Generative Design in Naval Architecture: A Survey

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Abstract

Generative design in naval architecture represents a transformative approach that leverages computational techniques such as parametric modeling and Generative Adversarial Networks (GANs) to enhance the efficiency and innovation of ship designs. Traditional ship design processes are often resource-intensive and limited by human intuition, whereas generative design explores broader design spaces, automating the generation and evaluation of multiple design iterations based on predefined parameters and constraints. This survey paper examines the motivations for adopting computational design techniques in naval architecture, highlighting the potential of generative design to overcome traditional limitations and optimize ship designs for both functionality and aesthetics. The survey outlines key concepts, including parametric modeling and GANs, and explores their applications within the field. Notably, generative design has been instrumental in optimizing complex systems, such as ship hull shapes, by minimizing resistance while adhering to volume constraints. Despite its advantages, generative design faces challenges, particularly in ensuring manufacturability and addressing high computational costs. Advanced GAN architectures, such as the Stylized Projected GAN (SPGAN) and REP-GAN, offer promising solutions by enhancing the quality, diversity, and efficiency of generated designs. Overall, the integration of generative design and advanced computational techniques holds significant potential for revolutionizing naval architecture, offering new opportunities for innovation and optimization in ship design. This survey highlights the key findings and future directions for research in this dynamic field, emphasizing the potential impact of these technologies on the future of naval architecture.

1 Introduction

1.1 Motivation for Computational Design Techniques

The adoption of computational design techniques in naval architecture is driven by the need to address the inefficiencies of traditional methodologies, which often demand substantial resources and are constrained by human intuition. Conventional ship design processes are marked by prolonged cycles and limited production capabilities, hindering the application of advanced machine learning methods. Generative Design (GD) emerges as a transformative approach, leveraging artificial intelligence algorithms to explore expansive design spaces and generate innovative solutions beyond conventional limits [1].

The rapid evolution of internet technologies and the growing computational power of personal computers have enabled the development of new computational design methods essential for enhancing design exploration in naval architecture. These techniques incorporate intelligent optimization strategies that adeptly navigate the complex design parameters intrinsic to ship design [2]. By automating the generation and evaluation of 3D CAD models, computational design significantly streamlines the conceptual design phase, allowing for quicker identification of viable designs [3].

Furthermore, the integration of topology optimization with generative models creates a novel framework for design exploration, facilitating the efficient discovery of materials with desired properties

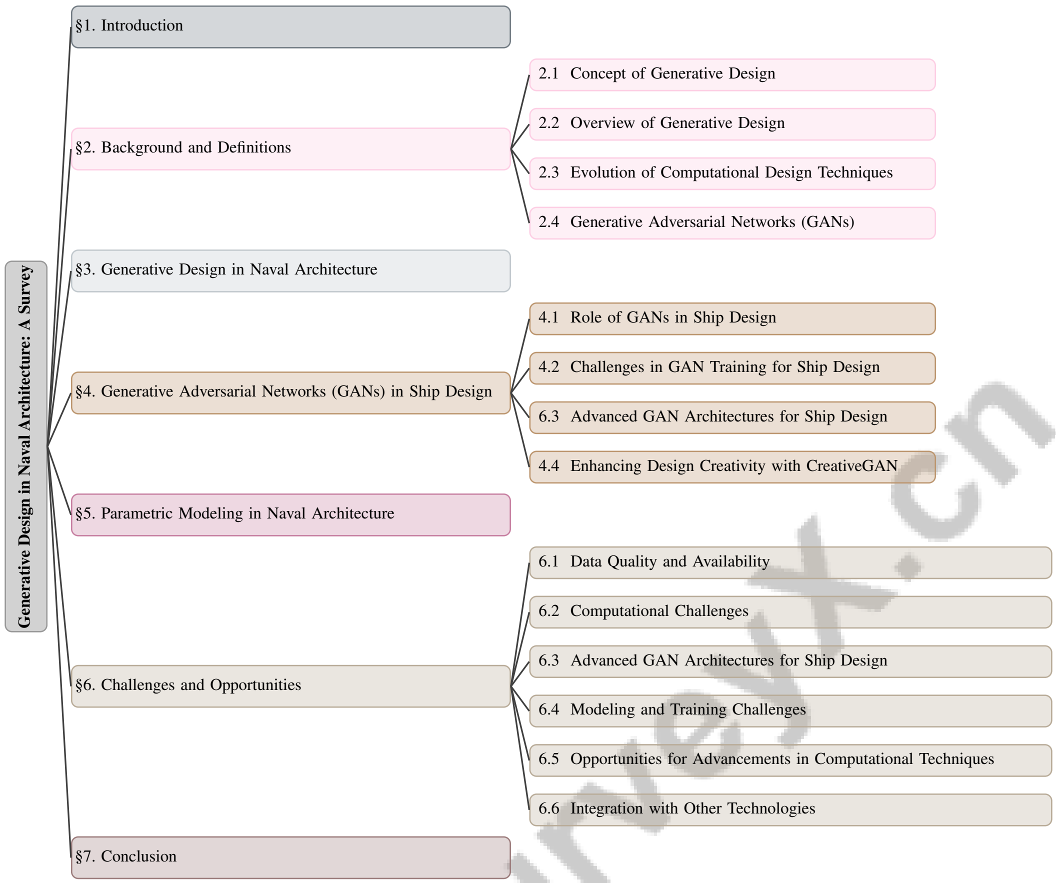

Figure 1: chapter structure

[1]. This approach is particularly pertinent in naval architecture, where high computational costs have historically hindered the optimization of ship hull designs [4]. Developing efficient computational frameworks is crucial for overcoming these challenges and enabling the creation of manufacturable CAD models that adhere to specific design criteria [5].

Despite the advantages of GD, challenges persist regarding the manufacturability of complex designs, which often necessitate manual adjustments due to standard manufacturing constraints [6]. Addressing these issues requires the development of design algorithms that incorporate physical constraints and account for real-world geometric uncertainties, ensuring generated designs are both feasible and robust [4].

The motivation for incorporating computational design techniques in naval architecture lies in the necessity to enhance design efficiency, flexibility, and innovation in response to the complexities of modern shipbuilding. Traditional design processes, heavily reliant on iterative human-driven methods, can be significantly optimized through generative AI and machine learning. These advanced computational approaches facilitate systematic optimization of ship hull designs by exploring broader design spaces and integrating multidisciplinary objectives, as demonstrated by datasets like "SHIP-D," which includes 30,000 hull forms to identify design trade-offs. By harnessing such technologies, the ship design cycle can be substantially shortened, leading to more cost-effective, high-performance vessels that meet the intricate demands of today's maritime industry [7, 8].

1.2 Structure of the Survey

This survey is organized to thoroughly examine generative design in naval architecture, focusing on computational design techniques such as parametric modeling and Generative Adversarial Networks (GANs). It begins with an introduction to the motivation for adopting these techniques, highlighting their potential to mitigate the limitations of traditional design methodologies. The background and

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definitions section provides an overview of key concepts, including generative design, computational design techniques, parametric modeling, and GANs, establishing a foundational understanding of their significance in naval architecture.

Subsequent sections delve into specific applications and impacts of generative design within the field. The section on generative design details how these techniques influence design processes, showcasing innovative applications and case studies. This is followed by an exploration of GANs in ship design, discussing their capability to generate novel hull designs and the challenges related to their training and implementation.

The survey also covers parametric modeling, outlining its principles and applications in ship design, and how it facilitates the exploration of design spaces and the creation of diverse alternatives. A dedicated section addresses the challenges and opportunities in applying generative design in naval architecture, including issues concerning data quality, computational challenges, and the integration of generative design with other technologies.

The conclusion summarizes the key findings, discusses future research directions, and considers the impact of these technologies on the naval architecture industry. Throughout the survey, insights from recent advancements in data-driven intelligent computational design (DICD) [9] and the development of generative systems like DeepCloud [10] are integrated, providing a roadmap for future exploration and application of these transformative technologies.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Concept of Generative Design

Generative design is a cutting-edge methodology leveraging computational algorithms to autonomously generate diverse design alternatives based on predefined constraints and objectives [3]. This approach excels in optimizing complex systems, such as thermal designs, by addressing boundary conditions and fluid-solid interactions [11]. By integrating machine learning and artificial intelligence, generative design explores diverse solutions, enhancing the design process with both qualitative and quantitative metrics.

Central to this process is the generation of models that maintain the statistical integrity of existing data while creating new data [6]. This capability is crucial for decision-making strategies involving sequential actions in parameterized component configuration [12]. Generative design algorithms streamline the design process by automatically generating geometries from user-defined specifications, making it accessible to non-experts [5].

The methodology balances engineering performance with aesthetics, vital for customer satisfaction [1]. Designers can sketch problems and generate multiple solutions, enriching the conceptual phase with innovative ideas [13]. However, ensuring manufacturability of complex geometries remains challenging, as traditional methods often prioritize functionality [14].

In naval architecture, generative design optimizes hull shapes to minimize resistance while adhering to volume constraints, showcasing its transformative potential [15]. This approach actively explores design spaces, moving beyond known solutions to discover innovative designs that meet structural and functional requirements [16]. The synthesis of optimization and structural integrity underscores generative design's significant impact on modern design practices across various fields.

2.2 Overview of Generative Design

Generative design is an innovative methodology that utilizes computational power to autonomously generate numerous design alternatives, increasingly used in architecture, industrial design, and mechanical engineering [4]. By manipulating parameters, it creates a broad spectrum of design options, contrasting with traditional manual shape crafting [3].

At its core, generative design involves setting specific goals and constraints that the algorithm uses to explore the design space and propose novel solutions. This enhances design efficiency and expands creative possibilities. By leveraging artificial intelligence and cloud computing, diverse design options are generated that may not be easily identifiable through conventional methods. Integrating generative design throughout the product development process allows designers to explore innovative solutions, improve decision-making, and achieve competitive product outcomes [5, 4, 17, 13, 18]. Iterative testing and refinement ensure optimized final outputs.

Generative design goes beyond form generation, incorporating functional performance metrics to balance aesthetics with engineering requirements. This approach offers significant advantages in fields requiring intricate optimization, such as thermal management and aerodynamic structures. By leveraging advanced AI techniques and real-time computational power, generative design efficiently produces optimized solutions, enhancing design aesthetics and performance. Consequently, it fosters a more innovative and effective design process across various engineering disciplines [1, 19, 20, 21, 18].

2.3 Evolution of Computational Design Techniques

The evolution of computational design techniques in naval architecture addresses traditional methodologies' limitations, such as high computational costs and restricted control over design parameters [2]. Early approaches focused on specific engineering metrics like hydrodynamics and structural integrity but struggled to explore complex design spaces efficiently [6].

Generative AI marks a significant milestone, automating and optimizing design processes across multiple objectives. Moving beyond conventional topology optimization, which emphasizes engineering performance without broader design context, generative design facilitates exploration of high-dimensional solution spaces, accommodating complex design sketches and decision-making processes [1, 12].

Challenges persist, particularly in topology optimization, where traditional methods often yield a single optimized design, requiring multiple iterations for performance verification [21]. This inefficiency has driven the development of sophisticated computational frameworks that integrate diverse datasets and manage missing values, enhancing generative design models' robustness and applicability [6].

The evolution of computational design techniques in naval architecture illustrates a dynamic progression driven by technologies like generative AI and machine learning. These innovations have led to sophisticated methodologies enhancing efficiency and flexibility. Conditional diffusion models, for example, enable ship hull design generation that meets specific constraints while reducing resistance. Utilizing extensive datasets like SHIP-D facilitates exploration of diverse design spaces and hull form optimization. This comprehensive approach streamlines the design process, reduces cycle times, and identifies trade-offs for improved performance, marking a transformative shift in naval architecture [22, 23, 7, 8]. These advancements enhance the ability to generate innovative and functional ship designs, addressing historical challenges and paving the way for future developments.

2.4 Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs), introduced by Goodfellow et al., have significantly impacted generative design by providing a robust framework for producing high-quality, realistic data across various domains. GANs consist of two neural networks: a generator that creates synthetic data samples and a discriminator that assesses their authenticity by distinguishing between real and generated data [24]. This adversarial training mechanism compels the generator to iteratively refine its outputs, effectively capturing complex data distributions [25].

In generative design, GANs play a crucial role in exploring and optimizing design spaces, facilitating the creation of innovative solutions that meet specific performance criteria. Methods like Generative Latent Nearest Neighbors (GLANN) improve image generation quality by combining the strengths of Generative Latent Optimization (GLO) and implicit maximum likelihood estimation (IMLE), providing an alternative to traditional adversarial methods [25]. Furthermore, GANs have been adapted to accurately recover latent variables, addressing challenges associated with Gaussian priors, which are essential for generating realistic designs [26].

Despite their transformative potential, GANs face challenges such as stability issues and mode collapse, which can affect the diversity and quality of generated designs. Advanced techniques have been developed to enhance the robustness and applicability of GANs in complex design tasks, ensuring generated outputs are both diverse and realistic [24]. Additionally, integrating GANs with optimization frameworks enhances their ability to generate near-optimal designs by leveraging neural networks alongside optimality conditions.

GANs represent a significant advancement in generative design methodologies, providing sophisticated tools for generating diverse and realistic design solutions. Their capacity to manage complex data distributions and integrate seamlessly with advanced optimization techniques underscores their relevance and transformative potential in the future of design across various fields. This is particularly evident in the development of AI-driven frameworks for generative design, which utilize deep learning and topology optimization to produce numerous innovative design alternatives. By employing generative models like GANs, these frameworks enhance aesthetic appeal and optimize engineering performance, allowing designers to explore new possibilities and assess the novelty of generated designs through anomaly detection. These advancements are poised to redefine the product design process, fostering greater creativity and efficiency in generating solutions tailored to specific design challenges [10, 18, 20, 1].

In recent years, the field of naval architecture has witnessed significant advancements, particularly through the adoption of generative design methodologies. This innovative approach not only transforms traditional design processes but also introduces a new paradigm in how architects and engineers conceptualize and execute their projects. As illustrated in Figure 2, the hierarchical structure of generative design is depicted, emphasizing its multifaceted impact on the industry. The figure highlights key areas such as the integration of advanced computational techniques, which enhance optimization and manufacturability, and the versatility of generative design in fostering collaboration among stakeholders. Furthermore, it underscores the capability of this approach to address and solve complex design problems, ultimately revolutionizing the way naval architecture is practiced.

3 Generative Design in Naval Architecture

3.1 Impact of Generative Design on Naval Architecture

Generative design has revolutionized naval architecture by integrating advanced computational techniques that enhance creativity and efficiency in ship design. This method enables the rapid generation and evaluation of numerous design iterations based on predefined parameters, optimizing traditional methodologies [3]. The complexity of naval architecture necessitates adaptable and efficient design strategies, making this capability particularly valuable. Innovations such as the Generalized Latent Variable Recovery (GLVR) method improve the accuracy of generative designs, enhancing the reliability of design models and facilitating the development of feasible ship designs [26]. These advancements illustrate the potential of generative design to optimize both functional and aesthetic aspects, leading to innovative outcomes.

Generative design significantly broadens creative possibilities by utilizing extensive datasets, such as the "SHIP-D" dataset comprising 30,000 hull forms. Techniques like Gaussian Mixture Models and generative adversarial networks enable designers to explore diverse hull designs while integrating multidisciplinary optimization objectives. This shift from traditional iterative processes to generative models allows for comprehensive exploration of design spaces, culminating in optimized ship designs that balance performance and creativity [23, 8]. The ongoing evolution of these methodologies promises further innovations in ship design.

As illustrated in Figure 3, generative design has emerged as a transformative methodology in naval architecture, leveraging advanced computational techniques to revolutionize design processes. The first image, labeled " ," depicts a flowchart in Korean that outlines the ideation process, emphasizing the structured steps in design research and product development. This process fosters a thorough understanding of audience needs and product requirements, laying the groundwork for subsequent design phases. The second image showcases a sophisticated machine learning model for generating 3D shapes, highlighting the integration of input conditions, classifiers, performance metrics, and guidance models. This model exemplifies the application of artificial intelligence in optimizing design outcomes, equipping naval architects with tools to explore an extensive array of design possibilities, thereby enhancing the performance and efficiency of maritime structures. Collectively, these examples underscore the significant influence of generative design on naval architecture, promoting innovation and efficiency in advanced maritime solutions [18, 22].

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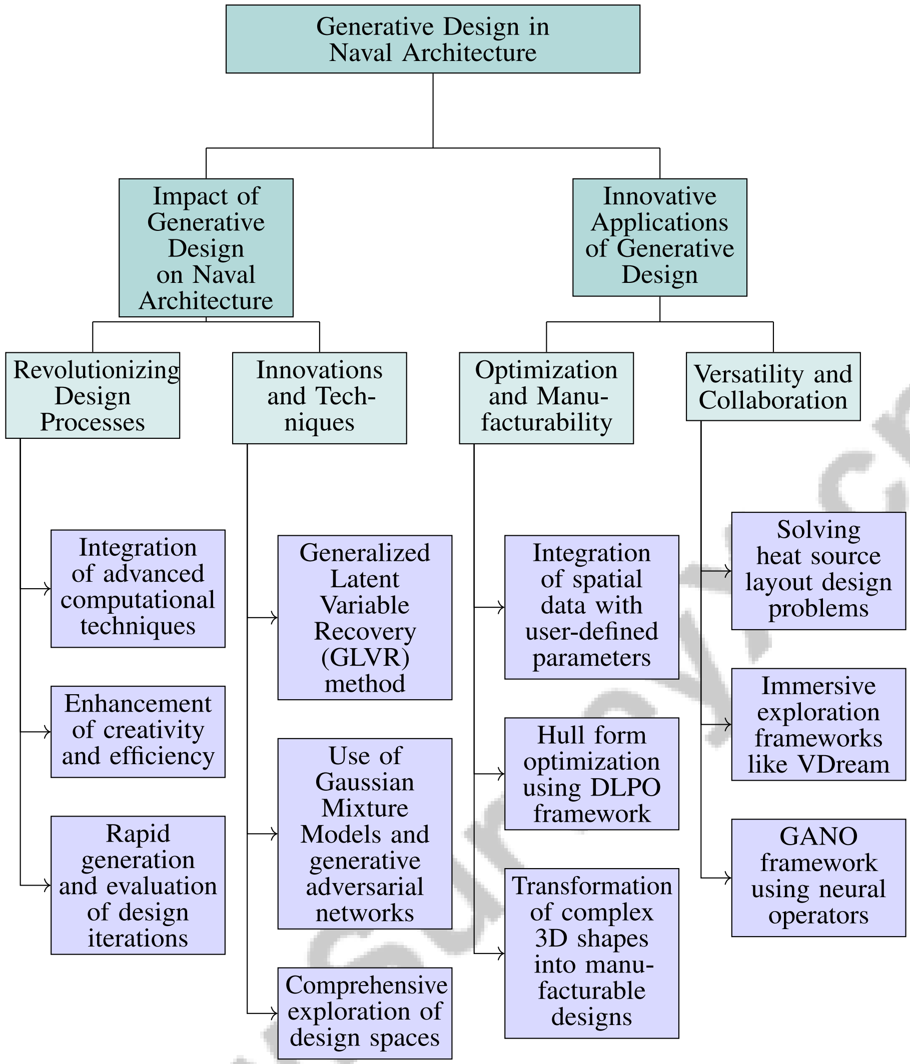
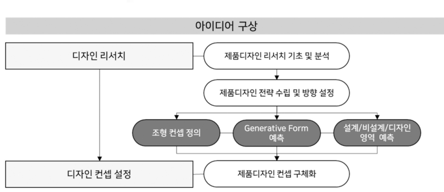
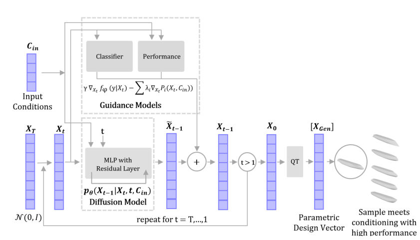


Figure 2: This figure illustrates the hierarchical structure of generative design in naval architecture, highlighting its impact on revolutionizing design processes and showcasing innovative applications. Key areas include the integration of advanced computational techniques, optimization and manufacturability, and the versatility of generative design in fostering collaboration and solving complex design problems.



(a) [18]



(b) A diagram illustrating a machine learning model for generating 3D shapes[22]

Figure 3: Examples of Impact of Generative Design on Naval Architecture

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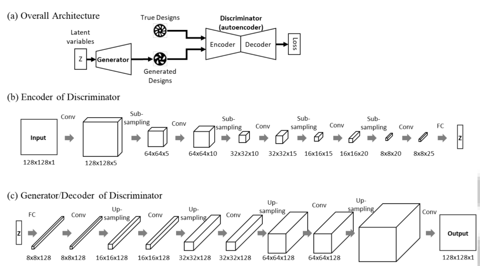
3.2 Innovative Applications of Generative Design

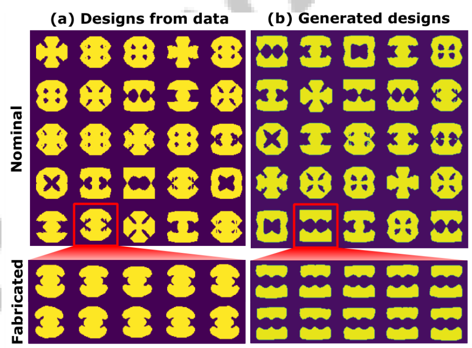
Generative design in naval architecture demonstrates its potential to create optimized, manufacturable, and aesthetically compelling designs. By integrating spatial data with user-defined parameters through generative algorithms, complex forms that are both functional and visually appealing can be produced [27]. Hull form optimization, using frameworks like DLPO, achieves high-quality predictions with minimal error rates, enhancing design efficiency [28]. Transforming complex 3D shapes into manufacturable designs represents another critical innovation, as generative design incorporates manufacturing considerations directly into the design process, ensuring that outputs are both innovative and feasible [29].

Generative design's versatility is further highlighted by its application in solving heat source layout design problems using adaptive artificial neural networks, exemplifying its capacity to yield optimal solutions across various engineering domains [30]. Immersive exploration frameworks like VDream and tools like DreamSketch facilitate rapid exploration of design alternatives, encouraging collaboration between engineers and designers, which is essential for driving innovation in the design process [31, 13]. The GANO framework employs neural operators to develop generative adversarial models capable of learning to generate functions from Gaussian random fields, further expanding the applications of generative design [32].

Generative design systematically optimizes ship hull designs—critical since the hull form constitutes approximately 70



(a) Overall Architecture of a Generative Adversarial Network (GAN) for Design Optimization[20]



(b) Designs from data vs. machine-generated designs[33]

Figure 4: Examples of Innovative Applications of Generative Design

As depicted in Figure 4, generative design facilitates the creation of optimized, novel design solutions by utilizing frameworks such as GANs for design optimization, which feature an intricate system comprising an encoder, discriminator, and generator. These components work synergistically, with the encoder transforming latent variables into a latent representation, which the discriminator uses to produce a design, while the generator creates designs from the latent representation. The second subfigure provides a comparative analysis between designs derived from actual data and those generated by a machine learning model, emphasizing the innovative potential of generative design. By leveraging advanced computational techniques, generative design enables the development of diverse, high-performance ship designs that meet specific constraints and performance requirements [20, 33].

4 Generative Adversarial Networks (GANs) in Ship Design

The integration of Generative Adversarial Networks (GANs) into ship design is advancing rapidly, prompting an in-depth analysis of their impact. Table 2 offers an in-depth categorization of GAN methodologies applied in ship design, detailing their roles, the challenges faced during training, and the advanced architectures employed to enhance design efficiency and creativity. This section delves into how GANs facilitate innovative and optimized ship designs, addressing the complexities inherent in modern naval architecture.

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Category	Feature	Method
Role of GANs in Ship Design	Generative Frameworks Output Enhancement Techniques	DGDF[1], MMC[21], GLANN[25] LI[24]
Challenges in GAN Training for Ship Design	Adaptive Training Strategies Efficient Sampling Techniques	COEGAN[34] REP-GAN[35]
Advanced GAN Architectures for Ship Design	Targeted Design Modification Dynamic Feature Enhancement	McGAN[14] mGANprior[36]
Enhancing Design Creativity with CreativeGAN	Generative Design Techniques	CG[17], SPGAN[37]

Table 1: This table provides a comprehensive summary of various Generative Adversarial Network (GAN) methodologies applied in ship design. It categorizes the approaches based on their roles, challenges, and advanced architectures, highlighting specific techniques and frameworks utilized in enhancing design creativity and overcoming training challenges.

4.1 Role of GANs in Ship Design

GANs have become instrumental in ship design by enabling advanced exploration of design spaces through complex data distributions, which is crucial for developing high-quality hull designs [1]. The application of Wasserstein GANs (WGANs) exemplifies this, generating optimized designs across various loading conditions and complexities, thus enhancing both efficiency and quality [21]. Integrating GANs with other techniques, such as REP-GAN, which reparameterizes the latent space sampling process, further refines design precision and efficiency [14].

Challenges such as mode collapse, where GANs produce limited outputs, are addressed by methods like GLANN, which combines Generative Latent Optimization and implicit maximum likelihood estimation for stable training and high-quality synthesis [25]. Visualization techniques assist in identifying missing object classes, refining GAN outputs [24]. The mGANprior method enhances image reconstruction by using multiple latent codes, essential for high-quality visualizations in ship design [36].

4.2 Challenges in GAN Training for Ship Design

GAN deployment in ship design faces challenges such as mode collapse, exacerbated by the high dimensionality of 3D spaces [34]. The vanishing gradient problem, particularly in complex architectures like StyleGAN, impedes training by making discriminator updates ineffective [38, 39]. Underwater visual degeneration further complicates training, necessitating real-time adaptive methods like GAN-RS for noise removal and visual enhancement [40, 41, 42]. Low sample efficiency also presents challenges, increasing computational costs and rejection rates [35]. Research focuses on advanced architectures and optimization techniques to improve GAN robustness and applicability in ship design tasks, addressing issues like training difficulties and premature convergence through quality-diversity algorithms and Novelty Search with Local Competition [43, 39].

4.3 Advanced GAN Architectures for Ship Design

Innovative GAN architectures such as ShipHullGAN leverage deep learning to revolutionize ship design, utilizing extensive datasets like SHIP-D for efficient hull shape optimization [44, 8, 39]. The Stylized Projected GAN (SPGAN) integrates transfer learning to generate high-resolution, structurally coherent alternatives, accelerating the design process. The mGANprior method improves image reconstruction fidelity, enhancing design realism [36]. REP-GAN, with its dual Markov chains, enhances sample efficiency and quality, crucial for optimizing hull designs [14]. The table-GAN framework ensures privacy and model compatibility through adversarial training, essential for integrating real-world data with synthetic models in ship design [14]. These advancements facilitate a shift towards AI-driven generative methodologies, enhancing efficiency and creativity in ship design by broadening design space exploration and integrating multidisciplinary optimization objectives [8, 39].

4.4 Enhancing Design Creativity with CreativeGAN

CreativeGAN significantly advances generative design by enhancing creativity in naval architecture through the generation of diverse design alternatives [17]. Using GAN principles, it explores extensive design spaces to discover unique solutions. The Stylized Projected GAN (SPGAN) within

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CreativeGAN optimizes sample efficiency, reducing computational overhead while maintaining high-quality image generation [37]. The 3D ProAmGAN architecture enhances design outputs by combining elements of 3D ProGAN and Style-AmbientGAN, offering naval architects tools for functionally optimized and aesthetically distinct designs [45]. By employing geometric principles, CreativeGAN mitigates common GAN challenges like mode collapse, ensuring robust and diverse outputs. Advanced technologies like generative AI and machine learning enable the optimization of ship hull forms, crucial for cost-effective and innovative designs [22, 23, 7, 8].

Feature	Role of GANs in Ship Design	Challenges in GAN Training for Ship Design	Advanced GAN Architectures for Ship Design
Design Scope	Hull Designs	3D Spaces	Hull Shape Optimization
Optimization Technique	Wgans Integration	Gan-RS Adaptation	Shiphullgan Usage
Challenge Addressed	Mode Collapse	Vanishing Gradients	Sample Efficiency

Table 2: This table provides a comprehensive comparison of the roles, challenges, and advanced architectures of Generative Adversarial Networks (GANs) in ship design. It highlights the specific design scopes, optimization techniques, and challenges addressed by different GAN methodologies, offering insights into their application and development in the field of naval architecture.

5 Parametric Modeling in Naval Architecture

5.1 Concept of Parametric Modeling

Parametric modeling is a computational design method that enables the creation of complex geometries through defined parameters and rules governing element relationships. This approach allows designers to systematically manipulate variables, generating alternatives that meet specific constraints and objectives. Algorithms facilitate this dynamic and iterative process, enabling rapid exploration and visualization of parameter changes, which is particularly beneficial in industries like automotive, architecture, and aerospace where customization and optimization are vital. By integrating structural optimization and generative design principles, parametric modeling enhances product development efficiency, ensuring designs meet performance criteria and reinforcing manufacturability and structural integrity [46, 22, 3, 18].

Key principles include parameterization, constraint-based design, and automation. Parameterization defines key variables for configuration exploration, while constraint-based design ensures functional and performance adherence [5]. Automation, driven by computational algorithms, rapidly generates and evaluates numerous alternatives, enhancing design efficiency and creativity.

In naval architecture, parametric modeling optimizes ship designs by exploring various hull shapes and configurations crucial for optimal hydrodynamic performance [15]. This approach reduces time and effort in the conceptual design phase, enhancing overall quality and innovation [3]. By integrating diverse data sources and constraints, it provides a holistic approach to ship design, allowing designers to navigate complex spaces effectively, ensuring designs meet functional and aesthetic requirements [5].

5.2 Application in Ship Design

Parametric modeling is essential in naval architecture, offering a robust framework for designing and optimizing ship structures. It facilitates systematic parameter manipulation, allowing exploration of numerous alternatives, valuable in the complex context of ship design. This approach enables engineers to assess and compare configurations through a unified generative framework that integrates structural optimization and manufacturability considerations, producing ready-to-manufacture parametric CAD models that enhance performance and ensure mass production feasibility [46, 29, 18].

In practical applications, parametric modeling advances ship design aspects like hull form optimization, structural integrity, and hydrodynamic performance, allowing designers to iterate quickly and assess performance against criteria and constraints [3]. This accelerates the design process and enhances final product quality and innovation.

Additionally, parametric modeling supports diverse data source integration and design constraints, enabling a comprehensive approach to ship design. By employing intelligent optimization techniques, naval architects efficiently navigate complex design spaces, ensuring innovative and functional final designs [5]. This integrative approach is beneficial in optimizing complex systems like hull forms, where multiple performance metrics must be considered simultaneously.

5.3 Exploration of Design Spaces

Parametric modeling is crucial in exploring design spaces within naval architecture, allowing efficient navigation and manipulation of complex parameters. This computational approach systematically varies design variables, generating solutions that adhere to constraints and objectives. Automating the iterative exploration process, parametric modeling identifies optimal configurations balancing performance, manufacturability, and aesthetics through a framework integrating topology, layout, and size optimization, resulting in ready-to-manufacture parametric CAD models meeting structural standards. Rapid parameter modification allows quick product variation development, enhancing customization and meeting user requirements in industries like automotive, aerospace, and architecture [5, 46, 22, 3, 18].

In ship design, exploring design spaces is valuable given challenges like hydrodynamic performance, structural integrity, and manufacturing feasibility [1]. Parametric modeling identifies innovative hull forms and configurations optimizing performance metrics like hydrodynamic efficiency and stability while addressing constraints like weight, material usage, and cost [15].

Integrating intelligent optimization techniques with parametric modeling enhances exploration by efficiently assessing complex, high-dimensional parameters [2]. This is advantageous in ship design, where evaluating alternatives can reduce development time and costs, leading to efficient and competitive designs [5].

5.4 Creation of Diverse Design Alternatives

Parametric modeling, through techniques like ShipHullGAN and conditional diffusion models, is vital in naval architecture for generating innovative and optimized hull designs. These methods use deep learning and generative adversarial networks to overcome traditional limitations, creating geometrically valid and feasible hulls meeting performance criteria like reduced drag and compliance with constraints. Leveraging extensive datasets and algorithms, these models enhance design versatility and reduce design time and costs [44, 22]. Parametric design principles allow systematic manipulation of variables to explore solutions adhering to constraints and objectives, advantageous in ship design where complexity necessitates flexible and efficient exploration.

Integrating parametric modeling with advanced optimization techniques rapidly generates multiple iterations, enabling solution evaluation and refinement based on quantitative metrics and qualitative criteria [1]. This accelerates the design phase and enhances creativity by uncovering innovative solutions not immediately apparent through traditional methods [3].

Moreover, parametric modeling incorporates diverse data sources and constraints, providing a holistic approach to ship design, essential in naval architecture for integrating datasets and parameters for optimal outcomes [5]. By enabling extensive design space exploration, parametric modeling empowers architects to develop innovative and efficient designs meeting modern shipbuilding demands [4].

6 Challenges and Opportunities

In exploring the multifaceted landscape of challenges and opportunities within the realm of generative design in naval architecture, it is essential to first examine the critical aspects of data quality and availability. This foundational element significantly influences the efficacy of generative design methodologies, as the quality and accessibility of data directly impact the generation of viable design solutions. The following subsection delves into the intricacies of data quality and availability, highlighting the challenges that persist and the implications they hold for the advancement of generative design in this field.

6.1 Data Quality and Availability

The effectiveness of generative design in naval architecture is heavily contingent upon the quality and accessibility of data, which are critical for generating viable design solutions. High-quality data ensures that the input parameters used in generative design processes lead to feasible and innovative ship designs [3]. However, challenges related to data quality and availability persist, posing significant obstacles to the full realization of generative design's potential in this field.

One of the primary challenges is the absence of standardized methods for dataset construction, which can result in inconsistent and incomplete data sets that hinder the performance of generative design algorithms [9]. The complexity of mixed data types, along with the presence of missing values, further complicates the application of generative design techniques in naval architecture, where precision and reliability are paramount [47].

Existing anonymization and perturbation techniques, while useful in protecting sensitive data, often compromise the quality and feasibility of the resulting designs [47]. Ensuring that input parameters lead to feasible designs remains a significant challenge that must be addressed to fully leverage the potential of generative design in naval architecture [3]. The development of advanced data synthesis techniques, such as Generative Latent Nearest Neighbors (GLANN) and mGANprior, offers promising solutions to these challenges by enhancing the stability and quality of GAN-generated designs .

6.2 Computational Challenges

The integration of Generative Adversarial Networks (GANs) in ship design introduces a range of computational challenges that can significantly affect both the efficacy and efficiency of the design process. These challenges arise from the need to manage large datasets, such as the "SHIP-D" dataset containing 30,000 hull forms, and to ensure the proper training of models like ShipHullGAN, which utilizes deep convolutional architectures to generate versatile ship hull designs. Traditional ship design methods are often limited by human-driven iterative processes, whereas GANs can explore a broader design space and incorporate multidisciplinary optimization objectives. However, the successful implementation of GANs requires overcoming issues related to data representation, model architecture selection, and the integration of physics-informed elements, all of which are crucial for generating innovative and feasible ship designs. [44, 8]. One of the primary challenges is the vanishing gradient problem, which arises during the training of GANs when the discriminator becomes overly proficient, leading to inadequate updates for the generator. This issue is further exacerbated by the high dimensionality inherent in 3D design spaces, making it difficult to achieve a comprehensive exploration of potential solutions .

Another critical challenge is mode collapse, a phenomenon where the generator fails to produce a diverse range of outputs, often resulting in the repetition of certain design patterns while neglecting others . This limitation can significantly hinder the creative potential of generative design methodologies in ship design, where diversity and innovation are crucial for optimizing both functional and aesthetic aspects of ship designs [1].

Furthermore, the high dimensionality of 3D design spaces presents a substantial challenge in the application of GANs to ship design. The complexity of design parameters involved in naval architecture can lead to difficulties in effectively navigating the design space and achieving optimal solutions [34]. This complexity necessitates the development of more advanced computational frameworks and optimization techniques to improve the robustness and applicability of GANs in ship design.

Advanced techniques such as Generative Latent Optimization (GLO) and implicit maximum likelihood estimation (IMLE) have been introduced to address some of these challenges, offering alternative approaches to traditional adversarial training methods and enhancing the stability and quality of GAN-generated designs [25]. These advancements demonstrate the potential of GANs to overcome inherent challenges and continue to drive innovation in ship design, providing new opportunities for the development of optimized and diverse design solutions [21].

Despite the existing challenges in the training and application of Generative Adversarial Networks (GANs) for ship design, ongoing research is actively addressing these issues. Recent advancements, such as the development of ShipHullGAN and the SHIP-D dataset, are facilitating a more efficient exploration of diverse design spaces and enhancing the optimization of ship hulls. These innovations leverage large datasets and machine learning techniques to streamline the design process, potentially leading to more innovative methodologies in naval architecture that can significantly reduce design cycle times and improve performance metrics in ship design. [44, 23, 7, 8]

6.3 Advanced GAN Architectures for Ship Design

6.4 Modeling and Training Challenges

The integration of Generative Adversarial Networks (GANs) into ship design has been transformative, yet it is accompanied by a set of significant modeling and training challenges. One of the primary difficulties encountered in training GANs for ship design is the issue of mode collapse, where the generator consistently produces a limited variety of outputs, thus failing to capture the full diversity of the design space . This limitation is particularly pronounced in high-dimensional design problems typical of naval architecture, where the complexity of the design space can exacerbate the challenge of effectively exploring potential solutions [34].

Another critical challenge in GAN training is the vanishing gradient problem. When the discriminator in a Generative Adversarial Network (GAN) becomes excessively skilled at differentiating between real and generated data, it results in minimal gradient updates for the generator. This stagnation hampers the generator's capacity to create a wide variety of outputs and high-quality designs, often leading to issues such as mode collapse, where certain data distributions are neglected. Consequently, the generator struggles to explore the full range of potential outputs, limiting its effectiveness and diversity in generated content. [48, 43, 49, 24]. This issue is exacerbated in ship design due to the inherent complexity and high dimensionality of design parameters, which can make it challenging to maintain a balanced adversarial training process.

The non-stationary nature of certain design processes also poses a significant challenge for GAN training in ship design. Traditional Generative Adversarial Network (GAN) models often encounter challenges when dealing with non-stationary processes, which can significantly hinder their capacity to produce realistic and diverse design outputs. This limitation stems from their inherent training difficulties, where the models must adapt to changing data distributions over time. Recent advancements, such as the integration of quality-diversity algorithms and alternative training methods like Fictitious GAN, aim to enhance the performance and diversity of generated outputs, addressing some of the shortcomings associated with traditional GAN approaches. [43, 50, 51, 52]. This limitation underscores the need for continuous advancements in GAN architectures and training methodologies to ensure their robustness and applicability in complex design tasks.

To address these challenges, researchers have developed innovative techniques that enhance the stability and performance of GANs in the context of ship design. For instance, the Generative Latent Variable Recovery (GLVR) method has been shown to improve the accuracy and reliability of GAN-generated designs by addressing the issue of latent variable recovery [26]. Additionally, the mGANprior method enhances image reconstruction quality by utilizing multiple latent codes, significantly improving the quality of image reconstruction compared to existing methods [36].

The application of Generative Adversarial Networks (GANs) in ship design, while promising, faces several significant challenges, including the need for robust datasets and effective model architectures. Ongoing research and development, such as the implementation of ShipHullGAN—a deep convolutional GAN trained on over 52,000 validated ship designs—aims to address these issues by enabling versatile and innovative hull design generation. This work not only explores a broader design space but also integrates multidisciplinary optimization objectives, paving the way for the full realization of GANs' potential in revolutionizing the ship design process. [44, 8, 39]. By advancing the robustness and efficiency of GAN training methodologies, it is possible to achieve more reliable and diverse design outputs, ultimately transforming the landscape of naval architecture and enabling the creation of innovative and optimized ship designs.

6.5 Opportunities for Advancements in Computational Techniques

The field of generative design in naval architecture stands on the brink of significant advancements, driven primarily by the evolution of computational techniques. One promising development is the Generalized Latent Variable Recovery (GLVR) method, which has shown substantial potential for improving the accuracy and reliability of generative design models. By effectively addressing challenges related to the recovery of latent variables, the GLVR method enhances the capability of generative models to produce precise and realistic ship designs [26].

The integration of Generative Adversarial Networks (GANs) with other advanced computational methods presents a unique opportunity to further refine the design process. Techniques such as

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Generative Latent Optimization (GLO) and implicit maximum likelihood estimation (IMLE) have been instrumental in overcoming challenges like mode collapse and improving the stability of GAN training [25]. The development of the mGANprior method exemplifies this trend, utilizing multiple latent codes to generate high-quality image reconstructions from intermediate layers of the GAN generator, which is particularly relevant for the intricate designs required in ship architecture [36].

The integration of neural operators with GANs, as demonstrated by the GANO framework, represents another significant advancement in computational techniques for ship design. By leveraging neural operators to learn and generate functions from Gaussian random fields, GANO enhances the generative capabilities of GANs, enabling the creation of diverse and innovative design solutions that meet complex performance criteria [32].

Despite these advancements, computational challenges persist, particularly in addressing issues such as mode collapse and vanishing gradients, which can limit the diversity and quality of generated designs . To effectively tackle the challenges associated with generative design, it is essential to advance the development of sophisticated GAN architectures and optimization techniques that can adeptly explore high-dimensional design spaces while ensuring the production of reliable, high-quality outputs. Recent innovations, such as the integration of quality-diversity algorithms like Novelty Search with Local Competition (NSLC) and methods like CreativeGAN, highlight the potential for enhancing diversity and creativity in design synthesis. These approaches not only improve the training of GANs by addressing issues of premature convergence and lack of uniqueness but also facilitate the automated generation of novel designs, thereby supporting human designers in their creative processes and driving innovation across various applications. [17, 43]

6.6 Integration with Other Technologies

The integration of generative design with other emerging technologies presents significant opportunities for advancing the field of naval architecture. By leveraging a broader set of data and computational tools, designers can further enhance the creativity and functionality of ship designs. One of the primary opportunities lies in expanding the dataset used for generative design processes, which can lead to a richer diversity of generated designs and potentially more innovative outcomes [53]. A more diverse dataset can provide a broader spectrum of design alternatives, allowing for more comprehensive exploration and optimization of the design space.

Moreover, the integration of generative design with other technologies, such as topology optimization and machine learning, can address some of the inherent challenges faced in ship design. For instance, combining topology optimization with generative models allows for the efficient discovery of new materials and design configurations that meet specific performance criteria [1]. This integration is particularly beneficial in naval architecture, where the optimization of complex systems, such as hull designs, is critical for enhancing performance and reducing manufacturing costs [4].

Despite these opportunities, challenges remain in ensuring that generative design tools effectively account for the subjective nature of human decision-making in the design process. The influence of designer biases and preferences can significantly impact the outcomes of generative design tools, and addressing this issue is crucial for maximizing their effectiveness [4]. Further research is needed to develop methodologies that can accommodate these subjective factors while maintaining the objective optimization capabilities of generative design.

7 Conclusion

This survey highlights the substantial impact of generative design in naval architecture, emphasizing the role of computational methods such as parametric modeling and Generative Adversarial Networks (GANs). These approaches, when integrated with sophisticated artificial intelligence, significantly enhance the creative and efficient exploration of ship design spaces. The ability to generate solutions that meet both functional and aesthetic demands is crucial in modern shipbuilding. GANs, in particular, have become central to this domain, offering robust tools for modeling intricate data patterns and creating diverse, high-quality design alternatives. Innovations in GAN architectures have addressed key challenges, such as mode collapse and gradient issues, leading to improved design outputs. Parametric modeling complements these advancements by enabling detailed exploration of design parameters, thus supporting the creation of designs that adhere to specific performance and aesthetic goals. Despite these technological advancements, challenges such as data quality, computational resources, and technology integration remain. Overcoming these hurdles could pave the way for further breakthroughs in computational design, fostering innovation in naval architecture.

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