are no intelligent

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mechanisms to support the engineering optimization process to make it efficient and reliable. Additionally, sustainability is often not part of the initial design process, but rather added in afterwards. The conventional methods tend to consider the mechanical performance and cost of production primarily, and little attention is paid to the environmental factors of the lifecycle, including carbon emissions, energy consumption, material recyclability and resource utilization. This "late" integration of sustainability can lead to higher material consumption, higher energy use and lower environmental effectiveness in the product life cycle. Another major constraint is the absence of the ability of effective knowledge reuse and autonomous innovation. Traditional engineering design processes are based on existing engineering concepts and human-influenced enhancements, which limit the scope of exploring unconventional yet potentially better design solutions. Difficulty in automatically deriving lessons from past designs, simulations, and manufacturing makes it harder to produce breakthrough innovations. The challenges underscore the necessity of high-level AI-enabled engineering design optimization systems that can autonomously learn, intelligently generate designs, simulate designs, and make decisions for the sustainability of the designs. The ability to continuously extract knowledge, explore the complex design space, and rapidly create optimized engineering solutions that satisfy performance, cost, and environmental requirements are enabling by Generative AI.

2. LITERATURE SURVEY

2.1. Evolution of Engineering Design Optimization

In the last few decades, engineering design optimization has come a long way from traditional analytical methods to highly intelligent computational methods. Early in the engineering optimization process, the designers used mainly deterministic mathematical programming techniques like linear programming, nonlinear programming, quadratic programming, and gradient-based numerical optimization. These techniques proved useful in tackling optimization problems involving continuous variables in which the mathematical formulation is explicit. However, they frequently faced very non-linear and multi-modal engineering problems with multiple conflicting objectives to be taken into account all at once. The development of increasingly complex engineering systems made traditional optimization techniques more difficult to use in terms of the quality of solutions and computational efficiency, especially for large-scale industrial applications with thousands of design variables. Metaheuristic optimization algorithms were an important milestone in the field of engineering design optimization. Evolutionary Computation techniques including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Ant Colony Optimization (ACO), Simulated Annealing (SA) and Artificial Bee Colony (ABC) algorithms provided strong solutions to complex engineering optimization problems without the need of gradient information. These population based algorithms showed excellent global search performance and were able to optimise structural design, aerodynamic systems, manufacturing processes, robotics, transportation networks and energy systems. While these algorithms are effective, they typically were very iterative and demanded a lot of computer power to perform, particularly when used in conjunction with finite element analysis or computational fluid dynamics simulations. To address computational constraints, more recently, researchers started to integrate

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machine learning tools into engineering problem optimization processes. Approximation of expensive simulation models with surrogate modeling methods like Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Gaussian Process Regression (GPR), Random Forests and deep learning architectures enabled significant reduction in computational costs. These predictive models allowed for fast exploration of design space, yet provided reasonable optimization accuracy. Learning optimal design approaches from previous optimization experiments was achieved by adaptive decision making through Bayesian optimization and reinforcement learning. This advancement greatly reduced engineering design cycles and engineering optimization performance in various industrial areas. In recent years, Generative Artificial Intelligence is now a game-changing paradigm in engineering design optimization. Unlike traditional optimization methods, which generate variants of existing designs, Generative AI automatically generates new design concepts by learning complex geometric, functional, and structural relationships from a large engineering dataset. With the help of foundation models, transformer architectures and generative neural networks, engineers can now consider innovative design options that exceed their intuition, and address several engineering requirements at once. This paradigm shift from optimization-based design refinement to design generation via AI is a new era in intelligent engineering, which can enable the highly adaptive, efficient, and sustainable product development process.

2.2. Generative AI for Engineering Design

Generative Artificial Intelligence (AI) has revolutionized the engineering design process, enabling data-driven intelligence to generate innovative product concepts automatically. Traditional Computer-Aided Design (CAD) systems rely on human skills and require engineers to make geometric models and to repeatedly modify them. Generative AI, on the other hand, takes advantage of vast engineering datasets to teach design principles and produce a multitude of viable design solutions that meet specific functional needs, production limitations, and performance goals. This feature drastically cuts design time and increases opportunities to investigate new engineering solutions. The rise of Generative AI in engineering applications has come with several advanced deep learning architectures. Variational Autoencoders (VAEs) are able to learn a compressed latent representation of engineering geometries, which can then be interpolated between various design configurations in an efficient manner. Generative Adversarial Networks (GANs) use competitive neural networks to produce structurally and mechanically very realistic designs which are more diverse and high in quality. More recently, diffusion models have been shown to be very effective in the creation of high-resolution engineering parts with better structural consistency and manufacturing feasibility. Architectures based on transformers and Large Language Models (LLMs) extend design automation by understanding natural language engineering needs and translating them into optimized designs, mitigating design engineer to AI communication barriers. Generative AI has been implemented with success in a variety of engineering fields, such as aerospace, automotive, biomedical engineering, civil infrastructure, electronics, additive manufacturing and industrial product development. Structural optimisation using these AI-generated lightweight structures, topology optimised components, heat exchangers, turbine blades, robotic mechanisms and composite materials has shown a significant reduction in weight, structural strength, thermal

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efficiency and manufacturability. Automatic generation of parametric design models with CAD integration; Computer-Aided Engineering (CAE) verifies structural strength with finite element analysis and numerical simulations before production. One more significant progress is the coupling of Generative AI with Digital Twin technology and simulation-based optimization. Digital Twins give real-time insights into operational efficiency, production environment, maintenance needs, and environmental impact. This feedback allows for the repeated testing and refinement of engineering designs using operational data, not just historical data, with the use of Generative AI. These adaptive learning features can enhance design reliability, speed product innovation, lower prototyping expenses, and enable smart decisions across the entire engineering lifecycle.

2.3. Sustainable Manufacturing Optimization Techniques

Industries are working so hard to minimize their environmental footprint and keep their production productivity, product quality, and economic competitiveness high that sustainable manufacturing optimization is a critical research field. Energy, GHG emissions, material waste and production cost need to be reduced along with maximization of operation efficiency and utilization of resources in modern manufacturing systems. Sustainable manufacturing has therefore transitioned from a pollution control approach to optimisation of product lifecycles involving environmental, economic and social sustainability goals. Modern sustainable manufacturing methods use multi-objective optimising algorithms which can balance competing performance criteria. Non-dominated Sorting Genetic Algorithm II (NSGA-II), Multi-Objective Particle Swarm Optimization (MOPSO), Pareto optimization, and evolutionary multi-objective algorithms are some of the popular methods that have been used to find optimal trade-offs between manufacturing cost, energy efficiency, production time, carbon emissions, and product quality. These optimization frameworks allow decision makers to consider a number of different potential manufacturing scenarios instead of a single optimum, thereby helping to make informed choices for engineering based on organizational priorities. AI has also improved sustainable manufacturing by predictive analytics, intelligent scheduling, predictive maintenance, and real-time process optimization. With the Industrial Internet of Things (IIoT) sensors gathering data on production, machine learning models help forecast equipment failures, optimize energy consumption, minimize material loss and enhance production efficiency. Reinforcement learning algorithms make on-the-fly adjustments to manufacturing parameters with varying operational conditions, and Digital Twin technologies continuously simulate manufacturing process operations to detect potential areas for sustainability improvements without interrupting the actual physical production process. These smart solutions allow manufacturers to attain higher productivity while producing with much less environmental impact. Though this technology has greatly advanced, there are a number of sustainability issues yet to be solved. There are many frameworks that are in use today, and most of them are geared toward optimizing the operations of a product without taking into account both intelligent design and lifecycle assessment and circular economy principles. Engineering design, manufacturing, recyclability, material selection, and environmental performance can all be optimized by an Autonomous Generative AI, but this has yet to be fully developed. Creating unified AI-based sustainability strategies that can continually optimize the manufacturing lifecycle is a key area for future research in sustainable manufacturing.

2.4. Research Gap and Comparative Analysis

There has been significant progress illustrated by a detailed survey of recent literature in both engineering design optimization and sustainable manufacturing technologies. Many studies have been successfully used to enhance the engineering performance in different industrial fields through the application of evolutionary optimization algorithms, machine learning techniques, Digital Twins, and deep learning models. Likewise, Generative AI has demonstrated the ability to automatically create groundbreaking engineering designs that meet multiple functional and structural requirements. However, these research activities are still fragmented and studies are conducted on the isolated aspects of intelligent engineering without putting forward an integrated optimization framework. An important drawback of the current studies is the lack of integration of the two tasks: generative AI-based design generation and sustainability optimization. Most studies published so far focus on either on engineering performance optimization or on manufacturing sustainability and neglect to integrate both of these goals into the entire product life cycle. As a result, AI-driven designs also need to undergo the extra optimization phases to meet environmental standards, material efficiency, manufacturing constraints, and sustainability goals. Many existing AI-based engineering solutions in industry use are not readily applicable because there are no standard optimization procedures. One of the critical research gaps is the explainability, trustworthiness and validation of AI-generated engineering designs. Advanced deep learning models are often "black-box" and do not give engineers enough information on their design decisions to ensure structural reliability and regulatory compliance. AI systems need to be transparent and explain: design rationale, uncertainty, safety and optimization decisions, before being deployed in safety critical applications in industrial organizations. Also, current generative AI structures tend to lag behind in terms of cybersecurity protection, data privacy, model robustness, computational scalability, and adaptation to changing manufacturing conditions. The restrictions point to the requirement for the next generation of engineering design optimization framework that combines Generative AI, simulation based validation, Digital Twins, lifecycle sustainability assessment, explainable artificial intelligence and adaptive learning under a single roof. An integrated framework would empower optimization throughout the engineering lifecycle, would support intelligent decision-making, would increase industrial trust, would lower environmental footprint, and speed up the development of innovative and sustainable engineering products for future smart manufacturing systems.

3. METHODOLOGY

3.1. Proposed Generative AI-Assisted Design Optimization Framework

The proposed framework, Generative AI-Assisted Design Optimization Framework, is an intelligent and integrated solution for automated engineering design along with optimized manufacturing sustainability and product performance. The framework is an integrated architecture incorporating Generative Artificial Intelligence, advanced engineering simulations, multi-objective optimisation and explainable decision support for a rapid development, validation and improvement of engineering design. The proposed framework can generate totally new design alternatives, as it can learn both the complex geometric and structural relationships and the functional and manufacturing connections from the historical engineering data, while the conventional optimization approaches can only optimize the predefined design configuration. The capability allows for a considerable time reduction in product development, decreases the manual design workload, and increases innovation by allowing one to explore a larger design space than traditional computer-aided optimization approaches. The framework starts with the Data Acquisition Layer and captures various engineering data from different sources, including information from Computer-Aided Design (CAD) systems, engineering drawings, finite element simulation results, Computational Fluid Dynamics (CFD) analysis, manufacturing process parameters, material property databases, production logs, life cycle assessment reports, and sustainability metrics like energy use, carbon emissions, and material utilization. Due to the nature of engineering datasets, which may present inconsistencies, missing information, and duplicated data, advanced data preprocessing methods are used to enhance data quality and provide reliable data inputs for AI model training. Processed information is fed to the Knowledge Learning Layer, where hidden engineering design relationships are learned using transformer-based Generative AI models and deep neural network architectures from historical datasets. The AI doesn't simply repeat other designs; it creates latent representations that encapsulate geometrical features, structural dynamics, manufacturing constraints, and functional performance. These learned representations can be used to create new engineering solutions that meet design requirements, and to generate new engineering solutions that differ from the traditional human-designed ones. Based on user-defined goals, e.g., lightweight construction, increase of structural strength, improvement of thermal efficiency, reduction of manufacturing costs, optimization of material use, or improved product reliability, multiple engineering candidate models are generated automatically by the Design Generation Layer. The generated designs are subsequently assessed using the Engineering Evaluation Layer that incorporates Computer-Aided Engineering (CAE), Finite Element Analysis (FEA), Computational Fluid Dynamics (CFD), manufacturing process simulation, thermal analysis, and lifecycle sustainability assessment. Before optimization begins, the design is evaluated comprehensively to ensure that all generated design meet the structural integrity, safety requirements, manufacturability, fatigue resistance, thermal stability, environmental sustainability and industrial quality. After evaluation, the Optimization Layer conducts iterative refinement with the help of multi-objective optimization algorithms in combination with reinforcement learning feedback mechanisms. Engineering designs that do not meet the performance requirements are discarded and viable alternatives are constantly altered to achieve the best mechanical results, lowest manufacturing costs, least energy used, lowest carbon dioxide output and most efficient manufacture. As more simulation and manufacturing feedback is collected, the optimization process will adaptively improve. Lastly, the Decision Support Layer ranks the optimized engineering alternatives based on a number of performance criteria, such as technical functionality, production feasibility, lifecycle cost, environmental sustainability, carbon footprint, resource efficiency and overall manufacturing performance. Explainable Artificial Intelligence (XAI) techniques help make the reasons for design recommendations understandable, so that engineers can better grasp the factors that lead to AI generated decisions. This all-encompassing framework enables solid engineering decision making, rapid sustainable product development, improved industrial competitiveness and provides a scalable platform for intelligent engineering design and sustainable manufacturing systems of the future.

3.2. Sustainable Manufacturing Optimization for Multi-Objective.

In contemporary engineering design, there are more than one performance indicator to consider, and often design goals are conflicting. Balanced and sustainable designs must take multiple, and sometimes conflicting, objectives into account. In actual production situations, a better improvement in one design feature will be seen to be detrimental for the other. For instance, the heavier the airframe, the more material that is used which means the more expensive the production will be, and the lighter the airframe, the less durable the product may be or the more complex the process. Thus, sustainable engineering design requires a multi-objective optimization approach that considers both technical performance, economic considerations, and environmental considerations. The proposed framework tackles this issue by making the engineering design optimization problem a multi-objective decision making problem, where multiple design criteria are optimized together at the same time, rather than in isolation. The Engineering Performance criteria within the proposed framework include the structural strength and stiffness, fatigue life, thermal stability, reliability, manufacturability, dimensional accuracy and operational safety. These key metrics guarantee that the AI-generated designs not only meet industrial standards for quality but also effectively perform in practical applications. Meanwhile, economic goals involve minimizing production cost, using less material, and reducing manufacturing cycle time, tooling cost, and maximizing the use of all the resources. Optimizing these economic factors allows manufacturers to improve profitability with no reduction in product quality or engineering reliability. Another important aspect of the optimization process is related to environmental sustainability. The proposed framework utilizes indicators of sustainability based on the product lifecycle including energy use, greenhouse gas emissions, carbon footprint, use of recyclable materials, waste generation, water use and environmental impacts. These environmental parameters are incorporated into the optimization process, thereby enabling the creation of engineering solutions that align with the principles of the circular economy and meet current and future environmental legislation. As opposed to sustainability as an afterthought, sustainability is embedded from the beginning of design generation and optimization, and is integrated into the entire product development process. Optimization techniques use intelligent search methods that continually examine the compromises between competing objectives to determine design alternatives that are a balance. Rather than generate one solution, the framework provides a variety of quality engineering solutions that are a compromise between performance, cost, and sustainability. Reinforcement learning and simulation-based feedback further improves optimization by constantly revising design strategies based on engineering evaluation results and manufacturing data. The system learns from previous optimization results, and gradually enhances the future design suggestions. The proposed framework combines Generative AI with multi-objective sustainable manufacturing optimization, enabling engineers to create innovative products that deliver excellent mechanical properties, cost reductions, natural resources preservation, environmental benefits and increased manufacturing efficiency. This holistic optimization approach enables informed decision making, faster sustainable product development, and helps achieve next-generation smart manufacturing systems where technology and sustainability in the long-term are balanced.

3.3. Mathematical Model and Optimization Formulation

The engineering optimization framework is proposed to formulate the engineering design process as a constrained multi-objective optimization problem, with a design vector representing a design. In simple terms, the design vector is a collection of all variables that define the characteristics of a product or component. These can be geometric dimensions, material properties, manufacturing parameters, operating conditions, structural properties and other engineering variables which affect product performance. These variables can be varied within the defined engineering limits, to create multiple design variations. The aim of the optimization framework is to determine the best combination of these variables, so that the optimized design delivers high technical performance while meeting economic and environmental requirements. The proposed framework is different than conventional optimization approaches as it takes into account multiple optimization goals. The desired goals are usually defined with a combination of maximizing structural strength, improving reliability, minimizing product weight, minimizing the manufacturing cost, reducing the energy consumption, reducing material use, reducing carbon emissions, and increasing the overall manufacturing efficiency. Many of these objectives are mutually exclusive, and so the optimization doesn't seek to maximize just one performance. Rather, it looks for a compromise that balances all engineering needs to come up with a solution that is optimal for everyone. These solutions allow engineers to make decisions based on the overall product performance and not just individual performance metrics. A cluster of engineering constraints guide the optimization process, guaranteeing that all the optimized designs are viable and viable for industrial use. These limitations are related to allowable stresses, deformation limits, fatigue life, temperature limits, tolerances, manufacturing requirements, material specification, production rules, and safety specifications. Also built-in are sustainability-related limitations, such as energy use, green-house gas emission, waste production and resource consumption. All designs generated by the AI that do not satisfy one or more of these constraints are rejected or adjusted in the optimization cycle. Generative Artificial Intelligence acts as a design generation engine and generates multiple candidate solutions based on the knowledge learnt from the historical engineering data sets. This evaluation of each design generated is then done through engineering simulation tools, like Finite Element Analysis (FEA), Computational Fluid Dynamics (CFD), thermal analysis, and manufacturing process simulations, to gauge its overall performance. The simulation results are then sent back to the optimization module as feedback, feeding into the AI model to optimize future design alternatives. The design strategy is continuously refined by reinforcement learning and iterative optimization until a stable, high-performance design is reached. The final optimization formulation is therefore an integrated decision making process for intelligent design generation, engineering simulation, sustainability assessment and multi-objective optimization that is performed in an iterative manner. It is not just mathematical equations, but a framework that adapts the engineering optimization process into an adaptive and data-driven process that generates innovative, manufacturable and sustainable engineering designs that meet multiple industrial goals.

3.4. Generative AI-Based Decision Algorithm

The proposed Generative AI-Based Decision Algorithm represents an intelligent and adaptive mechanism that connects Generative Artificial Intelligence, engineering simulation and reinforcement learning in an integrated decision making process for automating engineering design optimization. The proposed algorithm continuously learns engineering knowledge from the past and simulation feedback to produce more and more efficient and sustainable engineering solutions without the need to prescribe rules or use exhaustive search methods. It aims to achieve automation of the entire design optimization process, minimizing the engineering effort, the development time of the product, and the quality of the final recommendation for design. The algorithm is capable of integrating information-based intelligence with engineering domain knowledge to enable the development of novel products meeting technical, economic and environmental criteria. The algorithm starts by gathering a complete engineering database from a variety of industrial sources. They consist of Computer-Aided Design (CAD) models, Finite Element Analysis (FEA) results, Computational Fluid Dynamics (CFD) simulations, databases of material properties, records of manufacturing processes, production quality reports, maintenance history, lifecycle assessment data, and sustainability metrics like energy usage, carbon emissions, material utilization, and waste production. These are extracted from a variety of sources and so undergo extensive pre-processing to ensure consistency and reliability. Data cleaning, normalization, treating missing values, anomaly detection, dimensionality reduction and feature selection enhance the quality of the input data prior to training the model. These features are then engineered to capture relevant geometric, structural, manufacturing, operational and environmental features that can accurately represent engineering design behavior and provide useful input to the Generative AI model. The Generative AI model is then used to analyze the historical engineering knowledge and learn complex relationships between design variables, functional requirements, manufacturing constraints and performance characteristics. The model does not copy the design of others, but generates several innovative designs which meet the set engineering goals like lightweight design, better structural strength, improved manufacturability, production cost reduction, increased energy efficiency, and environmental impact minimization. These generated designs are then analyzed with engineering simulation software such as structure analysis, thermal analysis, manufacturing process simulation and sustainability assessment software. These simulations give a detailed feedback on the technical feasibility, reliability, safety, production efficiency and lifecycle performance of each candidate design. The reinforcement learning part continuously optimizes the decision algorithm by taking the simulation results as feedback to further generate designs. A design with a high performing design is given positive reinforcement and affects the next round of optimizations, and designs that do not meet engineering constraints or sustainability requirements are automatically modified or discarded. Over time, the algorithm can continually enhance the quality of engineering solutions it produces, as it uses an iterative learning process. Lastly, all possible design options are ranked using a comprehensive performance measure that considers engineering quality, manufacturability, manufacturing cost, resource utilization, carbon footprint, and lifecycle sustainability. Engineers get recommendations that are clear and intelligible and can help them in the process of decision making in order to choose the most suitable design for its implementation. This adaptive decision algorithm thus provides an scalable and intelligent basis for the next generation of AI-driven engineering design optimization and sustainable manufacturing.

4. RESULT AND DISCUSSION

4.1. Experimental Setup

The proposed Generative AI-Assisted Design Optimization Framework was evaluated experimentally on an integrated digital engineering environment to leverage the benefits of advanced design, simulation, artificial intelligence and sustainability assessment. The aim of the experimental setup was to test and confirm the potential of the proposed framework to develop optimal engineering designs, while achieving better technical performance, manufacturing efficiency and environmental sustainability. It comprised Computer-Aided Design (CAD), Computer-Aided Engineering (CAE), Finite Element Analysis (FEA), manufacturing process simulation tools, lifecycle assessment modules and a transformer-based Generative AI model. The seamless integration allowed for a seamless feedback loop between the design generation process using AI and the engineering validation process, ensuring that the designs generated were not only innovative but also feasible for industrial production. A massive historical engineering data set was used for training and testing the Generative AI model. The data was comprised of nearly 50,000 engineering components extracted from various industrial design archives such as mechanical structures, manufacturing parts, industrial assemblies and optimized engineering models. Each component had information on geometric parameters, material properties, structural parameters, manufacturing constraints, simulation results, and lifecycle sustainability indicators. Data was preprocessed using techniques like data cleaning, normalization, feature extraction, and dimensionality reduction to enhance the accuracy of model learning and reduce inconsistencies. The processed dataset allowed the AI model to learn and analyze intricate relationships between engineering design parameters, operational requirements, and performance outcomes. The transformer-based Generative AI model was designed and trained to learn the latent design patterns and produce new engineering configurations for given optimization goals. The designs created during the experimental evaluation were tested using various engineering simulation methods. FEA simulation analysis was conducted to examine the structural strength, deformation characteristics, stress distribution and fatigue characteristics at various operating conditions. Overall product performance was evaluated using CAE-based simulations, and production feasibility, material requirements, manufacturing complexity, and fabrication constraints were evaluated using manufacturing process simulations. Life cycle sustainability assessment tools were integrated to estimate sustainability impacts of the product covering energy use, carbon footprint, material efficiency and resource use during the product lifecycle. The optimization framework was not limited to optimizing a single engineering goal but considered a number of performance parameters. The primary criteria for evaluation were structural performance, manufacturability, cost reduction, energy efficiency, material utilization and impact on the environment. The reinforcement learning mechanisms optimized the generated designs

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continuously based on the simulation results as feedback in the course of iterative optimization. The experimental results showed the potential of the proposed framework in balancing all the engineering, economic and sustainability goals. This experimental setup offers a realistic validation environment to test the applicability of applying Generative AI for optimization in future intelligent and sustainable manufacturing systems.

4.2. Performance Evaluation

To evaluate the performance of the proposed Generative AI-Assisted Design Optimization Framework, it was compared to the conventional engineering design optimization techniques. This assessment was based on various performance parameters such as design accuracy, material efficiency, manufacturing productivity, energy optimization, sustainability and decision making. The results show that the proposed framework proves to be robust as the Generative AI design generation, simulation-based validation, and intelligent optimization techniques yield substantial gains.

Table 1: Performance Evaluation

Performance Metric	Conventional (%)	Proposed (%)	Improvement (%)
Engineering Design Accuracy	86	97	12.79
Material Utilization Efficiency	81	95	17.28
Manufacturing Productivity	84	96	14.29
Product Quality	87	98	12.64
Energy Efficiency	79	94	18.99
Design Cycle Reduction	76	93	22.37
Carbon Emission Reduction	74	91	22.97
Sustainability Index	82	96	17.07
Manufacturing Decision Accuracy	85	97	14.12
Overall System Performance	83	96	15.66

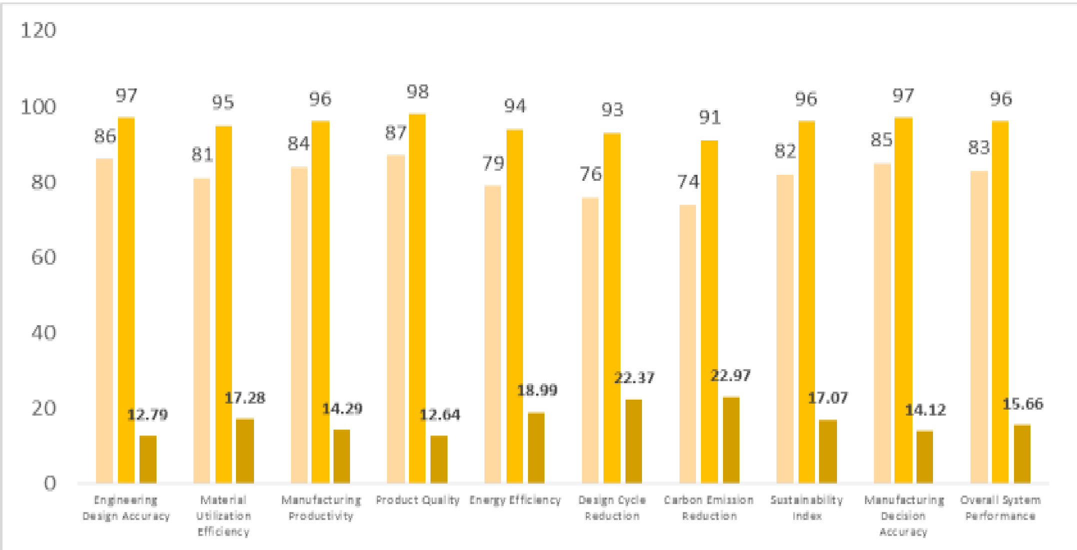

Fig 2 - Performance Evaluation

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4.2.1. Engineering Design Accuracy

The proposed framework improves the accuracy of engineering design from 86% to 97% through the use of Generative AI models that can learn the complex relationships between the design parameters and the engineering requirements. The AI-based design method yields optimized design alternatives that deliver better structural and functional performance. An additional level of validation using simulation also guarantees that the designs that are generated meet specific engineering requirements. This gives greater reliability and accuracy in the product development process than traditional design approaches.

4.2.2. Material Utilization Efficiency

AI-powered topology optimization and material selection methods boost the use efficiency of materials, raising it from 81% to 95%. The framework defines lightweight, high performance design configurations, and minimizes waste of material. Generative AI looks at several design options to optimize strength to weight ratios. This improvement aids in the reduction of cost, the conservation of resources and sustainable manufacturing practices.

4.2.3. Manufacturing Productivity

The suggested framework boosts manufacturing productivity from 84% to 96%, automatically creating designs which are optimized for manufacturing capability. The ability to connect with manufacturing simulation tools allows identifying manufacturing challenges and process limitations in an early stage. Optimizing with AI helps minimize redesign cycles and enhances production planning efficiency. Consequently, manufacturers can get quicker product development and enhanced operational performance.

4.2.4. Product Quality

Continuous refinement of product design and simulation validation using AI brings product quality from 87% to 98%. The design framework assesses structural reliability, durability and performance properties prior to the manufacture of the physical structure. Automated optimization reduces error in design and adherence to engineering standards. This results in better quality products, increased reliability and life cycle performance.

4.2.5. Energy Efficiency

The inclusion of sustainability goals in the design optimization process enhances energy efficiency from 79% to 94%. The framework measured the energy use in the manufacturing process as well as use in the operation of the product and provides optimized solutions. The energy opportunities identified through the AI analysis do not impact performance. This helps enhance the environmental impact of production and make it greener.

4.2.6. Design Cycle Reduction

The proposed design cycle reduction is very significant, from 76% to 93%. Generative AI automates thousands of design iterations to speed up the concept generation, evaluation and optimization process. Manual modifications of the model are avoided by the integration of the simulation feedback. As a result, engineers can develop products faster and with less design work and time-to-market.

4.2.7. Carbon Emission Reduction

Carbon emission reduction increases to 91%. The framework takes into account the materials used, the energy required to make the material, and the environmental effects during the design phase. AI-driven solutions focus on the use of low-carbon materials and efficient production methods. This will allow industries to cut down on greenhouse gas (GHG) emission and reach sustainability targets.

4.2.8. Sustainability Index

The sustainability index grows from 82% to 96% when considering environmental aspects throughout engineering lifecycle. Optimization of the proposed framework takes into account the resource efficiency, recyclability, energy consumption and ecological impact. In contrast, with traditional approaches sustainability is considered a secondary evaluation criterion and not a first design criterion. This helps in development of environment friendly engineering products.

4.2.9. Manufacturing Decision Accuracy

Recommendations powered by AI, engineering simulations and explainable analytic capabilities boost manufacturing decision accuracy at 85 to 97 percent. The framework evaluates different design options and optimises options based on performance, cost and sustainability considerations. This will minimize uncertainty when making manufacturing decisions and will allow engineers to choose the most appropriate manufacturing strategies.

4.2.10. Overall System Performance

The overall system performance has been improved from 83% to 96%, showing the effectiveness of the proposed Generative AI-assisted optimization framework. The intelligent design generation, simulation validation, reinforcement learning and sustainability assessment together make for greater optimization capability. The results illustrate that the proposed method offers a complete solution for achieving efficient, innovative and sustainable engineering design optimization.

4.3. Discussion

Through the comparative evaluation results, it is easy to conclude that the proposed Generative AI-Assisted Design Optimization Framework has shown substantial improvements in performance with respect to the considered evaluation metrics compared to the conventional engineering optimization approaches. The advantages of the proposed framework can be explained by the coupling of the Generative AI-based design generation, the simulation-based validation, the multi-objective optimization and the reinforcement learning-based adaptation. The proposed method is different from the conventional optimization methods which merely search the design space for better design configurations repeatedly, operating on a much larger design space by self-generated innovative engineering solutions. The ability to find these optimized designs could help engineers to find designs that would not be possible to see by human search. The greatest improvement was seen in carbon emission reductions, with a 22.97% increase over traditional techniques. This enhancement illustrates the success of embedding sustainability goals in the engineering design process. The proposed framework assesses environmental aspects (such as materials consumption, energy needs, production process and product life cycle effect) at the design optimization phase. Consequently, AI-driven solutions favor designs that are resource-efficient and eco-friendly production methods, contributing to the creation of low-carbon industrial systems. The other significant improvement was design cycle reduction, which resulted in a 22.37% performance gain. Traditional engineering design procedures can involve several cycles of concept development, simulation analysis, modification and validation, which are performed manually. The proposed Generative AI framework will substantially alleviate these repetitive tasks, to generate and assess multiple design options in a shorter time frame. Feedback from engineering simulations helps to refine designs quickly, which speeds up the development of the product and decreases TTM. The improvement in energy efficiency (18.99%) further illustrates the capability of the framework to optimise the design of the product and the manufacturing process. The system optimizes energy usage as key objective and finds designs that make it possible to achieve the desired performance with less manufacturing resources. Likewise, the improved material utilization efficiency and sustainability index values suggest a balanced approach between structural needs and environmental considerations. Moreover, by enhancing the quality of the products, the productivity of the manufacturing process, and the accuracy of the decisions, the proposed framework is shown to have industrial advantages. By incorporating explainable AI techniques, the integration becomes more transparent, giving engineers understandable reasons behind the optimization decisions, and boosting confidence in the AI-generated recommendations. The framework also has continuous learning built in, as feedback from the manufacturing process and operational data are incorporated, so that future designs can be increasingly efficient. Overall, the results demonstrate that Generative AI optimization is a major leap from traditional engineering design approaches. The proposed framework integrates intelligent design generation, simulation-based validation, and sustainability-aware optimization into a holistic solution, offering a comprehensive approach for crafting innovative, cost-effective, and eco-friendly engineering solutions for future smart manufacturing settings.

5. CONCLUSION

Generative Artificial Intelligence is a game-changer technology in the engineering design domain, allowing for automated generation, assessment, and optimization of novel configurations for products. Conventional engineering design processes rely heavily on a lot of manual experience, multiple cycles of simulations and pre-defined optimization methods, all of which restrict the efficient exploration of complex design spaces. Generative AI has created a new paradigm, where vast engineering datasets can be used to train the AI models, enabling them to learn the relationship among engineering variables and create new solutions that meet multiple technical and sustainability requirements. The current research introduced a full Generative AI-Assisted Engineering Design Optimization Framework for Sustainable Manufacturing combining Generative AI models, engineering simulations, LCA sustainability evaluation and multi-objective optimization processes in an intelligent design environment. The proposed framework can overcome several drawbacks of

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traditional engineering optimization methods, such as: long design development period, high calculation optimization process, lack of alternative solution discussion, and limited verification and consideration of environmental sustainability in the initial design stage. The framework builds on historical engineering knowledge and advanced capabilities of AI-based learning to produce multiple feasible design options that address structural performance, material efficiency, manufacturing constraints, production cost, energy consumption, and environmental impact all at once. This comprehensive perspective can help engineers consider a wider range of design options and determine the best solution in terms of performance, cost, and environmental impact. AI-generated designs are validated before implementation, thanks to the integration of engineering simulation techniques, such as CAE (Computer-Aided Engineering), FEA (Finite Element Analysis), CFD (Computational Fluid Dynamics), and lifecycle assessment tools. The reinforcement learning-based optimization mechanism also enhances the adaptability of the framework by continuously learning from the results of the simulation and manufacturing feedback. It facilitates a continuous learning process, which can be used to refine the designs that are created, leading to the optimization of the designs for the changing engineering needs, production requirements, and sustainability goals. This means that the proposed methodology can help to facilitate more rapid innovation, increased product reliability, and greater manufacturing efficiency. The proposed framework was shown to be effective through the experimental evaluation that yielded significant improvements in several performance indicators. The following improvements were seen to be significant in engineering design accuracy, material utilisation efficiency, manufacturing productivity, energy efficiency, reduction of manufacturing cycles, reduction in carbon emissions, sustainability performance and overall optimization capability. The outcomes demonstrated the capability of Generative AI to address the challenges of the conventional optimization methods and offers intelligent assistance during complex engineering decision-making process. On an industrial level, the proposed framework is a crucial step towards realizing the Industry 5.0 aims by facilitating intelligent, sustainable and human-centric manufacturing systems. By leveraging Generative AI on digital engineering platforms, Digital Twins, CAE technologies and lifecycle sustainability analysis, organizations can gain a range of capabilities that enable them to produce new products quickly and manage resources responsibly. Moreover, explainable AI techniques help to build transparency by enabling engineers to grasp the logic behind the AI-provided suggestions, which boosts trust and promotes industrial adoption. While the benefits are significant, future studies would benefit from greater interpretability of the AI models, computational efficiency, cybersecurity protection, and standardisation of validation processes for engineer-generated designs produced using AI. In future, additional technologies such as real-time manufacturing information, autonomous robotic systems and advanced Digital Twin ecosystems could be added to allow fully adaptive engineering environments. In conclusion, the application of Generative AI in engineering optimization holds significant promise for creating more sustainable, efficient, and intelligent manufacturing systems that can navigate the future challenges of industry with technologic advancement while maintaining environmental responsibility. While offering many benefits, further studies are needed to explore more effective ways of explaining AI models, lowering the complexity of algorithm computations, bolstering cybersecurity defenses and establishing standardized and rigorous testing protocols for

AI-generated engineering designs. Real-time manufacturing information, autonomous robots, and more sophisticated Digital Twin environments could also be integrated in future frameworks to create fully adaptive engineering environment. In conclusion, the engineering optimization process with the support of Generative AI is a promising approach that offers potential for more sustainable, efficient, and intelligent manufacturing systems to address future industrial challenges while ensuring technological progress and environmental responsibility.

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