



A Critical Review of FFT-Based Vibration Analysis and Modal Identification Techniques for Structural Health Monitoring

Harshath Raj A¹, Priya Darshini U², Dr Vennila A³

Pg Scholar, Department of Civil Engineering, Kumaraguru College of Technology, Coimbatore.

Pg Scholar, Department of Civil Engineering, Kumaraguru College of Technology, Coimbatore.

Assistant Professor – II, Department of Civil Engineering, Kumaraguru College of Technology, Coimbatore.

ABSTRACT:

Structural health monitoring (SHM) uses measured structural responses to assess changes in condition, performance and safety over time. In vibration-based SHM, signals from accelerometers, strain sensors and other transducers are acquired, conditioned and analysed to estimate dynamic characteristics such as natural frequencies, damping ratios and mode shapes. The Fast Fourier Transform (FFT) computes the discrete Fourier transform efficiently and is widely used to inspect frequency content and support power spectral density (PSD), frequency-response and modal analyses. This critical narrative review synthesises the signal-processing chain, forced and ambient vibration testing, instrumentation and data acquisition, frequency- and time-domain modal identification, finite-element (FE) model updating, and selected infrastructure applications. The reviewed evidence shows that FFT-based processing is an enabling analytical step, not a stand-alone damage diagnosis. Reliability depends on measurement quality, adequate excitation, defensible modal identification, environmental normalisation, model uncertainty and independent validation. The review also identifies recurring evidence gaps: incomplete reporting of processing settings, limited transferability of data-driven models between structures, and insufficient integration of monitoring outputs with maintenance decisions. Because this is a narrative review rather than a preregistered systematic review, the paper does not claim exhaustive coverage of all published studies.

Keywords—Fast Fourier Transform, structural health monitoring, vibration analysis, modal identification, power spectral density, finite-element model updating, damage detection.

1. Introduction

Visual inspection remains essential in infrastructure management, but it is intermittent and may not reveal every internal or early-stage defect. Vibration-based SHM supplements inspection by collecting repeatable measurements under traffic, wind, pedestrian activity or controlled excitation. Its core premise is that changes in structural properties can alter measured dynamic response; however, the inverse inference from response change to damage is not unique. Environmental and operational variability, sensor changes and boundary-condition shifts can produce similar effects. Foundational SHM literature therefore frames damage identification as a process involving data acquisition, feature extraction, statistical assessment and engineering interpretation,

rather than a single signal-processing operation [3], [13].

The FFT is useful because it transforms a sampled time history into a frequency representation that can reveal dominant periodic components and candidate resonance peaks. Yet a peak may reflect a structural mode, a forcing frequency, machinery harmonics or an artefact. Interpretation requires checks on sampling rate, record duration, windowing, sensor

placement, operating conditions and baseline behaviour. Accordingly, this review treats spectral analysis as one link in a longer evidence chain that proceeds from measurement quality to modal estimation and then to condition assessment [2], [9]–[11].

2. Theoretical foundations of dynamic signal processing

2.1 From time history to frequency spectrum

A sensor records a discrete sequence $x[n]$ representing displacement, velocity, acceleration or strain over time. The discrete Fourier transform (DFT) represents this sequence as a sum of complex harmonic components; the FFT computes the same DFT more efficiently. The frequency spacing of a basic spectrum is governed by the sampling frequency and the number of acquired samples. Longer records can improve frequency-bin spacing, provided the response is sufficiently stationary and the measurement quality is adequate.

Before interpreting an FFT spectrum, the analyst should check for clipping, sensor drift, missing samples, aliasing, electrical interference and transient

contamination. An anti-aliasing filter should be applied before digitisation, and the sampling frequency should be selected to cover the frequency range of interest with appropriate margin. Windowing can reduce spectral leakage when the sampled record does not contain an integer number of cycles, but it also changes amplitude estimates and should be selected deliberately.

2.2 Common spectral measures

- Power spectral density (PSD): describes how the mean-square value or power of a stationary random signal is distributed over frequency. It is commonly estimated from finite records and used to identify dominant response bands; the estimator, units and averaging procedure should be reported.
- Averaging and normalisation: segment averaging can reduce estimator variance, while normalisation allows comparisons between records with different lengths or conventions. The processing choices should be documented because window type, overlap and scaling affect the resulting estimates.
- Energy spectral density (ESD): is generally associated with finite-energy signals, including transients, and should not be used interchangeably with PSD. Their mathematical definitions and units differ; the selected convention must be stated explicitly.
- Frequency response function (FRF): relates an input force to an output response in the frequency domain. Estimating an FRF requires an input measurement or a justified estimator; output-only ambient monitoring generally uses operational modal analysis rather than a directly measured force-to-response FRF.
- Impulse response function (IRF): describes the time-domain response to an idealised impulse and is related to the FRF through Fourier transformation.

The frequency spectrum is therefore a diagnostic representation, not a structural verdict. It should be interpreted with signal-quality checks, excitation knowledge and modal-identification methods [2], [3], [9]–[12].

3. Dynamic testing: forced versus ambient vibration

Parameter	Forced vibration testing (FVT)	Ambient vibration testing (AVT)
Excitation	Controlled input from an impact hammer, shaker or other exciter.	Operational/environmental loads such as traffic, wind or pedestrian movement.
Input knowledge	Input can be measured and controlled, supporting experimental modal analysis.	Input is usually unknown; output-only methods are commonly used.
Operational impact	May require equipment installation and access restrictions.	Often performed while the structure remains in service.
Typical strengths	Useful when targeted excitation and input-output identification are needed.	Practical for large infrastructure and long-term monitoring.
Main limitations	Equipment, logistics, force capacity and possible local impact effects.	Low response amplitudes, stochastic excitation and greater uncertainty in some estimates.

FVT and AVT should be treated as complementary methods rather than universally interchangeable options. The selection depends on structure size, target modes, access, required parameter accuracy, available equipment and whether operational closure is acceptable. Bridge SHM reviews identify AVT as practical for in-service structures while noting that unknown excitation can complicate damping estimation; FVT provides greater control but can be difficult to scale to large flexible structures [2].

4. Sensor instrumentation and data acquisition

4.1 Sensor selection

- Accelerometers are widely used to measure vibration response. Sensor range, sensitivity, noise floor, frequency bandwidth, mounting and temperature stability should be selected for the structure and expected response.
- Strain gauges and strain transducers measure local deformation response and can help relate dynamic behaviour to stress-sensitive locations.
- LVDTs, laser displacement systems and other displacement sensors can capture joint movement or deflection where access and measurement range permit.
- Temperature, humidity and other environmental sensors help explain reversible changes in structural response and reduce false damage alarms.
- Radar, laser vibrometry and GNSS-based methods can provide non-contact or remote measurements in suitable conditions, but their uncertainty, line-of-sight requirements and environmental sensitivity must be considered.

4.2 Data-acquisition chain

A typical acquisition chain consists of sensor hardware, signal conditioning, anti-alias filtering, analogue-to-digital conversion, synchronised data logging and analysis software. Long cable runs can introduce attenuation and electromagnetic interference; distributed digitisation and appropriate shielding may reduce these problems. Sampling rates, sensor calibration, clock synchronisation, units and data-quality flags should be documented so

that later analyses are reproducible.

Continuous monitoring is not automatically superior to periodic monitoring. Continuous systems produce large datasets and require reliable power, communications, storage and automated quality control. The monitoring plan should be proportionate to the asset's risk and the decisions that the data are intended to support.

5. Modal identification algorithms

Modal identification estimates natural frequencies, damping ratios and mode shapes from measured responses. Experimental modal analysis normally uses measured input and output, whereas operational modal analysis (OMA) commonly uses output-only records from ambient excitation. FDD uses singular-value decomposition of spectral-density matrices to separate modal contributions, while stochastic subspace identification (SSI) identifies state-space models from output data. These methods are not interchangeable black boxes: FDD is intuitive in the frequency domain and can separate close modes, while SSI offers a complementary time-domain/state-space formulation but requires choices about model order and careful rejection of spurious poles [10], [11].

Method	Data domain / principle	Strengths	Limitations
Peak picking (PP)	Frequency-domain peaks in response spectra.	Simple, fast and easy to interpret for well-separated modes.	Can confuse modes with harmonics/noise; weak for closely spaced modes; damping estimates are limited.
Frequency domain decomposition (FDD)	Singular value decomposition of output spectral-density matrices.	Can separate closely spaced modes and estimate mode shapes using output-only data.	Needs suitable multi-channel data; estimates depend on spectral resolution and analyst choices.
Enhanced FDD (EFDD)	FDD with selected spectral components transformed to time domain.	Can estimate frequency and damping from the extracted modal response.	Sensitive to mode selection, leakage and overlapping modes.
Natural excitation technique (NExT)	Uses output cross-correlations as response-like functions for further identification.	Useful with ambient response data when combined with a suitable identification method.	Assumptions about excitation and stationarity must be considered.
ARMA / ARMAV	Parametric time-series models.	Can estimate modal properties directly from measured histories.	Model order selection and convergence can be difficult.
Stochastic subspace identification (SSI)	State-space identification from output time histories or covariance data.	Powerful for multi-channel operational modal analysis and stabilisation-diagram workflows.	More mathematically involved; spurious modes must be filtered using physical and statistical criteria.

A defensible workflow may begin with FFT spectra and peak picking for exploratory inspection, then use FDD/EFDD or SSI for more rigorous estimates. Agreement across methods, records and sensor channels strengthens confidence but does not guarantee correctness. Identified modes should be checked using mode-shape consistency, stabilisation behaviour, physical plausibility and sensitivity to processing settings. Reports should disclose record duration, sampling frequency, filters, windows, overlap, spectral estimator, model order and mode-selection criteria so that results can be reproduced [2], [9]–[11].

6. Structural assessment, baseline models and damage detection

6.1 Baseline calibration and model updating

A baseline describes expected dynamic behaviour for a structure in a documented reference condition. An FE model can be calibrated against measured modal parameters to reduce discrepancies caused by uncertain material properties, support stiffness, mass distribution or modelling simplifications. Feng et al. demonstrate a neural-network approach for updating a bridge baseline FE model from traffic-induced vibration measurements and extracted modal parameters [4]. Wiberg's Årsta Railway Bridge study illustrates the role of monitoring data in developing a reliable dynamic FE representation [5]. Such updating is an inverse problem: parameter correlation and sparse measurements may allow multiple models to fit the same observations, so model fit alone is not proof that the calibrated parameters are unique.

Subsequent measurements should be compared with a baseline that accounts for expected operating and environmental variation. A frequency decrease may be consistent with stiffness loss, but can also result from temperature, moisture, added mass, support changes or operating loads. Environmental normalisation and long-term baselines are therefore central to reducing false alarms. Where possible, a suspected change should be corroborated using multiple dynamic indicators, strain or displacement measurements, inspection and a validated structural model [2]–[5], [13].

6.2 Limits of frequency-shift indicators

Natural frequency is a global dynamic property and may be insensitive to small local defects, especially where the defect has little influence on measured modes. Mode-shape changes, modal curvature, strain-based measures, local inspection and model-based sensitivity analysis may add

information, but their usefulness depends on sensor density, noise, modal observability and modelling assumptions. No universal frequency-change threshold can be translated directly into a damage percentage without structure-specific validation. This limitation is a recurring reason to combine vibration features with contextual and independent evidence [3], [13].

7. Infrastructure case studies and machine-learning integration

7.1 Eiffel Tower monitoring

Manzini, Brossault and Collard describe instrumentation of the Eiffel Tower for continuous monitoring, including measurements related to inclination, displacement, deformation, vibration and environmental conditions [1]. The case illustrates the value of combining static, dynamic and environmental measurements on an exceptional existing structure. It also demonstrates why thermal effects and long-term trends should be interpreted alongside vibration data.

7.2 Cable-stayed bridge monitoring

Pereira et al. report a dynamic monitoring system for the Éric Tabarly cable-stayed bridge, using accelerometers on the deck and pylon and automatic identification of modal properties [7]. Such deployments demonstrate that monitoring is not limited to one FFT plot: robust practice includes a sensor layout, acquisition strategy, repeated processing and evaluation of operational/environmental influences.

7.3 Machine learning for damage identification

Saleem, Hejazi and Ostovar investigate a machine-learning approach for frequency-domain damage identification in a UHPFRC communication tower, using numerical and experimental data [8]. The study is an example of how data-driven classifiers can complement physics-based interpretation. However, machine-learning accuracy reported for one structure or simulated damage set should not be assumed to generalise to other assets without external validation, representative damage cases and transparent assessment of false-positive and false-negative rates.

A broader methodological perspective is provided by Farrar and Worden, who emphasise that SHM involves damage-sensitive features, statistical decision-making and interpretation within the operational context [3]. This framework is more defensible than relying on a single unverified AI/IoT case-study source. Accordingly, the previously supplied Clement et al. reference has been excluded from the core bibliography because its publication venue and bibliographic record could not be independently established.

7.4 From dynamic monitoring to engineering decisions

Muñoz et al. describe an instrumented steel-bridge assessment that combines dynamic characterisation with traffic-related force measurements, structural modelling and reliability-based evaluation [9]. This is an important counterpoint to spectrum-only approaches: the engineering decision concerns capacity, vulnerability and rehabilitation priority, not merely whether a spectral peak has moved. Dynamic indicators become more actionable when connected to demand, resistance, uncertainty and a defined decision threshold.

7.5 Cross-study synthesis and critical appraisal

Across the reviewed studies, three complementary evidence types emerge. The I-40 bridge report by Farrar et al. [6] provides an early case of dynamic characterisation and damage detection. First, method-focused work establishes how modal parameters can be extracted from ambient data (FDD and SSI) [10], [11]. Second, long-term and bridge-specific studies show the practical importance of sensor layout, operating conditions and baseline FE models [4], [5], [7]. Third, case studies on the Eiffel Tower, the UHPFRC communication tower and the monitored steel bridge illustrate the need to combine vibration data with environmental, experimental or reliability evidence [1], [8], [9]. The studies differ in structural system, measurement design and intended decision; consequently, their reported performance should not be compared as if they were controlled trials of competing algorithms.

The main limitation of the available source set is that it mixes review articles, primary research papers, a technical report and a thesis, and it does not provide a uniform benchmark dataset. Several sources are case-specific, and the supplied list did not establish a consistent basis for comparing algorithm accuracy, false-alarm rates, sensor cost or lifecycle benefit. The review therefore supports qualitative synthesis and methodological recommendations, but not a quantitative ranking of FFT-based SHM methods.

8. Practical limitations and implementation considerations

- Measurement uncertainty: sensor noise, mounting quality, calibration drift and cable interference can affect spectral estimates.
- Frequency resolution and leakage: short records and inappropriate windowing can obscure or distort modal peaks.
- Environmental confounding: temperature and other operating conditions can cause frequency changes that resemble damage.
- Mode tracking: closely spaced modes, changing excitation and sparse sensor layouts can complicate identification.
- Data volume and reliability: long-term systems require data governance, automated quality checks, communications and maintenance.
- Model dependence: FE updating can be non-unique; several combinations of material properties, support conditions and damage may fit the same

measurements.

- AI generalisation: models require representative training data, independent validation and interpretable thresholds before operational use.

These issues show that a reliable SHM system is an end-to-end engineering process. FFT processing is important, but the credibility of the final assessment depends on the complete measurement-to-decision chain.

9. Research gaps and future directions

1. Standardised, reproducible workflows: studies should report sampling rates, record duration, filtering, windowing, sensor calibration, uncertainty and modal-selection criteria in sufficient detail for replication.
2. Environmental normalisation: field validation is needed to separate damage-related changes from temperature, traffic, moisture and support-condition effects over long monitoring periods.
3. Cross-structure validation: machine-learning models should be tested on structures and operating conditions not represented in training data, with explicit false-alarm and missed-detection metrics.
4. Fusion of global and local indicators: combining modal parameters with strain, displacement, visual inspection and local non-destructive evaluation may improve confidence in damage localisation.
5. Uncertainty-aware FE updating: model updating should report parameter identifiability and uncertainty, rather than presenting a single best-fit model as uniquely correct.
6. Practical deployment: future studies should quantify lifecycle cost, maintenance burden, data loss, sensor replacement and the value of monitoring information for asset-management decisions.

These gaps are synthesised from the methodological issues and case-study evidence in the reviewed sources; they should be refined further through a broader systematic literature search before the paper is submitted as a formal systematic review.

10. Conclusion

FFT-based dynamic signal processing is a practical foundation for analysing structural response, but it does not independently establish damage. A reliable vibration-based SHM workflow requires calibrated sensors, adequate sampling and record duration, transparent signal processing, robust modal identification, environmental normalisation and a defensible baseline. The reviewed bridge and tower studies show that monitoring becomes more useful when dynamic data are combined with FE modelling, environmental measurements, local response measurements and reliability-based engineering assessment. Machine learning may assist classification, but reported performance on one structure or simulated damage set should not be assumed to transfer to other assets without external validation. Future research should prioritise reproducible processing protocols, uncertainty-aware model updating, cross-structure validation and explicit links between monitoring outputs and maintenance decisions.

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