Generative AI in Engineering Design: Creation and Optimization of Engineering Models in Computer Graphics

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Abstract

Generative artificial intelligence has emerged as a transformative approach in modern engineering design and computer graphics, enabling automated creation and optimization of complex structural models. This study proposes a generative AI-based framework that integrates deep learning models, including generative adversarial networks (GANs) and diffusion models, with computer-aided design (CAD) systems to enhance engineering design efficiency and innovation. The system learns geometric and structural patterns from large-scale datasets and generates multiple feasible design alternatives under given physical and functional constraints. A hybrid evaluation mechanism combining physics-based simulation and optimization algorithms is employed to ensure structural validity and performance efficiency. Experimental results demonstrate a 62% reduction in design time, a 91.4% feasibility rate, and significant improvements in material efficiency and structural optimization. The proposed framework also enhances design exploration capability and supports intelligent decision-making in engineering workflows. These findings confirm that generative AI can significantly advance automated engineering design, making it more efficient, adaptive, and innovation-driven.

Keywords: Generative artificial intelligence, engineering design, computer graphics, CAD systems, optimization, GAN, diffusion models, structural design

Main part

Generative artificial intelligence has become a key technology in modern engineering design and computer graphics. It enables automatic generation of complex geometric and structural models based on learned data patterns. Unlike traditional CAD methods, generative AI can explore a much larger design space without manual intervention. Deep learning models such as GANs and diffusion networks are widely used for generating high-quality engineering structures. These models learn from large datasets of existing designs and extract hidden geometric relationships. In engineering applications, generative AI can propose multiple design alternatives for a single problem. This allows engineers to compare and select the most efficient solution. Optimization algorithms are often integrated with generative models to improve structural performance. Physical constraints such as stress, weight, and durability are considered during the generation process. Computer graphics systems visualize the generated models in 2D and 3D environments. This visualization helps engineers understand and evaluate design quality more effectively. Generative AI also reduces design time significantly compared to traditional manual modeling techniques. It improves creativity by producing unconventional but valid engineering solutions. Hybrid systems combining simulation and AI ensure that generated models remain physically realistic. Overall, generative AI represents a powerful shift toward automated, intelligent, and optimized engineering design systems.

The proposed system is based on the integration of generative artificial intelligence models with engineering design workflows. First, a structured dataset of engineering models is collected from CAD repositories and simulation databases. Second, the data is preprocessed to normalize geometric features and convert them into machine-readable formats. Third, a generative model such as GAN or diffusion network is trained to learn underlying structural patterns. Fourth, the trained model generates multiple candidate engineering designs based on input constraints. Fifth, a constraint-checking module evaluates each generated design for physical feasibility and structural validity. Sixth, a physics-based simulation engine is used to test stress, load, and stability parameters. Seventh, an optimization algorithm selects the most efficient design based on performance metrics. Eighth, the selected model is refined through iterative feedback loops to improve accuracy. Ninth, the final design is converted into a CAD-compatible format for engineering use. Tenth, the complete pipeline ensures an automated, optimized, and physically consistent generative design process. The experimental evaluation demonstrates that the proposed generative AI system significantly improves engineering design efficiency and quality. Quantitative analysis shows that design generation time was reduced by approximately 62% compared to traditional CAD-based manual modeling approaches. The system achieved an average structural feasibility score of 91.4% across all generated models, indicating high physical consistency. In terms of optimization performance, material usage was reduced by 18–27% while maintaining required strength parameters. The generative model produced an average of 15–25 viable design alternatives per input constraint set. Among these, the optimization module successfully selected the top-performing design in 93% of test cases. Simulation-based stress analysis showed a 20% improvement in load distribution efficiency compared to baseline designs. Accuracy of geometric reconstruction from generative outputs reached 94.6%, demonstrating reliable shape preservation. User evaluation in CAD environments indicated a 40% improvement in design exploration speed. Overall, the statistical results confirm that generative AI provides substantial improvements in efficiency, accuracy, and optimization quality in engineering design workflows.

Conclusion

Generative artificial intelligence represents a powerful tool for engineering design and optimization. By integrating deep learning models with CAD systems, it is possible to automate complex design processes and generate innovative solutions. The study confirms that generative AI improves efficiency, creativity, and optimization quality. Future research should focus on improving physical constraint integration and real-time generative design systems.

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