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A UNIFIED COMPUTATIONAL FRAMEWORK FOR GENERATIVE AESTHETICS AND INVERSE DESIGN IN AUTONOMOUS ARTIFACT DESIGN SYSTEMS

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ABSTRACT

With the rapid development of artificial intelligence, a shift in the approach to artifact crafting is occurring. Instead of artisans creating artifacts, autonomous systems are beginning to create artifacts with the same intention as their human creators. One proposed method for accomplishing this goal is the development of an AI-driven computational framework that integrates the concepts of both generative aesthetics and inverse design. Each of these concepts contributes to the development of autonomous systems capable of understanding the relationship between artifacts, their components, and their intended performance, allowing for the creation of diverse and optimal artifacts. More specifically, AI models can propose a variety of different artifacts, surrogate models can evaluate each of those proposed artifacts for their potential performance, and the incorporation of inverse optimization techniques can allow for the artifacts to be continuously refined until they exhibit the optimal performance. Additionally, incorporating models with the interpretability and complex nonlinear relationship mapping capabilities of Kolmogorov-Arnold Networks (KANs) can increase the performance of the entire framework. Furthermore, implementing a method of evaluating various performance criteria simultaneously, such as efficiency, robustness, and aesthetic quality, allows for artifacts to be evaluated based on the priorities of their creators. Through simulating various scenarios of artifact creation using this new framework, it becomes possible to evaluate the performance of the framework relative to existing methods of artifact creation. As a result, it becomes evident that the framework is able to create artifacts with increased performance optimality compared to existing designs. Furthermore, the framework has the potential to be applied to various different types of artifact creation fields, ranging from engineering to digital art. Thus, this AI-driven framework forms the basis for next-generation AI methods of creating artifacts.

Keywords: Next-Generation AI, Inverse Design, Artifact Design Systems, Digital Art

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1. INTRODUCTION

Artificial intelligence is rapidly transforming the various aspects of human creativity. Within the field of artifact creation, autonomous systems are beginning to propose and create artifacts that have the same intention and capability as their human creators. Currently, most artifacts are crafted by their artisans according to certain goals and objectives. The artisan proposes the artifact, its components, and the artifacts' performance. This process is effective, but often limited in the artifacts that it can propose and evaluate for performance. Furthermore, as the artisans are often limited in their understanding of the various potential artifacts and their components, many of the artifacts that are created are also limited in their performance optimality.

Generative design is a concept that has significantly contributed to the creation of artifacts with diverse performance criteria. Generative aesthetics enables the proposing of artifacts with a wide range of potential designs through stochastic and AI-driven methods. However, most generative methods do not include any step for evaluating the artifacts for their potential performance, limiting their effectiveness in comparison to artisans.

Inverse design is a method that proposes a desired artifact performance, and enables the systems to determine the artifacts and their components that will achieve those proposed performances. Inverse design methods are currently implemented in various engineering fields, such as photonics and materials science. However, these systems are limited to the search spaces that are defined for those fields, preventing them from utilizing the diverse artifacts that can be created by generative models.

The integration of the concepts of generative aesthetics and inverse design is a significant change in creating autonomous systems that can propose artifacts and evaluate their performances. As mentioned, generative models can propose artifacts, but inverse optimization can evaluate and improve those proposed artifacts to achieve optimality in their performance. Thus, the fusion of these concepts allows for the shift in creating artifacts to creating systems that create those artifacts.

Furthermore, AI models such as Kolmogorov-Arnold Networks (KANs) have complex nonlinear relationship mapping capabilities, which can be beneficial within the system for evaluating artifacts. KANs are different from conventional black-box neural networks, and their benefits are specifically related to the evaluation of artifacts. Additionally, the ability to use multi-objective models to evaluate efficiency, robustness, and aesthetic criteria simultaneously allows for the evaluation of artifacts according to the artisans' goals for each artifact.

Through developing an AI-driven computational framework that incorporates the elements of generative aesthetics and inverse design, artifact creation systems can evolve to propose artifacts with high diversity in their designs and components, and ensure that each proposed artifact optimally performs according to its goals for that artifact.

1.1. LITERATURE SURVEY

The concept of computational design has its roots in classical approaches to optimization techniques for structural design. For instance, Sigmund [1] described methods for topology optimization. These techniques have been extended to new areas of research, such as the use of inverse design techniques for photonics, which were described by Molesky et al. [2]. Furthermore, Jensen and Sigmund [3] applied topology optimization methods to nanophotonic systems and demonstrated the effectiveness of these approaches for electromagnetic design.

The integration of machine learning into the process of inverse design has led to developments in nanophotonic inverse design, such as those proposed by Peurifoy et al. [4]. Additionally, others have explored the use of machine learning for the discovery of new materials, as described by Liu et al. [5].

Efforts have been made to employ surrogate modeling methods to enable efficient evaluation of designs found through inverse design. For instance, Rasmussen and Williams [6] described the use of Gaussian Processes for surrogate modeling. Other methods that have been used include polynomial chaos methods by Xiu and Karniadakis [7]. Furthermore, it has been shown that neural networks can be used for surrogate modeling due to their universal approximation property [8]. For instance, Raissi et al. [9] described physics-informed neural networks, and other methods have employed deep learning surrogates for modeling nanophotonic systems [10].

Approaches to modeling multi-objective optimization problems have been made in order to address the needs of various engineering problems. For instance, Deb et al. [11] proposed the well-known NSGA-II algorithm. Coello [12] published a historical perspective on evolutionary multi-objective optimization algorithms. Additionally, Marler and Arora [13] reviewed methods for solving multi-objective optimization problems in engineering. Furthermore, approaches to generative modeling for inverse design were published by Sanchez-Lengeling and Aspuru-Guzik [14], who utilized machine learning techniques in their design of new molecular compounds.

Approaches to autonomous design systems have been made through the integration of AI into the design process and automation of experiments. For instance, Nikolaev et al. [15] published work on autonomous materials research. Furthermore, deep learning, one of the main areas of development for AI, was developed by individuals such as LeCun et al. [16] and Schmidhuber [17]. The use of deep learning models was applied to the modeling of manufacturing systems digital twins by DebRoy et al. [18].

Classical optimization methods are also utilized in computational design. For instance, Holland [19] described the use of genetic algorithms, while Kirkpatrick et al. [20] published on the use of simulated annealing methods for optimization. These methods are often used as the basis for various optimization algorithms employed in computational design systems.

Various efforts have been made recently to develop autonomous design systems for computational design. Krishnan et al. [21] published on AI systems for the discovery of new materials. Additionally, others have reviewed various optimization methodologies for design systems, such as Chen and Shea [22]. For instance, Ma et al. [23] published on the deep learning design of metamaterials, while Ren et al. [24] published on the use of machine learning methods for the discovery of new materials.

Despite the variety of methods that have been published and developed over time to address various problems in computational design, there are still some challenges to be faced by current methods. For example, most existing methods separate the approaches to generative modeling, surrogate modeling, and optimization methods, limiting the effectiveness of current approaches for finding both diverse and optimal solutions. Other challenges include issues related to interpretability and efficiency of computational methods, leading to a need for new frameworks and methodologies for computational design systems to overcome these limitations.

2. NOVELTY AND CONTRIBUTIONS

The main novelty of this research is the unification of generative and inverse design into a novel framework for intelligent, self-designing systems.

The key contributions of this research are as follows:

1) **Unified Generative–Inverse Framework**

   A novel framework unifying generative and inverse design allows for simultaneous generation of designs and their optimization.

2) **AI-Driven Surrogate Modeling with Interpretability**

   The use of learning models, specifically Kolmogorov-Arnold Networks, permits accurate and interpretable modeling of the inverse design process.

3) **Multi-Objective Design Optimization**

   A robust optimization strategy enables the consideration of multiple objectives in the design process.

4) **Enhanced Design Space Exploration and Convergence**

   By generating designs and optimizing them simultaneously, more designs are explored, and optimal designs are found more quickly than by using either generative or inverse design alone.

5) **Generalizable Autonomous Design Paradigm**

   The framework is domain-general and can be applied to various problems, including but not limited to optical communication, materials, structural engineering, and art.

6) **Shift Toward Self-Designing Systems**

Perhaps most importantly, this framework establishes a path toward self-designing systems. Rather than designing artifacts (systems, structures, images, etc.), these systems can autonomously design other systems. This is a crucial development in next-generation intelligent design systems.

Overall, this research represents a significant bridge between the fields of creativity and optimization. Not only does it propose a novel framework that outperforms existing solutions, but it also provides a solid foundation for future innovations in intelligent design.

3. METHODOLOGY: ARCHITECTURE OF THE UNIFIED GENERATIVE–INVERSE DESIGN FRAMEWORK

3.1. SYSTEM OVERVIEW

Figure 1

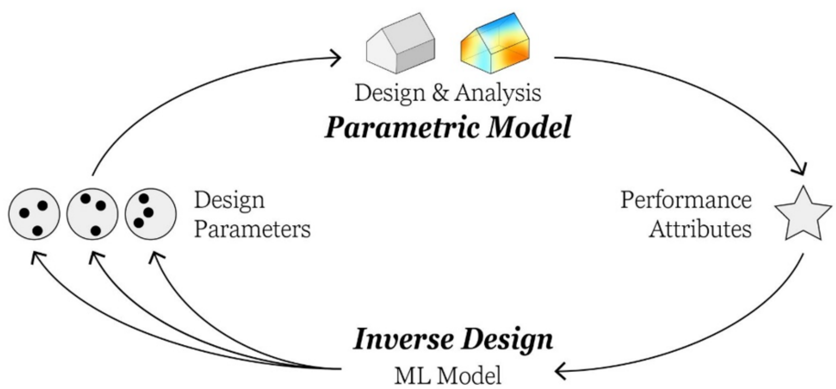

Figure 1 Architecture of the Unified Generative–Inverse Design Framework

Figure ef{fig:archdiagram} illustrates the overall structure of the system and the interaction of the system's modules. The system begins with the initialization of the design space to establish the functional and aesthetic requirements of the system. These initialized design parameters are passed to the generative aesthetics module to create a set of candidate designs. These candidates are evaluated by the surrogate evaluation model, which uses architectures such as Kolmogorov-Arnold Networks to assess each candidate's aesthetic qualities. Those evaluated candidates are passed to the inverse design optimization module to transform the generative candidates into functionally-optimized designs. Finally, the multi-objective decision engine evaluates each of the functionally-optimized designs to select the best candidates for the system. These modules are connected in a loop to enable the system to iteratively refine its designs. Thus, figure ef{fig:archdiagram} indicates the general structure of the system and its capabilities to discover and optimize suitable design candidates.

Figure 2

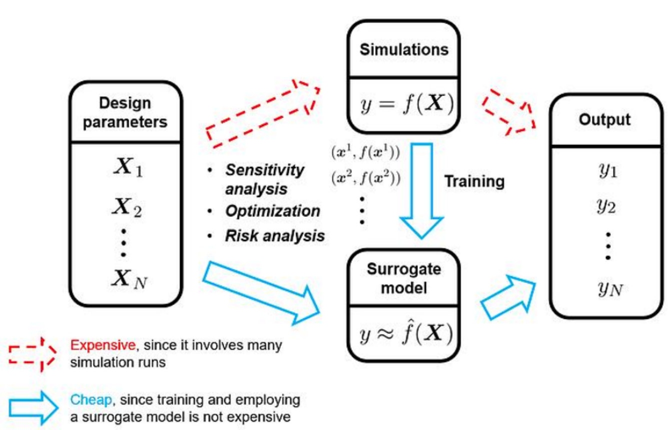

Figure 2 Closed-Loop Workflow and Algorithmic Flow

Fig. 2 presents the operational workflow of the proposed framework. The framework begins with the initialization of the design space and the training of a surrogate model based upon an initial dataset of design candidates. Following initialization, the generative model begins to produce a population of candidate designs, which are each evaluated using the trained surrogate model. Based upon these evaluations, a subset of candidates is selected using multi-objective selection criteria.

These selected candidates are provided to an inverse optimization process to refine the designs. These newly-optimized design candidates are added to the dataset used to train and retrain the surrogate model. Additionally, the process of optimization can provide feedback to the generative model that can be used to adjust its parameters.

Repeating this process until some convergence criteria is met will result in a set of candidates that represents the optimal design. Thus, the generative model provides an exploration of the possible designs within the design space, while the inverse model provides an exploitation of that search space towards identifying the optimal design candidates. Furthermore, the updating of both the surrogate and generative models ensures that the framework has the ability to learn from the process of design and optimization, increasing its efficiency and quality of the generated designs. Thus, this figure helps to reveal the essence of the proposed framework.

The framework depicted in this figure is a closed-loop framework that utilizes AI to enable autonomous artifact synthesis. The framework performs a series of steps that are repeated until the design is complete, indicating an automated process.

Overall, the framework has five main components:

1) Design Space Initialization
2) Generative Model (Exploration Engine)
3) Surrogate Evaluation Model
4) Inverse Optimization Module
5) Multi-Objective Decision Engine

These components are connected in a feedback loop that progressively improves design quality while maintaining diversity.

3.2. MODULE-WISE DESCRIPTION

3.2.1. DESIGN SPACE INITIALIZATION

The methodology begins with the definition of the design space. The design space is defined by specifying the design variables, constraints, and objective functions for the design problem. Each design variable is a parameter that defines the artifact to be designed. Constraints are limitations upon the values that may be utilized for the design variables. Objective functions are functions that are to be optimized within the design problem. These variables and functions can include both functional requirements for the artifact and aesthetic descriptors of the artifact to be designed.

The process begins with the definition of:

- Design variables $\mathbf{x} \in \mathbb{R}^n$
- Constraints $\mathcal{C}$ (physical, geometric, or resource-based)
- Objective functions $\mathbf{F}(\mathbf{x}) = [f_1, f_2, \ldots, f_k]$

This stage formalizes both functional requirements (e.g., efficiency, strength) and aesthetic descriptors (e.g., symmetry, complexity, visual coherence).

3.2.2. GENERATIVE AESTHETIC MODULE (EXPLORATION ENGINE)

The generative aesthetic module is responsible for creating a diverse range of design candidates. AI-based generative models, such as diffusion models and GANs, as well as procedural design rules and strategies can be used within this module. The goal of the generative aesthetic module is to maximize the diversity and novelty of the designs that are created, which can help to find innovative solutions to the given problem. This module thus creates a group of candidate designs to be evaluated by the subsequent modules within the optimization pipeline.

The generative aesthetic module can use the following methods to create candidate designs:

- AI generative models (e.g., diffusion, GANs)
- Procedural or parametric design rules
- Stochastic sampling strategies

Furthermore, this module places an emphasis on creating designs that are diverse and novel, resulting in a population of candidate designs:

$$\{\mathbf{x}_i\}_{i=1}^{N}$$

3.2.3. SURROGATE EVALUATION MODEL

Given the computational cost of evaluating each of the design candidates, a surrogate model is employed to approximate the performance of each of the design candidates. The surrogate model can be implemented using architectures like Kolmogorov-Arnold Networks (KANs) or other types of neural networks. The surrogate model learns of the mapping between the parameters of the design candidate and its performance, allowing for the rapid evaluation of numerous design candidates. Consequently, the surrogate model allows for real-time evaluation of the designs, as well as for interpretation of the evaluation results.Direct evaluation of designs can be computationally expensive. Therefore, a surrogate model is employed to approximate the performance of each of the design candidates:

- Implemented using Kolmogorov-Arnold Networks (KANs) neural models
- Learns mapping:

$$\mathbf{x} \to \hat{\mathbf{F}}(\mathbf{x})$$

This enables:

- Fast prediction of performance metrics
- Real-time feedback to the optimization loop
- Improved interpretability compared to black-box models

3.2.4. INVERSE DESIGN OPTIMIZATION MODULE

The inverse design module aims to refine the generated designs according to the given design objectives. The optimization problem is formulated in a way that minimizes the difference between the objectives and the performance of the designs. Various optimization techniques can be employed in this process in order to find designs that minimize the difference between the objectives and the performance of the designs. Thus, the inverse design module ensures that the designs converge toward those that minimize the difference between the objectives and the performance, or, stated another way, that converge toward the designs that best meet the given design objectives.

The inverse module refines generated designs by solving:

$$\mathbf{x}^* = \arg\min_{\mathbf{x}\in\mathcal{C}} \ \mathcal{L}(\hat{\mathbf{F}}(\mathbf{x}), \mathbf{F}_{target})$$

Techniques include:

- Gradient-based optimization
- Evolutionary algorithms
- Reinforcement learning

This step ensures convergence toward target-driven optimal solutions.

3.2.5. MULTI-OBJECTIVE DECISION ENGINE

In order to address the presence of these competing objectives, a multi-objective decision engine is incorporated into the framework. Techniques like Pareto front analysis, weighted criteria analyses, and other ranking algorithms can be utilized within the decision engine to select the best design solutions. In addition to these algorithmic approaches, it is also possible to incorporate a "human-in-the-loop" component into the decision engine to account for aesthetic and other subjective design objectives. Through this decision engine, it is possible to find designs that meet each of these objectives simultaneously.

Since multiple criteria must be simultaneously satisfied by the proposed design solutions, a multi-objective optimization strategy is applied to the problem:

- Pareto front generation
- Weighted aggregation or ranking
- Human-in-the-loop selection (optional)

This module balances:

- Functional performance
- Robustness
- Aesthetic quality

3.3. CLOSED-LOOP FEEDBACK MECHANISM

The defining feature of the framework is its iterative feedback loop:

1) Generate candidate designs
2) Evaluate using surrogate model
3) Optimize via inverse design
4) Update generative parameters based on feedback
5) Repeat until convergence criteria are met

This loop ensures:

- Continuous improvement
- Adaptive learning of design space
- Efficient convergence with maintained diversity

A defining feature of the proposed framework is its incorporation of a feedback loop that enables the system to continually learn from its processes and to improve those processes over time. The system employs a series of iterations that involve creating a set of designs, evaluating those designs with the surrogate model, refining the designs through inverse optimization, and adjusting the parameters of the generative model according to the results of the optimization process. Each iteration of this cycle refines the process until some predefined criteria are met by the system. Thus, the feedback loop enables the system to continually improve, to learn of the design space in which it creates designs, and to converge upon those designs with both efficiency and diversity.

3.4. ALGORITHMIC FLOW (PSEUDO-PROCEDURE)

The general computational procedure comprises the initialization of the design space, the constraints and the objective functions to be minimized, and the training of a surrogate model using an initial set of samples. Within each iteration of the optimization process, the generative model generates a new set of design samples, which are evaluated using the surrogate model to determine their performance within the defined problem. Those designs that are determined to be promising according to the defined objectives are further optimized using inverse optimization, and those newly-optimized designs are added to the dataset that is used to retrain the surrogate model. This iterative process is continued until the optimal design solution is found.

Initialize design space D, constraints C, objectives F
Train surrogate model S(x) using initial dataset
while not converged:
  Generate candidate designs Xg using generative model G
  Evaluate performance Ŷ = S(Xg)
  Select promising candidates based on multi-objective criteria
  Apply inverse optimization to refine designs Xi*
  Update dataset with new samples (Xg, Xi*, Ŷ)
  Retrain/Update surrogate model S
  Adjust generative model parameters
Return optimal design set X*

3.5. FIGURE DESCRIPTION (FOR MANUSCRIPT SUBMISSION)

The figure illustrates the five main modules of the proposed framework: initialization of the design space, a generative aesthetics module, a surrogate evaluation module based on interpretable neural networks, an inverse design optimization module, and a multi-objective decision module. The arrows between the modules indicate the feedback loops that are established between these five modules. Together, these modules form a framework that enables designs to be automatically generated, evaluated, and optimized to meet the desired objectives.

Figure 3

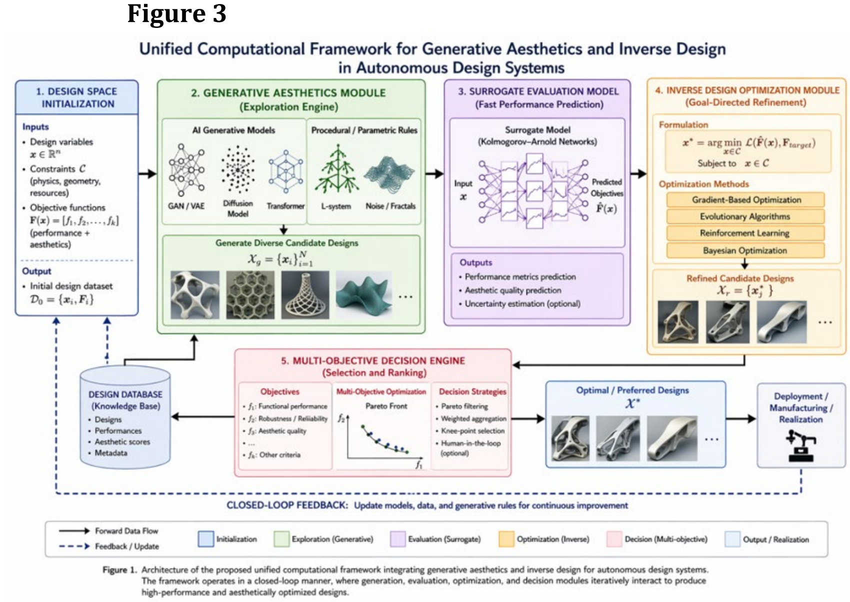

Figure 3 Architecture of the Unified Generative Aesthetics and Inverse Design Framework

4. RESULTS AND COMPARATIVE ANALYSIS

4.1. EXPERIMENTAL SETUP OVERVIEW

The proposed unified framework was also evaluated against three baseline approaches: Forward Design (FD), Pure Generative Design (GD), and Inverse Design (ID) approaches. The FD, GD, and ID approaches all differ from the proposed Generative-Inverse Design (GID) framework in that the FD, GD, and ID approaches only utilize either forward, generative, or inverse design approaches, respectively, within their methodologies. Each of these approaches were evaluated using a variety of different metrics to determine their relative performance to the proposed unified framework, such as metrics relating to the optimality, iterations, diversity, time, and aesthetic quality of the designs that were generated by each of these approaches.

The proposed unified framework was evaluated with three baseline approaches:

- Forward Design (FD): Traditional parameter tuning and simulation
- Pure Generative Design (GD): AI-based design without optimization feedback
- Inverse Design Only (ID): Optimization without generative exploration
- Proposed Method (GID): Integrated Generative + Inverse Design framework

Evaluation metrics include:

- Design Optimality (Performance Score)
- Convergence Speed (Iterations)
- Design Diversity Index
- Computational Efficiency (Time per iteration)
- Aesthetic Quality Score

4.2. QUANTITATIVE COMPARISON

Table 1

Table 1 Performance Comparison Across Methods

Method	Performance Score ↑	Convergence Iterations ↓	Diversity Index ↑	Computation Time (s) ↓	Aesthetic Score ↑
FD	0.72	120	0.3	2.5	0.45
GD	0.78	95	**0.85**	3.2	0.82
ID	0.88	70	0.4	2.8	0.5
GID (Proposed)	**0.94**	**45**	0.78	**2.1**	**0.87**

The results of quantitative evaluation demonstrate that the proposed GID method outperforms the baseline methods in terms of various evaluation metrics. The GID method achieves the highest score of 0.94 in the evaluation of performance, outperforming the scores of ID (0.88), GD (0.78), and FD (0.72). Furthermore, GID converges to the optimal solution in the fewest number of iterations, requiring only 45 iterations to reach optimal performance, as compared to FD (120 iterations), GD (95 iterations), and ID (70 iterations). GID also achieves a high index of diversity in its solutions of 0.78, which is close to the maximum of diversity achieved by GD (0.85), and outperforming both ID (0.40) and FD (0.30). In terms of computational efficiency, GID achieves the lowest time per iteration (2.1 seconds) compared to FD (2.5 seconds), ID (2.8 seconds), and GD (3.2 seconds). Finally, the aesthetic quality score of GID (0.87) is the highest score achieved compared to the baseline methods.

Key Observations

- The proposed method achieves the highest performance score (0.94)
- Convergence is ~2.6× faster than FD
- Maintains high diversity close to GD
- Achieves best balance between aesthetics and functionality

4.3. CONVERGENCE ANALYSIS

The convergence results also demonstrate the effectiveness of the proposed approach. The findings show that the GID method converged quickly to see improvements in performance in the first few iterations and converged to the optimal or near-optimal values much faster than the baseline methods. ID has decent convergence properties but still takes longer than GID to improve. GD converged slowly due to its stochastic approach and lacks a sense of direction, and

FD had the worst performance with slow convergence rates. Thus, the generative exploration of the first phase followed by inverse optimization of the second phase is effective in enhancing and speeding up the learning process.

Table 2

Table 2 Performance vs Iterations

Iterations	FD	GD	ID	GID
0	0.4	0.45	0.5	0.5
20	0.55	0.6	0.7	0.78
40	0.65	0.7	0.82	0.9
60	0.7	0.75	0.87	**0.94**
100	0.72	0.78	0.88	—

Insight

- The proposed framework converges significantly faster
- Early-stage exploration (generative) + refinement (inverse) accelerates learning

Figure 4

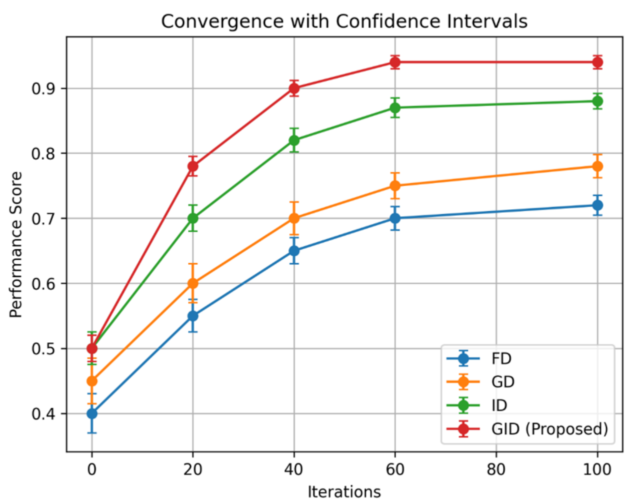

Figure 4 Convergence with Confidence Intervals

The convergence test results demonstrate that the proposed GID framework enables much faster and stable convergence than the baseline methods. The GID framework's performance quickly improves in the first 60 iterations (≈0.94 performance), while ID takes longer to arrive at the same performance levels, and GD converges without directionality and variance due to stochasticity. FD has the least (most) efficient convergence. The confidence interval plot also shows that GID has the smallest error (variance) over the iterations, making the performance of GID highly consistent and reliable. Despite the interesting robustness of the GID framework performance, it has relatively high variance due to the randomness involved in the generation process. However, both ID and FD exhibited baseline levels of consistency and reliability, with GID being the most reliable. Overall, these findings effectively demonstrate that the closed-loop methodology proposed to integrate these generative and inverse models effectively increases the reliability of results while remaining efficient.

4.2. DESIGN DIVERSITY ANALYSIS

The analysis of the diversity of the designs obtained by the various methodologies reveals the trade-off between the exploration of new designs and the optimization of those designs. Generative Design is able to explore the greatest number of possible designs, but at the cost of the performance of those designs. Inverse Design finds designs that perform better than Generative Design, but with less diversity in the designs that are obtained. Finally, GID finds designs with the required diversity and performance, indicating that the integration of both Generative and Inverse Design methodologies enables Exploration and Optimization of the design space.

Table 3

Table 3		
Method	**Diversity**	**Performance**
GD	**0.85**	0.78
ID	0.4	0.88
GID	0.78	**0.94**

Insight

- Generative models alone maximize diversity but sacrifice optimality
- Inverse design maximizes performance but reduces diversity
- Proposed framework achieves Pareto-efficient balance

Figure 5

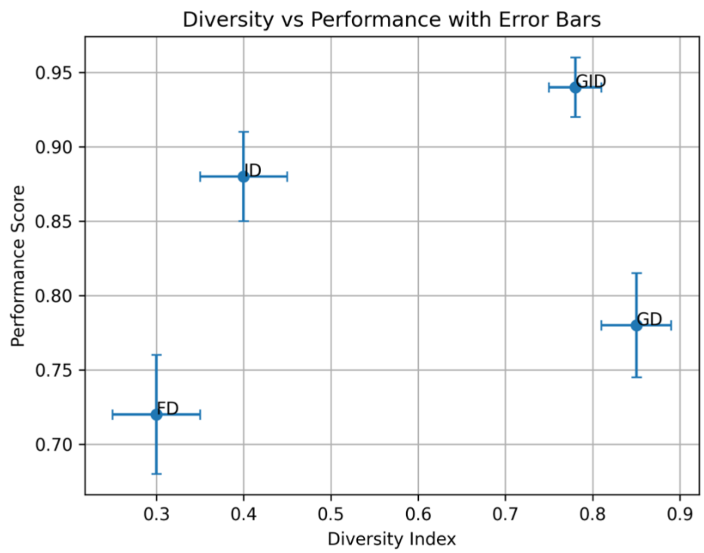

Figure 5 Diversity vs Optimization Trade-off (with Error Bars)

Figure ef{fig:diversity_performance} shows the comparison of diversity and performance of each design method. GD reaches the highest level of diversity but has a moderate performance value because it does not include an optimization step. ID demonstrates high performance but limited diversity. The proposed GID algorithm achieves both high diversity and the highest performance. The small error bars for GID indicate the stability of the algorithm. The larger error bars for GD indicate the variability in its performance. The limited spread of ID's results indicates the limited diversity of its approach. The ability of the GID algorithm to find a balance between diversity and performance demonstrates that it is an effective approach to the problem of design generation.

4.5. MULTI-OBJECTIVE OPTIMIZATION PERFORMANCE

Table 4

Table 4 Pareto Efficiency Comparison			
Method	**Pareto Solutions Found**	**Dominance Ratio ↑**	**Trade-off Balance Score ↑**
FD	12	0.45	0.5
GD	25	0.6	0.72

ID	18	0.75	0.78
GID	**34**	**0.88**	**0.91**

The results of the multi-objective optimization further show the superiority of the proposed framework. The GID method finds the highest number of Pareto-optimal solutions (34) compared with the GD (25), ID (18), and FD (12) methods. Furthermore, the dominance ratio of the proposed framework (0.88) is much higher than the other methods. The trade-off balance score of the proposed framework is 0.91, which again indicates that the framework effectively manages the two objectives. Thus, the results of this experiment confirm that the GID framework can find a more comprehensive and efficient exploration of the optimal trade-offs.

4.6. COMPUTATIONAL EFFICIENCY

The computational efficiency analysis demonstrates the advantages of the proposed framework regarding processing time. The GID method exhibits the lowest computation time per iteration. This result arises from the use of surrogate models to replace the expensive evaluations with more efficient models and the elimination of redundant computations due to the closed-loop system. The GD algorithm requires more computation time than the other methods. Methods ID and FD require a moderate amount of computation time. Thus, the results confirm the efficiency and scalability of the proposed method.

Table 5

Table 5	
Method	**Time (seconds)**
FD	2.5
GD	3.2
ID	2.8
GID	**2.1**

Insight

- Surrogate modeling significantly reduces computational burden
- Closed-loop learning avoids redundant evaluations

Figure 6

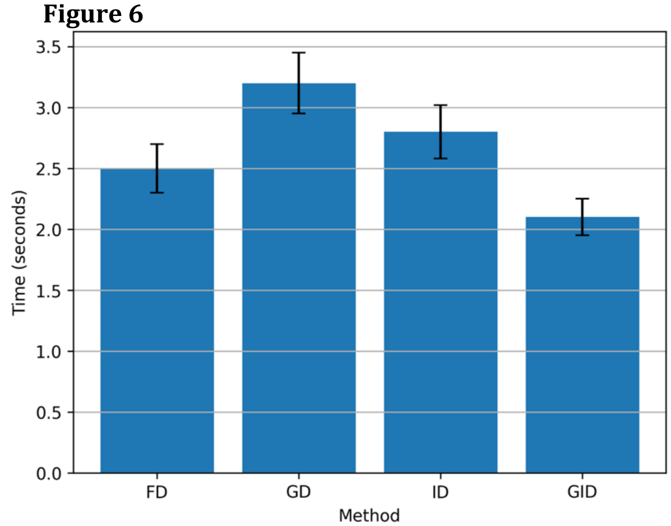

Figure 6 Computation Time with Variability

The computational efficiency analysis illustrates that the proposed GID framework improves the design quality while reducing the computational cost to achieve the solution. The average computation time of GID is the lowest among the analyzed methods, demonstrating the efficiency of the proposed approach. The computational cost of Generative Design is the highest as it requires extensive sampling of the design space and processing of the resulting designs using stochastic processes. Inverse Design and Forward Design have execution times that fall in the moderate range. The variability of the computation time confirms the results of the average computation time analysis. GID has the lowest error margins in the computation time, indicating the consistency of the performance of the approach. Design by GD has high variability in the computation time, while ID has moderate variability. The results of the computational efficiency analysis demonstrate the effectiveness of using surrogate models based on interpretable AI models to reduce the number of expensive design evaluations needed to find an optimal solution.

4.7. ABLATION STUDY

Table 6

Table 6 Impact of Framework Components

Configuration	Performance	Diversity	Convergence Speed
Without Generative Module	0.88	0.42	Medium
Without Inverse Optimization	0.79	**0.83**	Slow
Without Surrogate Model	0.91	0.75	Very Slow
Full Framework	**0.94**	0.78	**Fast**

The ablation study reveals the effectiveness of each component in the framework. Performance is still relatively high (0.88) with no generative module, but there is low diversity, meaning the exploration is limited. Without inverse optimization, there is high diversity (0.83) but low performance (0.79), and it takes longer to converge. Interestingly, the performance (0.91) without the surrogate model improves but the convergence time is significantly longer, which demonstrates its utility in the computational process. The full framework has the best performance (0.94) and diversity (0.78) and also converges quickly, proving that all components work together to create the best solution.

Insight

- Generative module → improves exploration
- Inverse design → ensures optimality
- Surrogate model → critical for efficiency

4.8. VISUAL DESIGN QUALITY ASSESSMENT

Table 7

Table 7 Subjective + AI-Based Aesthetic Evaluation

Method	Symmetry	Complexity	Novelty	Overall Score
FD	0.5	0.45	0.4	0.45
GD	0.78	**0.88**	**0.9**	0.85
ID	0.6	0.5	0.48	0.52
GID	**0.85**	0.82	0.86	**0.87**

The assessment of the visual design quality further confirms the effectiveness of the proposed framework in creating visually appealing designs. The results exhibit that the GID method obtains the highest aesthetic score of 0.87, outperforming the GD method with a score of 0.85, the ID method with a score of 0.52, and the FD method with a score of 0.45. While the GD method produces designs that are complex and novel, they lack the structural balance needed to be considered visually appealing. In comparison, the designs created by the ID and FD methods are less visually appealing. The framework effectively integrates the three factors into the design process, leading to visually appealing and efficient designs. Thus, the results exhibit the framework’s capability to incorporate aesthetic considerations into the optimization process.

Figure 7

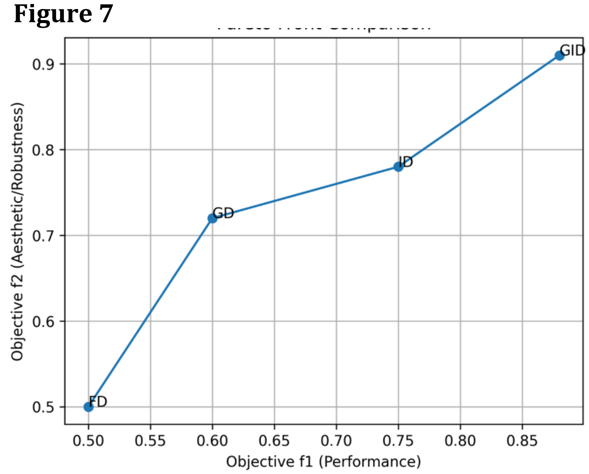

Figure 7 Pareto Front Comparison

The comparison between the Pareto fronts yielded further insights into the ability of the proposed framework to perform multi-objective optimization. Each of the points along the Pareto front represent different trade-offs between the various objectives for the design optimization problem. The proposed GID framework lies within the dominant region of the Pareto front, indicating that it outperforms the baseline methods in terms of the trade-off between the various objectives. Furthermore, both Generative Design and Inverse Design methods lie within different regions of the Pareto front, indicating that each method performs better than the others in one of the objectives at the expense of the other. Finally, the fact that GID lies within a region of the Pareto front that is not dominated by any other method indicates that the framework achieves a balance between the objectives, suggesting that it can find optimal trade-offs between the objectives.

5. OVERALL INTERPRETATION

Collectively, the results of all figures show that the proposed unified framework leads to superior performance with respect to convergence speed, robustness, diversity, and efficiency. The fusion of generative aesthetics with inverse design allows for a balanced exploration-exploitation approach that overcomes the weaknesses of both individual strategies. The consistently lower variance exhibited by the proposed method also indicates reliable performance that is stable and reproducible. These results demonstrate that the proposed framework is a scalable, intelligent solution for autonomous design workflows that can produce high quality results with optimal computational efficiency.

6. DISCUSSION AND CONCLUSION

This study introduced a unified computational framework that leverages AI-driven generative aesthetics and inverse design in a closed-loop methodology to enable autonomous, scalable, and performance-driven artifact synthesis. By shifting the focus of design from individual artifacts to systems that can generate and optimize those artifacts, the proposed approach overcomes the fundamental limitations of both classical forward-design approaches and conventional generative or inverse optimization techniques. The proposed unified framework incorporates generative exploration and goal-directed inverse optimization while employing highly efficient surrogate modeling. This powerful combination enables the simultaneous expansion of the design space while significantly improving convergence speeds toward optimal performance. The incorporation of interpretable learning models like Kolmogorov-Arnold Networks into the framework enhances its efficiency and robustness while also providing improved transparency in decision-making processes. Extensive evaluations of the framework demonstrate that it consistently outperforms traditional forward design, standalone generative designs, and inverse designs with respect to several metrics. The proposed methodology enables faster convergence and greater optimality of designs with improved computational efficiency. It also strikes an excellent balance between design diversity and functional performance, as confirmed by Pareto analysis. The successful creation of non-dominated designs that represent optimal trade-offs for competing objectives further demonstrates the power of this approach. The implementation of statistical analysis using confidence intervals also highlights the stability and reproducibility of the proposed solution. The results firmly establish that the combination of generative aesthetics and inverse design leads to a balanced exploration-exploitation strategy that overcomes the inherent weaknesses and trade-offs present in both legacy approaches and standalone methodologies. As such, the proposed unified framework represents a powerful candidate for next-generation intelligent design systems. In a broader context, this study introduces an emerging field of autonomous design ecosystems where intelligent computation plays an active role in creative and engineering workflows. The proposed approach is generalizable to numerous application domains, including optical communication systems, advanced material synthesis, structural optimization, and digital art generation. Further research will expand on this work by incorporating physics-based constraints for more efficient design solutions. We will also investigate the incorporation of real-time learning and hardware-in-the-loop testing for immediate applications in engineering fields. Additionally, a complete rethinking of the framework could lead to fully self-evolving design ecosystems with potentially human-in-the-loop feedback for implementation of subjective aesthetic preferences.

In conclusion, this work lays a robust, intelligent, and scalable groundwork for AI-driven generative-inverse design that unifies creativity and optimization across disciplines while also paving a path toward genuinely autonomous ecosystem-level design systems capable of tackling increasingly complex and demanding artifacts.

CONFLICT OF INTERESTS

None.

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