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Hybrid Optimization Approaches for Impeller Design in Turbomachinery: Methods, Metrics, and Design Strategies

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Abstract

Optimizing the design of impellers in turbomachinery is crucial for improving its energy efficiency, structural integrity, and hydraulic performance in various engineering applications. This work proposes a novel modular framework for impeller optimization that integrates high-fidelity CFD and FEM simulations, AI-based surrogate modeling, and multi-objective evolutionary algorithms. A comprehensive analysis of over one hundred recent studies was conducted, with a focus on advanced computational and hybrid optimization techniques, CFD, FEM, surrogate modeling, evolutionary algorithms, and machine learning approaches. Emphasis is placed on multi-objective and data-driven strategies that integrate high-fidelity simulations with metamodels and experimental validation. The findings demonstrate that hybrid methodologies such as combining response surface methodology (RSM), Box–Behnken design (BBD), non-dominated sorting genetic algorithm II (NSGA-II), and XGBoost lead to significant improvements in hydraulic efficiency (up to 6.7%), mass reduction (over 30%), and cavitation mitigation. This study introduces a modular decision-making framework for impeller optimization which considers design objectives, simulation constraints, and the physical characteristics of turbomachinery. Furthermore, emerging trends in open-source tools, additive manufacturing, and the application of deep neural networks are discussed as key enablers for future advancements in both research and industrial applications. This work provides a practical, results-oriented framework for engineers and researchers seeking to enhance the design of impellers in the next generation of turbomachinery.

Keywords: impellers optimization; CFD simulation; multi-objective optimization; surrogate modeling; turbomachinery; hybrid framework

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1. Introduction

Impellers and turbomachinery systems are fundamental components in energy conversion processes across various sectors, including power generation, aerospace propulsion, fluid transport, and thermal systems [1,2]. The increasing demand for higher energy efficiency, reduced emissions, and enhanced structural reliability has made the optimization of these devices a strategic priority in modern engineering [3]. Specifically, impellers directly influence the performance and stability of centrifugal compressors, axial pumps,

fans, and hydraulic turbines, which has driven ongoing research and continuous improvement in their design [4,5].

Recent decades have shifted from experimental and analytical approaches to simulation-based and data-driven optimization techniques. Advances in computational power and sophisticated numerical tools have facilitated this transition. Computational fluid dynamics (CFD) and the finite element method (FEM) have become standard techniques for fluid–structure interaction analysis, supported by turbulence models such as the Reynolds-averaged Navier–Stokes (RANS), shear stress transport (SST), and unsteady RANS (URANS) models, as well as cavitation prediction models like Zwart–Gerber–Belamri (ZGB) [6,7].

Concurrently, multi-objective evolutionary algorithms such as NSGA-II, the MOGA, and the AMGA have enabled the exploration of complex design spaces, yielding near-optimal solutions in scenarios involving conflicting objectives [8]. More recently, artificial intelligence (AI) and machine learning (ML) through models such as artificial neural networks (ANNs), XGBoost, and hybrid surrogate models have expanded the frontiers of performance prediction, uncertainty quantification, and rapid structural enhancement [9,10]. Despite the notable advancements reported in individual studies, there remains a lack of comprehensive reviews that systematically categorize, compare, and quantify the application of these methodologies to impeller design. This approach considers various optimization objectives, such as hydraulic efficiency, structural robustness, cavitation resistance, and manufacturability. Additionally, the synergy between classical simulations, AI-driven metamodeling, and additive manufacturing remains a promising yet underexplored research avenue.

While prior studies have explored optimization techniques for impellers, most adopt isolated or narrowly scoped approaches that are often limited to specific algorithms, singular objectives, or proprietary environments. For instance, some works rely solely on CFD-based geometric optimization [11,12] or statistical methods like RSM and Box–Behnken design within constrained parameter spaces [13,14]. More advanced research integrates AI and surrogate modeling [8,15], yet lacks a unified framework that enables generalization across diverse impeller types and objectives. Other studies demonstrate improvements in hydraulic efficiency, such as [16], which reported a 2.06% increase for FCI-PAT using a hybrid NSGA-II + RBF approach, which highlights the potential of combining evolutionary algorithms with neural networks.

In parallel, there is growing interest in greener and more sustainable turbomachinery design strategies [17,18], driven by environmental pressures and the need for operational efficiency. Notably, novel models are emerging that outperform traditional CFD in terms of prediction speed without sacrificing accuracy [19], and recent efforts have introduced collaborative design methodologies that are capable of increasing torque ratios by over 5% through distributed optimization across impeller stages [20]. However, despite these valuable contributions, the literature still lacks a modular and hierarchical framework that is capable of integrating multi-objective optimization, AI-driven prediction, CFD/FEM simulation, and experimental validation under a single methodology.

In contrast, this work introduces a novel modular and hierarchical optimization framework that unifies CFD/FEM simulation, surrogate modeling, and AI-based techniques under a flexible architecture that is adaptable to diverse impeller components and performance criteria. This integration allows for a customized path that is tailored to the design objective (e.g., efficiency, structural integrity, or cavitation control), bridging the gap between conventional simulation pipelines and modern, hybrid optimization strategies. Moreover, by explicitly incorporating open-source tools and proposing a route toward experimental validation and feedback learning, the proposed framework advances the state of the art beyond descriptive reviews toward an actionable and reproducible optimization methodology. This study proposes a comprehensive methodology for developing and optimizing impellers in hydraulic turbomachinery, integrating advanced sim-

ulation techniques, hybrid optimization strategies, and performance analysis. Key performance indicators, software trends, and the relationship between optimization methods and specific impeller components are emphasized. Finally, a modular, multidisciplinary roadmap is presented to guide next-generation impeller optimization, with current challenges, best practices, and future directions for both research and industrial implementation being addressed.

2. Materials and Methods

This review followed a structured and rigorous methodology for the identification, selection, and analysis of the scientific literature related to impeller optimization in turbomachinery, as illustrated in Figure 1. The process was based on high-impact academic sources, and prioritized computational and experimental approaches that demonstrated measurable improvements in energy efficiency, structural stability, and fluid-dynamic performance.

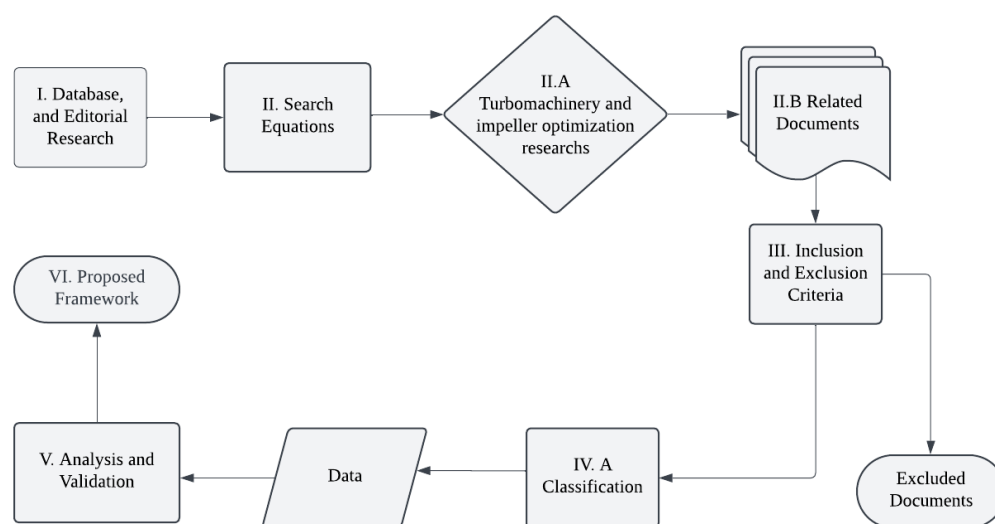


Figure 1. Flowchart of the applied methodology.

I. Initial research—the selection process focused on publications retrieved from leading academic databases, including Scopus, Web of Science (WoS), IEEE Xplore, SpringerLink, and Elsevier. Whenever possible, studies published in Q1 and Q2 journals were selected, with an emphasis on recent contributions from the last 10 years, particularly those published within the past 5. The selected studies addressed impeller optimization through advanced computational techniques and provided experimental validation or practical application.

II. Search strategy—to ensure precision and relevance, a rigorous search strategy was implemented using Boolean operators and strategically selected keyword combinations. Common search queries included terms such as “Optimization of impellers” AND “Computational Fluid Dynamics,” “Turbomachinery design” AND “Genetic Algorithms,” and “Impeller shape optimization” AND “Response Surface Methodology.” This approach was designed to capture studies that utilize cutting-edge simulation techniques or hybrid computational methodologies, with a clear focus on their practical applicability in impeller design and performance enhancement.

II.A. Filtering criteria—the first filtering criterion was focused on the number of citations, serving as an indicator of the study’s academic influence and recognition within the scholarly community. The next criterion prioritized studies that integrated both numerical simulation and experimental validation, or at least one of these elements, and which had

explicitly defined performance metrics, ensuring the inclusion of contributions with rigorous methodological foundations. These filters were critical for selecting high-quality studies that offer valuable insights into the optimization of impeller designs.

II.B. Data management—all studies that met the defined inclusion criteria were systematically organized in a structured database, which facilitated comprehensive classification, comparison, and cross-referencing. Each study entry was meticulously documented, including the type of optimization method employed, the targeted impeller component, the performance metrics used, the validation method, the publication source, and the year of publication. This systematic compilation of data enabled both qualitative synthesis and quantitative analysis, ensuring a robust and comprehensive review process that enhanced the scientific rigor of the methodology.

III. Inclusion and exclusion criteria—studies were included if they employed validated computational models, demonstrated quantifiable improvements in energy efficiency, structural integrity, or fluid-dynamic behavior, and presented innovative optimization methodologies applicable to impeller design. Studies lacking experimental or numerical validation, offering review content without comparative methodological analysis, or presenting unsubstantiated methodological limitations were excluded.

IV. Classification of optimization methods—after screening and analyzing the selected literature, the optimization methods were grouped into five main categories: CFD-based models, interpolation algorithms that use surrogate modeling techniques, evolutionary and bio-inspired algorithms, artificial intelligence and machine learning approaches, and hybrid or emerging frameworks. This classification enabled a comprehensive understanding of how different approaches are applied to various components and performance goals in impeller design.

V. Data analysis and validation—each selected study was analyzed both qualitatively and quantitatively, with special attention being given to improvements in energy efficiency, hydraulic and aerodynamic refinement, and improvements in structural robustness, including cavitation mitigation. Greater emphasis was placed on studies that validated their findings through experimental comparisons, such as wind tunnel testing or hydraulic bench experiments (Appendix A). Additionally, this review highlights the increasing role of machine learning in accelerating simulation processes and reducing computational costs through the use of predictive modeling and adaptive optimization schemes.

VI. Framework development—based on the insights that were gathered, a modular optimization framework is proposed to guide future impeller design efforts. This framework integrates computational simulation, data-driven modeling, and iterative refinement cycles, allowing for customization based on system constraints, design goals, and physical phenomena.

3. Results and Discussion

Recent studies have demonstrated the effectiveness of various optimization strategies for turbomachinery impellers, predominantly utilizing CFD, evolutionary algorithms (e.g., genetic algorithms), artificial neural networks (ANNs), and hybrid multi-objective approaches. As detailed in Table 1, aerodynamic and structural optimizations have resulted in significant performance improvements, including up to 6.7% efficiency gains, a 30% mass reduction, and a 2.5% increase in the pressure coefficient. The integration of machine learning models such as XGBoost and ANNs has further enabled rapid and accurate performance predictions, enhancing energy efficiency and reducing power demands. Particularly in centrifugal pump applications, hybrid CFD–AI methods have proven effective in mitigating cavitation, achieving up to a 19.3% performance improvement. These findings underscore the value of combining high-fidelity simulations with data-driven techniques for advanced impeller design.

Table 1. Optimized impeller design studies: summary and key findings.

Category	Study	Metric Improvement (%)	Optimization Approach	Reference
Centrifugal Compressor Optimization	Multi-objective optimization of impellers	Structural and aerodynamic optimization	CFD & RSM	[11]
	Design of experiment (doe) technique	Efficiency +3%, pressure ratio +11%	Experimental & Statistical	[14]
	Meridional profile optimization	Up to +3% efficiency at high flow rates	Geometry-Based Optimization	[12]
	Robust optimization under uncertainties	Pressure ratio +9.3%, efficiency +6.7%	Uncertainty Quantification	[21]
Axial & Mixed Flow Pumps	Multi-disciplinary axial-flow impeller design	Blade mass -10.47%, efficiency +0.61%	Approximation Model	[6]
	Mixed-flow pump optimization	Efficiency +6.47% (1.2QDES), +3.68% (QDES)	Inverse Design Method	[22]
	Turbopump impeller structure	Pressurization coefficient +2.5%	Response Surface Method (RSM)	[23]
Energy Efficiency & Performance Enhancement	Optimization in hydrogen fuel cell compressors	Power consumption -2.99%, isentropic efficiency +2.16%	Multi-Objective Genetic Algorithm	[24]
	Motor cooling fan optimization	Efficiency +8%, flow rate +18%	CFD & MOGA	[25]
	Mixing impeller optimization	Energy consumption -26.71%	Fluid-Structure Interaction	[26]
Machine Learning & AI-Driven Optimization	ML-based impeller performance prediction	Prediction in <1 s	Machine Learning	[15]
	Fatigue reliability modeling	XGBoost model achieves $R^2 > 0.93$	AI & Surrogate Modeling	[27]
	Automated defect detection in impellers	High accuracy & efficiency	Deep Learning	[28]
Additive Manufacturing & Topology Optimization	Impeller mass reduction	Mass -30%	Topology Optimization	[29]
	Structural enhancement for stress reduction	Stress -25%, mass -20%	Topology & Additive Manufacturing	[30]
	Hybrid manufacturing constraints	Weight -18.5%	Additive & Design Constraints	[31]
Hydraulic & Cavitation Performance	Cavitation-resistant impeller design	Performance +19.3%	Taguchi Optimization	[32]
	Hydrodynamic optimization of axial-flow pumps	Head +21.03%, efficiency +3.097%	CFD & Diffuser Blade Design	[33]
Aerodynamic & Structural Robustness	Aerodynamic robustness in compressors	Pressure ratio +70.1%, efficiency +18.7% ($\text{Max}\sigma$)	Response Surface & Evolutionary Algorithms	[34]
	Aeroelastic analysis of impeller blades	Explosion margin +4.31%, mass -23%	Modal Analysis	[35]
	Cfd-assisted impeller shape optimization	Efficiency +4.74%, head +7.69%	NUMECA & GA	[36]

Computational Fluid Dynamics (CFD) & Genetic Algorithms	Computational prediction of mixing efficiency	Efficiency +2.4%	Lattice Boltzmann Method	[37]
	Impeller shape impact on gas-liquid mixing	Axial gas distribution improved by 55%	Two-Phase CFD Simulation	[38]
Noise & Vibration Reduction	Psychoacoustic-based impeller noise reduction	Noise intensity reduced, efficiency +4.3%	Sound Quality Optimization	[39]
	Vibration intensity reduction in marine pumps	Lower vibration, efficiency improved	Multi-Condition Optimization	[40]
Multi-Objective & Genetic Algorithm-Based Optimization	Optimization of centrifugal impellers using ga	Improved efficiency & operational stability	GA & CFD	[41]
	Energy-saving impeller design	Efficiency +4.3%	MIGA-RBF Algorithm	[42]
Structural & Manufacturing Advances	Integrated blade-disk optimization	Weight -65%	Structural Optimization	[13]
	Erosion-resistant slurry pump design	Erosion rate density reduced	Discrete Phase Modeling	[43]
Miscellaneous & Novel Approaches	Satellite pump impeller optimization	Efficiency +3.55%, head +7.9%	Space Application-Specific Design	[44]
	High-efficiency submersible pump design	Efficiency +6.1%, head +3.5%	Taguchi Method	[40,45]
	Cfd-based centrifugal compressor optimization	Improved performance & stability	Computational Optimization	[41]

3.1. Comparative Visual Analysis of Optimization Strategies

To complement the quantitative summary presented in Table 1, a comparative visualization was developed to analyze the relationship between reported efficiency improvements and the estimated computational effort required by different optimization methodologies. This representation provides a decision-oriented perspective on the trade-offs inherent in various approaches.

Figure 2 includes a bubble chart correlating the efficiency gain (%) and computational time (in relative hours) for 10 representative techniques extracted from recent studies. Each bubble denotes a specific method, while its position reflects the computational time versus its performance gain. Notably, strategies combining machine learning and surrogate modeling, such as the use of NSGA-II with ANN or WTA-RBF-RSA-KRG, stand out by achieving higher efficiency gains (up to 23% and 10%, respectively), although they exhibit moderate to high computational costs. On the other hand, classical statistical methods such as Box-Behnken design or response surface methodology offer more modest improvements (1.8%–3.0%) but require significantly less computational time, which makes them more viable during initial design stages. This analysis reinforces the idea that hybrid and AI-enhanced approaches tend to offer superior performance in multi-objective scenarios, especially when accuracy, adaptability, and efficiency are prioritized. Visualization serves as a practical complement to the proposed modular framework, helping to guide the selection of techniques according to project-specific constraints and objectives.

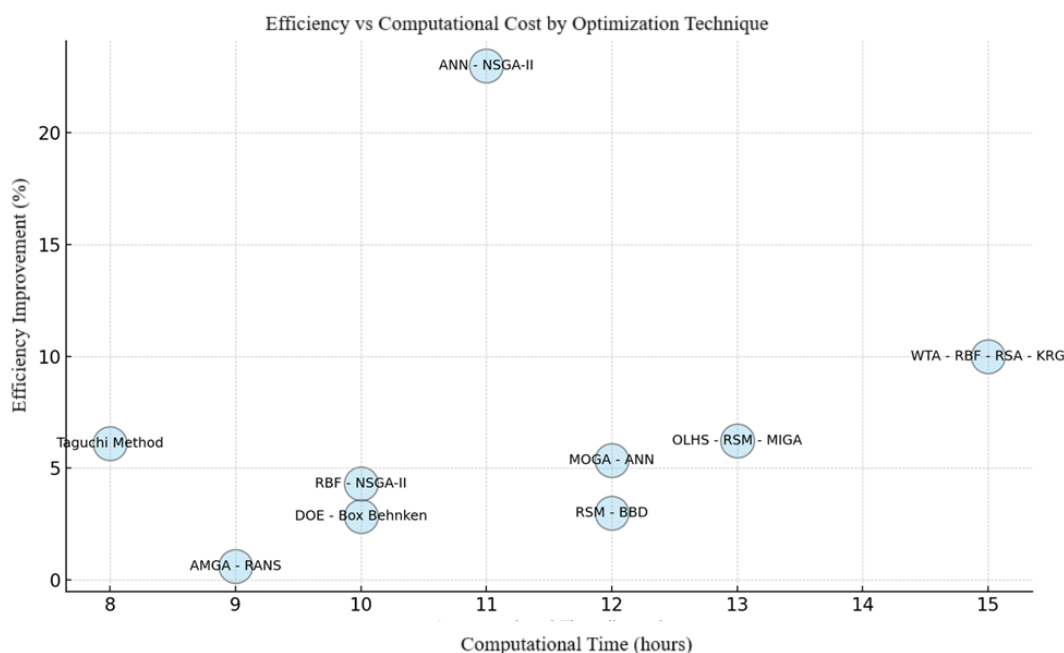


Figure 2. Efficiency vs. computational cost.

Various optimization techniques have been applied to impeller design, resulting in diverse outcomes in terms of efficiency, robustness, and performance. The most effective methodologies can be classified into six main categories: (1) CFD-based simulation models, (2) interpolation algorithms, (3) evolutionary algorithms, (4) artificial intelligence and machine learning, (5) hybrid methods, and (6) advanced and hybrid optimization models.

3.2. CFD-Based Simulation Models

CFD models are widely used to simulate the behavior of fluid in turbomachinery, as they enable the detailed analysis of hydraulic efficiency, aerodynamic profiles, and thermal performance (see Figure 3). These models solve Navier–Stokes equations, often with RANS, SST, or URANS turbulence models, to predict flow patterns and pressure distributions. In impeller design, CFD provides high-fidelity insights that support performance evaluation and geometric optimization.

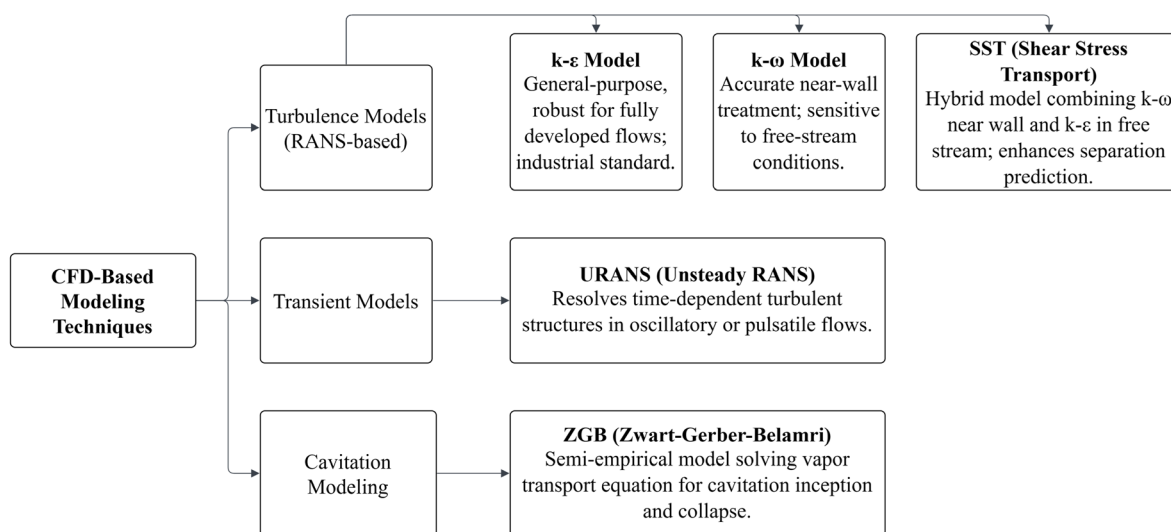


Figure 3. High-performance CFD-based models.

CFD models enable precise flow analysis and contribute to efficiency improvements [46]. Figure 2 shows the CFD-based models with the best results. Solving RANS equations requires modeling Reynolds stresses using turbulence models such as $k-\varepsilon$, $k-\omega$, and SST. The URANS equation extends the RANS equation for unsteady flows with large, non-periodic fluctuations, allowing their separation into a mean unsteady part and a turbulent fluctuation component. For CFD models, metamodellers trained with local model networks (LMN) and multi-layer perceptrons (MLPs) using steady-state Reynolds-averaged Navier–Stokes (RANS) simulations have optimized impeller designs [47]. While traditional RANS-based unsteady methods accurately predict single-impeller simulations, they show significant deviations in multi-impeller setups [48].

The SST model, widely used for centrifugal machinery, offers a balance between near-wall accuracy and far-field stability, although it may underrepresent turbulent shear transport [49,50]. For example, elliptical hub and shroud profiles optimized with SST yielded smoother flow transitions and lower secondary losses [12]. Other works have reported that they obtained improved performance through the use of discretized Navier–Stokes equations with realizable $k-\varepsilon$ models, particularly under varying flow rates [51]. Regarding cavitation models, they are typically resolved using RANS equations. The main cavitation models include the ZGB (Zwart–Gerber–Belamri), SS (Schnerr and Sauer), and FC (full cavitation) models, with ZGB demonstrating the highest accuracy among the three [52].

3.3. Interpolation Algorithms

Interpolation algorithms utilize mathematical models to identify optimal configurations that either maximize performance or minimize losses. Common techniques include response surface methodology (RSM), the Kriging approach, and design of experiments (DoE) approaches such as Box–Behnken design (BBD). These strategies facilitate the construction of surrogate models, which guide efficient exploration of the design space while reducing the computational effort (see Figure 4).

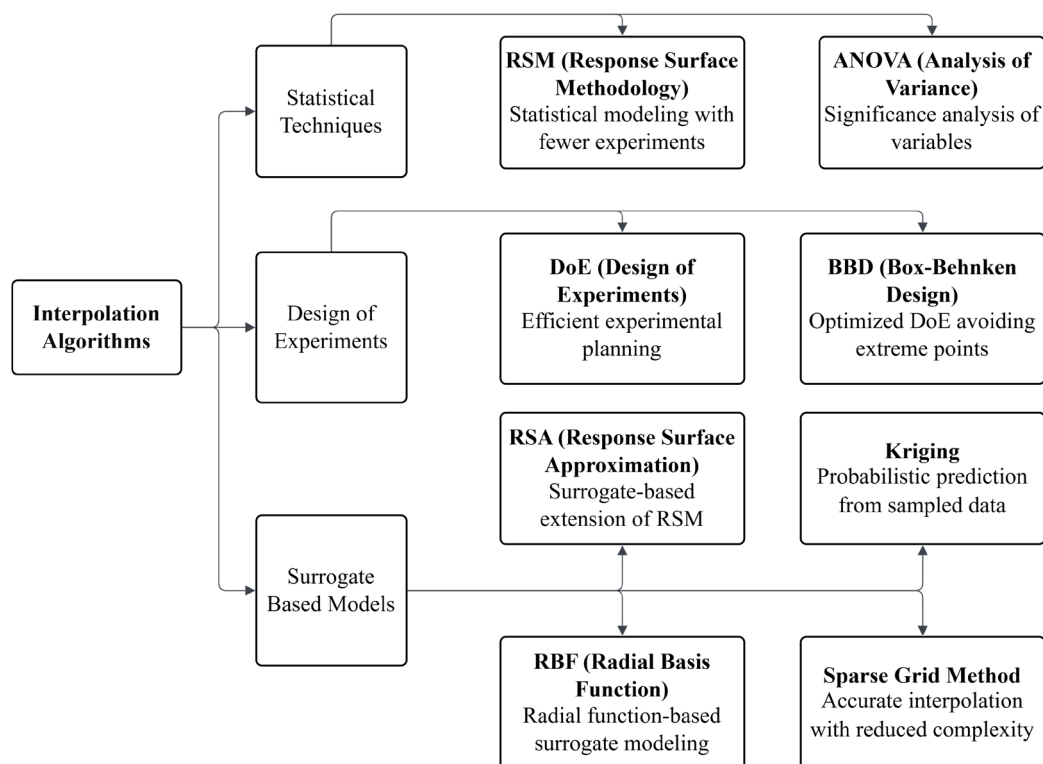


Figure 4. High-performance interpolation algorithms used in turbomachinery.

Design of experiments (DoE) and optimization methodologies enable the efficient statistical modeling of complex processes and thus minimize the experimental requirements. Reference [53] integrated Box–Behnken design (BBD), response surface methodology (RSM), and analysis of variance (ANOVA) to optimize input parameters, enhancing an energy recovery turbine. Similarly, [11] optimized a centrifugal compressor impeller using RSM and BBD, improving its aerodynamic efficiency and structural integrity via a multi-objective genetic algorithm (MOGA). Reference [14] employed RSM to construct surrogate models and identify optimal impeller designs, achieving 3% higher efficiency and an 11% increase in the pressure ratio. Likewise, [54] compared an optimized S-shaped impeller with a conventional radial one using DoE, RSM, and BBD, achieving efficiency gains of 2.85% and 1.67% through the use of single- and dual-objective optimization, respectively. Reference [23] enhanced turbopump impellers, increasing the pressurization coefficient ϕ_2 by 2.5%, reducing leakage by 8.2%, and improving the reverse flow by 6.7% under negative pressure sealing. Reference [55] applied RSM to a centrifugal pump with guide vanes, optimizing five design variables related to blade geometry and spacing, while [56] combined grey relational grade (GRG) analysis with RSM to optimize impellers in centrifugal fans.

Radial basis functions (RBFs) support geometric optimization [57]. Studies using RBF approximation and Sobol sensitivity analysis verified the feasibility of a dual-impeller solid–liquid mixing tank through both numerical simulations and particle image velocimetry (PIV) experiments, demonstrating enhanced mixing and particle suspension [58]. There is ongoing research on improving structural reliability analysis via an enhanced radial basis function neural network (RBFNN) [59]. On the other hand, Kriging interpolation, which is superior to low-order polynomial models, predicts outputs with high accuracy [60,61], although software limitations may affect its performance [62]. Meanwhile, the sparse grid method has been employed for numerical optimization, with [63] refining a pump model using adaptive Kriging, sparse grids, and MOGA-based neural networks.

3.4. Evolutionary Algorithms

Inspired by natural evolution, evolutionary algorithms are powerful tools for solving complex multi-objective optimization problems. Techniques such as genetic algorithms (GAs), NSGA-II, the MOGA, and the MIGA have been successfully applied to refine impeller geometry, improve flow uniformity, and enhance system stability. Their stochastic nature allows for the exploration of broad design spaces, which allows these methods to yield robust solutions in the presence of competing objectives.

Evolutionary algorithms have become essential in impeller optimization due to their ability to handle complex, multi-objective problems with conflicting design criteria (see Figure 5). Among these, the genetic algorithm (GA) is one of the most widely used techniques, drawing inspiration from natural selection principles [64]. In [41], the GA was employed to iteratively optimize the geometry of an impeller using commercial CFD tools, and the authors were able to significantly refine its performance over successive generations. When combined with response surface approximation (RSA), Kriging (KRG), and radial basis neural networks (RBNN), the GA led to a 0.974% increase in efficiency and a 21.03% rise in head; subsequent diffuser blade optimization added 3.1% efficiency and 10.2% head gain [33].

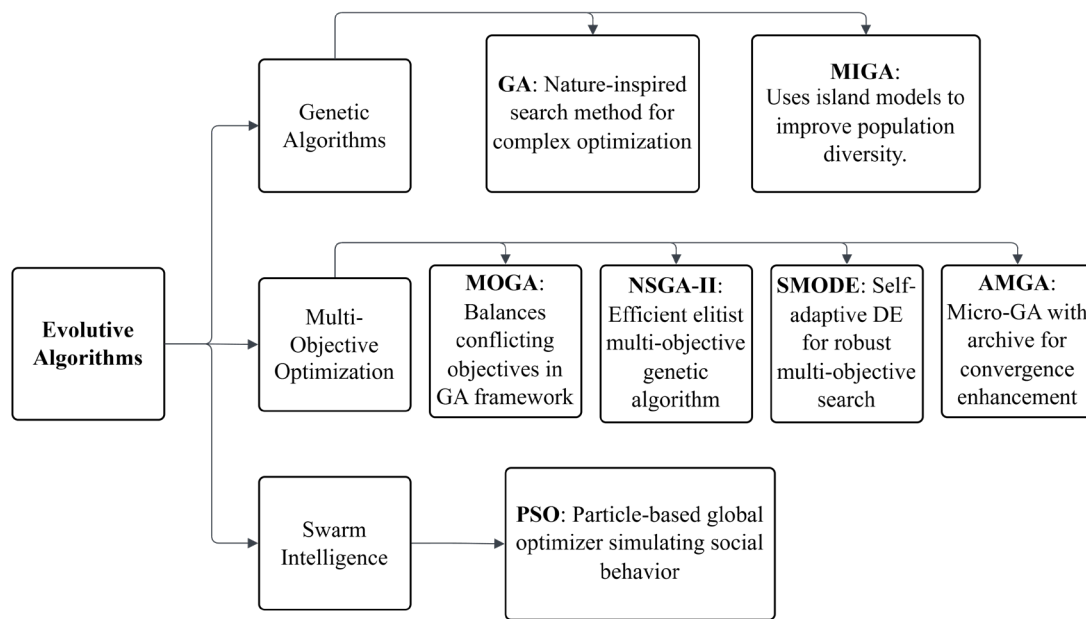


Figure 5. High-performance evolutionary algorithms for turbomachinery optimization.

The multi-objective genetic algorithm (MOGA) extends the capabilities of the GA by balancing trade-offs between competing objectives. It has demonstrated faster convergence and reduced computational time compared to traditional methods [65,66]. The MOGA combined with direct optimization (DO) and response surface optimization (RSO) reduced the energy consumption by 26.71% and increased the equivalent stress by 6.09% in stirred-tank reactors [26]. In turbocharger design, the MOGA improved the efficiency by 2% and the surge stability by 7% using SST and $k-\epsilon$ models [4].

The MOGA's impact extends to electric fan systems [27], where it enhanced efficiency by 8% and volumetric flow by 18%, and lowered winding temperature by 8 °C, reducing copper use. In centrifugal fans and pumps, efficiency gains of 1.7% [67] and 12% [68] were achieved using ANOVA, SST, and surrogate modeling. RSA and Latin hypercube sampling (LHS) further supported MOGA-based flow stabilization [4]. Surrogate model integration in [69] (KRG, RBF, RSA, WTA) improved impeller blade angles, boosting pump efficiency by over 10% with no head loss. These results illustrate the MOGA's versatility in combining with metamodels for enhanced design quality.

NSGA-II, known for its fast elitist sorting and lower computational complexity [57,70], often outperforms the MOGA in terms of efficiency in specific scenarios [71]. Hybrid approaches have leveraged NSGA-II with CFD, inverse design methods (IDMs), LHS, and RSM to optimize mixed-flow pumps, yielding efficiency increases of 0.63%, 3.39%, and 3.77% across different flow rates [72]. NSGA-II has also improved the design of splitter blades and wrap angles in high-viscosity oil systems [73].

The modified genetic algorithm (MIGA) introduces independent population clustering to avoid premature convergence [74,75]. Applied to hydraulic efficiency models trained via RBF and CFD-OLH data, the MIGA increased pump efficiency by 4.3% [42]. In [76], the MIGA was combined with RSM and DoE to optimize magnetic drive pumps for high-speed conditions, which improved their performance and flow uniformity [77]. Evolutionary algorithms have also been integrated into multidisciplinary design optimization (MDO) frameworks, with hydraulic and structural criteria being combined to achieve robust impeller performance under complex operational constraints [6]. The adaptive multi-objective genetic algorithm (AMGA) offers further refinement. In [78], an AMGA with 15,000 iterations reduced the blade mass by 10.47% while improving efficiency by 0.61%.

Another study [79] reported gains of 2.05% in overall efficiency and 8.89% in the loss margin. Nonetheless, NSGA-II remains preferable in certain applications due to its balance of speed and robustness [80].

In this study, NSGA-II was selected as the baseline multi-objective optimization algorithm within the proposed framework due to its widespread adoption, computational efficiency, and proven robustness across a wide range of turbomachinery design problems. Compared to other algorithms such as SPEA2 or MOEA/D, NSGA-II offers fast elitist sorting, diversity preservation through the use of crowding distance, and low parameter tuning complexity features that make it particularly well-suited for scenarios involving conflicting objectives and high-dimensional design spaces, such as impeller optimization [81,82]. Furthermore, the literature review conducted in this study revealed that NSGA-II is the most frequently employed algorithm in recent high-impact publications on turbomachinery optimization.

3.5. Machine Learning and AI

AI and ML techniques, including artificial neural networks (ANNs), XGBoost, and random forest models, are increasingly used to predict impeller performance, accelerate simulation processes, and guide optimization decisions. These models are trained on simulation or experimental data, and enable the fast and accurate prediction of efficiency, cavitation, fatigue, and structural response under varying conditions (see Figure 6).

Machine learning (ML) and artificial intelligence (AI) techniques have gained significant momentum in impeller optimization, enabling high-accuracy performance prediction, real-time diagnostics, and design enhancement (see Figure 6). Artificial neural networks (ANNs) are widely used due to their ability to model complex nonlinear relationships through layers of interconnected neurons [83]. In [84], ANNs predicted the slurry erosion in pump materials with high accuracy, eliminating the need for explicit physical equations. Although the backpropagation neural network (BPNN) is commonly used for nonlinear mapping, its predictive accuracy is limited in some cases [85]. Hybrid techniques such as ISSA-BPNN (BPNN + improved sparrow search algorithm) have demonstrated improved reliability over conventional models [86]. Notably, combinations with evolutionary algorithms have also demonstrated strong performance. For instance, GA-BPNN increased the efficiency of an impeller by 4.74% [36], while BPNN-MOGA improved the efficiency of a pump by up to 5.36% [8]. GA-BPNN was also employed to assess turbine durability [87], and iterative BPNN-NSGA-II frameworks were successfully used to optimize transonic axial compressors with an acceptable computational cost [88].

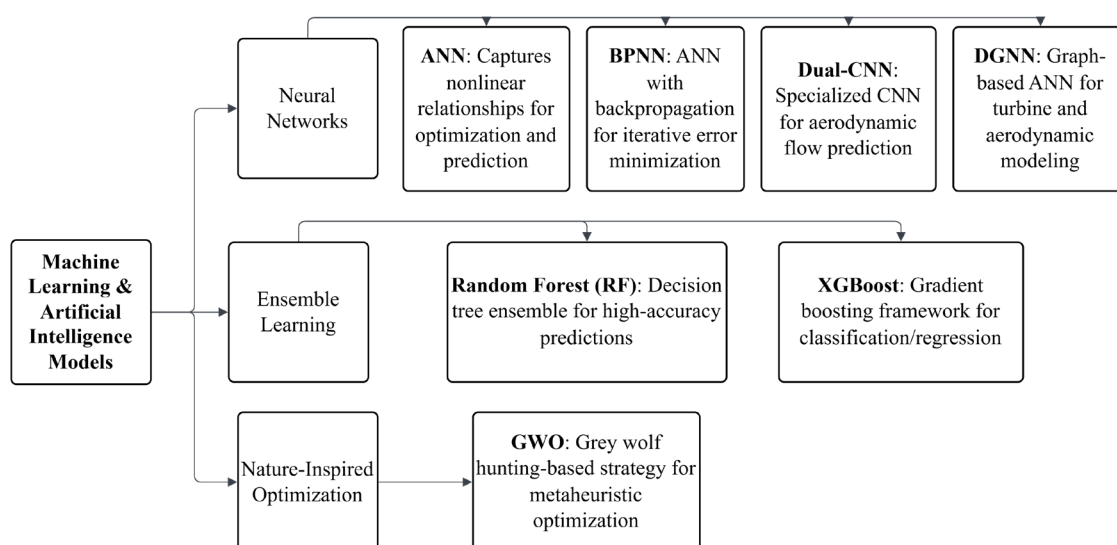


Figure 6. High-performance machine learning and AI techniques in turbomachinery optimization.

Tree-based ensemble methods, such as the random forest (RF) and extreme gradient boosting (XGBoost) methods, have proven effective for regression, classification, and defect detection in centrifugal machinery [89–91]. The RF method enables torque prediction and defect analysis, although it is limited by its execution time and low parallelism. XGBoost, by contrast, combines weak learners using boosting techniques to achieve higher accuracy and speed [92,93]. It has been successfully applied to cavitation detection [94], fatigue prediction [27], and centrifugal compressor optimization [94]. When coupled with the whale optimization algorithm (WOA), XGBoost significantly improved fatigue life predictions [27]. Compared to AdaBoost, KNN, and SVM, XGBoost achieved the highest accuracy (92.23%) in defect detection for submersible impeller systems [28]. The grey wolf optimizer (GWO) has also shown promise in turbomachinery. It has been used to reduce impeller mass, enhance anti-cavitation properties, and eliminate resonance risks [35,95,96]. In blood pump applications, a hybrid MOGWO-RF model increased pressure generation by 24% and reduced hemolysis by 48% [97]. More advanced neural architectures have emerged to address flow prediction and complex aerodynamic modeling. Dual convolutional neural networks (Dual-CNNs) outperformed traditional ANNs and Gaussian process regression (GPR) in reconstructing flow fields and predicting torque and efficiency [98,99]. Similarly, the dual graph neural network (DGNN) framework exhibited significantly improved turbine performance prediction accuracy over standard ANN models [10,100].

Although deep neural networks (DNNs) were not directly implemented in this study, their integration is envisioned as a future enhancement of the surrogate modeling phase. DNNs offer the ability to capture highly nonlinear relationships in complex design spaces, which is particularly valuable in turbomachinery optimization. Reference [101] demonstrated the use of fully connected feedforward architectures trained on CFD results to predict impeller performance, which enabled the replacement of expensive simulations within the optimization loop. In such approaches, DNNs are coupled with evolutionary algorithms to enhance their convergence speed and explore wider design domains. Incorporating these models into the proposed framework may significantly improve computational efficiency and model generalizability, especially when they are combined with transfer learning or physics-informed strategies.

3.6. Hybrid Methods

Hybrid optimization integrates multiple approaches—such as CFD, surrogate modeling, and bio-inspired algorithms—to leverage their respective strengths. Common combinations include RSM-NSGA-II, CFD-GA, and Kriging-ANN frameworks. These methods strike a balance between accuracy and efficiency, particularly in addressing problems that are characterized by uncertainty, conflicting objectives, and high-dimensional parameter spaces.

Robust optimization methods have become increasingly relevant in impeller design due to the need to account for uncertainty, variability, and manufacturing-induced deviations in real-world conditions (see Figure 7). The Monte Carlo (MC) method is widely used to quantify machinery performance under stochastic variability through probabilistic sampling [102]. In [21], NSGA-II-optimized impellers were validated with MC simulations, which confirmed their resilience to uncertainty. Additionally, the MC method has been employed for model-based uncertainty quantification [103] and, in combination with deep generalized neural networks (DGNNs), it enabled the robust optimization of turbine power output and efficiency [104].

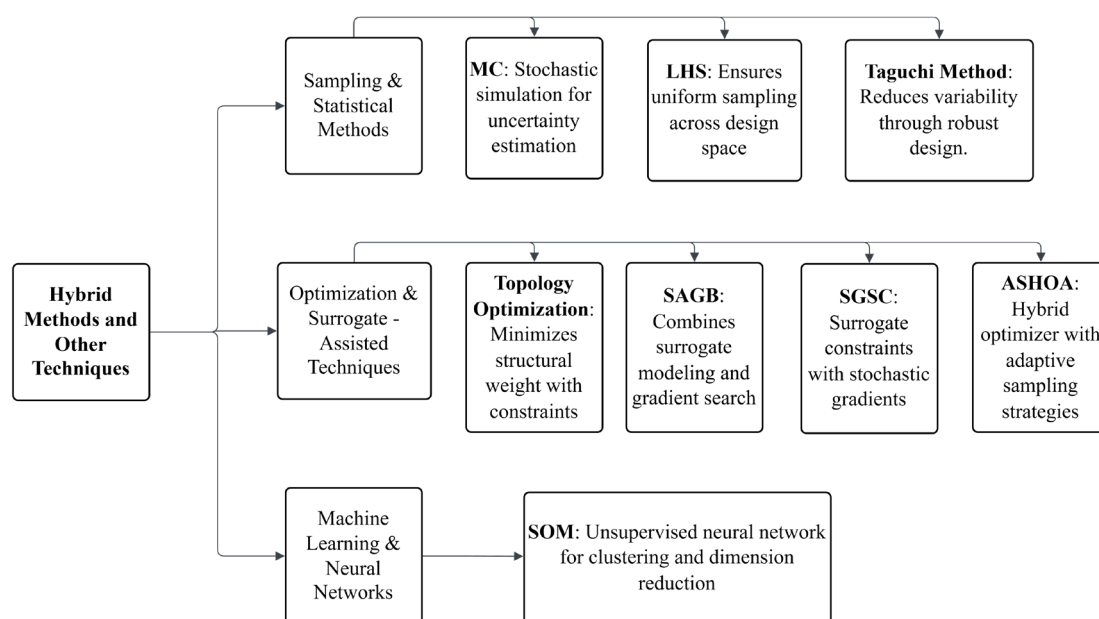


Figure 7. High-performance hybrid methods for turbomachinery optimization.

Latin hypercube sampling (LHS) offers efficient, non-repetitive sampling in high-dimensional spaces and has supported geometric optimization in double-suction centrifugal pumps, improving their efficiency, vortex control, and flow stability [62,105].

Taguchi methods have proven valuable for parametric design and process control. In [45], the use of modified mid-curvature cover geometry improved the performance of a submersible pump. References [106,107] reported gains of 3.5% in head and 6.1% in efficiency, as well as an optimized mixing performance in baffle-less tanks with inward-flow impellers, that were obtained using minimal experimental trials. Moreover, a 19.3% reduction in the cavitation number at the best efficiency point was achieved by coupling Taguchi optimization with the Zwart–Gerber–Belamri cavitation model [32].

Stochastic modeling frameworks like SGSC-SVR and subset simulation (SIS) have been applied to evaluate the effects of manufacturing uncertainties on centrifugal impellers. Validated through analytical functions, these methods deliver high prediction accuracy with reduced computational effort. SIS iteratively enriches the diversity of samples, achieving a balance between local search and global exploration [108]. Further, self-organizing maps (SOMs) have been used for intelligent fault detection in pumps, accurately identifying early-stage cavitation and impeller degradation using electrical motor signals [109]. In aerodynamic blade optimization, surrogate-assisted gradient-based (SAGB-II) algorithms have outperformed deterministic strategies (DADO, RADO), reducing both the statistical mean and standard deviation of key outputs [110].

Finally, the ASHOA (adaptive sampling hybrid optimization algorithm) framework combines Kriging metamodeling, data mining (ANOVA, SOM), and hybrid optimization to improve design space exploration in 3D transonic centrifugal compressors [111]. The ASHOA delivered search efficiency gains of 2–10× compared to benchmark methods, with the final designs achieving a 1.61% increase in isentropic efficiency, a 4.13% gain in the pressure ratio, and a 9.68% reduction in the peak stress.

3.7. Advanced and Hybrid Optimization Models

Recent advances incorporate robust optimization under uncertainty, topology optimization, digital twins, and deep learning architectures (e.g., DGNN, Dual-CNN). These frameworks aim to enhance aerodynamic robustness, structural performance, and manufacturability while accounting for variability in operating conditions. Their integration

with additive manufacturing and open-source tools further expands the potential for customized, high-performance impeller designs (see Figure 8).

Advanced and hybrid optimization methods have demonstrated considerable success in addressing complex design challenges in turbomachinery impellers, particularly in erosion control, structural integrity, cavitation resistance, and acoustic optimization (see Figure 8). In this sense, the discrete phase model (CFD-DPM) has become a key tool for erosion analysis in particle-laden flows. The study by [43] confirmed a reduction in the erosion rate density in optimized models using Finnie's formulation, while [112] employed dense DPM (DDPM) to simulate erosion caused by medium-grain sand in dense slurry conditions. Despite its accuracy, the DPM remains computationally intensive and requires significant model simplifications [113].

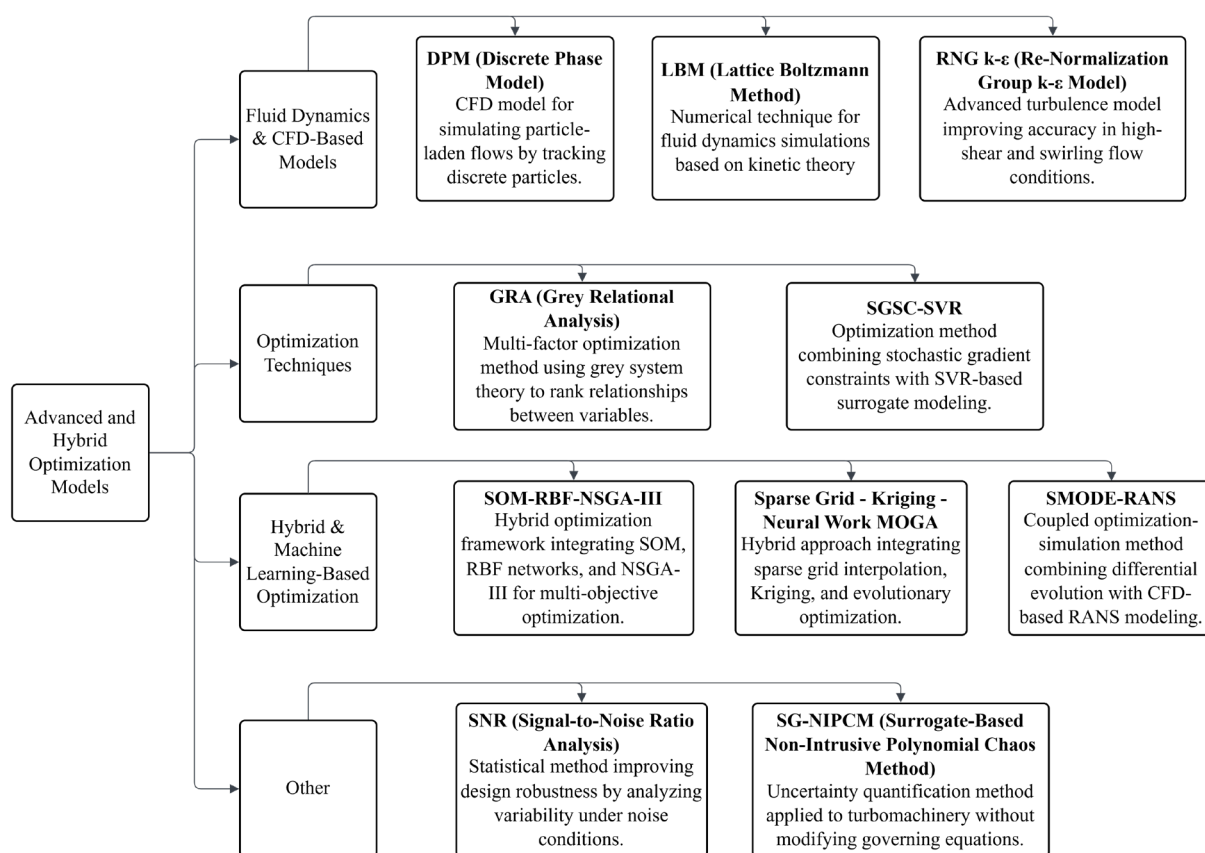


Figure 8. Advanced and hybrid optimization models.

The lattice Boltzmann method (LBM) is gaining attention as a promising alternative for simulating unsteady flows and multiphase dynamics. It has been used to model gas–liquid interactions in stirred vessels [37] and was shown to accurately predict flow phenomena in pump impellers under transient conditions [114], which indicates that it offers a viable alternative to Navier–Stokes solvers [37].

Turbulence modeling using RNG $k-\epsilon$ has yielded notable performance improvements. In [40], optimization led to a 4.3% increase in efficiency and a 30.5% reduction in vibration intensity in a marine centrifugal pump. Similarly, [38] showed a 55% improvement in axial gas-phase distribution using a 30° inclined-blade impeller.

Topology optimization (TO) has proven to be highly effective in reducing the mass of impellers and enhancing their structural behavior. Notable achievements include a 30% mass reduction in a 3D impeller for oil and gas applications [29], an 18.5% mass decrease with stress control in aerospace components [31], and a 25% stress reduction with a 20%

mass cut, resulting in higher operational speeds [30]. Additional applications include performance gains in small radial pumps [115], energy-efficient paddle mixers that were obtained via DEM-TO [116], and a 65% weight reduction that was obtained through nonlinear optimization [13].

Robust optimization under uncertainty has been implemented using SOM-based frameworks. In [117], SOM-RBF-NSGA-III improved the isentropic efficiency and pressure ratio by 0.6% and 0.5%, while reducing the standard deviations of these metrics by over 30%. SOM-Kriging models, in [21], yielded a 9.3% gain in the average pressure ratio, a 6.7% increase in efficiency, and an 11 dB reduction in the acoustic power level. The use of SMODE and SOM in [118] enabled the generation of 16 Pareto-optimal solutions for high-pressure impellers.

Other hybrid strategies have addressed specific optimization goals. For hydrogen fuel cell compressors, [24] used SNR analysis to reduce the power consumption by 2.99% and improve the isentropic efficiency by 1.24%. The cavitation performance was enhanced by 9–19.3% using Taguchi-ZGB modeling [32], while [119] demonstrated that adjusting blade wrap angles to 120° reduced the internal vortex losses in centrifugal pumps.

The integration of grey relational analysis (GRA) with Taguchi methods has improved the mechanical and hydraulic properties of 3D-printed impellers [120–122]. Structural and aerodynamic improvements were also validated through coupled 2D CFD, FEM, and turbulence modeling in [123], which lead to cost reductions in energy recovery turbines. In [124], a combined RANS- $k\omega$ SST, RMS, and ML approach improved the axial flow pump efficiency by 2%, while [125] used neural networks to accurately predict the energy conversion performance of impellers.

Lastly, psychoacoustic-driven geometry optimization, in [39], enhanced the sound quality of impellers by modifying their channel shapes, and [126] applied ANNs and the GA to optimize machining operations, achieving lower specific energy consumption and improved productivity.

3.8. Framework Proposal

Based on the comprehensive analysis of over 100 high-impact studies, this study consolidates the state of the art in impeller optimization into a structured and adaptable decision-making framework. While no novel algorithm or simulation tool is proposed, the contribution lies in the systematic integration of diverse methodologies into a coherent structure that can guide design decisions across different technical contexts. Current impeller optimization processes typically follow a series of structured phases that are aligned with key design objectives: (a) energy efficiency, by minimizing hydraulic and aerodynamic losses; (b) structural stability, through stress reduction and fatigue control; (c) cavitation mitigation, by improving flow uniformity and minimizing bubble formation; and (d) manufacturability and cost-efficiency, which ensure technical feasibility and scalability.

To address these objectives, we present in Figure 9 a general roadmap that integrates the key methodological phases involved in impeller optimization, including geometry definition, simulation, surrogate modeling, multi-objective optimization, and validation.

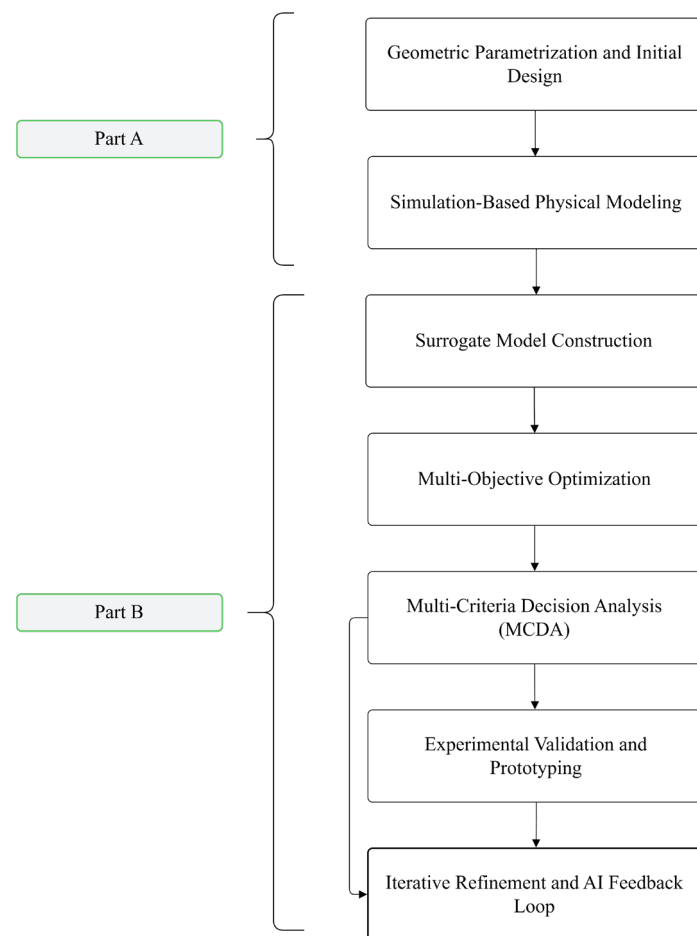


Figure 9. Proposed flowchart for impeller optimization.

Depending on the specific objective, different numerical strategies are applied. Figure 10 (Part A) outlines a modular simulation workflow that integrates CFD and FEM, which allowing for the appropriate selection of RANS, URANS/LES, or nonlinear FEM models based on the flow complexity, structural requirements, and computational constraints. This approach reflects the current state-of-the-art trend, where hybrid frameworks facilitate iterative cycles by balancing accuracy, cost, and experimental validation. Also, Figure 10 summarizes this simulation logic, showing how flow regime classification and performance criteria guide the selection of numerical methods. This modular simulation workflow allows designers to maintain a balance between computational cost and result accuracy, a key aspect for iterative optimization processes in turbomachinery.

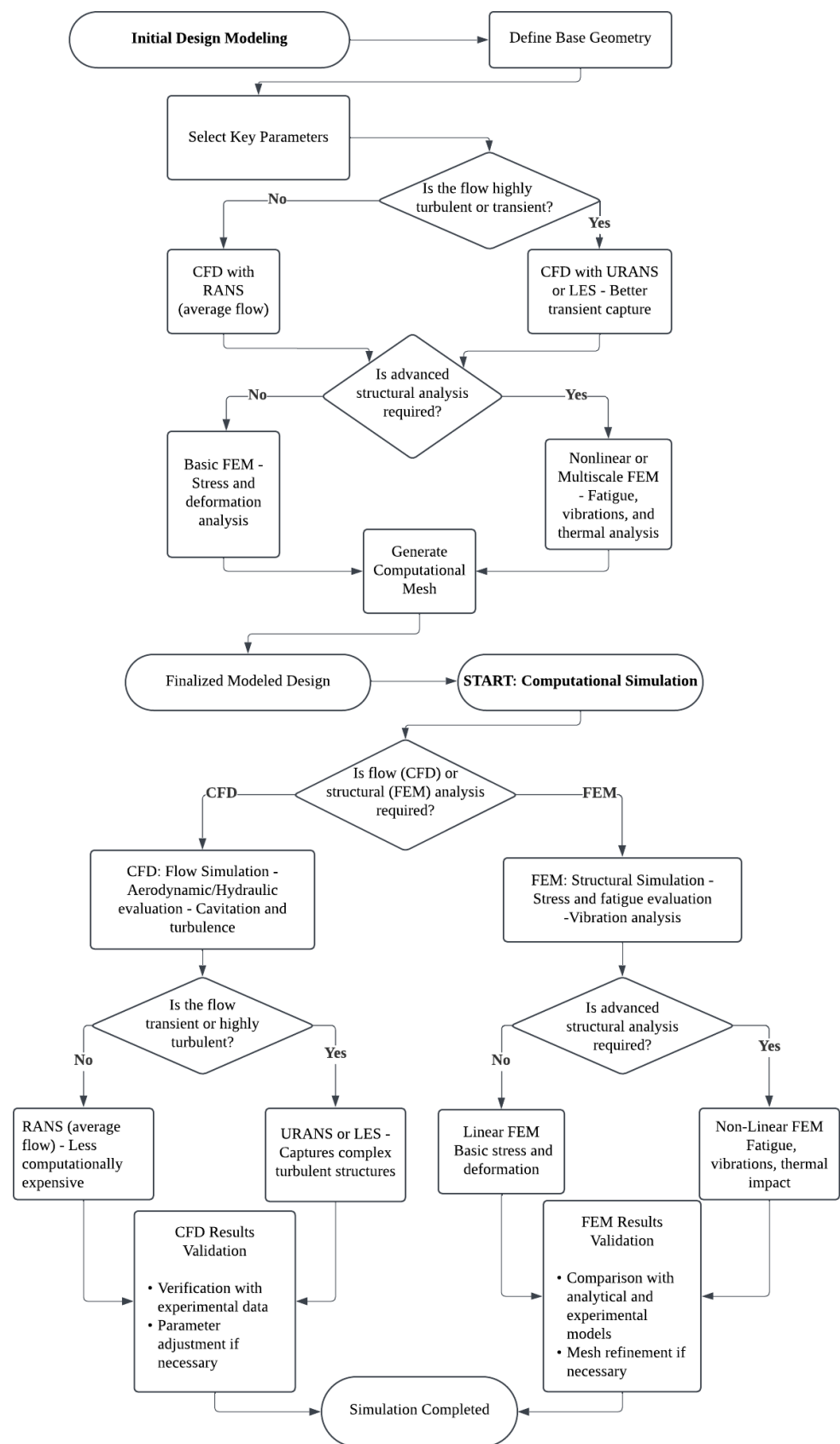


Figure 10. Flowchart of the applied methodology – part A.

To evaluate hydraulic and structural performance, CFD is used to simulate flow dynamics and optimize blade profiles, while the FEM is applied to assess stress distribution

and mechanical integrity. Within the proposed framework, the coupling between the CFD and FEM simulations follows a partitioned, sequential strategy based on a one-way data transfer scheme. Specifically, CFD simulations are first performed to obtain the pressure and velocity distributions along the impeller surfaces, which are then mapped as boundary loads onto the FEM structural domain. This transfer is executed using mesh interpolation techniques and synchronized through shared geometric references to ensure spatial coherence at the fluid–structure interface. RANS-based models such as SST, $k-\epsilon$, and $k-\omega$ offer robust steady-state predictions, while the URANS and LES models provide a better resolution of transient and turbulent phenomena. Optimization strategies vary depending on the component and objective. Figure 11 shows how efficiency gains differ across geometric regions (e.g., blades, hub, shroud), which reinforces the need for component-specific optimization paths. Complementarily, Figure 12 presents a heatmap that correlates optimization methods with component impacts, showing the effectiveness of hybrid and evolutionary techniques.

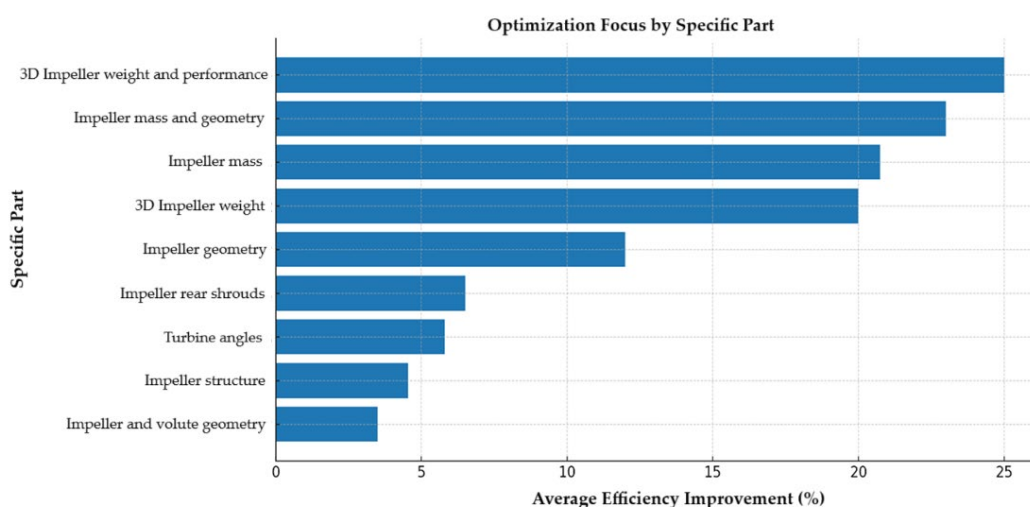


Figure 11. Optimization by specific part.

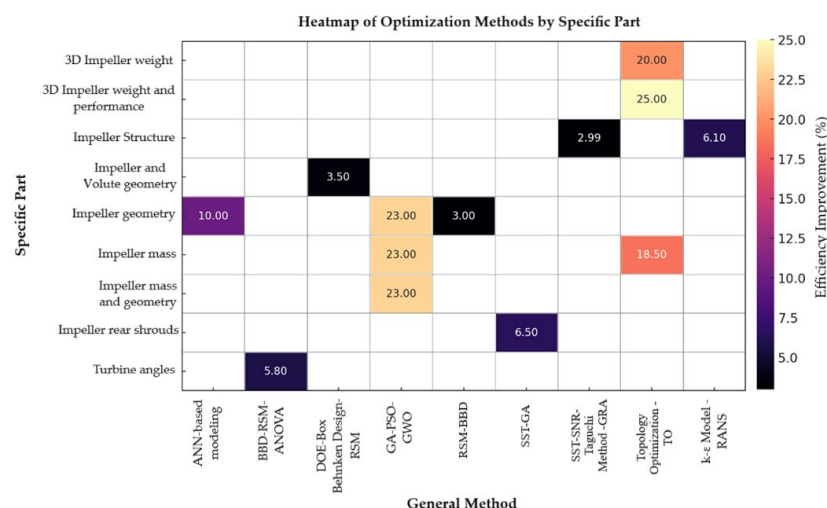


Figure 12. Heatmap of optimization methods applied to specific impeller components.

The heatmap reveals that evolutionary algorithms (GA, PSO, GWO) applied to mass and geometry yield the highest performance improvements ($\approx 23\%$), followed by hybrid methods like RSM-BBD and BBD-RSM-ANOVA. Structural optimization using topology

techniques and the classic CFD-assisted FEM shows more moderate efficiency gains (2.99%–6.1%) but contributes significantly to mass reduction and reliability.

Recent studies have made it possible to develop optimization configurations that are specifically oriented toward improving energy efficiency, structural integrity, and cavitation resistance (see Figure 13—part B). The figure illustrates how different modeling and optimization techniques such as RSM, Taguchi, LHS, ANNs, NSGA-II, and PSO achieve better results when they are aligned with the nature of the optimization goal. For instance, hybrid approaches that combine surrogate modeling with evolutionary algorithms are especially effective in contexts where both high accuracy and computational efficiency are required. In the proposed framework, surrogate models such as XGBoost, Kriging, and ANN models are trained using datasets generated from CFD and FEM simulations applied to multiple geometric design configurations. The performance of these models can be evaluated using standard regression metrics, including the coefficient of determination (R^2), RMSE, and mean absolute error (MAE), to ensure their predictive accuracy and generalization capability. To reduce the risk of overfitting, k-fold cross-validation and hyperparameter tuning strategies such as grid search or Bayesian optimization can be employed. Additionally, the training datasets are diversified through the use of DoE techniques, including LHS and BBD, to ensure broad coverage of the design space.

Visual representation reinforces the modular structure of the optimization process and underscores the importance of selecting techniques based on the physical characteristics and functional role of each design challenge.

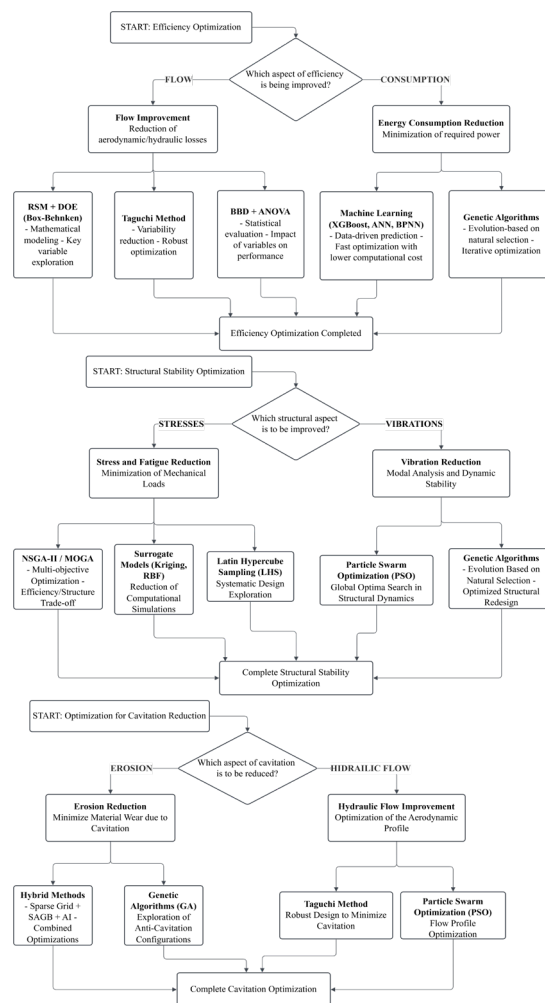


Figure 13. Flowchart of the applied methodology—part B.

A comparative analysis has been carried out with several proposed flowcharts, although it should be noted that most of them are specific to isolated case studies (Figure 14). In contrast to the conventional methodologies reviewed herein, the flowchart proposed in this research is distinguished by a hierarchical and modular integration that articulates the process of impeller design, simulation, and optimization through a multi-phase structure. Unlike the analyzed proposals, which primarily approach design from partial perspectives, such as statistical optimization, conventional CFD modeling, or limited parametric exploration. The present methodology establishes a complete pathway, from initial geometric modeling to iterative validation and improvement, with a clear separation according to the specific design objective (efficiency, structural stability, or cavitation mitigation).

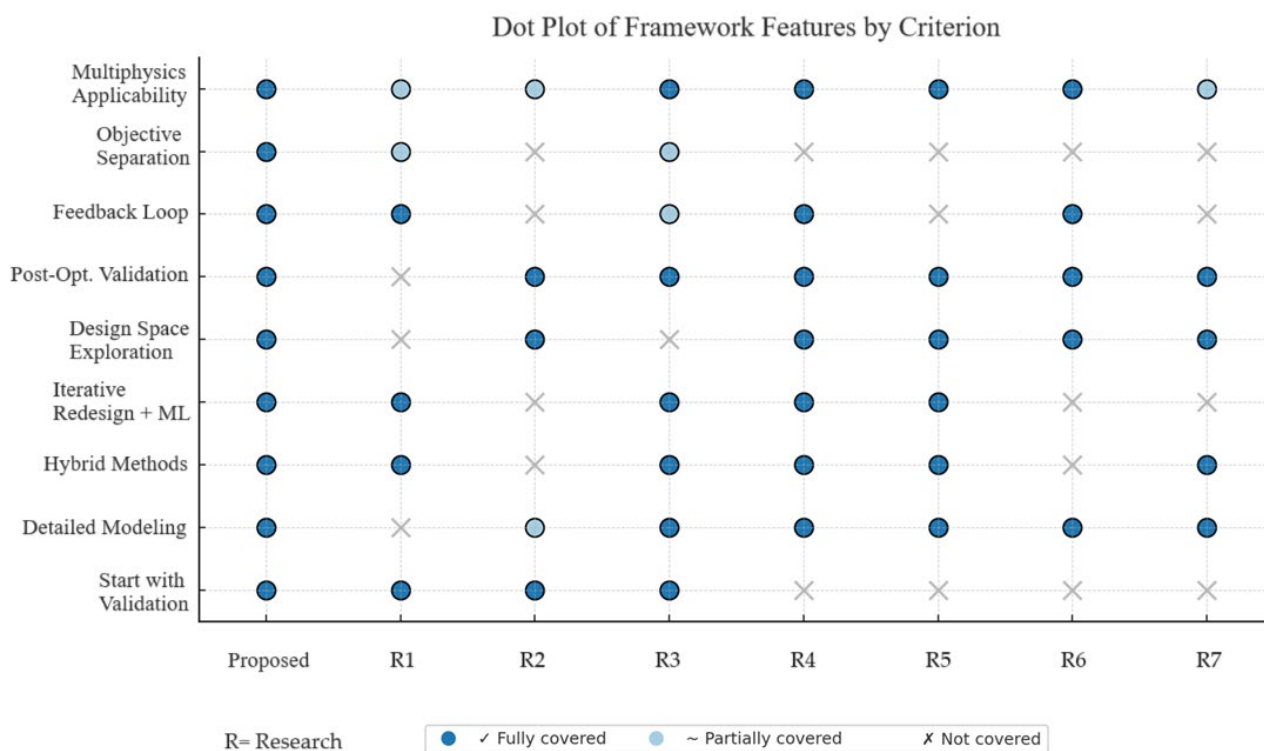


Figure 14. Comparison of the proposed flowchart with flowcharts from other authors. Note: R1 [116], R2 [127], R3 [128], R4 [124], R5 [32], R6 [43], R7 [33].

In general terms, Figure 9 introduces a modular roadmap that integrates the core methodological stages of impeller optimization geometry definition, simulation (CFD/FEM), surrogate modeling, multi-objective optimization, and experimental validation. This hierarchical structure guides the selection of techniques and tools according to the specific performance objectives. To support the simulation process (part A), we provide in Figure 10 a flowchart that enables the adaptive selection of numerical models, including RANS, URANS, or LES models for CFD and linear or nonlinear FEMs for structural analysis, depending on the flow complexity and mechanical constraints. The simulation results feed directly into predictive modeling or optimization modules, ensuring interoperability between the stages. For optimization strategies (part B), we present in Figure 13 a second flowchart that aligns specific techniques such as RSM, NSGA-II, ANN, or Taguchi methods with targeted objectives like efficiency, structural robustness, or cavitation control. Each methodological module is embedded as a dedicated pathway within the overall framework, which enables seamless transitions between phases through data-driven refinement, experimental feedback, and iterative improvement.

Compared to models such as that of [124], which employs weak and strong learning strategies to iterate over the design, or that of [127], which introduces historical penalization mechanisms within ensemble models, the proposed framework incorporates a CFD/FEM simulation stage that bifurcates depending on the complexity of the flow or structural domain. This enables the adaptive selection between URANS, LES, linear, or nonlinear analysis, which results in a more context-sensitive optimization process. This is further strengthened by the integration of hybrid techniques such as RSM, the GA, PSO, and machine learning algorithms tailored to the specific requirements of each optimization objective.

Unlike frameworks based solely on statistical techniques [32] or geometry generation through orthogonal tables [128], the inclusion of feedback mechanisms based on experimental validation and the possibility of iterative convergence makes the proposed approach a more robust tool for multiphysics scenarios. Furthermore, the decomposition of the optimization pathway by objective—hydraulic efficiency, cavitation reduction, or structural enhancement—facilitates the modular coupling of techniques, which enhances its applicability in both research environments and industrial practice. Overall, the proposed methodological framework not only unifies aspects that are typically treated in isolation in the literature but also organizes them into a functional system that maximizes flexibility, accuracy, and applicability in the design of turbomachinery impellers.

On the other hand, there is a clear predominance of proprietary commercial software in impeller optimization studies, with the ANSYS environment (CFX, FLUENT, ICEM, TurboGrid) being the most frequently employed, as evidenced in [43,45,58,119,123] (see Figure 15). These platforms offer the seamless integration of CFD simulations, FEM structural analysis, and optimization algorithms, which proves particularly advantageous for multiphysics and multivariable investigations.

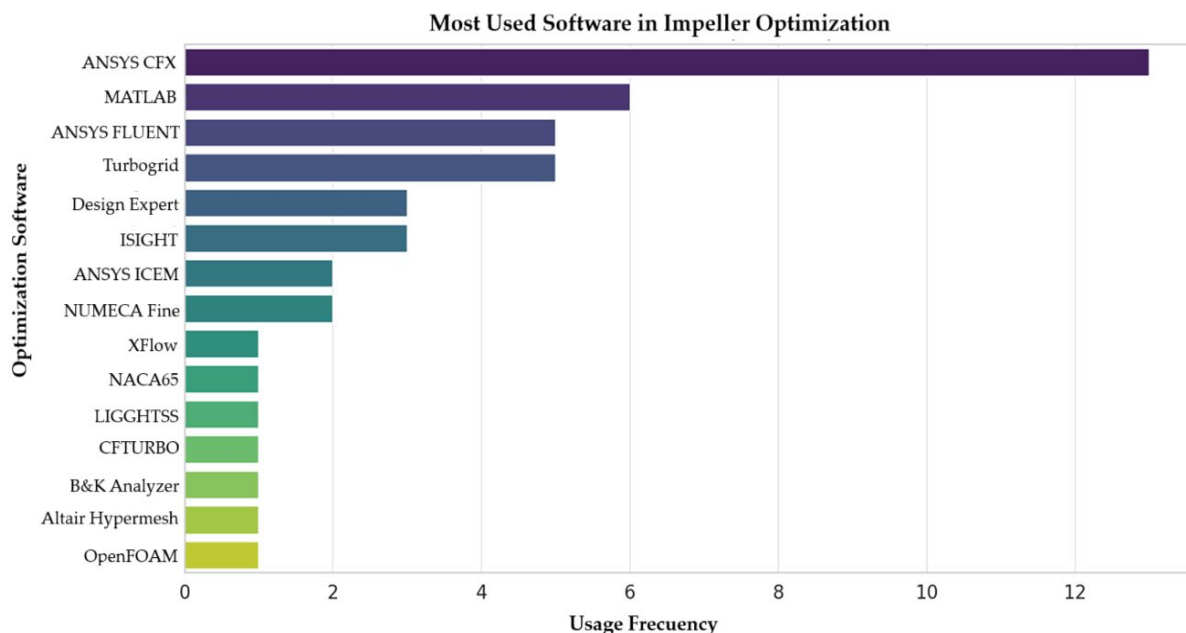


Figure 15. Most widely used software for impeller optimization.

MATLAB is also widely used [6,35,69,126], primarily for implementing evolutionary algorithms, regression models, and statistical analyses, as well as coupling surrogate models such as RSM, ANNs, and XGBoost [129]. In contrast, the use of open-source software like OpenFOAM remains limited but not absent. A few studies have successfully employed it for CFD simulations involving complex flow scenarios, albeit with increased demands in terms of configuration and validation [130]. Its lower adoption may be attributed

to the steep learning curve, the need for advanced programming skills, and the lack of direct integration with CAD tools or structural analysis modules.

Nevertheless, open-source environments offer notable advantages in terms of flexibility, scalability, and reproducibility within academic contexts. For CFD simulations in turbomachinery, OpenFOAM is the most widely used open-source platform due to its robust handling of rotating machinery, turbulence modeling (RANS, URANS, LES), cavitation, and multiphase flows. Its flexibility and script-based configuration make it suitable for custom impeller geometries and flow regimes. For structural analysis, CalculiX provides FEM capabilities that are applicable to stress and modal analysis in rotating components, although often with less integration than proprietary solutions. In surrogate modeling and optimization, Python-based libraries such as Scikit-learn (machine learning), DEAP (evolutionary algorithms), and PyDOE (design of experiments) are commonly employed. While commercial tools like ANSYS CFX or COMSOL offer more seamless workflows and integrated GUIs, open-source alternatives provide greater flexibility, transparency, and reproducibility, which are particularly valuable for academic research, custom workflows, and resource-limited environments.

Recent research [130,131] has shown a growing interest in integrating OpenFOAM with optimization algorithms and hybrid machine learning techniques. This contrast suggests that, although commercial software continues to dominate due to its robustness and ease of implementation, open-source platforms may gain greater relevance through the adoption of AI-driven methods, decoupled simulations, and optimized digital prototyping.

Most of the reviewed works emphasize the joint optimization of the geometry, weight, and performance in 3D impellers, achieving average efficiency gains above 20%, particularly in aerospace, energy, and turbopump applications [29].

Statistical approaches such as design of experiments (DoE), response surface methodology (RSM), Kriging, and Latin hypercube sampling (LHS) are widely used to build surrogate models that reduce the simulation cost and guide the search space. Multi-objective algorithms such as NSGA-II, the MOGA, the AMGA, and the MIGA have proven effective in balancing hydraulic efficiency and structural performance. Machine learning techniques such as the BPNN, XGBoost, and random forest algorithms enhance prediction accuracy and reduce computational effort. To integrate these techniques into robust frameworks, hybrid approaches are implemented, including surrogate-assisted optimization (e.g., RSM-BBD, KRG-RBF, sparse grid modeling) and bio-inspired algorithms such as the grey wolf optimizer (GWO) and particle swarm optimization (PSO). However, no optimization process is complete without rigorous experimental validation.

Rapid prototyping using 3D printing enables the physical testing of optimized impellers under controlled conditions. Depending on the specific design objective, physical prototypes can be tested in controlled environments such as hydraulic benches or wind tunnels. The key parameters that are typically measured include the flow rate, pressure head, torque, efficiency, vibration levels, and cavitation onset. These experimental results are then compared with CFD and FEM outputs to assess the accuracy of the simulations and to calibrate surrogate models. Discrepancies between predicted and measured data are used to refine boundary conditions, update material models, or adjust mesh resolution, which contributes to iterative model improvement and enhanced predictive capabilities.

Additive manufacturing is a validation tool and a driver of design constraints, particularly in the topology optimization stage. As demonstrated in recent studies [132], specific limitations such as the minimum wall thickness, overhang angle, and material anisotropy are incorporated directly into the optimization algorithm. This ensures that the resulting geometry is not only high-performing but also manufacturable without excessive post-processing. In the case of impeller design, FDM is commonly used due to its accessibility and material versatility, although it introduces trade-offs in surface quality and mechanical accuracy. Accordingly, the framework allows for iterative refinement and feedback between the simulation, optimization, and manufacturing stages. In contrast,

components such as rear shrouds, turbine angles, and impeller structures exhibit performance improvements ranging from 5% to 10%, which highlights potential avenues for future research focused on detailed structural design and vibrational analysis [133]. The relatively limited attention given to the impeller-volute assembly is partly attributed to its higher geometric complexity and the challenges involved in evaluating hydraulic couplings using conventional models. Nevertheless, recent studies have demonstrated notable performance enhancements through coupled numerical simulations.

Although the proposed framework was developed and illustrated primarily in the context of hydraulic turbomachinery, its modular and objective-driven architecture allows for straightforward adaptation to other classes of turbomachines, such as centrifugal compressors, axial fans, or mixed-flow impellers. The core methodology based on CFD/FEM simulation, surrogate modeling, and multi-objective optimization remains applicable, while the specific design constraints, boundary conditions, and performance metrics can be redefined according to the operational context. This flexibility is enabled by the modular structure of the framework, which allows each component (simulation, optimization, validation) to be customized or extended for different machine types.

4. Conclusions

This study proposes a structured integration of existing methodologies into a modular decision-making framework to support impeller optimization in turbomachinery. It integrates parametric geometry modeling, CFD/FEM simulations, surrogate modeling, multi-objective optimization, and experimental validation. This modular approach equips designers with a comprehensive tool to balance accuracy and computational efficiency, facilitating more effective and efficient impeller development. The iterative nature of the framework allows for continuous refinement, offering a dynamic methodology that adapts to the evolving needs of the design process.

One of the primary contributions of this framework is the targeted optimization of specific impeller components such as aerodynamic, structural, and cavitation-related features through a more tailored approach. Hybrid methodologies outperform single-method approaches: studies that integrate high-fidelity CFD/FEM models with surrogate modeling (e.g., ANN, Kriging, RBF) and evolutionary optimization (e.g., NSGA-II, MOGA) achieve superior results in terms of their hydraulic efficiency, structural reliability, and cavitation resistance.

Simulation and optimization strategies must be carefully aligned with the complexity of the design problem. This study emphasizes the importance of selecting appropriate modeling approaches such as RANS or URANS for fluid dynamics and linear or nonlinear FEMs for structural analysis based on the specific objectives and computational resources that are available. The proposed framework offers structured guidance for multi-objective optimization by organizing algorithm selection (e.g., RSM, Taguchi, NSGA-II) in accordance with targeted performance goals, and thus serves as a valuable tool for both academic research and industrial practice. Furthermore, the literature highlights the crucial role of experimental validation, uncertainty quantification, and iterative feedback loops in achieving reliable and transferable results, all of which are integrated into the final module of the framework. Finally, recent trends reveal an increasing emphasis on sustainable and interpretable optimization methods that prioritize not only performance but also cost-efficiency, environmental compatibility, and accessibility, marking a shift toward more responsible and practical design strategies in turbomachinery.

The proposed framework offers significant potential for future advancements in impeller design and optimization. The continued integration of hybrid optimization techniques, such as combining high-fidelity simulations with machine learning and surrogate models, could further improve the precision and efficiency of the design process. Additionally, the increasing use of open-source platforms like OpenFOAM, coupled with machine learning, provides greater flexibility and accessibility for both academic research

and industrial applications. The incorporation of additive manufacturing into the optimization process holds promise for enabling the creation of more complex and customized impeller geometries that were previously challenging to achieve with traditional manufacturing methods.

Further research into the physical interactions between impeller components under real-world operating conditions will be crucial for enhancing the accuracy of predictive models. This will enable the development of more robust and resilient impeller designs that can better withstand the demands of modern turbomachinery applications. By advancing these areas, this framework can significantly contribute to the development of next-generation impeller designs, offering both scientific and industrial benefits.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AMGA	Adaptive Multi-Objective Genetic Algorithm
ANN	Artificial Neural Network
ASHOA	Adaptive Sampling Hybrid Optimization Algorithm
BBD	Box–Behnken Design
BPNN	Backpropagation Neural Network
CFD	Computational Fluid Dynamics
CNN	Convolutional Neural Network
DADO	Deterministic Adaptive Design Optimization
DEM	Discrete Element Method
DGNN	Dual Graph Neural Network
DoE	Design of Experiments
DPM	Discrete Phase Model
FEM	Finite Element Method
GA	Genetic Algorithm
GRA	Grey Relational Analysis
GWO	Grey Wolf Optimizer
IDM	Inverse Design Method
IGWO	Improved Grey Wolf Optimizer
ISSA-BPNN	Improved Sparrow Search Algorithm + BPNN
KRG	Kriging
LBM	Lattice Boltzmann Method
LES	Large Eddy Simulation
LHS	Latin Hypercube Sampling
LMN	Local Model Network
MDO	Multidisciplinary Design Optimization

MC	Monte Carlo
MIGA	Modified Island Genetic Algorithm
ML	Machine Learning
MLP	Multi-Layer Perceptron
MOGA	Multi-Objective Genetic Algorithm
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
NUMECA	Software Suite for CFD (NUMERICAL MECHANICS Applications)
PSO	Particle Swarm Optimization
RANS	Reynolds-Averaged Navier–Stokes
RBF	Radial Basis Function
RBFNN	Radial Basis Function Neural Network
RF	Random Forest
RMS	Root Mean Square
RSA	Response Surface Approximation
RSM	Surface Methodology
SAGB	Surrogate-Assisted Gradient-Based
SGSC	Stochastic Global Sensitivity-based Calibration
SIS	Subset Simulation
SOM	Self-Organizing Map
SST	Shear Stress Transport
SVM	Support Vector Machine
TO	Topology Optimization
URANS	Unsteady Reynolds-Averaged Navier–Stokes
WOA	Whale Optimization Algorithm
XGBoost	Extreme Gradient Boosting
ZGB	Zwart–Gerber–Belamri (Cavitation Model)

Appendix A

Research	Results	Reference
A Study on the Multi-Objective Optimization of Impeller for High-Power Centrifugal Compressor	Structural and aerodynamic optimization of the impeller.	[11]
Optimization of a Centrifugal Compressor Using the Design of Experiment Technique	Efficiency and pressure-ratio optimization: +3% and +11%.	[14]
Optimization of Energy Recovery Turbine in Demineralized Water Treatment System of Power Station by Box–Behnken Design Method	The optimized model's efficiency is 1.8% higher.	[53]
Multi-Objective Optimization of a Regenerative Pump with S-Shaped Impeller Using Response Surface Methodology	Pump efficiency + 2.85% under single-objective optimization and + 1.67% under double-objective optimization.	[54]
The Optimization of a First-Stage Liquid-Sealing Impeller Structure for a Turbopump Based on Response Surface Methodology	Pressurization coefficient + 2.5%.	[23]
Multiobjective Optimization for the Impeller of Centrifugal Fan Based on Response Surface Methodology with Grey Relational Analysis Method	Head increased by 2.5845 m and efficiency improved by 2.88%.	[56]
Impeller Optimization in Crossflow Hydraulic Turbines	Reduced manufacturing costs using new impeller technology compared to conventional methods.	[124]
Multi-Disciplinary Optimization Design of Axial-Flow Pump Impellers Based on the Approximation model	Single-blade mass – 10.47%, while efficiency + 0.61%.	[6]
Design and Optimization of Meridional Profiles for the Impeller of Centrifugal Compressors	Elliptical curves showed acceptable performance vs. circular curves, with + 2.6% at low flow rates and + 3% at high flow rates.	[12]
Instabilities Identification Based on a New Centrifugal 3D Impeller Outflow Model	URANS simulation can reproduce the main features of rotational stall in the diffuser at 30% of the total cost.	[50]

Comprehensive Improvement of Mixed-Flow Pump Impeller Based on Multi-Objective Optimization	Pump efficiency + 0.63%, +3.39%, and +3.77% at 0.8QDES, 1. QDES, and 1.2 QDES , respectively.	[72]
A General Framework for Designing 3D Impellers Using Topology Optimization and Additive Manufacturing	Total impeller mass decreased by nearly 30%.	[29]
Additive Manufacturing and Topology Optimization Applied to Impeller to Enhance Mechanical Performance	Stress levels reduced by 25%, impeller mass decreased by 20%, leading to higher allowable speed and better overall performance.	[30]
Topology Optimization Design with Addictive Manufacturing Constraints for Centrifugal Impeller	Impeller weight reduced by up to 18.5%.	[31]
Aerodynamic Analysis and Design Optimization of a Centrifugal Compressor Impeller Considering Realistic Manufacturing Uncertainties	Decreasing blade angles counteracts the detrimental effects of positive blade-thickness errors.	[108]
Robust Optimization and Uncertainty Quantification of a Micro Axial Compressor for Unmanned Aerial Vehicles	Isentropic efficiency and pressure ratio increase by 0.6% and 0.5%, while reducing their standard deviations and that of mass flow rate by 32.4%, 41.2%, and 25.1%	[117]
Novel Multidisciplinary Design and Multi-Objective Optimization of Centrifugal Compressor used for Hydrogen Fuel Cells	Power consumption reduced by 2.99%, with a maximum isentropic-efficiency increase of 2.16%.	[24]
Cavitation Performance Enhancement of a Centrifugal Pump Impeller Based on Taguchi's Orthogonal Optimization	Cavitation performance improved by 19.3% at the best efficiency point.	[32]
Optimization of centrifugal pump impeller for pumping viscous fluids using direct design optimization technique	Operational stability and overall performance enhanced.	[134]
The Fan Design Optimization for Totally Enclosed Type Induction Motor with Experimentally Verified CFD-Based MOGA Simulations	Efficiency increased by 8%, volumetric flow rate by 18%, and winding temperature decreased by 8 °C.	[25]
Aerodynamic Robustness Optimization and Design Exploration of Centrifugal Compressor Impeller under Uncertainties	The average pressure ratio increased by 9.3% and average isentropic efficiency by 6.7%. Their standard deviations decreased by 7.5% and 15.4%, respectively, and the acoustic power level dropped by 11 dB.	[21]
Impeller Shape-Optimization of Stirred-Tank Reactor: CFD and Fluid Structure Interaction Analyses	Energy consumption decreased by 26.71%, while equivalent stress rose by 6.09%.	[26]
A Study on Suction Pump Impeller Form Optimization for Ballast Water Treatment System	Efficiency exceeded 12%.	[68]
Research on Cooperative Optimization of Multiphase Pump Impeller and Diffuser Based on Adaptive Refined Response Surface Method	Pressure increment increased by 38 kPa in the optimized model.	[63]
Energy-Saving Oriented Optimization Design of the Impeller and Volute of a Multi-Stage Double-Suction Centrifugal Pump using Artificial Neural Network	Efficiency increased by 2.05%, 3.56%, and 5.36% at 0.6Qd, 1.0Qd, and 1.2Qd, respectively, compared to the reference design	[8]
Centrifugal Pump Impeller and Volute Shape Optimization via Combined NUMECA, Genetic Algorithm, and Back Propagation Neural Network	Head and efficiency at the design flow increased by 7.69% and 4.74%. Further optimization raised head by 2.69 m and efficiency by 4.32%.	[36]
Impeller Optimization using a Machine Learning-Based Algorithm with Dynamic Sampling Method and Flow Analysis for an Axial Flow Pump	Optimized axial flow pump exhibits a 2% efficiency increase.	[125]
Machine Learning Based Design Optimization of Centrifugal Impellers	A single impeller-performance prediction with the machine-learning approach requires under 1 second.	[15]

Multi-Objective Optimization for Impeller Structure Parameters of Fuel Cell Air Compressor using Linear-Based Boosting Model and Reference Vector Guided Evolutionary Algorithm	For the $Max\sigma$ solution, the isentropic efficiency and pressure ratio increased by 18.7% and 70.1%, respectively. For the $Max\eta_c$ solution, improved by 23.0% and 48.9%, respectively.	[34]
Fatigue Reliability Evaluation for Impellers with Consideration of Multi-Source Uncertainties using a WOA-XGBoost Surrogate Model	XGBoost model achieves an R^2 above 0.93 in fatigue-life prediction.	[27]
Optimized Design of Solid–Liquid Dual-Impeller Mixing Systems for Enhanced Efficiency	Cloud height increased by 8.7%, and energy consumption decreased by 15.6%.	[58]
Automatic Detection of Surface Defects of Submersible Pump Impellers by Machine Learning Algorithm	High surface defect detection efficiency, high accuracy, high automation, and low cost.	[28]
Satellite Thermal Management Pump Impeller Design and Optimization	Efficiency rose by 3.55%, and head increased by 7.9%.	[44]
Modal Analysis and Structural Optimization of Integrated Bladed Disks and Centrifugal Compressor Impellers	Mass was reduced by 23%, explosion margin increased by 4.31%, and critical resonance conditions were eliminated.	[35]
An Improved Grey Wolf Optimizer (IGWO) Algorithm for Optimization of Centrifugal Pump With Guide Vane	Efficiency is 1.2% higher than the original pump, and the anti-cavitation performance is improved.	[96]
Novel Designs of Blade Mixer Impellers from the Discrete Element Method and Topology Optimization	Impeller shape can be modified to enhance mixing or reduce energy consumption.	[116]
Matching Optimization of a Mixed Flow Pump Impeller and Diffuser Based on the Inverse Design Method	Optimized pump's efficiency at 1.2QDES, 1.0Q QDES, and 0.8Q QDES increased by 6.47%, 3.68%, and 0.82%, respectively.	[22]
Improving Centrifugal Compressor Performance by Optimizing the Design of Impellers Using Genetic Algorithm and Computational Fluid Dynamics Methods	Operational stability and overall performance enhanced.	[41]
Hydrodynamic Optimization of the Impeller and Diffuser Vane of an Axial-Flow Pump	Total efficiency and total head were 0.974% and 21.028% higher. After diffuser-blade optimization, total efficiency and total head increased by 3.097% and 10.205%.	[33]
Hydrodynamic Optimization of the Impeller and Diffuser Vane of an Axial-Flow Pump	Overall efficiency improved by 2.05%, and loss margin improved by 8.89%.	[79]
Optimization of Impeller Blades of an Electric Water Pump via Computational Fluid Dynamics	$Q = Q_d$ increased from 20.5 m to 21.9 m, while pump efficiency rose from 66.7% to 72.3%.	[51]
Optimization Design of Energy-Saving Mixed Flow Pump Based on MIGA-RBF Algorithm	Experimental results show a maximum pump-efficiency increase of 4.3%.	[42]
Introducing Non-Hierarchical RSM and MIGA for Performance Prediction and Optimization of a Centrifugal Pump under the Nominal Condition	Efficiency improved by 3.717% post-optimization.	[74]
Optimization of the Impeller for Hydraulic Performance Improvement of a High-Speed Magnetic Drive Pump	Hydraulic efficiency of the optimal impeller was 6.23% higher.	[76]
Uncertainty Quantification and Aerodynamic Robust Optimization of Turbomachinery Based on Graph Learning Methods	Reduced losses and improved efficiency.	[104]
Uncertainty Quantification-Based Optimization of Centrifugal Compressor Impeller for Aerodynamic Robustness under Stochastic Operational Conditions	Mean pressure increased by 2.3%, mean efficiency by 2.9%, and the variance of the pressure ratio decreased by 14.3%.	[21]
A Gradient-Based Method Assisted by Surrogate Model for Robust Optimization of Turbomachinery Blades	Blade optimization is under robust design.	[110]
Topology Optimization of Static Turbomachinery Components	Final weight 65% lower than the original component.	[13]

Liquid-Vapor Two-Phase Flow in Centrifugal Pump: Cavitation, Mass Transfer, and Impeller Structure Optimization	Enhanced cavitation performance.	[120]
Mixing Optimization with Inward Flow Configuration Contra-Rotating Impeller, Baffle-Free Tank	High mixing efficiency and low torque at pilot scale.	[107]
Optimal Design and Performance Improvement of an Electric Submersible Pump Impeller Based on Taguchi Approach	Head increased by 3.5%, and efficiency rose by 6.1%.	[45]
Computational Prediction of the Just-Suspended Speed, N_{js} , in Stirred Vessels using the Lattice Boltzmann Method (LBM) Coupled with a Novel Mathematical Approach	Efficiency increased by 2.4%.	[37]
Analysis of Erosion Minimization for a Slurry Pump Using Discrete Phase Model Simulations	Erosion-rate density was reduced.	[43]
Multi-Condition Optimization and Experimental Verification of Impeller for a Marine Centrifugal Pump	Maximum vibration intensity decreased, and efficiency improved.	[40]
CFD Simulation of Impeller Shape Effect on Quality of Mixing in Two-Phase Gas-Liquid Agitated Vessel	Axial gas-phase distribution for the 30° impeller is about 55% better than others.	[38]
Validating Impeller Geometry Optimization for Sound Quality Based on Psychoacoustics Metrics	Noise intensity reduced, while energy performance increased by 4.3%.	[39]
Integrated Energy-Efficient Machining of Rotary Impellers and Multi-Objective Optimization	Improved machining with respect to materials.	[127]
Surrogate-Based Design Optimization of a Centrifugal Pump Impeller	The optimum pump-impeller design shows >10% improvement in pump efficiency.	[69]
Surrogate-Based Design Optimization of a Centrifugal Pump Impeller	Isentropic efficiency and total pressure ratio improved by 1.61% and 4.13%, respectively, while maximum stress decreased by 9.68%.	[111]

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