

Review

# Application of the Subspace-Based Methods in Health Monitoring of Civil Structures: A Systematic Review and Meta-Analysis

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**Abstract:** A large number of research studies in structural health monitoring (SHM) have presented, extended, and used subspace system identification. However, there is a lack of research on systematic literature reviews and surveys of studies in this field. Therefore, the current study is undertaken to systematically review the literature published on the development and application of subspace system identification methods. In this regard, major databases in SHM, including Scopus, Google Scholar, and Web of Science, have been selected and preferred reporting items for systematic reviews and meta-analyses (PRISMA) has been applied to ensure complete and transparent reporting of systematic reviews. Along this line, the presented review addresses the available studies that employed subspace-based techniques in the vibration-based damage detection (VDD) of civil structures. The selected papers in this review were categorized into authors, publication year, name of journal, applied techniques, research objectives, research gap, proposed solutions and models, and findings. This study can assist practitioners and academicians for better condition assessment of structures and to gain insight into the literature.

**Keywords:** subspace system identification; data-driven stochastic subspace identification (SSI-DATA); covariance-driven stochastic subspace identification (SSI-COV); combined subspace system identification; PRISMA; damage detection; vibration-based damage detection

## 1. Introduction

Structural health monitoring (SHM) is an emerging multidisciplinary field for damage detection and condition monitoring of structures [1,2]. Due to the complexity of civil structures and the associated ambient-induced uncertainty, the development of a reliable SHM is a challenging task. Vibration-based damage detection (VDD) is a promising field in SHM that deals with assessing the health state of structures using vibration parameters [3–5]. The key factor in VDD is to establish a reliable analytical model of a dynamic structure to estimate vibration parameters. Several researchers have reviewed

literature on the vibration testing and damage detection of structures. Fan and Qiao [6] provided a comprehensive review of VDD methods. Reynders [7] reviewed the applicability of damage detection system using vibration behavior of structure. Das et al. [8] conducted a comparative study to evaluate different VDD methods. Moughty and Casas [9] performed a review of VDD techniques for small to medium span bridges.

System identification methods provide a powerful tool to construct an analytical model of a dynamic system [10–13]. Subspace system identification aims to establish a mathematical model for resolving practical problems in various branches of science and technology, such as chemistry [14,15], computer science [16], electrical engineering [17], industrial engineering [18], bioscience [19] and even finance [20]. Using subspace system identification for modal analysis is a well-established field in the dynamics of structures [21,22]. VDD methods rely on observable variations in changes in modal parameters (resonant frequency, damping, and mode shape) or their derivatives as indicators of damage existence. Song et al. [23] and Reynders [7] reviewed subspace system identification for its use in VDD and modal analysis.

Structures in VDD can be broadly divided into two categories of: (1) mechanical engineering structures, such as airplanes [24], vehicle test rig [25], ship [26], and (2) civil engineering structures, such as bridges [27], buildings [28], offshore jackets [29], and dams [30]. It is difficult to sustain any clear distinction between mechanical and civil engineering structures but, as a general idea, they could be differentiated based on their characteristics. In general, mechanical and civil engineering structure are usually subjected to different loading and boundary conditions. Civil structures are stationary, massive, and heavy [31] and they have simple structural and geometrical configuration. Civil engineering structures can be modeled in the form of simple structural elements such as beams (e.g., in bridges and wind turbines) and frames (e.g., in buildings and offshore jackets). Shells and plates are mainly used in liquid retaining and transmitting structures (e.g., in dams, and pipes). However VDD methods are not suited for structures with changing dynamic characteristics such as dams and water reservoirs. Hence, the focus of the studies on VDD of civil engineering structures is to apply their developed algorithms on beam and frame structures. Though the requirement and deployment challenges for each class of VDD structure are different, diverse techniques are essential.

Subspace system identification is one of the popular methods in time-domain that was first proposed by Van Overschee and De Moor [32] to derive modal parameters. Peeters and De Roeck [33] enhanced its computational efficiency by extending the method to handle stochastic input data. Peeters and De Roeck also utilized stabilization diagram for subspace system identification to improve the quality of the identified results [34]. Overschee et al. [32] extended the concept of weight matrices in subspace system identification as a basis for using the column space of the extended observability matrix.

Based on the incorporated input and output data, identification methods can be classified into two categories: the methods that incorporates input-output measurements to identify system parameters; so-called input-output methods, and the approaches that just use unknown output measurements, termed as output-only methods [13,35]. Since output-only methods take all excitation forces as an unknown output, the obtained results are not controllable and repeatable. Moreover, the accuracy of results is greatly affected by variation in noise level [36–38]. Despite the mentioned challenges, output-only methods are preferred over input-output methods due to the technical difficulties associated with artificial exciting of large civil engineering structures that is the main requirement of input-output methods [39,40]. Kim et al. [41,42] conducted a comparison between input-output and output-only subspace system identification methods using a model of a support-excited multi-story frame structure. Modal parameters were extracted from an input-output state-space model and the obtained results were compared to the ones obtained from output-only response data. Higher accuracy was achieved using the input-output method.

The input-output algorithm is still a tempting choice for earthquake induced excitation. Mellinger et al. [43] developed a new scheme for modal identification using output-only and input-output methods. The quality of identified system parameters was evaluated using Monte Carlo analysis in

terms of accuracy of estimations and noise robustness. It was inferred that using input information provides more reliable results for modal identification. Xin et al. [44] evaluated the performance of data-driven stochastic subspace identification (SSI-DATA) using test data from offshore jacket-type platform. The efficiency and efficacy of three different excitation signals of impact, step relaxation and ground motion were investigated using both input-output and output-only algorithms. All procedures had excellent agreement with estimated modal frequencies of stronger modes. However, less accurate results were reported for damping ratios.

Stochastic subspace identification has been successfully applied for the modal analysis of several civil engineering structures [45,46]. Different authors have used the identical term of “SSI” to denote two different phenomena of “stochastic subspace identification” and “subspace system identification” [47–49]. In order to avoid confusion with the term “SSI”, from now on, SSI is only given to refer “stochastic subspace identification” category and no abbreviation is going to be used for subspace system identification throughout this paper.

Recently a large number of subspace-based methods have been applied for VDD of civil structures. However, the previously conducted surveys have not kept pace with the changing environment and diversity in this field. Therefore, there is a need for a systematic review and meta-analysis focusing on the most important recent studies conducted in the considered area. The presented review systematically addresses the available studies that employed subspace-based techniques in the VDD of civil structures and describes some contributions towards the development and application of a subspace system identification algorithm in recent years. Some new perspectives are considered in the current study including classification of the selected papers.

The outline of this review paper is as follows: Section 2 reviews literature about subspace-based dynamic identification and damage detection. The research framework including the PRISMA methodology is outlined in Section 3. Section 4 describes the results and the relation between key parameters in the selected papers. Finally, Section 5 ends with the concluding remarks and recommendations for future studies.

## 2. Literature Review

The pioneering works in the field of SHM of civil structures have used forced-vibration as their excitation source [50]. Input–output system models, termed also as combined subspace system identification, could be simply adapted to identify dynamic parameters in forced excitation. Nowadays, a combined subspace system identification method is generally applied in modal analysis and the health monitoring of seismic-excited civil structures. Potenza et al. [51] adapted subspace system identification algorithm for seismic monitoring of historical structure by means of an advanced wireless sensor network. Zhong and Chang [52] proposed a technique that adopted an orthogonal projection to eliminate the effect of earthquake input and noise. The obtained results for combined subspace system identification algorithm are more accurate than the ones extracted from output-only identification techniques [41]. However, forced vibration and seismic motions are not always practical solutions for SHM in civil engineering due to the associated interruption in serviceability and the potential hazard to the safety [53].

### 2.1. Classification of the Subspace System Identification Methods

Recent researches greatly deals with application of ambient excitation for damage detection and modal analysis of the in-service structures. Output-only subspace system identification also referred as stochastic subspace identification (SSI), could be simply adapted to identify dynamic parameters in ambient excitation. In a pioneering work, Overschee et al. [32] introduced stochastic subspace identification together with combined and deterministic models within a unified framework. The proposed stochastic subspace method used Hankel block matrix of the output data to analyze system and to extract state space model. Due to the direct use of the response data in the identification process, the method is named data-driven stochastic subspace identification or SSI-DATA. The state

sequence matrix is calculated before deriving state-space equation. SSI-DATA is a numerically robust algorithm that uses QR decomposition to project future data on the past subspace [54]. The methodology of SSI-DATA is provided in Figure 1.

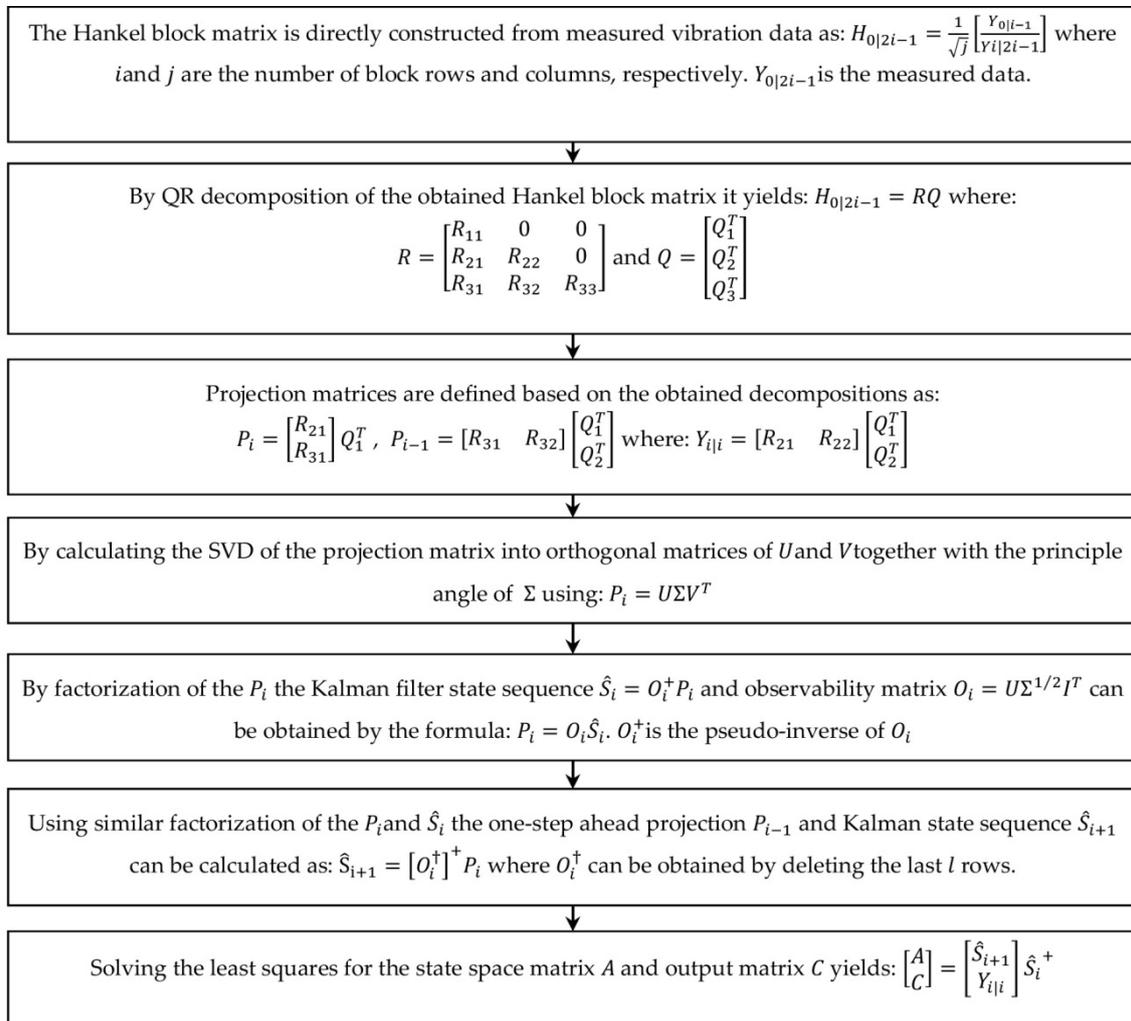


Figure 1. Methodology of the data-driven stochastic subspace identification (SSI-DATA) technique.

The introduced identification method by Overschee et al. [32] has received considerable attention due to its well-defined algorithm and data structure. However, the aforementioned algorithm is not suitable for complex data categories with a large number of sensors, large number of modes of interest, and existing turbulence or non-stationarity. To deal with the shortcomings of the algorithm proposed by Overschee et al. [32], several researchers proposed improving the convergence rates of transfer matrices to deal with large number of sensor data [55–57]. Studies such as those of Peeters and De Roeck [33] or Reynders and De Roeck [58] suggested to reduce the data complexity using subset data, so-called reference sensors. Advance processing of measurement data before the estimation of observability matrix [59–61] and introduction of recursive identification systems [62–64] are among the proposed solutions. In order to deal with complex data, Döhler and Mevel [65] introduced a new SSI-DATA algorithm using multi-order system identification. In this method a fast computation scheme using multiple-order observability matrix is suggested to solve the least squares problem. The computational burden of the proposed algorithm is much lower than the conventional algorithms. In another research, Döhler and Mevel [27] proposed an efficient SSI algorithm by reformulation and computation of uncertainty bounds. The obtained results from application of the method on Z24 Bridge showed that the algorithm is both computationally and memory efficient.

Nowadays, wireless sensor networks (WSNs) are widely used in SHM. However, the computational load is one of the main concerns regarding the application of WSNs. Hence, it is necessary to significantly reduce the computational burden and data processing efforts. Centralized algorithms are not suitable for sensor applications due to impractical computational and communication load, as well as its increased vulnerability. Cho et al. [66] presented a decentralized SSI-DATA algorithm implemented on the Imote2-based WSNs. The results obtained from an experimental test of a five-story shear building shows a similar accuracy for the centralized and decentralized subspace system identification algorithms.

Classical covariance-based subspace algorithms [67–69] took advantage of using output data to calculate covariance. To deal with output-only measurement, Peeters and De Roeck [33] used covariance between outputs and a reference outputs for health monitoring of ambient excited civil structures. The proposed SSI-COV method used correlation functions for modal identification. In this method, the response signal of the applied ambient excitation is considered as Gaussian white noise, equal to the covariance of the response signal. The methodology of SSI-COV is provided in Figure 2.

Using SSI-COV to extract damage features or modal parameters is a common practice in VDD. Basseville et al. [70] proposed using residual of SSI-COV and a local statistical approach for VDD. Sun et al. [71] defined a nonlinear subspace-based distance using covariance of the response signal in the Hankel matrix. The distance index indicates the deviation from the normal state, and reflects structural states. Zarbaf et al. [72] derived a frequency stabilization diagram using SSI-COV method. Then, hierarchical clustering was deployed to the stabilization diagrams to identify natural frequencies of each stay cable.

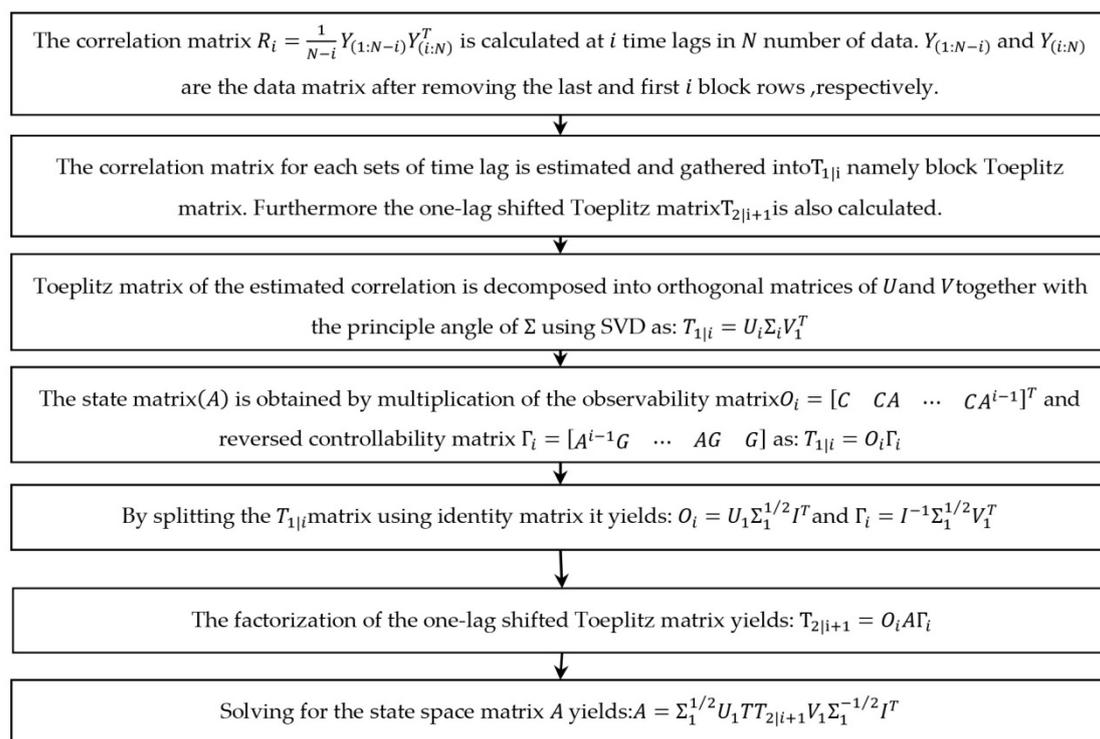


Figure 2. Methodology of the covariance-driven stochastic subspace identification (SSI-COV) technique.

For most VDD methods, it has been of great interest to study the effect of damage on eigenstructure of dynamic systems. Most of the VDD methods use modal parameters as their damage index. The dynamic characteristic of a structure can be extracted using eigensolutions [54].

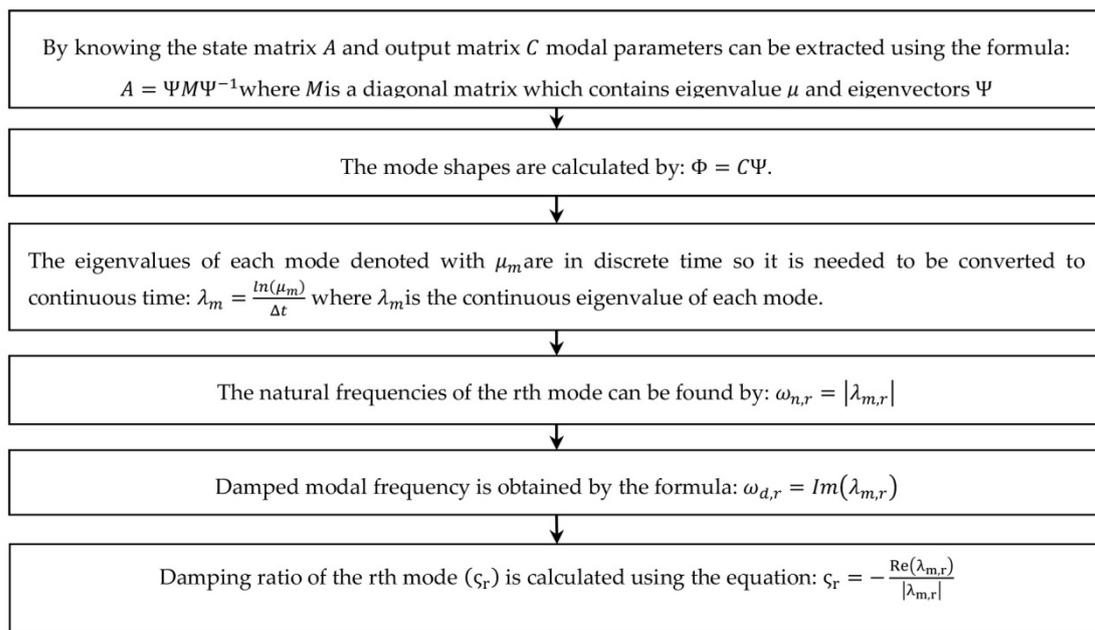
2.2. Application of Subspace System Identification for Modal Analysis

Subspace-based identification methods are widely used for modal parameter estimation in time-domain [73]. For most VDD methods, it has been of great interest to study the effect of damage on natural frequencies, mode shapes and damping ratios of a dynamic systems [74–76]. Table 1 shows a number of studies that have used the subspace algorithm for modal analysis.

**Table 1.** Some examples of the schemes that use subspace algorithm for modal analysis.

References	Extraction Method	Test Model	Specification
Saeed et al. [77]	RSSI-COV (SubID)	Composite beam and an CACTUS aluminium plate	Iterative procedure is used to improve identification results. A stabilization histogram is applied to spurious mode elimination
Reynders et al. [78]	SSI-ICOV (CSI-ic)	Simulated model of an industrial process tower	Hybrid vibration testing or OMAX model was adopted in this study.
Li & Chang [49]	Recursive SSI-COV-IV	Numerical models of a SDOF structure and ASCE steel frame structure	Model identification was conducted for a system with time-varying measurement noise
Loendersloot et al. [79]	RD-SSIcov	Numerical model and a small scale wind turbine tower	The random decrement (RD) method was selected in this study for its noise reduction capabilities.
Miguel et al. [80]	SSI-COV	Numerical examples and a laboratory model of cantilever beams	The model is appropriate to handle incomplete measurements data and truncated mode shapes. Stabilization diagram is adopted for post processing of modal data
Reynders & De Roeck [58]	CSI/ref	Z24 bridge benchmark structure	combined deterministic–stochastic subspace identification is used for modal analysis using this algorithm
Urgessa [81]	McKelvey frequency domain subspace algorithm	Uncontrolled cantilever plate	Natural frequency was predicted with an average error of 3.2% and damping ratio had average error of 2.8%
Goursat et al. [82]	used crystal clear stochastic subspace identification (CC-SSI)	Ariane 5 launch vehicle	Clear results even in the case of nonstationary data are obtained using this algorithm
Weng & Loh [83]	RSSI	3-story steel frame & 2-story reinforced concrete frame	In this method SVD algorithm is replaced by an advanced algorithm to update LQ decomposition.
Zhang et al. [84]	Improved SSI	A numerical example of 7 Degrees of freedom (DOF) and experimental model of Chaotianmen bridge	Less computing time due to not having QR decomposition. CH matrix is constructed as a replacement for Hankel matrix. Spurious modes are removed using model similarity index
Döhler et al. [26]	Fast CC-SSI	Operational data from a ship	Fast multi-order computation
Hong et al. [85]	ECCA-based SSI algorithm	FE model and experimental wind tunnel bridge model	Enhanced results are achieved for weakly excited modes and noisy response signal

The methodology of calculating modal parameters from state-space parameters of subspace system identification algorithm is presented in Figure 3.



**Figure 3.** Methodology of the calculating modal parameters from the state-space parameters of subspace system identification algorithm.

Vibration-based SHM is concurrently subject of intensive investigation. Most of the VDD methods use modal parameters to extract dynamic characteristic of structure.

### 2.3. Comparison with Other Algorithms

In recent years, several studies have been conducted to compare the performance of subspace system identification with other time domain (TD), frequency domain, (FD) and time frequency domain (TFD). This subsection provides a review of the studies with focus on advantages and drawbacks of the subspace system identification. Rainieri et al. [86] assessed the performance of SSI-COV and FDD for the modal identification of ambient excited structures. The results indicated that subspace system identification is a more appropriate choice for modal identification of closely spaced modal frequencies, however coupling effect yielded unreliable result for second pairs of the closely spaced natural frequencies. Furthermore, subspace system identification had the drawback of requiring human judgment to determine system order.

Giraldo et al. [87] presented an analytical comparison among eigensystem realization algorithm (ERA), subspace system identification, and auto-regressive moving average (ARMA) techniques for modal identification of ambient-excited structures. It is indicated that subspace system identification has provided the most accurate results for analytical and experimental tests. Magalhães et al. [88] compared SSI-COV and poly-reference least squares complex frequency (p-LSCF) algorithms using field data obtained from a concrete arch bridge. Both SSI-COV and p-LSCF found to give good results for mode shapes and natural frequency. However, better results were obtained for the daily variation of damping ratio using p-LSCF. Moaveni et al. [28] used SSI-DATA, multiple-reference natural excitation technique combined with eigensystem realization algorithm (MNeXT-ERA) [89], enhanced frequency domain decomposition (EFDD) [90], deterministic-stochastic subspace identification (DSI) [91], observer/Kalman filter identification (OKID)-ERA [92] and general realization algorithm (GRA) [93] for modal identification of a full-scale structure on a shaking table. The mode shapes identified by the subspace system identification algorithm were the most accurate. The measured damping ratio for SSI-DATA and MNeXT-ERA was higher than the ones obtained from EFDD.

Wang et al. [94] studied performance of subspace system identification, ERA, ARMA and Ibrahim time-domain (ITD) methods. A more stable result was reported for modal identification in a numerical

model using subspace system identification. However, ERA outperforms for field testing. Kim and Lynch [95] studied subspace system identification and FDD methods. Resolution problem was reported for FDD with output-only measurements data. Cunha et al. [96] compared the modal identification results of SSI-COV and FDD. The obtained results for both of the methods were too similar. Liu et al. [97] implemented modal analysis of the Lupu Bridge in Shanghai using subspace system identification, ERA, PolyMAX, polynomial power spectrum method (PPM), power spectrum z-transform method (PZM), EFDD, frequency spatial domain decomposition (FSDD), and wavelet transform (WT) under ambient excitation. The PolyMAX, PPM, PZM, EFDD, and FSDD are in FD. Subspace system identification and ERA are TD methods used in modal identification of structures whereas WT is in time/frequency-domain. Subspace system identification provided the most accurate results for modal parameters, but computational burden of the algorithm was found to be significant.

Ceravolo and Abbiati [98] conducted a comparative study among ERA applied to RDS, AR and SSI-DATA. All of the methods were robust enough to deal with modal identification in ambient condition, but subspace system identification showed superior performance. Generally, the comparison showed that subspace system identification algorithm outperformed for identification of natural frequency, mode shape, and damping ratio. However, the computational burden of the algorithm and determining user-defined parameters are two challenges that were reported as the main downside of using subspace system identification algorithm. In the next subsection, conducted studies to overcome these challenges and improve the performance of the subspace-based algorithms are highlighted.

#### 2.4. Challenges in the Practical Application

Several research studies have been conducted to enhance performance of the subspace system identification method. In this sub-section, the focus is on the problems involved in practical application of subspace-based damage detection. Among them merging sensors data, determining the optimum position for sensors, dealing with nonstationarity in the vibration signal, removing the uncertainties caused by environmental factors, eliminating spurious modes, improving performance of an identification scheme, determining the number of block rows and system order in subspace system identification are of the topics that is widely studied in subspace system identification. Most of these challenges are not specific to subspace system identification but generalize to all system identification methods.

In practical modal analysis of large civil engineering structures, dynamic response cannot be measured from all degrees of freedom (DOFs) in one setup. Merging sensor data, so called data aggregation, is used to reduce the number of transmissions in decentralized networks. Peeters [60] presented a subspace system identification approach to merge sensor data of different measurement setups with overlapping reference sensors. One of the solutions to merge multi-setup sensor data is to identify natural frequencies separately and merge the results in the next step. In this case inconsistency may arise due to mismatch of the identified frequencies. Another multi-setup method to deal with this problem is to merge the successive measurements, and to process them globally, instead of merging the identified natural frequencies. These methods are called post- and pre-identification merging method. Simultaneous measurement is considered as another choice for merging sensor data away from the multi-setup method. Mevel et al. [99] proposed post-identification method using SSI-COV for merging multiple non-simultaneously measured vibration responses through gluing natural frequencies and pole matching. Döhler et al. [100] used three subspace-based approaches of PoGER, PreGER and PreGER for merging non-simultaneously recorded measurement data. In another research, Döhler and Mevel [101] addressed a modular and scalable approach to solve the problem of dimension explosion in merging multi-setups. Furthermore, Döhler et al. [102] evaluated the statistical uncertainty in identified modal parameters using subspace system identification in multi-setup configuration. Orlowitz et al. [103] conducted a comparative study to investigate the relative advantages of multi-setup and simultaneous methods for merging multi-setup configuration. The post-identification method showed

a better correlation of mode shapes and natural frequencies, however, for the structures with changing dynamic characteristics such as dams and water reservoirs.

Subspace system identification has shown great potential in identification of dynamic parameters in civil structures. It was shown by Benveniste and Mevel [104] that the subspace algorithm is robust against nonstationarity caused by parameters such as varying operating load. Benveniste and Mevel [104] studied the impact of nonstationarity in the vibration signal on consistency of subspace system identification algorithm. It is reported that subspace algorithm ensures consistency against nonstationarity. Alicioğlu and Luş [105] assessed the effect of structural complexity and ambient uncertainty on identified modal parameters using SSI-COV and SSI-DATA techniques. It was demonstrated that the algorithm performed reliably in the identification of natural frequencies and improved efficiency was achieved by adopting a stabilization diagram. Clustering analysis was found to be promising to automate selecting of real modes.

Separating the effect of externally acting agents such as operational and environmental factors is important for successful damage detection. Several researchers have studied the effect of environmental variation in dynamic identification, as shown in Table 2. Hence, some researchers reported measuring externally acting agents along with measurement of the vibration response.

**Table 2.** Influence of environmental and operational condition on damage detection of structures.

Reference	Test Model	Environmental and Operational Effect
Sohn et al. [106]	Alamosa Canyon Bridge	5% daily change in natural frequency due to temperature variation
Liu and DeWolf [107]	Real-scale bridge	4–5% variation in natural frequencies during spring and winter were observed.
Nayeri et al. [108]	a full-scale 17-story building	Correlation between modal frequency and temperature is reported in a 24-h period.
Cornwell et al. [106]	Alamosa Canyon Bridge.	6% variation in modal frequencies have been recorded
Wood [109]	Bridge beam	Damp air caused decrease in natural frequency of structures
Xia et al. [110]	Reinforced concrete slab	2% increase was recorded when relative humidity was ranged from 15% to 80%.
Farrar et al. [74]	Alamosa Canyon Bridge	Variation in modal parameters is entirely dependent on the targeted structure
and Alampalli [111]		
Peeters et al. [112]	Z24 bridge	Frequency variation due to ambient, shaker and impact excitations was very small
Peeters and De Roek [113]	Z24-Bridge	Temperature differentials across the bridge deck as the driving forces for natural frequency variations.
Ni et al. [114]	Ting Kau Bridge	Temperature variation changes modal frequencies with variance ranged from 0.20% to 1.52% in the first ten modes.
Kim et al. [115]	Experimental model of a Euler–Bernoulli beam	Natural frequencies variation/ambient temperature from 0 °C to 30 °C was 19%, 10%, 13% and 7% for 1st, 2nd, 3rd and 4th modes, respectively.

Spiridonakos et al. [116] incorporated the variance of the uncertainties caused by humidity and temperature in identification of the modal parameters using subspace system identification. Two polynomial chaos expansion and independent component analysis were conducted to isolate structural variations caused by deviation of acting agents and extraction of structural features, respectively. Loh and Chen [117] addressed covariance-driven recursive stochastic subspace identification (RSSI-COV) for isolating environmental effect from anomaly caused by damage. Huynh et al. [118] analyzed the wind-induced vibration due to typhoons with various wind speeds. Deraemaeker [119] evaluated the robustness of subspace system identification method by introducing uncertainty into the FE model. It was shown that, other than the effect of externally acting agents, the inherent performance of an identification scheme plays an important role in accuracy of the estimation result. Then studying of the detectability of the dynamic parameters is of paramount importance. Magalhães et al. [120] studied the effect of several factors, including the proximity of natural frequencies, non-proportional damping, and accuracy of the identification algorithms, on the quality of the extracted damping ratios. Rainieri and Fabbrocino [121] investigated the influence of

the number of block rows and system order on estimation accuracy in subspace system identification algorithm. The most robust identification using a subspace system identification algorithm is obtained when the number of data goes to infinity. Short-length data cause estimation bias in modal identification. The bias error is intensified when dealing with systems having high damping and high frequency. Wang et al. [122] proposed a combined subspace system identification and ARX algorithms for VDD of Hammerstein systems. Li et al. [123] developed a subspace system identification algorithm to eliminate spurious modes caused by non-white noise. Brasiliano et al. [124] investigated the effect of non-structural elements on vibration parameters using SSI-COV and SSI-DATA. Cara et al. [125] discussed the modal contribution in each mode to the recorded vibration signal. In some structural systems ambient excitation is the only practical means to excite civil structure as a result; some of the modes are not influenced. Ashari et al. [35] introduced injecting auxiliary input to the subspace system identification algorithm to extract the unexcited modes. Several methods are used to introduce uncertainty including adding Gaussian perturbation into natural frequency or damping coefficients, adding independent Gaussian noise at each mode-shape measurement location and adding uncorrelated noise on the extracted vibration response.

Some other researchers studied the specific cases that may occur in practice. Pridham and Wilson [126] investigated the use of correlation-driven SSI to estimate damping ratio from short-length data sets. Banfi and Carassale [127] studied the effect of environmental variability and short-length measurement data in determining modal parameters. Marchesiello et al. [128] proposed short-time stochastic subspace identification (ST-SSI) to deal with time-variant identification. Markovsky [129] developed a subspace system identification algorithm for dynamic system with missing data. Brownjohn and Carden [130] compared the degree of uncertainty in black box identification from the author's experiences. Carden and Mita [131] summarized the challenges to extract accurate confidence intervals in the modal identification of civil structures using subspace system identification.

As demonstrated above, the most researched challenges in implementation of subspace system identification algorithm deal with merging multi-setup sensor data and improving the performance of the subspace algorithm for the identification of the modal parameters using short-length measurement data. In the next subsection, the use of subspace system identification in the development of software is presented.

### 2.5. The Software Packages

The subspace method has been used in many structural monitoring and modal analysis software programs. In this subsection, the software packages that used subspace system identification for modal identification and SHM are further investigated. ARTeMIS is a self-stand tool suite that utilized CC-SSI for operational modal analysis [132]. Reynders and De Roeck [58] developed MACEC for modal analysis in TD and FD. SSI-COV, SSI-DATA, combined deterministic-stochastic subspace identification (CSI), and their reference-based generalization (SSI-data/ref, SSI/ref and CSI/ref) are adopted in the software package. MACEC 3.2 is the latest version of the software [133]. ModalVIEW [134] software was developed under LabVIEW which used subspace system identification algorithm for modal analysis. Hu et al. [135] presented structural modal identification (SMI) and continuous structural modal identification (CSMI) for modal analysis within the LabVIEW environment. Goursat and Mevel [136] proposed COSMAD toolbox in Scilab, for in-operation damage identification that used SSI-COV as the basic identification tool in the software. Chang et al. [137] introduced structural modal identification toolsuite (SMIT) to study the modal parameters of natural frequency, mode shapes, and damping ratio.

Operational modal analysis (OMA) [138] is another software program that uses subspace system identification for the dynamic identification of structure and it has been used for the modal identification of several structures such as Berta Bridge [139] and Berke Arch Dam [140]. LMS Cada-X [141] is another software program employing subspace algorithm. The software is developed by LMS International in Leuven, Belgium. TestLab [142] is another software by LMS that was used extensively for modal

analysis. The software also used a subspace algorithm for parameter identification. Automated operational modal analysis (AOMA) [143] utilized a strong identification and stabilization diagram. The algorithm uses one user-defined parameter.

### 3. Methodology

For the research methodology of the present review paper, the preferred reporting items for systematic reviews and meta-analyses (PRISMA) is proposed by Moher et al. [144]. PRISMA statement consists of two main parts of systematic reviews and meta-analysis. Systematic reviews provide objective summaries of researches carried out on a specific field. An explicit and systematic method is used for identification, selection, appraisal, collecting and analysis of the data to answer clearly formulated questions about the studies included in the review. This is highly useful especially in wide research area to encompass the researches that focus on narrow aspect of the field [145]. The provided explicit framework to conduct the review is to ensure the procedure is objective and replicable by others. Meta-analysis is referred to as the statistical analysis recommended for integrating findings of the included studies. The main goal of using PRISMA statement is to help authors to improve reporting of literature reviews [146–149]. The PRISMA statement has been used in several studies to provide comprehensive literature review in various fields. In order to conduct the present review study, a three step procedure including search in literature, choosing the eligible published papers and data extraction and summarizing is employed.

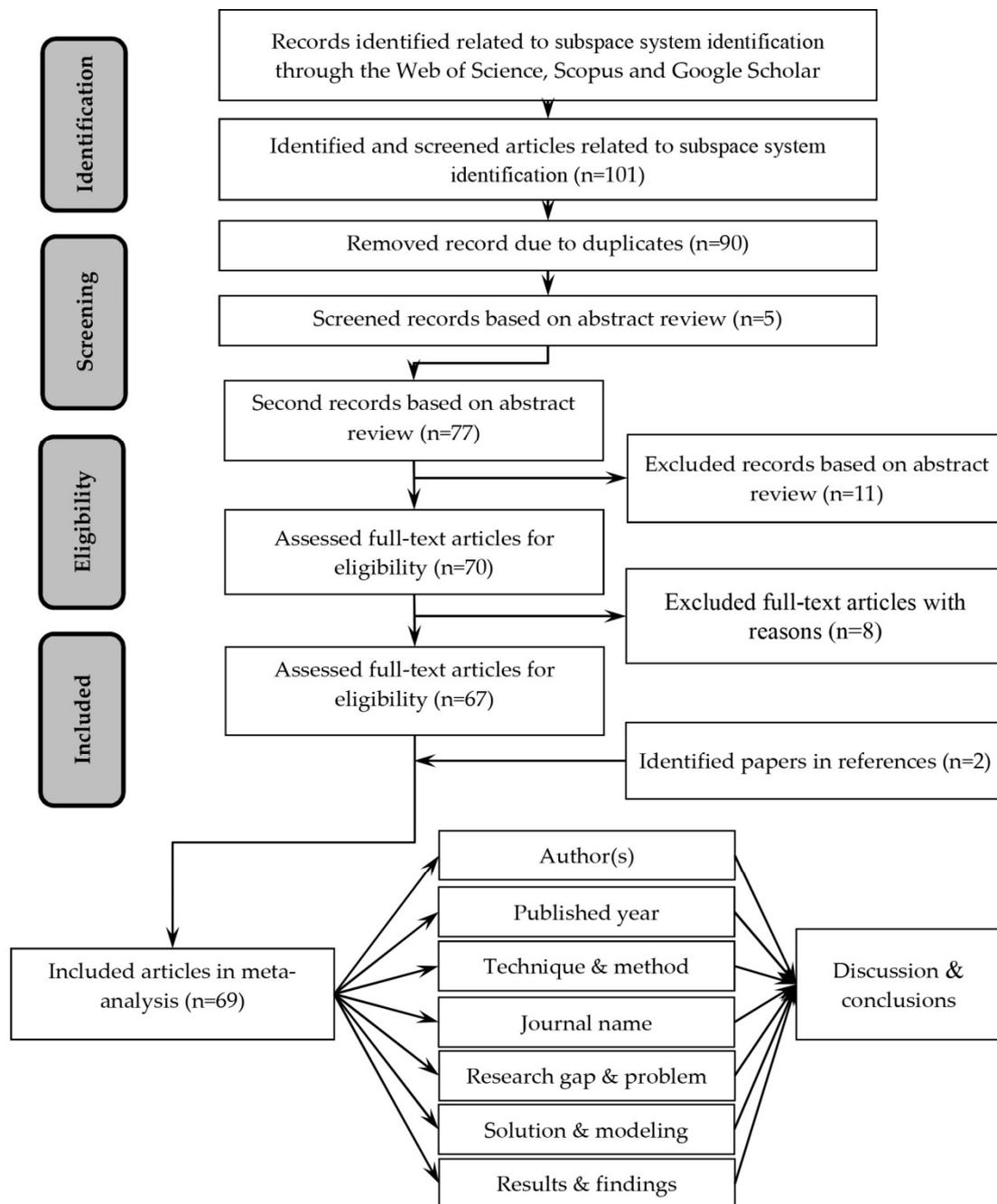
#### 3.1. Literature Search

Literature search was carried out by consulting three databases of Scopus, Web of Science, and Google Scholar for systematic review of the applications and methodologies on subspace-based SHM. Defining keywords for a systematic review and meta-analysis is more than just important. Selecting keywords from subject heading is of the best tools for efficient retrieval and survey of data from database [150]. Hence, in the first step, the following combinations were used in the keyword search: (“subspace system identification” AND (“structural health monitoring” OR “damage detection” OR “fault detection” OR “modal”)). Duplicates and unrelated articles; assessed from title screening; were excluded from the study. Following the database searches and title screening, eligibility of the retrieved records were assessed through abstract screening. The search process was iterative, and the studies that met the inclusion and exclusion criteria were continuously extracted till the end of the study. Moreover, the search terms were refined in the process of becoming familiar with literature. Other search keyword were also added in the course of the review process such as a combination of (“subspace system identification” AND (“output-only” OR “ambient excitation” OR “civil” OR “stochastic”)).

It is now about 25 years or more since subspace system identification was linked as an approach to the dynamic identification and SHM of civil structures. The literature search and eligibility assessment study shows that the time period 1995–2019 can be divided into two time intervals. The 1995–2008 can be characterized to development of the theoretical foundation and conceptualization of the framework that is discussed in introduction section. Hence, to deal with application and application-related topics more specifically, the scope of the literature search was limited to the papers published in the time frame of 2008–2019. An evaluation process was conducted to determine whether a publication must be retained in the final list.

The literature search was confined to the English language journal papers and the relevant works in the form of book chapters, non-indexed conference papers, editorial notes, master dissertations, doctoral theses, and textbooks were excluded from the review. Abstract review is the first screening of the papers for inclusion or exclusion that is conducted based on the pass/fail criteria. Using this criteria a total of 90 scholarly papers were identified. The duplicated records with redundant information were removed from the final search results. In this stage, 67 papers remained. All the above identified

articles were thoroughly read based on topics and abstracts while unrelated studies were removed. Totally, 69 potentially related studies qualified, as shown in Figure 4.



**Figure 4.** Study flowcharts for the identification, screening, eligibility and inclusion of articles.

### 3.2. Articles Eligibility

Article eligibility was assessed based on full-text reading of each manuscript obtained from the above process. In the final step all identified articles were carefully read in its entirety to confirm the significance and relevance to the review topic. In several previous studies, the combined subspace method is used for modal identification and SHM of civil engineering structures under the seismic excitation. However, the ambient excitation is the most common procedure for SHM of civil engineering structures; as a result the focus in the literature search is more on SSI-COV and SSI-DATA rather than the combined method. In the end, 69 articles were selected for the application of SSI in SHM

of civil structures from 31 scholarly international journals between 2008 and 2019 that satisfied the inclusion criteria.

### 3.3. Summarizing and Data Extraction

In the final step of our methodology, finally 69 articles were reviewed and summarized. Furthermore, all articles were reviewed based on various criteria such as the used technique and method, research gap and results and findings. We believe that, the reviewing, and classifying of articles can help to extract valuable and important information. Consequently, several recommendations were given for future studies. It is noteworthy that the difficult part during the accomplishment of the PRISMA method was to extract the implicit methodology in abstracts and the context of the selected articles. Hence, in order to provide sufficient information and unbiased decisions regarding the approach applied in the analysis, in most cases, the full manuscript was searched. The authors believe that this review could help the readers to find the most relevant and appropriate published studies regarding subspace system identification.

## 4. Distribution of the Subspace-Based Damage Detection Techniques

### 4.1. Distribution of the Papers on SSI-DATA Approach

Table A1 in Appendix A shows those studies which used SSI-DATA technique. A total of 31 studies have used SSI-DATA method alone or combined with other methods in various test structures such as beams and 2D frames, 3D frames structures and buildings, and bridges and other structures.

WSNs are promising future use technology and now are applied for SHM of civil engineering structures. Some of the studies in application of SSI-DATA algorithm are dealt with the limitations of WSNs facilities for data transmission and developing dense networks of low-cost wireless sensors for complex infrastructures [66,151,152]. To deal with the limitations of WSN facilities for data transmission Cho et al. [66] presented a decentralized SSI-DATA algorithm implemented on Imote2-based WSNs. An experimental test of a five-story shear building was used as the verification test. The identification results obtained from decentralized and centralized SSI techniques were close to each other. Kurata et al. [151] developed a novel internet-enabled wireless structural monitoring system for large-scale civil infrastructures. A wireless monitoring system was installed on New Carquinez Bridge to verify the applicability of the proposed framework. The obtained results verified the stable and reliable application of the proposed system on a large number of nodes. Kim and Lynch [152] introduced an indirect SSI-DATA algorithm based on Markov parameters customized for decentralized WSNs. The proposed strategy is verified by dynamic testing of a cantilevered balcony in a historic building. System properties were identified with a high accuracy.

FE model updating is a powerful tool in SHM to ensure that FE analysis reflects the real behavior of structures. Several researches on SSI-DATA were focused on practical limitation of FE updating and to validate a reliable FE model [153–155]. In order to validate FE models by applying identification methods, Nozari et al. [153] implemented an FE model updating framework to identify damage in a ten-story reinforced concrete building. Due to the limitations of experimental responses and measurement errors, the optimization in FE updating problem may reach multiple solutions in the search domain. To deal with this problem, Shabbir and Omenzetter [154] applied a methodology using particle swarm optimization (PSO) with sequential Niche technique (SNT) for FE model updating of a pedestrian cable-stayed bridge. It was shown that the proposed methodology gives more confidence for model updating. In order to know the dynamic behavior of complex buildings subjected to near-fault earthquakes, Foti et al. [155] used output-only EFDD and SSI-DATA to identify modal parameters of two buildings to update an FE model of the damaged structures. Testing was conducted on a complex building which was heavily damaged in an earthquake. After a series of improvements of the model, satisfactory agreement has been reached.

Several researches have been conducted to improve performance of classical SSI-DATA to be applied on continuous time SHM and enhance the efficiency [84,156–158]. In order to track the current structural state from building seismic responses, Chen and Loh [156] developed two recursive SSI-DATA algorithms using Bonafide LQ renewing algorithm and inversion lemma algorithm. Two sets of building seismic response data from a three-story steel structure and a four-story-reinforced concrete elementary school building were used for verification of proposed methods. The results show that subspace system identification inversion with forgetting factor could provide more accurate estimation of the stiffness change. Li et al. [157] developed a reference-based subspace system identification technique to identify structural flexibility using modal scaling factors. A numerical model of an RC bridge and a laboratory-scale simply supported beam were presented to illustrate the robustness of the proposed method. The examples, successfully illustrated the robustness of the proposed method. Dai et al. [158] presented a modified subspace system identification method for modal analysis of structures under harmonic excitation with frequencies close to natural frequencies of the structure. In this method, Hankel matrix was modified by adding harmonic vectors. Application of the algorithm on numerical lumped-mass dynamic system model and an in-service utility-scale wind turbine tower resulted in accurate estimation of the modal parameters. Zhang et al. [84] introduced a CH matrix as a replacement for a Hankel matrix and replaced a projection operator with the classical QR decomposition. A seven-DOF numerical model and experimental test of Chaotianmen Bridge were used to verify the method. An improved computational efficiency without losing the quality and separation of the spurious modes are the advantages achieved using the proposed algorithm. Further details of the selected papers of this section can be found in Table A1.

#### 4.2. Distribution of the Papers on SSI-COV Approach

Table A2 in Appendix A shows the studies with focus on the SSI-COV approach. From the data presented in this table, a total of 25 studies used SSI-COV in various structures including beams and 2D frames, 3D frames structures and buildings, and bridges. Some of these studies integrated SSI-COV approach with preprocessing or postprocessing stages [72,159–163].

In order to smoothen input signal and yield reliable modal parameters, Loh et al. [159] adopted singular spectrum analysis (SSA), for preprocessing of the response signal, and a stabilization diagram for postprocessing of the extracted modal parameters, respectively. The experimental test was carried out for the validation of the proposed algorithm using the long-term monitoring data of Canton Tower high-rise slender structure. It was found that the use of SSA as a pre-processing tool for SSI-COV improved the identifiability of modes using a stabilization diagram. To estimate the tension forces of the cables in cable-stayed bridges, Zarbaf et al. [72] adopted hierarchical clustering algorithm to identify natural frequencies of each stay cable in Veterans' Glass City Skyway Bridge. The agreement between the estimated results and the measured tension forces was good. Due to the need for the removal of bias and variance errors in the modal parameter estimation, Reynders et al. [161] used first-order sensitivity of the modal parameters and stabilization diagram to remove bias errors. A simulation model and measured vibration data of a beam and a mast structure were used for the verification purpose. The practicability of the proposed method was confirmed in a real-world application.

In order to improve the identifiability of the weakly excited modes Zhang et al. [162] introduced component energy index (CEI) and an alternative stabilization diagram to identify spurious and physical modes. A simulation model of a seven-DOF mass-spring-dashpot (MSD) system and the experimental model of a metallic frame structure subject to wind load were used for verification of the proposed scheme. Good performance was observed especially for the measurement data with low SNR. In order to identify structural changes in presence of environmental variation, Carden and Brownjohn [163] proposed a fuzzy clustering algorithm to extract state parameters from real and numerical poles. Data from Z24 Bridge and Republic Plaza Office Building in Singapore were used for experimental verification of the method. The inflicted damage on the Z24 Bridge was successfully

identified using the proposed method. The shifts in modes of the Plaza Office Building in Singapore were also clearly captured.

Several studies on SSI-COV were concerned with discrimination environmental and operational effect during the identification process by improving the inherent performance of the SSI-COV algorithm. Döhler et al. [164] presented an efficient and fast SSI-COV damage detection that is robust to changes in the excitation covariance. Three numerical applications were presented. It is reported that the new approach can better detect and separate different levels of damage.

Several researches on SSI-COV dealt with improving the damage detection process by introducing a damage sensitive and noise-insensitive features [71,165–169]. To discriminate changes in modal parameters caused by damage from those occurred due to environmental factors, Basseville et al. [165] designed a damage detection algorithm using null space residual,  $\chi^2$  test and a statistical nuisance rejection. A vertical beam made of steel and aluminum was tested under controlled ambient temperature for verification of the presented scheme. The relevance of the presented algorithm was illustrated using a laboratory-scale test structure. Balmès et al. [170] proposed the use of subspace residual as damage feature and  $\chi^2$  tests to discriminate the effect of noise from estimated modal parameters. A simulated bridge deck with controlled temperature variations was used for verification of the proposed method. Efficiency of the method on simulation model for various temperature cases was confirmed. Zhou et al. [168] used a residual of the subspace system identification and global  $\chi^2$ -tests for damage detection. A full-scale bridge benchmark was validated by numerical simulation. It is reported that the damage in tower was detected in the same time. In order to consider nonlinearity of structures for identification of modal characteristics Sun et al. [71] defined a nonlinear subspace distance as damage feature. The proposed index was validated by the data obtained from a viscoelastic sandwich structure (VSS) subjected to an accelerated ageing. It is shown that the designed index is very effective to evaluate the health state in the structure. Ren et al. [169] adopted Mahalanobis and Euclidean distance decision functions for the pattern recognition of a proposed damage index. One numerical signal and two simulated FE dynamic beam models were used for the verification of the proposed procedure. The method was capable of locating damage in FE beam structures. Details of selected papers which adopted the SSI-COV approach in their identification process are presented in Table A2.

#### 4.3. Distribution of the Papers on Combined Subspace System Identification Approaches

Table A3 in Appendix A shows the studies which used combined subspace system identification techniques. Based on results presented in the table, a total of 13 studies have used combined subspace system identification algorithms for analysis of various test structures. Though subspace system identification algorithm is originally a TD identification approach, some researchers have developed the FD version of the combined subspace system identification algorithm for identification of the vibration parameters [81,171]. In order to meet interpretation challenges associated with system identification obtained from measured sensor data, Urgessa [81] presented two FD system identification methods by adopting ERA and the McKelvey subspace system identification approaches. FE model of a plate structure was used for verification of the proposed algorithms. The methods were able to predict natural frequencies and damping ratio with a high accuracy. Akçay [171] proposed a two-step subspace algorithm by calculating minimal realization of the power spectrum samples and a canonical spectral factor. A numerical example is provided to illustrate the performance of the proposed algorithm. Serious drawbacks regarding reliable performance of the algorithm dealing with short data records and corrupted data were reported. Several studies are concerned with improving the performance of the combined subspace system identification algorithm [41,42,172,173] to deal with these problem. Kim and Lynch [41,42] presented a theoretical framework to extract actual physical parameters of structures using a physics-based model and a data-driven mathematical model. Numerical model of a multi-DOF shear building structure and experimental verification test of a six-story steel frame structure under support excitation were tested. The proposed grey-box framework has shown a promising performance

for SHM of civil engineering structures exposed to base motions. Gandino et al. [172] developed a novel multivariate input–output SSI-COV formulation for modal parameter identification. A 15-DOFs numerical example and an experimental application consisting of a thin-walled metallic structure were used for verification. The obtained results were similar to those reached by data-driven method. Verhaegen and Hansson [173] introduced data-driven input-output N2SID using convex nuclear norm optimization. Mathematical formulations are furnished to derive the theory of the N2SID algorithm. The sequence for derivation of the system parameters from N2SID was clearly demonstrated. Table A3 provides the information of the selected papers which applied combined subspace system identification approaches.

#### 4.4. Comparison among Identification Methods

Several subspace system identification methods have been applied for modal identification and VDD of civil structures. These methods are in the form of output-only or input–output algorithms. Output-only algorithms are used for vibration analysis of ambient excited structures. SSI-DATA and SSI-COV techniques are the two main output-only subspace system identification algorithms. SSI-COV algorithm uses the covariance of the raw time-history to reduce the dimensionality of the measurement data. Data reduction in SSI-DATA is performed using QR projection of the Hankel matrix. Both subspace system identification algorithms use SVD to determine the order of a dynamic system. The calculation of the covariance matrix is faster compared to calculation of the QR decomposition which is much slower. However, both algorithms are reported to perform well for the estimation of the modal parameters whereas SSI-DATA is expected to be theoretically more robust due to avoiding squaring up of the measurement data. Combined subspace system identification algorithm is used for identification of system parameters with known input data. More reliable results are obtained by using the input-output subspace system identification compared to the output-only scheme. Several algorithms are introduced based on the classical SSI-COV, SSI-DATA and the combined method to improve the performance of the subspace system identification for SHM application. The performance is enhanced either by change in structure of the underlying algorithms or by adding preprocessing or postprocessing steps to the original subspace system identification algorithm. In some cases, the subspace system identification algorithm is integrated with other analytical methods to yield higher performance.

#### 4.5. Test Structure's Classification

Selected articles are categorized into five different test structures including 2D structures, 3D frame structures and buildings, bridge structures, multiple test structures, and others. 2D structures are in the forms of simply supported beam, cantilever beam or 2D shear frames. Most of the applied 3D test structures for verification of subspace system identification algorithms in this study were in the form of 1-span shear building tested on shaking table for progressive damage test. Furthermore, some of the algorithms are applied into structures from two different categories such as “bridge, and 3D frame and buildings” which are classified within the multiple test structure groups. The category “others” include structures such as dam, wind turbine, chimney, tensegrity systems and sandwich structures. The distribution of the selected paper list based on test structures and applied subspace system identification methods is shown in Figure 5.

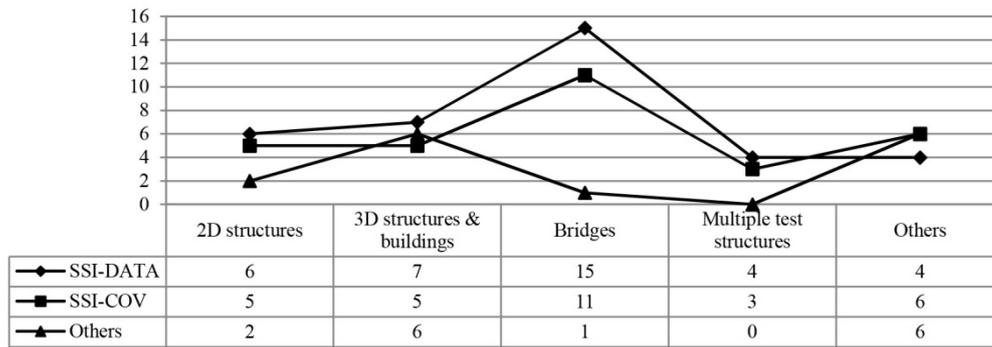


Figure 5. The distribution of the paper by the test structures and the applied subspace system identification methods.

### 5. Conclusions

In this review paper, the theory and applications with respect to recent developments of the subspace system identification approach in the modal identification and health monitoring of civil engineering structures are comprehensively reviewed. The applied test structures of these selected papers were classified into five groups. These papers are accessible via three important databases of Scopus, Google Scholar, and Web of Science. To this end, 69 studies were carefully selected about subspace system identification application in health monitoring of the civil engineering structures based on title, abstract, introduction, research method, and conclusion. A number of important issues with respect to subspace system identification application were extracted from the present literature review. The extensive of the selected studies were published in 2016. In total, papers were classified into five test structures including 2D frame structures, 3D frame structures and buildings, models tested on multiple structures and others. In this regard, bridge structures were the most likely candidate structure with 25 papers using SSI-DATA, SSI-COV, and combined subspace system identification approaches. In addition, 31 international journals were considered in the current review paper.

Output-only methods are generally applied for identification of the state-space parameters under ambient excitation where the combined method used seismic or forced vibration excitation. Test structures for input-output subspace system identification are generally 2D or 3D frames or buildings where in output-only subspace system identification, test structures are generally bridges. SSI-DATA is the most researched subspace system identification approach in health monitoring of the civil structures. The obtained results for SSI-DATA and SSI-COV algorithms are overall similar in the case of accuracy, but the computation time SSI-COV is much lower than the SSI-DATA approach. The research works contributed with the SSI-COV are mainly concentrated on improving the quality of the obtained modal parameters using preprocessing or postprocessing techniques. Stabilization diagram is the most applied postprocessing method to select physical modes and distinguish false and spurious modes. Additionally, some studies are conducted to introduce appropriate damage features for SHM. However, the research studies in the SSI-DATA are generally devoted to enhancing the intrinsic structure of the subspace system identification algorithm itself, or integrating with other soft computing approaches to deal with the problem.

This study confirms that subspace based damage detection approaches can help researchers and practitioners to overcome some uncertainties regarding the quality of the condition assessment in various application areas. The present review has some limitations, which are common to these types of studies and can be considered as an object of future studies. First, this review is focused mainly on the application of a subspace system identification algorithm for the health monitoring of civil structures rather than the theory and development of the classical subspace-based techniques. Second, the available papers of the publishers in Web of Science, Scopus, and Google Scholar till the end of November 2019 have been included in the identification process.

This review can be expanded to include future studies. Another limitation is that the collected data were from international journals while non-indexed conferences papers, textbooks, doctoral theses, and masters projects were excluded from the current study. Therefore, in the future studies, the data from the aforementioned resources can be collected and the obtained results can be evaluated with the data reported in this study. However, the authors believe that this paper has comprehensively reviewed the most published papers in international journals focusing on several aspects such as the authors, publication year, technique and methods, research purpose, gap and contribution, solution and modeling, and results and findings. It is recommended that future papers focus on different functions. In this regard, the current review paper presented some opportunities to find gaps that can be addressed for further study directions.

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## Nomenclature

ARMA	Auto-regressive moving average
CC-SSI	Crystal clear stochastic subspace identification
CSI	Combined deterministic-stochastic subspace identification
CSMI	Continuous structural modal identification
DOFs	Degrees of freedom
DSI	Deterministic-stochastic subspace identification
EFDD	Enhanced frequency domain decomposition
ERA	Eigensystem realization algorithm
FD	Frequency-domain
GRA	General realization algorithm
ITD	Ibrahim Time-domain
MIMO	Multiple-input multiple-output
MNExT-ERA	Multiple-reference natural excitation technique combined with ERA
MOESP	Multivariable output error state-space
MSD	Mass-spring-dashpot
OKID	Observer/Kalman filter identification
PPM	Polynomial power spectrum method
PRISMA	Preferred reporting items for systematic reviews and meta-analyses
PSO	Particle swarm optimization

PZM	Power spectrum z-transform method
RD	The random decrement
RSSI-COV	Covariance-driven recursive stochastic subspace identification
SHM	Structural health monitoring
SIMO	Single-input multiple-output
SMI	Structural modal identification
SMIT	Structural modal identification toolsuite
SSI	Stochastic subspace identification
SSI-COV	Covariance-driven stochastic subspace system identification
SSI-DATA	Data-driven stochastic subspace system identification
ST-SSI	Short-time stochastic subspace identification
TARMA	Time-varying analysis method using time-dependent auto-regressive moving average
TD	Time-domain
TFD	Time/frequency domain
VDD	Vibration-based damage detection
VSS	Viscoelastic sandwich structure
WSNs	Wireless sensor networks
WT	Wavelet transform

## Appendix A

**Table A1.** Distribution of the papers based on SSI-DATA techniques.

Author	Method	Research Objective	Research Gap and Problem	Solution and Modeling	Result and Finding
Priori et al. [174]	SSI-DATA	Proposed rules to determine the number of block rows and columns of the Hankel matrix	Need to define optimum value for -defined parameters in SSI	Vibration test on a scaled structure and tests on a real-size RC building.	Rules to determine the lower bound for the user-defined parameters of the SSI algorithm was discussed.
Pioldi and Rizzi [175]	Improved SSI-DATA	Adopted an improved SSI-DATA procedure and a refined FFD algorithm	Need to identify modal parameters from short-duration, non-stationary, earthquake-induced response	A numerical model of a ten-story frame structure under a set of selected earthquakes	Both rFDD and the SSI-methodologies turn out robust results.
Chen and Loh [156]	Improved SSI-DATA	Developed two algorithms of recursive SSI with BonaFide LQ renewing algorithm and matrix inversion lemma algorithm	Need to track structural current state from the building seismic response	A three-story steel structure and a four-story-reinforced concrete an elementary school building	The SSI Inversion with forgetting factor can provide more accurate estimation of the stiffness change.
Li et al. [157]	Reference-based SSI-DATA	Developed a SSI technique to identify structural flexibility using the modal scaling factors	Need to correct estimation of the structural modal scaling factor and flexibility characteristics	A numerical model of a RC bridge and a laboratory-scale simply supported beam	The Examples successfully illustrated the robustness of the proposed method.
Park and Noh Hae [176]	SSI-DATA	Adopted an iterative parameter updating	Need to deal with practical limitation of output-only methods	A numerical model of a 5-story shear building	The modal parameters are estimated with 85–99%. Updating further improves these accuracies.
Nozari et al. [153]	SSI-DATA	Implemented a FE model updating framework to identify damage in a 10-story reinforced concrete building.	Need to validate FE models by applying identification methods	A ten-story reinforced concrete building	The updated model parameters shown considerable variability across different sets.
Dai et al. [158]	SSI-DATA	Presented a modified SSI method for modal identification under harmonic excitation	Need for a SHM system to ensure proper performance and save maintenance costs in wind turbines	A numerical lumped-mass system model and an in-service utility-scale wind turbine tower	The modal parameters of the first two modes were accurately estimated.
Tarinejad and Pourgholi [30]	SSI-DATA	Proposed an algorithms using stochastic realization theory and canonical correlation analysis for operational modal analysis	Need to deal with uncertainties of unknown nature such as ambient noises and measurement errors.	Experimental tests on Shahid-Rajaei arch dam and Pacoima dam	More accurate natural frequencies are obtained compared to those of classic SSI.
Soria et al. [177]	SSI-COV, SSI-DATA & SSI-EM	Studied the influence of the environmental and operational factors using three SSI-based modal analysis techniques	Need to a low-cost vibration-monitoring system	A steel-plated stress-ribbon footbridge was used as the experimental case study	An excellent correlation for the lowest persistent vibration modes was reported.
Loh et al. [178]	SSI-DATA	Used SSI and a technique to remove spurious modes	Need to identification of an earthquake-induced structural response	One 7-story RC building and one mid-isolation building and an isolated bridge	The identified system dynamic parameters were used for seismic assessment of the structures.
Lardies [179]	SSI-DATA	Presented four different algorithms of (i) block Hankel matrix, block observability and block controllability and shifted versions	Need to determine the transition matrix	Numerical model of a two-DOF system and experimental model of a cantilever beam	The same results are obtained using these algorithms.

**Table A1.** *Cont.*

Author	Method	Research Objective	Research Gap and Problem	Solution and Modeling	Result and Finding
Cho et al. [66]	SSI-DATA	Presented a decentralized SSI-DATA implemented on the Imote2-based WSN	Need to deal with the limitations of WSNs facilities for data transmission	Experimental test of a 5-story shear building model using WSNs	The identification results obtained from the WSNs and the centralized were close to each other.
Shabbir and Omenzetter [154]	SSI-DATA	Proposed a particle swarm optimization with sequential niche technique (SNT) for FE updating	Need to deal with the limitation of FE updating problem	FE model updating of a pedestrian cable-stayed bridge is used to analyze the method	The proposed methodology gives the analyst more confidence for model updating.
Junhee et al. [180]	SSI-DATA	Applied a SSI technique to model guided wave propagation	Need to model complex dynamics behavior of wave propagation.	Welded plates of varying thicknesses	The algorithm was capable to simulate the propagating waves.
Yu et al. [181]	SSI-DATA	Investigated the time-varying system identification in temperature-varying environments.	Need to confirm the applicability of time-varying modal parameter identification algorithm	A steel beam with a removable mass	The effect of the thermal stresses on the natural frequency reduction is revealed
Foti et al. [155]	SSI-DATA	Used output-only EFDD and SSI to identify the modal parameters of two building to update a FE model	Need to know the dynamic behavior of complex buildings subjected to near-fault earthquakes	A complex building which was heavily damaged in an earthquake.	At first low agreement was found but finally satisfactory agreement has been reached.
Kurata et al. [151]	SSI-DATA	Developed a novel internet-enabled wireless structural monitoring system tailored for large-scale civil infrastructures	Need to develop dense networks of low-cost wireless sensors for large and complex infrastructure	Installed wireless monitoring system is on New Carquinez Bridge	The obtained results verified the stable and reliable application of the proposed monitoring system.
Ubertini et al. [182]	SSI-DATA	Proposed an automated SSI-based modal identification procedure, using clustering analysis	Increasing need to diffusion of continuous monitoring systems for structural condition assessment	Two bridges of iron arch bridge and a long-span footbridge	The reliable performance of the automated long term monitoring was verified.
Döhler et al. [102]	SSI-DATA and SSI-COV	Proposed an efficient stochastic SSI algorithm by reformulation and computation of uncertainty bounds	Need to a fast and reliable damage detection algorithm	The field vibrational data of the Z24 Bridge	The algorithm is both computationally and memory efficient.
Döhler and Mevel [27]	SSI-DATA & SSI-COV	Derived a new efficient algorithm for multi-order system identification using SSI method	Need to distinguish the true modes from spurious structural modes	Z24 Bridge data	The presented methods are faster than the conventional algorithms in use.
Kim and Lynch [152]	Indirect SSI-DATA	Introduced a SIMO model of SSI algorithm based on Markov parameters customized for the decentralized WSNs	Need to decentralized data processing due to its advantages consumption.	Dynamic testing of a cantilevered balcony in a historic building	System properties were identified with a high accuracy.
Zhang et al. [84]	Improved SSI-DATA	Introduced a CH matrix as a replacement of Hankel matrix and projection operator for QR decomposition	Need to improve the low computational efficiency of the SSI-DATA	A numerical model of a 7-DOF and an experimental model of Chaotianmen bridge	Computational efficiency and reject of the spurious modes without losing the quality are achieved.
Lardies and Minh-Ngi [183]	SSI-DATA	Applied improved SSI using modal coherence indicator to eliminates spurious modes and Morlet wavelet	Need to overcome the concerns about health state of the tension cables in cable-stayed bridges	Two experiments of stay cables in laboratory scale and Jinma cable-stayed bridge	The robustness and reliability of the subspace and the WT transform methods are demonstrated.

Table A1. Cont.

Author	Method	Research Objective	Research Gap and Problem	Solution and Modeling	Result and Finding
Weng and Loh [83]	RSI-DATA & RSSI-DATA	Developed an on-line tracking of the estimated system parameter using response measurements	Need to develop an on-line tracking of modal parameter without human interference	Seismic excitation of a 3-story steel frame and a 2-story reinforced concrete frame	Accurate results were obtained by identifying the model properties.
Carden and Mita [131]	SSI-DATA	Investigated the methods applied to estimate uncertainty and confidence intervals and summarized drawback of each method.	Need to deal with finite lengths of data for modal identification	Numerical models of a MSD system and experimental model of a suspension bridge	The drawbacks for reliable application of residual bootstrapping procedure are reported.
Brownjohn et al. [184]	SSI-DATA	Implemented the SSI procedure in the ‘virtual instrument’ for SHM of a 183 m reinforced concrete chimney	Need to overcome the concerns about large-amplitude response induced by interference effects	A 183 m reinforced concrete chimney for a coal-fired power station	The damping values show the tune mass damper to have been effective in controlling response.
Hu et al. [135]	SSI-DATA and SSI-COV	Introduced tools for modal identification in LabVIEW named SMI and CSMI	Need to computational tools for modal identification and long term vibration monitoring	Field data collected at Pinhão bridge and Coimbra footbridge	The potential of this software to obtain the natural frequencies and modal damping.
Marchesiello et al. [128]	ST-SSI	Two approaches of continuous wavelet transform and the ST-SSI is proposed and compared.	Need to take into account the effect of system variation in time-variant systems	A pinned–pinned bridge carrying a moving load	CWT was found to suffer from the drawback of edge effects compared to ST-SSI.
Deraemaeker et al. [185]	SSI-DATA	Examined two damage features obtained from SSI and peak indicators	Need to consider the effect of environmental condition in analysis	A numerical bridge model subject to noise and damage	All damages were detected using the proposed procedure.
Alcioğlu and Luş [105]	SSI-DATA & SSI-COV	Investigated the performance of output-only SSI-DATA and SSI-COV algorithms	Need to objectively determine the practical benefits of SSI and to find out the potential difficulties	FE model, physical laboratory model of a small scale steel frame and a long span suspension bridge	Both SSI algorithms are found to perform quite satisfactorily for operational modal analysis.
He et al. [186]	SSI-DATA	Simulated the wind-induced vibration response of a Bridge using FE model and stochastic wind excitation model	Need to study systematically the effects of damage scenarios in long-span cable-supported bridges	Simulation of the wind-induced vibration response of Vincent Thomas Bridge,	The framework was validated to study the effects of damage scenarios.

**Table A2.** Distribution of the papers based on SSI-COV techniques.

Author	Method	Research Objective	Research Gap and Problem	Solution and Modelling	Result and Finding
Zarbaef et al. [72]	SSI-COV	Adopted a hierarchical clustering algorithm to obtain tensions in the stay-cable	Need to estimate the tension forces of cables in cable-stayed bridges	The ambient response of the Veterans' Glass City Skyway Bridge	A good agreement between the estimated results and measured tension forces was observed.
Reynders et al. [187]	SSI-COV	Validated a method for estimating the (co)variance of modal parameters identified using SSI	Need to estimate the variance of modal parameters	A damaged prestressed concrete bridge and a mid-rise building	Good agreement is reported between the predicted uncertainty and the observation data.
Wu et al. [188]	SSI-COV	Developed a new SSI methodology to identify modal parameters of stay cables	Need to extract numerous modes in stay cable	The ambient response of the three stay cables of Chi-Lu Bridge	The feasibility of this new approach is verified successfully.
Zhou et al. [168]	SSI-COV	Used the residual of the SSI and global $\chi^2$ -tests built on that residual for damage detection.	Need to exploit possible damages in structure using output data	A full-scale bridge benchmark validated by numerical simulation	The damage in tower was detected in the same time.
Karami and Akbarabadi [189]	SSI-COV	Proposed an algorithm in two steps by integrating structural health monitoring with semi-active control strategy	Need to damage detection of large building structures using limited output data	A numerical model of a shear building structure	The algorithm could identify the damage accurately with saving time and cost due.
Attig et al. [160]	SSI-COV	Investigated performance of the combined SSI algorithms and a stabilization diagram for tensegrity systems	Need to identify structural changes in Tensegrity systems	A numerical models of a tripod simplex structure and a Geiger dome	Effectiveness of the proposed methodology was verified using the proposed methodology.
Sun et al. [71]	SSI-COV	Defined a nonlinear subspace distance to detect the deviation from the normal state, and reflects structural states.	Need to consider nonlinearity of the structures for identification of modal characteristics	A VSS subjected to accelerated ageing	The designed index is very effective to evaluate the health state.
Khan et al. [190]	SSI-COV	Employed EDA, outlier analysis and cross correlation to elucidate any defects and anomalies in the data.	Need to distinguish between abnormal data malfunctioning, and anomalies of the sensors	A cable stayed bridge over Sutong Yangtze river	The method was very effective to provide accurate real life results in the continuous SHM of bridges.
Guo et al. [191]	SSI-COV	Proposed a near-real-time hybrid framework for system identification of structures to deal with stationary and transient response	Need to simultaneously deal with stationary and transient responses of the applied excitation loads	Extensive numerical simulations as well as analysis of the internet enabled data of Burj Khalifa	The efficacy of the framework is demonstrated.
Mekki et al. [192]	SSI-COV	Applied a null-space Hankel matrix of correlation estimates	Need to study the dynamic response of structures on composite structures	Numerical and experimental of a one span composite bridge deck, formed by wood and concrete	The first natural frequencies were determined with an uncertainty below 0.15%.
Döhler et al. [164]	SSI-COV	Presented an efficient and fast SSI damage detection that is robust to changes in the excitation covariance	Need to investigate the change in unmeasured ambient excitation properties	Three numerical model	The new approach can detect better and separate different levels of damage.
Tondreau and Deraemaeker [119]	SSI-COV	Studied the effect of noise on the uncertainty of obtained modal parameters using SSI	Need to study the resulting uncertainty for modal analysis using the stochastic SSI method.	A numerical test of a supported beam, and the experimental model of a clamped-free plate	The uncertainty on modal damping and eigenfrequencies may exhibit a non-normal distribution.
Dohler et al. [193]	SSI-COV	SSI-COV together with their confidence interval estimation and a null space-based VDD	Need to consider the intrinsic uncertainty for a robust and automated SHM	A large scale progressive damage test of the S101 Bridge in Austria.	The proposed method is able to clearly indicate the presence of damages.

Table A2. Cont.

Author	Method	Research Objective	Research Gap and Problem	Solution and Modelling	Result and Finding
Hong et al. [85]	SSI-COV	Adapted enhanced canonical correlation analysis (ECCA) for state variable estimation	Need to determine model order and prevent failure of identification system	A FE simulation and field measurements of the Carquinez suspension bridge	The reliability of the new algorithm was verified through numerical analyses.
Loh et al. [159]	SSI-COV	Adopted singular spectrum analysis (SSA), for pre-processing and stabilization diagram for post-processing	Need to do some pre-processing to smooth noisy signal,	The experimental test on Canton Tower high-rise slender structure	The use of SSA as a pre-processing tool improved the stabilization diagram identifiability of modes.
Döhler & Mevel [101]	Modular and scalable SSI-COV	Proposed a modular and scalable SSI approach to improve retrieving the system matrices of a full system	Need to deal with the problem of merging sensor data of non-simultaneously recorded setups	Mathematical formulations	The application of the method for has been verified successfully.
Chauhan [194]	SSI-COV	Developed a unified matrix polynomial approach (UMPA) to explain the SSI algorithm	Need to explain and derive various experimental modal analysis algorithms in an easy way	Mathematical formulations	The sequences for derivation the system parameters from output data are clearly demonstrated.
Ren et al. [169]	SSI-COV	Introduced a new damage feature to reject the environmental effects. Two distance functions adopted for pattern recognition	Need to extract the damage-sensitive but environment-insensitive damage features	One numerical signal and two simulated FE dynamic beam models	The method was capable to locate damage in FE beam structures.
Basseville et al. [165]	SSI-COV	Designed a damage detection algorithm based on null space residual and a $\chi^2$ test to exploit the thermal model	Need to discriminate changes in modal parameters caused by damage	A vertical beam made of steel, and aluminium tested under controlled ambient temperature.	Relevance of the presented algorithms was illustrated using the laboratory test case.
Whelan et al. [195]	SSI-COV	Deployed a wireless sensor network with higher sampling rates with reliable large, dense array sensory network	The need to enhance data analysis methods for the data obtained from remote sensor-based SHM	A single-span integral abutment bridge	The feasibility and maturity of the distributed network of wireless sensor was confirmed.
Balmès et al. [170]	SSI-COV	Proposed using subspace residual as damage feature and $\chi^2$ tests to discriminate the effect of noise	Need to remove the effect of temperature and other environmental factors for VDD.	A simulated bridge deck with controlled temperature variations	Efficiency of the method on simulation model for various temperature models was confirmed.
Carden and Brownjohn [163]	SSI-COV	Proposed a Fuzzy Clustering Algorithm to extract state parameters from the real and numerical poles	Need to identify structural changes in the presence of environmental variation	The data from Z24 Bridge and the Republic Plaza Office Building (POB) in Singapore	The damage inflicted on the Z24 Bridge and the shifts in modes of the POB were clearly captured.
Reynders et al. [161]	SSI-COV	Used first-order sensitivity of the modal parameter and stabilization to remove bias errors	Need to remove of bias and variance errors in the estimated modal parameters	Simulation model and measured vibration data of a beam and a mast structures	Practicability of the proposed method was confirmed in real-life application.
Balmès et al. [170]	SSI-COV	Investigated damage localisation using clustering in the large-scale FE models.	Need for localization of damage in vibration-based methods.	A FE model of a bridge deck with a large number of elements	The algorithm was able to locate the damage in case of a FE model.
Zhang et al. [162]	SSI-COV	Introduced component energy index together with an alternative stabilization diagram to identify spurious and physical modes	Need to improve the identifiability of weakly excited modes	A 7 DOF MSD system and the experimental model of a metallic frame	Good performance was observed especially for measurements with low SNR.

**Table A3.** Distribution of the papers based on combined SSI techniques.

Author	Method	Research Objective	Research Gap and Problem	Solution and Modelling	Result and Finding
Marchesiello et al. [196]	Non-linear SSI	Introduced a modal decoupling procedure and the modal mass	Need to deal with variability of the identification results due to nonlinear effects	A multi-storey building model with a local nonlinearity	Significant improvements were highlighted in estimates obtained by the proposed approach.
Shi et al. [197]	MOESP	Used two SSI techniques sequentially and iteratively to extract modal parameters and estimates the ground acceleration.	Need to estimate the structural parameters of a under unknown ground excitation	A numerical and a laboratory test of a 3-story building model	The estimation of structural parameters is satisfactory and fairly robust.
Zhong and Chang [52]	Combined SSI	Adopted an orthogonal projection and IV approach to eliminate the effect of earthquake input and noise	Need for modal identification of time-varying structures under non-stationary earthquake excitation	Numerical model of a four DOF structure and a three DOF experimental building model.	The proposed algorithm can track the modal parameters quite well.
Verhaegen and Hansson [173]	input-output N2SID	Introduced a SSI using convex nuclear norm optimization	Need to an identification scheme for multivariable state space model by improving the classical methods	Mathematical formulations	The sequences for derivation the system parameters from N2SID is clearly demonstrated.
Potenza et al. [51]	SSI-COV & combined SSI	Focused on the seismic monitoring of a historical structure by means of an advanced WSNs	Need to analyse critical issues in the wireless data acquisition	The historical structure of the Basilica S. Maria di Collemaggio.	The monitoring system permitted to update a finite element model in the current damaged conditions.
Al-Gahtani et al. [198]	Deterministic SSI	Performed deterministic SSI on the obtained response signal after applying wavelet de-noising methods	Need to an system identification with low sensitivity to the inflicted noise	A numerically simulated model and experimentally measured rotor	The use of multi-wavelet de-noising result in a more accurate identification.
Gandino et al. [172]	Combined SSI-COV	Developed a novel multivariate SSI-COV-based formulation for modal parameter identification	Need to a reliable SHM systems with no memory limitation and work properly in presence of noise	A 15-DOF numerical example and an experimental application of a thin-walled metallic structure	The obtained results are similar to those reached by data-driven method.
Kim and Lynch [41]	SSI-DATA & combined SSI	Presented a theoretical framework to extract physical parameters using a physics-based and a data-driven models	Need to estimate physical modal parameters of structures	A multi-DOF shear building model and an experimental test of a six-story steel frame.	The proposed grey-box framework has shown a promising performance for SHM of civil structures.
Akçay [171]	Frequency domain subspace	Proposed a subspace algorithm by calculating minimal realization of power spectrum and a canonical spectral factor	Need to deal with the problem of system identification of dynamic systems.	A numerical example	Some drawback regarding reliable performance of the algorithm is highlighted.
Urgessa [81]	McKelvey SSI-FD	Presented two system identification methods based on eigensystem realization and the McKelvey frequency-domain SSI	Need to meet interpretation challenges associated with system identification	FE model of a plate structure	The methods were able to predict natural frequency and damping ratio with high accuracy.
Weng et al. [199]	Input-output SSI	Proposed a damage assessment method by adopting input/output SSI algorithm and a model updating method.	The need to validate FE models by applying input-output identification methods	A1/4-scale six-story steel frame structure and a two-story RC frame	The method was able to detect the damage locations and quantify the damage severity.
Reynders and De Roeck [58]	Combined SSI-DATA	Adopted modal decoupling and a new criterion from model reduction theory for automation of the modal analysis process.	Need to extract frequency content of limited number of modes from the narrow band ambient excitation	Field vibration data obtained from the Z24 Bridge	The most complete set of modes reported so far is obtained.
Kurka and Cambraia [167]	Multivariable combined SSI	Proposed a Multiple-input multiple-output (MIMO) input-output SSI method that uses multi-input and single-output (MISO) realization	A need to provide a robust model order determination using SVD.	Numerical model and a free-free spatial truss	Accurate modal parameters were estimated using this method.

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