

Review

State of the Art in Automated Operational Modal Identification: Algorithms, Applications, and Future Perspectives

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Abstract: This paper presents a comprehensive review of automated modal identification techniques, focusing on various established and emerging methods, particularly Stochastic Subspace Identification (SSI). Automated modal identification plays a crucial role in structural health monitoring (SHM) by extracting key modal parameters such as natural frequencies, damping ratios, and mode shapes from vibration data. To address the limitations of traditional manual methods, several approaches have been developed to automate this process. Among these, SSI stands out as one of the most effective time-domain methods due to its robustness in handling noisy environments and closely spaced modes. This review examines SSI-based algorithms, covering essential components such as system identification, noise mode elimination, stabilization diagram interpretation, and clustering techniques for mode identification. Advanced SSI implementations that incorporate real-time recursive estimation, adaptive stabilization criteria, and automated mode selection are also discussed. Additionally, the review covers frequency-domain methods like Frequency Domain Decomposition (FDD) and Enhanced Frequency Domain Decomposition (EFDD), highlighting their application in spectral analysis and modal parameter extraction. Techniques based on machine learning (ML), deep learning (DL), and artificial intelligence (AI) are explored for their ability to automate feature extraction, classification, and decision making in large-scale SHM systems. This review concludes by highlighting the current challenges, such as computational demands and data management, and proposing future directions for research in automated modal analysis to support resilient, sustainable infrastructure.

Keywords: automated modal identification; machine learning; deep learning; clustering analysis; stochastic subspace identification; structural health monitoring



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1. Introduction

Modal identification is a fundamental technique in structural dynamics that allows engineers to determine key dynamic properties such as natural frequencies, mode shapes, and damping ratios [1,2]. These parameters are critical for assessing the ability of civil structures—such as bridges, high-rise buildings, dams, and wind turbines—to withstand external forces like wind, seismic activity, and operational loads [3–5]. The dynamic behavior of these structures evolves over time as they are subjected to environmental stresses and shifts in their modal properties often signal the onset of damage or degradation.

The early detection of such changes through modal identification can prevent catastrophic failures by enabling timely interventions, ultimately extending the service life of critical infrastructure [6,7]. This makes modal identification a cornerstone of structural

health monitoring (SHM) systems, which provide the continuous, real-time monitoring of a structure's performance. By comparing the current modal parameters with the baseline values established during the early life of a structure, engineers can identify even subtle changes that might indicate a loss of structural integrity.

Traditional methods such as Experimental Modal Analysis (EMA) and operational modal analysis (OMA) have been widely applied to determine a structure's dynamic properties. EMA excels in controlled environments where input forces and output responses can be measured, but it is often impractical for large-scale structures [8–10]. OMA, relying solely on ambient excitations like wind and traffic, is more suitable for the in situ monitoring of operational structures. However, these methods depend heavily on manual interpretation, making them time-intensive and challenging to scale for long-term, real-time applications [11–13].

This reliance on manual processes represents a critical limitation, particularly in scenarios involving large infrastructure or complex systems where rapid and continuous data analysis is essential. [14–16]. To perform OMA, various approaches have been developed, primarily categorized into time-domain and frequency-domain methods.

Time-domain approaches focus on directly analyzing vibration signals over time. The most prominent technique in this category is Stochastic Subspace Identification (SSI) [17], which models the structure as a state-space system by applying matrix factorization methods such as Singular Value Decomposition (SVD). SSI can effectively handle noise and closely spaced modes, making it suitable for complex structures [18]. Another notable method is the Autoregressive Moving Average (ARMA) model, which uses system identification algorithms to create predictive models based on past response data [19].

Frequency-domain approaches, on the other hand, focus on analyzing the system's response in the spectral domain. Frequency Domain Decomposition (FDD) is one of the most commonly used techniques, relying on the SVD of the power spectral density (PSD) matrix to identify modal parameters from spectral peaks [20]. Its enhanced version, Enhanced Frequency Domain Decomposition (EFDD), improves accuracy by applying inverse Fourier transforms to estimate damping ratios [21]. Additionally, peak picking (PP), though simpler and more intuitive, is limited by its reliance on clear spectral peaks and is less effective in noisy environments or structures with closely spaced modes [22].

While these traditional approaches laid the groundwork for modern modal identification, their reliance on manual data collection and interpretation made them impractical for the long-term, real-time monitoring of complex structures [23–27]. This limitation drove the development of automated methods that can operate continuously with minimal human intervention.

The increasing complexity of civil infrastructure, coupled with the need for continuous, long-term monitoring, has led to the rise in automated modal identification. Automation addresses many of the limitations of traditional methods by reducing the reliance on manual data interpretation and enhancing the speed and accuracy of modal parameter estimation [28–32].

Automated Operational Modal Analysis (AOMA) systems have emerged as powerful tools for extracting modal parameters from large datasets in real-time, even under operational conditions that involve noise and environmental variability [33,34]. Automation enables SHM systems to provide continuous, up-to-date information on the dynamic behavior of structures, ensuring that potential damage can be detected early, long before visual signs of deterioration appear [35,36].

This automation can be implemented using various approaches, each offering unique advantages based on data characteristics, noise levels, and computational demands. Key methods in AOMA include FDD [37], ERA, Empirical Fourier Decomposition (EFD) [38],

Empirical Mode Decomposition (EMD) [39,40], and SSI [41–43], as well as Polyreference Least Squares Complex Frequency Domain (pLSCF) [44,45], PP, and Variational Mode Decomposition [46]. These techniques cover a range of frequency-domain and time-domain methods, enabling adaptability across diverse structural applications and conditions.

Despite the increasing adoption of automated methods, a comprehensive review summarizing their advancements, applications, and limitations is currently lacking. This gap highlights the need for a focused study on AOMA techniques.

In this study, we focus specifically on FDD, ERA, and SSI, as they are widely applied and have demonstrated robustness across various modal identification tasks. FDD offers a non-parametric and efficient frequency-domain solution for identifying peaks, making it straightforward to implement. ERA provides an accurate time-domain approach, constructing state-space models ideal for complex systems. SSI excels in handling noisy data through stochastic modeling, ensuring stable parameter estimation even under challenging conditions. Bayesian models bring the added benefit of probabilistic inference, incorporating prior knowledge and quantifying uncertainties, which is especially useful in cases of sparse or complex data. By exploring these methods in detail, this study underscores the flexibility and effectiveness of AOMA through commonly employed approaches, contributing to a comprehensive understanding of modal identification in operational environments. The current state of the art in AOMA is summarized in Figure 1.

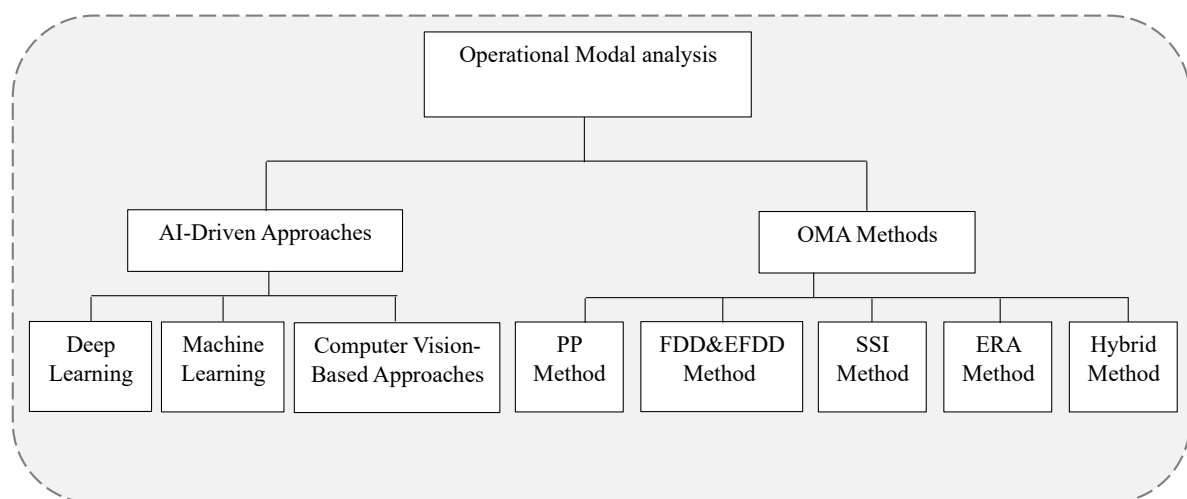


Figure 1. Summary of current state of the art in AOMA.

Figure 2 illustrates the number of papers reviewed in this study on AOMA per year, highlighting the increasing research interest and development in this field over time. Despite the growing interest in AOMA, a comprehensive review paper summarizing the advancements, methods, and applications of AOMA is currently lacking in the literature.

In this study, the authors reviewed 120 journal and conference articles related to automated modal identification, encompassing both traditional approaches and advanced methods employing artificial intelligence (AI). The articles were sourced from reputable databases, including the Scopus, Web of Science, ScienceDirect, ASCE Library, IEEE Xplore Digital Library, Sage, and Wiley Online Library. The literature search utilized specific keywords such as “automated modal identification”, “vibration-based modal analysis”, “machine learning for modal identification”, “deep learning in structural monitoring”, and related terms.

This paper reviews and compares various system identification methods, along with a wide range of case studies. While many methods are introduced, the primary focus is on providing a concise overview of their efficiency and areas of application. A more

detailed analysis of case studies for each method would require deeper categorization and examination, which is beyond the scope of this study.

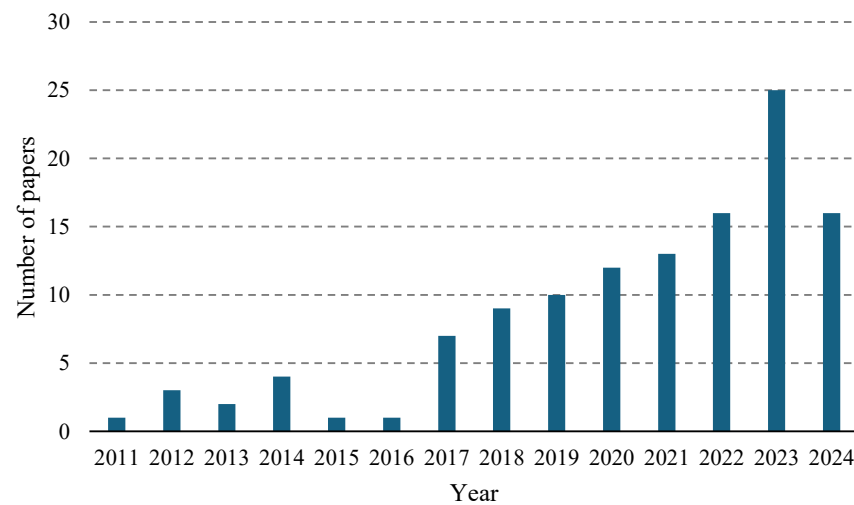


Figure 2. Trend of reviewed papers on AOMA per year.

It is important to recognize that different system identification methods are designed to address problems with varying levels of complexity and approaches. This means some methods perform exceptionally well for specific problems or case studies, while others may not be as effective, making direct comparisons challenging. For example, certain methods are tailored for large static structures, while others are designed for rotating machinery. Some methods consider system inputs in their calculations, while others rely solely on output data. Inputs may be assumed as random in some methods, whereas others allow for a combination of deterministic and random inputs. Additionally, some methods require prior knowledge of the system, whereas others can function without any pre-existing information.

Despite these differences, all the methods reviewed fall within the broader category of system identification techniques. This study aims to provide an overview of these methods, highlighting their capabilities, limitations, and areas of application.

2. AI-Driven Approaches for AOMA

Artificial intelligence (AI) has emerged as a transformative force in SHM, particularly in automated modal identification [47]. Unlike traditional rule-based AI systems that rely on explicitly programmed instructions, modern AI employs data-driven learning approaches to extract meaningful insights from structural response data. This advancement enables accurate, scalable, and efficient determination of modal parameters from complex sensor data. By leveraging pattern recognition, machine learning (ML), and data mining, AI-driven models automate the traditionally labor-intensive process of modal identification [48,49]. Figure 3 illustrates the hierarchical relationships in AI systems and the data processing pathways, comparing knowledge-based AI, classic ML, and deep learning (DL) approaches.

Early AI applications focused on tasks governed by well-defined rules, such as playing chess, where solutions could be encoded through hand-crafted algorithms. However, these systems struggled with intuitive tasks requiring experience and contextual understanding, such as object detection and speech recognition. To address these limitations, ML was introduced as a paradigm shift in AI, allowing systems to learn from data rather than relying solely on predefined rules. In the context of automated modal identification, this capability enables models to adapt dynamically to varying environmental and operational conditions.

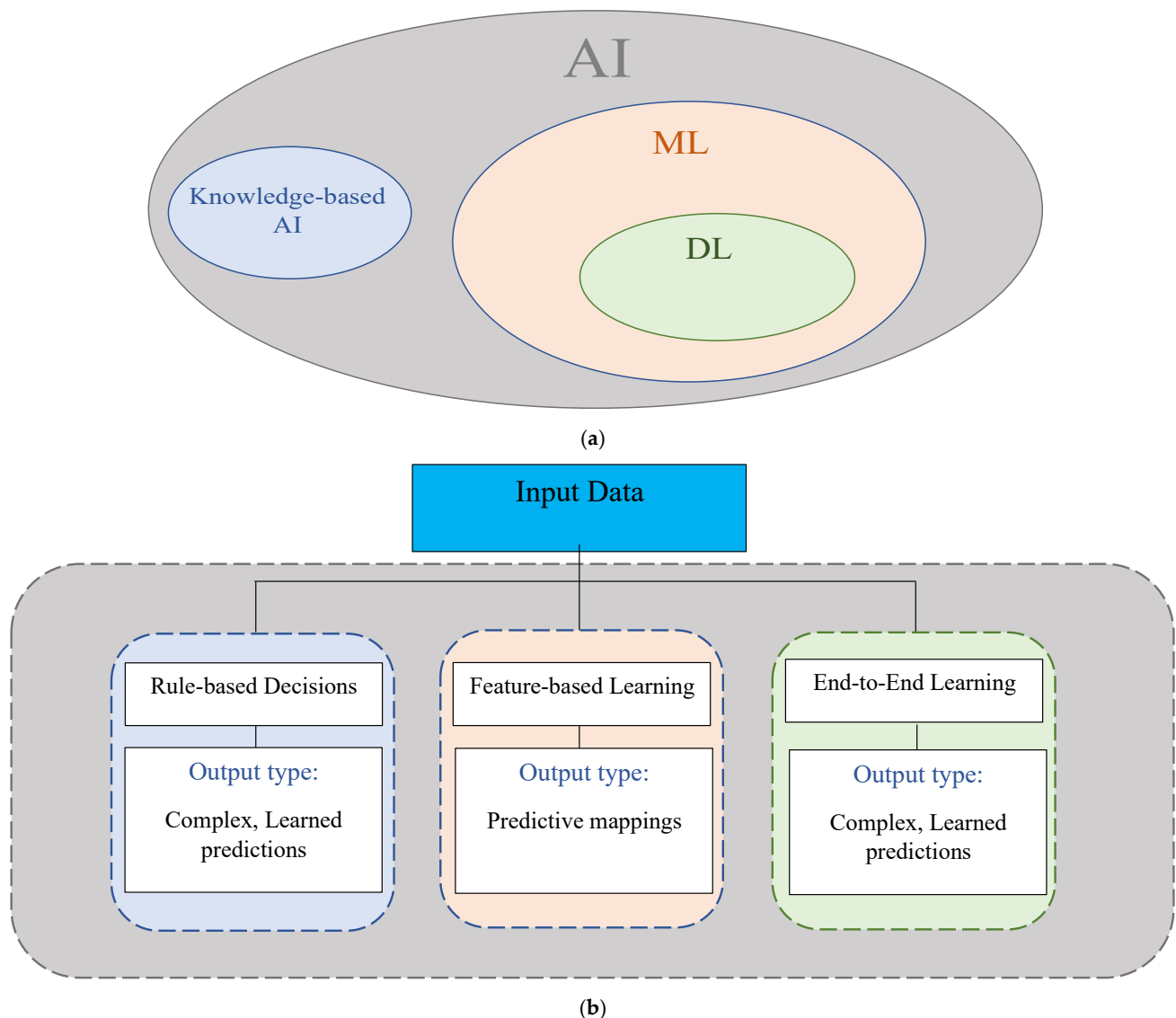


Figure 3. (a) A Venn diagram illustrating the nested relationships among AI, ML, and DL. AI encompasses ML, while DL is a specialized subset of ML. (b) Data processing in AI Systems: A flowchart showing the pathways of input data through three AI systems.

Key stages of AI-driven automated modal identification include data preprocessing, feature extraction, and model training. Data preprocessing ensures that raw sensor signals are cleaned and standardized for analysis. Feature extraction identifies relevant characteristics from structural response data, and ML algorithms are trained using labeled datasets to establish relationships between features and modal parameters.

AI-powered modal parameter estimation involves using data-driven algorithms to identify modal parameters. Traditional methods like SSI and FDD have been enhanced with AI-based models that apply Pattern Recognition Algorithms to detect temporal and spatial patterns in time-series data. These algorithms improve the accuracy of modal parameter extraction by automating repetitive tasks and reducing human error [50].

ML techniques such as Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) improved the accuracy of identifying damage locations and severity, even under noisy conditions [23]. Convolutional Neural Networks (CNNs) further accelerated the process by automating feature extraction, reducing reliance on manual intervention, and enabling the rapid analysis of large datasets. Moreover, deep learning models like autoencoders have proven scalable, effectively handling complex and large-scale infrastruc-

ture with diverse structural characteristics. These AI-based approaches not only overcome the limitations of traditional methods in terms of speed and consistency but also introduce robust capabilities for real-time and automated modal parameter extraction, positioning them as vital tools in modern structural health monitoring. For example, Li et al. [51] introduced an automated modal identification approach that integrates the DBSCAN algorithm with the SSI method, which was tested on the Dagangshan Dam. The findings demonstrate the effectiveness of DBSCAN in analyzing stabilization diagrams, surpassing other clustering techniques. The identified frequencies exhibited errors of less than 4%, and the mode shapes closely aligned with those derived from the finite element model, confirming the method's precision in identifying modal parameters.

Another major contribution of AI in modal identification is Optimization-Driven Parameter Estimation, where advanced optimization algorithms automatically tune model parameters. Techniques like Genetic Algorithms (GAs), Particle Swarm Optimization (PSO), and Bayesian Optimization explore large parameter spaces to optimize system variables such as model order, damping thresholds, and sensor placement configurations [52–54]. These algorithms enable the real-time adjustment of system models, ensuring that modal parameters are consistently and accurately estimated under changing environmental conditions.

2.1. ML Algorithms

ML serves as the foundation of AI-driven modal identification by enabling the extraction and classification of modal parameters through data-driven learning [55]. Supervised learning models, such as SVMs, Random Forests, Gradient Boosting Machines (GBMs), and ANN, are particularly effective when labeled datasets are available [56–58]. These models analyze historical data to classify structural modes, detect structural damage, and recognize changes in system behavior due to varying operational or environmental conditions [59].

When labeled data are unavailable, unsupervised learning models become essential. Techniques such as k-means clustering [28,60], fuzzy clustering [61], hierarchical clustering [62], Gaussian Mixture Models (GMMs) [63,64], density-based clustering [65–68], and multi-stage clustering [69,70] categorize modal parameters based on their statistical properties. This automatic classification helps distinguish true structural modal parameters from spurious ones, minimizing the need for stabilization diagram interpretation, which can be time-consuming, case-dependent, and error-prone.

In addition to supervised and unsupervised approaches, reinforcement learning methods have emerged as a powerful tool for AI-driven modal identification. Reinforcement learning (RL) algorithms, such as Q-learning and Deep Q-Networks (DQNs), iteratively optimize decision-making processes by interacting with the system environment. These methods are particularly advantageous for online modal identification and adaptive learning, where the model continuously improves its performance by receiving feedback from the environment, enabling the real-time classification of modal parameters and system state recognition under varying conditions.

Clustering, a core unsupervised learning technique, involves partitioning a dataset into distinct groups or clusters based on data similarity. In the context of modal identification, clustering helps isolate meaningful structural modes from noise. Different clustering methods offer unique strengths: k-means clustering is computationally efficient but assumes spherical clusters, while fuzzy clustering allows overlap among clusters by assigning membership probabilities. Hierarchical clustering builds a tree-like structure of nested clusters, offering insight into the dataset's structure without predefining the number of clusters. GMM assumes data are generated from a combination of Gaussian distributions, making them suitable for complex, overlapping clusters [63]. Density-based clustering,

such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN), identifies clusters based on data density, effectively detecting outliers and irregularly shaped clusters. Multi-stage clustering combines multiple algorithms to refine results, increasing accuracy and reliability in challenging scenarios [71].

ML models can be broadly classified into supervised and unsupervised learning algorithms. Supervised learning relies on labeled datasets, where the system learns from known input–output relationships to make accurate predictions. This process involves training models using human-annotated data samples. Conversely, unsupervised learning operates on unlabeled data, seeking patterns and structures within the dataset. The goal is to uncover meaningful clusters or associations without predefined labels.

2.2. DL Algorithms

In traditional and conventional ML methods, specific features and indices are analyzed, and clustering and classification algorithms operate based on these predefined indices. However, this approach may not always yield the most efficient performance for identification algorithms. To address this limitation, DL methods were developed and expanded. These methods provide higher capabilities to learning algorithms through more complex computations.

In DL approaches, the selection of features and indices is also handled by the algorithm itself, which can even lead to the creation of new features and feature extraction, offering a broader perspective for engineers. DL represents a new direction in ML, which is essentially an enhanced version of traditional methods with more detailed computations and refined characteristics. This approach provides users with various levels of learning algorithms, and naturally, as the range of available tools expands, the algorithms' capabilities and the knowledge accessible for the identification process also increase [72].

However, this comes at the cost of greater computational requirements. With the advent of faster processors, this additional computational demand is now more manageable, making the adoption of deep learning approaches increasingly feasible and justifiable.

DL methods, such as CNNs [73] and Recurrent Neural Networks (RNNs) [74], overcome these limitations by learning features directly from data through a hierarchical structure. CNNs excel at extracting spatial features from two-dimensional input representations like spectral images of vibration data, making them particularly effective for tasks such as object detection and image classification. Their ability to identify features across multiple layers enables them to capture intricate patterns such as edges, textures, and shapes without human intervention.

Similarly, RNNs and their advanced variant, Long Short-Term Memory [75,76] networks, are designed to handle sequential data by capturing temporal dependencies. This makes them well suited for analyzing time-series data where past information influences current predictions. In the context of vibration analysis, these models can track dynamic changes over time, providing robust mode tracking even in environments with operational variability and noise.

For instance, DL has been demonstrated to handle dynamic structural behaviors by learning non-linear dependencies and adapting to changes over time, which traditional ML methods may struggle to address. These characteristics position DL as a transformative tool for advancing automated modal identification and SHM practices.

2.3. Computer Vision-Based Techniques

Computer vision-based techniques utilize high-speed cameras and advanced image-processing algorithms to monitor structural vibrations. Unlike traditional sensor-based methods, which require accelerometers or strain gauges to measure responses, computer vi-

sion methods analyze the pixel intensity and motion data captured from videos of vibrating structures. Techniques like Digital Image Correlation (DIC), optical flow, and phase-based video motion magnification (PBVMM) are widely used to amplify and detect subtle structural motions, providing accurate displacement data for modal identification [77,78].

PBVMM, for instance, uses a multi-scale decomposition of video frames to extract motion signals encoded in the pixel phases. This technique is effective for identifying modal frequencies in low-amplitude vibrations of large structures such as bridges, bypassing the limitations of traditional methods that require direct sensor contact [79,80].

AI complements PBVMM by automating the analysis of the extracted pixel phase data, enabling more efficient and accurate identification of modal parameters. By integrating AI-driven algorithms with PBVMM, the process becomes more robust, especially in handling noisy datasets and complex structures, which further enhances the applicability of computer vision-based modal identification techniques.

ML techniques, such as Principal Component Analysis (PCA), Blind Source Separation (BSS), and Analytical Mode Decomposition (AMD), enable the extraction of modal parameters with minimal manual intervention. These methods process high-dimensional data to isolate and identify dominant vibration modes, even in noisy environments or when the excitation source is unknown.

For example, PCA reduces the dimensionality of the pixel motion matrix to reveal dominant modal patterns, while BSS further separates these patterns into individual modes. These AI-driven approaches ensure robust performance, making them ideal for analyzing large-scale structures and high-frame-rate video recordings. Additionally, compressed sensing techniques optimize the storage and transmission of large datasets by focusing only on critical motion components, reducing computational costs while maintaining accuracy [81,82].

2.4. Data Processing

Data processing is the first critical step in AI-powered modal identification, ensuring that input data are clean, relevant, and suitable for analysis. AI-driven Signal Filtering techniques use advanced algorithms such as Wavelet Transforms, EMD, and Kalman Filters to remove noise, isolate relevant features, and extract meaningful vibration signals from raw sensor data [83]. These methods are especially useful in real-world SHM applications where environmental noise from wind, traffic, and earthquake can obscure modal characteristics [84–86].

Another important preprocessing technique is Data Augmentation, where synthetic data are generated to expand training datasets and improve model robustness. Generative Adversarial Networks (GANs) and autoencoders are commonly used in this context to create realistic synthetic data that mimic real-world conditions. This reduces the risk of overfitting, particularly when labeled data are scarce, enabling models to generalize better across different structural configurations.

Feature extraction is perhaps the most crucial aspect of preprocessing. AI algorithms can extract features from both time-domain and frequency-domain data, such as peaks in the PSD, spectral energy distributions, damping ratios, and resonance frequencies. In complex systems, where modal behavior may change due to structural damage or varying environmental conditions, feature extraction methods such as PCA, Independent Component Analysis (ICA), and Sparse Component Analysis (SCA) isolate dominant vibration patterns while reducing data dimensionality.

The seamless integration of AI techniques into automated modal identification systems has made SHM systems more intelligent, adaptive, and scalable. By combining advanced data preprocessing, ML-based classification, deep learning-driven feature extraction, and

optimization-based model refinement, these systems achieve higher levels of accuracy and reliability. AI-powered SHM platforms can process large datasets in real time, detect subtle changes in modal properties, and issue early warnings about potential structural damage, all with minimal human intervention.

Future advancements in AI-powered modal identification are likely to involve even deeper integration of Hybrid Models, combining physics-based simulations with data-driven AI models. These hybrid systems can leverage physics-informed neural networks, which embed physical constraints into the learning process, ensuring that AI-driven predictions remain physically meaningful. As AI technologies continue to evolve, they are expected to redefine how SHM is performed, enabling the fully autonomous monitoring of critical infrastructure on an unprecedented scale.

3. AOMA Techniques

3.1. PP Method

Automated Peak Picking (APP) represents an important advancement in modal identification by applying automated processes to detect modal frequencies without the need for manual intervention. Traditional peak picking methods required engineers to manually identify peaks in the frequency response function (FRF) or power spectral density (PSD), which could be time-consuming and prone to human error [35]. In contrast, APP utilizes algorithms, often enhanced with machine learning, clustering techniques, or CNNs, to automatically scan frequency data, identify peaks, and determine modal parameters. ML algorithms identify patterns in large datasets, enabling the automated detection of modal peaks even in noisy conditions. Clustering techniques group similar frequency components or spectral features, isolating dominant modes and reducing data complexity. CNNs, leveraging their ability to analyze spectral images or time-frequency representations, detect spatial patterns associated with modal peaks, enhancing accuracy across varying noise levels.

This makes APP particularly valuable for real-time applications in structural health monitoring (SHM), where rapid and continuous data analysis is crucial. For example, in large infrastructure systems such as bridges, APP's ability to process high-frequency data efficiently ensures the timely identification of modal frequencies and mode shapes, enabling prompt decision making for maintenance or safety measures [87,88].

The APP offers significant improvements in the speed, consistency, and scalability of modal identification, addressing several limitations of manual peak picking methods. By automating the identification of peaks in frequency data and handling noise more effectively, APP has demonstrated its suitability for real-time and large-scale SHM applications [89].

For example, Hyunjun Kim and Sung-Han Sim presented a cutting-edge approach to modal identification using APP methods enhanced by Region-Based CNN [90]. The study specifically addressed challenges in detecting modal frequencies from noisy frequency-domain data. To validate the effectiveness of the proposed method, the authors conducted experimental tests on three case studies: a simply supported beam, a steel truss, and stay cables from the Jindo Bridge in the Korea. By training the model on synthetically generated data, the method demonstrated superior performance compared to conventional time-domain approaches, as evidenced by higher precision, recall, and F1 scores across all the test structures. For instance, the F1 scores for the proposed method were at least 0.92, whereas those for the time-domain-based method were no greater than 0.83. Furthermore, the computational time required by the proposed method was significantly lower, highlighting its efficiency for large datasets.

3.2. FDD and EFDD Methods

FDD and EFDD are widely used frequency-domain techniques in automated modal identification, particularly effective in applications involving SHM under ambient excitations. These approaches allow for the identification of essential modal parameters without the need for controlled excitation. FDD operates by analyzing the spectral density matrix derived from vibration data to identify prominent peaks corresponding to a structure's natural frequencies. EFDD builds on FDD by estimating damping ratios in addition to frequencies, providing a more detailed characterization of structural dynamics. Together, these methods have found extensive use in monitoring large civil structures, such as bridges and dams, where real-time assessment is critical and controlled testing may not be feasible.

One of the main advantages of FDD and EFDD in automated systems is their efficiency in quickly identifying modal parameters from ambient vibration data, making them particularly suitable for real-time applications. For example, in continuous bridge monitoring, automated FDD can analyze incoming data streams, identifying shifts in frequency that might indicate structural changes or potential damage. These methods are also relatively lightweight in terms of computational demands, especially FDD, which is advantageous for applications in distributed sensor networks or embedded systems where processing power may be limited. Additionally, EFDD's ability to estimate damping ratios provides crucial information on how energy dissipates within a structure, a key factor in understanding its response to dynamic loads, such as wind or seismic activity.

Despite these benefits, automated FDD and EFDD also come with notable limitations. Both methods rely on clear, distinct peaks in the frequency domain, making them vulnerable to inaccuracies in environments with high noise levels or closely spaced modes. In such cases, noise can obscure true peaks or introduce false ones, complicating the identification process and potentially leading to the misinterpretation of modal parameters. Furthermore, while EFDD extends FDD by including damping ratio estimation, this step remains highly sensitive to data quality and may yield less accurate results when noise or environmental variations are significant. This sensitivity can be especially problematic in low-damping structures, where EFDD may struggle to separate true damping characteristics from background noise.

To address these limitations, advanced signal processing techniques such as wavelet transforms, and time-frequency domain decomposition have been developed to mitigate noise. Table 1 presents a summary of FDD and EFDD methods, highlighting their main features, applications, and relevant case studies in AOMA to overcome these limitations.

Table 1. Overview of FDD and EFDD methods used for AOMA, highlighting their key features, application scenarios, and case studies.

Ref.	Novelties	Applications	Advantages
[37]	Automated FDD and SSI for OMA in SHM	Bridge	Automation reduces manual effort Robust against noise
[91]	Automated FDD in real-time flutter stability assessment	Airfoil Model	Real-time stability assessment; effective under ambient loads Mode tracking
[92]	Automated FDD in seismic monitoring	Dam	Automated and continuous monitoring Advanced data analysis capabilities
[93]	Improved FDD for automated modal identification	Bridge	Using time-related modal assurance criterion (MAC) to select only physical modes Using the CWT on correlation functions

Table 1. Cont.

Ref.	Novelties	Applications	Advantages
[94]	Combination of FDD with other automated methods	Frame Heritage Structure	Reduces the need for manual intervention in SHM
[95]	Automated FDD enhanced with CNN for identifying natural frequencies	Concrete Arch Dam	CNN enhances accuracy in noisy environments; capable of long-term monitoring
[96]	Introducing an automated FDD algorithm based on the Discrimination Factor (DF) and MAC	Cable-Stayed Bridge	Reduces manual effort in modal identification Enhances accuracy by distinguishing peaks with MAC and DF
[97]	Fully AOMA using EFDD	15-Story Frame Building	Noise and harmonic handling Reduced need for user interaction
[98]	Automated Mode Bandwidth Identification	Tower Masonry Star Vault Bell Tower Building	Noise resilience
[99]	No Initialization Phase Required	Tower Star Vault Bell Towers Building	Automated and efficient Robust against noise
[100]	Automated Pole Selection	Heritage Structure Masonry Vault Bell Tower Building	Robust against noise MAC-based stability diagram

3.3. SSI Method

SSI is a widely used time-domain method for OMA, enabling the extraction of modal parameters from response-only data. Unlike traditional input–output methods, SSI relies solely on measured outputs, making it suitable for large civil engineering structures such as bridges, dams, and high-rise buildings. The method is particularly valuable in environments where external excitation cannot be applied due to logistical or operational constraints [101,102].

The core of the SSI approach lies in representing a structure’s dynamic behavior using a state-space model. In this model, the system’s response is described through mathematical equations governed by the system’s matrices. These criteria are constructed using measured vibration data, commonly obtained from accelerometers. By applying matrix factorization techniques such as SVD or QR factorization, SSI extracts the structure’s modal properties. The resulting state-space model describes the dynamic response, enabling accurate modal parameter identification even in the presence of environmental noise [103].

The first step in automated SSI-based modal identification is data acquisition and preprocessing, where vibration data are collected from sensors placed on the structure. To ensure data quality, preprocessing techniques such as filtering, resampling, and data normalization are applied to reduce noise and maintain consistency across different datasets.

When high levels of noise are present in the collected vibration signals, filtering techniques and outlier detection methods, such as wavelet analysis, can help preserve system-related data while reducing noise and irrelevant information. This ensures that identification algorithms can produce accurate results based on clean and relevant data. Numerous studies have investigated the impact of signal–noise ratio on system identification methods, revealing a direct correlation between higher SNR and the increased accuracy of modal parameters.

A key aspect of automated methods is the use of data refinement techniques and algorithms that are generalizable and applicable to various systems. Additionally, when uncertainty analysis is incorporated into the identification process, statistical methods such as Monte Carlo simulation, bootstrapping, and others become essential for generating statistical datasets from the initial data. To calculate the uncertainty of modal parameters as a distinct metric, a significant diversity in the initial dataset is required. However, such diversity is often not achievable through a single measurement or data collection session. Consequently, the use of statistical methods, normalization, and resampling techniques becomes inevitable to ensure robust and reliable results.

Next, system identification is performed using the processed vibration data to compute system matrices. This is achieved through either covariance-driven (SSI-Cov) [104–107] or data-driven (SSI-Data) [108–110] algorithms. SSI-Cov estimates covariance matrices from the measured data, making it highly effective in environments with significant environmental noise [111]. Conversely, SSI-Data bypasses the intermediate covariance calculation, directly using raw time-series data, which is particularly beneficial for real-time monitoring applications.

Following system identification, model estimation is carried out using state-space representations. The algorithm estimates system matrices by applying numerical techniques like QR factorization or SVD. To ensure the comprehensive coverage of possible dynamic behaviors, different model orders are evaluated during this step.

Once the models are estimated, a stabilization diagram is generated by plotting the identified modal parameters across different model orders. This visual representation helps distinguish stable modes from noise-induced artifacts by tracking consistent modal frequencies, damping ratios, and mode shapes.

There are various approaches to selecting an appropriate model order. One of the most significant approaches is the use of complexity criteria. A complexity criterion is a mathematically formulated measure aimed at estimating the suitable model order based on the complexity of the system under study and the error introduced by system simplification.

In these complexity criteria, at least two terms are typically incorporated. One term supports the use of larger and more complex state-space models, leading to the selection of a higher model order. Conversely, the other term resists increasing the state-space model's size, striving for a lower model order that assumes a simpler state-space model with fewer degrees of freedom is more suitable for describing the system under study.

These criteria are treated as optimization problems, where the goal is to minimize the combined effect of the two terms. The model order that minimizes the sum of these terms is introduced as the estimated optimal model order. Subsequent identification processes are based on this estimated model order.

Different model orders result in the extraction of different modal parameters, and the accuracy and reliability of the extracted parameters determine the choice of the most appropriate complexity criterion. A well-chosen criterion is generalizable and can estimate the optimal model order for other systems in future identification tasks.

The next critical step is noise mode elimination, where spurious modes are removed by applying statistical validation criteria. Indicators such as the MAC [112,113], Modal Phase Collinearity (MPC) [114], Modal Transfer Norm (MTN) [28,115], and Mode Indicator Function (MIF) [13] assess the stability and reliability of the identified modes [116]. Threshold-based filtering is also applied to improve the accuracy of the stabilization diagram.

Hard Validation Criteria (HVC) and Soft Validation Criteria (SVC) play essential roles in the automated evaluation of modal parameters [71]. HVC applies strict numerical thresholds on properties such as damping ratios, frequency stability, and eigenvalue consistency, ensuring that only modes with well-defined dynamic behavior are retained. These criteria

reduce the likelihood of including spurious modes caused by noise. In contrast, SVC involves statistical measures that evaluate the overall reliability of identified modes by considering averages, standard deviations, and stability indices calculated over multiple models. This combination of HVC and SVC enhances the robustness of automated mode selection [117,118].

To enhance automated mode selection, clustering algorithms are employed. Techniques like k-means, DBSCAN, and hierarchical clustering group modal parameters based on stability, frequency, and damping characteristics [51,119]. These methods help separate true structural modes from noise-related artifacts, enabling reliable mode selection.

Additionally, outlier detection and validation methods such as the Thompson Tau test and Mahalanobis Distance are applied. These statistical tools filter out physically implausible modes, reducing false-positive detections and improving overall reliability.

It should be noted that the Thompson Tau test is a statistical method used to identify and remove outliers from a dataset by iteratively calculating each data point's deviation from the mean and comparing it to a threshold derived from a modified t-distribution; any point exceeding this threshold is considered an outlier and removed, ensuring a refined dataset for analysis. The Mahalanobis Distance, on the other hand, is a multivariate measure that accounts for correlations among variables to determine the distance between a point and the overall data distribution, making it particularly useful for anomaly detection by highlighting deviations from expected patterns. Both methods play a critical role in improving the reliability of data used in structural health monitoring and damage detection [120].

Finally, recursive system updates are performed in real-time monitoring scenarios. Recursive SSI (RSSI) continuously updates the system matrices as new data are collected, allowing the model to dynamically adapt to changes in the structure's environment and operational conditions.

By integrating these multi-stage processes, SSI has evolved into a robust and adaptive framework capable of supporting continuous, real-time structural health monitoring. Its ability to handle noisy environments, combined with scalability for large structures, has established SSI as one of the most effective methods for automated modal identification in SHM applications. Table 2 presents a summary of SSI-Data methods, emphasizing their key features, applications, and relevant case studies in AOMA.

Table 2. Summary of SSI-Data methods used in AOMA, highlighting their main features, clustering approaches, and application case studies.

Ref.	Clustering	Case Studies	Novelties
[121]	Hybrid Clustering Algorithm	Bridges	Full Automation Advanced Clustering Robust Noise Mode Elimination
[122]	K-means Hierarchical Clustering	Composite Cantilever Beam	User-Free Automation Adaptive Thresholds
[10]	Two-Stage Hierarchical Clustering	2-DOF System Simply supported beam Railway viaduct	Robust Mode Detection Advanced Clustering Technique Adaptive Thresholding
[123]	Hierarchical Clustering Distance Criteria	5-DOF system Simply supported beam Bridge	Pre-filtering of Spurious Modes Fully Automated Clustering
[124]	Hierarchical Clustering HVC and SVC	Apostol church Monastery of Jeronimos	Self-Adaptive Clustering Threshold

Table 2. Cont.

Ref.	Clustering	Case Studies	Novelties
[125]	K-means Hierarchical Clustering	18-story building Bridge	Automatic Cluster Thresholding Data-Driven Optimization
[126]	HVC Statistics-Based Clustering	Seven-story steel frame Footbridge	Self-Adaptive Clustering Criteria Two-Stage Spurious Mode Elimination
[127]	Statistical Clustering	Tower	Automated Framework
[54]	Fuzzy C-Means	Arch dam	Fully Automated Framework Adaptive Model Order Selection
[69,70]	Multiple Clustering Algorithms Improved Distance Evaluation	Buildings Dam	Ensemble Learning for Improved Accuracy Automatic and Robust Modal Identification Statistical Resampling for Uncertainty Estimation
[128]	Agglomerative Hierarchical Clustering HVC	Test Rig with Hydrodynamic Bearings (31 mm diameter, 18 mm length, and 90 μ m of radial clearance) Test Rig with Rolling Bearings (15 mm inner diameter)	Adaptive Clustering Threshold-Free Outlier Detection

Table 3 presents an overview of SSI-Cov methods, focusing on their main features, implementation techniques, and notable application case studies in AOMA.

Table 3. Summary of SSI-Cov methods, highlighting their key features, implementation techniques, and application case studies in AOMA.

Ref.	Clustering	Case Studies	Novelties
[129]	Hierarchical Clustering	Concrete arch bridge	Real-time automatic identification using a novel clustering algorithm
[28]	K-means Hierarchical Clustering	Bridge Footbridge	Fully automated workflow Adaptive thresholding
[130]	K-means (k = 2) Hierarchical Clustering	4-DOF system Experimental structures	Robust to noise and environmental changes
[58]	Hierarchical Clustering	Iron arch bridge	Automated modal identification using adaptive thresholds.
[131]	Hierarchical Clustering k-Means	Bridge	Automatic hierarchical clustering threshold Advanced mode validation criteria
[132]	Improved DBSCAN	A simulated arch bridge A concrete arch bridge	Model order selection Automated parameter optimization
[133]	Hierarchical Clustering	Arch dam	Uncertainty estimation framework Data-driven regression models
[51]	DBSCAN	Arch dam	Automated clustering
[73]	CNN-Based Classification	6-DOF system Tower Bridge	Introduction of uncertainty diagrams Deep learning integration
[134]	Fast Density Peaks Clustering	4-DOF system ASCE benchmark frame Bridge	Two-stage spurious mode removal Automatic cluster center selection Capable of tracking closely spaced modes

Table 3. Cont.

Ref.	Clustering	Case Studies	Novelties
[135]	Hierarchical Clustering Modified Modal Observability Correlation	Bridge Footbridge	Fully automated framework Overcoming traditional MAC limitations
[115]	Hierarchical Clustering	Masonry towers	Automatic cut-off threshold definition Validation with modal quality index
[136]	GMM	Four-story shear frame Footbridge	Capable of distinguishing closely spaced modes even under noisy conditions Automatically determines the optimal number of clusters
[137]	DBSCAN	Simply supported beam Bridges	Automated framework Uncertainty-driven filtering
[65]	DBSCAN	Bridge	Density-based clustering Automated parameter setting Improved detection of closely spaced modes
[138]	Three-Stage Hierarchical Sifting Process	Bridge	Fully automated monitoring system Advanced clustering
[139]	Fuzzy C-Means	Thin-walled cylindrical column Truss Beam	Automatic model order determination Hybrid filtering and clustering Robustness against noise
[140]	K-Average Nearest Neighbor DBSCAN	Bridge	Combines clustering results with the five-number summary method Automatic hyperparameter selection
[141]	Kernel Density Estimation Random Forest Classifier	Tower	Advanced clustering and filtering
[119]	Iterative Hierarchical Clustering	Frame Masonry building	Automatic outlier removal Adaptive distance metric
[142]	HVC SVC Hierarchical and Fuzzy C-Means Clustering	Simply supported beam (10 DOF system)	Enhanced automation framework
[143]	Improved K-Means	3-DOF system Dam	Automatic outlier detection and mode filtering Adaptive clustering framework
[144]	k-Means Clustering Hierarchical Clustering	3-DOF system 6-story shear building Tower	Adaptive data-driven thresholds Improved mode tracking and outlier removal

The advantages of SSI methods have been widely discussed. These methods, based on matrix algebra, provide extensive information that can be used at different levels of system identification depending on the level of user access. This means that in addition to modal parameters, they offer access to data such as the observability matrix, Hankel matrix, and more. The observability matrix captures the system's state-space representation, enabling the identification of modal parameters like natural frequencies, damping ratios, and mode shapes without requiring explicit input–output models. The Hankel matrix, formed from time-series output data, uses SVD to isolate the system's dominant dynamics while filtering out noise, ensuring the accurate estimation of system order and stable modes. Together, these matrices allow SSI methods to deliver reliable, noise-tolerant identification of dynamic properties, making them invaluable for analyzing systems under operational or ambient excitations.

However, one of the main challenges of these methods is determining the appropriate model order. To fully utilize the capabilities of SSI-based methods, it is essential to select a suitable state-space model for the system under study. A proper state-space model is one where the model order is sufficiently large to encapsulate all relevant system information and parameters. Choosing the correct model order is a critical initial step in the identification process, as it influences all the subsequent steps and the overall effectiveness of the method. Traditionally, the appropriate model order was determined by the user using a stabilization diagram.

Extensive research has been conducted in this area. Some studies have aimed to automate the stabilization diagram to estimate the model order, but these automated approaches do not always provide the best estimate for every system. Other studies begin the identification process with a state-space model of a larger-than-required order, then reduce the model order in later stages to match the system's needs. This approach is intelligent, as it only slightly increases computations, which are confined to the early stages of the identification process and do not carry over to later phases.

Given these considerations, selecting the appropriate model order is one of the key challenges in using SSI techniques. This issue is also relevant in hybrid methods that incorporate SSI techniques.

3.4. Eigensystem Realization Algorithm (ERA)

The automated ERA has emerged as a vital tool in modal identification for SHM, particularly for large structures subjected to ambient excitations. ERA simplifies the modal identification process by automating tasks that traditionally require manual input, making it suitable for the real-time, continuous monitoring of structures in operational conditions. This automation facilitates the accurate identification of key modal parameters, which are essential for assessing the structural integrity and dynamic behavior of civil infrastructure, such as bridges, buildings, and offshore wind turbines [145].

A significant advantage of automated ERA is its capacity to effectively filter out non-physical or spurious modes, which are often introduced by noise in ambient data. Automated ERA achieves this through advanced stabilization criteria and filtering techniques, such as the use of stabilization diagrams and threshold settings. These tools allow the algorithm to identify true modes while disregarding transient or irrelevant peaks, which can interfere with the accurate identification of structural modes. The result is a more precise and reliable modal analysis that provides a clearer picture of a structure's dynamic characteristics, even in noisy environments [146].

The combination of ERA with the Natural Excitation Technique (NExT) enhances its application in ambient conditions, where no controlled excitation is applied. NExT utilizes naturally occurring ambient forces, such as wind, traffic, or operational vibrations, to excite the structure. This natural excitation approach eliminates the need for artificial or active excitation systems, which can be intrusive, expensive, or logistically challenging, especially for large-scale structures like long-span bridges, high-rise buildings, or complex industrial facilities. By transforming these ambient responses into free decay responses or correlation functions, NExT prepares the data for modal parameter extraction without requiring direct force measurements.

When paired with ERA, this approach becomes even more advantageous. ERA, known for its robustness and computational efficiency, excels in extracting modal parameters such as natural frequencies, damping ratios, and mode shapes. It generates stabilization diagrams that systematically filter out spurious modes, enhancing the reliability and precision of modal identification even in noisy environments. This capability is crucial for SHM, where field data are often affected by environmental noise or operational uncertainties.

The integration of NExT with ERA offers significant practical benefits. It reduces operational complexity and eliminates the need for controlled test setups, allowing structures to be monitored under their normal operating conditions. This non-intrusive, automated, and efficient approach minimizes disruptions to the structure's functionality and drastically lowers the costs associated with traditional testing methods. Furthermore, the combination is particularly well suited for monitoring structures exposed to continuous environmental forces, providing an effective solution for long-term SHM.

The automated aspect of ERA also reduces the need for human intervention, making it highly efficient in applications where continuous monitoring is required. For instance, in the case of large bridges or tall buildings, ERA can track changes in modal properties over time without the need for constant manual adjustments. This automation enhances the consistency and reliability of SHM systems, ensuring that critical information on the structure's behavior is readily available for maintenance and safety assessments.

However, automated ERA can face challenges, particularly with structures exhibiting closely spaced modes, which can complicate the differentiation between true modes and noise. Additionally, while the algorithm reduces manual input, it still requires the careful selection of parameters, such as model order, to ensure optimal performance. Advances in ERA are focused on refining these parameter settings to improve accuracy and further minimize human intervention. Table 4 provides an overview of the ERA methods, emphasizing their key features, computational techniques, and notable application examples in AOMA.

Table 4. Summary of the ERA methods, highlighting their key features, computational techniques, and application examples in AOMA.

Ref.	Case Studies	Key Enhancements	Advantages
[147]	Bridge	Modal Similarity Index (MSI) and Mode Energy Level (MEL)	High accuracy in filtering spurious modes Energy-based mode filtering
[148]	Large-scale bridges	Stabilization Diagram and Extended MAC	Reduced data congestion Improved scalability and deployment
[149]	A plate model A truss model	Hierarchical Clustering and Distributed Processing	Independent processing at sensor nodes
[150]	Rotor blades	Application of Complexity Pursuit	Minimizes manual input in rotating structures
[145]	Offshore wind turbines	Automated and Consistent Damping Estimation	Reliable damping estimation under ambient noise
[151]	a 5-DOF Model Four-Layer Frame TV Tower	Hierarchical Clustering, Consistent Mode Indicator Output	Maintaining accuracy even with high levels of ambient noise

3.5. Hybrid Methods

Hybrid approaches have emerged as powerful solutions in automated modal identification. These methods combine multiple OMA techniques to improve accuracy, efficiency, and resilience against noise. By integrating parametric and non-parametric algorithms, hybrid approaches can handle complex environments and varying operational conditions effectively [152].

A major advantage of hybrid algorithms is their ability to enhance accuracy by merging advanced signal processing techniques like Second-Order Blind Identification (SOBI), and SSI. This combination ensures the precise separation of physical modes from spurious signals. Additionally, hybrid methods demonstrate strong noise resilience, allowing reliable performance even under challenging ambient conditions [153,154].

The integration of SOBI and SSI combines their strengths to enhance operational modal analysis. SOBI preprocesses vibration data, isolating modal contributions and reducing noise through Joint Approximate Diagonalization (JAD), simplifying data interpretation. SSI, a parametric method, provides high-accuracy estimates of modal parameters but often struggles with complex stabilization diagram interpretation. By using SOBI to preprocess and provide well-separated sources, the combined method simplifies stabilization diagrams, enhances mode discrimination, and improves robustness against noise. This hybrid approach delivers superior results, particularly for complex structures with weak excitation, overcoming the individual limitations of SOBI and SSI and yielding reliable natural frequencies and damping ratios.

Another critical benefit is the reduction in expert dependence. Hybrid algorithms automate complex tasks such as stabilization diagram interpretation, minimizing the need for human intervention. This capability streamlines long-term monitoring efforts and reduces operational costs. Automated systems can operate continuously with minimal oversight, enabling large-scale SHM deployments [155].

Real-time monitoring is another key feature of hybrid approaches. Their efficient computational frameworks allow the continuous assessment of infrastructure performance. Many hybrid algorithms dynamically adjust to changing environmental conditions, making them suitable for diverse SHM applications. The ability to detect early damage under operational loads enhances infrastructure safety and longevity.

4. Conclusions and Recommendations for Future Study

This review highlights significant advancements in automated modal identification techniques, with a particular emphasis on Stochastic Subspace Identification (SSI) and its integration with artificial intelligence (AI) and machine learning (ML) models. Automated approaches, including time-domain methods like SSI and frequency-domain techniques such as Frequency Domain Decomposition (FDD), have enabled more accurate and scalable solutions for structural health monitoring (SHM). These methods have evolved with advanced algorithms that improve modal parameter estimation, noise mode elimination, and mode tracking.

Topics such as model order selection in SSI methods and mode selection in the FDD approach are among the challenges addressed by various proposed methods. Another challenge in the field of system identification automation is the increased computational demand required to extract modal parameters in complex problems with high degrees of freedom. As the complexity of the studied system increases, the computational effort grows non-linearly.

With advancements in computer processing power and the use of intelligent algorithms, this challenge is being resolved, and in the near future, faster identification algorithms with more stable results, higher reliability, and lower computational costs are expected. These algorithms will make online system identification more practical and cost-effective, ultimately reducing maintenance expenses, periodic repairs, and system failure prevention.

Given the widespread adoption of artificial intelligence in recent years, enhancing the intelligence and generalization capability of automatic identification algorithms is not unexpected. Since most system identification algorithms aim to extract modal parameters and then classify and organize them, future research can explore various classification and clustering algorithms that examine the mode grouping process from different perspectives.

Incorporating diverse clustering approaches within a single identification algorithm enhances its generalization capability and leads to more stable results. In the cases of conflict or inconsistency among different clustering approaches used in a system identi-

fication algorithm, decision-making algorithms such as the Dempster–Shafer theory can be beneficial.

Challenges such as identifying double and multiple modes, modes with low observability, damped modes and systems with high damping, and systems subjected to combined excitations (random and harmonic) can be considered key challenges faced by intelligent system identification algorithms.

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Glossary

Abbreviation	Meaning
AI	artificial intelligence
AMD	Analytical Mode Decomposition
ANN	Artificial Neural Network
AOMA	Automated Operational Modal Analysis
APP	Automated Peak Picking
ARMA	Autoregressive Moving Average
BSS	Blind Source Separation
CNNs	Convolutional Neural Networks
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DF	Discrimination Factor
DL	deep learning
DQN	Deep Q-Network
EFD	Empirical Fourier Decomposition
EFDD	Enhanced Frequency Domain Decomposition
EMA	Experimental Modal Analysis
EMD	Empirical Mode Decomposition
FDD	Frequency Domain Decomposition
FRF	frequency response function
GANs	Generative Adversarial Networks
GAs	Genetic Algorithms
GBMs	Random Forests, Gradient Boosting Machines
GMM	Gaussian Mixture Model
HVC	Hard Validation Criteria
ICA	Independent Component Analysis
MAC	Modal Assurance Criterion
MPC	Modal Phase Collinearity
MEL	Mode Energy Level
MIF	Mode Indicator Function
ML	Machine Learning
MSI	Modal Similarity Index
MTN	Modal Transfer Norm
NExT	Natural Excitation Technique
OMA	operational modal analysis
PBVM	Phase-Based Video Motion Magnification
pLSCF	Polyreference Least Squares Complex Frequency Domain

PCA	Principal Component Analysis
PP	peak picking
PSD	power spectral density
PSO	Particle Swarm Optimization
RL	reinforcement learning
RNNs	Recurrent Neural Networks
RSSI	Recursive SSI
SCA	Sparse Component Analysis
SOBI	Second-Order Blind Identification
SHM	structural health monitoring
SSI	Stochastic Subspace Identification
SSI-Cov	Covariance-Driven Stochastic Subspace Identification
SSI-Data	Data-Driven Stochastic Subspace Identification
SVC	Soft Validation Criteria
SVD	Singular Value Decomposition
SVMs	Support Vector Machines

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