

TOPICAL REVIEW

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Topical Review

Systematic critical review of structural health monitoring under environmental and operational variability: approaches for baseline compensation, adaptation, and reference-free techniques

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Abstract

Structural health monitoring (SHM) plays a pivotal role in ensuring the safety, reliability and service life of engineering structures. In smart structures, networks of active-response materials (e.g. piezoelectric films, magnetostrictive patches, or fibre-optic cables), which convert mechanical and thermal stimuli into electrical or optical signals and act as the primary interface for continuous condition assessment. A persistent challenge is the influence of environmental and operational variability (EOV), particularly temperature changes, which can distort sensor measurements and either obscure or mimic genuine indicators of structural damage. Although numerous methodologies have been proposed to address this issue across various sensing platforms, a comprehensive comparative assessment across methodological categories remains lacking. This review critically examines 3 principal approaches developed to mitigate EOV: direct baseline compensation, adaptive and multi-baseline strategies, and reference-free techniques, including recent advances in transfer learning and hybrid physics-informed machine learning frameworks. A structured literature search spanning Scopus, Web of Science, IEEE Xplore and ScienceDirect underpins the analysis. Each approach is systematically evaluated, highlighting key benefits, limitations and suitability for varying operational scenarios. In addition, emerging trends, gaps and future research directions are identified, emphasising the need for hybrid models, real-time reference-free methodologies, robust uncertainty quantification and scalable population-based SHM solutions. The synthesis is intended to inform the design of next-generation smart, adaptable SHM systems regardless of sensing modality and their seamless integration into intelligent structures operating under complex real-world environmental conditions.

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Keywords: structural health monitoring (SHM), smart structures, environmental and operational variability (EOV), adaptive baseline techniques, reference-free methods, transfer learning

1. Introduction

Structural health monitoring (SHM) has become an increasingly critical field, bridging engineering, data science, and materials research. The goal of SHM is to maintain the safety and integrity of infrastructure, vehicles, aircraft, and other complex systems by detecting damage early and reliably [1]. However, in practice, SHM methods often face substantial challenges arising from environmental and operational variability (EOV), which can obscure or mimic genuine damage signatures [2]. Among these variables, temperature stands out as one of the most pervasive and problematic: changing thermal conditions can alter wave velocities, elastic moduli, and sensor responses, generating signals that are challenging to distinguish from those associated with real structural degradation [3]. In addition to temperature, other EOVs such as humidity, wind, traffic-induced loading, and uneven solar exposure have been shown to significantly affect structural responses, influencing modal frequencies, boundary conditions and material stiffness [4, 5]. These effects further complicate damage identification and necessitate the development of robust compensation and normalisation techniques. Addressing these influences remains a fundamental concern in the advancement of dependable SHM technologies.

Traditionally, a wide spectrum of SHM techniques rely on baseline datasets acquired from a so-called ‘pristine’ or ‘healthy’ structural state. When new measurements are obtained, they are directly compared against the baseline. Differences are interpreted as damage indicators. However, this approach can fail or become cumbersome when environmental or operational conditions significantly differ from those present during baseline acquisition. The repeated need to store or update baseline datasets for every anticipated condition leads to large data libraries and computational inefficiencies. As a result, research has progressed in 3 main directions:

1. Direct baseline compensation (signal-level) methods that seek to correct new measurements at the raw signal level by removing or compensating for environmental effects before comparing with a stored baseline.
2. Adaptive and multi-baseline strategies that systematically adjust, update, or synthesise new baselines to match current conditions, thereby reducing mismatch.
3. Reference-free approaches that dispense with the notion of a stored baseline altogether, relying on self-referenced or physics-based principles to detect damage without requiring ‘pristine’ reference data.

An important direction within reference-free methods is transfer learning (TL), particularly domain adaptation (DA),

Table 1. Abbreviation list.

Acronym	Full term
ADALINE	Adaptive linear neuron
BRF	Best reconstruction frequency
DA	Domain adaptation
DL	Deep learning
EOV	Environmental and operational variability
FE	Finite element
GAN	Generative adversarial network
GPR	Gaussian process regression
LSTM	Long short-term memory
ML	Machine learning
PCA	Principal component analysis
PBSHM	Population based structural health monitoring
SHM	Structural health monitoring
TL	Transfer learning
WT	Wind turbine

which enables generalisation across structures and environments. Rather than requiring extensive data collection under every condition, TL capitalises on data or models from alternative domains, such as different structures or simulations, to improve diagnostic performance in new target settings [6]. This approach is particularly relevant for large-scale SHM applications, including aircraft [7], bridge networks [8], and wind turbines (WTs) operating across varied climates [9]. A detailed review of these strategies is provided in section 4.5.

Table 1 lists the abbreviations used in this article, presenting precise and consistent definitions to ensure clarity and coherence in the subsequent technical discussions.

1.1. Broader scope and contributions of this review

Although a number of prior reviews have acknowledged the influence of EOV on SHM, they have primarily examined the phenomenon from limited perspectives. Wang *et al* [4] concentrated on modal frequency shifts caused by environmental conditions and discussed input–output and output-only normalisation techniques. Keshmiry *et al* [2] provided a broad overview of EOV effects on both SHM and non-destructive testing technologies, without offering a systematic analysis of mitigation methodologies. Rădulescu *et al* [5] conducted a bibliometric review focused on bridge monitoring and geomatic integration, highlighting underexplored environmental factors such as differential solar exposure. The present work advances the field by offering a comprehensive and methodologically structured review of EOV neutralisation techniques, encompassing signal-level compensation, adaptive and multi-baseline methods, and reference-free approaches. It further

Table 2. Key parameters and methodological criteria used in the structured literature search protocol.

Aspect	Specification adopted in this review
Databases searched	Scopus, Web of Science Core Collection, IEEE Xplore, ScienceDirect
Temporal coverage	Publications up to April 2025 (inclusive)
Language filter	English
Core keyword blocks	<ul style="list-style-type: none"> • ‘Structural Health Monitoring’ or ‘SHM’ • ‘Environmental and Operational Variability’ or ‘EOV’ • Compensation terms: ‘temperature’, ‘humidity’, ‘load’, and similar • Method terms: ‘baseline’, ‘reference-free’, ‘transfer learning’, ‘domain adaptation’
Generic Boolean syntax	(SHM OR ‘structural health monitoring’) AND (temperature OR environmental OR operational) AND (‘baseline’ OR ‘reference-free’ OR ‘transfer learning’ OR ‘domain adaptation’)
Eligibility criteria	Peer-reviewed, includes numerical simulation, laboratory experiment, or field validation, English language
Data items extracted	Structure type, sensing modality, environmental or operational factor studied, methodological family (direct, adaptive or multi-baseline, reference-free), validation level, principal performance metric

contributes by integrating recent developments in TL, DA, and hybrid physics-informed frameworks, thus providing the research community with a consolidated reference that spans algorithmic, data-driven, and physically grounded strategies.

1.2. Search methodology and keywords

To facilitate a rigorous and comprehensive review of the literature pertaining to structural health monitoring under the influence of EOV, a systematic and structured keyword-based search strategy was adopted. The selected terms were designed to reflect the principal themes, methodological developments, and technological paradigms relevant to this domain. *Core search terms* included ‘Structural Health Monitoring’, ‘Environmental and Operational Variability’ (EOV), ‘Temperature Compensation’, and ‘Damage Detection’, which were further complemented by *targeted expressions* such as ‘Reference-free Methods’, ‘Adaptive Baseline Techniques’, ‘Transfer Learning in SHM’, ‘Domain Adaptation’, ‘Guided Waves’, and ‘Machine Learning for SHM’. Boolean operators and wildcard extensions were employed to enhance the specificity and breadth of results across key scholarly databases, including Scopus, Web of Science, IEEE Xplore, and ScienceDirect. Search strings such as ‘SHM AND temperature variability’, ‘reference-free OR reference-free damage detection’, and ‘transfer learning AND structural diagnostics’ proved particularly effective in capturing methodological trends and research innovations. Additionally, specialised terms including ‘Lamb waves’, ‘time-reversal symmetry’, ‘physics-informed machine learning’, and ‘population-based SHM’ were integrated to ensure coverage of both classical signal-level approaches and contemporary data-driven frameworks. This approach enabled

the identification of a broad spectrum of studies, ranging from foundational signal-processing techniques to cutting-edge hybrid methodologies, thereby underpinning the critical evaluation of strategies designed to mitigate the effects of EOV in SHM systems.

All peer-reviewed articles published until April 2025 were captured by the structured keyword search, which was completed upon finalisation of this review. Only English-language publications presenting numerical simulations (including finite-element analyses), experimental testing, or field validation were retained; studies lacking any of these validation approaches were excluded to ensure a focus on rigorously validated methodologies. Table 2 represents the main elements of the search protocol; figure 1 illustrates the classification scheme adopted in this study for addressing EOV mitigation within SHM frameworks.

To further clarify the literature selection process, the initial structured search yielded a total of 386 records across all databases. After the removal of duplicates and screening of titles and abstracts, 142 articles underwent full-text assessment. Studies were excluded for the following principal reasons: lack of experimental, numerical, or field validation ($n = 38$), non-English language ($n = 8$), review or survey papers ($n = 4$), and topic out of scope ($n = 8$). Ultimately, 84 unique peer-reviewed research manuscripts met all eligibility criteria and were included in this review for methodological analysis. This approach strengthens the transparency and rigour of the literature selection process.

The following sections explore each family of methods. Section 2 addresses direct baseline compensation. Section 3 covers adaptive and multi-baseline methods. Section 4 explores reference-free approaches. Section 5 synthesises cross-cutting observations about the strengths and limitations



Figure 1. Taxonomy of mitigation strategies for EOVS mitigation in SHM.

of each group. Section 6 highlights future directions and emerging research opportunities. Finally, section 7 concludes with remarks on the outlook for robust, efficient SHM methods that mitigate EOVS.

1.3. Signal characteristics and EOVS effects

A signal refers to a time-domain record of a physical response, such as voltage, strain, acceleration, or displacement, which is measured by a sensor following an excitation or operational event in a structure.

As an illustration of the signals utilised in SHM and the effects of EOVS, the guided wave response of a composite plate is shown in figure 2. This system is a CFRP composite plate, comprising carbon fibre reinforced with epoxy resin, whose observations were released as the CONCEPT dataset [10]. In this test rig (see figure 3), an actuator located at the centre of the plate generated a ten-cycle, 250 kHz Hanning-windowed excitation pulse. Three PZTs (PZT 2, PZT 3 and PZT 4) recorded the resulting waveforms. It should be noted that figure 2(a) represents the actuator signal, while figures 2(b) and (c) present the received signals at PZT 3 and

PZT 4, respectively, under healthy conditions at 0 °C, 30 °C and 60 °C.

The received guided wave signals at both receiver locations clearly demonstrate the effect of temperature as an environmental variable. With increasing temperature, the amplitude of the first arrival and the overall signal peak diminishes systematically, indicating increased attenuation within the CFRP material. The final wave packet, likely corresponding to reflections, also shows reduced amplitude at higher temperatures. In addition, there is a visible delay in the arrival time of the main wave packet at elevated temperatures, which reflects a reduction in wave propagation velocity due to the temperature-dependent decrease in the elastic modulus. These observations highlight the importance of accounting for EOVS in SHM, as signal amplitude and timing can be significantly influenced by changes in ambient conditions rather than by damage alone.

2. Direct baseline compensation techniques

Direct baseline compensation methods are inherently simple and initially effective for managing short-term or moderate EOVS. These methods involve straightforward techniques, such

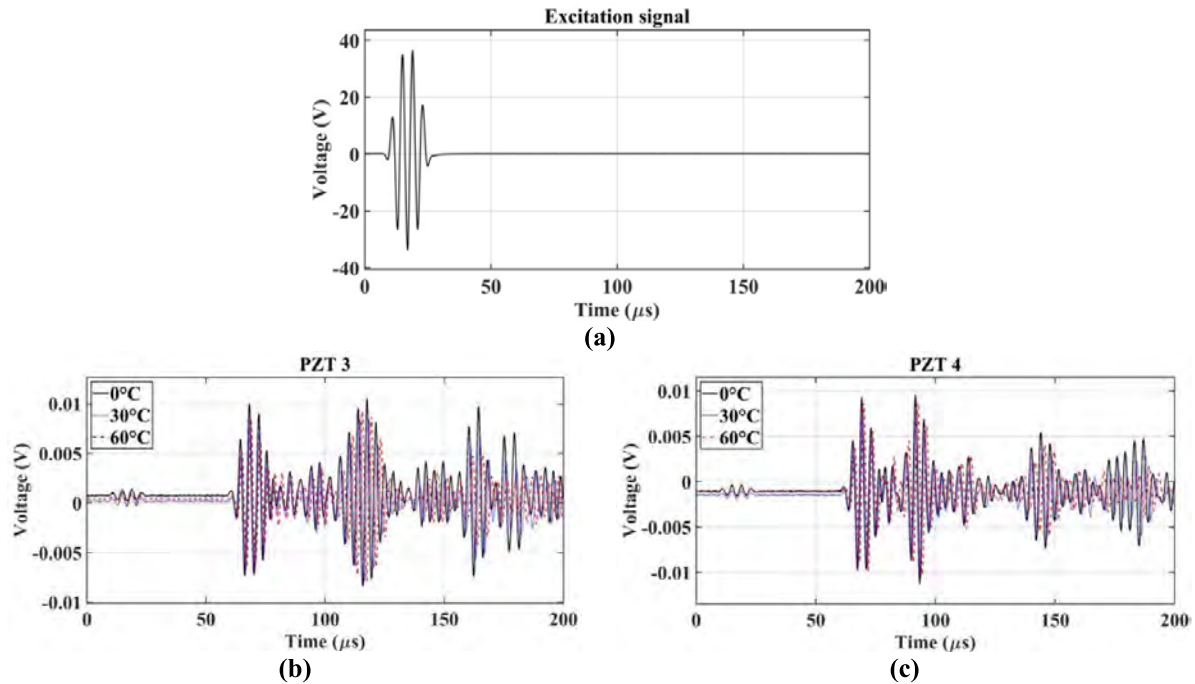


Figure 2. Multi-panel plot showing (a) the excitation pulse applied (b) guided wave signals received at PZT 3, and (c) guided wave signals received at PZT 4, at 0 °C, 30 °C and 60 °C on a CFRP composite plate under healthy conditions (CONCEPT dataset).

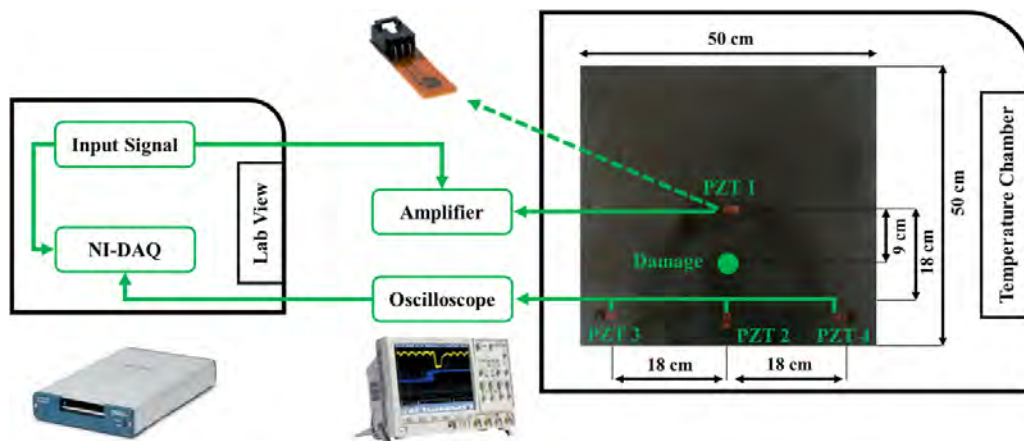


Figure 3. Test rig: CFRP plate with central actuator (PZT 1) and 3 receivers (PZT 2–4) in a thermal chamber at 0 °C, 30 °C and 60 °C.

as direct subtraction. However, their effectiveness significantly diminishes over extended monitoring periods due to structural changes, damage progression, and ageing effects, all of which progressively render original baseline measurements obsolete [11]. In order to clarify, Cury *et al* [12] reported from their six-month monitoring of a post-tensioned concrete box girder bridge on the A1 motorway in France those significant variations in modal frequencies arose due to temperature fluctuations. Their study necessitated advanced data normalisation methods to accurately differentiate between environmental effects and genuine structural modifications, such as bridge strengthening, illustrating the limitations of basic direct baseline techniques under prolonged or variable conditions.

Similarly, Peeters and De Roeck [13], in their one-year monitoring of the Z24 Bridge in Switzerland, demonstrated how temperature-induced changes in modal frequencies could be equal or surpass those caused by actual structural damage. This finding highlighted the risk of false damage indications when employing simplistic baseline subtraction methods without adequately compensating for environmental variability. Additionally, a long-term monitoring programme of the Tamar Suspension Bridge in the UK conducted by Koo *et al* [14] highlighted that substantial structural upgrade, including the installation of supplementary stay cables and the replacement of the deck system, fundamentally altered the structural baseline conditions. These modifications immediately

invalidated previous baseline measurements, thereby necessitating either updated baselines or more sophisticated adaptive compensation techniques. Despite these recognised limitations, direct baseline compensation remains universally applicable in diverse engineering contexts such as composite structures, metal plates, cables, and WT blades, primarily due to its simplicity and initial effectiveness.

2.1. Signal subtraction and phase compensation methods

A prominent illustration of subtraction-based approaches is the work of Nandyala *et al* [15], who proposed a modified delay-sum algorithm combined with a damage residue measure. Their method effectively handled thermal variations in composite plates, ensuring accurate localisation of impact damage by a calibration strategy that compares signals from geometrically similar paths and subtracts a ‘baseline residue’ from the ‘current state residue’. Mariani *et al* [11] extended this idea to the monitoring of pipe systems, integrating a dedicated phase compensation element to tackle transducer drift and velocity changes, halving spurious residual signals under moderate thermal swings. Meanwhile, Salmanpour *et al* [16] conducted a wide-ranging comparative study of guided wave temperature-correction techniques, culminating in a refined minimum-residual procedure that minimised mismatch across temperature windows, thus retaining critical damage features; they evaluated this framework on the damage detection of composite and aluminium plates under varying conditions. These foundational works highlight how straightforward methods like baseline subtraction can be improved by focusing on amplitude and phase alignment under EOV.

2.2. Adaptive filtering for environmental drift

Another approach within direct baseline compensation is the use of adaptive filtering. Wang *et al* [17] and Huang *et al* [18] employed ADALINE-based filters for Lamb waves in composite plates. Their adaptive weights evolve to capture temperature-driven velocity changes, eliminating the need to store multiple baselines at distinct temperatures. Instead, the filter continuously updates its coefficients to produce an enhanced residual signal dominated by damage-related scatter. Extending the application scope, Miao *et al* [19] employed an automatic baseline correction technique for strain gauge signals in bridges, effectively removing long-term drift caused by temperature or slow environmental effects. Although focusing on strain data rather than wave-based SHM, this approach underscores the generality of adaptive filtering as a broad signal-level EOV compensation strategy.

2.3. Real-time and simulation-aided compensation

A multitude of studies have attempted real-time or near-real-time direct compensation. For instance, Aryan *et al* [20] employed laser vibrometer together with high-fidelity finite element (FE) simulations to reconstruct baseline time-traces

corresponding to the current environmental and operational conditions in an aluminium plate, inherently accounting for temperature-induced variations. Salmanpour *et al* [21] demonstrated a single-baseline temperature correction scheme for composite structures undergoing large thermal alterations, reducing the overhead of storing a wide range of baselines. Outside the purely wave-based domain, Ai *et al* [22] deployed correlation-coefficient frequency shift compensation in electromechanical admittance of concrete structures under temperature swings, while Chen *et al* [23] used wavelet decomposition and machine learning (ML) to isolate thermal responses in cable structures, thereby retaining damage signatures. Simon *et al* [24] similarly devised a trend decomposition approach for radar-based WT blade monitoring, removing temperature-induced drift from the signal baseline subjected to EOV.

2.4. Benefits and drawbacks of direct compensation

Direct baseline compensation methods are inherently simple and are initially well-suited for managing short-term or moderate EOV. These strategies typically involve straightforward techniques such as direct subtraction. However, their effectiveness diminishes over time as structures experience progressive changes, such as damage or ageing, rendering the original baselines increasingly obsolete. This shift necessitates either the frequent updating of baselines or the adoption of more sophisticated correction schemes to maintain accuracy. Furthermore, significant variations in environmental conditions, particularly large temperature differences, can severely limit the effectiveness of these basic compensation methods. Despite these challenges, the application of direct baseline compensation extends across various fields, demonstrating its versatility. It has been successfully implemented in domains ranging from composites and metal plates to cables and WT blades, displaying its broad applicability.

3. Adaptive and multi-baseline strategies

Adaptive and multi-baseline strategies reduce dependence on a single static baseline by dynamically selecting or synthesising baselines. This flexibility allows the system to accommodate EOVs, resulting in a more robust and generalisable SHM framework.

3.1. Incremental and evolving baseline libraries

One line of research focuses on incremental or evolving baseline libraries to reduce the impacts of ambient factors. As an illustration, Putkis and Croxford [25] presented a continuous baseline growth method, adding newly acquired data into the reference library in small increments. This approach was tested on composite plates, showing improved sensitivity and diminished storage burdens compared to enumerating large sets of discrete baselines. Abbas *et al* [26] similarly investigated optimal baseline selection, dynamically re-selecting or updating baselines to minimise residual mismatches under

EOV; this strategy was evaluated on the monitoring of a stainless-steel beam. These techniques are especially valuable for long-term monitoring when structures experience gradual changes over months or years.

3.2. Data-driven virtual baseline synthesis

Instead of storing numerous baselines, researchers compute virtual baselines from a limited set of reference measurements. For example, Yue and Aliabadi [27] devised a scalable approach for anisotropic carbon-fibre-reinforced polymers, deriving dimensionless amplitude and phase compensation factors from only one or 2 measured baselines. Extrapolating those factors, baselines at arbitrary temperatures can be reconstructed efficiently. Fendzi *et al* [3] employed Hilbert-transform representations and linear parameter fitting to reconstruct baselines with minimal error across wide temperature ranges in SHM of composite structures. This data-driven notion of baseline ‘synthesis’ can significantly reduce storage demands in large-scale SHM deployments, provided the underlying model reliably captures environmental dependencies.

3.3. Regression and latent models

Recent research in SHM has progressed towards combining advanced regression techniques, such as Gaussian process regression (GPR), latent variable analysis and nonlinear stepwise methods, with physics-based wave propagation models. This integration enables the dynamic synthesis and adaptation of baselines to compensate for EOV, as demonstrated by rigorous experimental and field studies. To this end, Amer *et al* [28] introduced a physics-assisted GPR for guided-wave SHM, merging data-based insights with parametric wave models; their methodology was validated on an experimental aluminium coupon subjected to varying damage and load states, thereby demonstrating its capability to compensate for load effects under diverse conditions. Qu *et al* [29] pursued a multi-phase adaptive methodology, employing GPR to track gradual environmental drifts in offshore WT structures; their approach was applied to an offshore WT undergoing structural evolution, effectively capturing long-term variations in operational states.

Font-Moré *et al* [30] utilised latent variable models based on principal component analysis (PCA) to implicitly correct for EOV in vibration-based SHM; their study, which examined power spectral density spectra from a small-scale WT blade, underscored the method’s robustness in isolating damage-sensitive features. Roberts *et al* [31] emphasised robust nonlinear regression to remove confounding operational parameters; their technique was corroborated through experiments conducted on data from the Vestas WT blade, where regression residuals effectively enhanced damage detection by mitigating environmental influences. Jiang *et al* [32] combined generative adversarial networks (GANs) with long short-term memory

(LSTM) models to generate ‘moving baselines’ with uncertainty quantification; their work, based on ambient temperature measurements and static responses from a cable-stayed bridge, highlighted how advanced ML can facilitate dynamic baseline adaptation under complex thermal loads.

3.4. Comparative assessment of adaptive approaches

Adaptive and multi-baseline methods, particularly when enhanced by advanced regression techniques and physics-based models, significantly outperform single-baseline approaches under widely varying environmental conditions. However, these strategies often necessitate increased storage capacity for incrementally maintained baselines or entail greater modelling complexity when synthesising virtual baselines. Moreover, the accuracy of data-driven reconstruction is critically dependent on the range and quality of the training data, which must comprehensively represent the anticipated EOV.

4. Reference-free approaches

Unlike methods that adjust or store a static reference dataset, reference-free approaches are designed to operate without any prior pristine state record. Instead, they rely on various principles ranging from purely data driven learning to physics-based models to detect or localise damage in a self-referenced manner. This class of methods has attracted considerable interest due to its potential to simplify deployment and circumvent the pitfalls of baseline dependency under changing conditions.

4.1. Purely data-driven damage identification

Data-driven ML methods offer a versatile, baseline-independent approach to detect structural anomalies while compensating for environmental influences. Kashyap *et al* [33] presented a convolutional autoencoder approach (deployable via TinyML) for honeycomb composite sandwich structures, demonstrating the potential for real-time classification of damage versus temperature-induced changes. In the domain of railway infrastructure, Zhou *et al* [34] used advanced acoustic emission and clustering methods to detect anomalies in switch rails without a baseline. Meanwhile, Zhu *et al* [35] combined unsupervised shapelets with shift-invariant dictionary learning, again avoiding stored references. The effectiveness of this technique was assessed on the SHM of a composite structure. Though these data driven approaches can successfully account for environment driven changes, they often demand substantial training data covering a range of conditions, and the computational load can be significant, particularly if real time operation is required.

Despite their versatility, many data-driven ML approaches suffer from a lack of transparency, with their internal workings often described as ‘black-box’ models, which can complicate practical deployment in SHM systems. This limitation

may diminish user trust, hinder the explanation of automated decisions to engineers and operators, and present barriers to adoption in safety-critical environments [36]. In response, recent research has focused on integrating explainable artificial intelligence (XAI) techniques and interpretability frameworks to provide greater insight into model decision processes.

Among the most established XAI methods in SHM are feature attribution and model interpretability tools. For example, shapley additive explanations has been used to clarify the contribution of input features in load–deformation correlation analysis of long-span suspension bridges [37]. Local interpretable model-agnostic explanations has been applied to highlight influential measurement points in health monitoring networks of prefabricated buildings [38]. Gradient-weighted class activation mapping is frequently used to visualise salient regions in sensor data or images relevant for impact detection and localisation in aerospace composite structures [39].

Recent advances go further by embedding domain-specific visualisation and attribution techniques in deep learning (DL) frameworks for SHM. For example, Rezazadeh *et al* [40] used activation heat maps to visualise changes in the internal representation of a deep model before and after DA for rotary machine fault detection, thereby revealing how the model adjusts to new operational conditions. Vision transformer-based XAI approaches, as demonstrated by Azad and Kim [41], and deep Taylor decomposition, as in Parziale *et al* [42], further enhance the transparency of complex models in composite damage detection and Lamb wave-based SHM. Rezazadeh *et al* [9] visualised the evolution of instance weights for both source and target domains during the DA process, revealing how the model reallocates importance across different instances as it learns to address distribution shifts caused by temperature variations in WT blade damage detection process. Figure 4 presents an example from [9]; this scatter plot shows the changes in instance weights at different stages of adaptation, i.e. before adaptation, in the middle, and last epochs. This visualisation offers practitioners a transparent view of how DA mechanisms (more specifically instance-based techniques) improve model generalisability and reliability in SHM applications.

4.2. Physics-based reference-free detection

Physics-based reference-free methods exploit fundamental characteristics of wave propagation, such as time-reversal symmetry, acoustoelasticity, and wave reciprocity. A significant body of work has emerged from the exploitation of time reversal. Sharma *et al* [43] and Kapuria [44, 45] demonstrated that certain excitation frequencies, often termed ‘best reconstruction frequencies’ (BRFs), preserve time reversibility even under temperature variations in aluminium plate-like structures, while Zhu *et al* [46] examined a similar approach in the SHM of composite structures. The BRF is defined as the excitation frequency at which the time-reversed signal, when re-emitted after propagation, yields the highest reconstruction quality. This quality is typically quantified by metrics such

as maximum amplitude, energy concentration, or the correlation between the original and reconstructed signals, even as wave velocity changes due to environmental effects. In practical terms, the BRF is experimentally identified by conducting a frequency sweep and performing time-reversal experiments at each frequency, subsequently selecting the frequency that provides optimal reconstruction according to the chosen metric. Both experimental and numerical studies indicate that, for a given actuator and sensor configuration, the BRF is largely invariant with respect to temperature. This characteristic makes BRF-based methods particularly suitable for baseline-free damage detection. By operating at these frequencies, the method becomes effectively reference-free, as the damage index remains insensitive to environment-driven wave velocity changes.

Anton *et al* [47] introduced ‘instantaneous baseline’ concepts that compare concurrent wave paths instead of referencing past data in the health monitoring of aluminium plates. Mesnil *et al* [48] used a self-referenced approach for anisotropic composites, while Zhu *et al* [49] demonstrated linear reference-free techniques focusing on wave reciprocity in complex composite structures. An *et al* [50] successfully applied local reference-free methods to real *in situ* bridges, validating their resilience to varying ambient conditions.

Additionally, Shi *et al* [51] addressed baseline-free stress monitoring by using acoustoelastic Lamb waves. Their experiments on prestressed components of aluminium plate demonstrated robustness against EOV. Lee *et al* [52] developed baseline-free pipeline monitoring with optical fibre-guided laser ultrasonics, successfully testing on stainless steel pipes at temperatures up to 300 °C. Lakshmi [53] applied an energy-based method using fractal dimension analysis of time-history responses, with case studies on bridges and frame structures showing reliable performance under variable conditions. Lim *et al* [54] proposed a reference-free nonlinear ultrasonic modulation method that isolates fatigue crack spectral sidebands in the aluminium plates and aircraft fitting-lug specimens, while Qiu *et al* [55] advanced damage detection through distance compensation to mitigate temperature-induced wave velocity variations in the SHM of aluminium plates, Loshelder *et al* [56] applied apex-shifted transforms to overcome fluctuations in ambient temperature, pressure, and humidity in the health monitoring of a water-immersed steel specimen a bent aluminium plate, and high-density polyethylene specimen; Sohn *et al* [57] employed consecutive outlier analysis to counteract effects from changing operational loads in the condition screening of the composite structures.

4.3. Hybrid physics-informed learning frameworks

Researchers have also pursued hybrid approaches that incorporate both physics-based models and data-driven learning in a reference-free manner. Miele *et al* [58] and Koune and Cicirello [59] introduced multi-fidelity or disentangled representation learning frameworks that embed domain knowledge into ML pipelines, drastically reducing

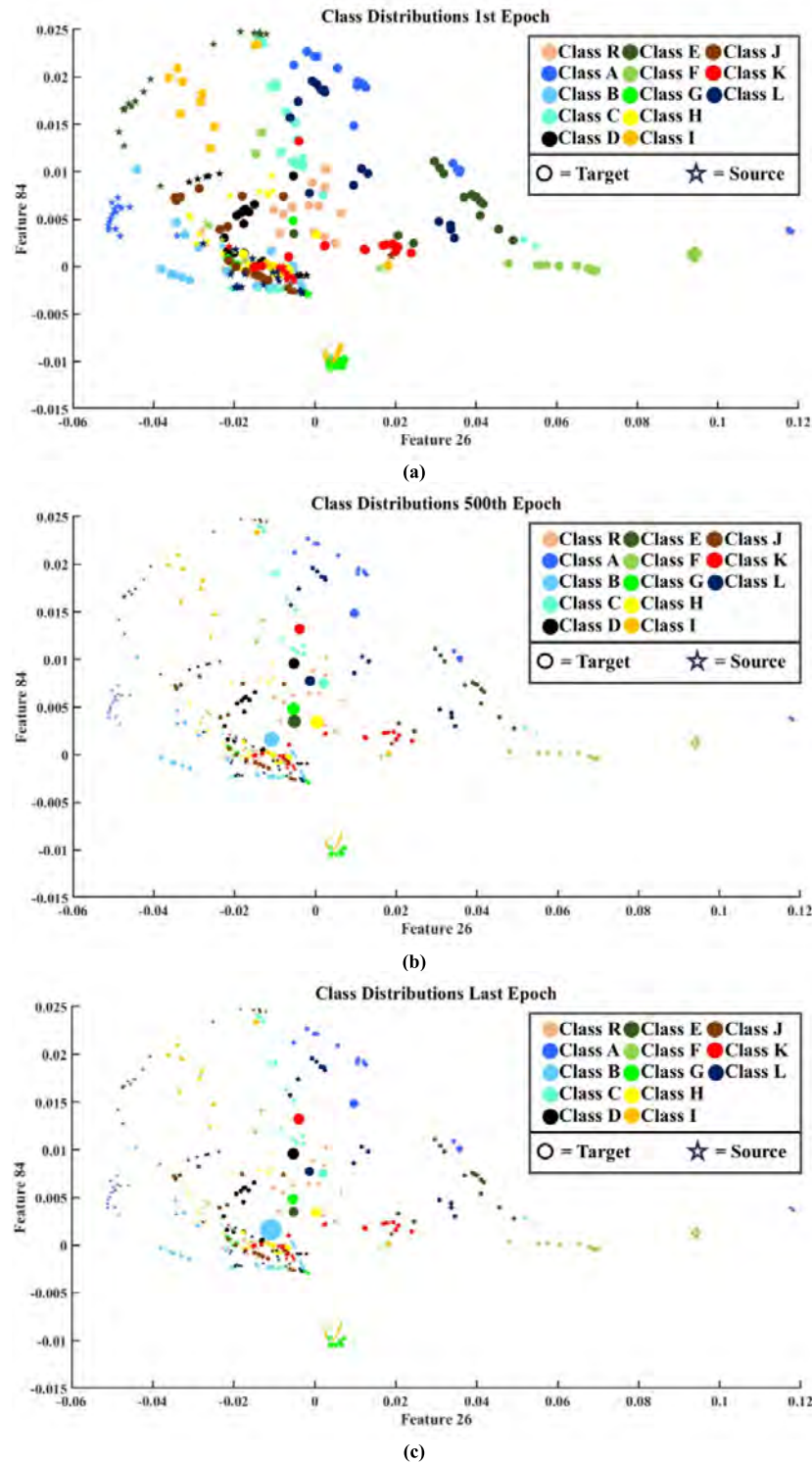


Figure 4. Scaled weight updates of source and target domain samples at (a) the first epoch, (b) epoch 500, and (c) the last epoch of learning process. Reproduced with permission from [9]. © The Author(s) 2025. [CC BY-NC 4.0](https://creativecommons.org/licenses/by-nc/4.0/).

the dependence on baseline data when evaluated on the concrete slabs and a Euler–Bernoulli beam model, respectively. Similarly, Wang *et al* [60] combined parametric identification with physics-informed neural networks for modelling temperature fields in bridge decks, while Pereira and Glisic [61]

integrated rheological models of concrete creep and shrinkage into neural networks, thereby capturing long-term environmental effects without needing a pristine reference. Amer and Kopsaftopoulos [62] used GPR embedded with structural damage indices, emphasising probabilistic quantification; they

examined this framework on the damage detection of a bridge. Bayesian approaches have also been explored in the SHM of bridges by Li *et al* [63] and Jiang and Kim [64], while Sohn *et al* [65] relied on redundant signal measurements to achieve temperature independence without baseline data in the health monitoring of aluminium plates. El Mountassir *et al* [66] combined PCA-based approaches with adaptive modelling to achieve damage detection in highly attenuating media in a reference-free manner in the pipeline systems.

4.4. Relative referencing and instantaneous baselines

While abundant reference-free methods rely on broad data-driven or purely physics-based techniques, multiple studies focus on relative or instantaneous references and scalable building-block paradigms to reduce reliance on a single stored 'pristine' baseline.

As an illustration, Lee *et al* [67] introduced relative baseline features for guided-wave SHM of composite and aluminium plates, relying on path-to-path comparisons to nullify global environmental shifts. Salmanpour *et al* [68] advanced this idea with an instantaneous baseline method that employs sensor mapping to enable real-time damage localisation under varying conditions in the composite plate-like structures. Yue *et al* [69] proposed a building-block philosophy that progressively validates temperature compensation strategies on smaller composite coupons before scaling up to large fuselage sections, thereby reducing recalibration overhead in complex structures.

4.5. Transfer learning for cross-domain SHM

TL offers a scalable framework for SHM by transferring knowledge from well-characterised domains to new, data-scarce environments. This section reviews key DA strategies under different supervision settings [70].

4.5.1. Domain adaptation under different supervision settings.

DA techniques in structural health monitoring are employed to overcome challenges posed by EOVS, such as ambient temperature fluctuations, operational load changes and external vibrations, which can significantly alter data distributions and compromise damage detection. In the context of TL, these methods are broadly classified according to the strategy they adopt (feature-based, instance-based or model based) and by the availability of target domain labels (operating in unsupervised, semi-supervised or supervised settings). Recent developments have also addressed the open-set scenario, in which the target domain may include previously unseen damage classes.

Feature-based approaches seek to transform the feature representations of both source and target domains into a common latent space where the EOVS effects on the SHM can be neutralised. For example, Bull *et al* [71] introduced a population-based structural health monitoring (PBSHM) framework for homogeneous populations in an operational wind farm, employing a mixture-model algorithm to capture the inherent variations among nominally identical WTs.

PBSHM is a structural monitoring approach that treats groups of similar structures as a single population rather than as separate, unrelated assets. Instead of creating an independent baseline or reference model for each individual structure, PBSHM combines data from all similar assets into one statistical framework. This combined approach helps to effectively use scarce damage data from a few structures to detect and diagnose potential faults across the entire fleet [72].

In practice, PBSHM first gathers data from a set of structures that are alike in design, function, or operating conditions. Examples include turbines in a wind farm, aircraft in an airline fleet, or bridges along a motorway [73]. By pooling these data, PBSHM establishes a collective understanding of what is considered normal performance for the entire group. Techniques such as clustering, transfer learning, and domain adaptation are then used to manage and account for any natural differences between individual structures, like slight variations in manufacturing, installation conditions, or environmental exposure. A practical example of PBSHM could be monitoring a fleet of wind turbines in a large wind farm. Normally, each turbine might have slight differences in vibration response due to variations in manufacturing, age, or wind conditions. By using PBSHM, data from all turbines are combined to create a single reference model that accounts for these small differences. If one turbine suddenly shows vibration patterns significantly outside the normal population range, it would be identified as potentially damaged or faulty and flagged for closer inspection [74–76]. The main advantage of PBSHM is that it efficiently leverages limited damage data and reduces the need for extensive and repetitive individual calibrations. It thus enables quick, consistent, and scalable monitoring across many similar structures, improving overall maintenance efficiency and safety.

In the context of multi-storey buildings, Gardner *et al* [77] investigated DA for SHM by introducing multiple TL techniques, such as transfer component analysis (TCA), Joint DA and Adaptation Regularisation based TL, to address shifts in data distributions across varying operational conditions. Moving to aircraft applications, Bull *et al* [78] further demonstrated the efficacy of TCA on experimental vibration data collected from tailplanes, revealing that combining partial datasets leads to a more consistent representation for damage detection. In the realm of bridge monitoring, Gigliani *et al* [79] applied a DA approach by aligning damage-sensitive features derived from FE model data with field measurements in a supervised framework. Complementing this work, Omori Yano *et al* [80] discussed the foundational aspects and critical importance of unsupervised feature alignment for TL in bridge SHM. Finally, Souza *et al* [81] presented a comprehensive study on unsupervised TL for bridges, employing Joint Distribution Adaptation to effectively align features across different structures and enhance damage detection when monitoring data are limited.

Instance-based approaches focus on reweighting or selectively sampling instances from the source domain to better match the target distribution. Quqa *et al* [82] adopt an instance-based unsupervised method for regional-scale bridge monitoring in which climate extremes induce variability; their

approach combines indirect monitoring techniques with satellite interferometric radar data.

Michau and Fink [83] applied unsupervised instance-based DA for anomaly detection by aligning feature distributions using adversarial learning and a novel multidimensional scaling loss. This enhances SHM by transferring complementary operational data across systems without requiring fault labels. The method is validated on bearings, jet engines, and image datasets, showing robust performance under domain shifts. Liu *et al* [84] introduce HierMUD, a hierarchical multi-task unsupervised DA framework for drive-by monitoring of bridges that mitigates variability by adaptively aligning feature distributions across multiple tasks. Rezazadeh *et al* [9] propose a TL framework for WT blades that addresses temperature-induced shifts in feature distributions by employing capsule neural networks, TL adaptive boosting and random forest-based instance weighting, an approach tailored for scenarios with limited data availability.

Model-based approaches achieve DA by directly adjusting or fine-tuning model parameters to extract domain invariant features. These techniques have proven effective in fault diagnosis across a broad range of engineering systems, owing to their straightforward methodology [40]. In a series of case studies in SHM, Zhou and Lai [85] develop a deep DA framework that integrates time and frequency domain feature extraction with a dedicated domain alignment module; their semi-supervised approach, tested on a WT blade and a lattice mast, mitigates EOV while accommodating open set conditions. Hong *et al* [86] describe a deep cross-domain adaptive semi-supervised method for stranded structures in which a multilayer convolutional neural network, combined with a multicore maximum mean discrepancy technique, is used to counteract variability in guided wave signals. Yang *et al* [87] further contribute by presenting a multi-source dynamic adaptive domain generalisation network for crack detection in composite structures operating under unknown temperature environments; their unsupervised method employs temperature-specific regressors whose outputs are fused via similarity metrics.

On the whole, these studies demonstrate that DA in structural health monitoring can be effectively implemented through feature-based, instance-based, and model-based strategies, each adaptable to supervised, unsupervised and semi-supervised contexts. The incorporation of open set approaches, as evidenced by the work of Zhou and Lai [85], provides a robust means of addressing scenarios where the target domain may present unforeseen damage classes, thereby enhancing the generalisation and practical applicability of structural health monitoring systems under real world conditions.

4.5.2. Simulation-aided and physics-informed transfer.

Simulation-aided and physics-informed transfer methods are especially valuable when experimental data are scarce due to extreme EOV, such as temperature fluctuations, load variations or changes induced by retrofitting. These methods utilise simulated data, derived from numerical models or simplified

physics-based representations, to fill data gaps and compensate for shifts in measured signals caused by environmental effects.

For ultrasonic guided wave SHM under EOV, Sawant *et al* [88] utilised a DA approach based on convolutional autoencoders with TL to compensate for temperature effects in composite structures, while Wang *et al* [89] addressed similar challenges in Lamb wave-based fatigue crack detection in aluminium specimen by aligning FEM-simulated and experimental signals through adversarial DA. In the context of impedance-based SHM, da Silva *et al* [90] employed TCA to map features between temperature-varied domains, enabling accurate structural state classification with minimal additional labelling in aluminium beam structures.

Focusing on bridges, Zhou *et al* [91] proposed a cross-domain damage identification strategy by combining generative adversarial networks with deep adaptation networks to mitigate data scarcity across different structural domains. Omori Yano *et al* [92] tackled retrofitting-induced domain shifts by applying TL to support continuous monitoring without retraining, while Tronci *et al* [93] introduced a novel framework that transfers feature extraction knowledge from speaker recognition via x-vector embeddings to improve vibration-based bridge SHM. Regarding structural changes due to repair, Wickramarachchi [94] developed a statistical alignment method integrated with DA to maintain damage sensitivity despite distributional shifts in long-term SHM data of a mast (tower-like) structure. For composite structures, Liu *et al* [95] demonstrated that physics-informed adversarial TL can effectively fuse synthetic and experimental monitoring data, enhancing the robustness of damage detection under complex failure modes; this approach was evaluated on the SHM of a composite specimen.

At a broader level, Furlong and Reichard [96] introduced a hybrid physics-informed DL model that integrates simplified structural simulations into a TL framework, improving generalisation in scenarios with scarce experimental damage data. Meanwhile, Ge and Sadhu [97] presented a physics-informed DA technique based on generative adversarial learning, embedding governing physical constraints within a self-attention-enhanced CycleGAN to align simulated and real signals; this framework was tested on two systems, i.e. a laboratory steel beam and a large-scale steel truss bridge. Liu *et al* [98] further proposed a manifold alignment method for liquid-cooled plates, bridging simulated and real data under temperature and loading variability to enable robust fault diagnosis. Collectively, these works underscore the broader trend of combining numerical simulations and physics-based representations with advanced machine learning algorithms to overcome data scarcity and distributional shifts in SHM.

4.5.3. Multi-task and hierarchical transfer frameworks.

A recent trend in TL for SHM is the development of multi-task and hierarchical frameworks that simultaneously address damage detection, localisation, and severity estimation. These frameworks benefit from shared representations across related tasks, thereby enhancing overall diagnostic performance.

For bridge systems, Duran *et al* [99] demonstrated a CNN-based TL approach using simulated training data to detect structural damage across different geometries. Building on this, Giglioni *et al* [100, 101] applied DA to multi-span girder bridges by aligning natural frequency features under varying operational conditions. In a related study on building structures, Astorga *et al* [102] extended the PBSHM concept by utilising ambient vibration data from nominally identical building stocks, thus underscoring the broader potential of TL frameworks in infrastructure applications.

4.6. Strengths and limitations of reference-free methods

Reference-free approaches in SHM minimise data storage requirements and are inherently resilient to environmental drift because they eliminate the need for extensive baseline libraries. Techniques such as relative and instantaneous referencing enable real-time comparisons without dependence on pristine reference states. However, these methods often require advanced understanding of wave physics, dense sensor networks, and make assumptions such as linear wave propagation or invariant mode shapes. These assumptions may not always hold in complex or evolving structural environments. As a result, practical implementation of reference-free methods demands careful calibration and comprehensive validation to ensure robust performance in diverse settings.

As detailed in section 4.5, TL techniques provide promising scalability by allowing knowledge transfer from well-characterised source domains to new, data-scarce target domains. However, their effectiveness relies heavily on structural compatibility between domains. Significant differences in geometry, material properties, boundary conditions, or operational environments can cause misalignment of feature distributions and physical behaviours. This can reduce transfer efficiency, lead to negative transfer, or require substantial adaptation and further training. Therefore, the successful application of TL in SHM often requires robust DA strategies, data augmentation, or hybrid models that integrate physics-based constraints in order to achieve reliable and generalisable performance across structurally diverse systems.

5. Synthesis and comparative insights

5.1. The baseline dependence spectrum

The dependence of SHM approaches on baseline data can be described along a spectrum, where each methodology presents unique advantages and limitations in relation to baseline requirements.

- Direct baseline compensation is simpler to implement in the short-term but struggles as baseline validity diminishes over time.
- Adaptive and multi-baseline solutions excel under wide temperature or operational ranges but may require large baseline libraries or sophisticated data-driven models.
- Reference-free methods circumvent reference datasets by exploiting physics-based invariants (e.g. time reversal, acoustoelastic invariants) or advanced ML solutions. They promise strong resilience to EOV but often demand more complex instrumentation or computational resources.

Figure 5 illustrates the distribution of representative studies across the 3 methodological categories reviewed in this paper. This visual summary provides an immediate snapshot of how research efforts are allocated among direct baseline compensation, adaptive and multi-baseline strategies, and baseline-free approaches.

As shown in figure 5, approximately 75% of the studies are categorised under baseline-free methods, while direct baseline compensation and adaptive or multi-baseline strategies account for 14% and 11% of the studies, respectively. This marked disparity reflects a pronounced trend in recent years within the SHM community towards the development and implementation of baseline-free approaches. These methods have become increasingly prioritised owing to their scalability and adaptability, especially as researchers seek to reduce dependence on baseline data and address the challenges of monitoring large-scale or heterogeneous infrastructure. This shift highlights the increasing role of advanced data-driven and physics-informed methodologies in enabling more robust and generalisable performance in the presence of environmental and operational variability.

To further illustrate how the reviewed methods have been practically applied across various structural categories, table 3 categorically summarises representative case studies. The table highlights methodological diversity and underscores the prominent focus given to specific structural types, notably bridges, composite materials, aluminium structures, and WTs. Additionally, it identifies other important but comparatively less-explored structures, such as buildings, cables, and pipelines.

Each structural type faces distinct challenges due to its exposure to specific EOV, as outlined below:

- Bridges are large-scale structures frequently exposed to substantial temperature and humidity fluctuations, as well as dynamic loading from traffic and wind. These variabilities necessitate adaptive baseline methods, DA, and physics-informed ML approaches capable of managing complex, long-term changes (e.g. [19, 32, 79, 81]).
- Composite structures, including plates, panels, and sandwich components, present challenges related to anisotropic properties, sensitivity to moisture ingress, and significant temperature-driven changes in wave propagation characteristics. Consequently, guided wave techniques, adaptive filtering, and reference-free methods are predominantly applied (for instance [3, 15, 17, 25]).
- Aluminium structures, such as plates, pipelines, and beams, commonly experience temperature-induced expansion and fatigue loading. Baseline subtraction, phase compensation, time-reversal, and DA techniques are effective in addressing

Distribution of Studies Across Categories Percentage

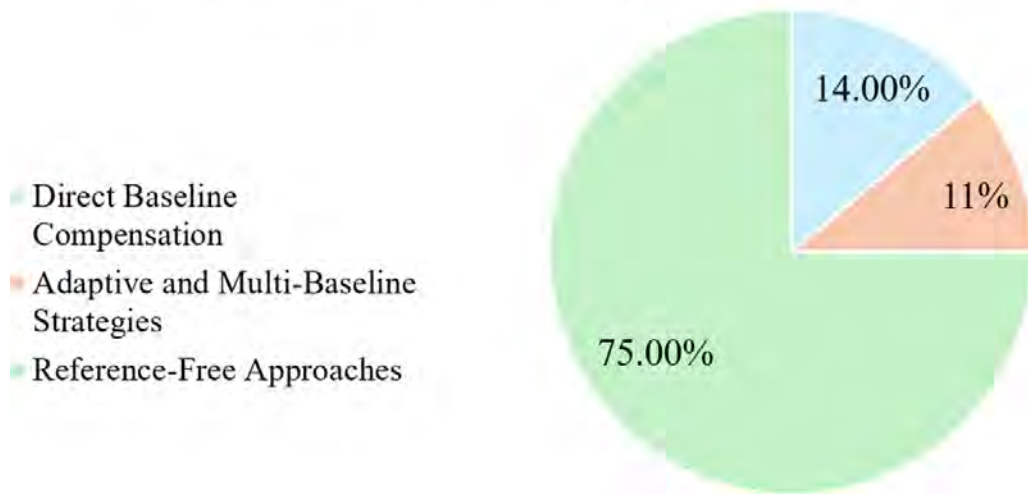


Figure 5. Distribution of representative studies across methodological categories for mitigating EOV in SHM.

these variabilities, particularly by compensating for wave velocity variations under different loading and thermal conditions (as demonstrated in [11, 16, 21, 44, 45]).

- WTs, particularly blades and towers, are subject to extreme dynamic loads, fatigue cycles, rapid thermal shifts, and substantial aerodynamic effects. Adaptive baseline synthesis, TL, and PBSHM methods are particularly suitable, enabling robust detection capabilities across turbine populations (e.g. [24, 29, 71, 85]).
- Buildings, especially multi-storey structures, encounter varying temperatures, wind effects, and operational loading. TL, DA, and population-based techniques are beneficial due to their ability to transfer knowledge efficiently across similar structures, thereby improving robustness under operational variability (see also [77, 102]).
- Cables, including stay cables in bridges, experience dynamic responses to temperature variations and wind-induced vibrations. Wavelet decomposition and ML-based compensation methods have proven effective in isolating and removing these environmental effects from structural response data (such as [23, 32, 56]).
- Pipelines, composed of steel or composite materials, are subjected to harsh operational conditions such as temperature gradients, internal pressure fluctuations, and corrosive environments. Guided wave and optical fibre sensing techniques, as well as reference-free approaches, are commonly adopted due to their capacity for long-range monitoring and resilience under these demanding conditions (as reported in [22, 47, 52, 66]).
- Miscellaneous structures, including rail switches and aircraft components, are affected by operational loads, fatigue, and temperature changes. Acoustic emission, nonlinear modulation, reference-free methods, and DA techniques

have been effectively implemented due to their adaptability and robustness across various structural configurations (e.g. [34, 54, 86]).

The results in table 3 reveal a clear research emphasis on composite materials, aluminium structures, bridges, and WTs, driven by their widespread industrial relevance and pronounced susceptibility to EOV. Adaptive baseline and reference-free methodologies dominate in bridge and composite monitoring, reflecting their suitability for prolonged and complex environmental interactions. Conversely, wind turbines frequently leverage TL and population-based techniques, capitalising on data-driven adaptability for fleet-wide management. Notably, SHM methods for buildings, cables, and pipelines remain comparatively less explored, highlighting promising areas for further research expansion.

5.2. Machine learning as a cross-cutting enabler

Across both baseline dependent and reference-free paradigms, ML is increasingly crucial for modelling the structures' behaviour, reconstructing baselines, and distinguishing damage signals under complex EOV. Simple feed-forward networks can yield moderate success, but more advanced architectures GPR, GANs, LSTM, variational autoencoders, or hybrid physics informed models are steadily improving performance.

To further clarify the diverse roles and strengths of ML within these methodological paradigms, table 4 provides a comparative summary of key techniques, their implementation purposes, and representative recent studies. While TL is a subset of ML, it is considered as a distinct category in table 4 due to its unique cross-domain transfer functionality.

Table 3. Categorisation of SHM case studies with representative references.

Category of SHM application	Structure type	Commonly used techniques	Typical EOVs studied	Representative references
Bridges	Steel, Concrete bridges	Adaptive baselines, DA, Physics-informed ML	Temperature, Load, Humidity	Miao <i>et al</i> [19], Jiang <i>et al</i> [32], An <i>et al</i> [50], Li <i>et al</i> [63], Giglioni <i>et al</i> [79], Omori Yano <i>et al</i> [80], Souza <i>et al</i> [81], Zhou <i>et al</i> [91], Omori Yano <i>et al</i> [92], Tronci <i>et al</i> [93], Duran <i>et al</i> [99], Giglioni <i>et al</i> [100], Giglioni <i>et al</i> [101]
Composite structures	Plates, Panels, Sandwiches	Guided waves, Adaptive filtering, TL, Reference-free	Temperature, Moisture, Load	Fendzi <i>et al</i> [3], Nandyala <i>et al</i> [15], Salmanpour <i>et al</i> [16], Wang <i>et al</i> [17], Huang <i>et al</i> [18], Putkis and Croxford [25], Yue and Aliabadi [27], Kashyap <i>et al</i> [33], Zhu <i>et al</i> [35], Zhu <i>et al</i> [46], Mesnil <i>et al</i> [48], Zhu <i>et al</i> [49], Sohn <i>et al</i> [57], Salmanpour <i>et al</i> [68], Yue <i>et al</i> [69], Sawant <i>et al</i> [88], Liu <i>et al</i> [95]
Aluminium structures	Plates, Pipelines, Beams	Baseline subtraction, Phase compensation, Time-reversal, DA	Temperature, Load, Fatigue	Mariani <i>et al</i> [11], Salmanpour <i>et al</i> [16], Aryan <i>et al</i> [20], Salmanpour <i>et al</i> [21], Amer <i>et al</i> [28], Sharma <i>et al</i> [43], Kapuria [44, 45], Anton <i>et al</i> [47], Shi <i>et al</i> [51], Lim <i>et al</i> [54], Qiu <i>et al</i> [55], Sohn <i>et al</i> [65], Wang <i>et al</i> [89], da Silva <i>et al</i> [90]
WTs	Blades, Towers	Adaptive baseline synthesis, TL, PBSHM	Temperature, Wind load, Fatigue	Simon <i>et al</i> [24], Qu <i>et al</i> [29], Font-Moré <i>et al</i> [30], Roberts <i>et al</i> [31], Bull <i>et al</i> [71], Bull <i>et al</i> [78], Zhou and Lai [85], Yang <i>et al</i> [87]
Buildings	Multi-storey structures	TL, DA, PBSHM	Temperature, Wind, Operational loads	Gardner <i>et al</i> [77], Astorga <i>et al</i> [102]
Cables	Stay cables	Wavelet decomposition, ML-based compensation	Temperature, Wind, Operational loads	Chen <i>et al</i> [23], Jiang <i>et al</i> [32], Loshelder <i>et al</i> [56]
Pipelines	Steel, Composite pipelines	Guided waves, Optical fibre techniques, Reference-free techniques	Temperature, Pressure	Ai <i>et al</i> [22], Anton <i>et al</i> [47], Lee <i>et al</i> [52], El Mountassir <i>et al</i> [66]
Miscellaneous structures	Rail switches, Aircraft parts	Acoustic emission, Nonlinear modulation, Reference-free, DA	Temperature, Load, Fatigue	Zhou <i>et al</i> [34], Lim <i>et al</i> [54], Hong <i>et al</i> [86]

Table 4. Role of ML across SHM methodologies.

SHM strategy	ML techniques employed	Principal function	Advantages	Limitations
Direct Baseline Compensation	ADALINE, Wavelet Decomposition, Simple Regression	Signal filtering and noise suppression	Straightforward implementation; low computational demand	Limited adaptability; ineffective under significant EOV
Adaptive and Multi-Baseline	GPR, PCA, GANs, LSTM, Latent Space Modelling	Virtual baseline generation and environmental drift tracking	Robust against gradual changes; predictive capabilities	Requires diverse, high-quality datasets and calibration
Reference-Free (other methods)	Autoencoders, Convolutional Neural Networks, Capsule Networks, Physics-Informed Neural Networks	Direct anomaly classification and damage localisation	No need for pristine baselines; applicable across domains	Computationally intensive; explainability and validation remain challenging
Reference-Free (TL techniques)	DA, TCA, GANs, Capsule Networks	Cross-domain generalisation and knowledge transfer	Reduces training burden; supports population-level SHM	Sensitive to domain mismatch; high computational cost

5.3. Trade-offs in data storage vs. computation

Specific methods (e.g. multi-baseline or large-scale DA) shift the burden from storing numerous baseline references to storing or processing large training datasets. Reference-free approaches, on the contrary, often diminish data storage needs but may require high computational overhead in wavefield reconstructions or multi-physics simulations.

5.4. Structural versatility and domain-specificity

The references cover a broad range of structures: composite plates, metallic fuselage panels, stay cables, WT blades, steel bridges, pipeline systems, and more. The fundamental wave physics often remains consistent, but each domain can impose unique constraints (e.g. high attenuation in composites, large temperature gradients in pipelines, or broad load variations in bridges).

5.5. Comparative methodological analysis

To better illustrate the distinguishing characteristics of the 3 major methodological families discussed in this review, i.e. direct baseline compensation, adaptive and multi-baseline strategies, and reference-free approaches, a comparative analysis is presented in table 5. This summary highlights their underlying principles, data dependencies, computational requirements, and practical suitability under varying EOV conditions.

Each methodological approach presents a distinct balance between practicality and performance. Direct compensation methods are simple and efficient but limited in adaptability. Adaptive techniques offer greater robustness under variable

conditions, though they require more extensive data and calibration. Reference-free approaches (see section 4.5) support cross-domain SHM via TL techniques, with trade-offs in computational cost and generalisability. The choice of method should therefore reflect the environmental complexity, data availability, and intended monitoring scope. Increasing reliance on ML across all categories underscores the need for rigorous validation and attention to model generalisability.

To provide a comparative visual synthesis of the reviewed methodologies, figure 6 presents a radar chart assessing the 3 principal SHM strategies: direct baseline compensation, adaptive and multi-baseline methods, and reference-free, across 6 critical performance dimensions. These dimensions include adaptability to EOV, computational demand, baseline dependency, data requirements, implementation simplicity, and scalability to fleet-level or cross-domain applications.

The scores assigned to each methodology were derived from a structured qualitative synthesis of the reviewed literature, reflecting consensus trends, empirical observations, and technical characteristics detailed in sections 2–5. For each performance dimension, empirical results and reported practical experience were examined to assess relative efficacy. A normalised scale from 0 (poorest performance) to 10 (strongest performance) was then adopted to convey observed strengths and limitations. For example, a low score for ‘baseline dependency’ indicates reliance on stored reference data, whereas a high score for ‘scalability’ denotes demonstrated applicability across multiple assets or domains. Further justification for each score is provided in table 6. This form of semi-quantitative comparison thereby facilitates a concise yet comprehensive understanding of the trade-offs between methodological choices and supports informed decision-making for practical SHM deployments.

Table 5. Comparative analysis of SHM methodologies for mitigating EOV.

Aspect	Direct baseline compensation	Adaptive and multi-baseline techniques	Reference-free methods
Core principle	Remove or suppress environmental effects from raw signals	Dynamically adjust or generate new baselines using statistical or ML	Detect damage without relying on a prior ‘healthy’ state
Data requirements	Single stored baseline per condition	Large datasets or multiple baselines for adaptation	Substantial training data or physics-informed models
Advantages	Simple, computationally efficient, quick to implement	Greater robustness over time, flexible to varying conditions	No baseline storage, high adaptability, scalable across domains
Limitations	Limited longevity, sensitive to large EOV	Requires more storage, sophisticated modelling, and calibration	Computationally intensive, requires model generalisability
Best use cases	Short-term monitoring, known temperature bands	Long-term monitoring with evolving structures	Large-scale systems, fleet monitoring, cross-domain applications
EOV handling strategy	Subtraction, phase correction, adaptive filtering	Virtual baseline synthesis, regression, latent space tracking	Time-reversal invariance, DA, relative referencing
Physics involvement	Low—mostly empirical	Moderate—can integrate physical models into ML	High—often hybrid with physical principles or simulations
ML usage	Limited or none	Moderate—for baseline synthesis and drift compensation	Extensive—DL, GANs, GPR, autoencoders, TL architectures
Notable techniques	Delay-sum subtraction, ADALINE filters, wavelet decomposition	GPR-based adaptation, latent variable models, PCA synthesis	Time-reversal symmetry, acoustoelasticity, TL, PBSHM
Representative studies	Nandyala <i>et al</i> [15], Chen <i>et al</i> [23], Simon <i>et al</i> [24]	Qu <i>et al</i> [29], Font-Moré <i>et al</i> [30], Jiang <i>et al</i> [32]	Zhu <i>et al</i> [35], Rezazadeh <i>et al</i> [9], Yang <i>et al</i> [87]

Table 6. Rationale and key literature sources informing the qualitative scores assigned to each SHM methodology across 6 performance dimensions.

Dimension	Scoring Rationale (Key References)
Adaptability	Reference-free methods handle diverse EOV best [44, 47]; direct compensation typically tailored to specific conditions [11, 17]; adaptive-baseline approaches exhibit moderate robustness [25, 29].
Computational Demand	Direct compensation is lightweight (straightforward signal processing) [11, 17]; adaptive-baseline models require moderate computation for regression or latent fitting [28, 30]; reference-free methods need more resources [9, 88].
Baseline Dependency	Direct compensation relies heavily on historical baselines that become obsolete [15, 16]; adaptive baselines mitigate but do not eliminate dependency by updating/synthesising [27, 29]; reference-free requires no baselines [47, 49].
Data Requirements	Direct compensation often needs only a single baseline per condition [16, 19]; adaptive baselines require multiple EOV samples to build/update virtual baselines [26, 32]; reference-free approaches often need larger, varied datasets [33, 35].
Implementation Simplicity	Direct methods employ established subtraction and phase-alignment procedures [11, 21]; adaptive baselines involve more complex workflows such as library maintenance or regression routines [25, 31]; reference-free implementations (e.g. GAN-based DA, physics-informed models) require advanced ML toolchains [48, 51].
Scalability	Direct methods scale poorly beyond single structures due to condition-specific baselines [11, 19]; adaptive baselines offer moderate scalability via PBSHM or multi-structure regression [71, 77]; reference-free and TL-based approaches are inherently scalable to large fleets or cross-domain tasks [78, 79].

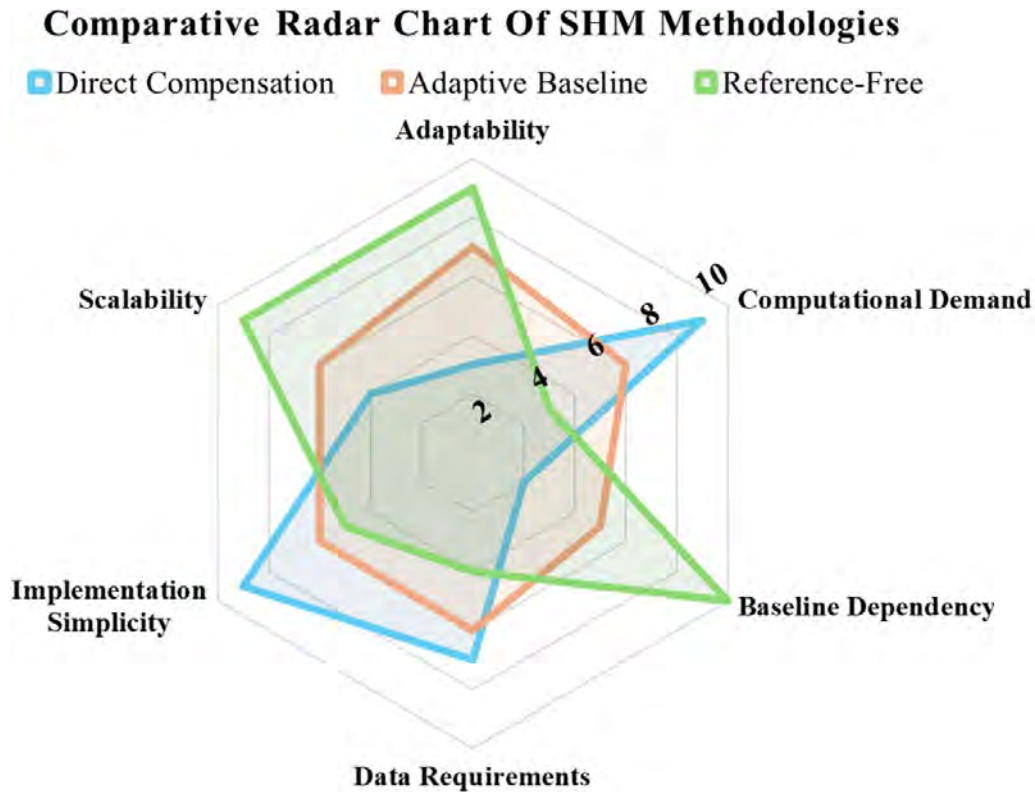


Figure 6. Radar chart comparing the three principal SHM methodologies across 6 performance dimensions.

As illustrated in figure 6, reference-free approaches exhibit superior adaptability and scalability, making them well-suited for complex, cross-domain SHM scenarios. However, this comes at the cost of increased computational demand and data requirements. In contrast, direct compensation methods offer implementation simplicity and minimal computational burden; however, they lack long-term robustness. Adaptive baseline techniques occupy a balanced position, offering moderate performance across most dimensions. These results highlight the necessity of aligning SHM methodology selection with operational constraints and system-level requirements.

6. Benchmark datasets for evaluating EOV effects in SHM

Evaluating methods for mitigating EOV in SHM demands access to rigorously standardised datasets; however, open-source repositories remain deficient because most fail to offer long-term, synchronised measurements that link structural responses and controlled damage states with systematically recorded environmental and operational conditions, and they rarely include the comprehensive metadata or harmonised formatting required for reproducible benchmarking. The remainder of this section, therefore, reviews representative benchmark datasets drawn from a range of structural systems, i.e. WT blades, composite plates, bridges and pipelines that explicitly incorporate EOV.

Wind turbines:

- **Small WT blade**
A small-scale turbine blade was dynamically tested in a climatic chamber over $-15\text{ }^{\circ}\text{C}$ to $+40\text{ }^{\circ}\text{C}$, instrumented with accelerometers, strain gauges, temperature and humidity sensors. Healthy and damaged states (lumped masses and surface cracks) were excited by white noise and sine sweeps, yielding synchronous acceleration, strain and thermal records for SHM validation under controlled environmental and operational loads in two sensor designation sets [103].
- **WT blade simulation**
A 4-element FEM cantilever model simulated flapwise vibrations under realistic turbulent wind (via TurbSim) and temperature-dependent stiffness. The dataset spans one year of seasonal EOV, a week of extreme heat and a month of gradual root-stiffness reduction (0%–25%) and provides 10 min time-series of displacements, rotations, velocities and angular speeds alongside the corresponding wind and temperature records [104].

Composite plates:

- **CFRP plate with temperature variations (Open Guided Waves dataset).**
A carbon-fibre composite plate instrumented with piezoelectric transducers was monitored across a wide range

of temperatures (approximately—50 °C to +70 °C). Ultrasonic guided wave signals were recorded at multiple frequencies for various thermal states, as well as in the presence of known artificial defects [105].

- **CONCEPT:** carbon-epoxy composite plate.

The CONCEPT dataset provides Lamb-wave measurements from a 500 mm × 500 mm × 2 mm carbon-epoxy laminate fitted with 4 piezoelectric transducers. The central transducer excites 5-cycle 250 kHz tone bursts, while the other 3 receive responses sampled at 5 MHz over 100 ms. 100 healthy signals were recorded at each of 7 temperatures from 0 °C to 60 °C in 10 °C steps. At 30 °C only, the study added 11 adhesive-putty damage states covering 0.196%–2.54% of the plate plus a healthy class, giving 12 health categories [10].

Bridges:

- **Z24 benchmark.**

A post-tensioned two-cell box-girder highway bridge near Koppigen, Switzerland, was equipped with 16 accelerometers and 48 environmental sensors that recorded hourly measurements of air temperature, humidity, wind, rain and traffic during the last 10 months of service in 1997–1998. After demolition had been scheduled, 16 progressive damage scenarios including pier settlement, concrete spalling and controlled tendon ruptures were introduced and bracketed by forced- and ambient-vibration tests at 100 Hz [106].

- **Bergsøysund end-supported pontoon bridge wave and wind response.**

The 931 m floating bridge carried 14 triaxial MEMS accelerometers (200 Hz), 6 microwave wave radars (50 Hz), 5 ultrasonic anemometers (32 Hz) and a GNSS displacement sensor (20 Hz). Raw data are transformed to a global coordinate system and provided at 10 Hz and 2 Hz with per-channel quality flags and transformation matrices embedded in a hierarchical HDF structure. Thirty-minute records are triggered by exceedance of wind, wave or motion thresholds, yielding more than 4 years of synchronous environmental forcing and structural response that span calm to severe North Atlantic storms. Supplementary material includes a reduced-order modal model (first 50 modes) and the opyndata Python utilities for automated import and visualisation. This combination of multi-sensor measurements, precise sensor geometry and long-duration exposure supports research on operational modal analysis, wave direction estimation, temperature-wave interaction effects and SHM normalisation on floating bridges [107].

Pipelines:

- **Ultrasonic guided wave pipeline monitoring.**

The dataset comprises guided wave signals for SHM of pipelines, designed to investigate temperature effects. The experiment involved monitoring a section of steel

pipe, rehabilitated with a composite wrap, over approximately 3 months using an ultrasonic guided wave system. A total of 236 records were collected: 207 in the baseline (undamaged) condition across varying temperatures, reflecting day/night ambient cycles, and 29 after introducing a corrosion-like defect (material loss) in 6 incremental stages. The dataset includes labelled signals for different temperatures and damage levels, allowing for the testing of temperature compensation strategies and the evaluation of damage detection or localisation techniques in the presence of thermal variability. The gradual defect progression enables assessment of sensitivity to minor and severe damage under consistent environmental conditions [108].

- **Benchmarking dataset for leak detection and localisation in water distribution systems.**

This dataset comprises 280 thirty-second recordings acquired on a laboratory-scale network reconfigured into both branched and looped layouts. Controlled leaks were generated by drilling orifice holes, milling longitudinal and circumferential cracks and by loosening flange gaskets alongside a no-leak baseline. Six experimental conditions combined steady flows of 0, 0.18 and 0.47 l per second and a transient reduction from 0.47 to 0 at around 20 s with the presence or absence of traffic and saw noise. Vibrational, acoustic and dynamic pressure fluctuations were captured using accelerometers, hydrophones and pressure transducers. Accelerometer and pressure data were sampled at 51.2 kHz and hydrophone signals at 8 kHz. This comprehensive suite of recordings enables rigorous evaluation of SHM methods under realistic EOV [109].

These datasets provide comprehensive resources, facilitating robust SHM method validation and advancement under realistic environmental and operational conditions. All referenced datasets are openly available for research, except the Z24 bridge dataset, which requires completion of a registration form with KU Leuven. Upon registration, access is free for non-commercial use, provided appropriate acknowledgement is given. Thus, all reviewed datasets can be readily accessed for academic research and benchmarking, supporting transparency and reproducibility in SHM studies.

7. Emerging trends and future research directions

To assess the evolving trends and prospective developments in the domain of mitigating EOV in SHM, a frequency and co-occurrence analysis was conducted using keywords extracted from the cited studies and is presented in figure 7. Keywords appearing at least 4 times in the source documents were retained, resulting in 18 representative terms. Larger nodes on the co-occurrence map correspond to higher keyword frequencies, while thicker edges indicate stronger co-occurrence relationships.

From figure 7, it is evident that the most frequent keyword is ‘SHM’, positioned at the centre of the network and

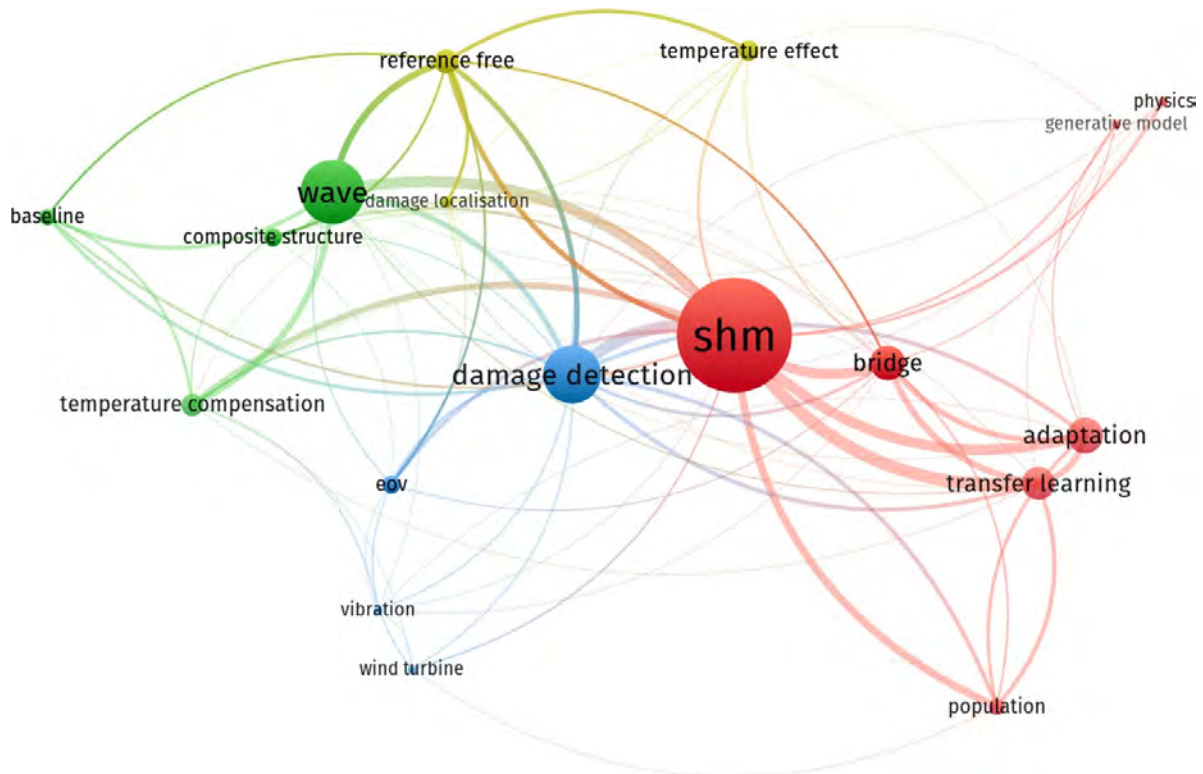


Figure 7. Co-occurrence map showing key term frequencies and connections in reducing EOV in SHM.

exhibiting strong connections to terms such as ‘damage detection’, ‘guided wave’, ‘domain adaptation’ and ‘transfer learning’. These clusters underscore the research community’s predominant emphasis on developing robust strategies for damage detection under EOV, particularly through wave-based monitoring and adaptive learning techniques. In contrast, keywords with lower frequencies such as ‘physics-informed’, ‘population-based SHM’, ‘damage localisation’ and ‘wind turbine’ highlight domains that remain comparatively underexplored and would benefit from further research attention.

The limited presence of ‘physics-informed’ approaches can be attributed to multiple technical and practical barriers. Firstly, the effective application of physics-informed methods often requires an in-depth understanding and accurate modelling of the physical principles that govern the monitored system, including wave propagation, material properties, boundary conditions, and EOVs. Such requirements become particularly prohibitive for complex or insufficiently characterised structures, where uncertainties in geometry, materials, or operational conditions make reliable modelling challenging. Secondly, the integration of physics-based constraints into ML models substantially increases methodological complexity and computational costs, which can hinder real-time implementation and scalability for large, real-world structures. Additionally, there is often a lack of comprehensive benchmark datasets that simultaneously provide sensor measurements and associated physical parameters, further impeding validation and widespread adoption of these frameworks. Consequently, while data-driven and baseline-free

methods have gained prominence in the literature, there remains significant potential for advancing physics-informed approaches to improve interpretability, generalisability, and physical consistency in SHM [110–112].

Although the field has made substantial progress, a number of key challenges remain:

I. *Universal, real-time reference-free SHM*

Most current reference-free methods are constrained by reliance on specific wave propagation modes or controlled laboratory environments, limiting their scalability and practical use in diverse, uncontrolled operational scenarios. To enable widespread real-world adoption, there is a pressing need for robust algorithms that can operate in near-real time without pre-recorded baselines, although remain sensitive to damage and resilient to variability. Furthermore, lightweight solutions requiring minimal calibration and demonstrably generalisable across various infrastructure types could significantly accelerate the practical deployment of SHM systems.

II. *Integration of hybrid physics-informed and data-driven approaches*

The co-occurrence of terms such as ‘generative model,’ ‘physics,’ and ‘wave’ alongside ‘SHM’ and ‘adaptation’ signals an increasing research interest in hybrid modelling. The integration of established physics-based principles, particularly wave propagation and material behaviour theories, with advanced ML architectures (e.g. generative models, physics-informed neural networks) demonstrates considerable promise. Future frameworks should

prioritise seamless integration, ensuring interpretability without compromising the adaptability and scalability provided by data-driven methods.

III. *Long-term monitoring under multiple EOV*

Beyond temperature effects, structural integrity is impacted by multiple, interacting EOVs such as fluctuating loads, moisture ingress, material ageing, and biological factors including biofouling and corrosion. Adaptive systems capable of simultaneously addressing these complexes, overlapping effects represent a crucial area for further development. Such systems must continuously learn and recalibrate in response to evolving conditions, ensuring long-term reliability and accuracy.

IV. *TL for complex and heterogeneous populations*

The cluster of keywords including ‘transfer learning,’ ‘adaptation,’ ‘population,’ and ‘bridge’ highlights a significant shift towards scalable, cross-domain SHM. However, effective knowledge transfer between structurally or materially heterogeneous systems remains challenging due to inherent differences in material properties, structural geometries, and damage mechanisms. Addressing these disparities through advanced DA, particularly multi-source, and unsupervised methods, is vital to broaden the applicability and robustness of SHM models across diverse infrastructure types.

V. *Uncertainty quantification and reliability*

Although numerous sophisticated models have been proposed to enhance SHM robustness against EOV, systematic uncertainty quantification has not yet become standard practice. The limited appearance of ‘generative model’ and ‘physics’ within existing frameworks indicates significant opportunities for embedding probabilistic reasoning methods, such as Bayesian inference and Monte Carlo dropout, within SHM solutions. Developing SHM frameworks capable of simultaneously identifying structural anomalies and rigorously quantifying predictive uncertainty is essential for widespread adoption in safety-critical infrastructure.

VI. *Scaling up to PBSHM*

Emerging approaches such as population-based and regional-scale SHM aim to monitor fleets of structures, including bridges, WTs, and pipelines, simultaneously. Achieving this requires integrating reference-free detection methods, adaptive learning techniques, distributed edge computing, and robust sensor fusion strategies. The deployment of big-data analytics frameworks and efficient data-sharing protocols will be essential for harmonising monitoring activities across large, geographically dispersed structural populations.

8. Conclusions and outlook

SHM continues to encounter significant challenges associated with EOV, especially those induced by temperature

fluctuations, complicating accurate and generalisable damage detection. This review has categorised current mitigation strategies into three principal groups: direct baseline compensation, adaptive and multi-baseline techniques, and reference-free methods, including those involving transfer learning and domain adaptation.

Direct baseline compensation methods offer simplicity and short-term effectiveness but lose accuracy and practical relevance as structures age or as environmental conditions deviate significantly from the initial baseline conditions. Adaptive strategies demonstrate improved resilience by dynamically updating or synthesising baselines using statistical and machine learning models; however, these approaches increase computational complexity and rely heavily on comprehensive, high-quality training data. Reference-free and transfer learning-based approaches remove the need for stored baselines entirely, enhancing deployment flexibility across various structural and environmental conditions. Nevertheless, their practical effectiveness depends crucially upon further improvements in computational efficiency, domain generalisation, and rigorous validation in realistic operational environments. Hybrid methods combining physics-based models with machine learning show particular promise, offering enhanced interpretability and adaptability, although their deployment raises critical questions regarding scalability across heterogeneous structures, real-time feasibility, and robustness when reliant on simulation-generated data.

To advance SHM effectively, future research should prioritise developing universally applicable and scalable reference-free techniques capable of real-time operation in diverse environmental conditions. Emphasis should be placed on integrating hybrid physics-informed learning frameworks, robust uncertainty quantification methodologies, and sophisticated transfer learning approaches. Addressing these priorities will ensure that SHM systems reliably and effectively support the monitoring of diverse, large-scale, cross-domain infrastructure in real-world settings.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://github.com/shm-unesp/DATASET_PLATEUN01.git.

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