Chapter 4
Fatigue Monitoring in Metallic Structures using Vibration Measurements

D.C. Papadioti, D. Giagopoulos, and C. Papadimitriou

Abstract A novel framework is proposed for estimating damage accumulation due to fatigue in the entire body of a metallic structure using vibration measurements from a limited number of sensors. Fatigue is estimated using Palmgren-Miner damage rule, S-N curves, rainflow cycle counting of the variable amplitude time histories of the stress components, or frequency domain stochastic fatigue methods based on PSD of the stress components. These methods can be applied to any point in the structure and construct the complete fatigue map of the entire structure, provided that the stress response characteristics (time histories or PSDs) at all desirable points are available. These stress response characteristics are predicted from limited number of vibration sensors using a high fidelity finite element model and different prediction methods, including Kalman filter type techniques, kriging approximations and modal expansion methods. The effectiveness of the proposed methods is demonstrated using simulated data from a chain-like spring-mass model and a small-scale model of a vehicle structure. The proposed framework can be used to construct fatigue damage accumulation and lifetime prediction maps consistent with the actual operational conditions provided by a monitoring system. These maps are useful for designing optimal fatigue-based maintenance strategies for metallic structures taking into account all uncertainties in modeling and fatigue predictions.

Keywords SHM • Output-only measurements • Strain and fatigue predictions • Kalman filter • Modal expansion

4.1 Introduction

A permanently installed network of sensors in a structure is often used to record output-only vibration measurements during operation. These vibration measurements provide valuable information for estimating important dynamic characteristics of the structures such as modal frequencies, mode shapes and modal damping ratios, updating finite element models, monitoring the health of the structure by identifying the location and severity of damage, identifying the temporal/spatial variation of the loads applied on the structure [1], estimating the state [2–5], and updating robust predictions of system performance [6, 7]. Recently, output-only vibration measurements were proposed to use for the estimation of fatigue damage accumulation in metallic components of structures [8]. This is an important safety-related issue in metallic structures since information on fatigue damage accumulation is valuable for structural risk assessment and for designing optimal, cost-effective maintenance strategies. Predictions of fatigue damage accumulation at a point of a structure can be estimated using available damage accumulation models that analyze the actual stress time histories developed during operation [9, 10].

The stress response time histories can be readily inferred from strain response time histories directly measured using strain rosettes attached to the structure. However, such predictions are only applicable for the locations where measurements are available. A large number of strain sensors are therefore required to cover all hot spot locations in large structures encountered in engineering applications. Due to practical and economical considerations, the number of sensors placed in a

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structure during operation is very limited and in most cases do not cover all critical locations. Moreover, sensors cannot be installed at some locations in the structures, e.g. underwater locations for fully submerged structures and offshore structures (oil refinery structures, offshore wind turbines, offshore steel jackets, etc.), and in-accessible areas of large structures. In addition, in monitoring applications of a number of structures, acceleration measurements are conveniently used instead of strain measurements.

To proceed with fatigue predictions one has to infer the strain/stress response time histories characteristics based on the monitoring information contained in vibration measurements collected from a limited number of sensors attached to a structure. Such predictions are possible if one combines the information in the measurements with information obtained from a high fidelity finite element model of the structure. It is important to note that such estimations will reflect the actual strain time history characteristics developed on the structure during operation and thus the corresponding fatigue damage accumulation estimates will be more representative of the fatigue accumulated in the structure at the point under consideration. Repeating such estimates at all points in the structure, one is able to develop realistic fatigue damage accumulation maps that cover the entire structure.

This work deals with the problem of estimating the strain time histories characteristics at critical locations of the structure using operational vibration measurements from a limited number of sensors and the use of such estimates to predict fatigue damage accumulation in the entire body of a metallic structure. The paper lays out the formulation for estimating fatigue using output-only vibration measurements and outlines methods for estimating the stress response history characteristics required in deterministic and stochastic fatigue theories. Similar estimation techniques can be used to estimate other important response characteristics in the entire body of the structure, such as displacements, velocities, accelerations, etc. The analyses in this study are restricted to the case of linear structures and stress response predictions at locations subjected to uni-axial stress states. The measured quantities are considered to be accelerations, displacements or strains or a combination of accelerations, displacements and strains. The deterministic and stochastic fatigue damage accumulation formulations are outlined in Sect. 4.2. The methods for estimating the strain response time history characteristics using operational measurements, that are required in the fatigue formulations, are presented in Sect. 4.3. An application on a chain-like spring-mass model and a small scale vehicle structure is used to demonstrate the effectiveness of vibration the framework in Sect. 4.4. Conclusions and future challenges are summarized in the last section.

4.2 Fatigue Monitoring using Operational Vibrations

4.2.1 Deterministic Fatigue Damage Accumulation

The Palmgren-Miner rule [9, 10] is used to predict the damage accumulation due to fatigue. According to this rule, a linear damage accumulation law at a point in the structure subjected to variable amplitude stress time history is defined by

$$D = \sum_{i}^{k} \frac{n_i}{N_i} \tag{4.1}$$

Where n_i is the number of cycles at a stress level σ_i, N_i is the number of cycles required for failure at a stress level σ_i, and k is the number of stress levels identified in a stress time history at the corresponding structural point. S-N fatigue curves available from laboratory experiments on simple specimens subjected to constant amplitude loads, are used to describe the number of cycles N_i required for failure in terms of the stress level σ_i. The number of cycles n_i at a stress level σ_i is usually obtained by applying stress cycle counting methods, such as the rainflow cycle counting, on the stress time histories measured or estimated for the point under consideration. The fatigue accumulation model can be revised to account for a non-zero mean stress according to the Goodman relationship [11]. The fatigue damage accumulation at a point requires that the full stress time histories are available. These estimates are obtained in Sect. 4.3 based on monitoring information provided from a limited number of acceleration, displacement and/or strain vibration sensors attached to the structure.

4.2.2 Stochastic Fatigue Damage Accumulation

For the cases where the full stress response time histories are not available from measurements, frequency domain methods based on spectral moments (e.g. [12, 13]) can be used to predict the expected damage due to fatigue using the linear damage law 4.1. The methodology assumes that the stress is considered to be a stationary Gaussian stochastic process and that the power spectral density of the stress process at a structural location is available. For linear systems excited by time-varying loads that can be modeled by stationary stochastic processes, these power spectral densities can be straightforward computed using available random vibration results [14].

Using frequency domain methods for fatigue estimation under stochastic excitations [12] and the continuous version of the damage accumulation law (1), the expected fatigue damage accumulation rate for a uni-axial stochastic stress process using the Dirlik formula [15] for the probability distribution of the stress levels for Gaussian stochastic stress processes, is given as a function of the spectral moments $\lambda_0, \lambda_1, \lambda_2, \lambda_4$ of the stress process [13], i.e.

$$\overline{D} \equiv \overline{D}\,(\lambda_0, \lambda_1, \lambda_2, \lambda_4) \tag{4.2}$$

Where the form of $\overline{D}\,(\lambda_0, \lambda_1, \lambda_2, \lambda_4)$ can be found in [13]. The expected time of failure due to fatigue (fatigue lifetime) is $T_{life} = 1/\overline{D}$, corresponding to a critical expected damage value $E[D] = D_{cr} = 1$. The aforementioned formulation assumes that the stress process at a point is uni-axial. For multi-axial stress states one can apply available methods [16] to extend the applicability of the present methodology. It is clear that the expected fatigue damage rate $\overline{D}$ at a point in the structure depends only on the spectral moments λ_i, $i = 0, 1, 2, 4$, of the stress process $\sigma(t)$. Using the definition of the spectral moments $\lambda_j = \int_{-\infty}^{\infty} |\omega|^j S_\sigma(\omega) d\omega$, the spectral moments and the fatigue predictions at a point of a structure eventually depend only on the power spectral density $S_\sigma(\omega)$ of the stress process $\sigma(t)$. The power spectral densities of the stress response processes at a point can be calculated from measurements, provided that these measurements are long enough to be considered stationary. This issue of predicting the power spectral densities of the stress processes in the entire body of the structure using measurements at limited locations is addressed at the next Sect. 4.3.

4.3 Strain Monitoring using Output-Only Vibration Measurements

The objective of this section is to predict the characteristics of strain responses, such as power spectral densities or full strain time histories, at all hot spot locations in a structure using output-only vibration measurements collected from a limited number of sensors attached to the structure. Such predictions are integrated with the fatigue damage accumulation laws to estimate the fatigue in the whole structure taking into account real measurements, instead of postulated excitation models that in most cases are not representative of the actual behavior of the structure.

It is assumed that the system can be represented by a linear model subjected to a number of excitations. The equations of motion are given by the following set of N second-order differential equations resulting from a spatial discretization (finite element analysis) of the structure

$$M\ddot{\underline{u}}(t) + C\dot{\underline{u}}(t) + K\underline{u}(t) = L\underline{p}(t) \tag{4.3}$$

Where $\underline{u}(t) \in \mathbb{R}^{N\times 1}$ is the displacement vector, M, C and $K \in \mathbb{R}^{N\times N}$ are respectively the mass, damping and stiffness matrices, $\underline{p}(t) \in \mathbb{R}^{N_{in}\times 1}$ is the applied excitation vector, and $L \in \mathbb{R}^{N\times N_{in}}$ is a matrix comprised of zeros and ones that maps the excitation loads to the output DOFs. The $\underline{y}(t) \in \mathbb{R}^{N_{meas}\times 1}$ measurement vector is expressed in terms of the displacement/strain, velocity and acceleration vectors as

$$\underline{y}(t) = L_a\ddot{\underline{u}}(t) + L_v\dot{\underline{u}}(t) + L_d\underline{u}(t) \tag{4.4}$$

Where L_a, L_v and $L_d \in \mathbb{R}^{N_{meas}\times N}$ are selection matrices for accelerations, velocities and displacements/strains, respectively. These measurements are generally collected from sensors such as accelerometers, strain gauges, etc.

Depending on whether the objective is to predict the power spectra densities or the full time histories of the strains, the following techniques can be applied.

4.3.1 Stationary Stochastic Excitations

A first attempt to compute the fatigue at the entire body of a structure using vibration measurements at a limited number of locations can be found in [8]. Assuming the excitation can be represented by a stationary stochastic process and the system is linear, the response is a stationary stochastic process. The power spectral densities $S_\varepsilon(\omega)$ of the strains at different locations where measurements are not available can be computed with respect to the cross power spectra densities $\widehat{S}_y(\omega)$ of the responses at measured locations. A Kalman filter approach, integrating information from the finite element model of the structure and the measurements, was presented to estimate the power spectral densities $S_\varepsilon(\omega)$. The cross power spectra densities $\widehat{S}_y(\omega)$ of the measured response are obtained by analyzing adequately long measured time histories. The PSD $S_\sigma(\omega)$ of the stresses are obtained by using the linear stress strain relationships for linear elastic material. Given the PSD $S_\sigma(\omega)$ of the stresses, the moments λ_i required in the stochastic fatigue prediction formulas are readily computed and used to provide an estimate of the damage accumulation using the formulation in Sect. 4.2.2. The whole formulation was presented for a single stochastic excitation but it can be readily extended to cover the case of several stochastic excitations applied at different points in a structure.

Another method that is applicable in the case of stochastic excitation and linear systems is the kriging technique [17] which, under stationarity conditions, can be used to predict the strain time histories at unmeasured locations in a structure in terms of the strain time histories measured at optimally selected locations [18]. An alternative Kalman filter-type method for wind-induced strain estimation and fatigue from output only vibration measurements that explicitly account for spatial correlation and for the colored nature of the excitation and fatigue predictions can also be found in [19].

4.3.2 Non-stationary Deterministic Excitations

The previous formulation assumes that the response can be considered to be stationary. However, for a number of applications the nonstationarity dominates the features of the excitation and the response, such as in civil engineering problems involving, for example, the passage of trains or heavy trucks over metallic bridges. The damage accumulation prediction proposed in [8] is not applicable in such nonstationary cases. New estimation methods capable of predicting the full acceleration and strain response time histories, applicable to the case of non-stationary excitations, have been developed in [20]. Specifically, a joint input-state estimation filter proposed in [20] was adopted and extended to estimate strain response time histories in the entire body of the structure using output-only vibration measurements collected from the sensor network. The approach is based on a filter that has the structure of the Kalman filter, which is used to jointly estimate the inputs and the full state of a linear system using a limited number of vibration measurements. This filter extends Gillijns and De Moor's [21] joint input-state estimation algorithms to handle structural dynamics applications. In contrast to the method proposed in [8], no assumptions are made on the spatial and temporal characteristics of the applied loads, as well as the number and location of the excitations on the structure.

The proposed methodology was validated using simulated data from a laboratory beam structure subjected to impulse-type and stochastic excitations as well simulated measurements from a railway bridge [22]. The proposed Kalman-type filters were demonstrated to be accurate for estimating acceleration time histories at unmeasured locations in the structure. For displacement and strain time histories, the filter estimates were inaccurate due to low frequency shift manifested in the time histories. Such inaccuracies were corrected by applying a high frequency filter to the modal estimates provided by the joint input-state estimation filter technique. The main steps of the joint input-state estimation algorithm based on combined acceleration and strain measurements can be found in [20]. This work can readily be extended for the case where the measured quantities are only strains by modifying the approach presented in Gillijns and De Moor's [23] for input-state estimation of systems to handle structural dynamics applications.

The stress time histories at a point of a structure are obtained by using the linear stress strain relationships for linear elastic material. Given the stress time histories, the damage accumulation due to fatigue are obtained by cycle count methods, S-N fatigue curves and the linear fatigue damage accumulation laws presented in Sect. 4.2.1.

Another class of techniques that can be used in the case of deterministic non-stationary excitation and linear systems is the modal expansion method. The displacement, acceleration and strain response of a structure at various locations can be represented as $\underline{u}(t) = \Phi\underline{\xi}(t)$, $\ddot{\underline{u}}(t) = \Phi\ddot{\underline{\xi}}(t)$, $\underline{\varepsilon}(t) = L_\varepsilon\Phi\underline{\xi}(t) = \Phi_\varepsilon\underline{\xi}(t)$, where $\underline{\xi}(t)$ are the modal coordinate vector, while Φ

and Φ_ε are the mode shape matrices for displacements and strains respectively. Using this expansion for the case of measured strain responses $\hat{\underline{\varepsilon}}(t)$, one can in principle obtain the modal coordinates from

$$\underline{\xi}(t) = \left(\Phi_\varepsilon^T \Phi_\varepsilon\right)^{-1} \Phi_\varepsilon^T \hat{\underline{\varepsilon}}(t) \tag{4.5}$$

Where for a nonsingular matrix $(\Phi_\varepsilon^T \Phi_\varepsilon)^{-1}$ the number of sensors should be at least equal to the number of contributing modes. Once these modal coordinates have been identified, then the strain responses $\underline{\varepsilon}_{pr}(t)$ at unmeasured locations can be obtained from equation

$$\underline{\varepsilon}_{pr}(t) = \Phi_{\varepsilon,pr}\underline{\xi}(t) \tag{4.6}$$

Where the mode shape component values $\Phi_{\varepsilon,pr}$ in Eq. (4.6) are based on those predicted by a finite element model of the structure. The mode shape components Φ_ε can be replaced by the ones identified by a modal identification method. It is worth noting that assuming that the response and the excitation can be represented by stationary processes, the PSD of the strain responses at unmeasured locations can also be predicted from the CPSD of the responses obtained from vibration measurements so that the stochastic fatigue techniques can also be applied.

It should be noted that optimal sensor location methods are already available to use for improving the accuracy of the estimates. The problem of optimizing the sensor locations is formulated as a problem of finding the sensor locations that provide the best estimates of the modal coordinates $\underline{\xi}(t)$. This problem has first been addressed in [24] and efficient computational techniques have been provided (see for example [25]) based on the mode shapes of a finite element model. A drawback of the formulation based on modal expansion is that the predictions are sensitive to model and measurement errors. Also, the predictions make efficient use of strain or displacement measurements which are less frequently employed in monitoring systems. For acceleration measurements one can derive $\ddot{\underline{\xi}}(t)$ and use double integration to estimate $\underline{\xi}(t)$. However, such double integration is a source of extra processing errors which are expected to affect the predictions of strains.

4.4 Applications

4.4.1 N -DOF Spring-Mass Chain-like Model

A 30-DOF spring-mass chain like model, shown in Fig. 4.1a, is used to demonstrate the effectiveness of the proposed methodologies. The model is comprised of two substructures. The first substructure contains the first body, with mass m_1, in the chain and the two spring attached to this mass, while the second substructure consists of the rest of the 29-DOF. This sub-structuring approach allows us to isolate the large components of the structure that behave linearly from the isolated parts that may behave nonlinearly. Thus the proposed methodologies can be applied to the linear substructures. It is assumed herein that the second 29-DOF substructure behaves linearly, while the first substructure may consist of nonlinear springs. Simulated, noise contaminated, response time histories are generated from the 30-DOF model by applying a triangular impact force to the body 1. Displacements, velocities, accelerations and strains are recorded and are used as the exact estimates against which comparisons of predictions from the 29-DOF model will be made.

Predictions of displacement, accelerations and strains are obtained from the proposed methods using the 29-DOF model. The input at the connection of the 29-DOF model with the other structure is considered unknown. Seven acceleration sensors are used at DOFs 1, 6, 11, 16, 21, 26 and 29 of the model. 5 % noise is added to the simulated data to account for modeling and measurement errors. The Kalman-type filter is used to estimate the state of the structure at all DOFs and then used to estimate the strains at the springs. The modal expansion method is also used to estimate the strains in the structure at all springs using simulated displacement or strain measurements at nine locations selected on either the mass or the springs. Results for strain predictions obtained from the Kalman-type filter and the modal expansion method are presented in Fig. 4.1b for the 19 spring of the 29-DOF model. The predictions are compared with the simulated measurements. Comparisons show that strain predictions from both methods are very close to the exact ones. As a result, the fatigue estimates using the proposed deterministic fatigue approach are very close to the simulated estimates.

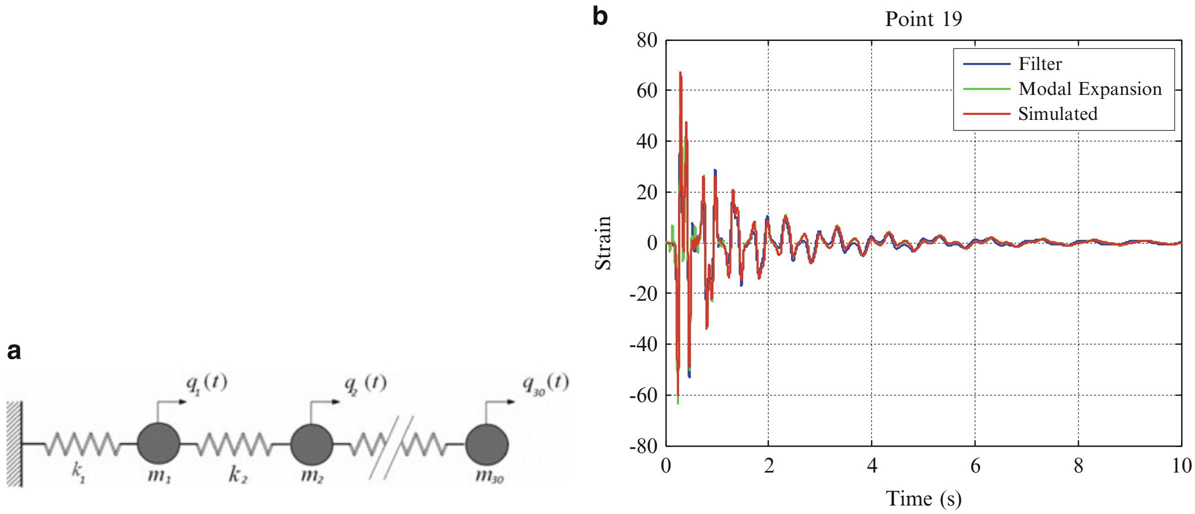

Fig. 4.1 (**a**) 30-DOF spring-mass chain-like model. (**b**) Estimated and simulated strain time histories at spring 19

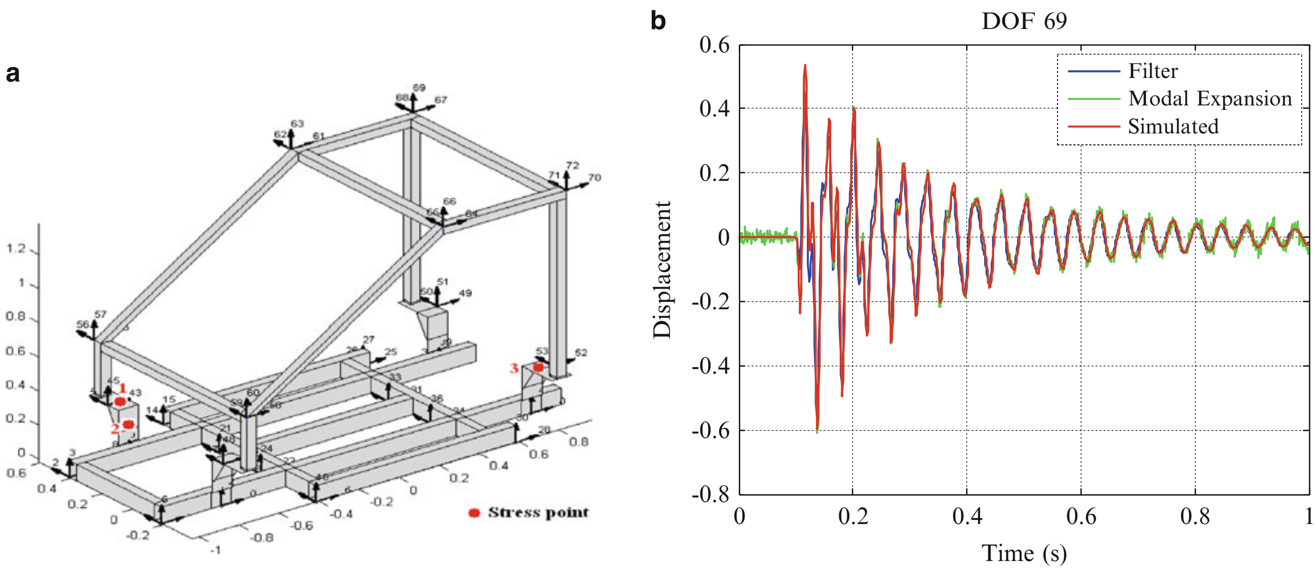

Fig. 4.2 (**a**) Scaled vehicle frame with measurement and prediction points. (**b**) Estimated and simulated displacement time histories at DOF 69

4.4.2 Small Scale Vehicle-like Frame Structure

The framework is also demonstrated using an experimental small scale vehicle-like body, shown in Fig. 4.2a. The vehicle structure is designed to simulate the frame substructure of a vehicle in a small scale of length 2 m, width 1 m and height 1.4 m. Figure 4.2a presents details of the geometrical dimensions of the frame. Details of material and geometrical dimensions of the frame can be found in [26]. Measurements are collected from eight locations using triaxial accelerations or displacement sensors. A detailed finite element model of the vehicle frame was created based on the geometric details and the material properties of the structure. The finite element model was created using three-dimensional triangular shell finite elements. A fine mesh model consisting of 15,202 finite elements and having 45,564 DOF was chosen for a detailed modelling of the experimental vehicle. The Kalman-type filter and the modal expansion method are used to estimate the state of the structure at all DOFs. The strain predictions are then obtained from the state estimates and the material properties.

Using the finite element model, simulated displacement and acceleration time history measurements are generated at selected locations. The excitations applied at the connections of the frame structure with the vehicle suspension are considered unknown. A 5 % noise is added to the simulated time histories to account for modelling errors. Twenty-four acceleration or displacement sensors are used at DOFs 1, 2, 3, 13, 14, 15, 25, 26, 27, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51 52, 53 and 54 of the model. The sensor locations are shown in Fig. 4.2a. The Kalman-type filter and the modal expansion method are used to estimate the state of the structure at all DOFs using the acceleration or displacement sensors, respectively. The displacement and strain predictions are then obtained from the state estimates and the material properties. Results for displacement predictions are presented in Fig. 4.2b for the DOF 69 of the structure, shown in Fig. 4.2a. The predictions are compared with the simulated measurements. Comparisons show that predictions from both methods are close to the exact ones corresponding to the displacement time histories generated from the finite element model. Such predictions are expected to yield strain predictions and fatigue estimates that are very close to the ones obtained from the simulated data.

4.5 Conclusions

A novel use of monitoring information for estimating fatigue damage accumulation in the entire body of metallic structures is outlined in this work. This is accomplished by combining fatigue damage accumulation laws with stress/strain predictions based on output only vibration measurements collected from a limited number of sensors. Methods for estimating strains by integrating high fidelity finite element model and estimation techniques were summarized. The predictions are currently based on linear model of structures. The accuracy of the proposed methods for fatigue predictions in the entire body of the structure depends on the number and location of sensors in the structures, the number of modes contributing in the dynamics of the structure, and the size of the model error and measurement error. Future directions include the design of optimal sensor locations for improving the predictions of strains in the entire body of a structure, as well as the extension of the proposed methodologies to cover nonlinear models of structures. Applications cover a large variety of metallic structures, including ground and air vehicles, civil engineering structures such as steel buildings, high towers and railway/motorway bridges, industrial structures, wind turbine blades and supporting structures/masts, offshore structures, etc. The proposed methodology can be used to construct fatigue damage accumulation and lifetime prediction maps consistent with the actual operational conditions provided by a monitoring system. Such fatigue maps are useful for designing optimal fatigue-based maintenance strategies for metallic structures using structural vibration information collected from a sensor network.

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