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Review

Literature Review on Fault Mechanism Analysis and Diagnosis Methods for Main Pump Systems

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Abstract

As a fundamental element in industrial fluid transportation, the main pump fulfills an irreplaceable function in critical infrastructure, including the energy, water conservancy, petrochemical, and sewage treatment industries. As the core component of key power equipment, its operating condition is intrinsically connected to the safety, stability, and reliability of the entire system. This paper provides a systematic review of the latest advances in fault mechanism analysis and diagnosis methods for main pump systems. First, the typical structural composition and functional characteristics of the main pump system are examined, and the occurrence mechanisms and evolution rules of typical faults, such as mechanical malfunctions and performance degradation caused by hydraulic imbalance, are discussed in detail. Second, the main technical approaches to fault diagnosis are summarized and reviewed, including diagnosis methods based on signal processing, modeling, data-driven techniques, and multi-source information fusion. The advantages, limitations, and application scopes of these approaches are comparatively analyzed. On this basis, the development trends in main pump fault diagnosis technology and the key challenges faced—such as strong noise, small sample size, and multiple fault coupling—are identified and discussed. Finally, future research prospects are put forward in view of the limitations of current research. This review aims to provide theoretical insights and technical support for advancing condition monitoring, fault diagnosis, and health management of main pump systems.

Keywords: main pump system; fault mechanism; fault diagnosis; signal processing; data-driven; model driving; fusion diagnosis

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1. Introduction

The main pump system is a critical component in nuclear power plants, large chemical plants, and ship propulsion systems, playing a pivotal role in ensuring the safety, reliability, and efficiency of the entire system. Research on fault diagnosis and health management not only deepens the understanding of the main pump itself but also provides a transferable theoretical basis and technical framework for intelligent condition monitoring of other key rotating machinery (such as compressors and fans) and even pipeline systems [1,2]. Operating under extreme conditions of high temperature, pressure, speed, and corrosiveness, the main pump is susceptible to failures such as bearing malfunctions, seal leakage, impeller erosion, and cavitation [3–5]. Failure to detect, diagnose, and address these issues promptly

and accurately can result in performance degradation, unplanned downtime, severe financial losses, and, in worst-case scenarios, catastrophic accidents that endanger human safety and environmental stability. Therefore, it is of both theoretical and practical importance to conduct a systematic analysis of fault mechanisms in main pump systems and to develop effective and reliable fault diagnosis methods that support predictive maintenance, thereby ensuring the long-term safe and stable operation of critical engineering equipment.

In recent years, significant advancements have been made in fault diagnosis research on main pump systems, driven by strides in sensor technology, signal processing, artificial intelligence, and big data analytics. At the fault mechanism research level, studies have focused on investigating the causes, evolution patterns, and impacts of typical faults on system performance. At the diagnosis method level [6–10], several technical approaches have emerged. Signal processing-based methods adopt time–domain, frequency–domain, and time–frequency analysis techniques to extract fault-sensitive features from monitoring signals such as vibration, noise, pressure, and current. Model-based methods establish precise mathematical models of the system, using residual analysis, state observers, and parameter estimation techniques to detect faults. Data-driven methods leverage historical operational data to learn intricate mapping relationships between fault modes and state features through machine learning and deep learning algorithms, showcasing high adaptability. Fusion-based methods seek to integrate the aforementioned approaches, aiming to enhance diagnosis accuracy, robustness, and timeliness by employing information strategies such as fusion, feature fusion, and decision fusion.

This review aims to systematically organize recent advancements in fault mechanism studies and diagnostic methods for main pump systems. The research scope encompasses an in-depth analysis of the structure and function of main pump systems, with particular focus on piston and centrifugal pumps. It elaborates on the typical fault mechanisms and evolution processes of bearing systems, seal systems, hydraulic components, and rotor systems. In parallel, fault diagnosis methods based on signal processing, modeling, data analysis, and information fusion are reviewed, with emphasis on their underlying principles, representative applications, and effectiveness in addressing engineering challenges such as high noise levels, limited data samples, and multiple fault interactions. Furthermore, this review explores the developmental context, current challenges, and emerging trends in this field. On this basis, potential research directions are identified, including the construction of fault evolution models, the development of intelligent diagnosis strategies, the advancement of condition evaluation techniques, fault prediction, and proactive mitigation measures under complex operating conditions. Special attention is given to diagnostic technologies employing multi-source signal analysis, such as vibration and pressure, to offer a comprehensive technical reference framework for researchers and engineers.

This review makes three distinctive contributions compared to existing literature. First, it provides a systematic analysis of fault mechanisms across different types. Beyond outlining diagnostic methods, it systematically deconstructs the physical essence and evolutionary patterns of faults in four subsystems of the main pump: bearings, seals, hydraulic components, and rotors. This establishes a solid theoretical foundation for diagnostic methods and creates a clear logical progression from mechanism to diagnosis. Second, it offers a comparative and critical evaluation of multidimensional diagnostic methods. Rather than simply enumerating methods, this review categorizes diagnostic approaches into four paradigms: signal processing, modeling, data-driven, and fusion. This classification constitutes a novel contribution and presents a general diagnostic flowchart for these methods. In addition, a comparative analysis table evaluates the advantages, limitations, and suitable scenarios for each method, thereby offering engineers a practical reference for method selection. Finally, the review addresses the challenges arising under extreme work-

ing conditions, such as those encountered in nuclear main pumps. It emphasizes practical engineering challenges like high noise levels, limited data availability, and multiple faults coupling, and then proposes targeted, forward-looking research directions, such as refining mechanism models, developing intelligent and robust diagnostic strategies, and exploring active mitigation measures to address these challenges effectively.

2. Main Pump Systems and Analysis of Typical Failure Mechanisms

2.1. Analysis of Structural Composition and Functions of the Main Pump

The main pump system can be broadly categorized into two types: plunger pumps and centrifugal pumps. Plunger pumps employ the reciprocating motion of a piston within a cylinder to vary the sealed chamber volume, thereby enabling suction and discharge purposes [11–13]. In contrast, centrifugal pumps drive fluid through the centrifugal force generated by impeller rotation. Both plunger pumps and centrifugal pumps share common elements such as shaft transmission components, support bearing systems, and sealed containment structures, and are equipped with standardized suction and discharge ports to facilitate directional fluid flow. The fundamental distinction between these two pump types lies in their operating principles and performance characteristics. Plunger pumps rely on the reciprocating motion of a piston or plunger to generate high pressure by periodically altering the volume of a closed cavity. Therefore, plunger pumps are well-suited to low-flow, high-viscosity conditions, where they provide high mechanical efficiency but are prone to seal failures and valve plate wear [14–17]. Centrifugal pumps, by contrast, are advantageous in high-flow and medium-to-low pressure applications, including the transport of particulate-laden fluids, as they create centrifugal force through the rotation of an impeller, converting fluid kinetic energy into static pressure energy. However, the secondary energy conversion in centrifugal pumps results in significant efficiency fluctuations. Moreover, high-speed rotation can lead to issues such as impeller cavitation and bearing vortex failure [18–21]. Under extreme conditions, the shaft power of a plunger pump increases steadily with load, yielding higher power generation efficiency compared to a centrifugal pump. The centrifugal pump, however, requires a reinforced anti-radiation design to mitigate potential sudden power surge risks in specialized environments such as nuclear reactors [22–24]. Although plunger and centrifugal pumps share structural components such as shafts, seals, and containment shells, they also share diagnostic challenges such as bearing wear, shaft failure, and distortion of vibration signals caused by shell attenuation [25–27]. The fundamental structural disparity between the two pumps significantly influences the diagnostic approach: the piston pump is prone to periodic shock faults due to the reciprocating motion of the piston, and its pressure signal is sensitive to seal failures under extreme conditions [28,29]. Centrifugal pumps, in contrast, display continuous weak fault signatures associated with impeller rotation, which are less distinct and prone to multi-mode aliasing under high-temperature and high-flow conditions [30,31]. Consequently, these inherent differences in fault generation mechanisms necessitate methodological distinctions in diagnostic approaches.

2.2. Analysis of Typical Failure Mechanism

The main pump system is a complex assembly comprising many components and subsystems. Under extreme service conditions, it is subjected to multiple physical field coupling, leading to fault behaviors characterized by complex mechanism, concealed feature, and accelerated degradation. These characteristics pose significant challenges in identifying root causes and elucidating underlying fault mechanisms. Based on fault location, failures in the main pump system can be broadly divided into four categories: bearing system faults, sealing system faults, hydraulic component system faults, and rotor system

faults [32–34]. In this review, the physical nature and evolutionary processes of typical faults are deconstructed by systematically summarizing and organizing representative cases, thereby establishing theoretical anchor points for subsequent intelligent diagnosis using multi-source signals.

2.2.1. Failure Mechanism of Bearing System

The bearing system, as the core supporting structure of the main pump, plays a pivotal role in maintaining rotor dynamic stability, transferring loads, and minimizing friction losses. Its failure can directly lead to excessive vibration, abnormal temperature rise, and, in severe cases, force the shutdown of the main pump. The primary failure modes include rolling bearing failure, sliding bearing failure, and mating interface failure, which generally result from combined factors such as lubrication contamination, thermal stress imbalance, and abnormal dynamic loads [33,35,36]. This section provides a detailed analysis of the typical failure mechanisms associated with these three major categories of bearing system failures.

- Rolling bearing failure: Rolling bearing failure primarily manifests as pitting, spalling, and cage fracture, primarily caused by contact fatigue under alternating stress [37,38]. The underlying mechanisms are as follows: Lei et al. [39,40] confirmed that cooling water intrusion into lubricants leads to oil film rupture, causing direct metal-to-metal wear; the generated wear particles further exacerbate surface spalling. Under elevated temperatures (>120 °C), bearing steel underwent annealing-induced softening, with a 20–30% decrease in hardness, thereby accelerating fatigue crack propagation. Chen et al. [41] developed a nonlinear dynamic model that revealed the sensitivity of whirl trajectory to slip: a 15% increase in the amplitude in the X-direction resulted in more than a 40% increase in the roller-raceway slip ratio. This whirl effect leads to oscillations of the minimum oil film thickness and micropitting under boundary lubrication conditions. Li et al. [42] further reported that the coupling of centrifugal force and gyroscopic moment triggered atypical spalling of aeroengine main shaft bearings under high-speed, light-load conditions. This spalling was characterized by axially distributed fish-scale cracks, distinct from the radial spalling typical of traditional Hertzian contact fatigue. Patil et al. [43] established a theoretical model that quantified the relationship between pitting size and harmonic components of the vibration spectrum, although multi-defect coupling was not taken into account. Cao et al. [26] extended the model and demonstrated through a five-degree-of-freedom rotor-bearing system simulation that multi-point damage can excite a 2–5 kHz high-frequency resonance band. However, the requirement of preset defect locations limited its engineering applicability. Recent research has focused on the optimization of fatigue life models and slip dynamics. Zhai et al. [44] proposed a performance degradation assessment model based on cluster migration distance, enabling early fatigue failure warning through vibration signal feature extraction. Xia et al. [45] combined machine learning algorithms, such as SVM and cluster analysis, to improve fault classification accuracy; however, reliance on high-quality labeled data constrains its engineering generalization ability. Lee et al. [46] verified that insufficient lubrication and misalignment are the primary causes of overheating failure and verified that abnormal temperature rises can be monitored in real time using infrared thermal imaging.
- Failure mechanism of sliding bearing: The failure mechanisms of sliding bearings, which rely on hydrodynamic lubrication to form a load-bearing oil film, primarily include oil film rupture, vortex instability, and material adhesion [47–49]. Wang et al. [50] identified rotor eccentricity as a factor causing uneven lubricant flow, which in turn induces half-speed whirl and self-excited vibration. Antunović et al. [51] re-

ported that solid particles embedded in the babbitt bushing can initiate scratching and plastic deformation. McKee et al. [52] demonstrated that local overheating softens the bearing alloy, leading to micro-welding with the journal. Recent research has further advanced the understanding of wear mechanisms, abrasive wear thermal runaway, and eddy instability. Traditional theory predicts a vortex frequency at half the power frequency; however, Wang et al. [50], using CFD simulation, found that turbulence in water-lubricated bearings at 15.4 MPa reduces the frequency to 0.48 times the power frequency, attributing the discrepancy to previously neglected fluid inertia effects. König et al. [53] demonstrated through acoustic emission signal analysis that particles larger than 5 μm can penetrate the oil film and embed into the soft liner, with embedding depth increasing under higher loads. This particle embedding can elevate the wear rate by 300%. Wang et al. [50] attributed wear primarily to fluid inertia forces, while Chen et al. [41] argued that the flexible deformation of the bearing housing plays a more predominant role. Current microscopic models address a single adhesion mechanism but fail to predict macroscopic lifetimes, whereas phenomenological models like the Archard equation rely heavily on empirical coefficients and therefore lack universality [53,54].

- Failure mechanism of mating interface: The failure of mating interfaces primarily manifests as interference-fit loosening, fretting wear, and interfacial debonding, typically caused by preload imbalance [55]. These failures can significantly reduce structural stiffness, trigger abnormal vibrations, and accelerate fatigue crack propagation. Li et al. [56] confirmed through residual stress analysis that concentrated interfacial shear stress during thermal cycling is the dominant cause of package module cracking. Needleman's [57] continuum model identified two debonding modes: ductile matrix and brittle interface. Dong et al. [58] showed through simulations that wear at the interference-fit edge of a hollow shaft was 150% greater than that of a solid shaft, due to uneven contact stress distribution resulting from the lower stiffness of the hollow structure. Additionally, wear depth predicted by the Archard equation indicated a shift in the crack initiation site from the fit edge to the interior, leading to a 40% reduction in the fatigue life for hollow shafts compared with solid ones. Recent studies on molecular and medium dynamics have focused on understanding the mechanisms of interface failure. Zhou et al. [59] argued that atomic bond fracture energy is the dominant factor, whereas Needleman [57] maintained that stress triaxiality T is the key parameter. The core challenge remains the absence of cross-scale correlation models, hindering the integration of micro-parameters into engineering criteria. Nonetheless, consensus exists that debonding is governed by intrinsic strength and stress state, fretting wear results from the interaction of kinematics and material response, preload must be dynamically aligned with interference, and insights from molecular dynamics regarding bond fracture should be incorporated into continuum-scale models.

The present research investigates the primary failure mechanisms of rolling and sliding bearings and explores potential strategies for enhancing their reliability through advanced diagnostic techniques and integrated design approaches. For rolling bearings, fatigue and lubrication failure are identified as the predominant degradation mechanisms. Machine learning-based diagnostic methods have shown promise in improving fault detection accuracy, though their effectiveness depends heavily on the quality of the training data. Key areas for future breakthroughs include the development of composite fault models and the investigation of bearing performance under extreme operating conditions. In the case of sliding bearings, the water film vortex theory provides a robust theoretical foundation. However, challenges persist in accurately modeling fluid inertia effects and ensuring material adaptability under high-parameter operating conditions. Integrated bearing

design approaches, such as the BSB concept, have demonstrated significant potential for improving reliability. Nevertheless, further research is needed to quantify fretting wear to optimize preload under coupled thermal–mechanical loading. Looking forward, this study suggests that future research should adopt a multidisciplinary approach, focusing on the development of cross-scale failure prediction models capable of capturing the evolution of micro-scale damage and its subsequent impact on the macro-scale dynamic response of bearing systems.

2.2.2. Failure Mechanism of Sealing System

The seal system plays a critical role in maintaining the integrity of the pressure boundary and preventing medium leakage in the main pump, and its failure directly threatens nuclear safety and environmental safety. Based on structural form, sealing failures can be divided into two categories: mechanical seal failures and packing seal failures [60–62].

- Mechanical seal failure: The mechanical seal is a critical component that forms a dynamic seal through contact between the rotating and stationary ring faces. Its failure primarily manifests as end-face wear, thermal cracking, and auxiliary system malfunction [63,64]. The predominant cause is dry running, where insufficient lubrication leads to a sudden increase in frictional heat at the sealing surfaces, resulting in thermoelastic instability, surface deformation, and the initiation of microcracks [52,61]. Shaft vibration further exacerbates the misalignment of the sealing surfaces, leading to localized contact stresses that exceed the material's yield limit and accelerate fatigue failure [46,65]. Antunović et al. [51] and Chittora [61] reported that the leakage from seal face clearances originates from the transmission of bearing vibration to the seal assemblies. Additionally, long-term operation can generate microcracks in sealing materials due to cyclic fatigue stress, leading to grease loss and a reduction in interface compression force, as observed by Berezhansky et al. [33]. Seal performance is particularly vulnerable under extreme conditions compared with conventional conditions. Lee et al. [46] demonstrated that during low-temperature start-up, the increased viscosity of sealing grease can result in dry friction at the seal interface, raising the wear rate by 40% compared with standard operating conditions.
- Packing seal failure mechanism: The sealing performance of packed glands relies on the axial compression force to induce radial expansion of the soft packing material, thereby filling the gap between the shaft and sleeve. However, the failure of such seals is often attributed to a combination of packing wear, thermal hardening, and stress relaxation [66]. Continuous friction between the packing and sleeve causes progressive material wear, enlarging the clearance and ultimately leading to leakage. Microscopic analysis by Bistriceanu et al. [65] revealed that aramid fiber packing subjected to cyclic loading experienced fiber fracture, resulting in a 12% reduction in sealing pressure. Furthermore, high-temperature conditions promote thermal hardening of the filler resin matrix, reducing its elastic deformability. Makay et al. [67] reported a 40% decrease in compression resilience in braided fillers above 120 °C, whereas metal foil fillers exhibited high-temperature resistance but caused increased journal wear. Additionally, relaxation of the bolt preload can cause uneven gland pressure, thereby inducing medium leakage along preferential paths within the packing layer. The nuclear main pump experiences thermal shock during a loss-of-coolant accident. Azarm et al. [68] demonstrated through a probabilistic model that vulcanized rubber hardens when the seal ring material's temperature gradient exceeds 200 °C/min, tripling the probability of elastic failure compared with normal conditions. Under high-pressure scenarios, Taylor [69] found that the Octagonal Gasket Flange relaxes due to the bolt temperature hysteresis, reducing the sealing compression force by

15–20%. Additionally, extreme pressure fluctuations expand the plastic deformation area of the gasket.

The two sealing types have advantages and disadvantages. Mechanical seals offer low leakage rates and long service life, but their complex structure leads to high maintenance costs, and the adoption of a double seal system increases expenses by up to 50%. In contrast, packing seals offer high fault tolerance and are easy to replace, but they suffer from poor high-temperature tolerance and require frequent preload adjustments. Recent studies have revealed several points of contention. Lee's work [46] suggests that lubricant purity is the key determinant of seal life, while Wong [70] attributes seal failure primarily to transient pressure shocks in nuclear main pumps. Phillips [71] emphasizes thermal deformation as the root cause of mechanical seal failure, whereas Chittora [61] claims the synergistic effects of vibration and wear as the dominant factor. The contrasting perspectives suggest that seal failure is best understood as a multi-field coupling instability involving mechanical, thermal, and chemical factors. Looking ahead, it is crucial to overcome limitations in material environmental adaptability and enhance the robustness of nuclear main pump sealing systems through intelligent monitoring approaches.

2.2.3. Failure Mechanism of Hydraulic Components

As the core energy conversion unit of the main pump (Reactor Coolant Pump, RCP), the hydraulic component converts mechanical energy into fluid kinetic energy, which directly affects the head, efficiency, and operational stability of the main pump. The impeller, guide vane, and wear ring are key components [72–74] most prone to failure.

- Impeller damage: The impeller's high-speed rotation propels the fluid, with its structural integrity crucial for maintaining head and efficiency. Common failures include blade fracture, cavitation, and wear. Bennekom et al. [75,76] identified casting defects as the primary cause of blade fractures. Zaman et al. [77] attributed cavitation mainly to bubble collapse in low-pressure regions impacting the blade surface. Zhou et al. [78] demonstrated that cavitation leads to impeller surface erosion and induces high-frequency impact vibrations, as revealed by vibration signal analysis. Numerical simulations by Gong et al. [79] indicated that the distribution of low-pressure regions is directly related to the geometry of the impeller inlet. Wang et al. [80] observed that during temperature transients, the cavitation erosion rate of PWR main pumps increases significantly, elevating the risk of seal failure. Tao and Li [81,82] highlighted that off-design operations, such as low load, can easily trigger flow separation and secondary flows, exacerbating hydraulic losses. For instance, under low-flow conditions, centrifugal pump outlet flow exhibits marked asymmetry, leading to head drop and the formation of a hump characteristic. Concurrently, Przybyla et al. [83] demonstrated that leading-edge wear results from foreign body impact or erosion by solid–liquid two-phase flow, as evidenced by aviation compressor impeller notch analysis. A central debate concerns the universality of cavitation prediction models. Wu et al. [84] argued that existing models lack adaptability to multiphase flow conditions and fail to capture the microscopic fatigue characteristics of materials.
- Guide vane failure: Guide vanes are essential fluid machinery components, serving to rectify flow and reduce vortex losses. The adjustment of their opening significantly affects pump efficiency and stability. Common issues associated with guide vanes include wear, deformation, and flow-induced vibration [85,86]. Wear is primarily caused by particle-laden fluid scouring [87], while deformation mainly results from fatigue accumulation [50] under high-frequency eddy loading. Visual experiments conducted by Song et al. [87] demonstrated that the wear rate of guide vanes increased with greater opening, and the maximum wear area is located on the blade pressure

surface, showing a positive correlation with fluid sediment concentration. Wang et al. [50] highlighted that high-frequency whirl in water-lubricated guide bearings can be transmitted to the guide vanes, inducing resonance and accelerating structural fatigue. Two-dimensional holography has demonstrated that the vertical rotation axis of a vertical Reactor Coolant Pump is lubricated by high-pressure water, which can lead to water film whirl faults. The characteristic frequency of this whirl is 0.48 times the power frequency, and the whirl amplitude can exceed 50%. Under normal conditions, the water film vortex can be suppressed by damping forces [88,89], but in extreme environments, the coupling of random fluid disturbance forces with the system's natural frequency can readily induce resonance instability [89–91].

- Wear of the mouth ring: Wear leads to increased clearance, diminishing efficiency and amplifying vibration [92]. Primary causes of wear include material mismatch in friction pairs and particle invasion [84]. Wu et al. [84,93] demonstrated via experiments and simulations that increasing front ring wear clearance from 0.2 mm to 0.5 mm results in a 12% decrease in pump head and a 150% increase in vibration velocity. DEM–CFD coupling simulations indicated a significant rise in flow field turbulence post-wear. Li et al. [94] noted that the uneven distribution of the self-lubricating phase in 1Cr13 MoS steel rings causes abrupt local friction coefficient changes, accelerating wear. Bonet-Jara et al. [95] developed a dynamic model of end-ring wear, employing the Runge-Kutta method to solve the rotor circuit equation, enabling real-time simulation of wear resistance changes for the first time. They observed that clearance enlargement exponentially decreases efficiency while linearly increasing vibration. Front ring wear reduces lift, whereas rear ring wear exacerbates vibration. Controversies exist in material selection: high-hardness alloys resist wear but are susceptible to stress corrosion cracking, while self-lubricating composites are expensive and last under 10,000 h [44,96]. Maintenance priorities also vary; for instance, FMEA analysis ranks ring wear as low risk, yet experimental evidence indicates it can lead to interlocking bearing failures [97,98].

Over the past decade, research on hydraulic component failure has increasingly adopted a multidisciplinary perspective. Wu and Huang [99] proposed an ensemble empirical mode decomposition (EEMD) method for analyzing non-stationary vibration signals, while Li et al. [93] quantified particle wear using a Computational Fluid Dynamics (CFD) and Discrete Element Method (DEM) coupled model. A common finding across these studies is that impeller cavitation, guide vane erosion, and mouth ring wear are strongly correlated with fluid–solid coupling effects. Surface modification can delay component failure, but it may alter fatigue crack propagation paths. However, current models are mostly calibrated under specific operating conditions and face challenges in generalizing to multiphase flows containing particles or gas. Furthermore, although Failure Mode and Effects Analysis (FMEA) suggests that the mouth ring wear risk is the lowest, experimental evidence demonstrates that vibration from this component can lead to chain damage in the bearing. The failure mechanism of hydraulic components is shifting from single-component analysis to system-level fluid–solid coupling modeling. Nonetheless, critical challenges remain, including understanding material interface behavior, ensuring adaptability to multiphase flow conditions, and developing intelligent operation and maintenance strategies.

2.2.4. Rotor Dynamic Fault

The rotor system is the core power transmission component of the Reactor Coolant Pump (RCP), and its dynamic behavior directly affects the stability and reliability of the system. Rotor dynamic failure is mainly governed by three kinds of mechanisms: critical speed, unbalance response, and fluid-induced instability. Systematic analysis of their causes and evolution requires a combination of theoretical modeling and experimental studies [100–103].

- Critical speed: The natural frequency of the rotor system and its rotation frequency can coincide at a specific speed, leading to resonance upon even minor excitation and resulting in a surge in amplitude [104,105]. The classical theory developed by Jeffcott [100] elucidates the abrupt changes in amplitude exhibited by rotors near the critical speed. The Jeffcott rotor model is a single-disk symmetric rotor, and its motion can be described by the following differential equations:

$$m\ddot{x} + c\dot{x} + kx = me\omega^2 cos(\omega t) \quad (1)$$

$$m\ddot{y} + c\dot{y} + ky = me\omega^2 \sin(\omega t) - mg \quad (2)$$

where m is the rotor mass, c is the damping coefficient, k is the bearing stiffness, e is the mass eccentricity, and ω is the rotational angular velocity. The solution shows that resonance occurs when $\omega_{cr} = \omega_n = \sqrt{k/m}$, and at the critical speed, the theoretical amplitude approaches infinity. Over the past decade, research has focused on the correction of complex boundary conditions. Furthermore, Zhang [106] demonstrated through a multi-field coupling model that thermal expansion of materials under high-temperature and high-pressure conditions can reduce the critical speed, while nonlinear variations in bearing stiffness can broaden the critical speed range. Comparative findings by Pennacchi et al. [107] focused on experimental validation, capturing bifurcation phenomena of axis trajectories through high-speed cameras. In contrast, research [106] preferred finite element method (FEM) simulations, which are computationally efficient but neglect turbulence effects. Controversies remain regarding damping quantification. The Muszynska model [108] assumed linear damping, whereas Wilkening [3], based on the case of nuclear power main pumps, demonstrated that fluid damping exhibits strong velocity dependence, necessitating the introduction of a nonlinear term correction. The limitation of current models lies in their inability to accurately characterize the transient over-critical process, along with the neglect of material creep effect under high-temperature environments, as highlighted in the separation margin design criterion [97,106] of the international standard API 610 [109]. Accurate prediction of critical velocity requires consideration of geometric nonlinearity, sealing effects, and thermal deformation, but the computational cost of high-fidelity models restricts real-time application.
- Unbalance response: Rotor mass eccentricity is a common source of excitation, and the corresponding response amplitude increases nonlinearly with rotational speed [110]. Lee et al. [111] demonstrated through a rotor–ball bearing system model that angular misalignment amplifies the unbalanced force, leading to a degeneration of the axis trajectory from an ellipse to a straight line. Recent progress in the field is reflected in the analysis of multi-fault coupling. Wang et al. [112] established a rotor model for a turbocharger, revealing that when imbalance and friction are coupled, the spectrum is dominated by the first-order harmonic (1×, corresponding to the rotation frequency), and the axis track exhibits a "0" pattern. Conversely, if the superposition is not centered, second-order harmonics (2×) are excited, and the track distortion resembles an "8" pattern. Methodologically, there are significant differences among

approaches. The lumped parameter method employed by Lee et al. [111] is computationally straightforward but limited in accuracy, while the method by Marscher et al. [97] extracts parameters from field vibration data, which is more representative of engineering practice but constrained by sensor layout. Active balancing devices offer superior efficiency compared to passive dampers, though they require precise installation. While laser dynamic balancing is cost-effective, it has a dynamic error margin of ±15% [112]. Ma et al. [113] introduced a flexible coupling–rotor system model that first quantifies the fluid inertia effect due to misalignment, yet it fails to address force transfer lag in multiphase flow media. Typically, unbalance diagnosis relies on vibration signals; however, the enclosed structure of the main pump restricts sensor placement, and fluid noise often masks power-frequency components, complicating accurate fault detection.

- Fluid-induced instability: Fluid-induced instability is primarily characterized by self-excited vibrations resulting from the interaction between fluid excitation forces and rotor motion, often manifesting as half-frequency whirl or whip. This phenomenon arises from a positive feedback loop caused by the phase difference between the fluid dynamic pressure field and rotor displacement. Instability occurs when high-pressure fluid generates an asymmetric pressure distribution within the bearing clearance or impeller seal, aligning the resultant force with the rotor's whirl direction [114,115]. Wang et al. [50] demonstrated, in the context of a nuclear main pump, that a 15.4 MPa high-pressure water flow induces a radial pressure gradient in the bearing gap. Changes in vortex displacement alter the clearance geometry, causing the fluid dynamic pressure field to amplify vortex amplitude, thus perpetuating a cycle of self-excited vibration. This effect is particularly pronounced in water-lubricated bearings, where water's low viscosity results in insufficient damping and ability to suppress the accumulation of eddy energy. Additionally, research has increasingly examined turbulence nonlinearity and the instability threshold. The classical half-speed vortex theory, which assumes a constant vortex ratio of 0.5, is notably weakened by turbulence effects. Zhai et al. [116] demonstrated via vertical rotor tests that turbulence in slotted bearings reduces the swirl ratio to 0.42–0.48, consistent with the 0.48 frequency-doubling characteristic measured in nuclear main pumps. This occurs because turbulence increases the fluid's equivalent mass, thereby altering the system's natural frequency. Additionally, Pennacchi et al. [107] found that misalignment decreases the instability threshold by 30% due to exacerbated pressure field inhomogeneities from geometric deviations. A central debate in fluid-induced instability concerns fluid excitation forces: the traditional Reynolds equation neglects inertia forces, leading to significant errors at high speeds [3]. In contrast, the CFD full model by Gao et al. [117] offers high accuracy but requires over 100 times the computational resources of the simplified model, severely limiting its applicability for real-time monitoring.

Current research on rotor dynamics failure mechanisms shows a dual trend of "model refinement" and "experimental validation". However, theoretical progress remains constrained by the complexities of multi-field coupling and bottlenecks in the manufacturing process. Over the next decade, research priorities should include intelligent algorithm-driven modeling, multi-scale coupling mechanism analysis, and the integration of active control technologies. This approach aims to establish a comprehensive technical framework with transparent mechanisms, precise predictions, and active control, ultimately supporting the 10,000-h fault-free operation of main pump systems.

According to previous studies, the most common main pump system failures are mechanical seal leakage and rolling bearing damage (Figure 1). A second frequent failure mode is impeller damage caused by fluid stress. Based on the above analysis, Table 1 summarizes the major failures of the main pump system and ranks the severity of each failure according to the proportion of occurrence of the failure, the impact of the failure on system performance, the degree of damage caused to the system by the failure, and recoverability.

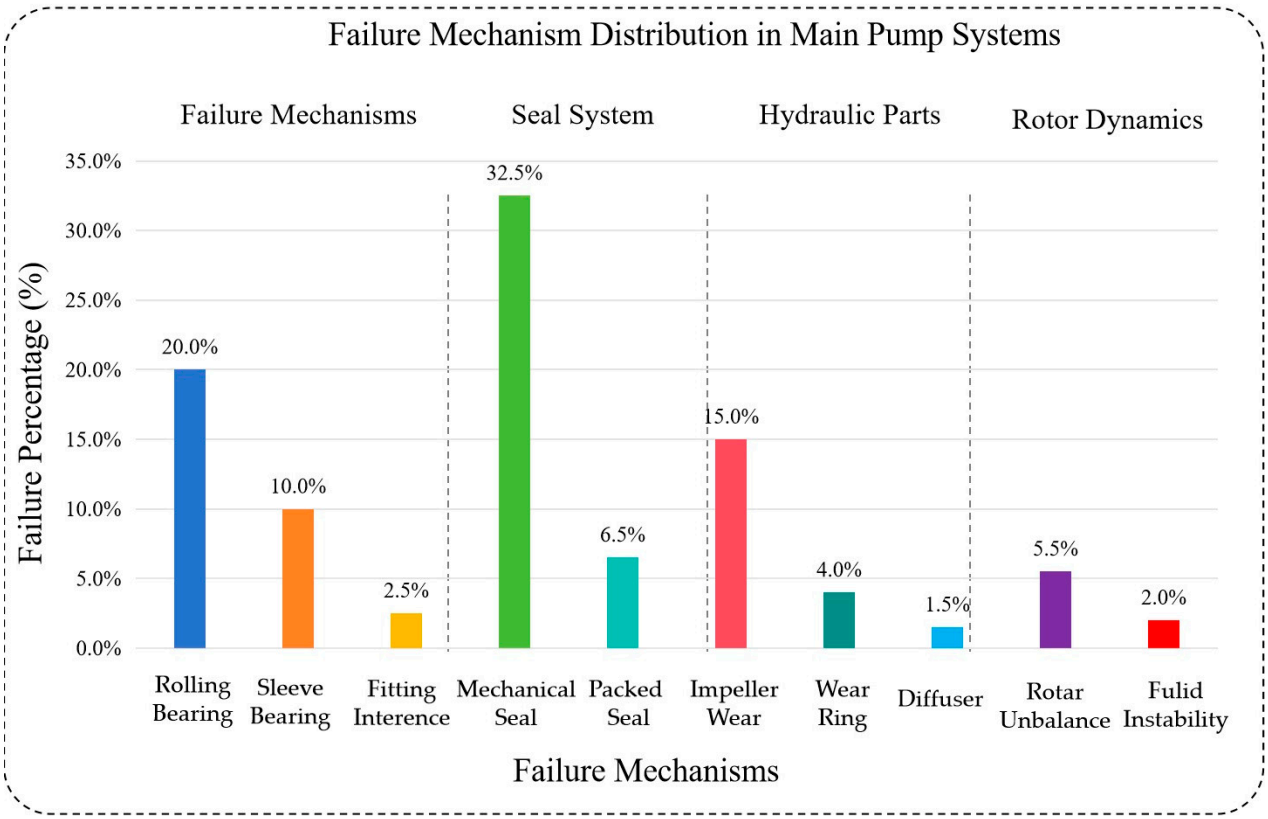


Figure 1. Types of main pump system failure [118].

Table 1. Summary of the main faults of main pump systems.

Component Category	Specific Component	Fault Causes	Impact	Severity Level
Bearing System	Rolling Bearings	Lubrication contamination (water/particles in oil), overheating (improper oil level/poor oil quality), misalignment, and fatigue wear.	Increased vibration, elevated noise levels, and temperature rise, leading to shaft damage or seizure.	High
	Plain Bearings	Oil whirl, journal/bearing friction, and insufficient lubrication.	Oil film failure and direct metal contact, causing high temperature and vibration.	High
	Fitted Interfaces	Shaft wear (corrosion/imbalance) and installation stress.	Increased clearance, exacerbating vibration and seal failure.	Medium
Sealing System	Mechanical Seals	Dry running, vibration, seal face wear, shaft vibration, and insufficient lubrication.	Medium leakage (e.g., glue solution), flushing phenomena, and pressure/flow reduction.	High
	Packed Seals	Vibration, foreign material blockage, and wear.	Reduced rotational speed, increased leakage, and decreased pump efficiency.	Medium

Table 1. *Cont.*

Component Category	Specific Component	Fault Causes	Impact	Severity Level
Hydraulic Components	Impeller	Cavitation (inlet pressure < saturation vapor pressure), wear (impurities/prolonged operation), blockage, and reverse installation.	Efficiency reduction, increased vibration/noise, unstable flow, and blade fracture.	High
	Guide Vanes	Wear and corrosion.	Hydraulic imbalance and flow channel blockage, exacerbating vibration.	Medium
	Wear Rings	Improper clearance (misalignment/wear) and dirty medium.	Increased internal leakage and reduced volumetric efficiency.	Medium
Rotor Dynamics	Critical Speed	Rotor resonance (design defects/deposits) and loose baseplate.	Sudden increase in amplitude, causing bearing/seal damage.	High
	Unbalance Response	Impeller imbalance, shaft bending, coupling wear, and piping stress.	Periodic vibration, inducing mechanical fatigue and component loosening.	High
	Fluid-Induced Instability	Cavitation, vortex shedding, and hydraulic excitation.	Low-frequency vibration and flow pulsation, potentially triggering structural resonance.	Medium

3. Fault Diagnosis Methods for Main Pump Systems

Fault diagnosis of main pumps is an engineering necessity to balance the three core objectives of safety, economy, and reliability. The process generally includes fault detection, identification, and location [119]. Fault detection involves comparing online measurement data with expected values to determine whether system equipment or component faults exist, and fault identification aims to accurately and quickly classify fault types. It should not only have the ability to distinguish genuine faults from non-fault disturbances and reduce false fault alarms, but also accurately identify various potential fault types to provide a decision-making basis for fault-tolerant control. Subsequently, fault location is required to pinpoint the specific fault position, thereby supporting subsequent maintenance. Effective fault diagnosis methods can significantly improve operational reliability and reduce maintenance costs. According to different diagnosis principles, they can be divided into signal processing-based methods, artificial intelligence and data-driven methods, multi-source information fusion-based methods, and knowledge-based methods.

3.1. Methods Based on Signal Processing

Signal processing-based fault diagnosis identifies and classifies faults by analyzing physical signals from equipment operation and extracting fault-related features [10,120,121]. As illustrated in Figure 2, this method relies on the principle that faults induce detectable changes in the statistical, frequency–domain, or time–frequency characteristics of operational signals. Techniques such as signal transformation, noise reduction, and feature extraction enhance the distinction between faulty and normal states, forming the basis for diagnosis [4,7,122]. The effectiveness of this method depends on three factors: signal quality, feature sensitivity, and noise suppression capability. Commonly employed analysis techniques include time–frequency analysis, signal decomposition and reconstruction, nonlinear signal processing, and physical characteristic demodulation. The subsequent sections elaborate on the application of these techniques in diagnosing faults in main pump systems.

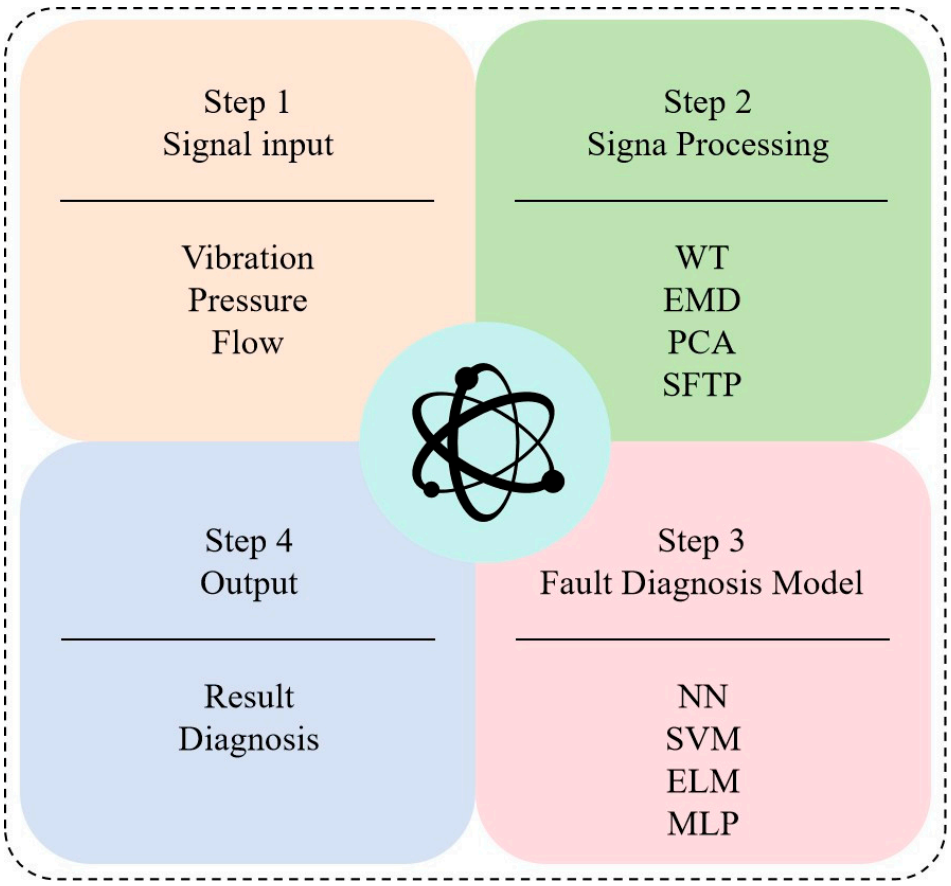


Figure 2. Flow chart of the fault diagnosis method based on signal processing [2].

3.1.1. Time–Frequency Domain Analysis Techniques

The core principle of time–frequency domain analysis for fault diagnosis is to capture the transient and harmonic components of non-stationary signals by jointly analyzing their temporal and spectral characteristics. This approach is particularly well-suited for diagnosing faults in rotating components of main pump systems, as their fault signatures often manifest as periodic modulation signals [123,124]. The effectiveness of time–frequency domain analysis has been extensively validated in the context of main pump fault diagnosis. Key differences among technical approaches proposed by various research teams lie in the signal processing strategy and feature fusion level. Traditional methods often struggle to adapt to variable-speed operating conditions of main pumps due to their fixed time–frequency resolution. At the feature fusion level, emphasis is placed on leveraging complementary information from multiple sensors to overcome the limitations of single-sensor data. Yang et al. [4,125,126] highlighted the relationship between time–domain, frequency–domain, and time–frequency–domain analyses, emphasizing that time–frequency analysis can effectively monitor the dynamic evolution of faults, thereby aiding in piston pump fault diagnosis. Dai et al. [7] demonstrated that wavelet packet decomposition can successfully isolate fault characteristic bands amid noise, such as weak shock signals indicative of hydraulic pump ball head loosening. Chao and Kamiel et al. [127,128] enhanced diagnostic robustness by integrating wavelet denoising with principal component analysis through vibration/pressure dual-sensor feature fusion. Zhu et al. [6] addressed the modal aliasing issue in nuclear main pump sliding bearing–rotor systems by replacing empirical modal decomposition with variational modal decomposition, significantly boosting decomposition efficiency. The core idea of VMD is to decompose the original signal $f(t)$ into K modal functions $u_k(t)$ (intrinsic modal functions, IMFs) with central frequencies ω_k, which is

achieved by solving a constrained variational problem. This problem aims to minimize the sum of estimated bandwidths of all modes while ensuring that the sum of all mode functions equals the original signal [129]. Specifically, the constrained variational problem is defined as follows:

$$\begin{gathered}\min_{\{u_k\},\{\omega_k\}} \left\{ \sum_{k=1}^{K} \| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \|_2^2 \right\} \\ \text{subject|to} \quad \sum_{k=1}^{K} u_k = f,\end{gathered} \tag{3}$$

where $\{u_k\} = \{u_1, u_2, \ldots, u_K\}$ is the decomposed K modes (IMF), each mode having a finite bandwidth and a central frequency, $\{\omega_k\} = \{\omega_1, \omega_2, \ldots, \omega_K\}$ is the center frequency of each mode, ∂_t stands for the partial derivative (i.e., time derivative), $\delta(t)$ is the Dirac function $*$ stands for the convolution operation, j is the imaginary unit, and $e^{-j\omega_k t}$ is the exponential term used for frequency modulation. Wang et al. [130] developed 16-dimensional eigenvectors across time, frequency, and time–frequency domains, employing kernel principal component analysis to reduce dimensionality and achieve precise identification of hydraulic pump composite faults. However, it is crucial to note that while time–frequency domain techniques excel in resolving non-stationary signals, extreme conditions such as high-radiation environments can cause sensor signal drift, and strong vibration background noise can lower the signal-to-noise ratio, leading to increased computational complexity and implementation challenges.

3.1.2. Signal Decomposition and Reconstruction Methods

In main pump fault diagnosis methods based on signal processing, signal decomposition and reconstruction techniques can detect early weak faults by separating fault characteristic components from complex signals [4,39]. Empirical mode decomposition (EMD) and singular value decomposition (SVD) are two core methods. The EMD method does not need preset basis functions and is suitable for nonlinear feature extraction from main pump vibration signals. SVD reconstructs the signal by retaining dominant singular values, so as to extract the main feature components in the signal and suppress noise [131,132]. Du et al. [133] introduced a hierarchical clustering method that integrates IMF energy entropy characteristics post-EMD decomposition to classify multiple faults in hydraulic piston pumps. Lan et al. [134] employed an Extreme Learning Machine (ELM) to intelligently identify IMF features derived from EMD, enhancing the efficiency of swashplate wear diagnosis. Liu et al. [132] developed an improved singularity analysis using the least-squares method, significantly boosting robustness in locating pump valve spring faults. Miao et al. [135] addressed the issue of sample scarcity in seawater hydraulic pumps by combining SVD with transfer learning, leveraging singular value feature transfer for fault knowledge across varying conditions. Yang et al. [136] assessed the noise reduction effects of VMD, EEMD, and ALIF, establishing that variational modal decomposition (VMD) offers superior noise suppression in hydraulic pump vibration signal processing. Dai et al. [7] highlighted the complementary nature of SVD and EMD, where SVD aids in noise reduction and EMD supports decomposition, thereby enhancing feature extraction reliability.

The main advantage of signal decomposition and reconstruction lies in its ability to isolate fault characteristics from a noisy background. Comparing the methods, SVD involves complex, large-matrix operations, whereas EMD is time-consuming due to its iterative process. EMD is adept at handling non-stationary signals but is susceptible to endpoint effects. SVD demands wavelet threshold pretreatment to enhance robustness in noisy environments. Both approaches depend on high-quality sensor data, yet the challenging conditions of the main pump often cause signal distortion, limiting the generalization

ability of existing methods with poor data quality [4]. A single method also struggles to address multi-fault coupling scenarios. Future research should focus on adaptive parameter optimization, multi-physical signal fusion, and the integration of mechanism-based models to improve interpretability.

3.1.3. Nonlinear Signal Processing Methods

Nonlinear signal processing method mainly aimed at fault characteristics caused by the nonlinear dynamics behavior of main pump systems, and fault diagnosis is achieved by capturing non-stationarity and complex coupling relationships within signals [137,138]. The core of this method is to use mathematical tools to analyze the geometric structure or higher-order statistical characteristics of signals directly, avoiding the limitations of linear models. Mathematical Morphology (MM) and Higher-Order Spectral Analysis (HOSA) are two representative methods.

Morphological signal processing, grounded in set theory and integral geometry, employs structural elements to expand, erode, open, and close signals, thereby extracting their geometric features. This approach is particularly sensitive to impulse-type faults. Čdina and Swelam [139,140] utilized a morphological filter to isolate a 147 Hz discrete frequency component from the noise spectrum for diagnosing cavitation faults in centrifugal pumps, successfully detecting characteristic frequency shifts in early cavitation stages. Notably, Jiang et al. [141,142] advanced this by integrating morphology with wavelet denoising, achieving weak-fault diagnosis of hydraulic pump ball head loosening through morphological fusion of vibration and pressure signals, with an accuracy exceeding 92%.

Higher-Order Spectral Analysis techniques, such as bispectrum and third-order cumulant analysis, can effectively suppress Gaussian noise and preserve nonlinear signal characteristics, making them particularly suitable for diagnosing faults associated with nonlinear resonance, including main pump cavitation and rotor misalignment [9]. For instance, Xue et al. [143] applied bispectrum analysis to centrifugal pump vibration signals, combined with a Support Vector Machine classifier, to identify cavitation and impeller imbalance faults with an accuracy 15% higher than traditional Fourier transform-based methods. Furthermore, Wang et al. [50,144] utilized two-dimensional holographic spectrum and time–frequency analysis to reveal the nonlinear relationship between whirl frequency and bearing lubrication pressure for water film whirl faults in nuclear main pumps, thereby providing a theoretical basis for vertical rotor fault diagnosis.

In summary, comparative performance analysis shows that the advantages of morphological signal processing lie in high computational efficiency and strong noise immunity, which are suitable for real-time monitoring, while high-order spectral analysis excels at revealing phase-coupling mechanism in nonlinear systems and has strong separation ability for composite faults. Although morphological signal processing has excellent stability under strong noise conditions, it requires a strict signal sampling rate; although high-order spectral analysis can suppress noise, it is difficult to embed portable equipment due to high computational complexity. The phase-coupling characteristics revealed by higher-order spectra depend on expert interpretation, while morphological characteristics are more intuitive, but the implicit information in the frequency domain may be overlooked. Future research should aim to overcome the limitation of single-physical-signal approaches and improve diagnostic completeness through vibration-acoustic emission-pressure multi-source heterogeneous signal fusion.

3.1.4. Physical Feature Demodulation Method

The physical feature demodulation method realizes diagnosis by extracting modulated signal features caused by faults, among which Envelope Analysis and Resonance Demodulation Technique are two core methods [145]. Envelope analysis is based on the characteristics of high-frequency resonance excited by the local imperfection impact. When bearings, gears, and other parts are damaged, periodic impacts modulate the high-frequency resonance signal, forming an amplitude modulation phenomenon. This method first extracts high-frequency components within the resonance frequency band using band-pass filtering, then demodulates the signal envelope via Hilbert transform, and finally identifies fault characteristic frequency [146,147] through spectral analysis. The Hilbert transform is used to calculate the analytic signal, thereby extracting the instantaneous amplitude and phase. For a real signal $x(t)$, its Hilbert transform $H[x(t)]$ is defined as follows:

$$H[x(t)] = \frac{1}{\pi}\text{p.v.}\int_{-\infty}^{\infty}\frac{x(\tau)}{t-\tau}d\tau, \tag{4}$$

where p.v. denotes Cauchy principal value, used to deal with integral singularities. The envelope signal $A(t)$ (instantaneous amplitude) is given by the modulus of the analytic signal:

$$A(t) = \sqrt{x^2(t) + (H[x(t)])^2} = |z(t)|. \tag{5}$$

The envelope spectrum obtained by performing a Fourier transform on the envelope signal $A(t)$ can clearly show the fault characteristic frequencies and their harmonics, so as to realize accurate diagnosis of bearings, gears, and other components. Resonance demodulation technology is further combined with variational modal decomposition and other adaptive decomposition methods to optimize the selection of resonance bands and enhance the ability of feature extraction in noisy environments [147].

Envelope analysis is a prevalent technique for detecting bearing faults in nuclear main pumps. Adams et al. [146,148,149] demonstrated its effectiveness in diagnosing bearing spalling in coolant pumps at nuclear power plants, successfully isolating fault shock signals from background noise. Resonance demodulation excels in high-noise environments: Zhang et al. [150] integrated VMD parameter optimization with resonance demodulation to precisely extract fault frequencies from locomotive bearing vibrations, significantly enhancing diagnostic accuracy over traditional methods. While Adams [146] relied on manual experience to select fixed frequency bands, Leite et al. [147] employed spectral kurtosis adaptation for frequency band optimization, albeit with increased computational complexity. Zhang et al. [150] utilized information entropy to quantify signal sparsity and adaptively adjust the demodulation interval, overcoming the susceptibility of traditional methods to non-stationary noise interference. Zhu and Han et al. [6,151] noted that single demodulation techniques lack sufficient separation capability for concurrent faults, necessitating integration with deep learning. Envelope analysis approach offers the advantages of straightforward implementation and cost-effectiveness, but it is sensitive to the selection of the resonance frequency band and exhibits limited environmental adaptability. In contrast, resonance demodulation enhances robustness through adaptive decomposition, yet it requires greater computational resources and faces challenges in real-time deployment. Physical feature demodulation technology improves diagnostic accuracy through continuous integration of intelligent algorithms, but it must overcome bottlenecks in extreme environmental adaptability and real-time performance before it can be widely applied to critical equipment such as nuclear main pumps.

3.1.5. Special Consideration for Signal Processing Methods in the Fault Diagnosis of Main Pumps

While signal processing technologies are widely applicable, their effective use in main pump fault diagnosis requires adaptation to the system's unique structure and operational conditions [152]. Vibration signals are the preferred choice for detecting bearing and rotor system failures in main pumps due to their sensitivity to mechanical shocks, especially given the high bearing failure rate [153]. Conversely, for identifying seal failures and internal leakage faults, signals such as outlet pressure pulsations and motor currents may offer richer fault information, directly impacting hydraulic performance rather than causing immediate severe vibrations [154]. In centrifugal main pumps, the modulation of impeller and guide vane passing frequency, shaft frequency, and their harmonics by bearing fault characteristic frequencies results in a complex sideband structure [155]. Careful discrimination is required during demodulation analysis to prevent misinterpretation. For instance, the reciprocating frequency of a piston pump's piston serves as a significant source of background interference. Moreover, main pumps operate in harsh environments characterized by hydrodynamic noise and electromagnetic interference, making the noise reduction step in the diagnostic workflow (Figure 2) essential. Advanced techniques like adaptive VMD or optimized resonance demodulation, as opposed to basic filtering, are necessary to isolate subtle early fault indicators from signals with low signal-to-noise ratios. Equipment like nuclear main pumps typically operates under stable conditions, producing relatively consistent signals. However, variations in speed and load, as seen in main pumps like ship pumps under different operational circumstances, can introduce indistinct characteristic frequencies. Addressing this necessitates enhanced time–frequency analysis resolution or order ratio analysis to mitigate the impact of speed fluctuations.

Despite their proven engineering effectiveness, signal processing-based methods remain highly dependent on prior knowledge and a precise understanding of signal characteristics. However, their performance is notably limited within the intricate operational environment of the main pump. Primarily, techniques like wavelet transform and VMD necessitate manual configuration of critical parameters (e.g., basis function, scale, and mode number K), directly impacting feature extraction and fault identification, and lacking adaptability. Consequently, the performance of algorithms with fixed parameters can significantly fluctuate under varying main pump operating conditions. Moreover, these methods predominantly involve shallow feature engineering, impeding automated learning of intricate nonlinear relationships between fault features and conditions, thereby exhibiting restricted resilience to complex faults and substantial background noise. Given that main pump faults often entail multi-mode coupling (e.g., rotor misalignment due to bearing wear), traditional signal processing methods face limitations in addressing such complexities. Lastly, signal processing heavily relies on high-quality sensor data with high signal-to-noise ratios. In real-world main pump operations under extreme conditions like high temperatures, intense vibrations, and electromagnetic interferences, signals are susceptible to distortion and weakening, rendering the method ineffective. As a result, there are significant upper limits to their diagnostic performance, often combined with model-based or data-driven approaches to improve reliability.

3.2. Model-Based Approach

The core diagnostic principle of model-based methods is to construct an accurate mathematical model of the system and compare the model output with actual monitoring signals (residuals) to achieve fault detection and isolation [156,157]. As shown in Figure 3, this approach relies on a deep understanding of the system's dynamic charac-

teristics. It describes the physical behavior of the main pump in the healthy state using mathematical equations and identifies faults when the actual system output deviates from the predicted model values [4,6,158]. The key factors in this diagnostic process include three aspects [7,159]: (1) the model must be sufficiently accurate to capture nonlinear system dynamics, particularly the effects of temperature and pressure variations under extreme operating conditions; (2) the feature generation step must effectively extract fault-sensitive information from the residual; (3) the mapping between symptoms and faults must cover all possible fault modes.

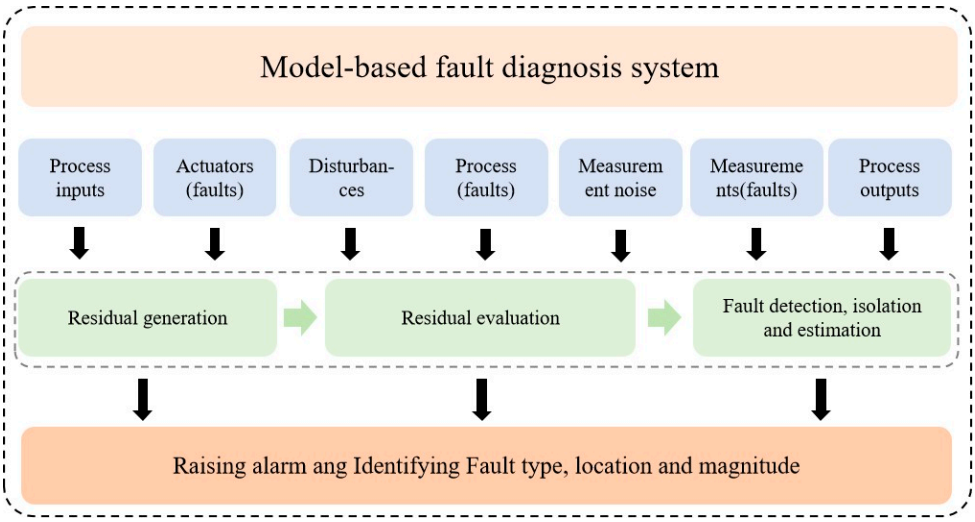


Figure 3. Model-based fault diagnosis method flow chart [160].

This kind of diagnosis begins with multi-source signal acquisition and preprocessing to eliminate noise interference. A mechanism model of the system in the non-fault state is then established, generating theoretical output values. Residual analysis produces fault symptoms by quantifying discrepancies between actual signals and model predictions. The location and classification of fault(s) are then determined based on predefined syndrome–fault association rules. The flowchart illustrating this fault diagnosis process is provided in Figure 3. Currently, there are three model-based methods: fault diagnosis using physical models, signal processing with feature extraction, and analytical redundancy-based model comparison. The following subsections provide a detailed overview of applying these three methods to diagnose faults in main pump systems.

3.2.1. Fault Diagnosis Methods Based on Physical Models

The fault diagnosis method based on physical model simulates the operating mechanism of the main pump by constructing an accurate system dynamics model and detecting faults through residual analysis of the model output and actual signals [161]. Its key advantage lies in reducing the dependence on a large number of fault data, especially in scenarios where fault samples are scarce under extreme conditions [4,14,162]. The core of the physical model-based approach is to construct a mathematical model M of the system and use the residual $\mathrm{r}(t)$, defined as the difference between the actual output and the model-predicted output, for fault diagnosis:

$$\mathrm{r}(t) = \mathrm{y}_m(t) - \mathrm{y}_M(t), \tag{6}$$

where $\mathbf{y}_m(t)$ is the actual output vector of the system measured by the sensor, and $\mathbf{y}_M(t)$ is the predicted output vector calculated by the model based on the system input $\mathrm{u}(t)$. Under fault-free conditions, the residual $\mathbf{r}(t)$ should approach zero; when a system fault occurs, the residual deviates significantly from zero, and its size and characteristics reflect

the type and severity of the fault. This section focuses on three typical methods: Bond Graph Modeling, Variable Predictive Models, and Nonlinear Frequency Response Analysis, systematically outlining their principles, applications, and limitations.

The dynamic behavior of multi-domain physical systems can be described using bond graph modeling, which represents energy flow and establishes the mathematical model of energy transfer paths through state equations. Fault diagnosis can be achieved by monitoring energy flow anomalies at critical nodes. Zhu [6] observed that an increase in the clearance between the piston ball and slipper leads to a sudden change in energy dissipation, and loose slipper faults were identified by comparing deviations between model predictions and measured power flow. Łatas et al. [162,163] developed a bond graph model for an axial piston pump and, by simulating torque fluctuations caused by swashplate wear, they successfully diagnosed slight wear faults of 10%, demonstrating the model's sensitivity to early faults. Gnepper et al. [163] further combined bond graph modeling with parameter estimation to improve the diagnostic accuracy of valve plate wear by adaptively updating model parameters. Bond graph modeling offers strong systematicity and the ability to characterize cross-domain coupling, making it particularly suitable for multi-physical field coupled main pump systems. However, the modeling process relies on precise physical parameters, and parameter drift can easily lead to model misalignment in extreme environments. Additionally, the real-time calculation requirements of complex models are high, which can make it challenging to meet the needs of online diagnosis.

The variable prediction model leverages physical constraint relationships among system state variables to detect failures via residual statistical analysis. Dai [7] employed the Bernoulli equation to monitor abnormal leakage flow and the moment balance equation to diagnose bearing eccentricity faults. Tang et al. [164] developed a variable prediction model for slipper looseness under variable load conditions, identifying early faults obscured by load fluctuations through residuals of pressure-flow coupling equations, achieving a diagnostic accuracy of 92%. Gnepper et al. [163] introduced a multi-layer diagnostic framework: the first layer detects leaks through pressure spectrum analysis, and the second layer combines leakage flow and vibration signals to pinpoint faulty components, significantly enhancing the identification rate of cavitation erosion in axial piston pumps. Compared to bond graph methods, the variable prediction model offers greater computational efficiency and engineering applicability, though it depends on expert knowledge to formulate constraint equations. Debates concerning model robustness persist: Zhu et al. [6] argued for dynamic adjustments of constraint equations under various operating conditions, while Yang et al. [4] proposed managing parameter uncertainty through fuzzy logic.

The nonlinear dynamics of the main pump produce harmonic components under certain excitations, allowing fault detection through analysis of high-order harmonic amplitudes and phase offsets in the system's frequency response function (FRF). Harris et al. [165,166] highlighted that slipper wear causes a nonlinear increase in the stiffness of the swashplate–slipper pair, significantly boosting the energy of the second harmonic. Lan et al. [134,167] employed swept-frequency excitation to provoke a nonlinear response in axial piston pumps, diagnosing wear by detecting an increase in energy entropy within the characteristic frequency band (3 to 5 times the fundamental frequency), enhancing diagnostic accuracy by 15% over traditional vibration analysis. The Enge-Rosenblatt team [163] and Guo et al. [168] integrate chaos theory with frequency response, utilizing the Lyapunov exponent to quantify system nonlinearity, enabling differential diagnosis of loose slippers and bearing failures. While this method is highly sensitive to early weak nonlinear faults, it requires a specialized excitation device, posing challenges in closed main pump systems. Additionally, extreme environmental conditions may degrade the signal-to-noise ratio, potentially leading to harmonic annihilation.

3.2.2. Model Methods Based on Signal Processing and Feature Extraction

The model method based on signal processing and feature extraction identifies fault modes by analyzing multi-source signals from the main pump system operation and extracting nonlinear features. Its core principle is to employ signal processing techniques to capture weak fault-induced feature variations and integrate intelligent algorithms for classification and diagnosis [121]. This section focuses on three typical methods: Nonlinear Output Frequency Response Functions (NOFRFs), Fuzzy Entropy (FE) and Hierarchical Fuzzy Entropy (HFE), and Symbolic Perceptually Important Points (SPIPs) and Hidden Markov Models (HMMs).

NOFRF captures dynamic changes induced by faults by mapping the nonlinear frequency-domain relationship between system inputs and outputs. The diagnostic principle posits that a main pump fault alters the system's nonlinear stiffness or damping, leading to abnormal energy distribution in specific frequency bands of the NOFRF amplitude spectrum. In practice, Ma et al. [169] designed a nonlinear unknown input observer to detect swashplate wear in hydraulic pumps. By integrating NOFRF to extract frequency-domain characteristics from pressure signals, they achieved early detection of weak faults with a diagnostic accuracy of 92.3%. This method excels in modeling nonlinear systems, particularly for isolating faults under complex conditions such as varying speeds and loads. Zhu et al. [6] noted that combining NOFRFs with Volterra series enhances diagnostic accuracy under variable load conditions, though model order selection still relies on prior knowledge.

Fuzzy entropy characterizes the state of a system by measuring the complexity of a time series. The core of fuzzy entropy is to calculate the probability-based fuzzy membership degree of signal patterns. Hierarchical fuzzy entropy is further introduced into multi-scale analysis to extract deep fault features [170,171] from the vibration signal of the main pump. Wang and Chen et al. [172,173] integrated multi-source information fusion with fractal dimension and applied hierarchical fuzzy entropy to analyze IMF components of hydraulic pump vibration signals. This approach successfully identified sliding shoe wear and plunger stagnation faults, achieving a diagnosis accuracy approximately 10% higher than traditional methods. The method's strengths include robustness to noise and sensitivity to weak fault features, though it suffers from high computational complexity, limited real-time performance, and reliance on experiential parameter adjustments for scale factor selection [4]. Chen et al. [173] introduced the EMD–AR (empirical mode decomposition–auto regressive) model, which improved feature separability using fractal dimension. However, EMD faces the endpoint effect issue. Kamiel et al. [128] combined EWT–PCA (Empirical Wavelet Transform–Principal Component Analysis) to enhance feature stability.

The SPIP–HMM method reduces data dimensionality through symbolic compression technology and achieves fault classification by leveraging the dynamic time-series modeling capabilities of Hidden Markov Models (HMMs). Initially, key inflection points of the original signal are extracted using Perceptually Important Points (PIPs), preserving the primary waveform structure. Subsequently, the PIP sequence is transformed into a symbol sequence by optimizing the symbol space partition using a genetic algorithm. Finally, the transition probabilities of the symbol sequence are modeled via the HMM, and the fault state is determined through the likelihood ratio. Ramasso [174] introduced belief functions to construct an Evidential Hidden Markov Model (EvHMM) framework, which reduced the false alarm rate by delaying decision-making and improved the accuracy rate by 12% in concurrent fault diagnosis of nuclear main pumps. Building upon this approach, Jia et al. [175] realized fault diagnosis of bearing damage and sliding shoe wear in hydraulic pumps, achieving an accuracy rate of 99.625% with only 0.025 s of signal data.

By fusing symbolic dimensionality reduction and probabilistic modeling, computational efficiency was significantly improved, particularly for short-time signal analysis. However, the symbolization process may lead to the loss of high-frequency detail information, and the Hidden Markov Model (HMM) is sensitive to initial parameters, necessitating optimization of the model training process using a clonal selection algorithm.

In summary, NOFRFs depend on the accuracy of physical models and are suited for straightforward failures with clear mechanisms. In contrast, FE/HFE emphasizes data-driven approaches and demonstrates strong generalization capabilities for complex nonlinear systems. SPIP–HMM balances modeling accuracy with data requirements but raises concerns about information loss during the symbolization process. While SPIP–HMM excels in computational efficiency and short-term signal diagnosis, NOFRFs demonstrate greater robustness in environments with strong noise. Although FE/HFE exhibits high feature sensitivity but is limited in real-time scenarios due to computational time.

3.2.3. Model Comparison Methods Based on Analytical Redundancy

The core diagnostic principle of the Analytical Redundancy-based Model Comparison is to detect faults by constructing mathematical models of system dynamics and analyzing the residuals between measurable variables and model outputs [176]. Specifically, this method generates a residual signal by comparing the deviation between the actual system output and the model prediction output, determining that a fault exists when the residual exceeds a predetermined threshold. Its primary advantage is that it does not require a large amount of historical fault data, enabling quantitative diagnosis of early faults. This method has been widely applied in the fault diagnosis of hydraulic systems, particularly in main pumps. Ma et al. [169,177] introduced a fault diagnosis method for hydraulic pumps using a nonlinear unknown input observer. By developing a dynamic pump model and designing an observer to produce residual errors, they successfully diagnosed leakage and efficiency degradation faults, demonstrating robustness against noise disturbances in experiments. Nonetheless, this method demands precise system parameters and is vulnerable to modeling inaccuracies. Tang et al. [164,178] developed a load-pressure coupling model to detect piston pump shoe loosening faults under variable load conditions. By comparing predicted and measured pressure values through analytical redundancy, they significantly enhanced fault detection sensitivity. However, this approach suffers from high computational complexity and limited real-time performance. Zhou [179] combined an analytical model with an expert system for fault diagnosis in reactor coolant systems, achieving online monitoring of the main pump rotor for medium-level faults.

In summary, the model comparison method based on analytical redundancy remains a primary approach for diagnosing main pumps due to its physical interpretability and sensitivity to early faults. However, it is essential to address its limitations in complex environments by integrating intelligent algorithm fusion and implementing online learning mechanisms.

3.2.4. Special Consideration for Model Methods in the Fault Diagnosis of Main Pumps

The model-based diagnosis paradigm holds a distinctive position in the realm of main pump fault diagnosis due to its profound physical insight and capacity to deduce conclusions without an extensive dataset of fault information. However, when transitioning from theory to the intricate domain of main pump analysis, this approach encounters a range of formidable engineering obstacles while also suggesting future developmental pathways. A main pump represents a complex electro-mechanical-hydraulic integrated system, making precise modeling of its mechanisms exceptionally challenging. Numerous physical parameters (e.g., clearance damping of friction pairs, fluid compressibility,

and component stiffness) must be meticulously determined during the establishment of a bond graph model or nonlinear dynamic model. These parameters are subjected to drift over time due to wear and corrosion during prolonged operation, leading to discrepancies between the model and the actual system, consequently triggering false alarms [180]. Hence, the pivotal aspect for enhancing diagnostic reliability lies in the advancement of online parameter identification technology, enabling the model to track equipment performance degradation and undergo adaptive updates. Moreover, every model inherently represents a simplification of the real system. Factors such as flow-induced vibration, inlet pressure fluctuations, load variations, and other unmodeled dynamics encountered by the main pump during operation can act as unknown inputs affecting the system, with the resulting residuals potentially being misconstrued as fault residuals, thus complicating the diagnostic decision-making process [181]. This is the significance of the nonlinear unknown input observer technique, which aims to distinguish fault effects from disturbance effects and improve the robustness of the model. The complex high-dimensional models designed for high-precision diagnosis impose substantial computational costs, limiting their suitability for real-time online applications. In practical engineering, balancing model accuracy with computational efficiency is crucial. A viable strategy is the adoption of a "digital twin" architecture, utilizing high-fidelity models in the cloud for in-depth analysis while deploying simplified or data-driven models at the edge for swift monitoring and diagnostics. Most model-based approaches are tailored for known, modelable failure modes. However, they often lack diagnostic capability for unexpected failure modes, such as sudden blade fractures, absent in training data, highlighting their limitations in open-set recognition.

In summary, while model-based methods excel in physical interpretability and early fault detection, their effectiveness heavily relies on model accuracy and completeness. These limitations hinder pure model methods from efficiently diagnosing complex and uncertain main pump systems. It is therefore urgent to integrate them with data-driven methods, leveraging the latter's strong nonlinear fitting ability and adaptability to unknown patterns, so as to establish a more robust and reliable hybrid intelligent diagnostic framework.

3.3. Data-Driven Approach

A data-driven fault diagnosis method for the main pump constructs a diagnostic model by analyzing historical operational data without relying on an accurate physical model [182,183]. Figure 4 illustrates a common flowchart for this data-driven fault diagnosis approach. The core principle is to employ machine learning algorithms to learn the mapping relation between fault characteristics and operational states, thereby enabling intelligent identification and classification of fault modes. The diagnostic process involves acquiring multi-source signals via sensors; extracting feature parameters from the time, frequency, and time–frequency domains; screening key features or fusing multi-source data to enhance information completeness; and finally, establishing a fault classification model using machine learning algorithms to determine both the type and severity of faults. Key factors in this process include signal quality, feature validity, and the model's generalizability and adaptability under extreme conditions [6,8,184]. This section reviews and analyzes intelligent diagnosis methods based on data-driven techniques, focusing on three highly generalizable approaches: traditional machine learning-based diagnosis, deep learning-based diagnosis, and transfer learning-based diagnosis [185].

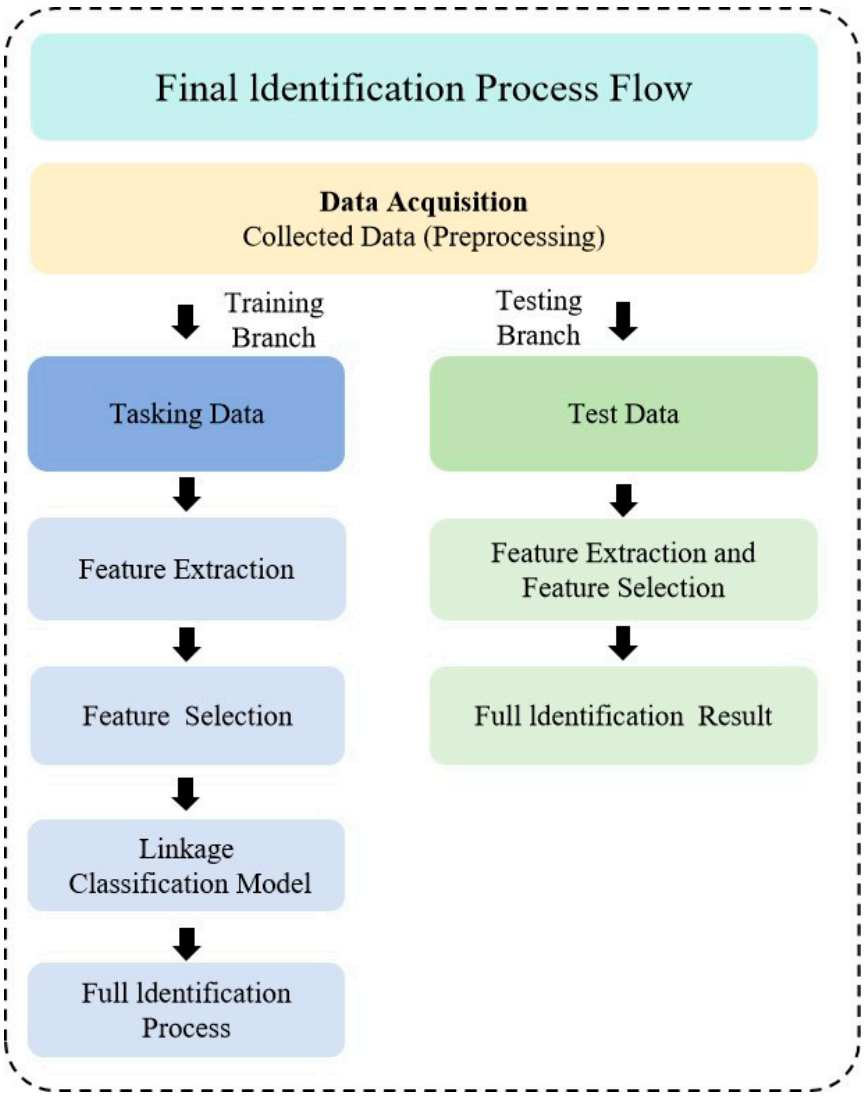


Figure 4. Flow chart of data-driven fault diagnosis method [186].

3.3.1. Traditional Machine Learning Intelligent Diagnosis Methods

Traditional machine learning methods mainly rely on data-driven feature extraction and pattern recognition techniques for fault diagnosis in main pump systems, in which Support Vector Machine (SVM), Extreme Learning Machine (ELM), and Entropy Theory are the core representatives [4,187,188].

Support Vector Machines (SVMs) enable effective fault classification in high-dimensional spaces by constructing optimal hyperplanes, particularly for small-sample nonlinear problems. The diagnostic process involves feature extraction, kernel function mapping, and classification decision-making. Support Vector Machines (SVMs) classify faults by constructing an optimal hyperplane that maximizes the margin between two classes of samples. The learning strategy translates into solving a convex quadratic programming problem:

$$\min_{\mathbf{w},b} \frac{1}{2} \parallel \mathbf{w} \parallel^2 \quad \text{s.t.} \quad y_i\left(\mathbf{w}^T\mathbf{x}_i + b\right) \geq 1, \quad i = 1, 2, \ldots n, \tag{7}$$

where $\mathbf{w}$ is the normal vector of the hyperplane, b is the bias term, and $\mathbf{x}_i$ is the eigenvector of the ith sample. The geometric meaning of $\parallel \mathbf{w} \parallel$ is the reciprocal of the classification interval, and minimizing $\parallel \mathbf{w} \parallel$ is equivalent to maximizing the classification interval,

thus obtaining optimal generalization ability. Xue et al. [143] developed a fault diagnosis method for centrifugal pumps based on vibration signals and SVMs. First, non-dimensional symptom parameters (NSPs) were extracted; then, SVMs were used to generate classification hyperplanes; finally, Dempster–Shafer theory was integrated to accurately identify faults such as cavitation and impeller imbalance, achieving a diagnosis accuracy of 92%. Li et al. [189] optimized the SVM feature fusion strategy in a rod pump system, significantly reducing training time and improving accuracy. Yu et al. [190] proposed that the integration of SVMs and multi-model probability fusion can enhance the detection speed of slow-developing faults by 30%.

The Extreme Learning Machine (ELM) is a computationally efficient machine learning algorithm characterized by random initialization of hidden layer weights and a single matrix operation. This approach offers the advantage of training efficiency. Jiang et al. [191] combined the voice print feature with ELM to enable non-contact diagnosis of axial piston pump faults. Specifically, they constructed an ELM classifier using wavelet packet denoising and Mel-Frequency Cepstral Coefficient (MFCC) feature extraction, achieving a recognition accuracy of 97.5% for sliding shoe wear and piston loosening faults, which is 40% higher than Support Vector Machine (SVM) and Backpropagation (BP) neural network methods. Furthermore, Lan et al. [134] demonstrated the robustness of ELM-based diagnosis for piston pump shoe wear, maintaining an accuracy of 94% even in noisy environments. Additionally, Wang et al. [130] employed the Empirical Wavelet Transform and Principal Component Analysis–ELM to improve the recognition accuracy of weak features to 96%.

Entropy theory quantifies system states by measuring signal complexity through metrics like sample and multiscale entropy. Chen et al. [192] enhanced transmission line fault detection by integrating ensemble empirical mode decomposition (EEMD) with power spectral entropy, a method later applied to hydraulic pump vibration analysis. Zhu et al. [6] demonstrated that entropy values serve as sensitive indicators of early piston pump wear, proving particularly effective for detecting weak faults under variable conditions. Additionally, they employed time–frequency entropy and multi-classification SVM fusion to address modal aliasing, achieving classification errors below 5%.

In conclusion, Support Vector Machine (SVM), Extreme Learning Machine (ELM), and entropy theory represent the foundational elements of traditional machine learning diagnostics, each possessing distinct advantages and limitations. Both SVM and entropy theory necessitate feature extraction, whereas ELM is capable of directly processing the original signal; however, the quality of these features significantly influences diagnostic accuracy. Regarding noise sensitivity, entropy calculations are susceptible to disruption by environmental noise, necessitating the integration of wavelet transforms and other noise reduction techniques. Optimization of SVM kernel function parameters can improve noise resistance, albeit at a high computational cost. For addressing real-time issues, ELM offers a considerably faster training speed compared to SVM, yet the random initialization of hidden layer neurons may result in variability in outcomes, necessitating multiple verifications.

3.3.2. Deep Learning-Based Intelligent Diagnosis Method

Deep learning-based intelligent diagnostic methods circumvent the reliance of traditional approaches on manual feature engineering by autonomously extracting high-order features from the original signal. These methods have emerged as a core technology for fault diagnosis in main pump systems. This section examines convolutional neural networks (CNNs) and recurrent neural networks (RNNs) [7,193,194].

Convolutional neural networks (CNNs) efficiently process high-dimensional data through mechanisms such as local connections, weight sharing, and hierarchical feature extraction. The fundamental architecture of CNNs comprises a convolutional layer, a pooling layer, and a fully connected layer, enabling the automatic learning of local spatial patterns [195] within signals. Convolutional layers are the core of CNN, extracting features by performing convolution operations on input data through convolution kernels (filters). Its calculation can be expressed as follows:

$$s(t) = (x * w)(t) = \sum_{a=-\infty}^{\infty} x(a) \cdot w(t-a) \tag{8}$$

For two-dimensional image processing (for time–frequency converted images), the discrete convolution operation is expressed as follows:

$$S(i,j) = (I * K)(i,j) = \sum_{m} \sum_{n} I(i+m, j+n) K(m,n), \tag{9}$$

where I is the input feature map (e.g., image or output of previous layer), K is the convolution kernel, and S is the output feature map. By learning multiple convolution kernels, CNNs can automatically capture hierarchical features ranging from edges and textures to complex fault patterns. In the domain of main pump fault diagnosis, CNNs are predominantly utilized for the image processing of vibrations, pressure, and other signals. Wen et al. [196] proposed converting one-dimensional vibration signals into two-dimensional grayscale images to facilitate fault diagnosis of self-priming centrifugal pumps using an improved LeNet-5 model, achieving a diagnostic accuracy of 99.48%. Tang et al. [197,198] employed continuous wavelet transform (CWT) to convert vibration signals of axial piston pumps into time–frequency maps, identifying faults such as loose sliders and valve plate wear through a five-layer convolutional structure, with a diagnostic accuracy of 99.98%. Notably, the advantage of CNNs lies in their ability to eliminate the reliance on traditional methods of artificial feature engineering, as demonstrated by the signal-to-image method proposed by Wen et al. [196], which significantly outperforms traditional methods like Support Vector Machines (SVMs). Zhu et al. [199] utilized an improved AlexNet model (B-AlexNet) combined with Bayesian optimization, achieving an identification accuracy exceeding 98% for five faults in a hydraulic piston pump, while also demonstrating insensitivity to noise interference.

Recurrent neural networks (RNNs) can effectively capture long-term dependencies in time-series data through their cyclic units, making them well-suited for direct processing of original vibration or pressure signals. However, RNNs suffer from the gradient disappearance problem. In contrast, Long Short-Term Memory (LSTM) networks, which employ gating mechanisms to control the flow of information, are better able to model long-term dependencies. The core of an LSTM cell lies in its gating mechanism, which includes the forget gate, input gate, and output gate. Taking the Forget Door as an example, the calculation process is as follows [200]:

$$f_t = \sigma\Big(W_f \cdot [h_{t-1}, x_t] + b_f\Big), \tag{10}$$

where σ is the sigmoid activation function, which compresses the output to a ratio between 0 and 1 to control the passage of information; W_f and b_f are the weight matrix and bias terms of the forget gate; $h_{t-1}x_t$ is the input at the current time. The forget gate determines which information is discarded from the cellular state. Zhao et al. [201] developed a hybrid CNN–LSTM model, where the CNN component extracts multi-scale features and the LSTM component learns the temporal dynamics of the time series, achieving an F1 score of

0.987 in the classification of main pump vibration signals. Zhang et al. [202] demonstrated the sensitivity of LSTM networks to hydraulic pump valve failures but found that their independent application is less robust to noise disturbances than convolutional neural networks (CNNs). The limited application of RNNs in the diagnosis of main pumps can be attributed to the fact that transient shock characteristics of pump failures are easily diluted over long sequences, necessitating optimization in combination with attention mechanisms [203] to improve their performance.

In conclusion, convolutional neural networks (CNNs) offer significant advantages in terms of robust spatial feature extraction and high accuracy. However, they are reliant on signal conversion, are sensitive to sensor configuration, and entail substantial computational demands. Long Short-Term Memory (LSTM) networks excel in time-series modeling, making them suitable for dynamic processes. Nonetheless, they exhibit slow training speeds and limited generalization capabilities with small sample sizes, resulting in inadequate real-time performance and challenges in fulfilling online diagnostic requirements. Currently, deep learning necessitates a substantial amount of labeled data, yet samples from extreme operating conditions of the main pump are limited. Transfer learning and generative adversarial networks have emerged as promising solutions to address these challenges.

3.3.3. Transfer Learning-Based Intelligent Diagnosis Method

Transfer Learning enhances the diagnostic capabilities of the target domain by leveraging knowledge from the source domain, thereby effectively addressing the diagnostic challenges posed by variable operating conditions and data distribution disparities in main pump systems [204]. The fundamental aspect of this process is cross-domain knowledge transfer. This section primarily provides a comprehensive analysis of three methodologies: Feature Mapping Transfer, adversarial training transfer, and Simulation-Measured Fusion Transfer [205–207].

Domain adaptation through feature mapping migration aligns feature distributions between source and target domains, reducing inter-domain discrepancies. Techniques such as Maximum Mean Discrepancy (MMD) or Manifold Learning are commonly employed to reconstruct the feature space and facilitate this alignment [196,200]. For instance, Yang et al. [208] proposed a migration framework based on Joint Distribution Adaptation, which enabled the successful transfer of laboratory bearing vibration data to locomotive bearing fault diagnosis, resulting in a 12.3% increase in diagnostic accuracy. Similarly, Zhang et al. [209] utilized feature map migration to diagnose hydraulic pump loose slider faults, minimizing distribution differences between simulation and measured signals using MMD and achieving an accuracy rate of 96.5%.

Adversarial training transfer employs a generative adversarial network (GAN) mechanism to produce domain-invariant features. The generator creates cross-domain features, while the discriminator differentiates between source and target domains, working in tandem to align features [204,210]. Xiang [210] introduced a simulation-driven anti-migration framework that generates high-fidelity fault samples to address the scarcity of measured data, achieving a classification accuracy of 98.2% for hydraulic pump diagnostics. Wang et al. [211] enhanced adversarial training by incorporating a Local Attention Mechanism, thereby significantly boosting the robustness of cross-sensor migration for axial piston pumps.

Simulation–measurement fusion migration optimizes target domain diagnostic models by integrating high-quality fault data from numerical simulations with empirical data, adjusting sample weights using algorithms like TrAdaBoost [212]. Miao et al. [135] constructed an auxiliary dataset from oil pump simulations, utilizing complementary set

empirical mode decomposition (CEEMD) and singular value decomposition (SVD) for feature extraction, and applied TrAdaBoost to transfer knowledge to the target domain, achieving a 30.5% improvement in diagnostic accuracy over traditional methods. Cai et al. [212] employed a digital twin-based auxiliary self-encoder for triple pump data analysis, achieving data fidelity exceeding 95%. Yang et al. [213] explored the unsupervised W-BDA domain adaptation method for electric submersible pump data analysis, resulting in an 18.7% increase in F1 score for small-sample generation.

To sum it up, feature mapping, adversarial training, and simulation–measurement fusion constitute the mainstream diagnosis methods based on transfer learning, each of which has advantages and disadvantages. Feature mapping has high computational efficiency and is suitable for real-time diagnosis, but it depends on distribution assumptions and has poor adaptability to extreme working conditions. Adversarial training transfer generates data enhancement to solve small sample problems, but there are unstable training and easy pattern collapse problems. Simulation–measurement fusion migration offers strong generalization and can effectively solve the problem of cross-medium migration, but it requires a high-precision simulation model and high engineering costs. Transfer learning can significantly improve the diagnostic robustness of the main pump in the presence of data scarcity and distribution offset. However, extreme case adaptability, multiple fault coupling diagnosis, and unsupervised migration remain core challenges.

3.3.4. Special Considerations for Data-Driven Methods in Main Pump Fault Diagnosis

The data-driven approach offers a promising solution for diagnosing complex faults and nonlinear degradation behaviors in main pump systems, where mechanism-based models often struggle. This method's powerful automatic feature extraction and pattern recognition capabilities make it well-suited to address such challenges. However, the core data-driven nature of this approach, combined with the high reliability requirements and extreme operating conditions of main pump applications, magnifies its limitations and creates a significant barrier to transitioning from "laboratory excellence" to "engineering practicality". These challenges underscore the inevitable trend towards integrating data-driven techniques with traditional methods to address the complexities inherent in main pump fault diagnosis and degradation monitoring.

The reliance of models such as deep learning on large, high-quality labeled datasets for training poses a significant challenge in the context of safety-critical equipment like nuclear main pumps. Data from these systems are typically imbalanced, with far more operational data but few failure samples, reflecting the fundamental design goal of avoiding failures. Furthermore, the extreme operating conditions of high temperature, high pressure, and strong vibration can lead to distortion and attenuation of sensor signals, making it difficult to consistently obtain "high signal-to-noise ratio" data [214]. This "data poverty" situation can easily result in overfitting or a sharp drop in the generalization ability of data-driven models, leading to a discrepancy between laboratory performance and real-world engineering performance. Additionally, the inherent lack of transparency and physical interpretability in the decision-making processes of these "black box" models presents a significant barrier to their adoption in safety-critical domains, where operators must understand the basis for critical decisions. To gain trust and enable the independent assumption of safety diagnosis responsibilities, it is crucial to address issues of model reliance and confidence in fault judgments. Failure to do so fundamentally hinders the application of these data-driven techniques in high-risk decision-making contexts [215]. The training and reasoning of complex deep models demand substantial computational and storage resources. Real-time monitoring of primary pumps often necessitates deploying diagnostic algorithms on resource-limited edge hardware. The large model size

and computational demands hinder meeting the requirements for timeliness, low power consumption, and cost-effectiveness in online diagnostics, posing significant barriers to practical application [216].

Confronted with fundamental contradictions, a singular data-driven paradigm falls short of meeting diagnostic needs, necessitating the development of targeted technology strategies and the advancement of converged architectures. To address data challenges, research should advance transfer learning, few-shot learning, and generative adversarial networks. High-fidelity simulation models and bench test data generate synthetic fault data, facilitating knowledge transfer to real main pumps and thereby reducing reliance on historical fault data. To bolster model credibility, interpretable artificial intelligence should be promoted, utilizing attention mechanisms and saliency maps to visualize key signal segments and frequency bands that inform model decisions. These visualizations should be linked to physical mechanisms, such as bearing failure characteristic frequencies, to resolve the "black box" issue and enhance human–machine trust. For model efficiency, research on model pruning, quantization, and distillation should be pursued to develop lightweight neural networks suitable for edge computing. This approach aims to significantly reduce model size and computational demands while maintaining performance to meet real-time constraints.

In conclusion, while data-driven methods hold significant promise for intelligent diagnosis, their practical application is constrained by data quality, model interpretability, and computational efficiency. These limitations hinder their ability to solely manage the health of the main pump system. Therefore, synergistic integration with mechanism-based model-driven methods is essential to develop hybrid intelligent diagnosis systems. This approach leverages the nonlinear mapping strengths of data-driven methods and the physical interpretability of model-driven techniques, ensuring decision reliability and enabling root-cause failure analysis. Such a complementary fusion is crucial for transitioning the intelligent operation and maintenance of the main pump from theory to practice.

3.4. Fusion-Based Approach

The fusion of multiple sensor data sources provides a more comprehensive and reliable assessment of the condition of complex systems, such as main pumps, compared with relying on a single sensor or diagnostic method. Vibration signals, for instance, are highly sensitive to mechanical shocks but less effective at detecting gradually developing seal leakage, while pressure signals can capture changes in hydraulic performance but are strongly influenced by operating conditions. By combining information from various physical parameters (e.g., vibration, pressure, acoustic emission, temperature, and current), the system can leverage the differential responses of these signals to different fault types, enabling cross-verification of the same fault through multiple data sources. This approach enhances the confidence and reliability of diagnosis results and improves the fault tolerance of the system, as it can still make correct judgments even when a sensor fails or a signal is contaminated by noise [217]. Information fusion can be implemented at three levels: data level, feature level, and decision level, each with its own advantages and disadvantages, as well as suitable application scenarios, as shown in Table 2. Together, these multi-level and multi-dimensional approaches constitute a robust fault diagnosis framework for complex machinery.

Table 2. Comparison table of different fusion levels.

Fusion Level	Description	Advantages	Disadvantages	Typical Methods	Applicable Scenarios
Data-level Fusion	Direct alignment, filtering, and fusion of raw sensor data.	Minimal information loss and theoretically highest accuracy.	Large data volume and high computational cost; requires precise sensor synchronization; sensitive to noise.	Wavelet transform and CNN directly processing multi-source signals.	Offline precision analysis and in-depth study of failure mechanisms.
Feature-level Fusion	First extracts features from each sensor signal, and then fuses the feature vectors.	Significantly compresses data volume; retains key information; high flexibility and strong robustness.	Quality of feature extraction directly affects the final result; complex fusion algorithm selection.	Feature concatenation, weighted fusion, and principal component analysis (PCA).	Most commonly used in online real-time or quasi-real-time diagnostic systems.
Decision-level Fusion	Each sensor or method first independently performs preliminary diagnosis, and then fuses the multiple diagnostic results.	Best fault tolerance; modular design and easy to expand; friendly to asynchronous sensors.	Maximum information loss; relies on the preliminary diagnosis performance of each sub-module.	Voting methods, D-S evidence theory, and Bayesian inference.	High reliability requirements, fault-tolerant control, and distributed monitoring systems.

The fault diagnosis method based on fusion achieves information complementarity and redundancy suppression at either the feature layer or the decision layer through data-level fusion. The flowchart illustrating common fault diagnosis methods based on fusion is presented in Figure 5. The theoretical foundation rests on the premise that different physical signals exhibit varying responses to the same fault, and multi-source information fusion can effectively extract the complementarity and correlation of fault characteristics [213,218]. Feature-level fusion transforms the original signals into fused time–frequency domain features via mathematical transformations, constructing high-dimensional feature vectors [213,219] using fractal dimension and energy features. In contrast, decision-level fusion employs intelligent algorithms to weight and integrate multi-source independent diagnosis results, thereby enhancing the final decision confidence [127,220] by adjusting the classification probability distribution. D–S evidence theory is an effective fusion method to deal with uncertainty. Let Θ be the recognition framework and the basic probability assignment (BPA) function $m : 2^{\Theta} \to [0,1]$ satisfy $m(\varnothing) = 0$ and $\sum_{A \subseteq \Theta} m(A) = 1$. For two independent evidence sources m_1 and m_2, Dempster's combination rule is

$$\begin{aligned} (m_1 \oplus m_2)(A) &= \frac{1}{1-K} \sum_{B \cap C = A} m_1(B) m_2(C) \\ K &= \sum_{B \cap C = \varnothing} m_1(B) m_2(C) \end{aligned}, \tag{11}$$

where K is called the conflict coefficient, which measures the degree of conflict between two evidence sources, and $\frac{1}{1-K}$ is the normalization factor, which ensures that the BPA condition is still satisfied after fusion. This rule effectively combines diagnostic results (as evidence) from multiple sensors or classifiers into a single comprehensive decision. The fusion method must emphasize several core elements: multi-source signals must be converted into physical feature representations through signal processing techniques, hierarchical fusion methods should be selected based on diagnostic requirements, and the performance of fusion models is contingent upon the coverage of training data. The flowchart of data-level fault diagnosis is depicted in the figure. This section systematically analyzes three methods to data-level fusion: feature-level fusion and decision-level fusion based on fusion methods.

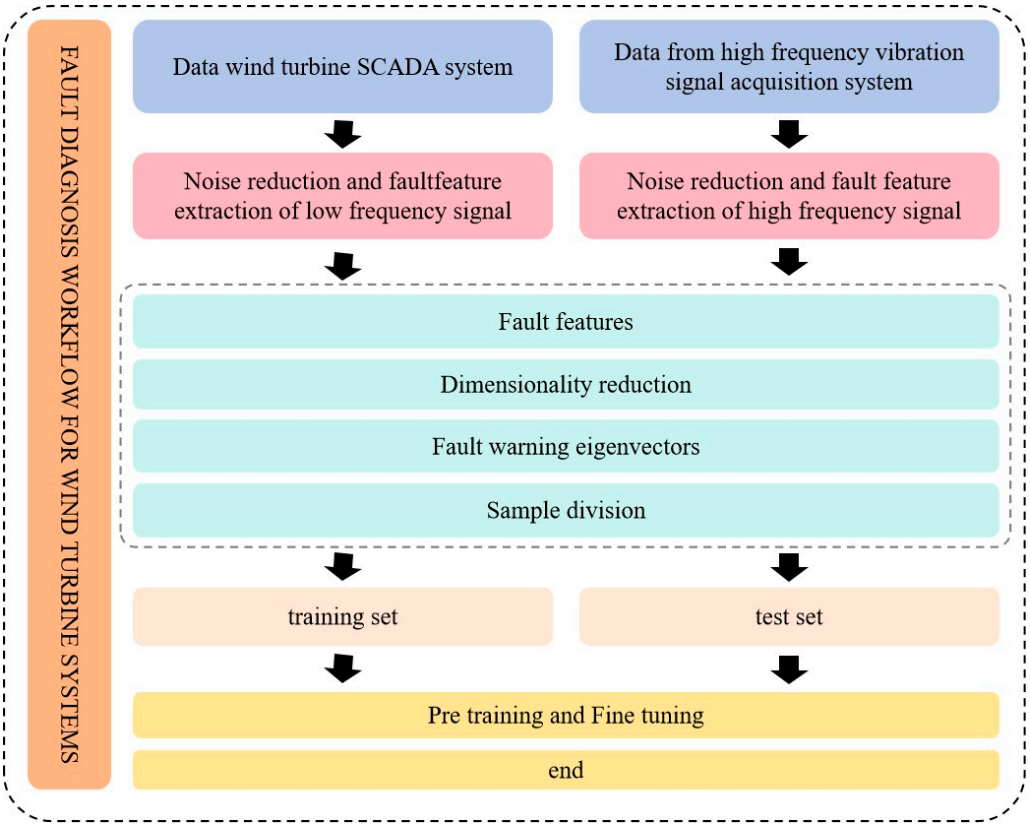


Figure 5. Flow chart of fault diagnosis method based on data level fusion [221].

3.4.1. Data Level Fusion

The fusion of multi-sensor data represents a robust paradigm for fault diagnosis and monitoring of critical machinery components, such as main pumps. By directly integrating the original signals from multiple sensors and conducting joint analysis, this approach enhances the integrity and reliability of feature extraction. For instance, Zhu et al. [222] combined wavelet analysis with an improved AlexNet network to directly fuse the vibration signals from hydraulic piston pumps, enabling high-precision identification of five fault states, including center spring failure and sliding shoe wear, with an accuracy rate of 98.7%. Similarly, Zhang et al. [223] significantly improved the significance of fault characteristic frequencies by fusing the original signals of stator current and radial electromagnetic force from a submersible motor to generate a fused correlation spectrum. Wang et al. [172] verified that this approach can improve the average accuracy of fault diagnosis by approximately 10%. However, data fusion techniques often have high computational complexity and require strict spatiotemporal synchronization of sensor signals, and their performance can degrade in strong-noise environments. Yan et al. [224] recently proposed a convolutional neural network approach to directly process multi-source vibration signals, circumventing the potential biases associated with manual feature extraction. This method achieved an accuracy rate of 97.3% under variable-speed conditions. Additionally, Wang et al. [172] combined wavelet transform and ensemble empirical mode decomposition (EEMD) to decompose the fractal dimension of the first five intrinsic mode functions (IMFs), constructing third-order tensor samples to address the challenge of nonlinear signal feature quantification. However, some studies have questioned the compatibility of data-level fusion for heterogeneous signals, such as vibration and acoustic emissions. Zhang et al. [223] highlighted that the physical dimensional discrepancy between current and vibration signals may lead to fusion distortion, emphasizing the need for standardized preprocessing.

3.4.2. Feature-Level Fusion

Feature-level fusion first extracts high-level features from sensor signals and then implements feature integration through dimensionality reduction or correlation analysis. At its core, this approach enhances pattern separability by leveraging feature complementarity [225–227]. This technology significantly improves the discrimination of fault characteristics by integrating multi-dimensional information, making it particularly suitable for complex scenarios with high signal noise and weak fault characteristics, such as those encountered under extreme working conditions of main pumps [4,223,227]. Over the past decade, feature-level fusion technology has made significant breakthroughs in the field of main pump fault diagnosis. Tang et al. [218] proposed a fusion framework combining continuous wavelet transform and convolutional neural networks, which converts vibration signals into time–frequency maps and inputs them into deep CNN models to achieve high-precision classification of hydraulic axial piston pump faults, outperforming traditional single-signal processing methods. Pei et al. [219] further designed a three-stage feature fusion method: the first stage used sparse local Fisher discriminant analysis to enhance the original feature discrimination; the second stage fused multi-source features through improved within-class correlation analysis; the third stage combined kernel local Fisher discriminant analysis for feature selection, resulting in a 12% increase in the accuracy of hydraulic pump degradation state recognition. Zhang et al. [228] introduced a deep feature fusion framework utilizing a fully convolutional network to extract deep features from multi-rate time series by stacking convolution blocks. This approach effectively enabled simultaneous identification of various fault types and degrees in hydraulic systems through a flattening splicing strategy. Tang et al. [218,227] emphasized time–frequency domain transformation and visual representation of fault features, while Pei et al. [219,220] focused on high-dimensional feature space manipulation, employing optimization algorithms to enhance feature separability. For environmental adaptation, Yu et al. [229] proposed a variance contribution rate weighted fusion method, which excels in weak fault detection but struggles with abrupt load changes. In contrast, Pei [219]'s three-stage method, though computationally intensive, remains stable under varying conditions.

3.4.3. Decision-Level Fusion

Decision-level fusion is the core strategy of multi-source signal fusion fault diagnosis. Its fundamental principle is to integrate the local decision results of multiple independent diagnosis modules and generate global diagnosis conclusions through advanced fusion rules [230,231]. This approach avoids directly dealing with the high-dimensional heterogeneity of the original data or feature layer, and instead utilizes the initial diagnosis confidence information of each sub-module to significantly enhance the robustness and fault tolerance of the diagnosis system [127,232,233]. For instance, Chao et al. [127] proposed a decision-level fusion framework based on convolutional neural networks, which improved the diagnostic accuracy of axial piston pumps to 98.7% by adjusting the classification probability distribution of multi-channel vibration signals, significantly outperforming the 92.3% accuracy of single-channel models. Similarly, Zhang et al. [202] developed a hyperparametrically optimized multi-signal fusion transfer convolutional neural network (OMTCNN), which integrates multiple physical signals through a weight assignment protocol to achieve 95% accuracy in cross-operating pump fault diagnosis, demonstrating its adaptability to complex signal sources. The methodological differences among research teams are primarily focused on fusion rule design and uncertainty processing mechanisms. Chao et al. [127,218] adopt a probability-weighted fusion approach, relying on the output classification probabilities from convolutional neural networks (CNNs) and requiring a large amount of labeled data to calculate efficient fusion rules. In contrast,

Jiang [234] employs Dempster–Shafer theory (DST) or Evidential Reasoning (ER) rules to handle evidence conflicts through basic probability allocation, which is more suitable for small-sample scenarios, but the setting of reliability factors in ER rules depends on empirical priors. On the other hand, SAE–DBN and other [233] models require manual feature engineering, which can be restrictive due to the quality of feature extraction. Conversely, OMTCNN [202] and other end-to-end models exhibit high automation, but they necessitate massive training data and have limited generalization ability under extreme conditions. Therefore, decision-level fusion has emerged as a systematic method in the field of multi-source signal fault diagnosis, with probability models and evidence theory as the core. The core value of this approach lies in improving the fault tolerance of the system through the complementary information provided by decision-level fusion. Future research should further explore adaptive fusion mechanisms and edge-computing deployment schemes to overcome limitations under extreme conditions and facilitate the engineering application of these techniques. The development of embedded diagnostic system for the main pump system can be guided by the design principles of intelligent monitoring frameworks established in other industrial infrastructures, such as pipeline systems and pressure vessels. Such an approach supports the creation of low-power, highly robust diagnostic systems. Furthermore, the integration of emerging sensing technologies, such as self-powered sensors based on friction nano-generators, can provide novel solutions to address the challenges of sensor power supply and layout under the complex operating conditions of the main pump system [2].

3.4.4. Special Consideration for Fusion Methods in the Fault Diagnosis of Main Pumps

The multi-source information fusion framework theoretically offers a comprehensive solution for addressing the complex fault diagnosis of main pumps by leveraging data-, feature-, or decision-level complementation and verification. However, effective fusion requires more than merely aggregating information; it necessitates a profound understanding of the main pump system's characteristics and encounters distinct complexity challenges during engineering implementation.

Fusion strategies at different levels address specific fault modes and diagnostic needs of the main pumps. Data-level fusion is ideal for precise offline analysis, such as the joint analysis of vibration and acoustic emission signal waveforms to explore the detailed mechanism of bearing crack initiation. However, this approach demands high synchronization and sensor data quality. In the challenging electromagnetic and vibration-prone environment of the main pump site, original signals are susceptible to contamination, making implementation difficult [202]. Characteristic-level fusion strikes a balance between diagnostic performance and computational efficiency. For instance, extracting time–frequency domain features from vibration signals and fluctuation features from pressure signals to form high-dimensional fusion feature vectors is well-suited for identifying complex faults in online monitoring systems, such as hydraulic imbalance due to bearing wear. Decision-level fusion excels in final diagnosis, where high reliability is required, offering strong fault tolerance. For example, if a vibration sensor indicates slight bearing wear and a performance model suggests increased internal leakage due to efficiency decline, D–S evidence theory can effectively integrate these findings. This approach evaluates a comprehensive assessment that seal wear is causing internal leakage, which in turn degrades bearing lubrication, thereby approaching the root cause of the failure.

The fusion approach holds significant potential, yet its inherent limitations are particularly evident in primary pump applications. First, the integration of multi-source information inevitably increases system complexity and substantially raises computational and communication overhead. This places greater demands on the hardware

computing platforms, which can be challenging to deploy in resource-constrained edge environments, potentially affecting real-time performance. Second, the varying sampling frequencies and response delays of different sensor modalities (e.g., vibration, pressure, and temperature) make accurate spatiotemporal synchronization difficult to achieve. Any synchronization errors diminish the effectiveness of the fusion process. When confronted with conflicting multi-source information, quantifying and managing the associated uncertainty remains challenging, as fusion rules inherently involve a degree of subjectivity. Finally, fusion cannot fundamentally improve the quality of individual information sources. If the input sensor signals have a low signal-to-noise ratio or are severely corrupted, the fusion result may amplify the erroneous information, leading to decision-making confusion. There is a clear performance ceiling for fusion systems, constrained by the least reliable input channels.

Future research should focus on developing more sophisticated fusion mechanisms to address these challenges. One approach is to investigate intelligent weighting strategies that dynamically adjusts the contribution of each sensor signal based on real-time quality metrics, such as signal-to-noise ratio, rather than relying on fixed weights or rules. This strategy enhances system robustness. Another approach involves transcending traditional hierarchies by exploring end-to-end feature fusion through deep learning, enabling the model to autonomously learn optimal fusion representations. Additionally, embedding fusion system within a digital twin framework for the main pump allows for the integration of simulation data from the virtual model to supplement and validate real sensor information, thereby creating a more robust cognitive closed loop. A third strategy is to design a lightweight fusion model for edge computing, minimizing computational and storage demands while maintaining accuracy, thus supporting advanced diagnostic functions in the field. While fusion-based diagnosis is crucial for achieving high reliability and intelligent operation and maintenance of the main pump, it is not a technology that can be applied indiscriminately. Its effective deployment requires careful tailoring to system characteristics, operational constraints, and specific diagnostic objectives.

3.5. Diagnostic Methods

The various diagnostic techniques for primary pump systems discussed in the preceding sections can be categorized into four major groups. To provide a more concise and comparative overview of the core principles and applicability of these diagnostic paradigms, Table 3 summarizes fault diagnosis approaches based on signal processing, modeling, data-driven analysis, and data fusion. This table outlines the working principles, ideal scenarios, advantages, and limitations of each approach. Building upon this, Tables 4–7 present a more systematic comparison of the specific technologies within these methods, detailing aspects such as signal types, real-time performance, typical failure modes, and applicable scenarios. Collectively, these tables provide a comprehensive reference for researchers and engineers to guide the selection of appropriate diagnostic methods for primary pump systems.

Table 3. Comparison of core characteristics of fault diagnosis methods for main pump systems.

Comparison Dimension	Signal Processing Methods	Model-Driven Methods	Data-Driven Methods	Information Fusion Methods
Core Principle	Direct feature extraction from signals (vibration and pressure)	Residual-based diagnosis using system	ML-based learning of fault-state mappings from historical data	Integration of multi-sensor/multi-method information

Table 3. *Cont.*

Comparison Dimension	Signal Processing Methods	Model-Driven Methods	Data-Driven Methods	Information Fusion Methods
Optimal Scenario	Periodic impact faults in rotating components	Parametric faults (sensors, actuators, and leaks)	Complex systems with ample data but no precise models	High-reliability systems with unreliable single sources
Main Advantage	Clear physical interpretation; minimal fault data needed	Strong explainability; reasoning and early warning capabilities	Powerful feature extraction; high accuracy for complex faults	Enhanced accuracy and robustness; good fault tolerance
Main Limitation	Expert-dependent; low intelligence; insensitive to unknown faults	Complex modeling; sensitive to parameter variations	Data quality/quantity dependent; "black box" models	Complex implementation; high computational/communication costs

Table 4. Comparison of signal processing diagnostic methods.

Diagnostic Paradigm	Signal Processing			
Specific Methods	Time–domain analysis.	Signal decomposition and reconstruction.	Nonlinear signal processing.	Physical feature extraction.
Advantages	Simultaneously captures time-frequency characteristics; suitable for non-stationary signal analysis.	Can separate fault feature components; effectively suppresses background noise.	Can reveal nonlinear characteristics of systems; detects weak nonlinear faults.	Directly extracts physical fault features (e.g., characteristic frequencies); strong engineering interpretability.
Disadvantages	Basis function selection depends on experience; requires parameter tuning.	Endpoint effects exist; high computational complexity.	Parameter optimization is difficult; requires high sampling rate data support.	Relies on prior knowledge for demodulation strategy design; insensitive to compound faults.
Signal Type	Vibration and noise.	Vibration and pressure.	Vibration and pressure.	Vibration.
Real-time Capability	Medium.	Medium.	Medium.	High.
Typical Applicable Faults	Bearing pitting, gear tooth breakage, and cavitation	Early bearing wear, pulley loosening, and valve plate failure	Rotor wear, misalignment, and nonlinear damage	Bearing spalling, ball damage, and gear local defects
Application Scenarios	Transient fault diagnosis in rotating machinery.	Early weak fault extraction in strong noise environments.	Fault diagnosis in complex dynamic systems.	Quantitative diagnosis of characteristic faults in rotating components like bearings/gears.

Table 5. Comparison of model-driven diagnostic methods.

Diagnostic Paradigm	Model-Driven		
Specific Methods	Physical Model.	Signal Processing and Feature Extraction Model.	Analytical Redundancy Model Comparison.
Advantages	Provides accurate and precise diagnostic estimates; strong fault isolation capability.	Improves diagnostic robustness; can handle certain noise and instability.	Robust to unknown disturbances; suitable for real-time systems with fast fault detection.

Table 5. *Cont.*

Diagnostic Paradigm	**Model-Driven**		
Disadvantages	High model complexity; not easily adaptable to system changes or new fault types.	Complex model training; improper feature selection may cause overfitting.	Model errors may cause false alarms; not suitable for strongly nonlinear or time-varying systems.
Signal Type	Pressure, flow, and speed.	Vibration and pressure.	Pressure, flow, and temperature.
Real-time Capability	High.	Medium.	High.
Typical Applicable Faults	System leakage, efficiency decline, and parametric faults.	Pulley wear, plunger sticking, and performance degradation.	Sensor faults, actuator faults, and control anomalies.
Application Scenarios	Efficiency decline or leakage fault diagnosis in hydraulic systems, suitable for internal system mechanisms.	Fault classification and early warning, suitable for nonlinear systems.	Detection of sensor faults or control system abnormalities, suitable for linear time-invariant systems.

Table 6. Comparison of data-driven diagnostic methods.

Diagnostic Paradigm	**Data-Driven**		
Specific Methods	Traditional machine learning.	Deep learning.	Transfer learning.
Advantages	Simple architecture, high classification performance, and strong noise immunity; can handle multivariate data.	Automatically extracts features, avoiding manual interference; excellent capability for processing high-dimensional data.	Can adapt to new scenarios or small data, reducing training requirements and data dependency.
Disadvantages	High computational complexity, requires large training data; parameter selection is ambiguous; decision process is opaque.	"Black box" nature leads to unclear decisions; long training time; stability affected by gradient issues.	Transfer effect depends on similarity between source and target; accuracy may be unstable in new environments.
Signal Type	Vibration and feature values.	Vibration images, time-series signals, and multi-source data.	Vibration, images, and multi-source.
Real-time Capability	High.	Low (training)/ Medium (application).	Medium.
Typical Applicable Faults	Bearing wear, misalignment, and impeller imbalance.	Compound faults, deep-seated faults, and unknown faults.	Cross-condition faults and small-sample faults.
Application Scenarios	Fan fault diagnosis in ventilation systems, suitable for situations with labeled historical data.	End-to-end intelligent diagnosis and prediction in industrial systems, suitable for big data scenarios.	Cross-condition diagnosis in industrial systems, solving small-sample and zero-shot problems.

Table 7. Comparison of diagnostic methods.

Diagnostic Paradigm	**Information Fusion**		
Specific Methods	Data-level fusion.	Feature-level fusion.	Decision-level fusion.
Advantages	Fuses raw data, complete information retention, and theoretically highest accuracy.	Reduces data dimensionality; strong robustness, can handle partial information loss.	Highest fault tolerance, can handle uncertainty; friendly to asynchronous sensors.
Disadvantages	Large data volume and complex processing; susceptible to noise and synchronization issues; high computational overhead.	Improper feature extraction may cause information loss; complex fusion algorithm selection.	Maximum information loss; decision delay may affect real-time performance.
Signal Type	Multi-source heterogeneous (Vibration + Pressure + Current).	Multi-source features.	Multi-source decisions.

Table 7. *Cont.*

Diagnostic Paradigm	**Information Fusion**		
Real-time Capability	Low.	Medium.	High.
Typical Applicable Faults	Multiple faults.	Compound faults.	System faults.
Application Scenarios	Offline precision analysis and in-depth study of failure mechanisms.	Most commonly used in online monitoring and diagnostic systems, balancing performance and efficiency.	Final decision-making in high-reliability requirements and fault-tolerant control systems.

4. Analysis of the Development of Fault Diagnosis Methods for Main Pumps

The time range of the relevant literature cited in this review covers from 1998 to 2024, with a total of 134 articles. Search engines such as IEEE Xplore, Elsevier, and China Knowledge Net were mainly used to collect and consult relevant research. The keywords used in the search included "main pump fault diagnosis", "fault feature extraction", "signal processing based", "model based", "data driven", and "fusion based", as shown in Figure 6.

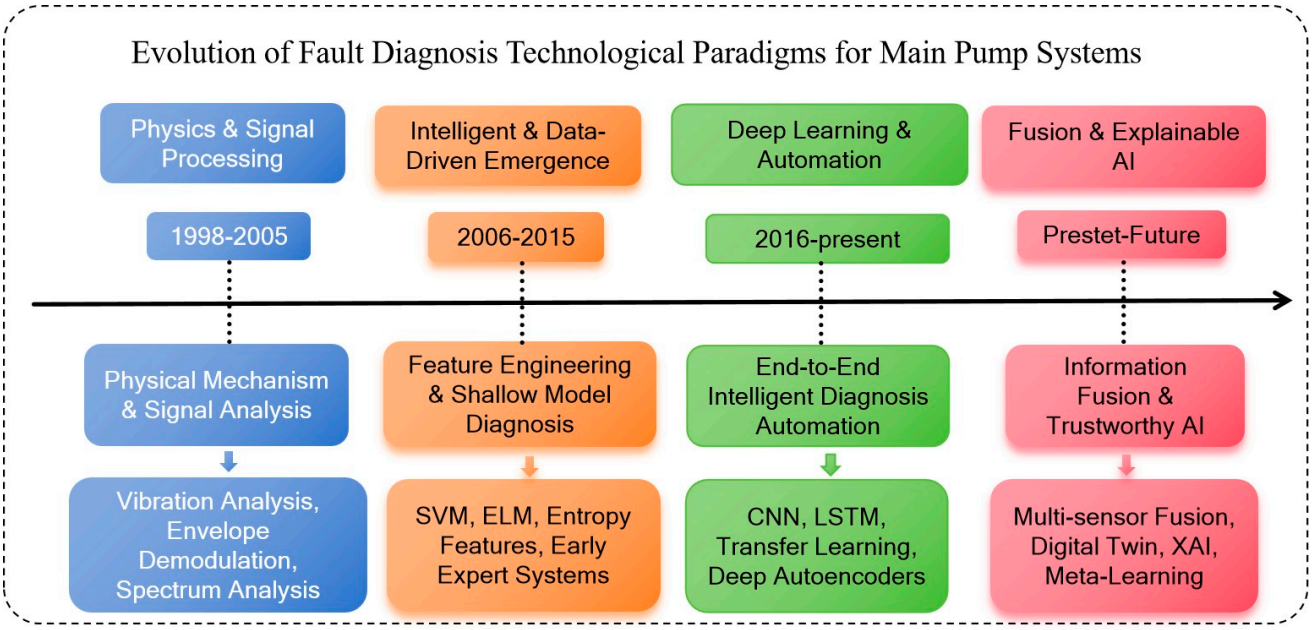


Figure 6. Papers published between 1998 and 2024.

The research landscape of fault diagnosis for main pump systems has not only expanded in volume but, more importantly, undergone significant evolutionary shifts in technological paradigms, as illustrated in Figure 6. This evolution reflects the field's response to increasing system complexity and the demand for higher reliability.

Initially, during the Physics and Signal Processing phase (1998–2005), research was dominated by methods rooted in physical principles and signal analysis techniques. Diagnostics relied heavily on vibration analysis, spectral analysis, envelope demodulation, and the establishment of physics-based models. The effectiveness of these methods was often constrained by the need for expert knowledge and prior understanding of fault mechanisms. The period from 2006 to 2015 marked the Emergence of Intelligent and Data-Driven paradigms. Driven by advances in machine learning and increased data availability, methods such as Support Vector Machines (SVMs), Extreme Learning Machines (ELM),

and feature fusion became prevalent. This shift began to reduce the dependency on deep physical insight and opened avenues for handling more complex, nonlinear fault patterns using historical operational data. Since 2016, the field has been firmly in the Deep Learning and Automation phase. The explosion of deep learning revolutionized fault diagnosis by enabling end-to-end learning from raw or minimally processed data. Convolutional Neural Networks (CNNs) for spatial feature extraction, Long Short-Term Memory (LSTM) networks for temporal dynamics, and Transfer Learning (TL) to address data scarcity became central to research efforts, pushing the boundaries of diagnostic automation and accuracy. Currently, we are transitioning into an emerging phase focused on Fusion, Explainability, and Adaptive Diagnostics. The core challenges lie in integrating multi-source information (data-level, feature-level, and decision-level fusion) for robust decisions, enhancing the trustworthiness of "black-box" models through Explainable AI (XAI), and developing adaptive systems that can evolve with the equipment through technologies like digital twins. This phase aims to move beyond isolated diagnosis towards integrated, transparent, and predictive health management systems, ultimately supporting the high-reliability requirements of next-generation main pump systems.

5. Core Challenges and Future Research Directions

The fault diagnosis of main pump systems has made significant advancements, yet it still faces substantial challenges in addressing the complexities and variabilities of real-world operating conditions, as well as the increasing demands for higher reliability. Building upon a comprehensive review of the literature, particularly the in-depth analysis of the strengths and limitations of different diagnostic approaches presented in Section 3, this section highlights three core challenges confronting this field and outlines forward-looking research directions to address them. The goal is to provide clear technical pathways and breakthroughs for future investigations.

5.1. Core Challenge 1: Failure Mechanism Coupling and Evolution Law Under Extreme Working Conditions Are Unclear

The failure of main pumps arises from a highly complex interplay among various physical fields, including mechanical, hydraulic, thermal, and fluid dynamics. However, existing fault mechanism studies often rely on single-fault modes or steady-state assumptions, lacking a systematic understanding of the evolution processes underlying multiple concurrent, coupled, and competing faults. As discussed in Sections 3.1 and 3.2, the performance boundaries of signal processing and model-based approaches are heavily dependent on the depth of understanding of the failure mechanism. Under extreme conditions, such as strong noise, variable load, and transient processes, the signal-to-noise ratio of fault characteristic signals can be extremely low and heavily masked. Additionally, the physical-chemical processes underlying slow-varying faults, such as material property degradation and interface fretting wear, are difficult to observe directly through external signals, resulting in insufficient generalization ability of data-driven diagnosis methods (Section 3.3) due to the absence of physical anchor points. The fundamental reason for these limitations is the absence of a complete quantitative correlation among the "physical mechanism–signal response–feature mapping", which remains a primary bottleneck restricting the accuracy and reliability of diagnostic approaches.

Future research should focus on developing a high-fidelity multi-physics simulation model to accurately replicate fault evolution under extreme conditions, such as thermal shock, cavitation, and misalignment. This involves quantitative modeling of crack initiation and propagation, seal failure, and bearing sliding mechanisms under fluid–solid–heat coupling. Building on this, a dynamic digital twin of the main pump system can be

constructed. This digital twin, continuously updated and calibrated with data-driven models, enables virtual mapping and iterative optimization of fault mechanisms and dynamic responses, offering a reliable physical basis for fault diagnosis. Additionally, integrating macroscopic system dynamics with microscopic material failure physics is essential to understand cross-scale transfer from microscopic damage, like fatigue and corrosion, to macroscopic performance degradation, such as efficiency decline and increased vibration. Using molecular dynamics and phase-field methods, the microscopic damage processes of key components, including bearings and seal rings, can be simulated. Experimental verification can then establish a correlation model between microscopic parameters and macroscopic characteristics, providing a theoretical foundation for early weak fault diagnosis.

5.2. Core Challenge 2: Insufficient Generalization and Reliability of Diagnostic Models in Complex Environments

Section 3.5 highlights the limitations of various diagnostic methods. Data-driven approaches, such as deep and transfer learning, are powerful but require extensive high-quality labeled data. In practice, main pump failure samples are scarce, and variable operating conditions lead to significant data distributional discrepancies, resulting in model overfitting and poor generalization. This disparity creates a notable gap between laboratory and field performance. Model-driven methods offer strong physical interpretability but are sensitive to model accuracy and parameters, making them vulnerable to parameter drift and unmodeled dynamics arising from system degradation. Fusion methods can enhance reliability, yet their design typically depends on prior knowledge and lacks adaptive optimization. Furthermore, existing methods often operate as "black boxes", lacking uncertainty quantification, which hinders trust in diagnostic results for high-risk decisions by operation and maintenance personnel.

Future research directions and breakthrough points in fault diagnosis: First, it is crucial to vigorously develop small-sample learning, zero-shot learning, and meta-learning frameworks. This would enable the model to quickly learn new fault patterns from a minimal number of samples. Additionally, the integration of interpretable AI techniques, such as attention mechanisms and saliency maps, can reveal the model's decision-making basis, enhancing the credibility of the results. Concurrently, the incorporation of Bayesian deep learning or evidence theory can quantify the uncertainty of diagnosis results, providing fault types and their associated confidence probabilities to support risk-controllable operation and maintenance decisions. Second, the exploration of online adaptive learning mechanisms is essential, allowing the diagnosis model to be continuously optimized using real-time data. This would enable the model to adapt to equipment aging and working condition drift. The development of lightweight neural network models and model compression technology can promote the deployment of algorithms to the edge, achieving real-time, localized intelligent fault diagnosis and reducing dependence on cloud communication. Building a collaborative architecture of "intelligent perception–edge diagnosis–cloud optimization" can form a closed loop of perception and decision-making. Third, the investigation of open-set recognition and active learning strategies is crucial. This would enable the system to identify and reject unknown faults and actively query the most valuable samples for expert labeling, thereby improving model performance at lower cost. Finally, a new paradigm of fusion diagnosis, driven by deep learning and physical models, should be developed. By embedding constraints and prior knowledge from physical models into data-driven models, this approach can enhance generalization ability and reliability in data-scarce scenarios.

5.3. Core Challenge 3: Leap from Fault Diagnosis to Predictive Maintenance and Proactive Health Management

Current research predominantly focuses on "passive diagnosis" post-fault. However, industry demands predictive maintenance and proactive health management (PHM) at the system level. This transition encounters three main challenges: first, remaining useful life (RUL) prediction technology is underdeveloped, with low accuracy in forecasting performance degradation trajectories and poor capability in predicting sudden failures; second, diagnosis, prediction, operations, maintenance decision-making, and control are disjointed, lacking closed-loop collaboration; third, there is an absence of system-level engineering architecture and standardized solutions to support PHM.

Future research should focus on dynamic digital twins as a central element, integrating real-time monitoring, historical operation data, and physical models to dynamically predict performance degradation and the remaining useful life (RUL) of key components. This approach aims to advance from fault diagnosis to health prediction. The development of RUL prediction methods using deep learning time-series models and performance degradation data should prioritize enhancing prediction accuracy and early warning capabilities. Additionally, efforts should be directed toward integrating fault diagnosis with fault tolerance control. Upon detecting or predicting a fault, the system should automatically reconfigure control laws, adjust operating parameters, or switch redundant units to actively isolate faults and maintain system functionality, transforming post-fault maintenance into proactive mitigation. Furthermore, the application of advanced intelligent sensing technologies, such as self-powered wireless sensors based on triboelectric nanogenerators (TENGs), should be explored to address power supply and signal transmission challenges in rotating part sensors, enabling ubiquitous state information sensing. By drawing insights from prognostics and health management (PHM) systems for complex equipment like aeroengines, a comprehensive health management ecosystem for main pump systems can be developed. This ecosystem would encompass "state perception, intelligent diagnosis, life prediction, operation and maintenance decision-making, and fault-tolerant control", ultimately achieving predictive maintenance and intelligent operation and maintenance.

6. Conclusions

This study systematically reviews advancements in fault mechanisms and intelligent diagnostic methods for main pump systems, establishing a comprehensive knowledge framework that spans from fundamental principles to intelligent technology applications. By deeply analyzing and comparing four diagnostic paradigms—signal processing, model-based, data-driven, and information fusion—this study clarifies the advantages, applicable scenarios, and limitations of each method. With a focus on the unique demands of nuclear main pumps operating under extreme conditions, it further identifies current research challenges and outlines key future development directions. The primary conclusions and contributions of this review are as follows:

6.1. Study Summary

The failure of the main pump system is a key factor limiting its high-performance, long-cycle, and reliable operation. First, the failure mechanisms and evolution laws of the four critical subsystems (bearings, seals, hydraulic components, and rotors) of the main pump are deeply analyzed, establishing the internal relationship between "mechanism and symptom". This provides a solid theoretical basis for fault diagnosis. Furthermore, four types of fault diagnosis methods are comprehensively summarized. Signal processing-based methods excel at extracting transient and nonlinear fault features from vibration

and pressure monitoring data, but their performance depends heavily on signal quality and prior knowledge. Model-based methods have the advantages of physical transparency and do not require a large amount of fault data, but their accuracy is limited by the model's accuracy and sensitivity to system parameter drift. Data-driven methods have become a research hotspot due to their powerful automatic feature extraction and pattern recognition capabilities, but their performance depends on high-quality labeled data, and their generalization ability under extreme conditions and small samples still needs improvement. Fusion-based methods effectively improve the accuracy and robustness of the diagnosis system by complementing information at the data, feature, or decision level, which is an important development trend for addressing complex system fault diagnosis. At present, with the deepening of the understanding of fault mechanism and the phased breakthrough of multi-source information fusion technology, the reliability of main pump fault diagnosis has been significantly improved and is gradually promoted and applied in industrial practice.

6.2. Comparison with Existing Reviews and Innovation

This paper distinguishes itself from existing reviews both domestically and internationally in three key areas. First, while most reviews concentrate on diagnostic algorithms, this work uniquely conducts an in-depth cross-fault analysis of the physical mechanisms in main pump bearings, seals, hydraulic components, and rotor subsystems. It offers a comprehensive description of the entire process from fault initiation through evolution to failure, providing a theoretical foundation for diagnostic technologies. Moreover, it establishes a coherent logical connection from the "physical essence" to the "diagnosis method".

This paper presents a comprehensive analysis of main pump diagnosis methods, classifying them into four distinct paradigms and providing a systematic comparison of their inherent advantages, core limitations, and typical application scenarios. The detailed examination (summarized in Tables 4–7) offers a direct and practical theoretical foundation for engineers and technicians to select appropriate methods when addressing specific diagnostic problems. Furthermore, this study closely aligns with the practical application context of nuclear main pumps, delving into the analysis of critical engineering challenges, such as strong noise, small sample sizes, and multi-fault coupling. The research prospects proposed, including deepening the multi-field coupling mechanism model, developing intelligent and robust diagnosis strategies, and exploring fault prediction and proactive mitigation measures, are not generic but rather targeted and forward-looking, aiming to address industry-specific pain points and provide a clear direction for future advancements.

6.3. Future Expectations

The main pump fault diagnosis technology has made significant advancements, yet it continues to face challenges under complex and long-term operating conditions. Crucial aspects that warrant further investigation include the fault evolution mechanism, online evaluation and verification of the diagnosis system, and the development of efficient fault mitigation strategies. Future research should focus on the following directions: First, a comprehensive coupling dynamic model that integrates multiple physical fields and failure modes should be developed at the mechanism and model level. This model should leverage digital twin technology to enable dynamic updating and verification. Second, at the diagnostic strategy level, more advanced cross-domain transfer learning, small-sample learning, and unsupervised/semi-supervised learning algorithms should be explored to enhance the adaptability and generalization capabilities of diagnostic models under extreme conditions. Finally, at the system integration level, the deep integration of fault

diagnosis, health management (PHM) systems, and fault-tolerant control systems should be promoted to establish a closed-loop intelligent operation and maintenance ecosystem of "perception–diagnosis–decision–control". The integration of materials science, micro–nano sensing, and other disciplines holds promise for developing a more intelligent, reliable, and autonomous health management ecosystem for primary pump systems. Leveraging self-powered sensing technology could address long-term power supply challenges faced by sensors, while insights from intelligent monitoring paradigms employed in other major equipment, such as aeroengine pipeline systems, could further enhance the predictive maintenance and the long-term safe operation of these critical pump systems.

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