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A REVIEW OF MODERN COMPUTATIONAL FLUID DYNAMICS AND ARTIFICIAL INTELLIGENCE METHODS FOR MODELING UNSTEADY PROCESSES IN CENTRIFUGAL PUMPS

Abstract. Centrifugal pumps are critical across various industrial sectors, yet their complex, three-dimensional, and unsteady turbulent flows pose significant challenges for traditional empirical design methods. This review aims to systematize modern research on the mathematical modeling of centrifugal pumps, emphasizing the application of advanced turbulence models and artificial intelligence (AI) to identify current trends and future prospects. A comprehensive analysis of over 70 peer-reviewed articles indexed by Scopus database, published between 2010 and 2026, was conducted. The methodology focuses on evaluating Reynolds-Averaged Navier-Stokes (RANS), Large Eddy Simulation (LES), hybrid RANS-LES approaches, and the integration of machine learning algorithms. The results reveal a fundamental paradigm shift from isolated computational fluid dynamics (CFD) simulations to integrated, AI-driven methodologies. While RANS and its unsteady (URANS) form remain the industry standard for evaluating baseline performance due to computational efficiency, LES and hybrid models (such as DES and SST-SAS) are increasingly utilized to achieve benchmark accuracy for complex transient phenomena like boundary layer separation and cavitation. Furthermore, high-fidelity CFD calculations are now predominantly used to generate training databases for deep neural networks. This synergy enables near-instantaneous multi-criteria geometry optimization, virtual sensor deployment, and predictive equipment diagnostics.

Keywords: Centrifugal Pump, Computational Fluid Dynamics, Turbulence Modeling, Artificial Intelligence, Hybrid RANS-LES, Optimization, Predictive Maintenance.

1. Introduction

Centrifugal pumps are widely used in the energy, chemical, marine, and other industrial sectors, where their use is driven by hydraulic characteristics such as stability and reliability, which in turn are largely dependent on complex turbulent phenomena. Pumping systems account for approximately 20% of total industrial energy consumption, which in turn confirms the need to improve their efficiency [1]. Traditional pump design approaches are largely based on empirical correlations with experimental results. Therefore, these methods often fail to account for complex three-dimensional flow structures, turbulence interactions, and cavitation phenomena within centrifugal pumps. Advances in computational fluid dynamics (CFD) have made it possible to conduct detailed analysis of internal flow behavior, allowing engineers to transition from empirical design to digital prototyping [1]-[5]. This review presents the results of an analysis of over 70 peer-reviewed studies published in journals included in the Scopus database, focusing on the applica-

tion of Reynolds-averaged Navier-Stokes (RANS), Large Eddy Simulation (LES), and hybrid RANS-LES approaches to centrifugal pump analysis. The review discusses the differences in the approaches used, the assumptions made to simplify the modeling, the computational requirements, and the practical applicability of each approach, with an emphasis on cavitation flows and unsteady operating conditions. Current and future research directions and limitations are also highlighted.

A centrifugal pump converts the kinetic energy of the impeller's rotation into hydraulic pressure. Fluid is captured at the inlet and accelerated circumferentially toward the impeller walls, where some of this energy is converted into pressure within the casing [6].

The main types and design options of centrifugal pumps can be classified as follows: single- and multi-stage [7]-[9], single- or double-entry [7], open, semi-open [1] and closed impellers [10], single-screw, multi-turn, diffuser [11], [12], chemically resistant [13], for abrasive/drainage media [14], multi-component (gas-liquid) [4], [15], drainage,

vacuum, electric, mechanical transmission, magnetically supported pumps [16], etc.

The main applications of centrifugal pumps include water supply, irrigation, heating, ventilation, air conditioning, oil and gas and refining, chemical and pharmaceutical industries, desalination, power generation, mining, and medicine.

The operational reliability and hydraulic efficiency of centrifugal pumps directly depend on the complex internal flow dynamics within the impeller-casing system. The flow environment is characterized by high turbulence, non-stationarity, and complex boundary conditions, which pose significant challenges for mathematical modeling.

Furthermore, the flow in the interblade channels is three-dimensional, curvilinear, and turbulent [5], making it impossible to model solely using classical hydraulic relationships [1], [2]. Local phenomena such as flow separation, secondary flow formation, and uneven velocity distribution across the channel width and circumference significantly impact the pump's energy performance and require accurate reproduction in a mathematical model [3]. Achieving high-precision characteristics requires the use of numerical modeling to enable the reproduction of the flow pattern and pressure field in the impeller, taking into account the pump's geometry and operating conditions.

Classic pump design methods rely on empirical relationships and physical testing, which do not always adequately account for complex three-dimensional turbulent flows and cavitation effects. Modern CFD enables accurate modeling of unsteady processes in impellers and diffusers. This,

in turn, enables the transition from empirical design to digital prototyping. However, CFD modeling is a resource-intensive process, especially when using high-fidelity turbulence models such as LES and detached eddy simulation method (DES or DDES), and transient analysis.

The purpose of this review is to systematize modern research on mathematical modeling of centrifugal pumps, taking turbulence into account and applying artificial intelligence methods, and to identify trends and prospects for further development.

2. Materials and methods

An analysis of trends in centrifugal pump modeling began with a search of the Scopus database to identify current methods, their intended uses, and key research objectives. To conduct the search, the following Scopus search query was generated:

(TITLE-ABS-KEY (centrifugal AND pump) AND TITLE-ABS-KEY (mathematical AND models) OR TITLE-ABS-KEY (mathematical AND model) OR TITLE-ABS-KEY (mathematical AND modeling) OR TITLE-ABS-KEY (numerical AND modeling))

The initial search yielded 1,471 articles covering the period 1970–2025. As shown in Figure 1, the number of publications using mathematical modeling methods is increasing annually.

Moreover, the majority of the papers were represented by the following countries (Figure 2).

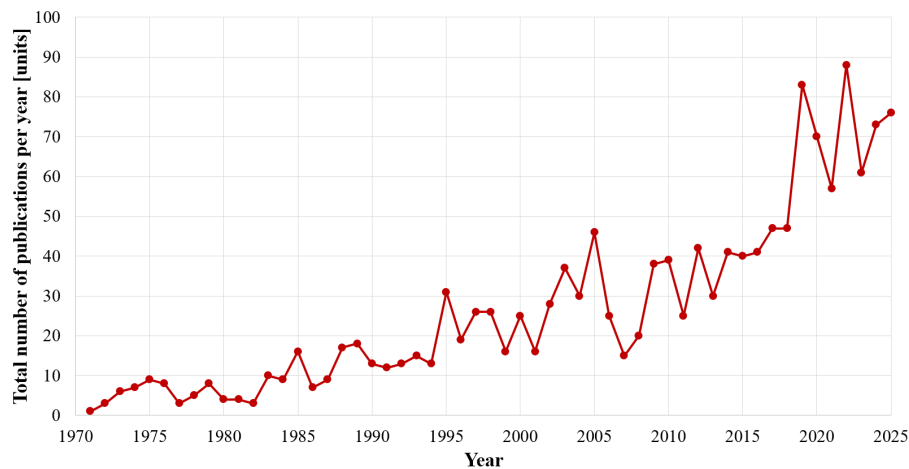


Figure 1. Distribution of annual number of publications for the period 1970–2025

The RANS solution method via averaging with velocity and temperature pulsations is the most common for engineering problems due to its lower computational cost compared to LES and DNS (Figure 4).

Within the RANS approach, different models are used such as k-epsilon (k- ϵ) and k-omega

$(k-\omega)$, as well as the Spalart-Allmaras model and the Reynolds stress models (RSM).

The LES method is used to model large-scale eddies explicitly, while small eddies are modeled using subgrid closure, which provides higher accuracy than RANS but requires more computational resources (Figure 5).

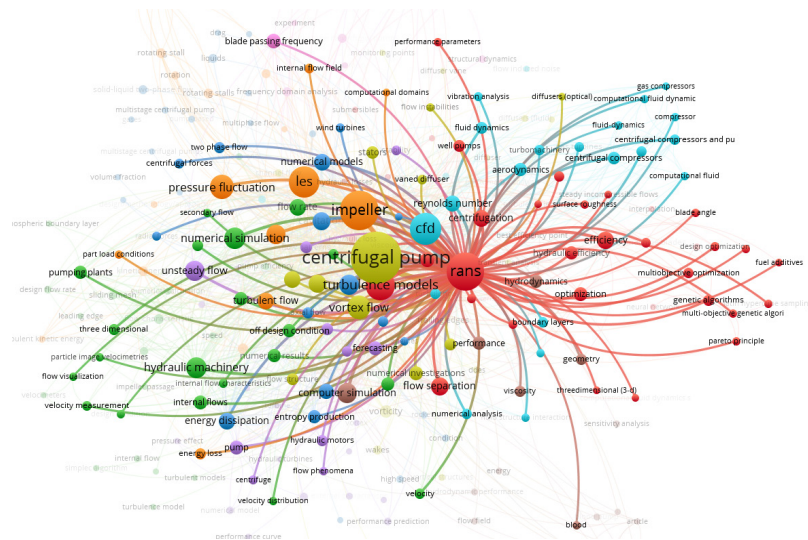


Figure 4. Distribution of publication activity based on search results for the RANS (Reynolds-Averaged Navier-Stokes) method

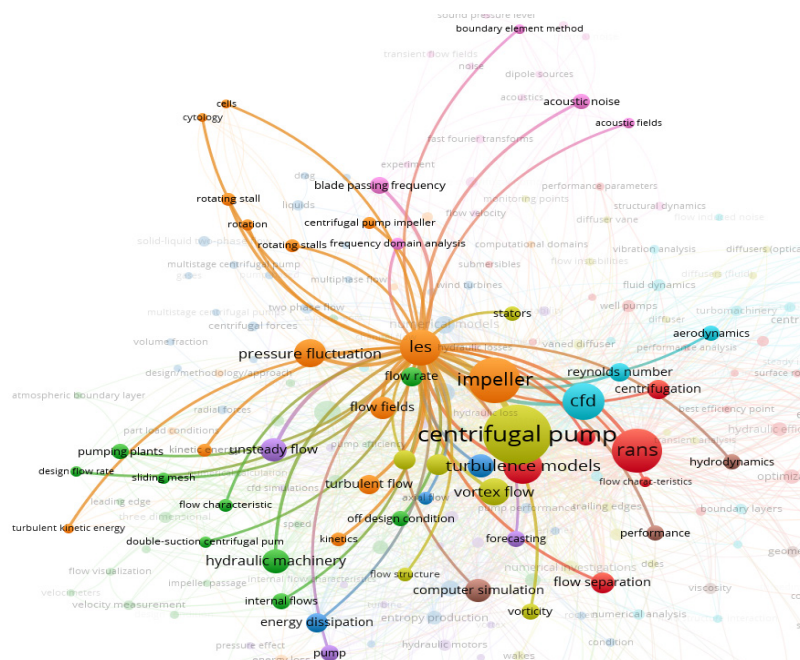


Figure 5. Distribution of publication activity based on search results for the LES (Large Eddy Simulation) method

To ensure high-quality selection and seamless verification, search results were limited to English-language and open-access publications. Only full-text original research and review articles published between 2010 and 2026 were considered. The final search query was as follows:

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( TITLE-ABS-KEY ( Centrifugal pump ) AND
TITLE-ABS-KEY ( mathematical models ) OR
TITLE-ABS-KEY ( mathematical model ) OR
TITLE-ABS-KEY ( numerical modeling ) OR
TITLE-ABS-KEY ( mathematical modeling ) )
AND PUBYEAR > 2010 AND PUBYEAR < 2026
AND ( LIMIT-TO ( LANGUAGE , "English" ) )
AND ( LIMIT-TO ( OA , "all" ) ) AND
( LIMIT-TO ( DOCTYPE , "ar" ) OR LIMIT-TO
( DOCTYPE , "re" ) )
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An initial automated search using specified parameters identified 180 publications using mathematical modeling to solve problems related to centrifugal pumps.

The next step involved a detailed manual screening of the abstracts and full texts of the retrieved papers. Of the 180 articles, over 70 of the most relevant were selected for the final review. To enhance the reliability of the study, strict criteria were defined for inclusion in the final selection: a comprehensive description of the mathematical apparatus or software used; clear detailing of the configuration and geometric parameters of the pumping equipment under study; and mandatory validation of the proposed mathematical or numerical model using the results of field experiments.

To ensure maximum transparency, reproducibility, and methodological rigor, the selection of the literature corpus was structured in strict accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. The step-by-step screening process, including the exact quantities of records identified, screened, and excluded at each stage, is visually summarized in Figure 6.

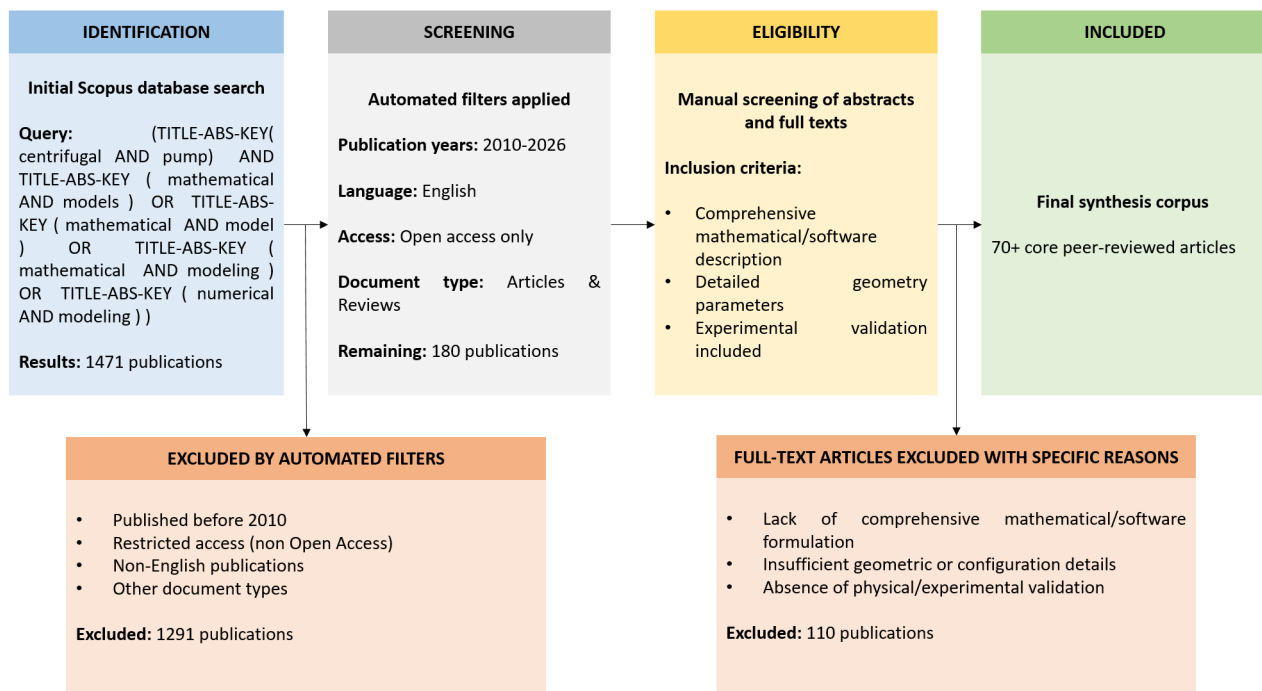


Figure 6. PRISMA flow diagram of the literature search, screening, and selection process for the systematic review

3. Results and discussion

The current stage of development in hydraulic engineering is characterized by a fundamental shift from traditional empirical design methods to the use of high-precision mathematical models and digital twins. The introduction of CFD methods has become an industry standard, enabling engineers and researchers to thoroughly analyze the complex, three-dimensional, and unsteady flow structures within the working parts of centrifugal pumps [5], [28]. Advances in computing power have led to the development of a comprehensive methodology in which numerical solutions to the Navier-Stokes equations work in synergy with advanced artificial intelligence algorithms.

As part of the comprehensive analysis of the review results, the main computational and analytical methods used to study centrifugal pumps were systematized and divided into 7 different categories:

1. Reynolds Averaging methods including RANS and URANS
2. LES

3. Hybrid RANS-LES Methods
4. Artificial Intelligence and Machine Learning Methods (AI/ML/DL)
5. Analytical and 1D Models, Systems Analysis
6. Interaction Models (FSI, Acoustics, Erosion, Entropy)
7. Parametric Computer-Aided Design (CAD) Modeling

It is important to emphasize that the modern approach to designing centrifugal pumps is deeply integrated and interdisciplinary, with inclusion of hydrodynamics, reliability theory, acoustics, and advanced digital technologies. Therefore, there is no strict or isolated barrier between the distinct types, hence, the same basic mathematical algorithm can be flexibly integrated into related fields and applied to multiple categories, complementing the capabilities of other methods.

Considering the evolution of approaches to the study of centrifugal pumps from a chronological point of view, a clear dynamics of change in dominant methods and a rapid complication of the mathematical apparatus can be traced (Table 1).

Table 1. Chronological table of the methods used

Year(s)	Methods and technologies used	Articles
2010–2017	Basic performance and cavitation calculations using RANS. The first sophisticated LES and one-dimensional (1D) predictive models (MATLAB) emerged.	[5], [6], [29]–[33]
2019–2021	Establishment of RANS and its transient form URANS as the standard for calculating cavitation. Use of LES for the analysis of flow stalls and periodic pulsations.	[15], [34]–[37]
2023	Widespread adoption of hybrid RANS/LES turbulence models including the DES or DDES. Integration of traditional CFD with neural networks (ANN, BPNN) to accelerate geometry optimization. The emergence of parametric CAD modeling (OpenCASCADE) and macroscopic models (Simulink).	[7], [9], [38]–[48]
2024	Application of high-precision hybrid DDES and Scale-Adaptive Simulation (SST-SAS) models. Widespread use of deep learning architectures (CNN, LSTM) to create surrogate models (digital twins). Solution of complex multiphysics problems: calculation of fluid elasticity (FSI), erosion (DPM), aeroacoustic noise, and the implementation of stochastic (probabilistic) degradation processes.	[1], [3], [10], [12]–[14], [49]–[70]
2025	Transition to intelligent optimization of hydraulic machines. Implementation of physically-informed neural networks (MENN), in-depth comparative analysis of methods (RANS vs. LES), implementation of virtual sensors, development of cavitation monitoring algorithms, and creation of predictive maintenance systems based on Python/ML.	[2], [4], [8], [16], [28], [71]–[77]

An analysis of the prevalence of algorithms shows that in the early stages, up until 2017, basic stationary RANS methods and simple one-dimensional analytical models, which were used primar-

ily to estimate overall energy parameters, had an absolute advantage. As available computing power increased between 2019 and 2022, detailed transient analysis, namely URANS and LES methods,

became the industry standard, allowing researchers to move on to studying the complex topology of transient processes, pressure fluctuations, and cavitation. However, a real methodological shift is recorded in modern publications from 2023 to 2026, specifically the abundance of classical “pure” hydrodynamic calculations has gradually begun to decline in favor of high-precision hybrid turbulence models (such as DES, DDES, and SST-SAS), and the undisputed and most widespread trend of recent years has been the implementation of artificial intelligence and deep learning algorithms, which today

serve as the main tool for creating instant surrogate models, predictive wear diagnostics, and multi-criteria automated optimization of flow-through geometry.

As Table 2 shows, the majority of industrial and research calculations are based on RANS approaches and their unsteady form URANS [50], [64], [78]. The main advantage of these mathematical models is the strict balance between computational efficiency and sufficient engineering accuracy when predicting averaged energy characteristics like pressure, power and overall efficiency of process.

Table 2. Summary table of modern methods for modeling centrifugal pumps

Group of methods	Applied algorithms and models	Description and tasks to be solved	Articles
RANS and URANS	Steady-state RANS and unsteady URANS methods. Turbulence models: SST k- ω , k- ϵ (incl. RNG and Realizable), Wray–Agarwal, Reynolds stress model.	A traditional approach that balances accuracy and computational cost. It is used to calculate averaged characteristics (pressure, efficiency), predict cavitation and separated flows, and generate training databases for artificial intelligence.	[1]-[5], [8], [9], [11], [13], [14], [16], [30], [31], [33], [34], [37]-[44], [48]-[50], [53], [55], [57], [58], [62]-[65], [67]-[71], [74], [77]-[79]
LES	LES with Subgrid Models (SGS): Smagorinsky-Lilly, Dynamic Mixed, WALE.	A high-precision instrument that directly resolves the dynamics of large vortex structures. It is used for analyzing transient pressure pulsations, hydroacoustic noise, boundary layer separation at low flow rates, and shear stress in blood pumps.	[16], [29], [36], [41], [52], [53], [55], [59], [74], [80]
Hybrid RANS-LES methods	DES, DDES, SST-SAS, Zonal and Screened Simulation.	An effective compromise that automatically switches between RANS in near-wall layers and LES in areas of massive shear flows. Provides accurate visualization of cavities and shear failures without the enormous overhead of pure LES.	[7], [15], [35], [52], [54], [55]
Methods based on artificial intelligence and machine learning	Neural networks: ANN, BPNN, CNN, LSTM, GCN, Physically Metamodels: Kriging, Response Surface Model. Optimizers: Particle Swarm, Genetic Algorithm.	Methods are used for instant prediction of energy parameters, multi-criteria discrete optimization of blade geometry, and the creation of digital twins for diagnosing cavitation, wear, and residual life.	[2], [9], [11], [13], [38], [42], [43], [45], [48]-[51], [62], [67], [68], [73], [75], [79], [81]
Analytical and 1D models, systems analysis	Reduced order models, 1D predictive codes, Gamma process, Euler, Darcy-Weisbach differential equations.	Development of «virtual flow meters» for flow calculation without physical sensors, prediction of gradual degradation, analysis of system dynamics of pump arrays in networks with variable pressure and calculation of pump operation in reversible turbine mode.	[1], [32], [37], [47], [60], [61], [64], [66], [76]
Interaction models	Two-way fluid-structure coupling, Sharp MLS penalty for flexible bodies. Acoustic analogies. Discrete phase model with Finney erosion model. Entropy generation method.	Study of deformation of flexible blades, calculation of microcutting of metal by solid particles in hydraulic mixtures, localization of sources of vibroacoustic noise inside the housing and precise localization of energy loss zones due to analysis of entropy production.	[8], [14], [34], [57], [59], [69]

Table continued

Group of methods	Applied algorithms and models	Description and tasks to be solved	Articles
Parametric CAD software modeling	Platforms based on OpenCASCADE, Autodesk Inventor Professional.	Engineering automation of end-to-end 3D design. Instant generation of error-free spatial blade and spiral geometry based on strict mathematical relationships, eliminating edge interference before transfer to CFD solvers.	[10], [46]

Among the many turbulence closure methods, the most popular is the Menter two-parameter shear stress transport (SST $k-\omega$) model [1], [3], [4], [63], [64]. Its ability to combine the accuracy of the $k-\omega$ model in blade wall boundary layers with the robustness of the $k-\epsilon$ model in free flow makes it effective in predicting localized fluid separation zones. However, RANS models have fundamental limitations. Due to the physical nature of averaging, they tend to smooth out small-scale turbulent fluctuations and overestimate turbulent viscosity, making them insufficiently accurate when modeling highly unsteady phenomena such as boundary layer separation or explosive cavitation development at low flow rates [35], [41], [52].

To overcome the accuracy barriers of RANS, modern methodology LES can be implemented. LES directly resolves the dynamics of large energy-carrying vortex structures (using Navier-Stokes filtering and subgrid models such as the Smagorinsky-Lilly model), which is critical for analyzing high-frequency pressure fluctuations, hydroacoustic noise, and unstable operating modes [16], [29], [36], [41], [80]. However, due to the high requirements for computational grid density and time step, “pure” LES modeling near solid walls remains resource-intensive. An innovative compromise was the use of hybrid RANS-LES mathematical models, such as the DES or DDES and SST-SAS [7], [15], [35], [52], [54]. In these models, the algorithm automatically switches, where in stable near-wall layers, the economical RANS calculation is used, and when massive shear flows or cavities form in channels, the mathematical apparatus switches to the eddy-resolving LES mode.

The difference in accuracy between RANS and LES models depends on the specific operating mode of the hydraulic machine. However, in areas of complex turbulence and unsteadiness, the LES method demonstrates high accuracy, with an error of only about 3% compared to real-world physical experiments, such as laser-assisted flow visualization [16]. Due to these performance indicators, LES is recog-

nized as a digital benchmark that can be used to validate and calibrate simpler RANS models, thereby reducing the cost of physical testing [16].

When examining accuracy in specific operating modes and empirical implementations, the following picture emerges. Under nominal operating conditions, both RANS and LES demonstrate comparable and highly accurate prediction of pressure and other characteristics [41], [55].

However, at non-nominal conditions, at low flow rates and during the flow stall, the difference becomes significant. Modeling at flow rates of approximately 20% of the nominal value, when boundary layer separation occurs in the pump, the pressure curve calculated by the LES method proves to be the most accurate [41]. Moreover, LES perfectly captures the domain frequency of pressure pulsations, which is approximately 35% of the pump rotor speed [41]. Under the same conditions, RANS methods, due to the nature of mathematical averaging, excessively smooth the turbulent viscosity, thereby underestimating the scale of stall vortices and distorting the amplitudes of acoustic peaks [41]. Furthermore, RANS models exhibit localized deviations in areas where the flow abruptly separates from the walls, such as in the outlet nozzle area. The most observable difference occurs in the design of medical blood pumps, where stationary RANS fundamentally underestimates the level of instantaneous turbulent shear stress, thereby failing to capture small-scale vortices in microgaps. Using RANS in such applications leads to the selection of geometrically incorrect blades that may lead to blood destruction, while LES produces a completely different, physically safe configuration.

A fundamental barrier to the LES method is its significant resource requirements. In concrete terms, the computational cost of non-stationary calculation methods (which include LES) is often 30-50 times higher than the cost of stationary approaches of the RANS family [71]. Due to the need to construct an extremely fine computational grid and use a small time step, LES requires considerable resources,

which means that the LES method cannot yet be recommended for routine numerical modeling of industrial pumps [53]. At the same time, classical RANS calculations converge in a comparatively shorter time (for example, in one optimization problem, the SST $k-\omega$ model converged in just 25 minutes) [78]. However, directly searching for the optimal shape using highly accurate non-stationary methods requires months of continuous supercomputer operation [42].

A key methodological shift of the last decade has been the deep integration of complex mathematical calculations with machine learning and deep learning models [50], [75], [79]. Traditional parametric optimization required running thousands of CFD simulations, which took months of supercomputer execution. Today, CFD is often used solely as a generator of training datasets [48], [49]. Surrogate mathematical models are constructed based on these data sets. Kriging models, backpropagation artificial neural networks, and response surface methods demonstrate the highest accuracy in approximating complex nonlinear processes [9], [48], [68], [75], [79]. The trained surrogate model enables the almost instantaneous prediction of pump parameters when changing blade geometry [48], [75], [79]. The

resulting surrogate models serve as the basis for heuristic global optimization algorithms, such as the Genetic Algorithm or the Particle Swarm Optimization (PSO) [2], [9], [13], [48], [49]. This combination of algorithms (e.g., CFD + Kriging + PSO) enabled the transition to multi-criteria geometry optimization, where the mathematical program simultaneously searches for a blade profile that maximizes energy efficiency, minimizes net positive suction head, and suppresses vibrational flow noise [13], [48], [49], [75].

Furthermore, deep learning architectures, such as hybrid CNN-LSTM pipelines, have become the foundation for creating predictive mathematical systems and virtual sensors [67], [73]. Such models, trained on CFD results and vibroacoustic spectra, are capable of real-time diagnostics of cavitation initiation, predicting pressure degradation, and estimating the remaining life of a pump, implementing the concept of intelligent predictive maintenance [60], [67], [73], [81].

An analysis of the software used shows that modern centrifugal pump research and design relies on a powerful ecosystem of commercial and open source computing platforms (Table 3).

Table 3. Summary table of centrifugal pump research software

Software package / Language	Description and tasks to be solved within the framework of the research	Articles
ANSYS CFX	A specialized CFD package for rotating turbomachines. It is widely used for calculating steady and URANS flows, analyzing cavitation (thermal effects, hydrogen, water), assessing unsteady pressure fluctuations, and automated optimization of diffuser geometry. It features a built-in expression language for defining complex boundary conditions (e.g., modeling leaks in seal microgaps).	[3], [5], [11], [13], [30], [33], [48], [55], [64]-[66]
ANSYS Fluent	A powerful universal CFD solver. It is widely used for high-precision calculations using the LES and URANS methods, as well as for modeling aeroacoustic noise, fluid elasticity, multiphase flows with solid particles (DPM), and detailed spectral analysis of stall vortices under off-design operating conditions. It is often integrated with neural networks to generate training databases.	[9], [15], [37], [57], [58], [63], [67], [71], [79] and also the general ANSYS family in articles [1], [7]-[8], [12], [14], [29], [31], [34]-[36], [38]-[39], [41], [44], [49], [56], [62], [68]-[70], [74], [75], [80], [81]
MATLAB / Simulink	A leading environment for mathematical calculations, one-dimensional (1D), and systems analysis. It is used for tuning heuristic optimization algorithms (genetic algorithms), statistical design of experiments, developing macroscopic models of induction motor-pump coupling, and modeling stochastic degradation (wear) using the Gamma Process. It enables the design of virtual flow meters and calculation of pump array operation in turbine mode.	[13], [32], [45], [60], [61]

Table continued

Software package / Language	Description and tasks to be solved within the framework of the research	Articles
CAD systems (Autodesk Inventor, SolidWorks, CFTurbo)	They are used for preliminary analytical blade profiling, creating precise 3D models of complex helical branches, virtual assembly of parts, and for checking spatial interference between edges before transferring them to CFD mesh generators.	[78], [60], [10]
OpenCASCADE (C++, Qt)	An open-source graphical geometric kernel. It was used by scientists to develop their own independent, specialized CAD platform, which enables the automatic generation of complex spatial surfaces of doubly curved blades (using B-splines) based on input hydraulic parameters.	[46]
Alternative CFD packages (OpenFOAM, Simcenter STAR-CCM+, COMSOL)	OpenFOAM (open source) is used for high-fidelity transient simulations using hybrid DDES methods. Simcenter STAR-CCM+ is in demand in the automotive industry for complex multiphase (VOF) cavitation analysis in supercars. COMSOL Multiphysics is used for basic comparative analysis of turbulence models.	[4], [54], [78]
Custom Code, Python, and Machine Learning Methods	Programming languages (primarily Python) and specialized libraries are used to train neural network ensembles (CNN-LSTM, Random Forest, SVM). These are used to diagnose cavitation onset using vibration spectrograms (virtual sensors), as well as to write custom mathematical solvers (for example, the new immersed boundary finite element method for fluid elasticity problems in flexible bodies – FSI).	[59], [73] as well as AI in [2], [9], [42], [48], [50], [51], [62], [65]–[67], [75], [81]

Commercial solvers of the ANSYS family (Fluent and CFX) remain the undisputed leaders in CFD, becoming the de facto industry standard for complex 3D turbulence and cavitation analysis. However, in recent years, a clear trend towards cross-discipline approaches has been observed, with engineers increasingly abandoning isolated CFD analysis, and integrating fluid dynamics packages with mathematical and statistical environments, such as MATLAB or Python. This allows for the automation of routine tasks, training of neural networks, and running global optimization algorithms without human intervention. Parametric CAD systems, ranging from the classic Autodesk Inventor to open platforms based on OpenCASCADE, are also being actively used for the instant generation of error-free blade shapes.

4. Conclusions

The current stage of development in hydraulic engineering is characterized by a fundamental shift from isolated empirical tests to comprehensive interdisciplinary mathematical modeling. The main trend in recent years has been a shift away from using CFD solely as a final verification tool. Today, complex Navier-Stokes calculations work in synergy with advanced algorithms. For example, they act as reliable database generators for training deep neural networks, which then perform instantaneous performance prediction, multi-criteria optimization,

and predictive diagnostics of equipment wear.

An analysis of the review results has allowed a division of the applied mathematical apparatus into seven main categories, recording a total of 95 applications of these methods in the analyzed articles. Reynolds averaging (RANS and URANS) remains the undisputed winner, accounting for 43 applications, or 45.3% of the total. This approach is most often used to find the optimal balance between computational efficiency and engineering accuracy when calculating basic characteristics and generating datasets for artificial intelligence. The second most popular and fastest-growing approach is the use of artificial intelligence, recorded in 19 cases, or 20.0% of all applications. Surrogate models such as Kriging or neural networks, as well as heuristic optimizers, are widely used to create intelligent digital twins and automated geometry optimization in fractions of a second. LES were used 10 times (10.5%) as a convenient tool for analyzing complex transient phenomena, such as boundary layer separation and high-frequency pressure pulsations. Analytical and one-dimensional models, as well as system analysis, accounted for 9 applications (9.5%) and are in demand for macroscopic analysis, stochastic degradation prediction, and system dynamics assessment of pump arrays in networks. Innovative hybrid methods, such as DES or DDES and SST-SAS, which automatically switch between economical wall-mounted simulations and accurate vortex resolution in the flow core, were used in 6 cases (6.3%). A sim-

ilar share of 6 applications (6.3%) was accounted for by highly specialized physical interaction models, including two-way fluid-structure coupling, acoustic analogies, and erosive wear calculations. This distribution is completed by software parametric CAD modeling with 2 applications (2.1%), aimed at the automatic mathematical generation of error-free spatial geometry of blades.

The mathematical gap between these methods, with RANS being 30-50 times faster and LES capable of guaranteeing an error of up to 3% in the most complex vortex structures, has given rise to two major modern trends. First, engineers are rapidly shifting to hybrid models (DES, DDES, SST-SAS), which require only a fraction of the resources of pure LES but provide similar accuracy in separation zones. Second, high-precision and time-consuming calculations are now used once to create training databases, after which neural networks in fractions of a second predict the results, replacing the resource-intensive computations of supercomputers.

The ecosystem of applied software, analyzed across 70+ articles, clearly demonstrates the monopoly of commercial computing platforms amid growing deep integration with programming environments. The absolute industry leader is the ANSYS family of software suites, including Fluent and CFX, which was used in 50 articles, accounting for 69.4% of the total research volume. This platform has become the de facto standard and serves as the primary computational testing ground for solving problems of any complexity from multiphase cavitation to rotor-stator interaction. The high proportion of in-house code, Python, and machine learning frameworks, recorded in 12 articles (16.7%), demonstrates the widespread shift toward intelligent design, where researchers write their own scripts for training neural networks, integrating global search algorithms, and developing virtual sensors. The traditional mathematical environments of MATLAB and Simulink were used in five articles (6.9%) to tune heuristic optimization algorithms, develop macroscopic actuator control systems and 1D predictive codes. Alternative CFD packages, such as OpenFOAM, Simcenter STAR-CCM+, and COMSOL, were used sparingly in three articles (4.2%) for high-fidelity hybrid transient simulations due to availability of open-source code or for specific automotive applications. Three articles (4.2%) also used CAD systems, including Autodesk Inventor and OpenCASCADE, as the foundation for the automated design of complex helical bends and blade splines.

Thus, modern research has finally established a conveyor-based design structure, in which powerful commercial packages, primarily ANSYS, use RANS models to generate highly accurate data arrays, after which intelligent algorithms instantly analyze them, identify areas of inefficiency, and optimize the flow paths of equipment.

The choice of mathematical framework for studying centrifugal pumps depends strictly on the engineering problem at hand and the available computing resources. For the vast majority of routine calculations, evaluating basic energy characteristics, and generating large sets of training data, fast and cost-effective Reynolds averaging methods such as RANS and URANS are optimal. However, if the problem requires benchmark accuracy in studying complex transient phenomena, high-frequency pressure pulsations, boundary layer separation, or the design of sensitive medical blood pumps, it is necessary to switch to high-precision but extremely resource-intensive LES or its hybrid compromises, such as DES and SST-SAS. Once reliable hydrodynamic databases are obtained via RANS or LES, machine learning algorithms and surrogate neural networks come into play. These should be selected for instant multi-objective optimization of flow-through geometry and the creation of intelligent systems for real-time predictive equipment diagnostics. In turn, to solve macroscopic problems of network system dynamics, predict gradual wear, as well as for highly specialized multi-physics calculations (for example, erosion from solid particles or hydroelastic deformation of flexible blades), it is advisable to use 1D analytical algorithms and flow-structure interaction models.

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Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, N.S. and A.A.; Methodology, N.S.; Validation, A.S. and N.S.; Formal Analysis, A.S.; Investigation, A.S.; Resources, A.S.; Data Curation, A.S.; Writing – Original Draft Preparation, N.S.; Writing – Review & Editing, N.S.; Visualization, A.A.; Supervision, N.S.; Project Administration, N.S.; Funding Acquisition, N.S.

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