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Review

Modal Identification Techniques for Concrete Dams: A Comprehensive Review and Application

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Abstract: Throughout history, the implementation of structural health monitoring systems has played a crucial role in evaluating the responses of dams to environmental and human-induced threats. By continuously monitoring structural integrity and analyzing dynamic characteristics, these systems offer a robust alternative to traditional visual inspection methods, ensuring the long-term safety of dams. This paper delves into the intricate process of operational modal analysis applied to dams, encompassing data collection, preprocessing, and the utilization of diverse modal identification techniques across both time and frequency domains. Moreover, it explores innovative approaches aimed at overcoming challenges encountered in previous methodologies. Also, the evolution of automated modal identification techniques and their application in dams are investigated. It explores the advancements in this field and their implications for enhancing the efficiency and accuracy of modal analysis processes. Furthermore, this paper evaluates the effectiveness of damage detection methods in dams based on operational modal identification.

Keywords: dam; modal analysis; operational modal identification; sensors; automated modal identification; damage detection; dam health monitoring

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1. Introduction

Structures undergo a multitude of stresses and strains throughout their lifespans, encompassing both static forces like the weight of occupants and furnishings, as well as dynamic forces such as wind, seismic activity, and vehicular traffic [1–3]. These loads impose various pressures on structural elements, gradually accumulating damage over time.

In response to the diverse range of loads and the potential for cumulative damage, continuous monitoring emerges as a critical component of structural maintenance and safety management. Through the implementation of monitoring systems that track key parameters like strain, displacement, vibration, and environmental conditions, engineers can gain valuable insights into the structural health and performance over time [4,5]. Identifying deviations from expected behavior at an early stage allows for prompt intervention and the implementation of preventive measures, which helps mitigate risks and prolong the lifespan of structures. Consequently, proactive monitoring not only aids in identifying existing damage but also facilitates predictive maintenance strategies, enhancing resilience and ensuring the long-term sustainability of built infrastructure [6–8].

Understanding and analyzing the vibrational behavior of structures is fundamental in engineering disciplines, given its direct correlation with dynamic performance, stability, and resilience [9–11]. Vibration, an intrinsic phenomenon in structural systems, is influenced by various factors including external forces, material properties, and geometrical configurations. Modal analysis emerges as a powerful tool in deciphering the intricate dynamics of structures, providing insights into their modal characteristics and response to dynamic loads [12,13]. Through modal analysis, engineers can gain a deeper understanding of natural frequencies, mode shapes, and damping characteristics, enabling them to optimize designs, assess structural integrity, and mitigate the adverse effects of vibrations.

Thus, modal analysis plays a pivotal role in enhancing the efficiency and safety of structural systems across various engineering disciplines.

Structural vibrations manifest in intricate patterns, featuring distinct modes of oscillation that correspond to natural frequencies and their associated mode shapes. These modal characteristics offer essential insights into the structural behavior, empowering engineers to anticipate and address potential risks stemming from dynamic loading scenarios [14].

Modal analysis serves as a cornerstone technique in structural engineering for examining the dynamic behavior of mechanical systems. It entails the identification of natural modes of vibration, along with their corresponding frequencies and mode shapes, under different loading conditions [15]. These natural modes signify the unique vibrational patterns demonstrated by the structure when exposed to external forces or disturbances. Through modal analysis, engineers can gain a comprehensive understanding of the structural response to dynamic loads, facilitating informed design decisions and enhancing the overall performance and safety of the structure. Modal analysis encompasses various techniques for extracting the dynamic characteristics of structures, each with its unique approach and advantages. Two commonly used techniques are Experimental Modal Analysis (EMA) and operational modal analysis (OMA) [16,17].

EMA is a traditional method used to characterize the dynamic behavior of structures through physical testing. It involves exciting the structure with controlled inputs, such as impact hammer strikes or shaker excitation, and measuring the resulting response using sensors, such as accelerometers or laser vibrometers [18]. EMA aims to identify the modal characteristics of the structure under consideration. By analyzing the frequency response data obtained from multiple test points, EMA provides valuable insights into the structural dynamics [19].

The use of EMA in civil engineering structures is challenging due to their large size and low frequency range. Obtaining output data or structural responses typically involves installing sensors at various points and recording their data. For large engineering structures such as bridges, dams, and buildings, creating controlled and measurable artificial excitation as input to the system is often complex and requires expensive equipment [14,20]. Additionally, simultaneous random forces such as wind loads and traffic are applied to the structure along with artificial excitation, making it difficult to separate the effects of each. If these forces are not measured accurately, EMA cannot provide accurate estimates of modal parameters. Therefore, EMA is typically limited to laboratory environments, and alternative solutions are needed for real-world civil engineering structures [21].

OMA is a technique used to extract modal characteristics from ambient vibration data collected during the normal operation of a structure [22,23]. Unlike EMA, which requires controlled excitation, OMA utilizes naturally occurring vibrations induced by environmental or operational loads, like earthquakes, traffic, or machinery. OMA can identify the modal characteristics of the structure without the need for external excitation. However, OMA may be susceptible to noise and uncertainties inherent in ambient vibration data, requiring careful data preprocessing and validation [24,25]. The steps of OMA are presented in Figure 1.

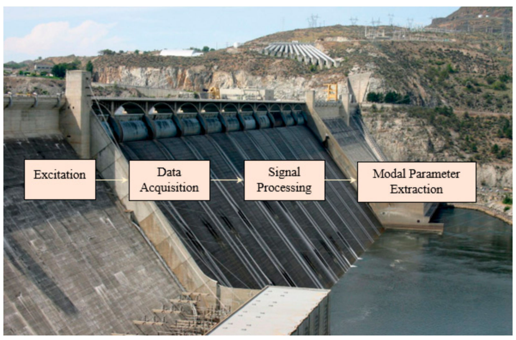

Figure 1. Main steps of OMA.

To the best of the author's knowledge, no comprehensive review currently exists that consolidates all papers on the topic of modal identification of concrete dams. This work aims to fill this gap by systematically reviewing and synthesizing existing studies, providing a detailed analysis of the various modal identification methods applied to concrete dams, and identifying major research gaps and emerging trends in this area. Figure 2 shows a diagram outlining the key components of the current review paper. It presents a comprehensive overview of OMA, covering the entire process from the acquisition of structural data to their utilization in applications related to dam structural health monitoring (DSHM). This paper commences with a discussion on the instrumentation system (Section 2), followed by an exploration of modal identification methods in both time and frequency domains in Section 3. Recent advancements in modal identification, including the development of automated algorithms employing machine learning and artificial intelligence are presented in Section 4. In Section 5, the application of OMA in dam health monitoring and damage detection is examined. Finally, this paper concludes with a summary of the most significant findings in Section 6.

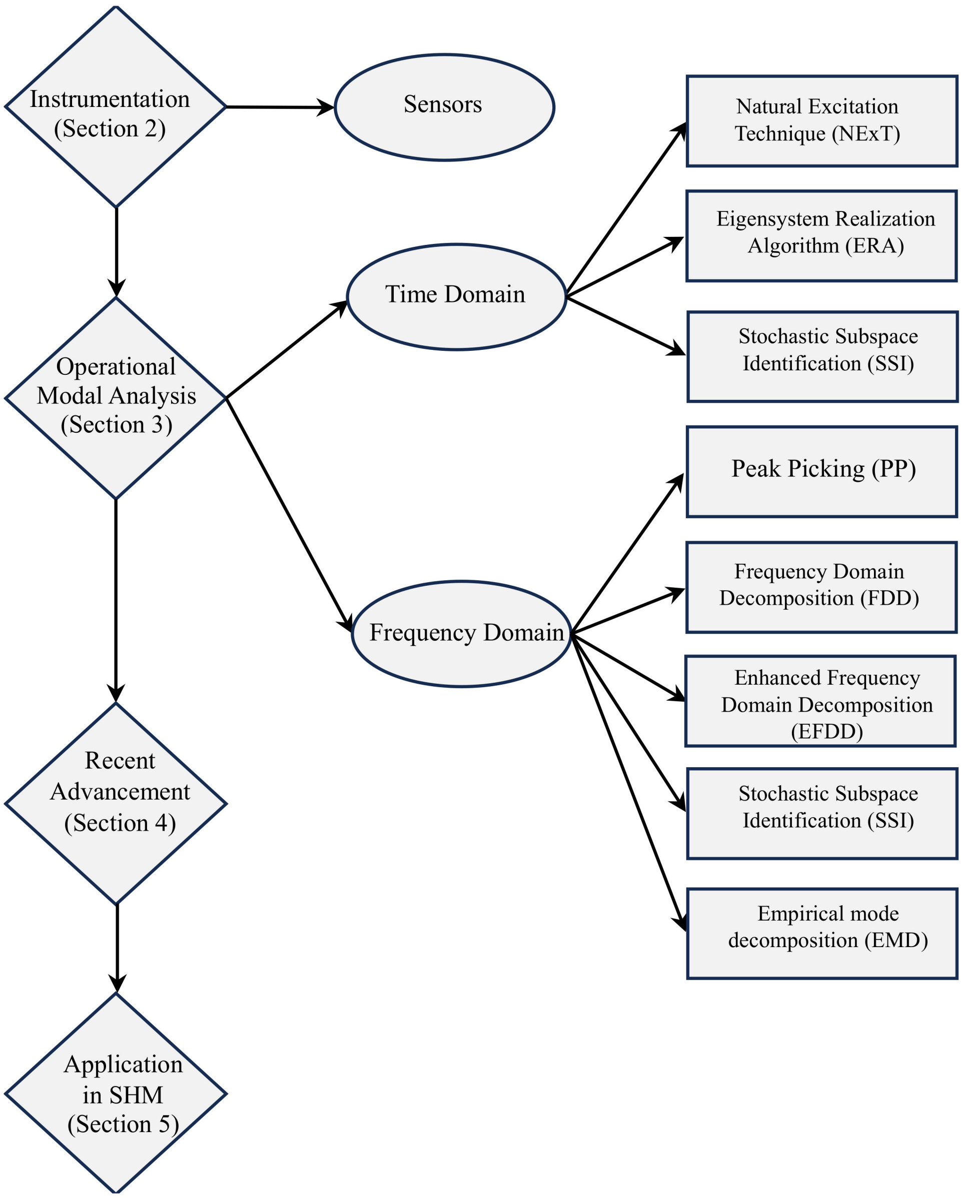

Figure 2. Key components of the current review paper.

Figure 3 shows the papers contributing to this review article, categorized by their publication years from 1990 to 2023. The notable increase in publications in recent years can be attributed to various factors, including advancements in modal identification techniques. Additionally, the evolution of signal processing methods has played a significant role in this positive trend. Furthermore, the development of new approaches, driven by machine learning and artificial intelligence, has also contributed to the surge in research output in OMA. Enhanced computational power and the integration of big data analytics have further supported this growth, enabling more complex and accurate analyses.

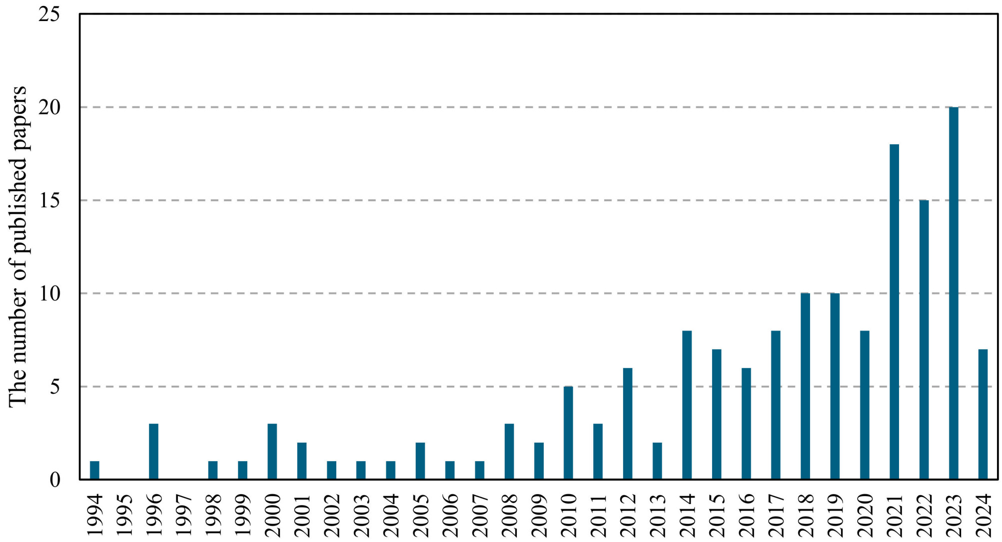

Figure 3. Contributions of the papers included in this study.

2. Instrumentation

Instrumentation plays a key role in monitoring the structural health and behavior of dams, ensuring their safety and stability over time [26]. In the context of modal identification, instrumentation provides valuable data that help engineers understand the dynamic characteristics of dams and detect any potential issues or changes in their behavior. Various types of instruments are used for this purpose, each serving a specific function and providing unique insights into the dam's performance [27].

One of the most commonly used instruments in dam monitoring is the accelerometer, which measures the acceleration of the dam structure in response to dynamic forces such as seismic activity or water flow [28,29]. By analyzing the acceleration data collected from accelerometers placed at different locations on the dam, engineers can identify the natural frequencies, mode shapes, and damping ratios of the structure, which are essential parameters for modal identification [28].

In addition to accelerometers, other types of instruments such as strain gauges, piezometers, and inclinometers are also used to monitor various aspects of dam behavior. Strain gauges measure the strain or deformation of the dam's concrete or steel components, providing insights into the structural integrity and load distribution within the dam. Piezometers measure water pressure in the dam's foundation or reservoir, helping engineers assess the hydrostatic and hydrodynamic forces acting on the structure. Inclinometers measure the inclination or tilt of the dam's embankment or foundation, allowing engineers to detect any potential instability or movement of the structure [29].

Selecting the location and number of sensors for monitoring the dynamic behavior of dams is a critical task that requires careful consideration of several factors. One primary role in this process is to ensure adequate coverage of key areas of the dam that are most susceptible to dynamic forces and potential structural issues [30]. Engineers typically identify critical zones such as the dam crest, downstream face, abutments, and foundation, where sensors should be strategically placed to capture the most relevant data. As depicted in Figure 4, proper sensor selection and installation during the setup phase are essential to provide engineers with the necessary documentation for obtaining high-quality data and informed decision-making [31]. For optimal collection of vibrational signals in dams, sensors should be strategically placed at critical locations including the dam's crest, upstream and downstream faces, spillways, and outlets. Additional sensors in the gallery or interior access tunnels, foundation, abutments, and key structural joints are essential for capturing vibrations caused by operational loads.

Figure 4. Proper sensor selection and installation in dams.

The number of sensors deployed depends on the size, geometry, and complexity of the dam, as well as the specific objectives of the monitoring program. Additionally, factors such as the type and sensitivity of sensors, budget constraints, and data analysis requirements also influence the decision-making process. By strategically selecting the location and number of sensors, engineers can effectively monitor the dynamic behavior of dams and ensure the safety and stability of these critical structures. Numerous researchers have explored optimal sensor placement (OSP) techniques [32,33].

Kang et al. [34] introduced a virus coevolutionary parthenogenetic algorithm to address OSP issues, drawing from both genetic algorithms and virus evolutionary theory. Unique parthenogenetic operators, tailored for combinatorial optimization, replace traditional genetic algorithms operators, enhancing convergence speed and reducing premature convergence through virus infection mechanisms that coevolve host and virus populations. Lian et al. [35] introduced a novel approach to OSP in large structures, addressing the limitations of the Effective Independence Method. Their method employs a unique fitness function derived from the nearest neighbor index, optimizing sensor locations to maximize modal observability while minimizing redundancy. A hybrid algorithm, blending improved discrete particle swarm optimization with the clonal selection algorithm, effectively optimizes this fitness function. He et al. [36] devised a novel fitness function addressing spatial correlation in multiaxial sensor placement to alleviate information redundancy. This function is optimized using the integer-encoding multi-swarm particle swarm optimization algorithm, enabling effective selection of sensor locations for modal parameter identification. Zho et al. [37] introduced a new sensor optimization criterion merging the effective independence and modal strain energy methods. To handle the complexity of modern concrete arch dams, a quantum genetic algorithm was applied to optimize the sensor network on the dam's upstream surface. Chen et al. [38] conducted a computational study on an arch dam model using 20 sensors to validate the method's feasibility. They compared existing methods using criteria like modal assurance, kinetic energy, Fisher information, and root-mean-square error to assess their strengths and weaknesses. Vosoughifar and Khorani [39] assessed a novel method using modified modal assurance criterion (MAC) coordinates and transferring time history analysis results to the frequency domain for dam structural health monitoring. Cao et al. [40] introduced the distance coefficient–multi-objective information fusion algorithm for OSP in large-scale structures. A European distance metric mitigates redundancy between sensors, while an optimized objective function, guided by information entropy principles, ensures a balance between sensitivity and robustness. Altunisik et al. [41] employed the Enhanced Frequency Domain Decomposition (EFDD) and Stochastic Subspace Identification (SSI) techniques to extract modal parameters. They determined optimal sensor positions using the Effective Independence Method, guided by target mode shape matrices derived from ambient vibration tests on the dam with numerous accelerometers. Subsequent measurements were conducted at these specified locations. Giahi et al. [42] computed modal parameters for two concrete dams, healthy and damaged, via the finite element method. Varying concrete modulus reductions simulated damage levels. Sensor placement was optimized using the MAC method, compared with a new approach. Table 1 provides a list of some of the instrumentation methods employed in DSHM.

Table 1. Different instrumentation methods for DSHM.

Instrumentation Method	Cost	Sensitivity	Deployment Complexity	Data Quality	Application Scope
Accelerometers	Moderate	High	Easy	High	Suitable for detecting vibrations in a wide frequency range.
Seismometers	High	Very High	Moderate	Very High	Ideal for capturing low-frequency ground motions.
Strain gauges	Low	Moderate	Easy	Moderate	Effective for measuring deformation but less effective for dynamic modal analysis.
Laser Doppler Vibrometers	High	Very High	Moderate	Very High	Non-contact method providing precise vibration measurements.
GPS	High	Moderate	Complex	Moderate	Useful for monitoring large-scale movements but less sensitive to high-frequency vibrations.
Fiber Optic Sensors	High	High	Complex	High	Ideal for monitoring strain and temperature changes over long distances.
Microelectromechanical Systems (MEMSs)	Low to Moderate	High	Easy to Moderate	Moderate to High	Compact, cost-effective solutions suitable for dense sensor networks.

At the installation stage, it is crucial to select and install the proper sensors and provide the necessary documentation to engineers to ensure high-quality data collection and informed decision-making. Optimal locations include the dam crest and base for overall dynamic response and base interactions; upstream and downstream faces to monitor differential movements; and mid-height elevations for vertical modes of vibration.

3. Operational Modal Analysis (OMA)

OMA, referring to output-only modal analysis, represents a sophisticated method for identifying the modal characteristics of a structure [43,44]. OMA proves invaluable in scenarios where the structure's size precludes artificial excitation or where a complete shutdown of the system is unfeasible. Instead of controlled inputs, OMA relies on ambient forces or cyclic loads inherent to the structure for excitation. Its independence from input excitation renders OMA particularly suitable for analyzing structures subject to random excitation induced by their surrounding environment [21].

OMA encompasses a range of data processing algorithms, each tailored to address specific challenges encountered during the analysis. However, processing data in OMA presents inherent complexities and may yield erroneous outcomes, despite seemingly reasonable results. To address this challenge, researchers have developed diverse OMA techniques over the past three decades, each offering unique approaches and methodologies.

These techniques, which will be explored in detail in the following section, aim to enhance the accuracy and reliability of modal parameter identification in OMA applications [45].

3.1. OMA Approaches

Modal identification algorithms play a crucial role in structural analysis and dynamic testing by extracting modal parameters from measured data. These algorithms are used to identify the modal characteristics of a structure. In recent years, there has been significant progress in the development of modal identification algorithms, leading to a wide range of approaches [46]. These algorithms can be broadly categorized into frequency-domain, time-domain, stochastic, state-space, and hybrid methods. Each of these methods has its own set of principles and advantages, making them suitable for different scenarios. Frequency-domain methods, such as Peak Picking (PP), Polyreference Time Domain (PTD), Frequency-Domain Decomposition (FDD) [47,48] and EFDD [49], analyze vibration data in the frequency spectrum, making them well suited for identifying modal parameters associated with distinct vibration frequencies [50]. On the other hand, time-domain techniques, including the Ibrahim Time Domain (ITD) method [51], process data in the time domain, offering insights into the dynamic behavior of structures over time. Stochastic methods, such as the SSI technique, are based on statistical techniques and can handle uncertainty in the measured data [52–54]. These methods provide a probabilistic estimate of the modal parameters, taking into account the noise and measurement errors. For example, the SSI method has been applied in the analysis of aerospace structures, where the measured data are often contaminated with noise and the modal parameters need to be estimated with high precision. State-space models, such as the Eigensystem Realization Algorithm (ERA), offer a different approach by representing the dynamic behavior of the structure in a mathematical framework [55,56]. Algorithms based on state-space models leverage the power of state-space models to estimate modal parameters. They offer advantages such as the ability to handle complex systems with multiple inputs and outputs, as well as the capability to capture system dynamics accurately. These algorithms have been successfully used in the analysis of mechanical systems, such as rotating machinery, where the system dynamics are highly nonlinear and the modal parameters need to be estimated with high accuracy. Finally, hybrid approaches combine the strengths of different algorithms, such as time-domain, frequency-domain, and stochastic techniques, to improve the accuracy of modal identification. By integrating multiple approaches, these algorithms can overcome the limitations of individual methods and provide more robust and reliable results. For example, a hybrid method that combines the ITD method with the PTD method has been developed for the analysis of civil structures, where the input signals are both time-varying and periodic, and the modal parameters need to be estimated with high accuracy [57,58].

3.1.1. Peak Picking (PP) Method

In 1994, Felber presented how to use this method in practical work in his doctoral dissertation conducted at UBC University in Canada and applied it to bridges [59]. The PP method in modal identification is a widely used technique for extracting modal parameters from measured response data. This method relies on identifying peaks in the frequency response function (FRF) or power spectral density (PSD) plot corresponding to the natural frequencies of the structure. By detecting these peaks, modal frequencies, damping ratios, and mode shapes can be estimated. The PP method involves several steps, starting with the acquisition of vibration data from sensors mounted on the structure of interest. Once the data have been collected, they are typically processed to obtain the frequency-domain representation using techniques such as Fourier transform or spectral analysis.

In the frequency-domain representation, peaks corresponding to the resonant frequencies of the structure are identified. These peaks represent the dominant vibration modes of the structure and can be detected using various peak detection algorithms. Commonly used algorithms include simple thresholding, peak interpolation, and curve fitting techniques. Once the peaks are identified, they are analyzed to extract modal parameters.

The natural frequencies are determined by the frequency location of the peaks, while the damping ratios can be estimated based on the width and shape of the peaks. However, it is important to note that the PP method has limitations, especially when dealing with noisy or closely spaced modes [60,61]. In such cases, false peaks may be detected, leading to inaccurate estimation of modal parameters. Additionally, the method may struggle to identify lightly damped modes or modes with low signal-to-noise ratios. The PP method has been employed by several researchers to extract the modal parameters of dams. For example, Darbre et al. [62] conducted ambient vibration tests on the 250 m high Mauvoisin arch dam, obtaining resonance frequencies. Initially, frequencies rose with the water level, then declined due to increased water mass and stiffening from closed construction joints. Earthquake data from 12 accelerographs complemented the ambient test results. Also, Pereira et al. [17] introduced an algorithm that integrates the PP and covariance-driven Stochastic Subspace Identification (SSI-Cov) methods. They conducted ambient vibration tests on six distinct concrete dams. A novel methodology was employed to account for estimated uncertainties, evaluating the impact of noise on modal estimate quality and assessing sensor suitability for dam testing.

3.1.2. FDD Method

The FDD method was first introduced by Brincker et al. [63] in 2000 as a novel technique for modal parameter estimation in structural dynamics. This innovative approach revolutionized the field by offering a robust and efficient method for identifying modal parameters from measured response data. FDD operates in the frequency domain and is particularly effective for analyzing complex structural systems with closely spaced modes and varying operating conditions. FDD aims to extract the modal parameters of a structure from measured FRF data [64].

At its core, FDD leverages the concept of Singular Value Decomposition (SVD) to decompose the measured FRF matrix into its constituent modes. The key idea is to analyze the singular values and vectors of the FRF matrix to identify the underlying modal properties of the structure. Singular values represent the energy associated with each mode, while singular vectors represent the corresponding mode shapes.

FDD utilizes the output PSD akin to the PP method. However, it performs SVD of the output PSD, which is estimated at discrete frequencies $\omega = \omega_i$ [63]. This decomposition is conducted to discern single-degree-of-freedom models of the system [65]. Singular vectors estimate the mode shapes, while the associated singular values denote the spectral densities of the SDOF system. For repeated modes, the rank of the PSD matrix corresponds to the multiplicity of these modes. Consequently, the SV function acts as a Modal Indication Function, helping to locate modal frequencies by pinpointing peaks in the SV plots. Mode shapes can be derived from the relevant singular vectors. Since SVD effectively distinguishes between signal space and noise space, it allows for the clear identification of closely spaced or repeated modes from the SV plots. FDD is particularly advantageous for modal identification in dams because it can accurately extract modal parameters from output-only measurements, making it suitable for real-world applications where input data may be limited or unavailable. The method is non-parametric and builds upon the classic PP approach, providing a reliable way to identify the structural dynamics of dams [66]. Many researchers have employed the FDD method for the modal identification of dams. For example, extensive ambient vibration tests on the Karun IV arch dam were performed by Tarinejad et al. [67]. Signal processing of ambient and seismic records was performed using the non-parametric FDD-WT method. The resulting mode shapes and damping ratios for consistent modes were extracted and compared. Damadipour and Tarinejad [68] monitored the health of a concrete arch dam using an integrative method called FDD-WT. This method combines FDD and wavelet transform to address damping value inaccuracies. Utilizing seismic records from earthquakes between 1994 and 2008, including Northridge, San Fernando, and Chino Hills, they evaluated dynamic characteristics and structural health. Analysis revealed severe damage during the 1994 Northridge earthquake around the fourth second, with linear vibrations observed in subsequent earthquakes. Tarinejad and Damadipour [69] extended the FDD-WT method to address errors from asynchronous sensor sensing, aiming to broaden its application to various structures. The enhanced method corrects time delays between sensors, employing time–frequency-domain decomposition. Moreover, Byjebta et al. [70] detailed a monitoring system for the Roode Elsberg dam. They provided three-month operation results, tracking the first three natural frequencies using FDD. The effects of environmental and operational loads on these frequencies were analyzed.

3.1.3. EFDD Method

The EFDD method was proposed shortly after by Brincker et al. [71]. In addition to providing more accurate calculations of natural frequencies and mode shapes, this approach also allows for the estimation of modal participation ratios. The EFDD method has become one of the most popular techniques for OMA in extracting structural modal parameters. Moreover, EFDD incorporates additional enhancements to improve accuracy and robustness, particularly in scenarios involving closely spaced modes, noisy data, and varying operating conditions. One of the key enhancements in EFDD is the utilization of advanced signal processing techniques to preprocess the measured data before performing modal parameter estimation. These techniques may include noise filtering, baseline correction, data smoothing, and outlier detection to improve the quality of the FRF data and enhance the accuracy of modal identification [48,72,73].

Another enhancement in EFDD involves the incorporation of model-based approaches to refine the estimation of modal parameters. This may include the use of mathematical models or finite element models to provide additional insights into the dynamic behavior of the structure and assist in identifying closely spaced modes or complex modal interactions. The EFDD method has been employed by many researchers for extracting the modal parameters of structures. For instance, Sevim et al. [74] conducted finite element calibration of the Berke Arch Dam using Operational Modal Testing, comprising analytical and experimental approaches. The analytical part involved developing a 3D finite element model and determining vibration characteristics. In the experimental part, ambient vibration tests were conducted, and the EFDD method was employed. Analytical model calibration minimized differences between analytical and experimental natural frequencies, yielding results largely consistent with the experimental model. Sevim et al. [75] investigated the modal characteristics of a prototype arch dam–reservoir–foundation system using OMA. They conducted ambient vibration tests on a laboratory-scale model, capturing modal characteristics. Accelerometers placed on the dam's crest collected signals during empty and full reservoir conditions. In another study, they conducted ambient vibration tests to identify the structural properties of concrete arch dams utilizing the EFDD technique [76,77]. The study found consistent and satisfactory agreement across all measurements, indicating the effectiveness of the method for structural identification of concrete arch dams. Altunisik et al. [78] investigated the impact of retrofitting on the dynamic properties of a damaged laboratory arch dam model. Using high-strength structural mortar and carbon fiber-reinforced polymer, they repaired and strengthened the model. Through ambient vibration tests, changes in modal parameters were observed before and after retrofitting. The EFDD method analyzed the dynamic characteristics, revealing significant increases in natural frequencies post-retrofitting, indicating effective restoration of initial properties. In another paper, they examined how varying reservoir levels affect dynamics of an arch dam model under damage, repair, and strengthening conditions by using EFDD methods [79]. Altunisik et al. [41] explored OSPs and the efficacy of dynamic characteristics identification for arch dams. Laboratory testing was conducted, followed by field verification at Berke Arch Dam in Turkey. Initial ambient vibration tests were performed with candidate sensor locations, utilizing the EFDD and SSI methods. Subsequently, tests were repeated at optimal sensor locations determined by the Effective Independence Method, confirming their effectiveness in dynamic characteristic identification. In another study, they investigated the time-dependent changes in dynamic characteristics of laboratory arch dam models using ambient vibration tests [80]. Tests were conducted on undamaged, minor-damaged, and severely damaged dam bodies. Davoodi and Eghbali [81] investigated stationary records from several days, analyzing them with the 4-Spectrum, FDD, and EFDD methods. The 4-Spectrum method ensured reliability in modal frequencies but had potential errors due to separate control of the sensors' spectra. FDD utilized SVD for data analysis, while EFDD, slightly more accurate, used a special peak selection algorithm. Guo et al. [82] conducted modal analyses of the Saint-Guérin dam using experimental and numerical techniques. Employing EFDD for ambient vibration data, they identified 10 natural frequencies and modal shapes. The fluid-element method showed promise for accurate prediction of higher modes, enabling model calibration with experimental data for continuous monitoring. In another study, Guo et al. [83] examined ambient vibration data from an arch dam to identify modal frequencies using the EFDD technique. Subsequently, they calibrated and validated a numerical model based on the experimentally obtained frequency values.

3.1.4. ERA Method

The ERA is a time-domain technique used to determine modal parameters and reduce the model of dynamic systems based on input–output data. This algorithm estimates the state-space representation of a dynamic system from its mathematical model. Using the ERA when the model order is not known in advance leads to the generation of computational modes. Furthermore, the results of identification with this algorithm are not reliable when the sampling time is not appropriate or when initial conditions are non-zero [84,85]. Recently, research has been conducted to address these issues and improve the ERA. Jianwei Zhang and Yina Zhang [86] combined the natural excitation technique (NExT) and ERA to identify modal parameters of ambient-excited hydraulic structures. Modal confidence factors were used to eliminate false modes. Moreover, Li et al. [87] performed an experimental study of flow-induced vibration for roller-compacted concrete dams. They combined the NExT, SE method, and ERA/DC method, and effectively calculated roller-compacted concrete dams' model dynamic characteristics, demonstrating the improved HEME technology's accuracy and effectiveness. Moreover, Zhang et al. [88] used the ERA and SSI to identify modal parameters of a roof overflow powerhouse under ambient excitation. To address noise, system order, and false modes, they applied ensemble EMD for noise reduction, Random Decrement Technique for extracting free-decaying responses, and singular entropy increment spectrum to determine system order. They also used multiple criteria to eliminate false modes.

3.1.5. SSI Method

Overschee and Moor were among the first to propose an SSI to extract modal parameters of structures based on their state-space models [89]. The fundamental operation of the SSI method involves defining a mathematical model for the target structure and then calibrating it through multiple iterations to ensure the predicted responses from the mathematical model closely match the actual responses of the structure. Therefore, this method requires initial knowledge about the order of the model. The recorded responses used to calibrate the mathematical model can result from either random forced vibration or free vibration. When the data are obtained from random forced vibration, it is conveniently assumed that the unknown external forces are uncorrelated random signals. The SSI algorithm can be performed both by directly using the system's responses (DATA-SSI) and by using the covariance of these responses (COV-SSI) [90]. Many studies have been conducted on the application of the SSI method for modal identification in dams, highlighting its effectiveness and reliability. For instance, Sevim et al. [91] conducted ambient vibration tests on a prototype arch dam–reservoir–foundation model to determine its natural frequencies, mode shapes, and damping ratios. Both methods proved highly effective in identifying modal parameters. Additionally, a 20–25% difference in natural frequencies between empty and full reservoir states was observed. Bukenya et al. [92] assessed the effectiveness of three SSI algorithms, including unweighted principal component analysis, principal component analysis, and canonical variate analysis, for identifying the modal parameters (natural frequencies and damping ratios) of the Roode Elsberg Dam in South Africa. The study revealed that while all three algorithms provided similar estimates for natural frequencies, they differed significantly in their estimation of damping ratios. Moreover, Tarinejad and Pourgholi [93] introduced a novel technique for OMA utilizing Stochastic Realization Theory and Canonical Correlation Analysis. Unlike previous methods, it performs identification directly in the prediction space by extracting orthonormal vectors of data space, promising superior accuracy and efficiency. Applied to the Shahid-Rajaee arch dam's forced vibration test results, it yielded more accurate natural frequencies and identified three modes previously unseen. Additionally, it successfully processed ambient vibration records of the Pacoima dam during the 2001 San Fernando earthquake. Pirboudaghi et al. [94] conducted damage detection based on system identification of concrete dams using an extended finite element–wavelet transform coupled procedure, highlighting the changes in modal characteristics due to time-varying crack forms in the dam body. Huokun et al. [95] proposed a dynamic inversion method for high arch dam and foundation material parameters based on measured vibration response. It involved arch dam prototype testing, SSI for modal parameters, and constructing a response surface model for dynamic elastic modulus. Optimized through a genetic algorithm, the method accurately inverted the dynamic elastic modulus, ensuring consistency with measured modal parameters. This approach offers a novel strategy for material parameter determination during dam operation. Fang et al. [96] used SSI-DATA to identify the modal parameters of concrete dams based on seismic response sequences for dynamic material parameter back-analysis. They emphasized selecting input signals with near-uniform power spectra and combining stabilization diagrams with power spectral density curves to distinguish false modes, ensuring accurate identification of the dam's dynamic characteristics. Moreover, Cheng et al. [97] utilized the RSSI method to extract modal parameters from concrete dams using strong-motion records. The GYAST algorithm, an advanced subspace tracking method, facilitated online eigenvalue decomposition. GYAST's computational efficiency and robustness were advantageous. The integration of GYAST with RSSI aimed to enhance modal identification accuracy and efficiency. Li et al. [98] analyzed the impact of four user-defined parameters in SSI-COV for modal identification of high arch dams. Two FE models of the Dagangshan dam were assessed. Suggestions for parameter selection were proposed based on dynamic property identification. The results revealed a radiation-damping effect of semi-unbounded foundation rock ranging from 0.6% to 2.0% for the first four modes. Using seismic records, the COV-SSI algorithm by Mao-Hua et al. [99] constructs multiple Hankel matrices to identify modal parameters of high earth-rock dams. Hierarchical clustering detects natural frequencies and damping ratios, automating modal parameter identification and reducing human error. Li et al. derived an analytic discrete-time stochastic state-space model connecting SOBI and SSI-COV [100]. SOBI obtains modal responses and a modal matrix, then SSI-COV identifies modal parameters. Pourgholi et al. [101] utilized balanced Stochastic Subspace Identification to extract modal parameters of the Karun IV Dam. They investigated user-defined parameters' impact, filtered noise, homogenized modal properties, validated physical modes, and conducted sensitivity analysis to find optimal models with minimum error in estimating modal characteristics. Wang et al. [102] proposed a novel methodology for identifying modal parameters of arch dams using the multi-level information fusion and constructed a technical framework. The correlation variance contribution algorithm and adaptive variational mode decomposition method ensure accurate identification of natural frequencies and damping ratios, while ISSI identifies structural mode shapes by avoiding signal truncation errors and blind order determination, enhancing overall accuracy. Furthermore, Pourgholi et al. proposed a new figure of merit for tracking system ill conditioning by analyzing errors in SSI through inversion [103]. Unlike the condition number, this figure of merit uses all singular values. A semi-automatic SSI method using this figure of merit optimizes Hankel matrix dimensions, clusters frequency/damping to remove outliers, and validates modal shapes. Clustering based on frequency/damping is employed to address the system's over-determination and eliminate outliers. Additionally, Liu et al. [104] proposed an algorithm combining determined-order SSI with adaptive variational modal decomposition to accurately extract modal parameters of arch dams, even under discharge excitation. They utilized sensitivity analysis with OTM and ANOVA, and a Bayesian-optimized LSTM neural network to map dynamic elastic modulus to modal parameters, enhancing inversion analysis precision.

3.1.6. Empirical Mode Decomposition (EMD) and Hilbert–Huang Transform (HHT)

The EMD method is essentially a newly developed algorithm in the field of signal processing. The EMD method, sometimes referred to as the HHT [105], decomposes a signal into a series of intrinsic mode functions and then enables the use of the Hilbert transform. The main advantage of the EMD method is its ability to decompose any type of signal into compatible and efficient components without losing time-domain information [106]. Many researchers have utilized the EMD and HHT methods for the modal identification of dams; for example, a new denoising method, WTEMD, was proposed by Zhang et al. [107] to enhance precision in denoising vibration signals of flood discharge structures with low SNRs. Wavelet filtering partially removed white noise, followed by EMD to obtain intrinsic mode functions. Esmaielzadeh et al. [108] utilized the HHT method to assess damage in concrete gravity dams, crucial for structural safety. They introduced a novel criterion, the Relative Frequency Error, based on frequency changes, effectively pinpointing damage locations. Additionally, two damage indexes, linked to the size of the Relative Frequency Error vector, were proposed to gauge damage severity. The results indicate that the first index, proportional to the Relative Frequency Error, provides better predictions of structural damage compared to the second index, inversely proportional to Relative Frequency Error. Also, Li et al. [109] proposed a self-adaptive denoising method for seismic signals of high arch dams, addressing non-stationarity and low SNRs. The method combined ensemble empirical mode decomposition with wavelet threshold and singular spectrum analysis (SSA). Using continuous mean square error criteria, it distinguished high- and low-frequency components of intrinsic mode functions, achieving superior denoising compared to traditional methods. Simulation and measured signal analysis confirmed the method's effectiveness in identifying natural frequencies. Qiao et al. [110] combined the Random Decrement Technique (RDT) with the HHT to identify the modal frequency and damping ratio of a concrete gravity dam. This involved filtering the original signal with a bandpass filter, obtaining multiple intrinsic modal functions using EMD, extracting free attenuation functions with RDT, and applying the HHT combined with least squares fitting to determine modal parameters. Mirtaheri et al. [111] devised a system for detecting damage in dam structures using system identification. An optimization algorithm minimizes nondiagonal MAC matrix entries to optimize sensor placement, enhancing detection precision. Their approach combines the HHT and wavelet transform (WT) to extract structural dynamics. Mode shapes are made differentiable using the cubic-spline technique, and Continuous Wavelet Transform (CWT) detects damage by analyzing residual mode shape curvatures. This comprehensive method improves the accuracy of damage detection in dam structures. Wei et al. [112] proposed an improved modal identification approach for arch dam flow discharge vibrations using complete ensemble empirical mode decomposition with adaptive noise and masking signal processing with the HHT. This approach aimed to suppress modal confusion and enhance accuracy in identifying modal parameters, offering potential advancements in structural analysis. Guo et al. [113] propose an enhanced wavelet threshold–EMD and RDT method for the modal identification of arch dams. The method effectively filtered noise using wavelet thresholding and EMD, followed by further noise reduction with DFA. Improved RDT is utilized for modal identification. The approach was applied to measured vibration response analysis, extracting modal characteristics of high arch dam structures, demonstrating its efficacy. Moreover, Li et al. [114] enhanced the traditional HHT for the precise identification of closely spaced modes in structures like arch dams. They proposed an automatic moving-window technique to mitigate end effects and optimize frequency and damping ratio estimation. Additionally, Barbosh and Sadhu [115] proposed a hybrid time–frequency method for AE data, aiming to predict damage severity and localization. They applied Multivariate Empirical Mode Decomposition to extract AE components corresponding to different damage levels and used the Gaussian Mixture Model for classification. Damage location was determined by calculating the distance between Gaussian centroids. The method outperformed traditional approaches in predicting severity and localizing damage using AE data.

Moving on to the weaknesses of each algorithm, it is important to consider the limitations that frequency-domain methods, time-domain methods, and stochastic methods may encounter in their respective applications. Frequency-domain methods, such as the PTD and FDD methods, have limitations in handling nonlinearity and non-stationarity. These methods assume linearity and stationarity in the data, which may not always hold true in real-world scenarios. For example, in structural analysis, the behavior of a structure may change over time due to environmental factors or structural damage. If these changes are not accounted for, the results obtained from frequency-domain methods may be inaccurate and lack robustness. On the other hand, time-domain methods, like the ITD method, may struggle with handling large datasets. These methods require a large amount of computational resources and time to process and analyze the data. For instance, in dynamic testing of a large-scale structure, such as a bridge or a tall building, the amount of data collected can be enormous. Processing and analyzing these data using time-domain methods can be time-consuming and may not be suitable for real-time applications or situations where quick results are needed. Lastly, stochastic methods, such as SSI algorithms, can be computationally expensive when performing uncertainty analysis and other approaches. The high computational costs associated with these methods may limit their practicality in certain applications, especially when dealing with large-scale systems or complex structures. For example, in the field of aerospace engineering, the analysis of the dynamic behavior of an aircraft can involve a large number of variables and parameters. Performing uncertainty analysis using stochastic methods can be computationally demanding and may require significant computational resources. The weaknesses of each algorithm discussed above highlight the challenges and limitations that researchers and practitioners may face when using modal identification algorithms. By understanding these weaknesses, it becomes important to explore alternative approaches or hybrid methods that can overcome these limitations and provide more accurate and efficient results.

In summary, modal identification techniques have evolved significantly, each offering unique strengths and limitations. The PP method is straightforward and easy to implement, making it ideal for initial modal analysis in structures with well-separated modes. However, it struggles with closely spaced modes and noise sensitivity, leading to inaccuracies in complex systems. FDD enhances traditional methods by decomposing the spectral density matrix, allowing for the identification of modes under operational conditions without input data. Despite its effectiveness in dealing with noise, FDD can be less accurate in identifying damping ratios and may require postprocessing for detailed mode shapes. EFDD extends FDD by incorporating time-domain analysis to extract damping ratios, providing a more comprehensive modal analysis. While EFDD offers improved accuracy, it demands more computational resources and sophisticated algorithms. Stochastic Subspace Identification (SSI) excels in complex, multi-degree-of-freedom systems and is robust against noise and operational variabilities, making it suitable for operational modal analysis. Its primary drawback is the need for extensive computational effort and expert knowledge for accurate implementation and interpretation. ERA is powerful for systems with multiple modes and provides detailed modal parameters from time-domain data, but it requires high-quality input and is computationally intensive. EMD allows for the adaptive decomposition of signals into intrinsic mode functions, useful for nonlinear and non-stationary systems. EMD's disadvantage lies in its sensitivity to noise and mode mixing, which can complicate the analysis. HHT builds on EMD by applying Hilbert spectral analysis, offering a high-resolution time–frequency representation of signals, particularly beneficial for analyzing transient phenomena. However, HHT can be computationally demanding and requires careful interpretation of results due to potential issues with mode mixing and boundary effects. Each of these approaches provides distinct capabilities, making them suitable for various applications depending on the complexity of the structure and the specific requirements of the modal analysis. The strengths and weaknesses of various modal identification methods are presented in Table 2.

Table 2. Strengths and weaknesses of different methods for modal identification.

Method	Strengths	Weaknesses
PP	- Simple and easy to implement.	- Accuracy is highly dependent on data quality. - Limited to well-separated modes.
FDD	- Effective for systems with closely spaced modes. - Provides clear physical insights. - Less sensitive to noise compared to PP.	- Assumes linearity. - Can be less accurate for heavily damped systems.
EFDD	- Extends FDD with automated modal extraction. - Improved accuracy in estimating damping ratios. - Suitable for non-stationary data.	- Computationally more intensive than FDD. - May require user-defined parameters for accurate results.
SSI	- Handles ambient excitation well. - Accurate in estimating modal parameters. - Applicable to lightly or heavily damped systems.	- Requires more complex algorithms and data processing. - Higher computational cost.
ERA	- Effective for both time- and frequency-domain data. - Suitable for real-time analysis. - Good for systems with closely spaced modes.	- Requires good-quality data for accurate results. - Can be sensitive to noise.
EMD	- Adaptable to nonlinear and non-stationary data. - Decomposes signals without predefined basis functions.	- Mode mixing can occur, leading to ambiguity. - Computationally intensive and lacks a strong theoretical basis for complex systems.
HHT	- Effective for analyzing nonlinear and non-stationary signals. - Provides time–frequency–energy representation.	- Sensitive to noise. - Requires careful interpretation of results. - More complex to implement compared to traditional methods.

3.2. Recent Advancement in Modal Identification Algorithms

Recent advancements in modal identification algorithms have focused on improving their robustness and noise-handling capabilities. Advanced signal processing techniques, like wavelet analysis and the EMD method, have been developed to address these limitations. For example, wavelet analysis allows for the extraction of modal parameters even in the presence of significant noise or interference. It achieves this by decomposing the signal into different frequency components and analyzing each component separately. Similarly, the EMD method breaks down the signal into intrinsic mode functions, which represent different oscillatory modes, and extracts the modal parameters from these functions. These techniques have proven to be effective in handling noisy data and improving the accuracy of modal identification [116].

In addition to signal processing techniques, machine learning algorithms have also been applied to modal identification to enhance automation and accuracy. Examples of machine learning algorithms applied in this context include neural networks and support vector machines. These algorithms can learn from large datasets and make predictions based on patterns and correlations. By training the algorithms on a dataset of known modal parameters, they can then be used to automatically identify the modal parameters of new data. This reduces the need for manual intervention and improves the reliability of the identification process. For example, a neural network can be trained on a dataset of vibration data and corresponding modal parameters, and then used to predict the modal parameters of new vibration data [104,117,118].

Furthermore, Bayesian statistical methods have been utilized to incorporate prior knowledge and uncertainty analysis into modal identification algorithms. These methods consider the uncertainties in the measurements and model parameters, providing more reliable estimates of the modal parameters and their associated uncertainties. For instance, Bayesian inference can be used to update the probability distribution of the modal parameters based on the measured data and prior knowledge. This allows for a more comprehensive analysis of the uncertainties involved in the modal identification process [119–121].

These recent advancements in modal identification algorithms contribute to the goal of providing a thorough examination of various algorithms. They address the weaknesses of existing algorithms by improving their robustness and noise-handling capabilities. Advanced signal processing techniques enable the extraction of modal parameters even in the presence of significant noise or interference. Machine learning algorithms enhance automation and accuracy by learning from large datasets and making predictions based on patterns and correlations. Bayesian statistical methods incorporate prior knowledge and uncertainty analysis to provide more reliable estimates of modal parameters and their associated uncertainties. By incorporating these advancements, the understanding and application of modal identification algorithms in structural analysis and dynamic testing can be greatly enhanced.

4. Evolution of Fully Automated Algorithms in Modal Identification

The evolution of automated algorithms in modal identification represents a significant advancement in structural dynamics analysis. Historically, modal identification processes relied heavily on manual intervention, requiring experts to manually select modes and adjust parameters. However, with the advent of automated algorithms, the modal identification process has become more efficient, accurate, and accessible [122–124].

The transition towards automation began with the development of numerical algorithms that could analyze large datasets and extract modal parameters with minimal user input. These algorithms utilized mathematical techniques such as matrix factorization and eigenvalue analysis to identify modal characteristics from measured response data [125].

As computational power increased and machine learning techniques emerged, the capabilities of automated modal identification algorithms expanded further. Machine learning algorithms, such as neural networks and support vector machines, were trained on vast datasets of structural responses to learn patterns and correlations associated with modal parameters. Subsequently, these algorithms could automatically detect and extract modal features from new datasets, eliminating the need for manual intervention [126].

Furthermore, the integration of Bayesian statistical methods into automated modal identification algorithms enabled a more comprehensive analysis of uncertainties. By incorporating prior knowledge and considering measurement uncertainties, Bayesian approaches provided more accurate estimates of modal parameters and their associated confidence intervals [127].

Today, state-of-the-art automated algorithms in modal identification combine advanced signal processing techniques, machine learning algorithms, and Bayesian statistical methods to offer robust and reliable modal parameter estimation. These algorithms can handle noisy data, adapt to varying operating conditions, and provide detailed insights into the dynamic behavior of structures. Pereira et al. [128] studied the dynamic behavior of the Baixo Sabor arch dam during its initial six months of operation, including the reservoir-filling phase. The use of the SSI-Cov method facilitated modal identification by analyzing covariance matrices of measured structural responses, crucial for understanding water–structure interaction effects and updating numerical models. Automated operational modal analysis was presented by Pereira et al. [129] using the SSI-Cov method. This algorithm, involving cluster analysis and uncertainty quantification, effectively reduced outliers and improved confidence in modal estimates, significantly decreasing the standard deviation of frequency and damping estimates for the four studied modes. They utilized continuous dynamic monitoring data from a concrete arch dam to assess the benefits of quantifying uncertainties in modal characteristics [130]. They focused on the impact of considering these uncertainties in automated OMA, modal tracking, and data normalization. Applying SSI-Cov to 30 min datasets yielded clusters, with the greatest benefits observed in using estimated uncertainties to remove outliers during modal tracking. Shuai et al. [131] proposed an automatic modal identification method, combining DBSCAN and SSI algorithms, validated on the Dagangshan Dam. The results indicate DBSCAN's robustness in interpreting stabilization diagrams, outperforming other clustering methods. Identified frequencies' errors are within 4%, and mode shapes match finite element model results, affirming the procedure's accuracy for modal parameter identification. Moreover, Mostafaei et al. [132] introduced an automated method for modal parameter estimation, utilizing SSI, classification, and clustering techniques. Unlike traditional methods, this approach eliminates the need for repeated data measurements, enhancing efficiency with just one dataset. Also, Li et al. [133] proposed a three-stage automated OMA algorithm merging the SOBI and SSI-COV methods, leveraging both parametric and non-parametric techniques. This approach eliminates ambiguity in stabilization diagram interpretation while maintaining accuracy, yielding more reliable modal parameters without sacrificing precision. Li et al. [134] introduced a method integrating SSI, sparrow search algorithm (SSA), and K-means to automate modal parameter identification for high arch dams. It begins with SSI utilizing seismic monitoring data, followed by an enhanced stabilization diagram creation to mitigate unstable damping ratios. Abnormal poles are flagged using outlier detection, SSA refines clustering, and K-means performs final modal parameter identification, offering a comprehensive automated approach. Furthermore, an automated modal identification algorithm using output-only data was introduced by Mostafaei et al. [135]. Their stochastic subspace algorithm identifies modal parameters without requiring a model degree, estimated via the Singular Value Criterion. Diverse clustering algorithms, including Dempster–Schaffer Theory for data fusion, enhance accuracy. The algorithm addresses parameter uncertainty and utilizes statistical resampling for limited datasets. Covering data collection, signal processing, and model reduction, this approach integrates various fields to identify modal parameters and quantify uncertainty, advancing modal identification methods. Liu et al. [136] proposed a beat vibration analysis model for overflow dam piers using adaptive variational modal decomposition (VMD) and COV-SSI. They developed a mathematical model to study beat vibration generation conditions and used adaptive VMD and automatic modal analysis to extract main vibration components, facilitating a comprehensive analysis of beat vibration mechanisms.

Table 3 presents the methods employed for automated modal identification in the literature review. The results indicate that the most favored algorithm for modal identification is the SSI method. SSI's popularity stems from its robustness in handling noisy data, its ability to provide reliable estimates of modal parameters, and its effectiveness in both time- and frequency-domain analyses. Furthermore, SSI can efficiently deal with ambient excitation, making it highly suitable for real-world structural health monitoring applications.

Table 3. Methods employed for automated modal identification in the literature review.

References	Employed Methods for the Automated Modal Identification
[128]	SSI-COV
[129]	SSI-COV
[130]	SSI-COV
[131]	DBSCAN and SSI algorithms
[132]	SSI and Fuzzy C-Mean algorithm
[133]	SSI-COV
[134]	SSI, SSA, and K-means
[135]	SSI and Dempster-Schaffer Theory
[136]	Adaptive VMD and COV-SSI

5. Applications in DHM

Damage can significantly affect the behavior and structural integrity of dams. Various factors, such as aging infrastructure, environmental stresses, and unforeseen events like earthquakes or floods, can lead to deterioration or damage of dams [137–140]. Cracks in concrete, erosion of embankments, or malfunctioning of mechanical components can compromise the stability and functionality of a dam. These damages can disrupt the flow of water, increase seepage, or weaken the overall structure, posing serious risks to downstream communities and ecosystems. Additionally, damages may escalate if not promptly identified and addressed through effective monitoring and maintenance protocols. Therefore, integrating robust damage detection and assessment mechanisms into dam health monitoring systems is essential to mitigate risks and ensure the long-term safety and reliability of dams [141].

As shown in Figure 5, there are five stages in categorizing structural damage. The process begins with detecting the presence of damage, followed by identifying its location, type, and severity. The final step involves predicting the area of the structure most likely to be affected. Each step relies heavily on the previous ones; for example, mistakes in detecting or localizing damage can lead to errors in assessing its severity, which in turn affects the accuracy of predictions.

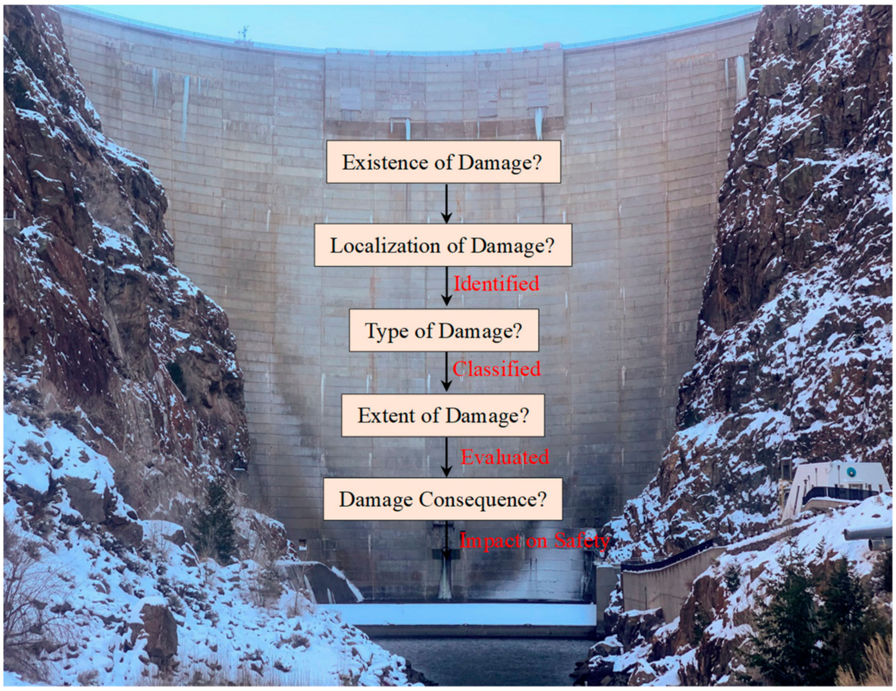

Figure 5. Damage hierarchy in dams.

During the regular operation of a concrete arch dam, the structure's inherent modal parameters remain constant over time and can be determined using established time-invariant structural modal identification techniques. Conversely, if the arch dam sustains damage due to seismic activity, the modal parameters will evolve over time as damage accumulates and progresses. In such situations, a time-varying modal parameter identification method is required to accurately capture the changing modal properties [142]. OMA plays a crucial role in the damage detection of dams by leveraging ambient vibration data collected during the regular operation of the structure. Unlike traditional methods that require controlled excitation, OMA utilizes naturally occurring vibrations induced by environmental or operational loads. By analyzing the modal characteristics of the structure without external excitation, OMA can identify changes in dynamic behavior caused by damage or deterioration. This allows engineers to detect and assess the extent of damage in dams, enabling timely maintenance and ensuring the structural integrity and safety of the dam over its lifespan.

Various approaches are employed for damage detection in dams, each offering unique insights into their structural health. These methods include monitoring changes in the natural frequencies of the structure, alterations in mode shapes, and the application of techniques such as modal curvature, modal strain energy, and modal flexibility analysis. Researchers have extensively utilized these methods in modal identification studies to detect subtle changes indicative of damage or deterioration in dams [24,143,144].

Lotfollahi-Yaghin and Hesari [145] utilized wavelet transform for effective damage detection, especially in identifying sudden stiffness fluctuations. Damage effects are clearer in low scales, aiding noise localization, while wider scales enhance noise but reduce clarity. Proper scale selection is crucial; higher scales detect small damages, while lower scales are recommended for damages near support. Dmey, Sym, Bior, Ciof, Db, and Haar wavelets are useful for crack detection, with Coif, Db, and Sym showing superior efficiency in locating cracks. Türker et al. [146] demonstrated effective damage detection on a concrete arch dam model. Their method involves model updating of finite element models using experimental modal test results. They considered a random damage scenario, focusing on web thickness as the damage parameter, and analyzed the first five natural frequencies to investigate the impact of the damage. The HHT was utilized by Esmaielzadeh et al. [108] to analyze the response of a dam subjected to horizontal earthquakes. By assessing changes in natural frequencies from measured accelerations, they introduced a parameter, Relative Frequency Error, effectively identifying damage location and predicting severity in concrete gravity dams with high accuracy. Moreover, Pirboudaghi et al. [94] proposed a seismic cracking identification method for concrete dams using XFEM-COH and CWT. XFEM-COH introduces cracking capability to the dam structure, allowing detection without initial cracks. They compared FEM and XFEM-COH under seismic excitation, favoring XFEM's potential for comprehensive damage risk assessment. CWT-based system identification detected system changes, crack initiation, and exact damage localization. Hamidian et al. [147] introduced a novel method for detecting damage in irregular structures, combining wavelet analysis with ANFIS. The ANFIS technique, employed to predict irregular point structural responses within a regular domain, aligned well with wavelet transformation. Also, Esmaielzadeh et al. [148] investigated earthquake-induced dam damage using signal processing algorithms. Pine Flat Dam's destruction was linked to reduced elasticity in certain elements. They employed DTFT, wavelet, and Wiener transforms to analyze intact and damaged scenarios, with DTFT proving most effective. The algorithms highlighted differences in node accelerations. DTFT and wavelet transform showed superior detection thresholds compared to Wiener transform, enhancing damage assessment precision. Zuo et al. [149] studied seismic failure in a concrete arch dam model with embedded piezoceramic transducers. They used an EMI method to detect post-earthquake damage and proposed a new damage-sensitive feature factor based on a 3D EMI model. Experimental results suggest its effectiveness but highlight the need for further investigation. Mirtaheri et al. [111] presented an approach utilizing CWT on residual curvature derived from mode shapes. Their goal was to discern structural characteristics and detect damage using just six sensors. However, this resulted in merely six data points for each mode shape, rendering curvature calculation unfeasible. To overcome this limitation, they applied the cubic spline technique. Zar et al. [150] introduced a vibration-based damage detection method for arch dams using least-square support vector machines and salp swarm algorithms. Least-square support vector regression establishes a surrogate model linking dynamic elastic modulus with modal parameters. Slap swarm algorithms minimize an objective function comprising vibration data for dynamic parameter identification.

Mohebian et al. [151] utilized the modal curvature-based damage index to detect damage in dam structures, leveraging changes in curvature distribution of mode shapes to pinpoint affected areas through analysis of pre- and post-damage modal curvature deviations. Si et al. [152] proposed a rapid method for identifying damage location and degree in concrete arch dams subjected to extreme events like earthquakes or terrorist attacks. Their approach integrated wavelet transform, wavelet packet decomposition, BP neural networks, and D-S evidence theory. By analyzing dynamic characteristics data, including curvature mode differences, wavelet coefficients, and wavelet packet energy changes, they successfully identified damaged areas. Additionally, Xiangyu et al. [153] proposed a denoising contractive sparse deep autoencoder model for arch dam anomaly detection, considering varied water levels. However, its unsupervised learning limits its application to different scenarios. Introducing domain adaptation with maximum mean discrepancy criterion enhances the model's performance. Results show increased F1 scores by up to 24.27%. The adapted model improves generalization and robustness across diverse scenarios, enhancing anomaly detection capabilities for arch dam projects. YiFei et al. [154] developed a novel method for structural damage identification, utilizing surrogate modeling and a hybrid optimization strategy called HKOGA, combining a K-means clustering optimizer with a genetic algorithm. The method substitutes computationally expensive finite element models with sparse polynomial chaos expansion, significantly enhancing optimization efficiency. Zar et al. [155] introduced a novel method using radial basis function neural networks and the Jaya algorithm for DSHM, requiring only one user-defined parameter. This approach swiftly detects damage under dynamic conditions, integrating DEM and modal parameters. It reduces computational time and remains robust against noise, ensuring efficient and accurate damage detection in complex dam structures. Furthermore, Li et al. [156] introduced a structural damage identification method merging surrogate modeling and evolutionary optimization, enhancing efficiency and accuracy. They fused three surrogate models using a weighted average, improving generalization. A tailored movement strategy for Termite Life Cycle Optimizer enhanced robustness. The method, validated on a damaged dam model, showcased over 100 times improvement in computational efficiency compared to conventional SDI approaches. In their study, Qiu et al. conducted shaking table tests to investigate the dynamic failure behavior of a gravity dam model, analyzing and comparing the structural dynamic characteristics and damage patterns under different scenarios [157].

6. Conclusions

This paper offers a thorough review of OMA techniques applied to dam health monitoring. It encompasses various aspects, including instrumentation and both time- and frequency-domain modal identification techniques such as PP, FDD, EFDD, SSI, ERA, NExT, and EMD. Moreover, the recent evolution in OMA and the development of automated modal identification are discussed. Finally, the use of OMA methods in DHM is investigated. Limitations, key principles, and future challenges for achieving accurate and reliable OMA outcomes for DSHM can be summarized as follows:

- Instrumentation plays a foundational role in OMA, and selecting the appropriate sensing system to meet specific requirements is crucial. Sensor placement and installation must be performed with precision to ensure accurate modal identification outcomes, requiring careful handling and maintenance. Many existing dams were not instrumented during their construction, resulting in limited available data. For these dams, only specific types of sensors, such as GPS and total stations, can be installed now, which presents significant challenges in developing a DSHM model based on such limited data. Innovative approaches and improved sensor technologies and installation techniques are needed to enhance data collection and analysis for dams with limited initial instrumentation. Also, the SSI method emerges as the predominant choice in automated modal identification algorithms.
- Regarding the optimal reliability, efficiency, precision, and applicability of various modal identification techniques in the time and frequency domains, the SSI method is widely favored by researchers. The SSI method emerges as the predominant choice in automated modal identification algorithms.

- Applying sophisticated techniques like machine learning enhances the accuracy of OMA outcomes for DSHM. This ensures model applicability across different dams, accommodating variations in their geometric configurations and material properties. Moreover, incorporating wavelet transformation into OMA methodologies for DSHM could offer enhanced noise reduction and feature extraction capabilities, further refining modal parameter identification.
- Unlike the extensive research in building and bridge health monitoring, DHM has been relatively underexplored. Therefore, there is a pressing need for research to develop algorithms for damage detection and estimating the remaining useful life of dams.

Several areas warrant further investigation to enhance the effectiveness of modal identification techniques for dam infrastructure. Future research should focus on developing advanced algorithms that can better account for environmental variability and operational conditions, improving the reliability of modal parameters under different load scenarios. Additionally, there is a need for more extensive field validation of these methods on diverse dam types and conditions to establish generalized guidelines. Integrating emerging technologies such as machine learning and data fusion from multiple sensor types could offer promising avenues for improving damage detection and localization. Furthermore, exploring cost-effective and scalable instrumentation solutions will be crucial for widespread adoption and real-time monitoring of dam health. Addressing these areas could lead to more robust and accurate modal identification, thereby enhancing the safety and longevity of dam infrastructure.

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Glossary

Abbreviation	Meaning
CWT	Continuous Wavelet Transform
SSI-Cov	covariance-driven Stochastic Subspace Identification
DSHM	dam structural health monitoring
ERA	Eigensystem Realization Algorithm
EMD	empirical mode decomposition
EFDD	Enhanced Frequency-Domain Decomposition
EMA	Experimental Modal Analysis
FDD	Frequency-Domain Decomposition
FRF	frequency response function
HHT	Hilbert–Huang Transform
ITD	Ibrahim Time Domain
MAC	modal assurance criterion
NExT	natural excitation technique
OMA	operational modal analysis
OSP	optimal sensor placement
PP	Peak Picking
PTD	Polyreference Time Domain
PSD	power spectral density
RDT	Random Decrement Technique
SVD	Singular Value Decomposition
SSA	sparrow search algorithm
SSI	Stochastic Subspace Identification
VMD	variational modal decomposition
WT	wavelet transform

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