Chapter 7

On the Advanced Optimization Techniques for the Aerodynamic Design of Turbomachinery

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Introduction

Optimization in engineering has become an essential tool for improving design efficiency and performance across various fields, leveraging advancements in computational power and algorithmic strategies (Bian & Priyadarshi, 2024; Kose & Kaya, 2018; Velasco et al., 2024; Ayaz & Kamisli Ozturk, 2021). Turbomachinery design optimization has evolved significantly in recent decades and is driven by these developments. The complex nature of turbomachinery flows, involving three-dimensional viscous effects, secondary flows, and multiple performance objectives, necessitates sophisticated optimization approaches. Traditional design methods, mainly relying on empirical correlations and engineering experience, are increasingly being supplemented or replaced by automated optimization techniques.

The evolution of optimization methods in turbomachinery design has progressed from simple gradient-based approaches to advanced machine-learning algorithms (Xu et al., 2024). This progression has been enabled by increased computational power and an improved understanding of complex flow physics. Modern optimization techniques can simultaneously handle multiple design variables and constraints while considering various performance metrics such as efficiency, pressure ratio, and structural integrity (Li & Zheng, 2017; Xu, 2024). Recent developments in artificial intelligence and machine learning have introduced new possibilities in turbomachinery optimization (Zou et al., 2024). These methods offer potential advantages in handling high-dimensional design spaces and reducing computational costs through surrogate modeling. However, selecting and implementing appropriate optimization strategies remains challenging and requires careful consideration of problem-specific requirements.

This study presents a comprehensive analysis of advanced optimization techniques applied to turbomachinery design. The strengths and limitations of different optimization strategies, their practical implementation challenges, and emerging trends in the field are examined. The following sections explore various advanced optimization methods used in turbomachinery design, with a discussion of their principles, advantages, and applications. The third section provides an in-depth analysis of the strengths and weaknesses of these optimization techniques, followed by a detailed look at the practical challenges encountered in their implementation. The study concludes with insights into future directions in optimization research, highlighting promising trends and areas for further exploration.

Advanced Optimization Methods in Turbomachinery Design

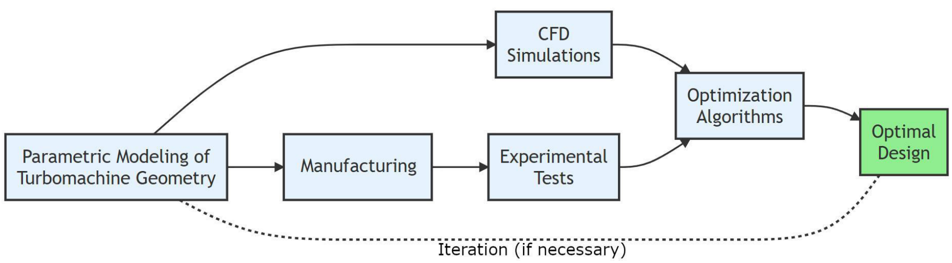
The aerodynamic optimization of turbomachinery has evolved significantly, moving from traditional trial-and-error methods to advanced computational approaches that allow for the systematic and efficient exploration of complex design spaces (Lavimi et al., 2024). As illustrated in Figure 1, the modern turbomachinery optimization workflow begins with the parametric modeling of component geometry, where flexible design parameters are established. This is followed by performance evaluation through computational fluid dynamics (CFD) simulations or experimental testing, providing critical insights into how the design performs under various conditions. Insights from these steps feed into optimization algorithms, which generate the optimal design. If necessary, iterations are performed to refine the design further, ensuring convergence to the best possible solution.

Recent advancements in optimization methods have significantly expanded the capabilities of turbomachinery design (Sagebaum et al., 2023). Techniques such as surrogate modeling, adjoint-based methods, and machine learning-driven approaches have transformed how engineers approach high-dimensional and nonlinear design challenges (LI et al., 2023; J. Luo et al., 2022). Surrogate models enable rapid design space exploration by approximating the results of computationally expensive high-fidelity simulations, drastically reducing the time required for optimization. Adjoint methods, on the other hand, leverage gradient information with exceptional precision, allowing for the optimization of intricate geometries and flow characteristics with minimal computational cost. Meanwhile, machine learning and neural network-based approaches have introduced data-driven solutions that are particularly effective in handling large datasets and predicting performance metrics under complex and dynamic conditions (Zou et al., 2024).

The following sub-sections provide an in-depth examination of these advanced methods, highlighting their strengths and applications in turbomachinery design. Adjoint and gradient-based techniques are emphasized for their precision in high-dimensional optimization problems. Metaheuristics, such as genetic algorithms and particle swarm optimization, are noted for their flexibility in addressing nonlinear and multimodal objectives. Surrogate-based approaches offer computational efficiency, while neural networks and deep learning (introduce the scalability needed for modern aerodynamic challenges. Hybrid methods combine the benefits of these techniques, enabling robust and versatile solutions. Together, these methodologies represent a paradigm shift in turbomachinery optimization, allowing engineers to push the boundaries of performance and innovation.

Figure 1

Schematic representation of optimization methodology in turbomachinery design process



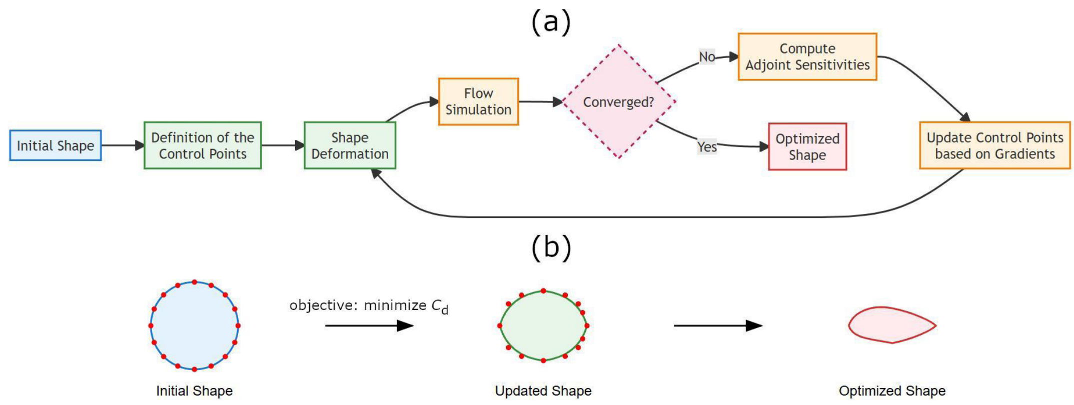
Adjoint and Gradient-Based Optimization

In turbomachinery design, classical optimization methods have played a significant role; however, their limitations have prompted the exploration of more advanced techniques, as they often struggle with the complexity and high dimensionality of turbomachinery design problems. These methods can be computationally expensive and may become trapped in local optimal, failing to identify the global optimum (Kim et al., 2019; T. Liu et al., 2019). As a result, researchers have increasingly turned to gradient-based methods, particularly the adjoint method, which offers a more efficient means of calculating sensitivity functions and derivatives of objective functions independent of the number of design variables (Lavimi, 2023; Rubino et al., 2021; Walther & Nadarajah, 2015; L. Wu et al., 2021). One prominent development area involves using adjoint-based techniques for calculating gradients. These techniques enable designers to optimize blade shapes for multiple objectives, such as minimizing pressure losses, maximizing efficiency, and ensuring robust performance under varying operating conditions.

In adjoint optimization, control points are defined around the shape, and their positions are modified within specified limits during optimization. As the shape changes, the flow around it must be recalculated. This requires completely re-meshing the domain or moving the existing mesh points from their initial positions. The first approach, re-meshing, is more suitable for significant geometric changes but is computationally expensive. In contrast, the second approach, mesh deformation, is better suited for minor shape modifications and is less time-intensive. Regardless of the method used, it is crucial that the generated mesh ensures smooth variations in the objective function to minimize noise in the computed gradients (Schramm et al., 2018). Figure 2 shows the systematic process of adjoint-based shape optimization for turbomachinery applications. The flowchart in Figure 2(a) illustrates the iterative optimization procedure, beginning with an initial shape definition and control point placement, followed by shape deformation, flow simulation, and adjoint sensitivity computation until convergence is achieved. As a representative example, Figure 2(b) demonstrates how the geometry might evolve from a simple circular initial shape to the final optimized airfoil profile through strategic manipulation of control points. This example transformation illustrates the concept of shape evolution guided by the objective of minimizing the drag coefficient (C_d), with the intermediate updated shape representing a transitional stage in the optimization process.

Figure 2

(a) Flowchart of the adjoint-based shape optimization process (b) Representative example showing the progression of shape optimization from initial circular shape to optimized shape with the objective of minimizing drag coefficient (C_d)



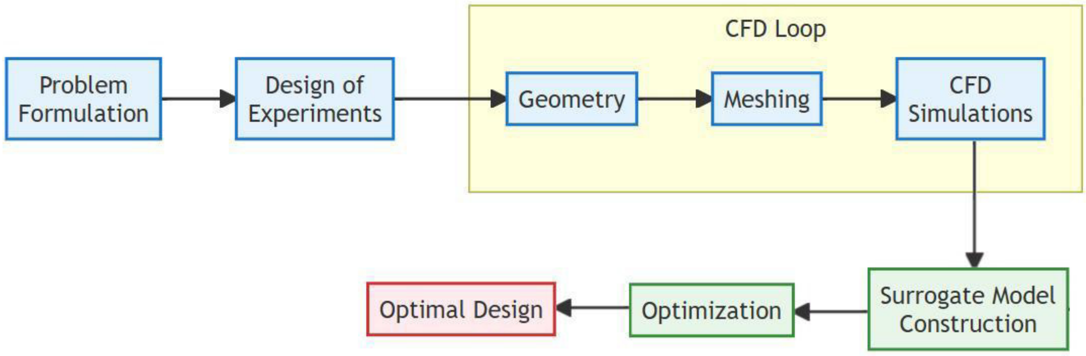
A discrete adjoint framework has been shown to facilitate efficient aerodynamic optimization by leveraging adaptive polynomial chaos expansion to mitigate uncertainties in flow conditions, improving design robustness significantly (Zhang et al., 2023). Recent studies have emphasized the importance of incorporating unsteady flow dynamics into optimization frameworks, recognizing the inherent transient nature of turbomachinery operations. Adjoint methods combined with harmonic balance solvers have effectively addressed unsteady aerodynamic damping and vibration stability in compressor cascades, improving operational reliability (H. Huang & Ekici, 2014; Rubino et al., 2020). Similarly, fully turbulent adjoint approaches leveraging time-domain methods have demonstrated accurate gradients for multirow configurations, enabling enhanced efficiency gains compared to traditional steady-state assumptions (Ntanakas et al., 2018). Unsteady optimization frameworks have also extended to multistage environments, showing remarkable capabilities in improving compressor performance by optimizing transient flow behavior (C. Ma et al., 2017). Another noteworthy development is incorporating robust optimization strategies to address flow conditions and design parameter uncertainties. Gradient-based methods assisted by surrogate models or adaptive response surfaces have proven effective in quantifying and mitigating the impact of such uncertainties. For example, surrogate-assisted gradient-based optimization methods have been validated for improving aerodynamic robustness in transonic turbine blades, outperforming traditional deterministic approaches (J. Luo et al., 2022). Furthermore, advanced frameworks utilizing polynomial chaos expansions have enhanced the efficiency of robust aerodynamic design processes (Zhang et al., 2023).

Advancements in geometry parameterization techniques have also complemented gradient-based methods by providing flexible and accurate representations of blade shapes. Methods based on Non-Uniform Rational B-Splines (NURBS) and shape derivatives have facilitated the seamless integration of parameterization into optimization workflows, ensuring smooth transitions between baseline and optimized geometries (Agromayor et al., 2021). Multi-objective optimization, aided by gradient-based Pareto front approximation, has enabled designers to balance conflicting objectives, such as efficiency and pressure loss, with reduced computational costs (Vasilopoulos et al., 2021). Recent studies highlight a clear trajectory toward integrating gradient-based optimization with high-fidelity modeling, robust uncertainty quantification, and advanced parameterization techniques. These developments underscore the transformative potential of gradient-based approaches in achieving high-performance and resilient turbomachinery systems.

Surrogate-Based Optimization

Surrogate-based optimization (SBO) is designed to tackle computationally expensive optimization problems by approximating the original high-fidelity model with a computationally efficient surrogate model (Koziel et al., 2011). The surrogate model acts as a proxy, reducing the computational burden while retaining reasonable accuracy. The working principle of SBO involves constructing surrogate models—such as polynomial regression, kriging, radial basis functions, or neural networks—based on a limited number of high-fidelity simulations. These models are then iteratively refined by adding new samples in areas of interest, balancing design space exploration with the exploitation of known high-performance regions (Queipo et al., 2005). Figure 3 illustrates the critical steps in a surrogate-based optimization process that utilizes CFD simulations. Kaya et al. (2021) employed a similar approach for the aerodynamic optimization of a wind turbine blade using CFD.

Figure 3
Flowchart of Surrogate-based Optimization based on CFD Simulations



SBO has found widespread applications in engineering that require complex simulations and high-dimensional optimization, especially in aerospace and turbomachinery design. Its effectiveness has been demonstrated in diverse disciplines, including aerodynamics, structures, and propulsion.

The effectiveness of surrogate models in turbomachinery optimization is underscored by their ability to facilitate rapid evaluations of design alternatives while maintaining accuracy in performance predictions. Zhao et al. (2024) developed a prescreening surrogate-model-assisted multi-objective differential evolution optimizer for highly loaded axial compressors, demonstrating notable improvements with efficiency increases and surge margin improvements. In addressing manufacturing uncertainties, Cheng et al. (2023) introduced a novel surrogate model combining self-organizing mapping and neural networks, improving efficiency and reducing performance variability.

The application of surrogate models spans various turbomachinery types and optimization challenges. Kim et al. (2010) demonstrated their effectiveness in centrifugal compressor impeller optimization using three-dimensional Reynolds-averaged Navier-Stokes equations while Heo et al. (2016) applied these techniques to mixed-flow pump optimization. In the context of low-pressure turbines, Baert et al. (2020) tackled high-dimensional design spaces with 350 parameters, achieving efficiency gains of 0.5 points through online surrogate-based optimization. Kong et al. (2021) further demonstrated the method's versatility in low-pressure axial fan design, achieving efficiency improvements through kriging-based surrogate models.

Advanced applications have shown promise in complex design scenarios. Persico et al. (2019) developed a sophisticated approach for non-conventional turbomachinery, achieving a 50% reduction in cascade loss coefficient for supersonic turbine nozzles. Mondal et al. (2019) introduced a multi-fidelity global-local approach for transonic compressor optimization, effectively combining rapid low-fidelity evaluations with targeted high-fidelity simulations. Q. Wang et al. (2022) successfully applied surrogate-based optimization to counter-rotating open rotors while Cao et al. (2022) implemented non-parametric surrogate models for low-pressure steam turbine exhaust systems.

The integration of surrogate models with advanced optimization algorithms has further enhanced their effectiveness. Song et al. (2014) demonstrated this by combining genetic algorithms with artificial neural networks for radial compressor optimization. Kozaket al. (2020) coupled high-fidelity flow modeling with a surrogate management framework for gas turbine optimization. These hybrid approaches have proven particularly effective in managing the trade-off between computational cost and design accuracy, enabling more efficient exploration of complex design spaces while maintaining solution quality.

Metaheuristic-Based Optimization

Metaheuristic algorithms are widely employed in turbomachinery design to address the complexity and nonlinearity of design optimization problems. These algorithms handle multidimensional, multimodal, and highly constrained design spaces shared in turbomachinery applications. Unlike gradient-based methods, metaheuristics do not rely on derivatives, making them highly versatile for problems with discontinuities or non-smooth objective functions. This section reviews the applications, strengths, and advancements of metaheuristic techniques in turbomachinery design, along with insights from the literature.

Metaheuristic algorithms have been found to be extensively valuable for optimizing various components of turbomachinery, including blades, compressors, turbines, and casings. For example, optimizing radial flow turbines has demonstrated the efficacy of coupling metaheuristic algorithms with CFD simulations. Studies have shown that Grey Wolf Optimizer (GWO) outperforms other algorithms in achieving higher temperature drops by optimizing blade inlet angles and improving casing design for better pressure recovery (Mehrnia et al., 2020). Similarly, the aerodynamic performance of single-stage transonic axial compressors has been enhanced by hybrid algorithms like the combination of genetic algorithms (GA) and particle swarm optimization (PSO), which optimize parameters such as stall margin and peak efficiency (Dinh et al., 2024; Vuong & Kim, 2021).

Swarm-based algorithms such as artificial bee colony and PSO have proven effective in multi-disciplinary optimization frameworks. These methods, combined with high-order CFD solvers, have been employed for addressing aero-mechanical challenges, providing reliable and efficient designs under complex constraints (Ampellio et al., 2016). Furthermore, bio-inspired algorithms like Genetic Algorithms, Flower Pollination Algorithm, and Cuckoo Search have been utilized to optimize geometries for axial turbomachinery, highlighting their adaptability to diverse design conditions and constraints (Ait Chikh et al., 2018).

Metaheuristic algorithms offer several advantages in turbomachinery design. Their flexibility allows them to tackle multi-objective optimization problems, such as maximizing efficiency while minimizing pressure losses. Advanced variants, such as hierarchical dynamic switching PSO, introduce adaptive mechanisms that enhance convergence rates and global search capabilities, effectively preventing premature convergence (Yan et al., 2024). These improvements are particularly beneficial for complex optimization tasks like turbine blade profile design, where global optima are challenging to identify.

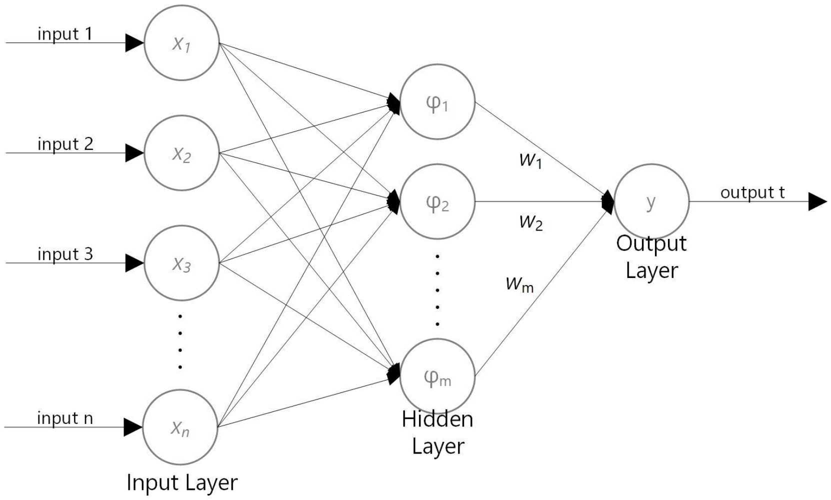
Another strength lies in their ability to incorporate surrogate models, which reduce computational costs without compromising accuracy. For instance, surrogate-based optimization methods, combined with PSO, have been used to design dual-bleeding recirculation channels in compressors, resulting in significant improvements in stall margin and operational stability (Vuong & Kim, 2021). This integration of metaheuristics with machine learning techniques, such as neural networks, has also enabled advancements in reliability prediction and dynamic modeling for turbomachinery systems (Bai et al., 2021).

Neural Networks

Neural networks (NNs) have become an indispensable tool in engineering design and optimization, offering exceptional capabilities for performance prediction, design exploration, and uncertainty quantification (Ünler & Seyfi, 2022). Their ability to model complex, nonlinear relationships between design parameters and performance metrics has made them a cornerstone for surrogate modeling, optimization, and robust analysis. Various NN architectures have been developed to suit applications, including multilayer perceptrons (MLPs), learning vector quantization, and radial basis function networks (RBFNNs). These networks are categorized based on data flow as feed-forward or recurrent and by learning approaches such as supervised training or self-organizing techniques. Figure 4 illustrates the general architecture of an RBFNN.

Figure 4

A General Architecture of a Radial Basis Function Neural Network (RBFNN)



One of the primary roles of NNs is as surrogate models for predicting performance metrics based on geometric or operational parameters. Ghorbanian and Gholamrezaei (2009) demonstrated this through an artificial neural network that effectively mapped the relationship between compressor design variables and aerodynamic performance. This work established the foundation for using NNs as predictive tools, reducing the dependency on full-scale simulations. Similarly, Barsi et al. (2021) employed NNs to optimize the design of a hydraulic propeller turbine, showing how these models can drive significant performance improvements through geometric modifications.

The integration of NNs with advanced optimization algorithms has further expanded their utility. For instance, Sakaguchi et al. (2016) combined NNs with genetic algorithms to enhance optimization efficiency by rapidly evaluating design alternatives. This hybrid approach leverages the speed of NNs for surrogate modeling and the global search capabilities of genetic algorithms, enabling faster convergence to optimal solutions. Another notable example is Du et al. (2022) applied series convolutional neural networks to optimize the end-wall profile of turbine stator blades. This method improved aerodynamic performance and required minimal training data, outperforming traditional surrogate models in accuracy and efficiency.

Neural networks are also pivotal in addressing uncertainties in turbomachinery operations, such as variations in operating conditions or material properties. Dual Graph Neural Networks (DGNNs) have been used for robust aerodynamic optimization, accurately predicting flow field behavior under multi-source uncertainties. Li et al. (2023) demonstrated that incorporating DGNNs into optimization frameworks led to designs that enhanced power output and efficiency while minimizing performance variability, ensuring robust performance across diverse operating scenarios.

Another significant NNs application is modeling fluid-structure interactions, such as blade flutter and aeroelastic stability. Graph Convolutional Neural Networks (GCNNs) have been employed to predict aerodynamic damping and stability margins with remarkable precision and speed. By replacing traditional high-cost simulation methods, GCNNs enable rapid analysis of aeroelastic phenomena, allowing for faster iteration during the design phase.

In scenarios with limited access to high-fidelity data, Multi-Fidelity Graph Neural Networks (MFGNNs) have demonstrated exceptional capability by integrating low- and high-fidelity datasets (Li et al. (2023) and Liu et al. (2024) showed how MFGNNs achieve accurate predictions for flow field characteristics while minimizing computational costs. This approach bridges the gap between computational efficiency and predictive accuracy, making it a powerful tool for turbomachinery optimization.

Deep Learning Approaches

Deep learning (DL) has emerged as a transformative tool in turbomachinery optimization, demonstrating unparalleled capabilities in managing the intricacies of large datasets and highly nonlinear relationships inherent in complex aerodynamic and thermodynamic systems. Its ability to learn directly from data without requiring explicit physics-based modeling makes it particularly well-suited for addressing challenges in modern turbomachinery design.

Recent studies underscore the diverse applications and advantages of deep learning across different aspects of turbomachinery. Shrivastava et al. (2022) employed deep learning models combined with nonlinear optimization techniques to dramatically reduce turbocharger rotor design cycle times—from days to hours—while preserving the accuracy of dynamic performance predictions. This represents a significant leap in accelerating the iterative design process, a key challenge in industrial applications.

For predictive modeling in aerodynamic systems, Fesquet et al. (2024) showcased the superior capabilities of U-net architectures over traditional surrogate models like POD-Kriging. By leveraging deep neural networks, their approach effectively predicted 2D wake-flow fields and critical performance metrics for fan rotor blades, delivering both precision and computational efficiency. This advancement highlights how deep learning can address challenges in high-fidelity flow field simulations while reducing reliance on costly numerical computations.

Geometric deep learning has also gained traction as a specialized branch within DL applications for turbomachinery. Gouttiere et al. (2023) applied geometric convolutional neural networks to optimize the Rotor 37 test case, achieving a notable improvement in isentropic efficiency, verified through CFD validation. This study illustrates the power of continuous learning and geometry-aware models in tackling three-dimensional optimization challenges. Building on this foundation, Du et al. (2022) introduced dual convolutional neural networks for turbine blade profile optimization. The method achieved exceptional accuracy, with prediction errors below 0.5% for 99% of validation samples, and reduced computation times to a staggering 3 milliseconds per evaluation.

Transfer learning has proven highly effective when faced with limited training data—often a constraint in engineering domains. Deng et al. (2024) demonstrated this by employing deep transfer learning to optimize transonic rotor performance. By fine-tuning pre-trained models, they improved tip-loading distribution, achieving significant aerodynamic gains without requiring extensive datasets. Such techniques hold promise for applications where data collection is constrained by cost or physical limitations.

In addition to design optimization, deep learning has shown its strength in operational efficiency enhancements. Huang et al. (2024) introduced a data-driven multi-agent deep reinforcement learning framework for optimizing air compressors in industrial aerodynamic systems. By integrating historical operational data with advanced reinforcement learning principles, their approach addressed the challenges posed by cyclic production schedules and dynamic load profiles. The model outperformed conventional energy efficiency and operational cost strategies while ensuring system stability and security.

Moreover, DL's potential extends to monitoring and diagnostics. Cao et al. (2021) applied deep neural networks to predict gas path degradation in gas turbines. Their work demonstrated that DL models can extract meaningful patterns from complex datasets, enabling early detection of performance anomalies and informing proactive maintenance strategies.

Hybrid Methods

Hybrid optimization methods have gained attention in turbomachinery design due to their ability to combine the strengths of multiple approaches, such as surrogate modeling, advanced simulation techniques, and optimization algorithms. These methods effectively balance computational efficiency and design accuracy, which is critical in optimizing complex and computationally expensive systems like turbomachinery. By integrating data-driven techniques with physics-based models, hybrid methods enable faster convergence, improved performance predictions, and enhanced exploration of design spaces.

For instance, artificial neural networks (ANNs) are frequently hybridized with evolutionary algorithms to exploit the predictive accuracy of ANNs and the global search capabilities of evolutionary methods. ANNs excel in approximating nonlinear relationships within the design space, while evolutionary algorithms are adept at exploring diverse regions of the space to find global optima. Villar et al. (2018) demonstrated this synergy by employing feedforward neural networks and evolutionary algorithms to optimize the aerodynamic performance of counter-rotating open rotors. Additionally, the work of Lavimi (2024) highlights the role of NNs alongside other surrogate models, such as polynomial response surface methods and Kriging, in aerodynamic optimization tasks. Moreover, integrating NNs with advanced optimization algorithms has led to significant advancements in turbomachinery design. For example, Song et al. employed a multidisciplinary design optimization approach that combined NNs with a self-adaptive multi-objective differential evolution algorithm to enhance the aerodynamic performance of a transonic turbine stage (Y. Wang et al., 2020). This synergy between NNs and optimization algorithms not only improves the accuracy of performance predictions but also accelerates the convergence of optimization processes.

Similarly, methods integrating surrogate models like Kriging with optimization techniques offer computationally efficient solutions for high-dimensional design problems. Bellary et al. (2016) compared various Kriging variants, including ordinary, universal, and blind Kriging, in optimizing a centrifugal impeller. The study highlighted how hybridizing Kriging models with hybrid genetic algorithms provided both accuracy and computational efficiency, enabling significant performance improvements in impeller design. Blind Kriging, in particular, achieved the best results by effectively modeling the complex flow characteristics of the system, reducing recirculation, and increasing efficiency. Luo et al. (2017) utilized proper orthogonal decomposition-based hybrid models for flow reconstruction and aerodynamic optimization in turbomachinery blades. Integrating POD modes, derived via singular value decomposition, with nonlinear regression techniques and adaptive Latin hypercube sampling ensured precision and computational efficiency.

Combining manual and automatic differentiation (AD), hybrid differentiation techniques also exhibit significant advantages in sensitivity analysis and gradient-based optimization. Wu et al. (2023) developed a hybrid adjoint solver by integrating AD with manually optimized code to reduce memory consumption and computational cost. Applied to NASA Stage 35 and Aachen turbines, the method efficiently optimized multi-row turbomachinery designs, highlighting its practical utility in large-scale, computationally intensive problems.

In addition to these examples, hybrid approaches that integrate radial basis function networks with dimensionality reduction techniques, such as principal component analysis, further exemplify the potential of hybrid methods. Ma et al. (2010) employed such a combination to optimize centrifugal compressor impellers, demonstrating the adaptability and effectiveness of hybrid approaches in turbomachinery design optimization.

Strengths and Weaknesses of Optimization Techniques in Turbomachinery Design

Optimization techniques play an essential role in turbomachinery design by enabling engineers to address complex, high-dimensional challenges and achieve optimal performance. These methods facilitate the navigation of multimodal and nonlinear design spaces, accommodating diverse constraints and performance metrics. However, each technique has specific strengths and limitations that influence its suitability for different design problems. Factors such as computational cost, sensitivity to noise, and the ability to handle uncertainty often determine their effectiveness in real-world scenarios.

Table 1 provides a detailed summary of the primary optimization methods employed in this domain, outlining their advantages, limitations, and notable applications in the literature. Genetic algorithms, for example, are renowned for their global search capabilities, excelling in finding solutions for highly complex and multimodal problems. Neural networks, in contrast, offer unmatched speed and precision in surrogate modeling, rapidly predicting performance metrics based on geometric or operational parameters. Deep learning techniques further expand these capabilities by efficiently processing large datasets and handling intricate geometries. Hybrid methods combine these strengths, leveraging the complementary advantages of different techniques to tackle multifaceted optimization challenges.

Despite their utility, these methods face challenges such as scalability in high-dimensional design spaces, overfitting in data-driven approaches, and computational intensity in gradient-free methods. Addressing these limitations often requires innovative integration of techniques, such as embedding physical constraints into machine learning models or employing multi-fidelity approaches to balance accuracy and computational cost. The analysis presented in this section provides a roadmap for selecting and tailoring optimization strategies to meet the demands of turbomachinery design.

Table 1

Strengths and Weaknesses of Optimization Techniques in Turbomachinery Design

Optimization Method		Key Strengths	Key Weaknesses	Example study in Turbomachinery Design
Meta-Heuristic Optimization	**Genetic Algorithms (GA)**	- Global search capability - Handles complex, multi-modal problems - Flexible with non-linear objectives	- Computationally expensive - Convergence to local optima possible without proper tuning	- Sakaguchi et al. (2016) have combined GA with NNs for turbine design optimization
Neural Networks	**Neural Networks (NNs)**	- Fast surrogate modeling - Captures non-linear relationships - Reduces simulation costs	- Requires large datasets for training - Sensitive to overfitting and hyperparameter choices	- Ghorbanian & Gholamrezaei (2009) have used NN for compressor performance prediction
	Physics-Informed Neural Networks (PINNs)	- Integrates physical laws - Reduces reliance on data-driven methods - Improves prediction reliability	- High computational cost for training - Complex implementation	- Salz et al. (2023) have used PINNs for airfoil optimization
Deep Learning	**Deep Learning (e.g., CNNs, DCNNs)**	- Handles large datasets effectively - Adaptable to complex geometries - Predicts performance with high precision	- Requires extensive computational resources - Overfitting risks with limited data	- Du et al. (2022) have applied DCNNs for turbine blade profile optimization
	Reinforcement Learning (e.g., DMA-DRL)	- Adapts to dynamic environments - Excels in operational efficiency optimization - Handles multi-agent scenarios	- Long training times - Requires detailed reward function design	- Huang et al. (2024) have used DMA-DRL for operational optimization of air compressors
Hybrid Approaches	**Hybrid Approach**	- Combines strengths of different methods - Balances exploration and exploitation - Accelerates convergence	- Implementation complexity - Requires careful tuning of combined models	- Villar et al. (2018) have applied NN and evolutionary algorithms for counter-rotating rotor optimization
Adjoint Optimization	**Adjoint Optimization**	- Provides high sensitivity accuracy - Efficient gradient-based optimization	- Limited to differentiable models - Can be computationally expensive for multi-row problems	- Wu et al. (2023) have used an adjoint solver for multi-row turbomachinery design
Surrogate-Based Methods	**Surrogate-Based Optimization (SBO)**	- Reduces computational costs - Effective for expensive simulations - Provides interpretable models	- Relies heavily on surrogate model accuracy - Requires careful sampling design	- Shrivastava et al. (2022) have used surrogate models for turbocharger rotor design optimization
	Kriging (Ordinary, Blind, etc.)	- Accurate interpolation for small datasets - Provides uncertainty quantification	- Computationally expensive for high-dimensional problems - Limited scalability	- Bellary et al. (2016) have compared Kriging variants for centrifugal impeller optimization

Challenges and Future Directions

While significant advancements have been made in turbomachinery optimization, critical challenges persist that demand innovative solutions. Managing high-dimensional design spaces and capturing complex flow physics remain formidable tasks, often requiring a delicate balance between computational efficiency and solution accuracy. Additionally, robust design optimization under uncertainty—essential for ensuring reliable performance across varying operating conditions—is an area requiring further exploration. Validation of advanced optimization techniques through experimental studies is also critical for bridging the gap between theoretical advancements and practical implementation.

Recent developments in metaheuristic algorithms tailored for turbomachinery applications have begun addressing these challenges (Hakan Cetin & Zhu, 2023). For instance, neuroevolutionary strategies that integrate ant colony optimization with long short-term memory neural networks have shown promise in predictive maintenance, particularly for predicting turbine engine vibrations (ElSaid et al., 2018). Experimental validation has further bolstered the role of metaheuristics in design optimization. Studies on high-load axial flow compressors have demonstrated the effectiveness of multi-objective PSO algorithms, achieving notable gains in peak efficiency and stall margin (S. Huang et al., 2024). Similarly, integrating metaheuristics with dynamic weight strategies, as exemplified by the SDWPSO-BPNN models, has significantly improved reliability predictions for turbochargers, outperforming conventional methods (Bai et al., 2021).

The future of turbomachinery optimization lies in hybrid methodologies that combine the strengths of metaheuristics, surrogate models, and machine learning. Physics-informed neural networks (PINNs), which embed domain-specific knowledge such as the Navier-Stokes equations, hold the potential to improve the accuracy and reliability of optimization outcomes. Transfer learning, enabling the reuse of pre-trained models with limited data, offers a promising avenue for reducing computational demands in scenarios with sparse high-fidelity datasets. Focusing on sequential decision-making, reinforcement learning presents a compelling solution for optimizing operational strategies and diagnostics in real-time. Moreover, experimental validation will continue to play a pivotal role in ensuring that advancements translate effectively into real-world performance, fostering the development of more reliable and efficient turbomachinery systems.

Conclusion

Advanced optimization techniques have revolutionized turbomachinery design, enabling engineers to navigate complex design spaces and achieve unprecedented performance. Gradient-based methods, metaheuristics, surrogate models, neural networks, deep learning, and hybrid approaches have each contributed to this progress. The key strengths of specific optimization methods include genetic algorithms excelling at global optimization for complex problems, neural networks rapidly predicting performance, deep learning effectively handling large datasets and complex geometries, and hybrid methods synergistically combining multiple techniques. However, challenges remain in computational efficiency, uncertainty quantification, and experimental validation. Future research should explore hybrid methods, physics-informed models, transfer learning, and reinforcement learning to push the boundaries of turbomachinery optimization further. By addressing these challenges and leveraging emerging techniques, engineers can design the next generation of highly efficient, reliable, and sustainable turbomachinery systems.

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