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# *Generative AI for Engineering Design Automation*

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## *Abstract*

*Engineering design automation is rapidly transforming due to advances in generative artificial intelligence (AI). Generative AI models such as generative adversarial networks (GANs), variational autoencoders (VAEs), diffusion models, and large language models (LLMs) enable automatic creation of design concepts, geometries, layouts, and system architectures with minimal human intervention. These models can learn from existing engineering datasets and generate optimized, innovative, and manufacturable designs across domains like mechanical components, electronics, civil structures, and aerospace systems. This paper presents a comprehensive review of generative AI techniques for engineering design automation, covering model architectures, workflows, applications, benefits, and challenges. A generalized generative design automation framework is proposed to illustrate integration with CAD/CAE tools and digital manufacturing. Case studies in topology optimization, circuit design, and product conceptualization are discussed. Finally, future research directions including physics-informed generative models, human-AI collaborative design, and trustworthy AI in engineering are outlined. The study shows that generative AI can significantly reduce design cycle time and enable exploration of large design spaces beyond traditional optimization methods.*

***Keywords:*** *Generative AI, engineering design automation, generative design, CAD automation, topology optimization, diffusion models, AI-assisted design*

## INTRODUCTION

Engineering design traditionally relies on iterative processes involving modeling, simulation, prototyping, and testing. Engineers manually explore design alternatives based on experience and constraints. However, modern engineering systems are becoming highly complex, requiring exploration of vast multidimensional design spaces.

Conventional optimization and rule-based automation methods are often insufficient to discover innovative or optimal solutions. Generative artificial intelligence introduces a paradigm shift in design automation. Instead of only optimizing predefined parameters, generative AI can automatically synthesize new design geometries and configurations. These models learn statistical patterns from historical engineering data and generate new candidates that satisfy constraints or objectives.

The concept of generative design has existed earlier in computational engineering, especially in topology optimization and parametric design. But modern AI techniques significantly expand its capability by enabling data-driven design creation rather than only physics-based optimization. Recent progress in deep learning, computational geometry, and CAD integration is accelerating this transformation.

**Engineering design automation using generative AI offers several advantages:**

- Exploration of large design space automatically
- Multi-objective optimization capability
- Reduced development time and cost
- Novel and non-intuitive design discovery
- Integration with digital manufacturing

This paper reviews the current state of generative AI in engineering design automation, presenting architectures, workflows, and applications across disciplines.

## FUNDAMENTALS OF GENERATIVE AI IN ENGINEERING DESIGN

Generative AI refers to a class of machine learning techniques that can learn statistical patterns from existing datasets and then produce new samples that follow similar distributions. Unlike discriminative models that only classify or predict, generative models can synthesize new engineering artifacts such as geometries, structures, circuits, layouts, or complete system configurations. In engineering design automation, this ability is highly valuable because the design space is often extremely large and difficult to explore manually.

In traditional CAD-based design, engineers specify parameters and constraints and then iterate manually to achieve desired performance. Generative AI instead learns relationships between geometry, function, and constraints from historical design data. Once trained, the model can generate many feasible and optimized design candidates automatically. These candidates can be further evaluated using simulation or analytical models. Therefore, generative AI acts as an intelligent design synthesizer rather than only an optimizer.

Engineering design data can exist in multiple forms such as 2D sketches, 3D meshes, voxel grids, parametric CAD features, circuit schematics, or textual specifications. Generative models must therefore operate on structured and unstructured representations simultaneously. This requirement has led to development of specialized architectures for geometric and multimodal design generation.

### Key Generative Model Types

Several generative AI architectures are particularly relevant for engineering design automation. Each model type has different strengths depending on design representation, dimensionality, and constraints.

### Generative Adversarial Networks (GANs)

Generative Adversarial Networks consist of two neural networks trained simultaneously in a competitive framework: a generator and a discriminator. The generator attempts to create synthetic design samples, while the discriminator tries to distinguish between real designs from dataset and generated ones. Through this adversarial training process, the generator gradually learns to produce realistic and high-quality designs that follow underlying distribution of engineering data.

In engineering design applications, GANs are typically used for geometry synthesis and topology generation. For example, a GAN can learn distribution of structural brackets or lattice geometries from CAD datasets and then produce new designs that maintain structural patterns. The generator network usually outputs voxel grids, point clouds, or mesh representations which are later converted into CAD surfaces.

GAN-based generative design is especially useful when design space is complex and non-linear. Since discriminator provides feedback on realism, generated geometries often resemble manufacturable structures. Conditional GAN variants also allow generation under constraints such as load conditions, boundary conditions, or material type. This makes GANs suitable for engineering tasks like structural topology synthesis, microstructure design, and antenna shape generation.

However, GAN training is known to be unstable and sensitive to hyperparameters. Mode collapse is another issue where generator produces limited variety of designs. In engineering context this reduces diversity of candidate solutions, which is undesirable. Additionally, GAN outputs may lack explicit parametric representation needed for CAD editing.

**Advantages:**

- Produces high-quality realistic geometry
- Captures complex structural distributions
- Can learn manufacturable patterns Supports conditional design generation

**Limitations:**

- Training instability and convergence issues
- Mode collapse reducing design diversity
- Difficult mapping to parametric CAD
- Requires large dataset

**Variational Autoencoders (VAEs)**

Variational Autoencoders are probabilistic generative models that learn compressed latent representation of design data. A VAE consists of encoder network that maps input design into latent vector and decoder network that reconstructs design from latent space. During training, model learns smooth latent distribution that approximates underlying design manifold.

In engineering design automation, VAE latent space is extremely useful because it provides continuous and interpretable representation of designs. Engineers can explore design variations by sampling or interpolating within latent space. Small changes in latent vector produce gradual geometry changes, enabling parametric exploration and optimization.

For example, VAE trained on airfoil geometries can generate new airfoil shapes by sampling latent variables. Designers can then optimize aerodynamic properties by navigating latent space instead of modifying geometry manually. Similarly, VAEs have been used for mechanical part families, truss layouts, and material microstructures.

Compared to GANs, VAEs typically produce smoother and more stable outputs but sometimes lack sharp geometric detail. Reconstruction objective often leads to blurred or averaged shapes. Nevertheless, VAEs are preferred when latent representation and controllability are important.

**Advantages:**

- Smooth continuous latent design space
- Enables interpolation and parametric exploration
- Stable training process Good for design optimization tasks

**Limitations:**

- Lower geometric fidelity compared to GANs
- Blurred or averaged features
- May miss fine structural details

### Diffusion Models

Diffusion models are recent generative architectures that generate data by reversing a gradual noise corruption process. During training, real design data is progressively corrupted by adding noise over multiple steps. The model learns to reverse this process and reconstruct original data from noise. During generation, random noise is iteratively denoised into structured design output.

Diffusion models have shown remarkable performance in image synthesis and are now being applied to 3D geometry and engineering structures. Compared to GANs, diffusion models are more stable to train and can generate highly diverse samples without mode collapse. They also provide better coverage of design distribution, which is important for exploring engineering design spaces.

In engineering applications, diffusion models are used for topology optimization, lattice generation, architectural layouts, and aerodynamic shape synthesis.

Because generation is iterative, constraints can be incorporated during denoising steps. For instance, structural boundary conditions or load constraints can guide generation toward feasible topology.

Another advantage is that diffusion models can operate on high-dimensional data such as voxelized 3D shapes or point clouds. Emerging research shows that diffusion-based topology generation can outperform

GAN-based methods in both diversity and structural performance.

However, diffusion models are computationally intensive and require many iterative steps during generation. This may limit real-time design automation applications.

**Advantages:**

- Stable and reliable training
- High diversity and fidelity
- Good coverage of design space
- Supports constraint-guided generation

**Limitations:**

- High computational cost
- Slow generation process
- Complex implementation

### Large Language Models (LLMs) for Design

Large Language Models trained on technical documents, CAD scripts, and engineering knowledge can generate structured design information from textual inputs.

Unlike geometric generative models, LLMs operate primarily in symbolic and semantic design space. They can translate human requirements into design specifications, parametric scripts, or system architectures.

In engineering workflows, LLMs enable text-to-design automation. Designers can describe requirements in natural language such as dimensions, functions, or constraints, and model produces CAD commands or parametric modeling scripts.

These scripts can be executed in CAD software to automatically create geometry. LLMs also assist in generating engineering documentation, bill of materials, design rules, and control logic. Integration of LLMs with CAD APIs allows automated generation of sketches, extrusions, assemblies, and feature trees. This capability significantly reduces manual modeling effort in conceptual design stage.

Another important role of LLMs is multimodal coordination. They can connect textual requirements with geometric generative models and simulation tools. For example, LLM interprets design requirement and conditions geometry generator accordingly. Thus, LLMs act as high-level design planners while GANs/VAEs/diffusion models act as geometry synthesizers.

Despite their flexibility, LLM outputs may not always be physically valid or dimensionally consistent. Therefore, integration with constraint solvers and CAD kernels is necessary.

## GENERATIVE DESIGN AUTOMATION WORKFLOW

Generative AI integrates with engineering design tools forming automated workflows. A general pipeline is shown in Figure 1.

*Figure 1: Generative AI-based Engineering Design Automation Framework*

## DATA PREPARATION

Engineering datasets include CAD models, topology structures, circuit layouts, or simulation results. Preprocessing involves:

- Geometry encoding (voxels, meshes, point clouds)
- Constraint annotation
- Performance labels

Data quality significantly affects generative performance.

### Generative Model Training

The model learns mapping from latent variables to design outputs under constraints.

**Training objectives may include:**

- Reconstruction loss
- Adversarial loss
- Physics constraint loss
- Performance prediction loss

### Design Generation and Optimization

After training, new designs are generated by sampling latent space.

**Optimization loops refine generated candidates using:**

- Simulation feedback
- Surrogate models
- Reinforcement learning

### CAD/CAE Integration

Generated geometries are converted into CAD-compatible formats.

**Integration enables:**

- Finite element analysis
- CFD simulation
- Manufacturability evaluation

### Manufacturing and Validation

Final designs are validated through prototyping or digital twins. Additive manufacturing is particularly suitable for complex generative designs.

## APPLICATIONS OF GENERATIVE AI IN ENGINEERING DESIGN

Generative AI is applied across multiple engineering disciplines.

### Mechanical Component Design

Generative models create lightweight mechanical structures optimized for strength and weight. Examples include brackets, lattice structures, and load-bearing components.

Topology optimization using generative AI can produce organic shapes not achievable by traditional CAD modeling. Aerospace industries use AI-generated brackets reducing weight by up to 40%.

### Structural and Civil Engineering

AI-based generative design creates structural layouts, truss systems, and building forms satisfying load and safety constraints. Diffusion models can generate architectural floor plans with functional constraints.

**Benefits include:**

- Material efficiency
- Load-optimized structures
- Rapid conceptual design

### Electronic Circuit and PCB Design

Generative AI automates circuit schematic generation and PCB layout routing. Models learn from existing circuit libraries to create new configurations meeting electrical constraints.

**Applications:**

- Analog circuit topology synthesis
- FPGA layout generation
- Antenna geometry design

AI-generated antennas show improved bandwidth and miniaturization.

### Automotive and Aerospace Design

Generative AI assists in aerodynamic shape optimization and structural design. Diffusion models can generate airfoil shapes optimized for lift-to-drag ratio.

Aircraft components designed using generative AI often show:

- Reduced mass
- Improved aerodynamic efficiency
- Lower manufacturing complexity

### Product Conceptual Design

LLMs and multimodal generative models enable text-to-product design. Designers specify requirements in natural language and AI generates CAD concepts.

**Example workflow:**

Requirement → AI concept sketches → CAD geometry → Simulation

This accelerates early-stage product development.

## COMPARISON WITH TRADITIONAL DESIGN OPTIMIZATION

*Table 1: Traditional Optimization vs Generative AI Design*

| Aspect | Traditional Optimization | Generative AI Design |
|---|---|---|
| Design space exploration | Limited parameters | Large latent space |
| Novelty | Low | High |
| Computation | Simulation heavy | Data driven |
| Automation level | Semi automated | Fully automated |
| Creativity | Human dependent | AI assisted |
| Manufacturability | Constrained | Learned |
| Multi objective | Difficult | Natural |

Generative AI complements rather than replaces physics-based optimization. Hybrid approaches combining both provide best performance.

## BENEFITS OF GENERATIVE AI FOR ENGINEERING DESIGN

### Accelerated Design Cycle

Generative models produce thousands of candidate designs quickly, reducing conceptual design time.

### Exploration of Non-Intuitive Solutions

AI discovers organic or unconventional geometries beyond human intuition.

### Multi-Objective Optimization

Generative AI can simultaneously consider weight, strength, cost, and manufacturability.

### Design Personalization

Models can generate customized designs for specific user or environmental conditions.

### Integration with Additive Manufacturing

Generative designs often include complex lattices suited for 3D printing.

## CHALLENGES AND LIMITATIONS

Despite advantages, generative AI design automation faces several issues.

### Data Availability and Quality

Engineering datasets are limited and proprietary. Poor data leads to unrealistic designs.

### Physics Consistency

Generated geometries may violate physical laws or engineering constraints.

### CAD Compatibility

AI-generated shapes may be difficult to convert into parametric CAD models.

### Interpretability

Understanding why AI generated certain design is difficult.

### Trust and Certification

Safety-critical industries require validated designs. AI outputs must be certified.

### Computational Cost

Training 3D generative models requires high computational resources.

## EMERGING RESEARCH DIRECTIONS

### Physics-Informed Generative Models

Combining deep learning with physics equations ensures feasible designs.

### Human-AI Collaborative Design

Future design tools will allow engineers to guide generative models interactively.

### Reinforcement Learning-Driven Generative Design

RL agents can optimize generated designs using performance rewards.

### Generative Design in Digital Twins

AI-generated designs can be tested in virtual twin environments before manufacturing.

### Multimodal Engineering AI

Integration of text, geometry, simulation, and manufacturing data into unified generative models.

## CASE STUDY: AI-BASED TOPOLOGY OPTIMIZATION

Topology optimization aims to find optimal material distribution in structures. Traditional methods use gradient-based optimization. Generative AI provides faster alternatives.

**Workflow:**

- Dataset of optimized structures generated by simulation
- Train GAN/VAE to learn topology distribution
- Generate new structures for given loads
- Validate using finite element analysis

**Results from research show:**

- 100× faster design generation
- Comparable structural performance
- Higher diversity

Generative topology optimization is especially useful in aerospace bracket design.

## PROPOSED GENERATIVE AI DESIGN AUTOMATION ARCHITECTURE

A unified architecture for engineering generative design automation is shown below.

***Figure 2: Generative AI-based Engineering Design Automation Framework***

**Key features:**

- Multimodal generative model
- Physics-aware evaluation loop
- CAD integration
- Manufacturing readiness

## FUTURE OUTLOOK

Generative AI is expected to become core component of engineering CAD systems. Future CAD tools may include built-in generative engines that automatically create optimized designs based on requirements.

**Trends likely to shape future:**

- AI-native CAD platforms
- Real-time generative design
- Cloud-based collaborative AI design
- Autonomous engineering systems

In long term, engineering design may shift from manual modeling to AI-guided specification-driven creation.

## CONCLUSION

Generative AI is transforming engineering design automation by enabling automatic creation of optimized, innovative, and manufacturable designs. Techniques such as GANs, VAEs, diffusion models, and large language models allow exploration of vast design spaces beyond traditional optimization methods. Applications across mechanical, civil, electronic, aerospace, and product design demonstrate significant reductions in design time and improvements in performance.

However, challenges related to data availability, physics consistency, CAD integration, and certification remain. Future research focusing on physics-informed generative models, human-AI collaboration, and trustworthy AI will be essential for adoption in safety-critical industries.

Overall, generative AI represents a paradigm shift from manual design toward intelligent autonomous design automation, and is expected to play central role in next-generation engineering systems and digital manufacturing ecosystems.

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