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TOPICAL REVIEW

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Topical Review

Empirical mode decomposition and its variants: a review with applications in structural health monitoring

Mohamed Barbosh, Premjeet Singh and Ayan Sadhu

Department of Civil and Environmental Engineering, Western University, London, ON, Canada

E-mail: asadhu@uwo.ca

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Abstract
Structural health monitoring (SHM) is one of the most emerging approaches for early damage detection, which leads to improved safety and efficient maintenance of large-scale civil structures. Data-driven vibration-based SHM techniques rely on sophisticated signal processing methods to analyze and interpret the complex measured data collected from the instrumented structures. Empirical mode decomposition (EMD) is one of the robust time-frequency decomposition techniques that has been widely used in SHM. Numerous studies have used EMD and its variants in different applications specific to structural modal identification and damage detection, which have been presented in various academic journals, conference papers, and technical reports. This paper presents a comprehensive and systematic review and summary of applications of EMD and its variants that have been extensively implemented in SHM. A brief background and illustration of EMD and its variants are presented first to show their performance under various cases, followed by a detailed literature review of their recent applications specific to SHM.

Keywords: structural health monitoring, empirical mode decomposition, EEMD, MEMD, TVF-EMD, modal identification, hybrid methods

(Some figures may appear in colour only in the online journal)

List of acronyms

DOF	Degree of freedom
DWT	Discrete wavelet transform
EMD	Empirical mode decomposition
EEMD	Ensemble empirical mode decomposition
FEM	Finite element modeling
HT	Hilbert transform
HHT	Hilbert-Huang transform
IMF	Intrinsic mode function
MDOF	Multi degree-of-freedom
MEMD	Multivariate empirical mode decomposition
RDT	Random decrement technique
SHM	Structural health monitoring
STFT	Short-time Fourier transform
TF	Time-frequency
TMD	Tuned mass damper
TVF-EMD	Time-varying filtering-based empirical mode decomposition
WT	Wavelet transform

1. Introduction

Large-scale infrastructure such as buildings, bridges, towers, stadiums, wind turbines, and tunnels offer impetus to rapid growth and urbanization of today's society. However, these structures may lose structural integrity due to exposure to operational loading, aging, and environmental conditions, which may cause potential danger to public safety. Structural health monitoring (SHM) offers attractive strategies to evaluate the current state of the structure, detect future damage, and find suitable real-time retrofitting methods for critical structures. SHM systems (Chang *et al* 2003, Carden and Fanning 2004, Xu and Xia 2012, Farrar and Worden 2013, Neves *et al* 2017) lead to effective tracking of structural performances under various traffic, operational and environmental conditions. With the aid of SHM systems, it is possible to examine the health and integrity of civil infrastructure by extracting useful information of structure from the measured data using next-generation sensors (Cunha *et al* 2013, An *et al* 2019, Sony *et al* 2019). Once the data is collected, the primary motive is to analyze the measured vibration data and extract damage sensitive features using robust system identification methods (Amezquita-Sanchez and Adeli 2014). Traditional signal processing techniques whether in time or frequency domains assume the signal to be stationary and linear (Ibrahim and Mikulcik 1973, Juang and Pappa 1985, Zhang *et al* 1985, Allemang and Brown 1998, Perry and Koh 2000, Brincker *et al* 2001, Ma *et al* 2005). This assumption does not hold good for non-stationary vibration signals of aging structures subjected to complex excitation such as traffic load, high-intensity wind gusts, and earthquakes (Entezami and Shariatmadar 2019a). Adaptive time-frequency (TF) analysis is required to extract damage sensitive features from these non-stationary signals of time-varying systems.

TF methods provide an improved representation of the TF domain variation of energy of a signal simultaneously (Sadhu 2013, Perez-Ramirez *et al* 2016). In the past two decades, TF methods have become increasingly popular towards SHM of civil structures. Wavelet transform (WT) (Wang and Deng 1999, Hong *et al* 2002, Douka *et al* 2003, Loutridis *et al* 2004, Sadhu *et al* 2019), empirical WT (Yuan *et al* 2018), Wigner-Ville distributions (WVD) (Tang *et al* 2010, Goyal and Pabla 2015, Zoubi *et al* 2019), blind source separation (BSS) (Sadhu *et al* 2017), Hilbert Huang transform (HHT) (Huang *et al* 1998, Xu *et al* 2003, Bahar and Ramezani 2012), empirical mode decomposition (EMD) (Yang and Chang 2009, Tang *et al* 2011), random decrement technique (RDT) (Zhang *et al* 2015, Zhang and Song 2016, Kodestani *et al* 2018) and short-time Fourier transform (STFT) (Nagarajaiah 2009, Nagarajaiah and Basu 2009, Ditommaso *et al* 2012, Mata *et al* 2013) are the most popular TF methods that have been used in modal identification for large-scale civil infrastructure. WT can be viewed as an extension of the traditional Fourier transform with adjustable window location and size (Hou *et al* 2000). The advantage of WT lies in its capability to examine local data adaptively that can provide multiple levels of details of the original signal. Therefore, this approach can retain the transient behavior of data. However, its performance strongly depends on the choice of basis functions. BSS methods can separate the source waveforms from their observed mixtures without the knowledge of system information and the sources (Sadhu. 2013). RDT is a technique to extract the free decay signal from responses excited by zero-mean Gaussian white noise.

HHT is explicitly designed to analyze nonlinear and non-stationary data and represents its TF energy variations. It is a combination of EMD and Hilbert Spectral Analysis (Huang *et al* 1998). EMD method can be employed to decompose any complex multicomponent data into a finite number of intrinsic mode functions (IMFs). Unlike many other TF methods, EMD is adaptive (e.g. free of any basis function) and undertakes decomposition based on a local characteristic of the data (Huang *et al* 1998) of a single-channel measurement. Due to this property, EMD has been widely used as the SHM technique to extract the complex dynamic behavior of structures. In general, EMD decomposes any measured data of structures into multiple mono-component signals (i.e. modal responses), which are analyzed for structural condition assessment.

This paper presents a review of recent studies and developments of EMD and its applications in SHM. More than 120 papers are reviewed that covered specific applications of EMD as a modal identification and damage detection tool for structural systems. The novel contribution of this paper is to present an extensive literature review of EMD specific to vibration-based structural monitoring and maintenance of civil engineering systems. This paper is organized as follows. First, the background, numerical and experimental illustration of EMD and its variants are presented, followed by the literature review of applications of EMD, its variants, and the hybrid methods. Finally, the key conclusions are summarized with a comprehensive list of applications, merits, and limitations of the EMD methods.

2. Background of EMD and its variants

A brief background of EMD and its variants is presented in this section.

2.1. Empirical mode decomposition (EMD)

EMD is a TF domain signal decomposition technique that has gained significant popularity in the area of output-only modal identification of structures (Huang *et al* 1998, Yang *et al* 2004). The EMD method decomposes a multi-component signal into a set of oscillatory waveforms known as IMFs that are intended to be single-frequency components. An IMF is a function that satisfies following two conditions (Huang *et al* 1998): (a) the number of extrema and the number of zero-crossings have to be either equal or differ at most by one in the whole data set, and (b) at any point, the mean value of the envelope denoted by the local maxima and the local minima is zero. The procedure of extracting an IMF is called *sifting*. Suppose $y(t)$ is the signal to be decomposed, the main steps of EMD are as follows:

1. Connect all the local maxima and minima by using a cubic spline to extract the upper and lower envelopes.
2. Find the mean of upper and lower envelopes, which is designated as $m_1(t)$.
3. Determine the difference between the signal $y(t)$ and the mean $m_1(t)$, $i_1(t) = y(t) - m_1(t)$ which could be the first IMF.

4. Check if $i_1(t)$ meets the two conditions of IMF that are mentioned above. If $i_1(t)$ meets both conditions to be an IMF, then $i_1(t)$ is the first IMF of the original signal $y(t)$.
5. If $i_1(t)$ does not meet the requirements of IMF, the sifting process will be repeated by treating the $i_1(t)$ as original signal until it meets the two conditions of the IMF.
6. The original signal is subtracted from the IMF, and the sifting process is repeated to decompose the data into n IMFs.

Finally, the signal $y(t)$ can be expressed as:

$$y(t) = \sum_{j=1}^{n} i_j(t) + r_n(t) \tag{1}$$

where $i_j(t)$ $(j = 1, 2, 3, \ldots, n)$ represents the IMFs of the original signal $y(t)$ and $r_n(t)$ is a residue of $y(t)$. Ideally, every IMF must have only one frequency component. However, sometimes one IMF contains several frequency components, which are known as *mode-mixing*.

2.2. Variants of EMD

EMD has shown excellent capabilities in decomposing the nonlinear and nonstationary signals. However, the traditional EMD has some limitations, such as the mode-mixing problem in the resulting IMFs and its difficulties in dealing with multichannel vibration measurements. To overcome the mode-mixing in the IMFs, especially while analyzing signals with closely-spaced frequencies and measurement noise, EMD was expanded to its variants, which are ensemble EMD (EEMD) and time-varying filter-based EMD (TVF-EMD). Other than the mode-mixing problem, EMD can deal with only single data measurement. Recently, EMD was extended to its multivariate version known as Multivariate EMD (MEMD), which is capable of decomposing multichannel vibration signals.

2.2.1. Ensemble EMD (EEMD). EEMD exploits a noise assisted data analysis, which was proposed by (Wu and Huang 2005) to alleviate the mode mixing in EMD. The key idea is to add a white noise, which has a uniform TF space (Wu and Huang 2009) at different scales, to the measured signal. Through multiple superpositions and averaging operations of EMD, the artificially added white noise is eliminated, and the measured signal with multiple frequency content is projected onto proper scales of reference. In this way, the EEMD eliminates the mode mixing problem and preserves the physical uniqueness of the resulting decomposition. Primarily it consists of the following steps:

- White noise is added to the measured signal $y(t)$

$$y_k(t) = y(t) + w_k(t) \tag{2}$$

where $w_k(t)$ is kth white noise and $y_k(t)$ is kth sequence of the measured signal.

- Apply EMD in $y_k(t)$ and decompose it into n IMFs

$$y_k(t) = \sum_{j=1}^{n} i_{k,j}(t) + r_k(t) \tag{3}$$

- Repeat the previous two steps, say m times, (i.e. $k = 1, 2, 3, \ldots, m$) with different white noise sequences, where the standard deviation of the simulated white noise is kept constant (Guo and Tse 2013). It should be noted that the number of ensembles ($i.e.m$) needs to be set *a priori* in EEMD. However, by increasing the number of samples in the ensemble, the effect of the added white noise can be reduced to a negligibly small level. In general, an ensemble size of a few hundred leads to a perfect result.
- Estimate the ensemble average of each decomposed IMF as the final IMF,

$$\bar{i}_j(t) = \frac{1}{m}\sum_{k=1}^{m} i_{k,j}(t) \tag{4}$$

$$x(t) = \sum_{j=1}^{m} \bar{I}_j(t) + \bar{r}_m(t) \tag{5}$$

where $\bar{i}_j(t)$ is the i-th IMF that is the ensemble mean of the corresponding IMFs obtained from m white noise sequences, and $\bar{r}_m(t)$ is the mean of the residues.

2.2.2. Multivariate EMD (MEMD). The traditional EMD method is suitable just for analyzing single data measurement, and it faces significant mode-mixing issues while dealing with multiple data measurements. Furthermore, the joint information between multiple sensors cannot be utilized due to the individually treated signals at each sensor locations (Sadhu 2017). To address this limitation, the standard EMD was recently extended to its multivariate form suitable for a multichannel signal (Rehman and Mandic 2010). In MEMD, the multidimensional envelopes are generated by taking signal projections along with different directions, and then the local mean of signals can be obtained by taking the average of these envelops. In the case of analyzing n-dimensional signal, a quasi-Monte Carlo lower deviation sequence is used to create a group of uniformly distributed points on a unit $(n-1)$-sphere (Rehman and Mandic 2010). Consider an n-dimensional signal $y(t) = [y_1(t), y_2(t), \ldots, yn(t)]$ and $U^z = [u_1^z, u_2^z, \ldots, u_n^z]$ which denotes a set of directional vectors along with z-th directions on a (n_1) sphere. To perform MEMD, following steps are used (Rehman and Mandic 2010):

- Estimate the direction vectors, U.
- Find the z-th projection, $p^z(t)$ of the input signal $y(t)$ over the zth direction vector, V^z, for all z $(z = 1, 2, \ldots, K)$, where K is the number of direction vectors U).
- Determine the corresponding time t_i^z of maximum $p^z(t)$ for all z.
- Interpolate $[t_i^z, y(t_i^z)]$ to extract multidimensional envelopes, $\theta^z(t)$.
- Obtain the mean of envelope $E(t)$ by:

$$E(\mathrm{t}) = \frac{1}{K}\sum_{z=1}^{K}\theta^{z}(t) \tag{6}$$

- Extract the residual $R(t)$ using $R(t) = y(t) - E(t)$. If $R(t)$ satisfies the stopping criteria of multivariate IMF, repeat the above steps to $(y(t) - R(t))$ until the next order IMF is diminished. Otherwise, apply it to $R(t)$.

2.2.3. Time-varying filtering-based EMD (TVF-EMD). In the traditional EMD method, the estimation of the local mean can be observed as a unique form of low pass filtering. In TVF-EMD (Li *et al* 2017), a B-spline approximation is adopted as a criterion to select a TVF. Most of the present works use B-splines as an interpolation tool with a polynomial spline. However, TVF-EMD uses B-spline functions, which are piecewise polynomials with time-varying cut-off frequencies. With such property, the TVF-EMD can deal with single vibration measurements to identify all frequencies without any mode-mixing issue in the modal responses. To form the desired signal, the polynomial portions are joined together. In B-spline space, each signal can be estimated by (Li *et al* 2017):

$$b_z^n(\mathrm{t}) = \sum_{j=-\infty}^{+\infty} q(j)\,\beta^n\left(\frac{t}{z} - j\right) \tag{7}$$

where $q(j)$ is the B-spline coefficient, and it is enlarged by a factor of z. The signal (or approximation result) is determined by n, z, and $q(j)$. The B-spline approximation is used to determine the B-spline coefficients $q(j)$ that minimizes the approximation error. Assume $v_z^n(t) = \beta^n\left(\frac{t}{z}\right)$ and the asterisk denotes the convolution operator. For an original signal $y(t)$, $q(j)$ is determined by minimizing the approximation error δ_z^2 (Li *et al* 2017):

$$\delta_z^2 = \sum_{t=-\infty}^{+\infty} \left(y(t) - \{q\} * v_z^n(t)\right)^2 \tag{8}$$

where $\{-\}_{\uparrow z}$ is the up-sampling operation by z. After introducing the concept of B-spline approximation (i.e. revealing its low-pass filtering property), the solution of $q(j)$ is,

$$q(j) = \{c_z^n * y\}_{\downarrow z}(q) \tag{9}$$

where $\{-\}_{\downarrow z}$ is the down-sampling operation by z and c_z^n is the pre-filter denoted by,

$$c_z^n = \left\{\left(\{v_z^n * v_z^n\}_{\downarrow z}\right)^{-1}\right\}_{\uparrow z} * v_z^n \tag{10}$$

$b_z^n(\mathrm{t})$ can be rewritten now as:

$$b_z^n(\mathrm{t}) = \{c_z^n * y\}_{\downarrow z} * v_z^n(t) \tag{11}$$

By checking the equations, there are three steps to carry out the B-spline approximation of a signal. The signal y is first band-pass filtered through a pre-filter v_z^n. Next, by a factor of z, the band-limited signal is decimated. Finally, the approximation is reconstructed using a post-filter v_z^n.

3. Systematic evaluations of EMD and its variants

In this section, EMD and its variants are illustrated using a suite of simple examples to introduce these methods to the general readers. The examples are selected in such a way that they can mimic real situations of SHM applications.

3.1. Sine example with well-separated frequencies (C1)

To illustrate the performance of EMD and its variants, a mixture of three harmonic signals, where $f_1 = 1.4$ Hz, $f_2 = 3.5$ Hz, and $f_3 = 7$ Hz, respectively, is considered as shown below.

$$y_1 = \sin(2\pi f_1 t),\ y_2 = \sin(2\pi f_2 t),\ y_3 = \sin(2\pi f_3 t) \tag{12}$$

$$x(t) = y_1 + y_2 + y_3 \tag{13}$$

Figure 1(a) shows the mixture $x(t)$ with 10% measurement noise and its resulting IMFs that are extracted from EMD, EEMD, and TVF-EMD, respectively. This example is analogous to a real vibration data containing well-separated natural frequencies. Figure 2 shows the Fourier spectrum of the mixed-signal and the IMFs obtained from EMD, EEMD, and TVF-EMD. It can be observed that EMD, EEMD, and TVF-EMD have successfully extracted the mono-component IMFs of $x(t)$ even with a 10% measurement noise. However, EEMD results in better performance in both the time and frequency domain.

3.2. Sine example with closely-spaced frequencies (C2)

Structural systems are often equipped with closely-spaced modes due to the presence of passive dampers (e.g. tuned mass dampers), symmetric shapes, and a large number of degrees of freedom. To simulate such closely-spaced frequencies, the frequencies of the sine signals in equation (12) are changed to 0.5, 0.8, and 1.4 Hz, respectively. EMD, EEMD, and TVF-EMD are then applied to decompose $x(t)$. Figure 3 shows the Fourier spectrum of mixed-signal and IMFs obtained from EMD, EEMD, and TVF-EMD under 10% measurement noise. It can be observed that TVF-EMD results in better identification of closely-spaced frequencies as compared to EMD and EEMD, where there is a significant mode-mixing in the resulting sine signals.

3.3. Dynamical system (C3)

A 4 degree-of-freedom (DOF) dynamical system is now considered to illustrate the performance of EMD, EEMD, and TVF-EMD. The lumped mass of each floor is 20 kg, and the stiffnesses of first, second, third, and fourth floor are assumed to be 8 KN m^{-1}, 7 KN m^{-1}, 5 KN m^{-1}, and 3 KN m^{-1}, respectively. Modal damping is considered as 2%, and the resulting natural frequencies are 0.98, 2.4, 3.76, and 5.21 Hz, respectively. The model is excited by the Imperial Valley earthquake at its base. Figure 4 shows the Fourier spectra of the floor vibration measurements, which indicates closely-spaced frequencies as well as low energy mode in

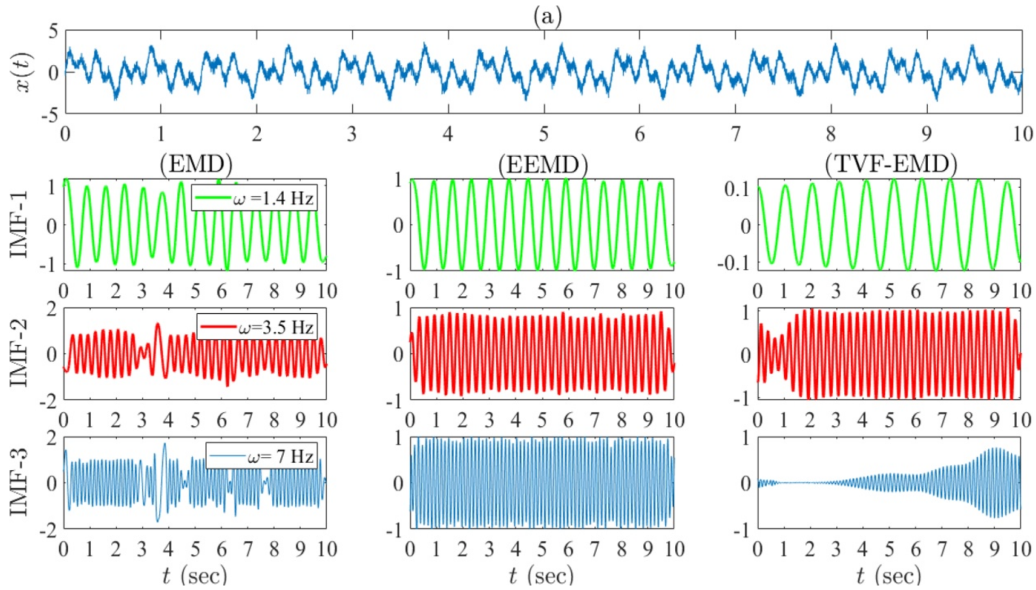

Figure 1. The mixed-signal and its IMFs obtained from EMD, EEMD, and TVF-EMD.

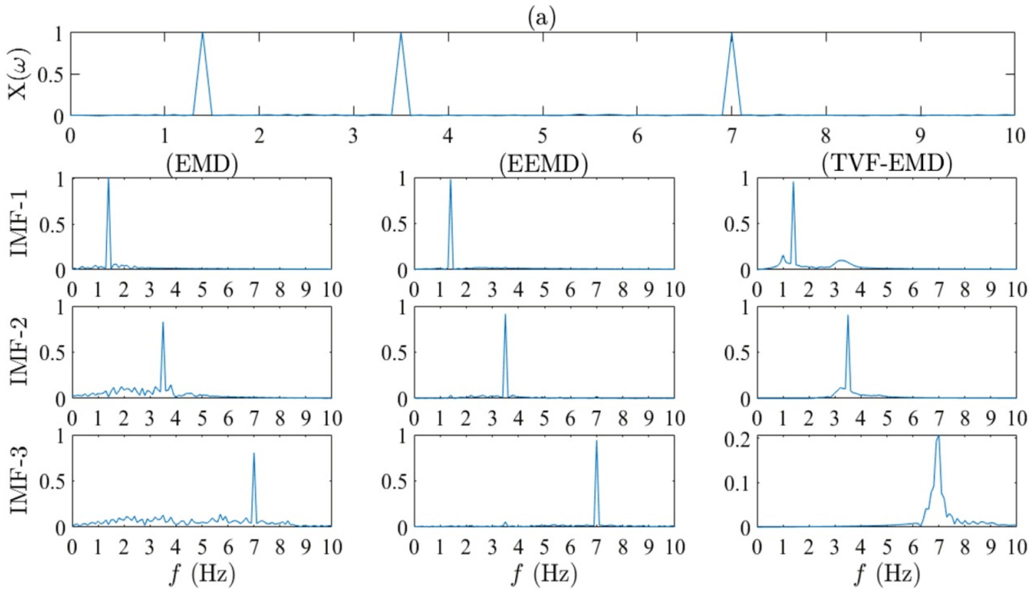

Figure 2. Fourier spectrum of the mixed-signal and IMFs obtained from EMD, EEMD, and TVF-EMD.

higher frequency (i.e. a real case of structural system identification under ambient excitation). EMD, EEMD, and TVF-EMD are applied to the first-floor vibration measurements. Figure 5 shows the Fourier spectrum of the resulting IMFs obtained from EMD, EEMD, and TVF-EMD that extracted the mono-component IMFs. It is observed that the first IMF of EMD results in a spurious mode, whereas the fourth IMF has mode-mixing. EEMD results in mode-mixing in both third and fourth IMFs, whereas TVF-EMD has clearly separated all four frequencies.

Finally, table 1 provides a summary of the processing time and presence of the mode-mixing issue in EMD and its variants, obtained from different numerical studies. It can be seen that the overall processing time of TVF-EMD increases, which makes TVF-EMD computationally expensive. However, the accuracy of TVF-EMD is far better than EMD and EEMD in the context of the mode-mixing.

3.4. Experimental study

A six-story experimental model is used to validate the performance of EMD, EEMD, and TVF-EMD, as shown in figure 6. The first three floors of the model have masses of 2.47 kg, and the other three floors have masses of 1.12 kg. The model is placed on a shake table that is connected to a shaker (manufactured by Crystal Instruments®) using a stringer. The uniaxial accelerometers (with a sensitivity of 100 mV g^{-1}) are placed at each floor of the model, and the sensors are connected to the data acquisition system to acquire the vibration data. The model is excited using a random shaking for 60 s via a control

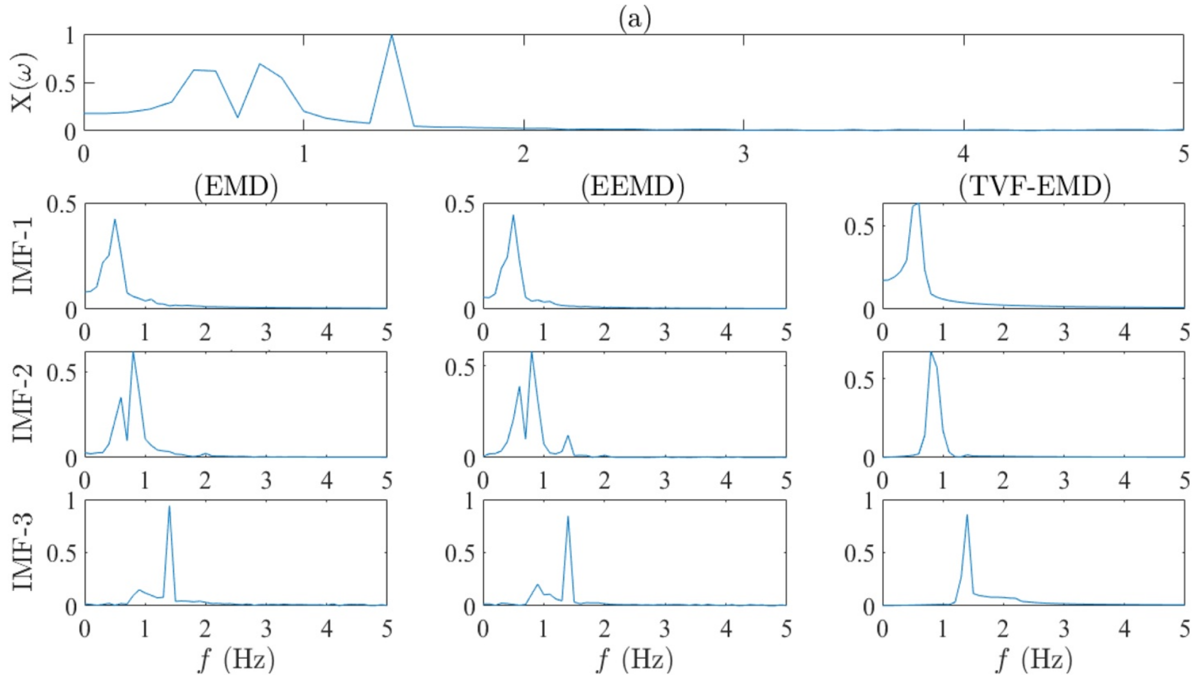

Figure 3. Fourier spectrum of the mixed-signal and IMFs obtained from EMD, EEMD, and TVF-EMD.

Table 1. Processing time and presence of mode-mixing in EMD, EEMD, and TVF-EMD.

	C1		C2		C3	
	Time (s)	Mode mixing	Time (s)	Mode mixing	Time (s)	Mode mixing
EMD	3.2	—	2.8	1	1.0	1
EEMD	318	—	139	2	40	2
TVF-EMD	850	—	806	—	225	—

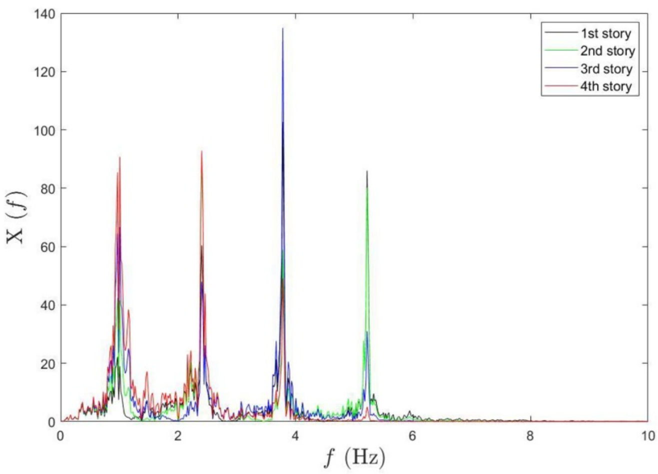

Figure 4. Fourier spectra of the simulated measurements at various DOFs.

system attached to the modal shaker, and then the vibration data is collected using the sensors. Figure 7 shows the Fourier spectra of the vibration measurements at a few selected floor locations, where it can be seen that the fourth and fifth modes are closely spaced. Moreover, some of the modes also have very low energies. The six natural frequencies of this 6 DOF model are estimated as 4.5, 10.7, 18.7, 25.6, 28.3, and 38.7 Hz, respectively.

To illustrate the performance of EMD methods with different sensor locations, EMD, EEMD, and TVF-EMD are applied to the first, third, and fifth-floor vibration measurements, respectively. Figures 8, 9, and 10 show the Fourier spectra of the resulting IMFs obtained from EMD, EEMD, and TVF-EMD using the first-floor, third-floor, and fifth-floor response. It can be observed that some IMFs extracted from EMD (first column) and EEMD (second column) have the spurious modes and mode-mixing issue, whereas TVF-EMD (third column) has extracted all the mono-component IMFs very clearly. Table 2 contains a summary of the processing time and presence of the mode-mixing issue in EMD and its variants (i.e. EEMD and TVF-EMD) using different floor vibration measurements (i.e. first, third, and fifth) of the 6-DOF experimental model. It can be seen that the overall processing time of TVF-EMD increases, which makes it computationally expensive. However, the performance of TVF-EMD is far better than EMD and EEMD in the context of the mode-mixing.

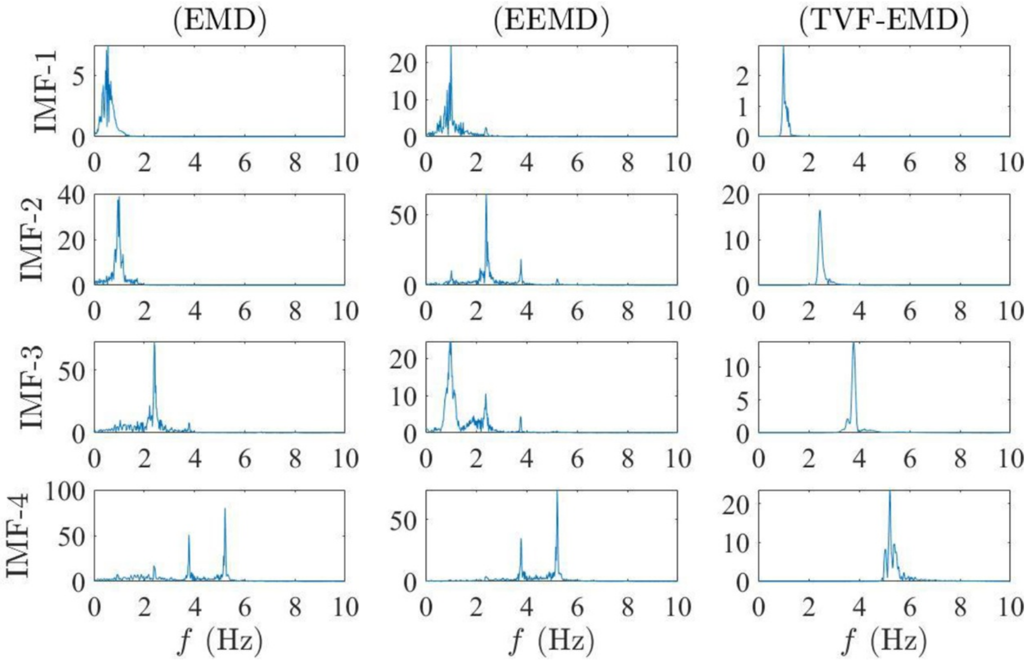

Figure 5. Fourier spectra of the resulting IMFs obtained from EMD, EEMD, and TVF-EMD.

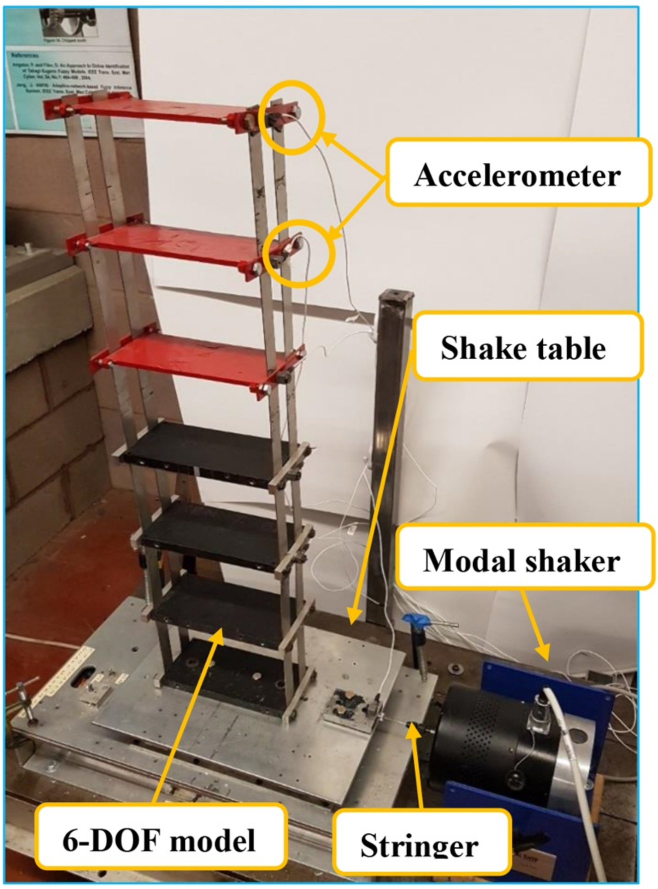

Figure 6. Experimental model.

Finally, table 3 summarizes the key merits and fundamental limitations of the EMD method and its variants.

4. Literature review

With a brief background, the numerical and experimental illustration of EMD methods, a comprehensive literature review is presented next in chronological order focussing on EMD-based methods specific to SHM.

4.1. Applications of EMD

Since 2004, EMD has been extensively used to solve various challenges of system identification, damage detection, structural control, and condition assessment of structures. In most studies, the only single measurement was analyzed using EMD. Yang *et al* (2004) first time utilized EMD and HT to identify instant and severity of damage in the presence of measurement noise. The results were compared with RDT using the ASCE benchmark data of the multi-storied building. The authors mentioned that EMD method might not be able to detect the damage if the measurement has a high level of noise and a small damage signature. Xu and Chen (2004) applied EMD to identify instant, location, and severity of damage in a three-story experimental model subjected to a series of free vibration, random vibration, and earthquake excitation. The results showed that EMD could accurately detect the instant, severity, and the multiple damage events which make EMD a suitable tool for SHM of the real structures.

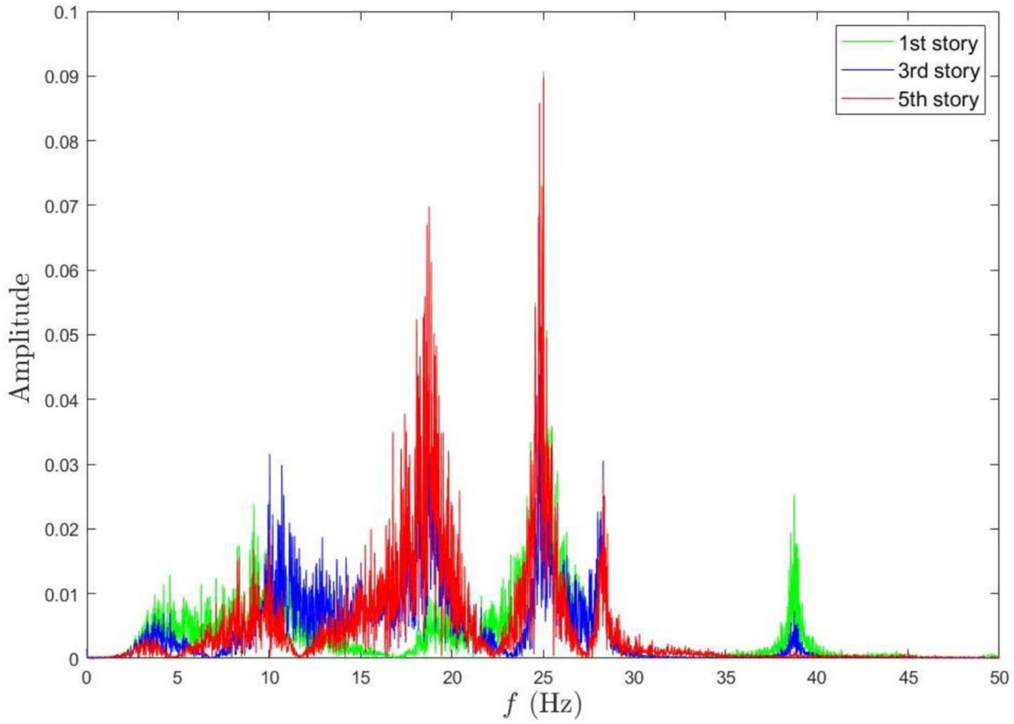

Figure 7. Fourier spectra of the floor vibration measurements of the experimental model.

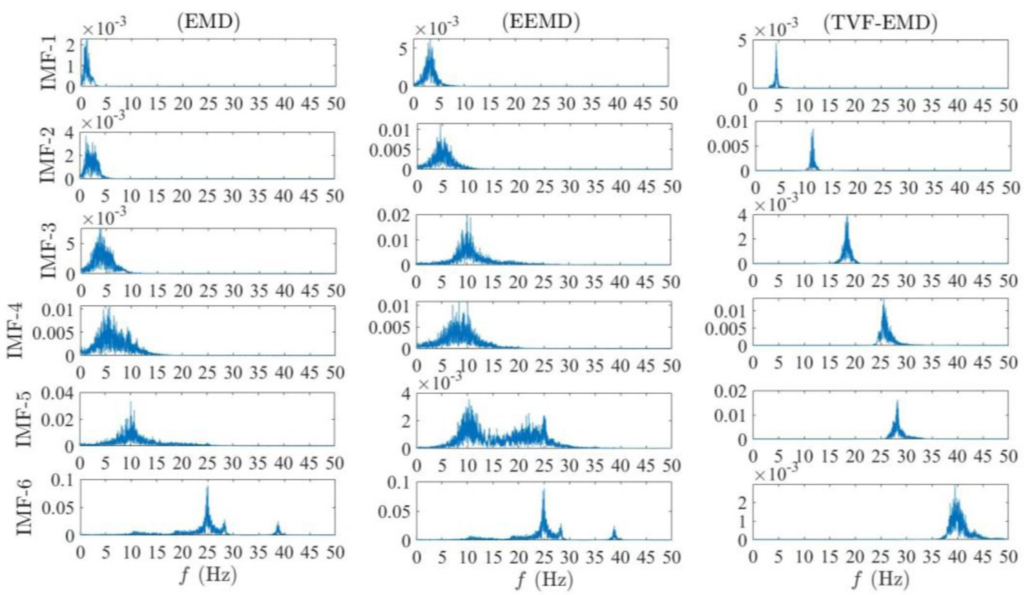

Figure 8. Fourier spectra of the resulting IMFs obtained from EMD, EEMD, and TVF-EMD using the first-floor response.

Table 2. Processing time and presence of mode-mixing in EMD, EEMD, and TVF-EMD using the measured data of the experimental model.

	$X_1\ (t)$		$X_3\ (t)$		$X_5\ (t)$	
	Time (s)	Mode mixing	Time (s)	Mode mixing	Time (s)	Mode mixing
EMD	1	2	1	2	1	2
EEMD	210	2	238	2	175	2
TVF-EMD	1550	0	1360	0	2375	0

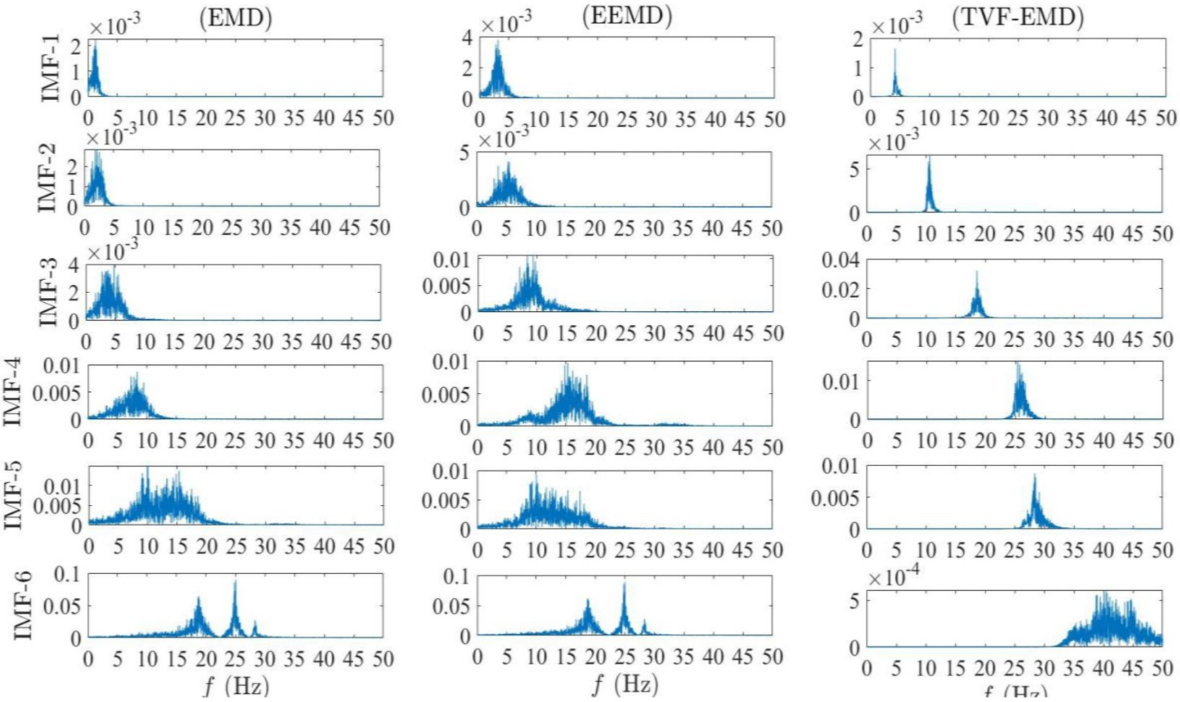

Figure 9. Fourier spectra of the resulting IMFs obtained from EMD, EEMD, and TVF-EMD using the third-floor response.

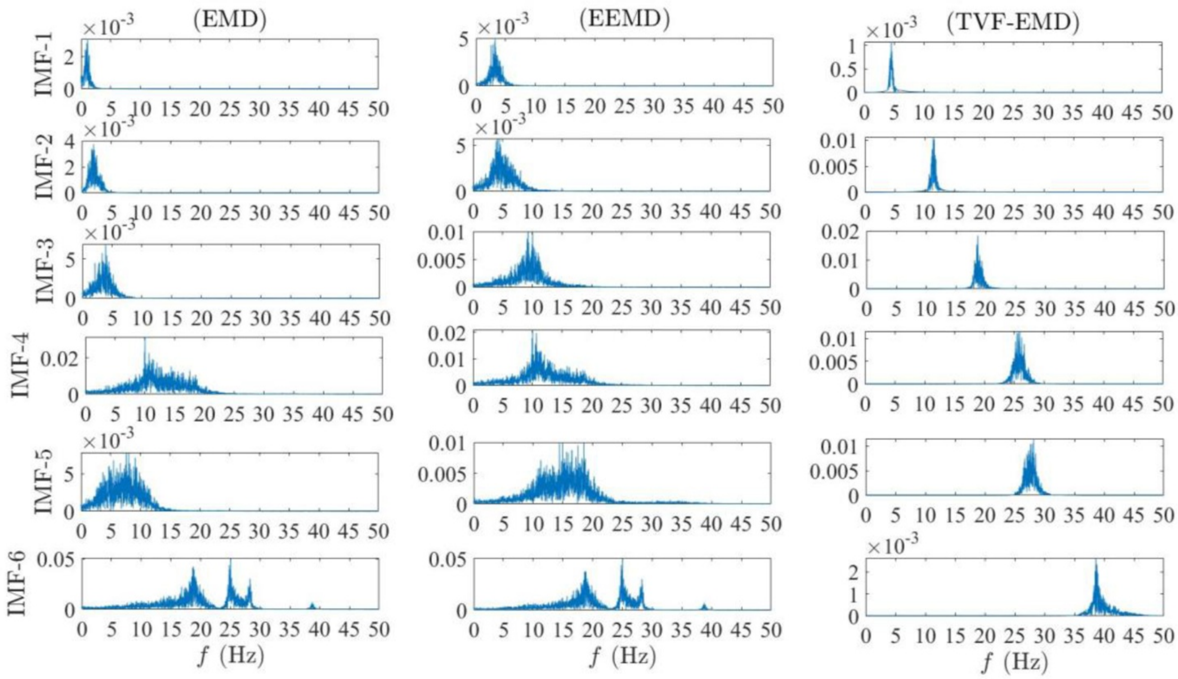

Figure 10. Fourier spectra of the resulting IMFs obtained from EMD, EEMD, and TVF-EMD using the fifth-floor response.

Yu and Ren (2005) used EMD to extract the modal parameters of a full-scale arch bridge under ambient excitation. The identified results were compared with stochastic subspace identification and peak-picking methods. The results showed that EMD was successfully able to extract the natural frequencies, damping ratio, and mode shapes of the bridge. In another study, Cheraghi and Taheri (2007) proposed a novel damage index using EMD to determine the existence and intensity of damage in aluminum and PVC pipes subjected to hammer impact, and the results were compared against WT. It was concluded that EMD was capable of detecting the location and severity of the damage. On the other Rezaei and Taheri (2009, 2010) utilized EMD to detect the presence, location, and severity of damage in steel pipes and beams excited by impulse

Table 3. Summary of the key merits and limitations of the EMD method and its variants.

	Merits	Limitations
EMD	• Provide time and frequency domain information of the signal. • Able to analyze the nonlinear and nonstationary signals. • Free of any basis functions, therefore self-adaptive in nature.	• Utilizes a single measurement and cannot use joint information of the multichannel measurements. • Mode-mixing and end effects may appear in the resulting IMFs. • Results in a finite number of IMFs that require post-processing. • Needs intermittency criteria to achieve better results.
EEMD	• Eliminate the mode-mixing issue in the resulted IMFs.	• Requires an artificial noise added to the signal. • Needs significant user-intervention. • Computationally intensive than EMD
MEMD	• Suitable for multichannel signals. • Computationally efficient. • Capable of extracting the low energy and closely spaced frequencies.	• Results in the mode-mixing in the IMFs.
TVF-EMD	• Performs well under noisy signals. • Results in the least mode-mixing and end-effects among EMD variants. • Capable of extracting the closely spaced modes. • Intermittency criteria are not required.	• Computationally intensive.

hummer with both aluminum and hard plastic tip. The authors proposed that EMD technique can be a relatively cost-effective non-destructive testing tool since it deals with only a single channel measurement.

Yinfeng *et al* (2010) used EMD and vector autoregressive-moving-average model to identify the presence and severity of damage at multiple locations under various earthquake events. The authors suggested that more studies were needed to investigate the relationship between the damage severity and the proposed damage index. In another study, Nagarajaiah and Basu (2009) utilized EMD and other TF methods such as STFT, WT, and HT to extract modal parameters of several dynamical systems subjected to free vibration and random excitation, and the results were compared with RDT. Chen (2009) integrated EMD and HT to identify the frequencies and damping ratios of a long-span bridge under wind force and of structures with closely-spaced modes. The authors used HHT to determine the instant and severity of damage in a three-story experimental structure under free, random excitation, and El Centro earthquake excitation. The author concluded that EMD is a suitable SHM tool for different types of civil structures due to its capability of dealing with various data such as wind, GPS, acceleration, and strain measurements.

Bradley *et al* (2010) utilized EMD to identify the presence and severity of damage in beam structure subjected to a moving load. In another research, He *et al* (2011) integrated EMD with RDT to obtain natural frequency and damping ratio of a steel truss bridge under ambient vibration. The results were compared with the peak-picking method using vibration data collected from the Nanjing Yangtze River bridge. The results showed that EMD-based RDT could be a suitable modal identification technique for large-scale civil structures. On the other hand, Meredith *et al* (2012) utilized moving average filter and EMD to detect an instant and severity of damage in a beam structure under different moving loading scenarios. The results showed that the proposed method was able to detect a crack of 10% of the beam depth in a signal collected at a velocity of 10 ms^{-1} with an SNR of 5.

He *et al* (2012) used EMD with intermittency criteria to extract and reconstruct dynamic responses of a cantilever beam and ASCE benchmark data under different challenging situations such as noise level, high damping ratio, closely spaced modes, and sensor location. The results represented the accuracy of the proposed method in case of analyzing signals with a high damping ratio. The authors concluded that the proposed method was able to reconstruct the responses of numerical models that have 5% or less noise, with only a 5% error. Furthermore, Ditommaso *et al* (2012) compared the performance of the standard transfer function method, horizontal to vertical spectral ratio, STFT, EMD, and S-Transform to extract the modal responses and investigate the dynamic behavior of Falkenhof Tower subjected to ambient noise and explosion. The authors, however, pointed out the mode-mixing issues in some of the IMFs resulting from the EMD.

Chang and Kim (2011) used EMD and proper orthogonal decomposition to extract structural displacement responses and mode shapes under impact and moving load. The results were compared with directly measured displacement, modal assurance criteria, and energy difference tracking method using the data collected from a three-story experimental model and a real bridge. On the other hand, (Meredith and González 2012) utilized EMD to identify the location and severity of damage under a moving load. The results showed the efficiency of the proposed method under various damage scenarios using a quarter-car vehicle-bridge numerical model. It was mentioned that the proposed method was able to detect as low as 10% loss in stiffness in case of vehicle passes over the damage location. In another study, (Wan *et al* 2014) used EMD to reconstruct structural dynamic response under the presence of noise and closely spaced modes. The results were compared with the theoretical response using a six-story numerical model subjected to a transient, stochastic, and periodic excitation.

Reddy and Krishna (2014) used EMD to conduct damage detection in beams and bridge models using strain data. The results presented that EMD can detect even a 0.01% reduction in stiffness for a beam and up to 0.5% for a real bridge. On the other hand, (Razi and Taheri 2014) utilized EMD to identify the existence and progression of a notch in submerged pipes under impact and chirp excitation. The results showed that the chirp excitation method was more accurate than the impact method for damage detection of the submerged pipes. Lofrano *et al* (2014) used EMD to identify localized damage of structure under free vibration. A comparison between the experimental and numerical results was shown using the parabolic steel arch structure. In another study, Qin *et al* (2015) utilized improved EMD to extract natural frequencies and damping ratios under ambient vibration. The results were compared with FEM, peak-picking, and stochastic subspace identification using vibration measurements collected from the Songtoujiang railway bridge. The results proved the significant efficiency of the proposed method compared to the other methods.

Wu *et al* (2016) applied EMD to undertake damage detection and assess the bearing capacity using a numerical beam model and a real bridge subjected to the moving loads. The results showed that EMD method could accurately identify the location and intensity of the damage. Lu *et al* (2016) proposed EMD, a multi-fractal spectrum, and an artificial neural network for fault diagnosis of hydraulic turbines. They used EMD to extract approximate coefficients of various signals with faults using the data collected from the Lijiaxia Power Plant. He *et al* (2016) used EMD with intermittency criteria to extract and reconstruct strain-stress responses under the presence of noise using sparse and remote sensor data. The results were compared with the theoretical ones using two numerical models and an experimental beam structure. Based on the experimental study, it was concluded that using more sensors can improve the performance of the proposed method. Song *et al* (2017)used EMD and the natural excitation technique to identify the natural frequency and damping ratio of the Tingkau bridge. The results showed that the proposed method could accurately extract the structural modal parameters, which makes it a suitable candidate tool for system identification of large civil structures.

In Rostami *et al* (2017), the authors utilized EMD, EEMD, and Smooth EMD that adopted WT in the sifting process of EMD to separate the overlapped modes in concrete covered pipes under various cases. The proposed method was validated using an experimental study, and the results presented the capability of the proposed method for separating the overlapped modes in the signal. In another study, (Reddy and Krishna 2017) used EMD to detect the presence and location of damage using a 3-DOF experimental structure under random excitation. The authors concluded that EMD was able to detect the damage from the response signal that has a measurement noise of less than 40%. Paul *et al* (2017) utilized EMD and changes in phase space topology to identify the severity and location of damage in the IASC-ASCE benchmark structure affected by seismic excitation. EMD was used to identify the presence and location of damage using a finite element vehicle-bridge interaction model Obrien *et al* (2017). The results showed that EMD method could identify the location of the damage, irrespective of the road profile.

Yang *et al* (2018) used a combination of EMD and support vector regression machine to extract natural frequencies, damping ratios, and mode shapes of the structure under free vibration. The results were compared with standard EMD using a four-story experimental model. The results proved the high performance and efficiency of the improved EMD method compared to the standard EMD. On the other hand, Ni *et al* (2018) utilized variational mode decomposition and EMD to identify the instantaneous frequency of 4-DOF numerical model and a bridge subjected to free vibration and moving load. The results showed that the proposed method was more accurate than EMD-based methods. Lu and Tang (2018) used adaptive harmonic WT and EMD to extract the critical features of the wave signals for SHM. The results of adaptive harmonic WT were compared with EMD using a beam structure.

Chen *et al* (2018) utilized EMD and sparse coding as a dictionary to provide a sparse representation of structural responses under random excitation. The results of EMD were compared with sparse coding using the numerical and experimental beam models as well as a truss structure. It was found that the sparse coding dictionary was more efficient and accurate than EMD-based dictionary, since the smaller sparsity can be obtained using the sparse coding dictionary. On the other hand, Perez-Ramirez *et al* (2019) used EMD to alleviate the noise in vibration measurements collected from a real-life tall building subjected to seismic and ambient excitation, and five-story steel structure under an earthquake. The results proved that EMD was effectively able to deal with the high-frequency noise. In another research, Feng *et al* (2019) proposed EMD and RDT to obtain modal parameters of the multi-DOF numerical and experimental structural systems subjected to stationary excitation. The results showed that the proposed method was successfully able to extract the modal parameters with an improved computational efficiency

Jiahui *et al* (2019) proposed a power spectrum-based EMD to identify the modal frequencies of the container crane structure under its operational condition. The full-scale results were compared with the finite element models. The results proved that the proposed method was capable of identifying the frequency and avoiding the false modes compared to finite element results. On the other hand, Lofrano *et al* (2019) used orthogonal EMD to detect the presence and location of damage i a 4-DOF model and a two-hinged parabolic arch system under free vibration. In another research, Qiao and Li (2019) combined EMD, RDT, and HT methods to extract the modal frequency and damping ratio using earthquake-induced responses of a concrete gravity dam. The results of the proposed technique were compared with those obtained using the peak point picking method, the time-series model, the natural excitation technique with HHT, in a finite element model. The proposed method was successively able to extract the first five frequencies and damping ratios of a dam. Shao *et al* (2019) used a combination of EMD and fractal conservation law to de-noise and filter the vibration data collected from a full-scale long-span bridge. The results of the proposed filter were compared with the other methods and showed the high performance of the proposed filter over the other techniques.

4.2. Applications of EEMD

Similar to EMD, EEMD offers signal decomposition of the data from a single measurement. However, EEMD gained significant promises as it alleviates the mode-mixing issues of EMD. Amiri and Darvishan (2015) compared the capability of EMD and EEMD as signal processing tools by extracting the acceleration responses of a nonlinear steel moment frame. The results showed that EEMD is more appropriate for signal decomposition, where the amplitude is more suitable as a measure for damage detection in nonlinear systems compared to the frequency-band index. Aied *et al* (2016) applied the EEMD method to the mid-span acceleration response of a bridge to capture the sudden stiffness changes. Minor stiffness changes were successfully identified in cases of relatively high vehicle speeds, and even significant noise since EEMD can separate high-frequency components related to stiffness changes from other frequency components associated with the vehicle-bridge interaction system.

Zhong *et al* (2018) presented an approach that combined the optimized EEMD and 2D-MUSIC algorithm for real-time impact localization on composite structures. The proposed method was validated using the experimental data collected from a cross-ply glass fiber reinforced composite plate. The results showed that the proposed method was accurately able to find the impact location and proved that the proposed method was an appropriate tool for the real-time impact localization of composite structures. In Zhu *et al* (2018), the authors developed an extraction method combining mode decomposition, data reduction, and BSS to understand the temperature effects on bridge responses. EMD and EEMD were used for signal decomposition, whereas principal component analysis was utilized for data compression. The unique feature of the study was that it offered extraction of temperature-induced structural response without any information on loading conditions. The results showed that EEMD, integrated with BSS, provided better performance than the standalone EMD.

Dong *et al* (2019) investigated the identification of vibration sources and the energy distribution of offshore wind turbines by combining optimized spectral kurtosis and EEMD. It was shown how the characteristics of structural vibrations changed from environmental excitation to harmonic excitation as the rotating speed was increased. The authors recommended that the need for further studies to investigate the relationship between the rotating frequency and structural modal frequencies of offshore wind turbines under various operational conditions. In another study, Entezami and Shariatmadar (2019a) proposed a new hybrid algorithm based on an improved EEMD that combined adaptive signal decomposition with adaptive noise and auto-regressive moving average model. An automated approach was formulated in this study to select the most relevant IMFs to damage and reduce redundant IMFs. The results were validated by using a numerical shear-building model and an experimental benchmark structure. It was proved that the proposed method could accurately reduce the number of redundant IMFs compared to EEMD.

Zhu and Malekjafarian (2019) estimated the natural frequencies of a bridge by combining EMD and EEMD using drive-by measurements. An interactive vehicle-bridge model was created to illustrate the proposed method. In their study, the EMD method was employed to decompose the measured signals, and subsequently, EEMD was used to solve the mode-mixing problem. The results demonstrated that EEMD outperforms the EMD since EEMD is less sensitive to the measurement noise. Entezami and Shariatmadar (2019b) proposed a hybrid algorithm in a combination of EEMD and the autoregressive model for feature extraction. Correlation-based dynamic time warping method employing the use of random high-dimensional multivariate features was proposed to detect the severity of the damage. The results proved that the proposed method performed better compared to the EMD-autoregressive approach. A novel data analysis method that combined permutation entropy and spectral substitution with EEMD (Huang *et al* 2019) showed that the technique could extract multiple frequencies from the data with significant noise. Data collected from the full-scale bridge was analyzed using the proposed method, where the results indicated the capability of the proposed method to extract multi-frequencies.

Perez-Ramirez *et al* (2015) proposed a new methodology based on the synchro-squeezed WT to identify the natural frequency and damping ratio using ambient vibration measurements. The authors compared the proposed framework with the complete EEMD and the short-time multiple signal classification algorithms using numerical simulations. The results showed that complete EEMD is sensitive to noise and cannot detect closely spaced frequencies. The short-time multiple signal classification algorithm provided pseudo-spectrum of the signal, limiting the estimation of damping ratios. Xiao *et al* (2019) explored complete EEMD with adaptive noise for the first time to extract the spectrum signature of the vehicle–bridge response. This method was validated using vibration data collected from a full-scale bridge under a passing vehicle. The results of the proposed method were compared with the conventional power spectra, spectrograms, scalograms, and EMD and showed the efficiency of the proposed method. On the other hand, Soman (2020) utilized EEMD to detect the severity and location of damage using an experimental tripod model under various damage scenarios. The author concluded that, although EEMD is computationally intensive, it performs better than EMD.

4.3. Applications of MEMD

Unlike EMD and EEMD, MEMD shows its potential to perform signal decomposition using multichannel measurements. Sadhu (2017) explored MEMD for the first time as a modal identification method of structural systems. This method was verified using two different numerical models and a bench-scale experimental model. The results showed the efficiency of MEMD method using multi-data measurements, which made it a suitable tool to extract the modal parameters of using the multichannel measurements of large-scale structures Sadhu *et al* (2014). This study resolved the mode-mixing of MEMD using the EEMD method. Recently, Barbosh *et al* (2018) explored MEMD to extract the modal parameters of various civil engineering structures using multichannel signals under different practical situations. MEMD method was validated utilizing multichannel vibration data that was collected from a suite of numerical, experimental, and two full-scale structures such as the Canton Tower in China and a highway bridge in Canada. Due to the mode-mixing issue in some modal responses, a powerful BSS technique, namely, Independent Component Analysis, was used, which involved less computational effort and time. It was concluded that the proposed method was able to extract the closely spaced with 2% separation and low-energy modes, which makes it a suitable candidate as a modal identification tool using multiple vibration measurements collected from various types of structures.

Salehi and Azami (2019) explored the MEMD for the first time as a structural damage detection tool based on vibration data. MEMD was applied to determine the severity and location of damages and was validated by conducting numerical and experimental studies. The results showed that the performance of the proposed method was improved when the damage location was far from the inflation points of the corresponding mode. In another research, Azami and Salehi (2019) used MEMD to extract the structural damage feature from the vibration responses. MEMD was used to detect the presence and location of damage, which was validated using both numerical and experimental beam models. The results showed that the proposed technique was able to identify the location of multiple damages. Lately, Celik *et al* (2020) used a noise-assisted version of the MEMD to extract the modal parameters of civil structures under the operational load using multichannel data of various experimental and full-scale studies. The authors applied complete EEMD with adaptive noise to alleviate the mode-mixing issue in the resulted IMFs obtained from MEMD. It was concluded that the proposed method was successfully able to extract the modal parameters even in case of using measurements with a short duration.

4.4. Applications of TVF-EMD

Recently, Lazhari and Sadhu (2019) explored the TVF-EMD method as a modal identification tool for structural systems using a single mobile wireless device to collect the vibration data. The TVF-EMD method was validated using a set of numerical, experimental, and real-life structure studies using a decentralized sensing technique that can be deployed using mobile wireless sensors. The results proved the significant performance of the proposed method under measurement noise and closely-spaced frequencies. In another recent study, Singh and Sadhu (2020) integrated TVF-EMD within the building information modeling (BIM) framework of a real bridge to include system identification in the BIM model and develop a visualization tool using the long-term SHM data.

5. Hybrid EMD methods

Lately, there have been significant researches that integrated EMD with the other TF methods to develop a more robust SHM tool specific to particular applications. For example, several hybrid approaches are developed by combining EMD with WT, BSS, and different machine learning methods to extract the modal parameters, detect damage in structures and achieve better results than the standalone EMD. The following sections are dedicated to present this literature related to hybrid EMD methods.

5.1. EMD-WT

Li *et al* (2007) proposed the EMD method integrated with WT to undertake damage identification using the vibration data of civil structures. Numerical and experimental studies were conducted to verify the capability of the hybrid method to discover the severity and location of the damage. The results showed that the proposed technique was more accurate than the WT method to determine the damage instant and was more sensitive to stiffness changes. They mentioned that the proposed method could be used as a damage detection tool in both structural and mechanical systems. They recommended further work associated with the magnitude of the wavelet coefficient and the location of the damage and the selection of mother wavelet. In another study, Wang *et al* (2016) proposed a soft-thresholding filter based on the discrete WT and EMD method as a structural damage detection tool using lamb wave signals. Finite element simulation and an experimental model of an aluminum sheet were used to validate the proposed technique. The authors showed that the proposed method was able to identify the severity and location of the damage.

Zhang *et al* (2017) explored the combination of wavelet threshold and EMD as a modal identification method of a dam using operational vibration measurements. The authors mentioned that while using EMD to analyze vibration data collected from the discharged structure, endpoint effect and mode-mixing issues appeared in the resulting IMFs. The proposed method was used to suppress these issues, and the results indicated that the wavelet threshold and EMD method were accurately capable of extracting the modal parameters of a large flood discharge structure in the presence of noisy measurement as compared to other de-noising methods. Ke (2017) proposed a hybrid EMD and wavelet packet transform-based method to de-noise GPS-based structure monitoring data. Field measurements were decomposed into a set of IMFs, and high-frequency IMFs were denoised using a wavelet packet. The author mentioned that the limitations of using only EMD or wavelet packet were the motivation of this study. The proposed method was tested using a three-story frame excited by the El Centro earthquake. It was effective in extracting vibration features and weakening the multipath effect with low frequency.

5.2. EMD-HT

Loh *et al* (2001) integrated EMD with the HT method to conduct SHM using ground motion data. A seven-story model and two real-life bridges were used to verify the efficiency of the proposed method. In another study, Yang *et al* (2003) explored a technique based on the Hilbert–Huang spectral analysis to decompose signals of an MDOF linear system under free vibration data and identify the modal characteristics of structures. First, EMD was used to decompose the vibration data, and then the amplitude and phase-angle time histories were extracted using the HHT method. Three numerical models were conducted to validate the proposed technique. The results proved that the proposed method was successfully able to identify the modal parameters of structures. The authors mentioned that the number of sifting in EMD was increased to extract an accurate result of some high-frequency modes, which required more computational effort and time.

Chen and Feng (2003) proposed a new technique to improve the performance of EMD for decomposing narrowband signals since the standard EMD has a weakness to identify different components in narrowband signals. Numerical models and full-scale bridge studies were considered to validate the proposed technique in various cases. The results showed that the proposed method was capable of decomposing the narrowband signals and identifying the time-variant characteristics of structures. On the other hand, Chen *et al* (2004) applied the EMD-HT method to determine the modal parameters of the Tsing Ma bridge under typhoon Victor. The results showed the high performance of the proposed method as a modal identification tool for large structures under typhoon excitation. The authors mentioned that since this study was conducted using only one typhoon, more real-life structures under other typhoons could be investigated to verify the proposed technique. Unlike damage detection, Varadarajan and Nagarajaiah (2004) investigated the effect of the semi-active variable stiffness-tuned mass damper to control and reduce the response of high-rise buildings subjected to wind force. They applied EMD and HT methods to identify the frequencies of a 76-story building. The results showed the high performance of the semi-active variable stiffness-TMD system over TMD and active tuned mass damper.

Pines and Salvino (2006) explored a new technique that combined EMD and HHT to identify the location and extent of damage in structures subjected to the earthquake excitation. Both numerical and experimental models were used to validate the performance of the proposed technique under different damage cases. The results demonstrated that the proposed method was able to track the damage and could be a suitable candidate as a damage detection tool for civil structures. In another study, Chen *et al* (2007) proposed the EMD-HHT method as a damage detection tool based on vibration measurements of large structures. To alleviate the end effects in EMD, the axisymmetric signal extension method was used. Wingbox model was considered to demonstrate the efficiency of the proposed method and its performance towards structural damage detection. They recommended that more studies could be focused on establishing the relationship between structure damage severity and the location with the extracted feature.

Spanos *et al* (2007) proposed EMD combined with HT as a damage detection tool using structural systems subjected to earthquake excitation. A 20-story steel frame model was used to verify the proposed methods, and the results showed that the proposed method was able to monitor and identify the damage in civil structures under seismic excitation. On the other hand, Yinfeng *et al* (2008) proposed an improved HHT method, which was based on the time-varying autoregressive moving average model to identify the instantaneous frequencies of IMFs extracted from EMD. The results of the proposed method were compared with original HHT, STFT, and WT, which indicated the improved performance of the proposed method over other methods and showed that it could be a suitable tool for structural damage detection.

Nagarajaiah (2009) applied EMD, HT, and STFT methods to identify the instantaneous frequencies of structural systems equipped with smart TMDs under different types of excitation. The efficiency of the proposed methods was shown using a set of numerical and experimental building structures equipped with smart TMDs. Lately, Garcia-Perez *et al* (2013) proposed a combination of wavelet packet transform and EMD to identify the location and severity of single and multiple combined damages in truss-type structures. The results proved the high efficiency to identify multiple damages using a five-bay truss model. Trung (2019) utilized HHT to identify instantaneous variations in dynamic characteristics of bridge caisson foundation under liquefaction. Xu *et al* (2020) used a combination of EMD and HT to identify the location of leakage in the pipeline structure using a single acoustic emission sensor. The proposed method validated using *in-situ* experiment studies on a pipe under different pressure conditions. The results showed the efficiency of the proposed method for leakage localization in pipelines.

5.3. EMD-BSS

Hazra *et al* (2010) proposed an algorithm (modified cross-correlation (MCC)) based on BSS, called the MCC-EMD method, to retune TMDs to their optimal states using ambient vibration measurements. The identification algorithm was leveraged to estimate the natural frequency and mode shape of the primary structure necessary for the re-tuning of a TMD. The proposed framework used EMD to separate the closely spaced modes and the MCC method to resolve the remaining well-separated modes. Hazra *et al* (2011) solved the undetermined modal identification of structures using the MCC. The authors generated IMFs of the measurements using EMD and subsequently treated the IMFs as pseudo measurements in an iterative process. The results showed that the need for sensor measurements at all relevant degrees was not necessary to identify the mode shapes using limited sensors.

Hazra *et al* (2012) used the resolution and sparsity provided by TF decomposition of signals while retaining the advantage of second-order BSS methods. The structural modes of an airport control tower equipped with supplemental devices such as TMDs were identified using a hybrid approach combining second-order blind identification and EMD. The proposed method was effective in dealing with situations involving the presence of low energy modes, under-determined mixing matrix, and closely-spaced modes.

Table 4. Comprehensive summary of the literature.

Literature	Approach	Application
	Damage detection	
Yang *et al* (2004)	EMD and HT	ASCE benchmark building data
Xu and Chen (2004)	EMD	Experimental model
Pines and Salvino (2006)	EMD and HT	Experimental studies
Chen *et al* (2007)	EMD and HT	Wing-box model
Cheraghi and Taheri (2007)	EMD and WT	Pipe
Li *et al* (2007)	EMD and WT	Experimental studies
Spanos *et al* (2007)	EMD and HT	Experimental studies
Yinfeng *et al* (2008, 2010)	EMD and time-series model	Building
Rezaei and Taheri (2009, 2010)	EMD	Pipes and beams
Bradley *et al* (2010)	EMD	Beam structures
Esmaeel *et al* (2011)	EMD	Bolted joints
Razi *et al* (2011)	EMD	Fatigue crack
Esmaeel and Taheri (2012)	EMD	Delamination
Meredith *et al* (2012)	EMD and filters	Beam structures
He *et al* (2012)	EMD	ASCE Benchmark data
Meredith *et al* (2012)	EMD	Simulation studies
Garcia-Perez *et al* (2013)	EMD and WT	Experimental model
Reddy and Krishna (2014)	EMD	Beams and Bridges
Razi and Taheri (2014)	EMD	Pipes
Lofrano *et al* (2014)	EMD	Steel arch structure
Yang and Yang (2016)	EMD and Machine Learning	Earthquake-induced motion
Wu *et al* (2016)	EMD	Bridge
Wang *et al* (2016)	EMD and WT	Experimental studies
Lu *et al* (2016)	EMD and Artificial Neural Network	Turbines
Paul *et al* (2017)	EMD	ASCE benchmark data
Obrien *et al* (2017)	EMD	Numerical studies
Lofrano *et al* (2019)	Orthogonal EMD	Numerical and experimental studies
Xu *et al* (2020)	EMD and HT	Pipes
Amiri and Darvishan (2015)	EMD, EEMD	Experimental studies
Aied *et al* (2016)	EEMD	Bridge
Entezami and Shariatmadar (2019a)	EEMD, time-series model	Numerical and experimental studies
Soman (2020)	EEMD	Tripod experimental model
Salehi and Azami (2019)	MEMD	Experimental studies
Azami and Salehi (2019)	MEMD	Numerical and experimental studies
	System identification	
Loh *et al* (2001)	EMD and HT	Bridge
Yang *et al* (2003)	EMD and HT	Numerical studies
Chen and Feng (2003)	EMD	Bridge
Chen *et al* (2004)	EMD and HT	Typhoon-induced vibration
Yu and Ren (2005)	EMD	Arch bridge
Chen (2009)	EMD and HT	Long-span bridge
Nagarajaiah (2009)	EMD, HT, and STFT	Building model with a TMD
Nagarajaiah and Basu (2009)	EMD and other TF methods	Simulation studies
Hazra *et al* (2010)	EMD and BSS	Simulation studies
Hazra *et al* (2011)	EMD and BSS	Undetermined system identification
Chang and Kim (2011)	EMD and POD	Bridge
He *et al* (2011)	EMD and RDT	Full-scale bridge
Hazra *et al* (2012)	EMD and BSS	Airport tower
Ditommaso *et al* (2012)	EMD and other TF methods	Tower data
Wan *et al* (2014)	EMD	Numerical studies
Qin *et al* (2015)	EMD	Railway bridge
He *et al* (2016)	EMD	Experimental studies
Song *et al* (2017)	EMD and NeXT	Bridge
Rostami *et al* (2017)	EMD and EEMD	Pipes
Reddy and Krishna (2017)	EMD	Experimental studies

(Continued)

Table 4. (Continued).

Literature	Approach	Application
Zhang *et al* (2017)	EMD and WT	Dam
Yang *et al* (2018)	EMD and SVM	Experimental studies
Ni *et al* (2018)	EMD and VMD	Bridge
Lu and Tang 2018)	EMD and WT	Beam
Chen *et al* (2018)	EMD and Sparse coding	Experimental studies
Trung (2019)	EMD and HT	Bridge foundation
Perez-Ramirez *et al* (2019)	EMD	Building
Feng *et al* (2019)	EMD and RDT	Experimental studies
Zhu and Malekjafarian (2019)	EMD and EEMD	Indirect bridge monitoring
Jiahui *et al* (2019)	EMD	Container crane
Qiao and Li (2019)	EMD, RDT, and HT	Concrete dam
Shao *et al* (2019)	EMD and fractal conservation law	Bridge
Entezami and Shariatmadar (2019b)	EEMD and time-series	Experimental studies
Xiao *et al* (2019)	EEMD with adaptive noise	Bridge
Perez-Ramirez *et al* (2015)	EEMD and WT	Numerical studies
Sadhu (2017)	MEMD and EEMD	Experimental studies
Barbosh *et al* (2018)	MEMD and BSS	Tower and bridge
Celik *et al* (2020)	MEMD and Complete EEMD with adaptive noise	Experimental grandstand and full-scale bridge
Lazhari and Sadhu (2019)	TVF-EMD	Experimental studies
Varadarajan and Nagarajaiah (2004)	EMD and HT	Tall building
	Anomaly detection	
Ke (2017)	EMD and WT	Experimental studies
Zhong *et al* (2018)	EEMD and 2D-MUSIC	Experimental studies
Zhu *et al* (2018)	EMD and EEMD	Experimental studies
Dong *et al* (2019)	EEMD	Wind turbine
Huang *et al* (2019)	EEMD	Bridge

5.4. EMD-machine learning methods

Esmaeel *et al* (2011) proposed a vibration-based damage detection methodology employing EMD that could detect the damage due to loosened bolts. The experimental results showed that EMD offered a significant improvement in the detection and progression of damage in bolted joints. Razi *et al* (2011) formulated an efficient non-destructive tool to solve the problem of fatigue crack identification. The authors proposed a vibration-based technique to detect fatigue cracks in structures using EMD. The method was able to detect fatigue cracks of different sizes that were deliberately introduced in an aluminum beam using a cyclic load. The technique detected and quantified damage progression and was more sensitive to damage detection and quantification than other existing frequency-based methods. (Esmaeel and Taheri 2012) focused on early-stage detection of delamination and proposed an EMD based non-destructive damage detecting methodology. The technique used piezoelectric sensors to capture the vibration signature of the structure. The method was able to differentiate the delamination locations and thickness. Through experimental and computational investigations, the authors accurately depicted the existence and growth of damage in composite beams.

Yang and Yang (2016) worked on the short-term prediction of strong earthquake ground motions and proposed a multi-step prediction method based on EMD and machine learning. The proposed methodology, firstly, decomposed acceleration time histories of ground motions into IMFs using EMD and employed the use of extreme machine learning methods to predict the IMF components.

Finally, table 4 shows a comprehensive summary of the literature discussed in this paper with an application sequence of damage detection, system identification, and anomaly detection in chronological order.

6. Conclusions

EMD has gained significant popularity in SHM due to its ability to deal with nonlinear and nonstationary signals. Unlike many other TF methods, EMD is adaptive (e.g. free of any basis function) and performs signal decomposition based on the local characteristic of the data using only single-channel measurement. The use of single-channel data is one of the most significant advantages of EMD over the existing TF methods that need measurement data at various locations of the structures. However, depending on the specific applications, EMD results in mode-mixing and end-effects that have been resolved by the different researchers in the literature in form of various hybrid methods. In the past few years, diverse applications of EMD and its variants are reflected in SHM through numerous publications. In this paper, the authors presented a comprehensive review of EMD and its variants specific to SHM applications.

Based on the existing literature, it can be concluded that the traditional EMD cannot perform satisfactorily and results in mode-mixing, end effects, and a large number of redundant IMFs in most vibration measurements collected from large-scale flexible structures. In the last few years, EMD has been expanded to its variants such as EEMD, MEMD, TVF-EMD, and different hybrid versions that can overcome these limitations. This paper has provided a comprehensive review of EMD and its variants highlighting their potential use in infrastructure monitoring of civil engineering structures and presented a comprehensive list of relevant literature, that will benefit to the SHM community and the practitioners.

Despite several challenges of EMD, it is anticipated that the EMD-based methods have the potentials to be one of the powerful signal decomposition tools that can be used within today's modern sensing techniques. Recent advances in sensors result in smart sensors such as cameras, drones, passing vehicles, and robots that are decentralized in nature and rely on a single sensor measurement. In these sensing applications, EMD can be embedded as a relevant system identification tool due to its capability of handling a single-channel measurement. With the current advances in Machine Learning and Deep Learning techniques, EMD also holds an excellent potential to extract features of the long-term monitored data. These features can be integrated within the framework of Artificial Intelligence to reduce the overall dimensionality of the big data obtained from the large-scale structures. It is anticipated that the future trends will be seen towards leveraging EMD's capabilities of signal decomposition and feature extraction within the context of smart sensors and big data to solve complex problems in SHM.

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ORCID iD

Ayan Sadhu https://orcid.org/0000-0001-5685-7087

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