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The Past, Present and Future of Structural Health Monitoring: An Overview of Three Ages

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ABSTRACT

This paper presents an overview of the discipline of structural health monitoring (SHM), organised in terms of three proposed ages. The first age is delineated by the prehistory of SHM and the period where nondestructing testing methods evolved into an organised set of principles built upon physics-based models; this age ended when the model-based approaches reached an impasse in terms of their ability to properly deal with real-world problems. The second age of SHM began with a transition to data-based methods based on statistical pattern recognition, which provided a holistic approach to SHM problems for the first time. This age arguably ended when the methods foundered in situations where the necessary training data were scarce. It is argued here that the third age began with the development of population-based SHM, which has been designed to overcome the problem of data scarcity. As there is very limited space in a single article to provide a comprehensive overview, an appendix has been provided here that gives a very systematic bibliography of SHM reviews—a meta-bibliography.

1 | Introduction

The realisation of methods for automated and objective assessment of structural health and safe residual life has long been regarded as a highly desirable research objective across the whole spectrum of engineering disciplines. Timely and accurate detection and assessment of damage offer clear benefits in terms of both economy and safety. The advantages of reaching this goal have led to a great deal of research and development over decades. Progress has been made and the technology is arguably on the cusp of widespread industrial uptake. The aim of this paper is to give an overview of the historical developments in structural health monitoring (SHM), paying close attention to stagnation points in that history and explaining how the relevant barriers were overcome. There will be discussion of some of the challenges that remain and a suggestion of how SHM needs to further evolve in order to meet those challenges.

It is useful to begin with a definition; in quite general terms, '*SHM is the process of implementing a damage-detection strategy for aerospace, civil and mechanical engineering infrastructure*' [1]. It is important to note at the outset that SHM is not the only means of implementing a `damage-detection strategy'; the overview [2] discusses four main classes of diagnostic technologies: nondestructive evaluation (NDE), SHM, condition monitoring (CM) and statistical process control (SPC). However, SHM will be the focus of the current paper; the authors taking the viewpoint that CM and SPC are distinguished by their focus on problems outside the structural context (CM is largely concentrated on rotating machinery and SPC is directed at chemical and material processes). Furthermore, NDE will mainly be discussed in historical terms as a discipline which evolved (in a sense), into SHM. NDE will be understood here to encompass damage-identification methods based on taking the structure or system of interest out of operation and inspecting using instruments requiring an a *priori* specification of the area of concern.

The SHM process will be considered to compliment (or extend) traditional NDE[1] by evolving the technology into a quantitative, autonomous, online and *in situ* monitoring methodology, applicable on a more global scale. Many regard SHM to be distinguished by the fact that it exploits permanently installed sensor networks and does not take the structure of interest out of operation. SHM also has the goal of minimising the human-in-the-loop component of the damage assessment process. This paper will focus on the evolution of SHM technologies consistent with these distinctions.

A `history' of SHM cannot disregard previous histories; in fact, the current work will present quite a personal viewpoint. To provide balance, an Appendix is provided here, which attempts to give a comprehensive list of previous reviews and overviews. Considering the broader literature, a search using one of the most widely used browsing tools reveals that the term "*Structural Health Monitoring*" first appeared in a paper title in 1990 [3]. However, it is important to note that there are many papers describing studies that can be classified as SHM (even though the term was not used), that predate the 1990 paper, such as the extensive literature on damage detection in offshore oil platforms that appeared in the 1970s and 1980s [4]. Furthermore, the large body of literature that focusses on CM of rotating machinery (which is regarded here as a subdomain of SHM) dates back to the 1920s [5]. There are many SHM literature reviews or overview articles that have appeared over the years (as detailed in the Appendix). These articles provide detailed insight into the evolution of various aspects of SHM technology [4, 6]. However, some of these reviews are quite dated [4, 6] and most—because of the large amount of SHM literature that has appeared in the last 30 + years—only have a narrow focus; for example, on certain specific sensing technologies (e.g., smart phones), specific application areas for SHM (e.g., offshore structures) or specific data analysis methodologies (e.g., deep learning). As well as providing references, Appendix summarises and categorises this extensive body of SHM review literature.

In the face of such a vast body of SHM review material, it is important to identify the contribution that this overview article aims to make. Like many technologies, SHM has seen repeated cycles of relatively-rapid advances followed by periods of stagnation. In SHM specifically, the stagnation often results when methodologies that have been demonstrated with numerical simulations or with well-controlled laboratory experiments are faced with real-world applications. The resulting hiatus is then overcome when new technologies, often based on developments from fields outside of NDE and SHM, are adapted to address SHM shortcomings. The intent of this paper is to summarise, at a high level, the evolution of SHM technology, based on the premise that two of the stagnation points have actually required something of the order of a paradigm shift in order to make progress; this premise leads naturally to the breakdown of SHM history into three ages. This paper will attempt to delineate these three ages, arguing that the third age has just begun. It is also important to note that this summary will only have a limited discussion of specific SHM application domains. Such discussions are left to the considerable number of application-specific review articles summarised in Appendix.

2 | The Genesis of SHM: The First Age

As discussed in Farrar and Worden [6], the interest in identifying damage has been around as long as man has used tools and built structures. Early qualitative damage-detection methods were based on human tactile sensing of changes in perceived vibration and/or sensing of audible changes in acoustic signatures. The most-cited example is perhaps the railway wheel-tapper's method. In many cases, such approaches to damage detection can be very effective, and they are so intuitive that many people adopt these practices in everyday life, for example, qualitatively identifying damage in an automobile based on changes in vibration or acoustic signatures—so-called `squeaks and rattles'. Often, these methods satisfy the online, *in situ* monitoring aspect of the SHM definition above; however, they are still heavily dependent on the human-in-the-loop in the measurement and data analysis aspects of SHM. One cannot argue that these human-sensing approaches to SHM represent a "rapid advance" as they have developed over millennia. Furthermore, the qualitative nature of these assessments and the limitations of human-sensing modalities place strict limitations on such approaches, that is, **a *stagnation point***. These limitations motivated the development of what are currently known as NDE or nondestructive testing (NDT) technologies [7]. Modern NDE techniques arguably started to emerge in the late 1800s; they saw more rapid advancement and adaption in practice during the 1940s–1960s, particularly as portable instruments became available which could measure various physical effects like acoustic emissions. By the 1970s and 1980s, traditional NDE also reached a stagnation point, associated with several issues:

1. Many of the methods were, and still are, qualitative (not quantitative).
2. Most NDE methods can only examine a relatively small area of the structure or system; they are very local, not global.
3. Some methods can only be applied to exposed surfaces, which often necessitates disassembly of a system to apply the NDE method; not online, *in situ* monitoring.
4. The application of the methods and interpretation of the results requires significant human interactions in the measurement and data analysis processes; not autonomous.
5. In almost all cases, the structure or system must be taken out of service to apply the NDE method; again, not online or *in situ* monitoring).

With this stagnation point in NDE technology as a motivator, the structural dynamics community started to actively pursue research in what is now known as SHM. The basic hypothesis that this community adopted was based on the widely accepted theory that a structure's dynamic response to operational and/or environmental loading, or to loads applied specifically for the diagnostic purposes, is a function of the structure's mass, stiffness and energy dissipation properties. There is now extensive experimental evidence from a wide variety of application domains (aerospace, civil and mechanical engineering systems) that supports this theory. Possibly the most significant paper in this early stage of SHM development is [8]. The hypothesis is:*damage will alter the dynamic properties of a structure, which in turn will alter the measured dynamic response of the structure. Therefore, damage can be inferred from changes in the structure's measured dynamic response*. In principle, all dynamic properties might change as a result of damage, but the exact damage modality will shape which parameters are most sensitive. For example, a fatigue crack will produce a localised increase in flexibility or decrease in stiffness, with a consequent reduction in resonance frequency which is, in turn, observable by experimental modal analysis. If the crack faces rub as the structure vibrates, there will be an increase in damping. Such observables, which are sensitive to damage, are commonly called *features*, particularly in the context of data-based SHM. Such features, which are derived from the mass, stiffness and-energy dissipation properties of the structure of interest, are *global properties* of the structure, so it was anticipated that changes in dynamic response measurements could identify damage on a more global scale. It is therefore clear to see why there was so much interest in SHM, at a time that NDE was experiencing the stagnation described above. If the SHM hypothesis was shown to be valid, it would address four of the five issues above associated with the stagnation point for NDE, leaving only the issue that the vibration-based methods still required significant human interaction in the data-analysis process.[2] Two main technologies then emerged, associated with vibration-based SHM.

2.1 | Forward Modelling

By the 1980s, and as direct result of the evolution of commercial finite-element (FE) codes, the structural dynamics community had well-developed tools for forward-modelling approaches to predict when and where damage might occur in a structure. These forward-modelling approaches consisted of creating a discrete digital structural model based on the geometry and material properties of the actual structure of interest, the boundary conditions and the structural element connectivity. Next, an assumed load, or a loading scenario based on *in situ* measurements, was digitally applied, and the response of the structure was predicted by the model using computer calculations. The predicted response would then be compared to some strength, stability or deformation failure criteria to assess if the given loading would produce damage.

At the time, the processor and memory capabilities of digital computers limited the level of detail in such models to tens or hundreds of degrees of freedom in the 1970s. In contrast, today at one co-author's laboratory, problems on the order of thirty to fifty *million* degrees of freedom are routinely analysed. Arguably, FE modelling is one of the most revolutionary engineering tools to have been developed in the last century. Unfortunately, this approach to modelling engineering systems is not very effective for near-real-time damage assessment in operating structures, because of the still-existing limits to available computer power. There are also gaps in the physical knowledge required. It is difficult to incorporate the local initial conditions (e.g., material flaws and residual stresses) that are present in all engineered systems, into such models; unfortunately, these initial conditions often dictate damage initiation. It is generally difficult to model actual damage mechanisms, for example, delaminations in composite materials; this difficulty also extends to modelling joints in (even) undamaged structures, for example, welds, rivet lines and adhesive joints. Finally, the loading applied to a structure in simulation does not necessarily reflect the actual loading experienced by a system, especially if the structure experiences random loading. It is also difficult to accurately simulate the temporal and spatial variability in operational and environmental loads that occur in most deployed structures. As a result, dynamic inputs need to be defined that represent the envelope of load distributions that might be encountered (e.g., aerodynamic loading on aircraft, hydrodynamic loading on offshore platforms and seismic loading on civil infrastructure) or a worst-case loading scenario that can be defined. In general, these approaches are adequate for most design purposes, but they do not reflect the actual loading that dictates the current state of structural health. Finally, these simulations require experimental validation over a wide range of operational and environmental conditions and such validation can be costly and time-consuming. These issues generated a *stagnation point* for forward modelling, and the SHM community turned to *inverse-modelling* methods.

2.2 | Inverse Modelling

Within the time-frame of the 1970s–1980s, two other factors contributed significantly to the advancement of SHM technology. Firstly, there was an industry 'pull' for better damage-detection technology, primarily from four distinct application domains: aerospace structures, civil infrastructure with particular emphasis on bridge structures, offshore oil platforms and rotating machinery. In addition, there was emerging technology from other fields that could be directly adapted to the SHM problem, including lower-cost sensing, increased computing power, data storage and improved telemetry, as well as new sensing modalities. As depicted in Figure 1, based on the foundations provided by NDE and its associated stagnation, the industry 'pulled' relevant enabling technologies from other fields and drew significant interest from researchers in the structural dynamics community; SHM emerged as a serious discipline in the early 1990s, with a primary focus on deterministic inverse modelling.

Throughout the 1990s and into the early 2000s, significant research was carried out on different deterministic *inverse-modelling* approaches to SHM. The general concept behind such approaches is that one begins by measuring the dynamic response of the structure in its undamaged condition. Typically, dynamic properties such as mode shapes and modal frequencies are extracted from these measurements to use in the modelling process. As an example, the first mode obtained from 26 accelerometer measurements on a bridge structure [9] is shown in Figure 2. Next, an FE model of the bridge is constructed. Properties of the model, in this case the material properties of the concrete deck and piers and the connectivity of the girders to the piers, are adjusted so that the model accurately predicts the undamaged measured modal properties. In the case of the bridge example [9], the first mode shape predicted by the model is shown in Figure 3. This step

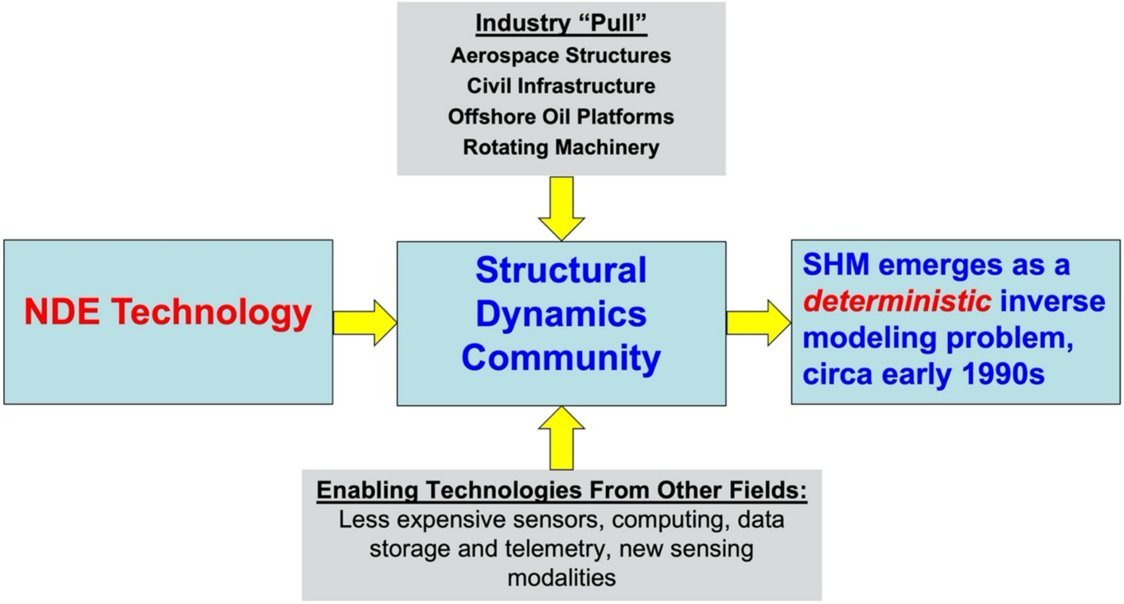

FIGURE 1 | The confluence of NDE technology, industry 'pull' and the enabling technologies that led the structural dynamics community to develop deterministic inverse-modelling approaches to SHM.

FIGURE 2 | First mode of a highway bridge in its undamaged condition, as identified from experimental measurements.

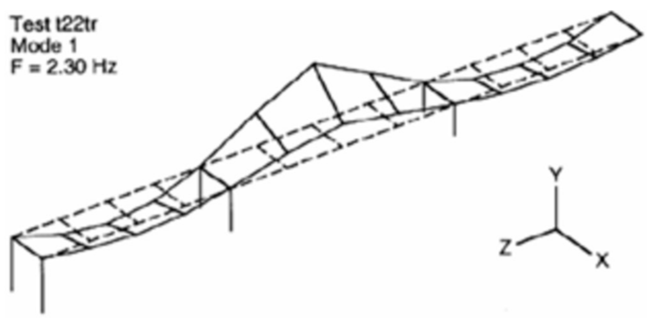

FIGURE 4 | First mode of the bridge identified from experimental measurements after damage had been introduced.

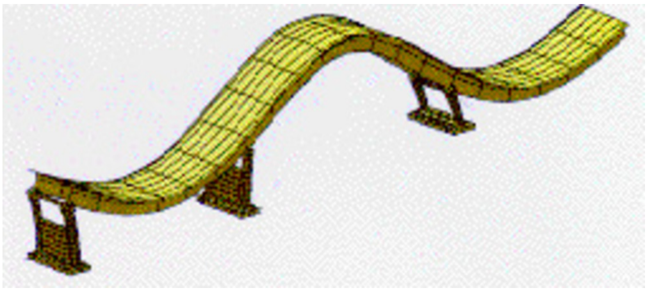

FIGURE 3 | First mode of the bridge predicted by an FE model that has been updated to match the response observed in Figure 2.

is referred to as *FE model updating* and presents significant technical difficulties as it is an ill-posed problem, despite the development of various sophisticated mathematical methods [10]. At this point, the assumption is made that an experimentally validated model of the undamaged structure is available. The process is then repeated after a possible damage event (or after some 'inspection' period).

For the case discussed here, a cut was made in one of the bridge girders at the middle of the centre span to simulate damage from a fatigue-crack. New dynamic response measurements were made, and new modal properties were extracted from the data acquired, with the structure in a *possibly* damaged condition (Figure 4). The validated undamaged FE model was updated again based on the new modal properties acquired from the potentially damaged structure so that the model now accurately predicted those measured modal properties (Figure 5). The stiffness or flexibility indices of the two models were then compared to identify that damage was present, where the damage was located and to provide a quantified assessment of the extent of damage (Figure 6).

The earliest examples of using these inverse-modelling approaches to SHM appeared in applications to offshore oil platforms that were conducted in the 1970s[3]. In the 1980s and 1990s, much of research into this approach was undertaken by the aerospace engineering community who were focussed on assessing damage to truss structures that would be deployed on the international space station. However, as more research

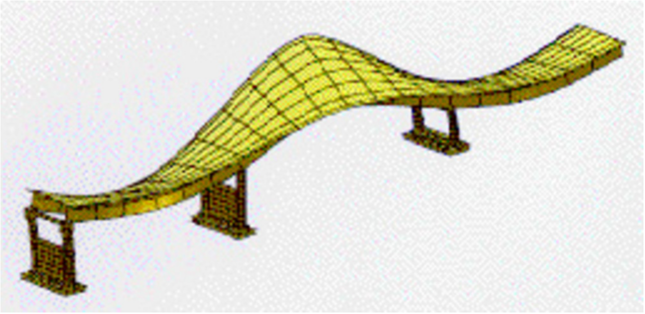

FIGURE 5 | First mode of the bridge predicted by the FE model after the model shown in Figure 3 has been updated a second time to match the results shown in Figure 4.

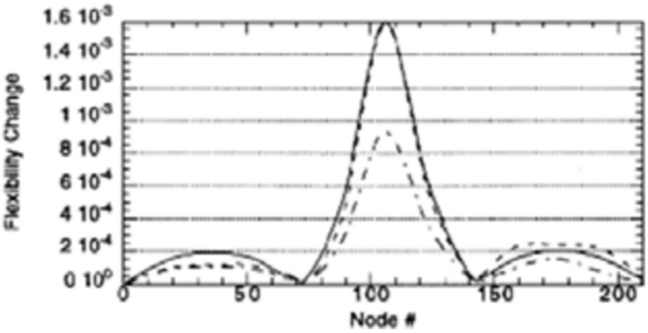

FIGURE 6 | Change in flexibility coefficients that resulted from the introduction of damage into the bridge.

was conducted on these inverse-modelling approaches and they were applied to *in situ* structures with their associated sources of variability, some significant challenges were encountered that led to **a new stagnation point** in the evolution of deterministic inverse-modelling approaches to SHM. The issues included the following:

1. Almost all inverse-modelling approaches at the time assumed that the structure could be accurately modelled as a linear system before and after damage. For the bridge example discussed above, the torch cut in the girder that was used to simulate a fatigue crack was actually wide enough that it did not open and close under the applied dynamic loading, so in this case the linear system assumption was valid—the simulated crack only changed the geometry of the structure. However, an actual `breathing' fatigue crack could exhibit nonlinear response characteristics under actual operational and environmental loading conditions, which would pose challenges for the model-updating process as the features used in the updating process (modal frequencies, mode shapes) are not strictly defined for the damaged systems.

2. Typically, there is a significant mismatch in the experimentally measured DOFs (26 in the bridge example above) and the DOFs in the numerical model (on the order of 10,000 for the bridge example), which necessitates either extrapolation or condensation in the updating process. These processes can adversely impact the ability to identify local damage.

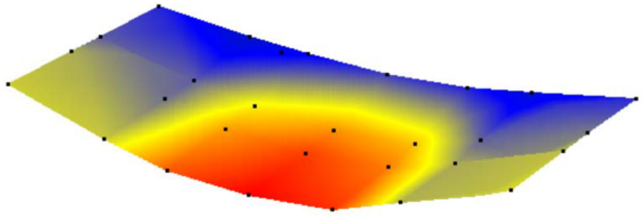

FIGURE 7 | First bending mode of a bridge span measured at 10:00 AM.

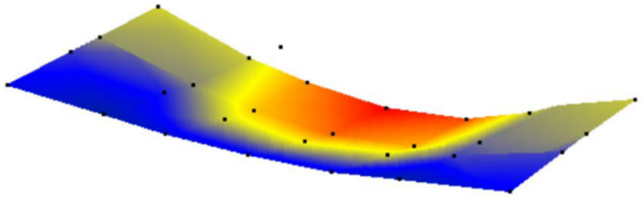

FIGURE 8 | First bending mode of the bridge span shown in Figure 7, measured at 5:30 PM the same day.

3. The inverse-modelling approaches have difficulty accounting for the environmental and operational variability that is associated with almost all *in situ* structures. As an example, Figure 7 shows the first mode of an undamaged bridge structure measured in the morning, and Figure 8 shows the same mode when measurements were made in the early evening on the same day [9, 11, 12]. This bridge is symmetric about its centreline and oriented in a north–south direction. The skewed first bending mode is caused by the sun heating one side of the bridge in the morning and the other side in the afternoon. The question then becomes which mode to use in the model-updating process. Note that for *in situ* monitoring, varying traffic loading will also produce changes in the mass properties of the bridge.

4. Damage usually needs to be severe enough to alter the load path through the structure before it will produce significant changes in the low-frequency global dynamic properties of the structure that are used in the updating process.

5. Extracting the features from the measured data (most commonly modal parameters), updating the models and assessing changes in the models that are indicative of damage usually require a significant human-in-the-loop effort and can be computationally time-consuming.

3 | The Second Age: Data-Based SHM

The technical issues associated with the model-based approach to SHM are largely the result of the following: (a) the difficulty of providing an accurate model of the structure (and damage), (b) the difficulty in accommodating uncertainties (unknown loading conditions, operational and environmental variations (variations in measurements) and (c) the ill-posed nature of the inverse problem. To address the stagnation point associated with inverse- modelling approaches to SHM, around the year 2000, a number of researchers realised that the damage-detection process could be posed as a problem in *statistical pattern recognition* (SPR) or *machine learning* (ML). Following a period of exploration by the community, a quite general SPR paradigm for SHM was proposed that included the following steps [13]:

1. Operational evaluation.
2. Data acquisition.
3. Feature selection and extraction.
4. Statistical model development for feature discrimination.

Tables 1–3 attempt to track, at a high level, the evolution of technologies that have been used by the SHM community to address Steps 2–4 of this paradigm.

The SPR paradigm is very general and, in fact, does not preclude the use of deterministic physics-based models. However, the major impact to the field that resulted from the realisation that SHM is best defined as a problem in SPR was the adaptation of mature pattern-recognition technologies previously developed for other applications (e.g., econometrics, speech pattern recognition, credit-card fraud detection, radar and sonar detection

TABLE 1 | Evolution of sensing technology used in structural health monitoring.

Sensing, data processing and telemetry technologies	Approximate time of adoption by the SHM community
Qualitative visual, audio and tactile feel	As long as man has used tools and built structures
Quantitative sensors (strain and acceleration)	1940s
Quantitative sensors (velocity)	1950s
Specialty sensors (e.g., neutron detectors for reactor core barrel diagnostics)	1960s
Eddy-current noncontact proximately sensors	Late 1960s
Real-time fast Fourier transform analysers	1970s
Continued reductions in cost of computer processor and memory hardware	1980s to present
Fibre-optic sensors	Mid-1990s
Wireless embedded systems	Early 2000s
Energy harvesting	Early 2000s
Macrofiber composite sensor/actuators	Early 2000s
Robotic inspection systems	Early 2000s
Video-based motion measurements	Mid 2010s
Augmented reality	Mid-2010s

TABLE 2 | Evolution of damage-sensitive features used in structural health monitoring.

Features	Approximate time of adoption by the SHM community
Qualitative vibration amplitudes and acoustic frequencies	As long as man has used tools and built structures
Quantitative vibration amplitudes	1940s
Statistical model parameters (e.g., signal root mean-square amplitude)	1940s
Physics-informed waveform comparisons	1970s
Modal parameters	1970s
Inverse model updating	1970s
Time series model parameters and residual errors.	Late 1990s
Time-frequency measures (e.g., Holder exponent)	Early 2000s
Information measures (e.g., entropy measures)	Early 2000s
High-dimension features (used with deep learning)	Mid-2010s

TABLE 3 | Evolution of statistical modelling and data science applications to structural health monitoring.

Of statistical modelling and data science technology	Approximate time of adoption by the SHM community
Rotating machinery signal statistics (1940s)	1940s
For the most part statistics and data science was ignored by the inverse modelling community	1970s-Early 2000s
Statistical process control	Mid-1990s
Novelty detection	Late 1990s
Machine-learning classifiers	Early 2000s
Auto-encoders	Early 2000s
Detection theory	Mid-2000s
Info-gap robustness assessments	Early 2010s
Value of information	Mid-2010s
Deep learning	Mid-2010s
Population-based SHM	Early 2020s

and syndromic surveillance for epidemic outbreaks). A significant advantage of the adoption of SPR was that a great deal of the associated technology was probabilistic and thus provided a natural and powerful means of accommodating uncertainty. Furthermore, ML and SPR were undergoing a period of massive development in the 21st century, and the advances being made in machine-learning algorithms for pattern recognition were also being adapted to the SHM problem.

The SPR methods resulted in data-driven approaches to SHM that are free from the more rigid constraints imposed by physics-based modelling. As mentioned above, these approaches have been shown to be better suited to handle the operational and environmental variabilities that are encountered in all *in situ* SHM applications. Additionally, these methods are well suited for online, *in situ* monitoring, and with *sufficient training data*,[3] these methods can minimise the human-in-the-loop aspect of the SHM decision-making process. Finally, it should be noted that as these data-driven methods were developed, they led to the definition of a set of fundamental axioms for SHM [14, 15], a set of `universal' guiding principles.

At the same time (the early 2000s) that the data-driven methods were beginning to be adapted to SHM, lots of research on ultrasonic guided-wave approaches to SHM was reported in the literature and at SHM conferences. However, guided-wave approaches arguably tend to suffer from the same limitations as most NDE methods. In their current state of development, for the most part, they do not have the ability to be deployed for online, *in situ* monitoring and they require significant human interaction.

Since the early 2000s, there has been a significant amount of work on data-driven approaches to SHM, and although these approaches addressed some of the issues with inverse, deterministic-modelling approaches, they too had reached a *point of stagnation* in the mid-to-late 2010s. The issue with these data-driven methods primarily stems from the fact that they are almost completely dependent on training data. To account for operational and environmental variability, the training data may need to be acquired for long periods of time to encompass most of the variability that might be expected. Furthermore, it is rare that training data are available from the damaged systems. To overcome these limitations, some researchers have proposed to turn to *population-based SHM* in the early 2020s.

4 | The Third Age: Population-Based SHM

The current section is a little more speculative; it is not yet clear that population-based SHM (PBSHM) represents a paradigm shift in the sense that moving to data-based SHM proved to be; however, what is true is that PBSHM clearly has the potential to overcome the data challenges that appeared to stagnate the discipline recently.

The main problem is with the availability of data. A data-based approach requires data appropriate to the diagnostic problem under consideration. For a given structure, damage detection can be carried out in an *unsupervised way*, in which only data for the normal condition are required. SPR/ML technology based on novelty detection then suffices to detect deviations from normal condition [16]. If a higher-level of damage identification is needed—for example, damage-location—a *supervised* classifier algorithm will be needed and this will require damage-state data spanning all the possible states of interest, labelled accordingly. There is a clear problem here for very high-value structures; most high-value structures are designed conservatively, so that damage within the design life is rare; if damage does occur, damage-state data will not be available because (a) the structure is retired and so monitoring is not needed anymore or (b) the structure has been repaired and is now in a new normal condition. It is financially inconceivable that copies of an aircraft say, would be damaged in multiple ways to provide data to train an algorithm; providing data from forward modelling would provide problems as discussed in Section 2.

One way out of this dilemma is provided if the structure of interest is an identical copy of another structure for which damage-state data are available. One could then train on the data-rich structure and assume that the resulting classifier generalises to the data-poor structure. Unfortunately, even nominally-identical structures will often differ enough that generalisation is not guaranteed, for example, because of manufacturing variations or differences in the environment in which the structure is embodied. Fortunately, a recent development in ML allows one to develop classifiers for data-poor structures, given only data for a `similar' problem. This technology is called *transfer learning* (TL) [17]. The important point here is that the problems of interest have to be 'similar'; if there are significant differences, the process of TL can make matters *worse*—a phenomenon called *negative transfer*. The idea of PBSHM then is to monitor a *population* of structures, so that diagnostic capability for a data-poor structure is possible if the population contains another data-rich structure which is similar to the initial one.

It is useful here to introduce some terminology. The data-rich structure which helps the inference is referred to as the *source* structure; one also refers to the source SHM problem. The data-poor structure of interest for which inference is required is called the *target* structure. If the population of structures is composed of nominally identical objects—like a wind farm composed of the same model of turbine—it is referred to as a *homogeneous* population. If one has a homogeneous population, one is faced with a simpler PBSHM and a broader range of techniques becomes available, based on the fact that one can *assume* that the SHM problems are similar [18]. A more complicated situation arises when the population contains quite different structures—the *heterogeneous* case [19–21].

The most general PBSHM problem—for heterogeneous populations—breaks down into two main stages:

1. Given a new target structure, can one find another structure in the population similar enough to act as a source, so that positive transfer is ensured.

2. Carry out the transfer.

Neither of these problems is at all simple. In the first case, the proposed solution has been to find an abstract representation of the structures, so that the representations live in a metric space, so that 'similarity' is replaced by a 'distance' in the space; low distance implies high similarity. The construction of the abstract representation is carried out in two stages, as depicted in Figure 10, for a wind-turbine.

First, one identifies the main components of the structure; one tries to capture the *essence* of the structure of interest by breaking it down into the simplest set of components which express the topology and functionality of the structure (Figure 9a); these components are then labelled (Figure 9b). The resulting model is called an *irreducible element* (IE) model. The IE model is then converted to an *attributed graph* (AG), where the vertices of the graph correspond to IEs, and an edge is added if two elements are connected in the physical model [19]. The term 'attributed' means that each vertex or edge can carry a vector of parameters; for example, the node attributes might summarise the dimensions and material properties of a given IE. The critical point here is that the space of graphs is a metric space and thus equipped to give a distance between structures. If that distance is small enough, one can proceed to attempt transfer between structures. In fact, once the AG model is established, there are multiple means of constructing the metric; the method used in [19] is based on finding the maximum common subgraph of the two AGs of interest; the greater the common subgraph, the greater the similarity and the lower the distance.

There are many different methods of transfer learning; so far, the main methods used for SHM have been based on *domain adaptation* (DA). DA is based on the idea of moving the feature data into a harmonised latent space (i.e., representing the data in both domains), constructed such that a classifier trained on source data will also generalise to target data [22].

The remainder of this section will illustrate the processes; for details on the theory and computation, the reader is referred to the original references [19, 20]. One of the first major tests of PBSHM—going beyond synthetic data—was to examine a population of real bridges. A population of eight structures was considered [19], composed of two beam-and-slab bridges,

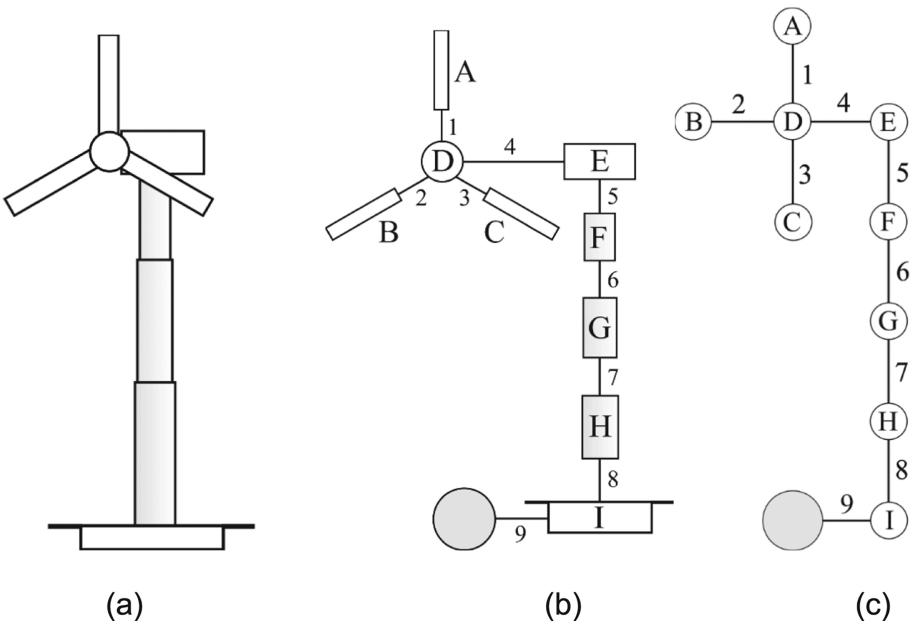

FIGURE 9 | Determining the abstract representation of a wind-turbine structure: (a) identification of main components of the given structure, (b) labelling the *irreducible elements*, (c) conversion to the attributed graph. The shaded grey circles in (b) and (c) represent 'ground' nodes, so the edge '9' is the connection to ground.

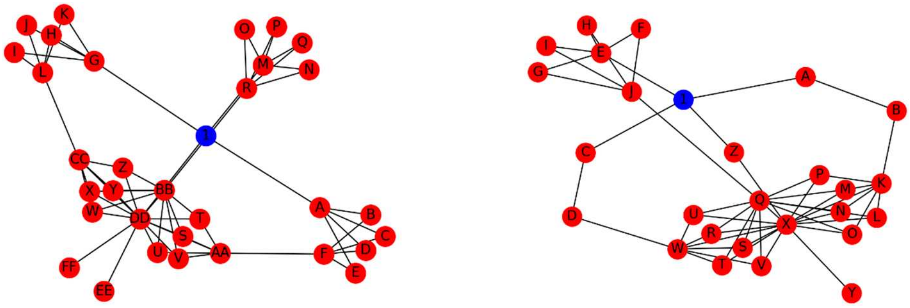

FIGURE 10 | AG representations of two real beam-and-slab bridges.

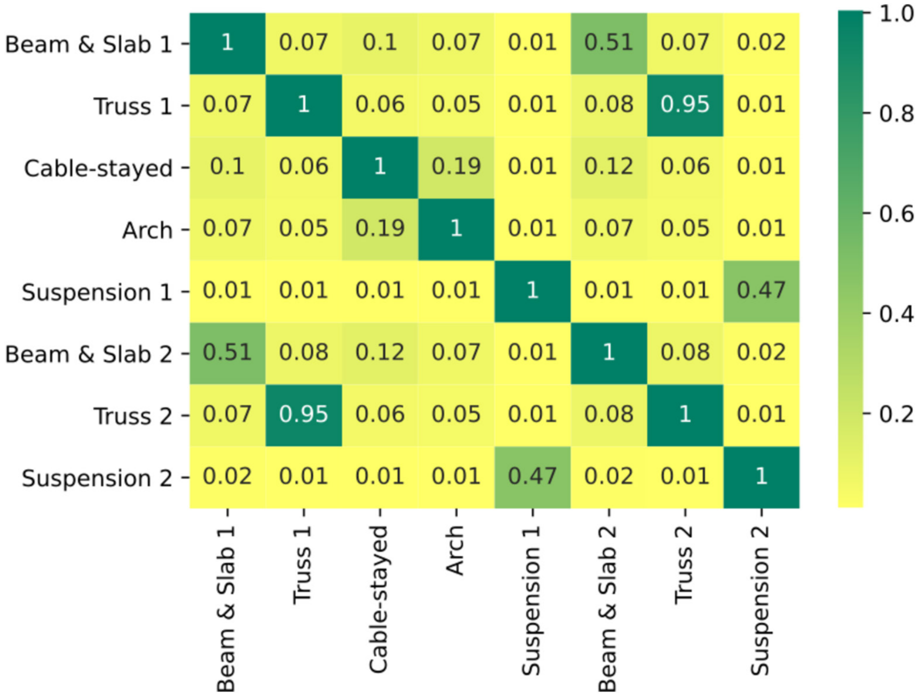

FIGURE 11 | Comparison/similarity scores across a population of eight real-world bridges.

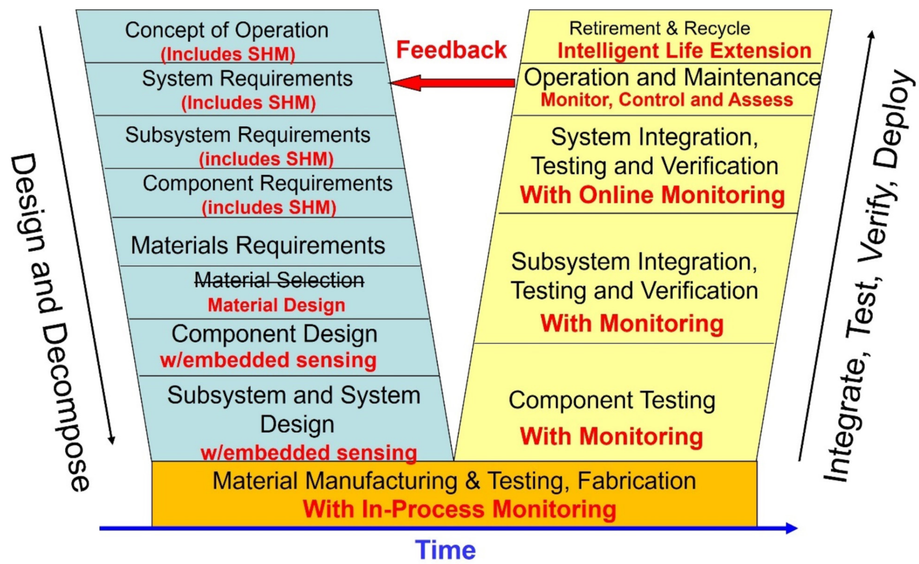

FIGURE 12 | The items in red show how robust SHM technology can modify the traditional lifecycle engineer V beginning in the upper left when the concepts of operation are defined for the system.

two truss bridges, two suspension bridges, an arch bridge and a cable-stayed bridge. Figure 10 shows the IE models for the two beam-and-slab bridges. It is amusing to note that the two graphs appear to look more like birds than bridges; this is because the topology is captured by the graph topology which is independent of the way in which the graphs are represented visually.

The first major test of the concepts was to compute the similarity measures for the population; the results are shown in Figure 11. The metric used is the maximum common subgraph, scaled so that complete correspondence gives a score of unity, while complete dissimilarity gives a score of zero. The results are excellent; the pairs (beam-and-slab, truss and suspension) give high similarities; all other comparisons give low scores. Note that the diagonal compares each bridge to itself, thus yielding perfect scores.

The next PBSHM stage is to effect transfer; this has been illustrated using a number of simulated examples and also on real-world structures. Successful transfer between two real-world bridges is demonstrated in [23, 24]; transfer between the wings of two different models of aircraft is shown in [25]. Once transfer is realised, the results of classifiers can be incorporated as usual in appropriate decision-support tools.

5 | Conclusions and Remaining Challenges

The previous sections have summarised the evolution of SHM technology over an approximately 50-year period. Those approaches taken to develop SHM capabilities have reached a number of stagnation points (as all technologies experience), and then new approaches have been developed to address the stagnation points. The major stagnation points allow a convenient division into three ages of SHM. Despite all these efforts, there are still outstanding challenges that will require further advances in SHM technology. Some of these challenges, which can be tied to the four-step SPR paradigm, are as follows:

- The ability to define the damage that needs to be identified (operational evaluation). Particularly challenging for new systems without any maintenance history and for the new paradigm of population-based SHM
- There is no widely accepted procedure to demonstrate rate of return on investment in an SHM system (operational evaluation). In fact, this issue might be addressed by an appropriate risk-based approach to SHM/PBSHM, and research in this direction is currently underway. Many companies consider such economic analyses proprietary
- Saint Venant's principle: This principle is essentially the issue of sensitivity to damage. Discontinuities in a structure only influence the strain field in the local vicinity of the discontinuity; this places a lower bound on the number of sensors needed and their density on the structure (data acquisition). In terms of vibration-based SHM, global dynamic properties are typically insensitive to local damage
- There is no accepted SHM sensing system design methodology (data acquisition)—almost all systems, with the exception of rotating machinery monitoring systems, are unique designs.
- Understanding how the damage-sensitive features will change with varying environmental and operational conditions (feature extraction, data acquisition and statistical modelling). Additional sensors may be needed to characterise the environmental and operational conditions. Training data may need to be acquired over long periods of time to fully capture the range of variability the system will experience.
- Developing a principled approach to feature selection (feature extraction). Most feature selection is done by physics-informed engineering judgement
- Setting classification boundaries (statistical modelling). Defining these boundaries will entail managing the trade-off between false-positive and false-negative damage indications and can potentially be accommodated in a full risk/utility-based (PB)SHM.
- Managing large volumes of data from an online monitoring system (data acquisition). The SHM community can learn how this data management is done successfully in other contexts where ML is applied (credit card fraud detection, syndromic surveillance).

There is also a fundamental disconnect between the way researchers and industry practitioners develop solutions to SHM problems. Researchers typically begin by defining a methodology and then show it works on a generic problem (often matched to the methodology). On the other hand, industrial practitioners tend to define a specific problem and then develop a solution for that problem without concern for how generally that method can be applied.

Finally, there is the 'Catch 22' issue of SHM system validation. Owners and operators will not invest in SHM technology until it can be demonstrated on *in situ* systems. However, in general, these owners and operators will not allow the people developing the SHM system to potentially damage a high-capital expenditure system solely to demonstrate the capabilities of the SHM system. Currently, validation data from damaged systems are scarce, although PBSHM has been conceived to overcome this problem if possible.

It is anticipated that this stagnation point-new development cycle of SHM technology advancement will continue into the foreseeable future. The goal of this process will be to develop simple (can be operated by engineers and technicians without advanced degrees), reliable, adaptable, low-cost, low-maintenance SHM systems. These systems will be validated with numerically generated and experimentally acquired data so that the SHM system has a quantified probability of detection for predefined damage scenarios under all anticipated sources of operational and environmental variability. A major potential of PBSHM lies in removing the boundaries between model-based and data-based SHM. As all structures are converted into AG representations, PBSHM does not distinguish between models and real structures. In fact, there is no requirement that a model have such high fidelity that it closely matches the structure; in fact, it need only be close enough for transfer, in the population metric. Such advancements will allow SHM technology to become part of the lifecycle design process early on when defining the concepts of operation for a new engineered system as illustrated in Figure 12. In parallel with these, technological advancements will be the further development of codes and standards for the implementation of SHM in different application domains. An extensive set of codes and standards currently exists for rotating machinery monitoring and (e.g., ISO standards [26]), and a relatively new standard has recently appeared for aerospace applications [27]. Such codes and standards are a clear indication that the technology has matured to the point where industry is ready to adopt SHM in these specific application domains.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Endnotes

[1] The term *nondestructive testing* (NDT) is very often used instead.

[2] Of course, as modal analysis methods increased in their sophistication, they became themselves much more automated, thus removing (to a great extent), the final issue associated with NDE.

[3] The 'sufficient training data' clause turned out to be the problem.

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Appendix

This appendix summarises the many SHM review articles in Tables A1 to A4 below that have previously appeared in refereed journal publications. It is important to note that there are some highly-cited SHM review articles that were not published in journals; however, the authors felt it was important to only include surveys that have been subjected to a peer-review process and that are easily obtained by the SHM community (although not necessarily without cost).

These articles have been categorised into three topic areas: 1. Their Application focus, 2. Their Sensing Modality focus, and 3. Their Data Analysis Methodology focus. Many of the reviews address more than one of these topic areas and, hence, will be listed in multiple tables. The reviews listed in Table 1, are general and address multiple applications, multiple sensing modalities and multiple data-analysis methodologies. The citation listing is presented by year the review was published. Within a given year, there is not specific order to the citations.

TABLE A1 | General Structural Health Monitoring Literature Reviews

Review Topic	References
General Reviews	A-2, A-4, A-5, A-36, A-38, A-41, A-48, A-57, A-67, A-74, A-79, A-81, A-93, A-160, A-197, A-206, A-258, A-260,

TABLE A2 | Structural Health Monitoring Reviews Focused on Specific Applications

Application Focus	References
Adhesive and bonded joints	A-222, A-229
Aerospace Structures	A-32, A-37, A-64, A-66, A-68, A-120, A-135, A-138, A-151, A-189, A-231
Agricultural Structures	A-181
Asphalt Pavements	A-140
Benchmark Studies	A-57
Bolted Assemblies	A-243
Civil Infrastructure: Buildings and Bridges	A-1, A-3, A-8, A-13, A-17, A-24, A-27, A-29, A-31, A-46, A-55, A-76, A-77, A-78, A-83, A-84,A-89, A-102, A-110, A-131, A-135, A-159, A-165, A-166, A-185, A-198, A-199, A-207, A-212, A-216, A-217, A-219, A-223, A-234, A-235, A-237, A-245, A-251, A-259, A-275, A-276, A-277, A-278, A-280, A-284, A-298, A-301, A-303
Concrete and Concrete Structures	A-65, A-116, A-164, A-188, A-191, A-192,A-281, A-284
Composite Materials and Structures	A-12, A-32, A-44, A-51, A-61, A-64, A-70, A-90, A-122, A-129, A-139, A-143, A-145, A-177, A-186, A-189, A-189, A-201, A-213, A-221, A-227, A-236, A-242, A-249, A-292, A-293, A-296
Cultural Heritage & Historic Structures	A-87, A-105, A-184, A-269
Dams	A-225
Fluid Storage Tanks	A-254
Health and Usage Monitoring Systems (Aircraft & Rotorcraft)	None found
Hot Gas Components in Gas Turbines	A-123
Inland Waterways and Ports	A-299
Marine Structures	A-183, A-244, A-268
Masonry structures	A-100, A-187, A-193, A-240
Mines	A-108
Offshore Wind Jacket Structures	A-262
Oil & Gas Infrastructure (Onshore & Offshore)	A-43, A-130, A-268, A-273
Pipeline Structures	A-42, A-141, A-194, A-273
Railroads and Track Structures	A-9, A-149, A-232
Rotating Machinery	A-6, A-7, A-16, A-50, A-71, A-73, A-95, A-106, A-107, A-114, A-128, A-132, A-154, A-155, A-167, A-169, A-220, A-230, A-233, A-238, A-255, A-263, A-264, A-279, A-287, A-288, A-289
Timber Structures	A-147, A-148
Wind Turbines	A-23, A-34,A-53, A-60, A-62, A-63, A-80, A-104, A-111, A-119, A-202, A-302

TABLE A3 | Structural Health Monitoring Reviews Focused on Specific Sensing Modalities

Sensing Technologies	References
Acoustic Emission	A-108, A-179
Augmented and Virtual Reality	A-271
Bio-Inspired Sensing	A-121
Carbon coated piezoresistive fiber sensor	A-178
Carbon Nanotubes	A-65, A-70, A-192, A-213, A-295, A-296
Connected and Automated Vehicles	A-174
Corrosion sensors	A-130
Doppler Radar	A-190
Electromechanical Impedance	A-18, A-35, A-91, A-109, A-152, A-172, A-229
Embedded Sensors	A-205
Energy Harvesting	A-26, A-68, A-88, A-235
Fiber Optic Sensing	A-21, A-25, A-30, A-31, A-37, A-39, A-40, A-55, A-56, A-64, A-66, A-138, A-149, A-159, A-164, A-179,A-191, A-195, A-244, A-282
General Sensors Overview	A-252
Global Navigation Satellites &GPS Technology	A-49, A-126, A-161, A-163
Ground Based Radar	A-111, A-240
High-Temperature Environment	A-171
LIDAR	A-212
Low-Frequency Methods	A-14
MEMS	A-125
Multi-Sensor Approaches	A-145
Mxene sensors	A-209
Nanocarbon-based solutions	A-133, A-251
Noncontact Sensing	A-196, A-270
Optimal Sensor Placement	A-124,A-153, A-253, A-283
Piezoelectric actuators	A-33
Piezoelectric Sensing	A-96, A-102, A-115, A-129, A-144, A-163, A-239, A-257
Piezoresistive Sensing	A-178, A-186
Renewable Energy Methods	A-150
RFID Strain Sensing	A-99, A-265
Robotic Systems (ground and aerial)	A-92, A-175, A-180, A-228
Self-Reporting Mechanochromic Composites	A-227
Self-Sensing Cement Composites	A-291, A-295
Sensor Networks	A-10
Sensor Validation	A-98
Shear horizontal wave transducers	A-182
Smart Aggregate	A-274
Smart Phones	A-272
Smart Sensing Technology	A-101, A-127, A-140, A-226
Smart Skin	A-231
Strain	A-52
Through-Thickness Electrical Conductivity	A-139,
Ultrasonics	A-83, A-168
Vision Sensing	A-170,
Wireless Sensing	A-11, A-15, A-40, A-47, A-54, A-61, A-94, A-125, A-134, A-226, A-235, A-275,A-286

TABLE A4 | Structural Health Monitoring Reviews Focused on Specific Data Analysis Methodologies

Data Analysis Methodologies	References
Acoustic Scattering	A-59, A-249
Convolution Neural Networks	A-155
Data Fusion	A-158
Data Visualization	A-271
Deep Learning	A-128, A-131, A-136, A-157, A-165, A-169, A-220, A-236, A-256, A-266, A-279, A-288, A-290
Data Science	A-117, A-156, A-208
Empirical Mode Decomposition	A-50, A-58
Entropy	A-106
Environmental and Operational Variability	A-19, A-142, A-176, A-216, A-225, A-239, A-261
Generative adversarial networks	A-215
Guided Waves	A-82, A-221, A-222, A-224, A-241, A-285, A-294, A-297
High -Dimension Data Analytics	A-218
Information Processing	A-24,
Internet of Things	A-97, A-146, A-193, A-217, A-235
Local Mean Decomposition	A-132
Low-Frequency Methods	A-14
Machine Learning/Artificial Intelligence	A-22, A-107, A-110, A-118, A-146, A-162, A-165, A-173, A-184, A-200, A-203, A-207, A-219, A-224, A-232, A-234, A-236, A-270, A-284, A-300
Machine Vision/Image Analysis	A-45, A-85, A-86, A-185, A-248, A-267, A-289
Multi-Sensor Approaches	A-145
Multispectral Technique	A-211
Neutral Axis Location	A-69
Nonlinear Dynamics	A-28, A-292
Optimization Algorithms	A-87, A-118, A-137, A-153, A-283,
Population-Based Methods	A-200
Post-Earthquake Assessments	A-214
Reliability Metrics	A-204
Resonance Demodulation	A-263
Self-Sensing Concrete	A-246
Sensor Network Paradigms	A-103
Signal Processing	A-75, A-287, A-294
Simulated Annealing	A-250
Stochastic Functional Model–Based Method	A-112
Symbolic Vibration Data	A-72
Temperature Tracer Method	A-210
Time Frequency Analysis & Wavelet Transform	A-20,A-71, A-73, A-238,
Time Series Analysis	A-113
Transfer Learning	A-236
Unsupervised Learning Methods	A-247

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