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Cavitation Flow Mechanisms and Fluid Dynamics Optimization Trends in Small Water Pumps

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***Abstract*—Small centrifugal pumps are core basic equipment for fluid transport, waste heat circulation, and cooling systems in energy and power engineering. Consequently, internal cavitation flow represents the most prominent fluid dynamics problem restricting their efficiency, stability, and service life. More precisely, cavitation is a typical gas–liquid two-phase unsteady flow phenomenon involving complex physical mechanisms such as liquid vaporization, bubble growth, shedding, collapse, and the evolution of multi-scale vortex structures. It is evident from industrial statistical data that approximately 30% of small pump failures are directly or indirectly related to cavitation, efficiency reductions caused by cavitation can reach 20%–40%, and severe cavitation erosion can shorten impeller life by more than 50%. This paper therefore provides a systematic and rigorous review of the current application status of fluid dynamics theory and numerical simulation methods in cavitation mechanism analysis, flow loss identification, and structural optimization. From this review, several important conclusions can be drawn naturally and appropriately: hybrid RANS-LES models can improve flow resolution accuracy in cavitation regions by 30%–50% compared with conventional URANS models in strongly curved flow passages; deep learning-based vibration/acoustic signal recognition methods have already achieved diagnostic accuracy above 95% for incipient cavitation; and a lightweight Vision Transformer model achieves 100% recognition accuracy for eight cavitation states under multi-noise environments, with a single inference time of only 15.4 milliseconds. However, it is undeniable that clear and prominent research bottlenecks still remain in this field: turbulence–cavitation coupling models have insufficient capability in capturing cross-scale vortex structures, multi-field coupled simulation systems are not yet mature, the cavitation evolution law under variable operating conditions lacks quantitative description, and the intelligence level of optimization design needs to be improved. Accordingly, the future development trends are very clear: cross-scale refined CFD simulation, construction of multi-field coupling systems, precise optimization for energy saving and loss reduction based on entropy production theory, and intelligent simulation optimization with deep integration of fluid dynamics and artificial intelligence. This paper provides excellent theoretical reference value for hydraulic performance* *optimization, cavitation suppression design, and high-efficiency energy-saving renovation of small fluid power equipment.*

I. INTRODUCTION

1.1 Research Background and Engineering Significance

Since fluid machinery performs fundamental functions such as energy conversion, medium transport, and heat transfer in energy and power engineering systems, it constitutes a key unit for the efficient and stable operation of power equipment. Small centrifugal pumps (typically with a power rating below 100 kW and an impeller diameter less than 300 mm) have highly mature and typical applications in industrial cooling cycles (generator set cooling, data center heat dissipation), HVAC systems, new energy vehicle thermal management (battery cooling, motor cooling), internal combustion engine auxiliary water supply, domestic booster water supply, and solar thermal utilization, among other fields. More importantly, this type of pump exhibits prominent operational characteristics including compact structure, cost sensitivity, highly variable operating conditions, and frequent start–stop cycles; therefore, its hydraulic performance exerts a direct and significant influence on the energy efficiency and reliability of the systems it serves.

Compared with large-scale hydraulic machinery (such as hydraulic turbines and large marine pumps), small water pumps feature small passage dimensions (hydraulic diameter frequently less than 50 mm), strongly curved geometries (the ratio of relative blade curvature radius to passage dimension can fall below 0.2), and steep local velocity gradients (near-wall velocity gradients can reach on the order of $10^5\ s^{-1}$). This results in a highly non-uniform pressure field, making it extremely prone to generating low-pressure zones at the impeller inlet, blade suction surfaces, and the volute tongue region. When the local static pressure drops below the saturated vapor pressure of the fluid, the liquid vaporizes to form cavitation bubbles, thereby triggering cavitation.

The detrimental effects of cavitation on small water pumps are multi-dimensional. In terms of hydraulic performance, as cavitation bubbles occupy the effective flow area, the head–flow curve drops steeply; once cavitation intensity exceeds the critical threshold, the pump head can fall abruptly by 15%–25%, with an accompanying efficiency loss of 20%–40%. Regarding vibration and noise, bubble collapse generates micro-jets (with velocities on the order of 100 m/s) and shock waves (with local pressures reaching the GPa order), exciting structural vibrations in the pump casing and radiating broadband cavitation noise, typically with a frequency spectrum between 1 kHz and 100 kHz. With respect to material erosion and failure, prolonged cavitation attack produces honeycomb-like erosion pits on impeller surfaces, resulting in material loss rates of up to 0.1–1 mm per year, which can ultimately lead to blade fracture. From a system safety perspective, cavitation in equipment such as residual heat removal pumps in nuclear power plants and rocket fuel pumps can easily cause abrupt performance degradation, posing a direct and dangerous impact on operation. Therefore, understanding the cavitation flow mechanisms in small water pumps, developing high-precision prediction methods, and creating intelligent perception technologies constitute frontier topics for improving the reliability and energy efficiency of power equipment.

1.2 Scope of the Review

This paper focuses on two core scientific issues concerning cavitation flow in small water pumps: first, high-fidelity numerical modeling of turbulence–cavitation coupling; second, data-driven intelligent sensing and control technologies for cavitation.

II. FUNDAMENTALS OF FLUID DYNAMICS IN THE ANALYSIS OF SMALL WATER PUMP PERFORMANCE CHARACTERISTICS

2.1 Basic Physical Processes of Cavitation Flow

From the perspective of fundamental fluid dynamics theory, the core condition for cavitation inception is that the local static pressure falls below the saturated vapor pressure of the medium. During the high-speed rotation of a pump impeller, the relative motion of the fluid causes a sharp increase in local flow velocity on the blade suction surface. According to Bernoulli's principle, an increase in flow velocity corresponds to a decrease in static pressure; when the pressure drops below the vapor pressure, the liquid undergoes a phase change and cavitation bubbles are generated [14]. Cavitation flow encompasses a multi-stage fluid evolution process: cavitation inception in low-pressure zones, accumulation and growth of bubble clusters, transport of bubbles with the main flow, and collapse in high-pressure regions. Bubble collapse produces localized micro-jets and impact pressures, which are the direct cause of hydraulic loss and structural erosion. Simultaneously, the mixing of bubbles with the liquid medium alters the density distribution of the flow field, induces unsteady vortex structures, intensifies flow disorder within the pump, and leads to significant degradation of the pump's head, efficiency, and flow characteristics. The key parameter for determining the occurrence of cavitation is the cavitation number, defined as the difference between the reference pressure and the vapor pressure divided by half the product of the fluid density and the square of the reference velocity. Cavitation begins to appear when the cavitation number falls below the critical cavitation number. Under rated operating conditions, the cavitation number of small water pumps typically ranges from 0.1 to 0.5, and the low-pressure region at the impeller inlet can easily exceed the critical value.

2.2 Core Fluid Dynamics Theories and Their Applications in Pump Cavitation

2.2.1 Turbulence Modeling Theory

The flow inside a pump is high-Reynolds-number turbulence (Reynolds number typically between 10^5 and 10^6), and turbulence models are used to simplify the description of complex turbulent fluctuation effects. The standard k-ε model is effective for fully developed turbulence, but exhibits significant errors when predicting strongly swirling flows and flows with large curvature; for example, pressure prediction errors in the tip leakage vortex region can reach 20%–30%. The SST k-ω model combines the advantages of the k-ω model in the near-wall region with those of the k-ε model in the far-field region, providing accurate prediction of flow separation under adverse pressure gradients, and its prediction error for the cavitation inception location on the blade suction surface is approximately 40% smaller than that of the k-ε model [13]. The physical concept of hybrid RANS-LES models (such as DES, DDES, and zonal RANS-LES) is to employ RANS in the near-wall region to reduce computational cost, while using LES to resolve large-scale vortex structures in the mainstream region. DES has already achieved LES-level accuracy (with errors less than 5%) in calculating the shedding frequency of cavitation clouds, at a computational cost only 1/5 to 1/10 that of LES [2,3,18]. Although the theories discussed form the foundation of CFD simulations, sufficient evidence in recent years has demonstrated that traditional models exhibit systematic deviations with respect to cavitation-induced turbulence anisotropy and cross-scale vortex structures, which has led to the emergence of methods such as turbulence injection corrections.

2.2.2 Cavitation Phase-Change Models

The essence of cavitation flow is the mass transfer between the liquid and vapor phases. Currently, the commonly used cavitation models can be summarized as the Zwart model, the Schnerr–Sauer model, and the Kunz model [17]. The Zwart model is derived from a simplified bubble dynamics equation and introduces a nucleation radius (1 μm) together with empirical coefficients (condensation coefficient 0.01, vaporization coefficient 50). When the local pressure falls below the vapor pressure, the liquid evaporates to form bubbles; when the pressure recovers, the bubbles condense and disappear. The Schnerr–Sauer model is formulated based on bubble number density, which eliminates the sensitivity to the empirical nucleation radius parameter and provides more reliable predictions in certain situations. The Kunz model employs different time scales for evaporation and condensation and is suitable for simulating unsteady strong cavitation. At present, the empirical coefficients used in these models have all been calibrated from simple flow fields (such as Venturi tubes and two-dimensional hydrofoils), and systematic calibration has not yet been performed for applications in the complex flow passages of small water pumps. When the vaporization coefficient in the Zwart model varies within the range of 50–200, the predicted vapor volume fraction can differ by as much as ±40% [3].

2.2.3 Multiphase Flow and Multi-Field Coupling Theory

Gas–liquid two-phase flow models include the VOF model (suitable for large-scale phase interfaces), the Mixture model (computationally efficient, most commonly used in cavitation simulations), and the Eulerian two-fluid model (suitable for high phase fractions). Regarding fluid–structure interaction, the impact force from cavitation collapse excites blade vibration, which in turn alters the pressure distribution in the flow field, forming two-way coupling. Weak coupling only transfers pressure fluctuations, whereas strong coupling solves the fluid and structural equations simultaneously. In terms of acoustic coupling, the propagation of cavitation-radiated noise can be solved through acoustic analogy methods; however, most current studies still treat acoustic analysis as a post-processing step rather than solving it simultaneously with the flow field.

III. LITERATURE REVIEW

3.1 Cavitation Flow Mechanisms and High-Fidelity Numerical Methods

3.1.1 Development Timeline of Cavitation Numerical Simulation

The research history of cavitation numerical simulation can be broadly divided into three stages. The first stage (before 2000) was dominated by potential flow theory and experimental observation; numerical simulation was limited by computational resources and mostly employed simplified bubble dynamics models. In the second stage (2000–2015), RANS methods became mainstream, with the k-ε and SST k-ω models widely used for pump cavitation simulation, and researchers began systematic comparisons of the predictive capabilities of different turbulence models. In the third stage (2015–present), hybrid RANS-LES methods have developed rapidly, and approaches such as DES and zonal RANS-LES have been progressively applied to complex engineering flows. Concurrently, data-driven methods have begun to enter the field of cavitation identification, forming a dual-track pattern in which numerical simulation and intelligent sensing advance in parallel.

3.1.2 Major Findings from Experimental Studies

Since early cavitation research relied primarily on experimental observations, high-speed imaging (with frame rates up to 100,000 frames per second) has been effectively employed to observe the unsteady processes of cavitation cloud growth, shedding, and collapse; particle image velocimetry (PIV) has accurately captured the vorticity field around the cavitation region; and pressure sensor arrays have reliably recorded the pressure fluctuation spectra induced by cavitation. The results thus obtained naturally serve as an excellent benchmark for numerical model validation [15]. In small water pumps, cavitation most readily occurs at the impeller inlet leading edge (blade inlet edge) and on the blade suction surface near the leading edge. Under low flow rate conditions, a backflow vortex appears at the impeller inlet, and the low pressure at the vortex core promotes earlier cavitation inception, such that the critical cavitation number can increase by 0.1 to 0.2 compared with the rated operating condition. A modulation relationship exists between the shedding frequency of the cavitation cloud and the blade passing frequency and its harmonics, and the shed bubble clusters collapse in the downstream high-pressure region, generating broadband impact.

3.1.3 Evolution and Comparison of Numerical Methods

Since the URANS method has the lowest computational cost but is clearly insufficient in resolving the unsteady cavitation shedding process, the resulting cavitation region exhibits a "pseudo-steady state," and consequently fails to reasonably reproduce the periodic collapse of cavitation clouds, with pressure fluctuation amplitudes underpredicted by 30%–50% [2,3]. As hybrid RANS-LES represents a compromise between accuracy and computational cost, recent studies on axial-flow pumps have shown that, in comparison, the head fluctuation amplitude predicted by URANS is 30% of the experimental value, that by DES is 80%, and that by LES is 90% [1]. It can therefore be naturally and appropriately concluded that DES possesses engineering-applicable predictive capability for the unsteady characteristics of pump cavitation. Because the zonal RANS-LES model provides a very clear and reasonable analysis of the tip leakage vortex flow characteristics—employing RANS in the near-wall region, LES in the mainstream region, and smoothly blending the turbulent stresses at the interface between the two zones—it achieves an approximately 60% improvement over URANS in cavity morphology agreement when predicting cavitation in the tip clearance of mixed-flow pumps [2]. With respect to grey area mitigation, since the hybrid RANS-LES method suffers from a “grey area” in the RANS-LES transition region (excessive dissipation of turbulent kinetic energy and delayed generation of resolved eddies), the newly proposed turbulence injection method introduces artificially perturbed turbulent kinetic energy at the interface. This naturally and reasonably accelerates the transition of the grey area towards a fully turbulent LES state, thereby reducing the prediction error of the cavitation cloud shedding frequency from 25% to 8% [3]. The applicable scenarios of the various models are summarized as follows: the k-ε RANS model features low computational cost but poor accuracy in cavitation inception location (deviation often >15%), making it suitable for rapid steady-state performance evaluation; the SST k-ω RANS model has moderate cost and better cavitation inception accuracy (deviation 5%–10%), suitable for design at rated conditions; DES involves moderately high cost and good cavitation inception accuracy (deviation <5%), and is capable of capturing the dominant shedding frequency, making it suitable for unsteady cavitation analysis; LES has extremely high cost (10 to 100 times that of RANS) and the best accuracy, suitable for mechanism research and database construction.

3.1.4 Progress in Cavitation Model Parameter Calibration

Since the empirical coefficients of traditional cavitation models have not been appropriately calibrated for different pump types, and the open-source platform OpenFOAM allows users to customize the transport equations and their coefficients, this platform provides an excellent opportunity for parameter inversion. Several data-driven calibration methods have emerged recently [11]. Bayesian inversion takes experimental data such as the cavitation number and pressure fluctuation spectra as constraints and uses statistical methods to obtain the posterior distribution of the coefficients. This naturally yields a calibrated Zwart model for a centrifugal pump, where the optimal vaporization coefficient is adjusted from the default value of 50 to 120, reducing the predicted vapor volume fraction error from 40% to 12% [3]. Machine learning parameter optimization, by extracting features from pressure signals and inversely predicting cavitation coefficients, can provide continuous and reliable quantitative estimation of the cavitation intensity (with a mean absolute percentage error less than 5%), thus naturally offering a new approach for dynamic calibration of model coefficients [4]. Furthermore, authoritative reviews have clearly pointed out that, although hybrid RANS-LES methods combined with high-resolution grids are currently employed, existing cavitation models still lack sufficient capability in reproducing the turbulence anisotropy downstream of the cavitation region. The fundamental reason is that the coupling mechanism between the phase-change process and turbulence generation has not been reasonably incorporated into the models. It is therefore essential to develop improved cavitation transport equations that include turbulence–cavitation cross terms, introducing corrections based on turbulent kinetic energy or vorticity into the phase-change source term. As this section has provided a concise overview of the evolution of cavitation numerical simulation from URANS to the hybrid RANS-LES era, it is natural to point out that although the accuracy has improved, the operating-condition dependence of model coefficients and the turbulence–phase-change coupling mechanism remain the major issues.

3.2 Cavitation-Induced Hydraulic Loss and Pressure Fluctuations

3.2.1 Entropy Production Theory for Quantifying Hydraulic Loss

It can be naturally and reasonably derived from the second law of thermodynamics that irreversible losses (viscous dissipation, turbulent dissipation, and cavitation impact) can be characterized by the entropy production rate, which can in turn be explicitly divided into a contribution from viscous dissipation of the mean flow (wall friction and flow separation) and a contribution from turbulent kinetic energy dissipation of the fluctuating flow (breakdown and cascade of vortex structures). Hence, the total entropy production is proportional to the hydraulic loss and serves as a quantitative indicator of irreversible dissipation [25,26]. Typical conclusions from applying the entropy production method to analyze cavitation flow in small water pumps include: the entropy production in the cavitation region accounts for 30%–60% of the total pump entropy production, while its volume fraction is generally below 10%, indicating that cavitation is an ultra-high-intensity source of energy dissipation; the spatial distribution of entropy production can very clearly and naturally reveal two entropy production peak zones in the tip leakage vortex and the cavitation cloud collapse region, respectively; and because the entropy production rate increases by 2–5 orders of magnitude as cavitation intensifies, this constitutes the direct cause of the abrupt head drop [27].

3.2.2 Relationship Between Pressure Fluctuation Characteristics and Structural Vibration

Unsteady cavitation shedding induces periodic pressure fluctuations with typical frequency characteristics including: a low-frequency component (approximately 0.1–0.5 times the blade passing frequency) corresponding to the large-scale periodic growth and shedding of the cavitation cloud, which has the largest amplitude; the blade passing frequency and its harmonics, caused by blades passing the volute tongue or rotor–stator interaction, where cavitation amplifies the blade passing frequency fluctuation amplitude (by a factor of 2–3); and broadband noise generated by the collapse of cavitation micro-jets, so it can be naturally and reasonably considered that its energy is concentrated between 1 kHz and 100 kHz. From the perspective of the coupling mechanism between cavitation pressure fluctuations and structural vibration, shock waves act on the blade surface, exciting blade bending and torsional mode shapes. When the fluctuation frequency approaches the natural frequency of the blade, resonance occurs, leading to accelerated fatigue fracture. Measured results confirm that the root-mean-square value of pump casing vibration acceleration under cavitation conditions is 5–10 times greater than that without cavitation. Although one-way coupled fluid–structure–acoustic analysis is already quite mature, studies on two-way strong coupling (where structural deformation feeds back to influence the flow field pressure) remain scarce, primarily due to high computational cost and the difficulty in ensuring numerical stability in multi-physics simulations. From the existing analysis, it can be concluded that since numerical simulation methods for acquiring cavitation information involve high computational cost and poor real-time performance, they are not suitable for direct online monitoring in engineering field applications; this has consequently driven the emergence of data-driven intelligent cavitation sensing methods.

3.3 Data-Driven Intelligent Sensing and Identification of Cavitation

This section represents the fastest-growing direction in recent years, evolving from traditional single-threshold judgment to multimodal deep learning recognition. A large number of high-accuracy, interpretable, and lightweight methods have emerged.

3.3.1 Vibration Signal Methods

Since vibration acceleration sensors are mounted on the pump bearing housing or casing, it is convenient to directly acquire broadband signals from the measured object, typically with a sampling rate of 5 kHz to 50 kHz. The multi-scale convolutional neural network (TF-WFMSCNN) method first applies wavelet time–frequency transformation to the raw vibration signals, thereby naturally and reasonably deriving multi-scale convolutional layers that separately extract high-frequency details, mid-frequency structures, and low-frequency trends, and then employs a fusion layer to effectively combine the features at different scales. This approach has achieved an average accuracy of 98.6% in identifying five cavitation states (none, incipient, slight, moderate, severe) and can, through visualization, directly analyze the frequency bands of interest: the 5–8 kHz band is most sensitive to incipient cavitation, which is in good agreement with physical principles [4]. The CNN-KAN combination first uses wavelet coherence analysis and the Stockwell transform to convert one-dimensional vibration signals into two-dimensional time–frequency spectrograms, then employs a CNN to extract spatial features, and finally uses a Kolmogorov–Arnold network as the classifier. The proposed method thus achieves an accuracy of 97.2% in cavitation identification under multiple operating conditions (five flow rate points). The multi-scale fusion deep convolutional neural network uses convolutional kernels of different scales in parallel to extract sensitive frequency bands, and also reasonably and naturally designs a frequency-band attention module for automatic weighting. As a result, this method exhibits excellent robustness to noise and still maintains an accuracy above 90% at a signal-to-noise ratio of 0 dB [23].

3.3.2 Acoustic Signal and Pressure Signal Methods

Since acoustic emission sensors (frequency range 100 kHz–1 MHz) are extremely sensitive to the micro-jets of incipient cavitation, they can detect cavitation inception 0.5–2 seconds earlier than vibration signals [21]. The Gramian Angular Field (GAF) + DenseNet method first transforms one-dimensional acoustic signals into two-dimensional images using the Gramian Angular Field transformation, which naturally preserves temporal correlations, and then reasonably inputs them into a DenseNet for classification, thereby avoiding manual feature extraction. Consequently, this method achieves an accuracy of 96.5% in identifying six states of a centrifugal pump and is more sensitive to incipient cavitation. The method combining fractal dimension with bidirectional long short-term memory (BiLSTM) networks utilizes the nonlinear fractal dimension features (box-counting dimension and correlation dimension) of pressure fluctuation signals to supplement BiLSTM's extraction of forward and backward temporal dependencies. This enables BiLSTM to perform excellently in processing non-stationary sequences of cavitation evolution under variable operating conditions, achieving a recognition accuracy approximately 5% higher than that of standard LSTM [12].

3.3.3 Small-Sample and Interpretability Methods

Since it is very difficult to obtain large amounts of labeled cavitation data (especially fault data) in industrial field settings, small-sample learning is of great significance for practical applications. A physics-informed data augmentation method, proposed for water hydraulic axial piston pumps, employs a data augmentation strategy with clear physical meaning. Starting from prior knowledge such as the cavitation number variation range and the phase relationships of pressure fluctuations, it applies operations such as time stretching and amplitude modulation to the original signals to generate physically consistent synthetic samples. Classification is then performed using XGBoost, achieving an accuracy of over 90% with only 30 training samples, which is 15% higher than that of conventional augmentation methods [9]. Furthermore, because Bayesian networks can model the causal dependencies among variables (cavitation causes pressure fluctuations, pressure fluctuations cause vibration, and vibration is detected by sensors), unlike the black-box nature of deep learning, Bayesian networks can provide the posterior probabilities of various faults along with intuitive and reliable physical explanations (e.g., "cavitation probability 75% because the energy in the 5 kHz band of the vibration spectrum is abnormal"). Consequently, when used to diagnose seven types of faults, the interpretability of such networks is highly welcomed by maintenance personnel [24]. The multimodal causal inference chain constructs an inference chain from sensor signals to fault causes: first determining the physical events (bubble collapse) corresponding to the characteristic frequency bands of the signals, and then identifying the fault type. With each step based on reliable physical models, this approach can naturally avoid spurious correlations in purely data-driven methods.

3.3.4 Lightweight Design and Embedded Deployment

Since edge computing requires models with few parameters and fast inference, it is naturally necessary to design models that satisfy both requirements. This paper presents a very clear and structured introduction to a lightweight Vision Transformer (ViT) framework. Flow field visualization images (cavitation bubble morphology) captured by a high-speed camera are used as labels, and eight-channel vibration signals are simultaneously acquired to train the ViT model. By reasonably adopting strategies such as reducing the number of attention heads and employing depthwise separable convolutions for embedding, the model's parameter count is compressed to approximately 5% of that of the original ViT. More notably, on an embedded device, a single diagnosis requires only 15.4 milliseconds with a power consumption below 10 W. The recognition accuracy for eight cavitation states reaches 100% in a noise-free environment, and remains at 96.3% even under a strong background noise of 60 dB [23], making it highly suitable for on-site deployment at pumping stations. Furthermore, as the CNN-BiLSTM hybrid architecture has been optimized to be embeddable at the microcontroller level, it has been used for early warning of incipient cavitation, where tests have shown that it can issue an alarm 0.8 seconds earlier than the traditional vibration amplitude threshold method.

3.3.5 Overview of Technological Evolution

A review of the literature from 2002 to 2025 reveals that intelligent cavitation identification can be divided into three stages. The first stage (2002–2012) employed time-domain statistics (peak value, root mean square) and frequency-domain features (spectral peaks) combined with thresholding or fuzzy logic to estimate incipient cavitation, with very low sensitivity. The second stage (2013–2018) used shallow machine learning methods (support vector machines, random forests, BP neural networks) combined with handcrafted features (wavelet packet energy, empirical mode decomposition), achieving an accuracy of 80%–90% [22]. The third stage (2019–2025) has adopted deep learning (CNN, RNN, Transformer), self-supervised learning, multimodal fusion, and other methods, with the best accuracy already exceeding 98% [9]. The review indicates that future directions include three aspects: unsupervised domain adaptation (operating condition transfer), federated learning (data privacy), and end-to-end closed-loop cavitation control.

Although the cavitation phenomena have been elaborated upon in the preceding sections, to practically resolve these problems it is essential to either suppress cavitation at the design source or actively and reasonably mitigate its detrimental effects. This therefore naturally leads to research on anti-cavitation optimization based on fluid dynamics.

3.4 Anti-Cavitation Optimization Research Based on Fluid Dynamics

3.4.1 Impeller Blade Profile Optimization

The objective of optimization is to minimize the extent and intensity of the low-pressure region on the blade suction surface as much as possible. To this end, several approaches are employed. With regard to inlet incidence angle adjustment, for small flow pumps, appropriately increasing the positive incidence angle (5°–10°) can make the inlet velocity distribution more uniform; therefore, this method is adopted, though it slightly reduces the efficiency at the rated operating point. By adopting leading-edge elliptization, the cross-section of the blade leading edge is changed from a circular arc to an ellipse, thereby reducing the local acceleration peak and consequently delaying cavitation inception. CFD optimization results indicate that an elliptical leading edge reduces the critical cavitation number by 0.05–0.1. The method of blade loading distribution reconstruction uses a curve to control the blade pressure distribution, thereby avoiding an abrupt pressure drop on the suction surface. Multi-objective optimization methods (balancing efficiency and anti-cavitation capability) can be used to obtain the Pareto front solution set [28].

3.4.2 Flow Passage Structural Optimization Schemes

By adjusting the volute tongue clearance, increasing the gap between the impeller and the volute tongue is beneficial for suppressing rotor–stator interaction pressure fluctuations; however, it reduces volumetric efficiency. Therefore, it is generally considered that a reasonable clearance is 3%–6% of the impeller outer diameter. In terms of inlet pre-swirl design, since installing stationary guide vanes or a tangential inlet upstream of the impeller can generate pre-swirl in the same direction as the impeller rotation, this improves the inlet flow conditions and consequently enhances the anti-cavitation capability, albeit with additional hydraulic losses.

3.4.3 Data-Driven Optimization: A New Paradigm

Since traditional CFD optimization requires thousands of simulations, the computational cost is prohibitively high. Consequently, surrogate model approaches that have emerged in recent years naturally and reasonably utilize Graph Neural Networks (GNNs) to learn the mapping between geometric parameters and the flow field. Specifically, CFD mesh nodes are treated as a graph structure, and the relationships of physical quantities between adjacent nodes are learned through a message-passing mechanism. This leads to the proposed rotation-equivariant hypergraph neural network, which, given the impeller geometric parameters, can accurately predict the cavitation volume distribution within milliseconds with a relative error below 5%, whereas conventional CFD requires several hours. This approach therefore reduces the optimization cycle from several months to several days, which also excellently demonstrates the advantages of the hybrid "mechanism-driven + data-driven" model [28,30].

IV. MAJOR BOTTLENECKS IN CURRENT RESEARCH

4.1 Limited Accuracy of Turbulence and Cavitation Models

RANS-type models cannot directly resolve the small-scale anisotropic turbulence in cavitation regions, and even DES suffers from the mismatch of turbulent kinetic energy dissipation in the "grey area." Authoritative research groups have clearly pointed out that existing models cannot reasonably reproduce the peak turbulence intensity downstream of cavitation clouds, with errors reaching 100% [3]. A more fundamental issue is that the empirical coefficients adopted in cavitation models (such as nucleation radius and vaporization coefficient) are all calibrated based on simple flow fields, and are therefore inapplicable to the variable-curvature flow passages of small water pumps. Without calibration, the correlation coefficient between the predicted vapor volume fraction and experimental data is merely 0.4–0.7. Furthermore, existing macroscopic phase-change models cannot resolve the micro-scale dynamics of individual bubbles (bubble–bubble interactions and shock wave propagation), which have a direct determining effect on the collapse impact force. The most fundamental problem at present is not a lack of more sophisticated models, but rather a long-standing imbalance between "model complexity" and "parameter calibratability": developers continuously introduce more complex multi-scale models, yet these models introduce even more parameters than the Zwart model, which are extremely difficult to calibrate reliably through experiments, and the actual accuracy in engineering applications has not improved. Therefore, future efforts should prioritize the development of simplified models with fewer parameters, physical interpretability, and ease of calibration, and must avoid blindly pursuing numerical "high fidelity."

4.2 Incomplete Multi-Field Coupled Simulation Framework

The vast majority of studies calculate the flow field first and then apply the pressure fluctuations as loads onto the structure, neglecting the feedback of structural deformation on the flow field. However, for flexible blades or thin-walled components, deformation can alter the flow passage geometry and thereby affect cavitation development. The radiation and propagation of cavitation noise are often analyzed only as a post-processing step, rather than being solved simultaneously with the flow field. Fully coupled calculations are extremely costly and no practical solution yet exists. The heat absorption during cavitation vaporization can cause a local temperature drop (especially in thermally sensitive fluids), thereby affecting the vapor pressure. Small water pumps are generally assumed to operate isothermally, but under high-temperature conditions (above 80 °C) the error becomes non-negligible. Multi-field coupling research suffers from a "precision trap": researchers often attempt to couple all physical fields simultaneously, which inevitably leads to an explosion in computational cost and model instability. A more pragmatic and efficient approach is hierarchical coupling: for most engineering problems, one-way fluid–structure coupling is already sufficient, and two-way coupling should be used only when the risk of resonance is high or large deformations occur in flexible components; acoustic and thermal effects are better analyzed separately in post-processing and need not be forcibly incorporated into the transient solution.

4.3 Insufficient Research on Cavitation Evolution Under Variable Operating Conditions

Over 80% of the literature takes the rated flow rate point as the research subject. However, small water pumps often operate within a range of 0.5 to 1.2 times the rated flow rate, and the cavitation morphology caused by backflow vortices under partial load conditions is distinctly different from that at the rated point. Under variable speed operation (variable frequency drive), the cavitation number varies with the square of the rotational speed, while the changing Reynolds number simultaneously affects the turbulence structure. Current research often couples the rotational speed effect with the cavitation effect, lacking an independent understanding of each governing law. The "cavitation memory effect" under frequent start–stop cycles—where residual micro-bubbles on the impeller surface after a brief shutdown can act as cavitation nuclei and promote cavitation upon restart—has rarely been studied. The crux of the disconnect between academia and industry lies in the fact that laboratory research habitually acquires "clean" data under steady-state, idealized conditions, whereas actual pumps suffer the most severe damage under variable operating conditions and frequent start–stop cycles. Therefore, future research should shift from a "rated-point orientation" towards a "full operating-condition map." Even systematic investigations on only a few typical off-design conditions would yield engineering value far exceeding that of one more high-precision simulation at the rated condition.

4.4 Empirically Biased Optimization Design with Low Intelligence

Most optimizations take either efficiency or cavitation margin as the sole objective and are performed only for a single operating point, whereas multi-condition, multi-objective Pareto optimization is actually required. Optimization often relies on CFD trial-and-error rather than first identifying loss sources through analyses such as entropy production and then making targeted modifications, resulting in a large number of iterations. Although intelligent identification has developed rapidly, a closed loop that feeds identification results back into the optimization design has yet to be established—the automation level of the entire chain of "perception → diagnosis → optimization → control" remains low. This is due to a mismatch in technology maturity: intelligent identification is approaching practical application, whereas intelligent optimization is still at the academic research stage. The fundamental reason is that cavitation optimization itself is a high-dimensional, multi-constrained, strongly nonlinear problem. Although the surrogate models currently used (such as graph neural networks) are fast, their capability to explore the design space still cannot compare with that of physical simulations. Therefore, the most feasible and robust approach in the short term is human–machine collaborative optimization: using intelligent identification for fault diagnosis, manually determining the optimization direction through entropy production analysis, and finally verifying with CFD. It is not advisable to rush towards a fully automatic closed loop.

V. DEVELOPMENT TRENDS OF FLUID DYNAMICS IN THE FIELD OF SMALL POWER PUMPS

5.1 Cross-Scale High-Fidelity CFD Simulation Becoming Mainstream

Although traditional RANS will ultimately be replaced by DES, LES, and even Direct Numerical Simulation (DNS), engineering applications will inevitably adopt a hierarchical strategy due to computational cost constraints. Routine design employs a well-calibrated SST k-ω RANS model with a cavitation model, and its coefficients should be optimized using machine learning [13]. For critical components and unsteady analysis, zonal DES or turbulence injection hybrid methods are adopted, which can effectively predict the cavitation shedding frequency and fluctuation amplitude [2,3]. Fundamental research, based on LES/DNS on simplified geometries (e.g., two-dimensional hydrofoils), builds cavitation turbulence databases and develops improved subgrid-scale models and phase-change models [16]. The multi-resolution method represents a noteworthy breakthrough direction: LES is used in the cavitation region (where fine resolution of small scales is required) and RANS in the far field, coupled through overset grids or immersed boundary methods.

5.2 Construction of Multi-Field Coupling and Full-Condition Fluid Dynamics Systems

The fluid-structure-thermal-acoustic integrated simulation platform couples a CFD cavitating flow solver, a finite element structural vibration analysis code, a boundary element acoustic solver, and a heat conduction solver together; however, current commercial software can only achieve one-way coupling. Consideration of cavitation thermal effects: small pumps transporting hot water (above 60 °C) or cryogenic liquefied gases inevitably involve the latent heat of vaporization, requiring the energy equation to be solved and coupled with the cavitation model. Because fluid, structure, and noise are intrinsically linked, fluid-structure-noise co-optimization can be performed from the perspective of minimizing cavitation erosion and radiated noise.

5.3 Precise Optimization for Energy Saving and Loss Reduction Based on Entropy Production Theory

The entropy production method guides optimization from the perspective of global energy dissipation, which is more rational than simply reducing the vapor volume fraction. Entropy production decomposition can identify the dominant loss mechanisms: total entropy production can be decomposed into three parts—viscous dissipation of the mean flow, turbulent kinetic energy dissipation, and cavitation phase-change dissipation—and optimization should be conducted accordingly [25–27]. Entropy production minimization topology optimization automatically designs the flow passage shape using the entropy production rate as the objective function, and studies have shown that it can reduce losses by 15%–20%. In combination with unsteady entropy production analysis, transient loss variations at different cavitation stages can inform active control measures (such as varying rotational speed or inlet pressure).

5.4 Intelligent Simulation Optimization Through the Integration of Fluid Dynamics and Artificial Intelligence

5.4.1 Intelligent Sensing and Predictive Maintenance

Multi-source signal fusion inputs multimodal data—such as vibration, acoustic emission, pressure, current, and temperature—into Transformers or Graph Neural Networks for end-to-end cavitation state identification and remaining useful life prediction. Fusion models achieve an accuracy 8%–12% higher than single-signal models [4,6,9]. In terms of domain adaptation transfer learning, the data distributions differ considerably across different pump types and operating conditions; employing domain-adversarial neural networks for cross-condition cavitation identification is beneficial for reducing calibration costs.

Edge AI deployment enables lightweight models to run in real time on ARM or FPGA chips and to interface with programmable logic controllers, thereby facilitating timely detection of incipient cavitation and enabling closed-loop suppression.

5.4.2 Intelligent Simulation (AI for CFD)

Physics-informed neural networks (PINNs) incorporate the Navier–Stokes equations and cavitation transport equations as physical constraints embedded into the loss term of the neural network, enabling the training of flow field surrogate models that conform to physical laws using sparse data. This approach has already been applied to the computation of cavitating flow over two-dimensional hydrofoils, achieving a 100-fold speedup [29]. Graph neural network surrogate models treat the CFD mesh as a graph structure and learn the mapping from geometric parameters to the physical quantities (pressure, velocity, vapor fraction) at each node. Rotation-equivariant graph neural networks preserve physical symmetry, yielding higher prediction accuracy [28]. Bayesian deep learning methods treat model coefficients as random variables, employ variational inference to obtain their posterior distributions and perform uncertainty quantification, and are applied to the automatic calibration of cavitation model coefficients.

5.4.3 Data-Driven Optimization and Design

Generative design employs Generative Adversarial Networks or diffusion models to directly generate blade profiles that satisfy cavitation performance constraints, replacing traditional parametric sweeping [30]. Multi-objective Bayesian optimization solves for the Pareto front in a design space of tens of dimensions using a Gaussian process surrogate model, and can reduce the number of CFD calls by 80% compared with genetic algorithms.

5.5 Deepening Research on Flow Mechanisms Under Extreme Conditions and in Lightweight Equipment

For high-speed micro-pumps (e.g., UAV fuel pumps and electronic pumps with rotational speeds up to 50,000–200,000 rpm), the cavitation number is extremely low, and the centrifugal force field significantly affects the distribution of cavitation nuclei; traditional models therefore need to incorporate rotational corrections. Regarding non-Newtonian and gas-containing media, when small pumps transport slurries, liquids containing microbubbles, or polymer solutions, the cavitation characteristics are entirely different from those in pure water, necessitating the development of generalized Newtonian fluid cavitation models. In terms of cryogenic medium cavitation, thermodynamic effects dominate in liquid hydrogen and liquid oxygen pumps, and cavitation models must be coupled with the energy equation.

VI. CONCLUSION

6.1 Main Conclusions

1. Mechanisms and modeling: Cavitation is a typical multi-scale gas–liquid two-phase unsteady flow. Existing RANS models have obvious limitations in capturing transient cavitation vortex structures. Hybrid RANS-LES methods (zonal DES, turbulence injection) have improved the prediction accuracy of cavitation dynamics to a level approaching LES within an acceptable computational cost. More importantly, the empirical coefficients in cavitation models are highly sensitive, and parameter calibration methods based on Bayesian inversion and machine learning can reduce prediction errors by more than 50%.

2. Intelligent sensing: Deep learning has already achieved mature application in cavitation state identification. Methods such as CNN, Transformer, and LSTM, using vibration, acoustic emission, and pressure signals as inputs, have attained recognition accuracies exceeding 98% under laboratory conditions. Lightweight ViT models have enabled embedded real-time diagnosis in 15.4 milliseconds. Physics-informed data augmentation and causal inference chains have addressed the problems of small samples and black-box models. This field has entered a new phase characterized by “precision, interpretability, and edge deployment.”

3. Optimization design: Traditional anti-cavitation optimization is based on empirical trial-and-error. Entropy production analysis serves as an excellent tool for identifying loss sources. Graph neural network-based surrogate models have shortened the optimization cycle from several months to a few days. However, systematic research on multi-field coupling (fluid–structure–acoustic–thermal) and wide operating conditions (variable flow rate, variable speed, frequent start–stop) remains insufficient.

4. Development trends: Cavitation research on small water pumps is undergoing three major transformations: from macroscopic statistics to cross-scale high-fidelity modeling, from single flow field to multi-physics coupled system simulation, and from empirical design to data-intelligence-driven predictive maintenance and autonomous control. Accordingly, the deep integration of fluid dynamics and artificial intelligence (physics-informed neural networks, graph neural network surrogates, active control closed loops) represents the most promising breakthrough direction.

6.2 Research Prospects

In summary, cavitation research on small water pumps has already formed a technical chain of "high-fidelity numerical methods → multi-source sensing → entropy production optimization → intelligent closed-loop control." The challenges that need to be further addressed in future research include developing few-parameter, easily calibratable engineering cavitation models, thereby reducing the dependence on empirical coefficients. It is also necessary to establish an open experimental database covering full operating conditions, which will support cross-condition generalization of intelligent algorithms and promote closed-loop verification from "diagnosis" to "control," ultimately achieving intelligent anti-cavitation operation of small water pumps. This will provide solid support for the high-efficiency, low-carbon, and highly reliable operation of energy and power systems.

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