Coupling physics-based models with wireless sensor networks for structural health monitoring

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Abstract: In wireless structural health monitoring (SHM) systems, the over-the-air transmission of large data sets – apart from being unreliable – may drastically reduce the power autonomy of wireless sensor nodes, thus raising the need for continuous power supply, which effectively cancels the "wireless" nature of the sensor nodes. To address the aforementioned shortcomings, this paper reports on advantageously utilizing the embedded computing capabilities of wireless sensor nodes for extracting information on the structural properties on board, i.e. without resorting to centralized data acquisition. Drawing from emerging paradigms associated with the digitalization of physical processes, e.g. using digital twins, the embedded physics-based modeling concept presented herein couples physics-based models of structures with wireless sensor networks. In particular, physics-based models, which are frequently adopted in SHM for mapping the outcome of (typically model-agnostic) data analysis to structural behavior phenomena perceivable by structural engineers, can be embedded into wireless sensor nodes, facilitating advanced local autonomous data analysis on board the sensor nodes. The embedded physics-based modeling concept is validated via simulations, showcasing the capability of the embedded physics-based models to yield information on the structural properties. The results of the proposed concept are expected to align SHM practices with digitalization paradigms that form the backbone of Industry 4.0.

Keywords: Structural health monitoring, wireless sensor nodes, embedded computing, physics-based models

1 Introduction

The importance of predictive structural maintenance of the built environment has been gaining growing traction with the civil engineering community, following the recent devastating effects of climate change on aging civil infrastructure [1]. Representing a subsidy to traditional nondestructive evaluation (NDE), conducted within the framework of predictive structural maintenance, structural health monitoring (SHM) has been proven a reliable strategy for extracting information on structural conditions [2]. By providing abundant structural response data, typically on a long-term basis, SHM aims to cover the discontinuities resulting from the periodicity of traditional NDE methods, such as visual inspections [3]. Moreover, the “digital” nature of SHM, largely involving data analysis and artificial intelligence techniques [4], aligns well with emerging digitalization paradigms that have been infiltrating physical processes across a wide spectrum of activities, such as traffic management and building energy management, which form the backbone of Industry 4.0 [5, 6].

In recent years, SHM has been implemented in several structures that mostly comprise parts of critical civil infrastructure [7]. However, SHM strategies are still limited to structures with high impact on public safety and well-being or to structures of strong academic interest. The widespread adoption of SHM is significantly hindered by the high installation costs of cable-based sensor networks, which are required to collect structural response data [8]. The advances in wireless sensing technologies have been able to partly address the high budgetary requirements, owing to the low cost of wireless sensor nodes and the elimination of cabling [C9]. Nevertheless, practitioners have not been expressing the same trust in wireless SHM systems as in cable-based SHM systems, especially for long-term SHM, due to the limited reliability and robustness of wireless communication as well as to the limited power autonomy of wireless sensor nodes. As a result, the modern SHM landscape involves well-established cable-based strategies and sporadic wireless strategies, usually decided on the basis of cost-benefit analyses conducted by stakeholders of critical infrastructure [10].

In an attempt to boost the adoption of wireless technologies for SHM, researchers have been targeting the shortcomings of wireless sensor networks [11]. Specifically, the embedded computing capabilities of wireless sensor nodes have advantageously been used to embed data analysis algorithms to avoid wirelessly transferring structural response data to centralized servers. With embedded data analysis, wireless sensor nodes are tasked to autonomously extract the information on structural conditions locally (i.e. on the on-board processors), and only communicate the results of data analysis. However, since the computational resources of wireless sensor nodes can hardly support on-board numerical analysis, most embedded data analysis approaches have been based on model-agnostic data-driven modeling methods [12, 13]. Despite its efficiency, data-driven modeling is only capable of yielding global information on structural conditions (e.g. sparse experimental mode shapes), which may be less sensitive to structural damage compared to the rich information obtained from physics-based modeling.

Aiming to advance embedded data analysis, this paper presents a concept for coupling physics-based modeling with wireless sensor networks. In particular, the proposed concept seeks to enable wireless sensor nodes to leverage the descriptive and predictive capabilities of physics-based models on board for extracting richer information from structural response data as compared to data-driven modeling. Each wireless sensor node is tasked with analyzing its structural response data using a partial physics-based model of the monitored structure, corresponding to the surroundings of the sensor node, which is created using substructuring. Thereupon, the complete picture of the structural condition is obtained by collaborative analysis of the results of individual wireless sensor nodes. The validity of the embedded physics-based modeling concept is showcased via simulations on a shear frame structure. In what follows, Section 2 presents the theoretical foundation of the embedded physics-based modeling concept, and Section 3 covers the simulations, serving as validation of the proposed concept. The paper ends with a summary and conclusions as well as with a brief discussion on follow-on future research.

2 Mathematical background of the embedded physics-based modeling approach

In this section, the mathematical background of the proposed embedded physics-based modeling concept is shown via a simple example of a multi-degree-of-freedom (MDOF) oscillator. For the sake of simplicity, the oscillator used in this section follows the “stick” model paradigm, i.e. only translational degrees of freedom are considered. The MDOF oscillator is essentially an assembly of n lumped masses m_i ($i = 1\ldots n$) on n beam elements with stiffness k_i ($i = 1\ldots n$) and damping values c_i ($i = 1\ldots n$), as shown in Figure 1.

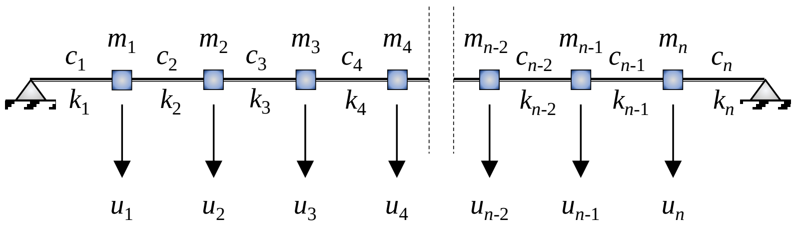

Figure 1: Multi-degree-of-freedom oscillator.

Under the effect of loading conditions P_i ($i = 1\ldots n$), the structural response is approximated using the equations of motion:

$$\mathbf{M}^{n\times n}\ddot{\mathbf{u}}^n(t)+\mathbf{C}^{n\times n}\dot{\mathbf{u}}^n(t)+\mathbf{K}^{n\times n}\mathbf{u}^n(t)=\mathbf{P}^n(t). \tag{1}$$

In Equation 1, $\mathbf{M}$, $\mathbf{C}$, $\mathbf{K}$ are the $n\times n$ mass matrix, damping matrix and stiffness matrix, respectively, of the oscillator. The structural response (displacement) is expressed by the n-sized $\mathbf{u}$ vector, and $\dot{\mathbf{u}}$ and $\ddot{\mathbf{u}}$ represent the velocity vector and the acceleration vector, respectively. Finally, t denotes time. The basis of the embedded physics-based modeling concept lies in the ability of individual wireless sensor nodes to analyze data locally collected, using the physics-based models without extensive wireless communication with the rest of the network. However, the inherently coupled nature of the equations of motion prevents directly embedding the physics-based models into the sensor nodes, because any mathematical operation using the models (e.g. applying equations of motion) would require extensive data exchange with neighboring sensor nodes. Instead, prior to embedding the physics-based model, the monitored structure is segmented into substructures, each containing internal degrees of freedom and interfaces, as shown in Figure 2.

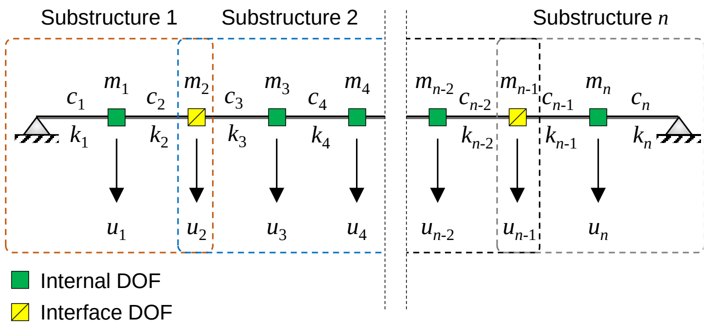

Figure 2: Substructuring of the physics-based model.

As a result of the substructuring, the oscillator physics-based model is segmented into n partial models. Each partial model, corresponding to one substructure, can then be embedded into the wireless sensor nodes that measure the internal degrees of freedom of the substructure. As will be shown below, using the equations governing the oscillation of the internal degrees of freedom, estimates on the acceleration response of the interfaces can be obtained. Specifically, considering substructure 1 from Figure 2, the equation of motion of DOF 1 under the effect of load $p_1(t)$ is:

$$m_1\ddot{u}_1(t)+(c_1+c_2)\dot{u}_1(t)+(k_1+k_2)u_1(t)-c_2\dot{u}_2(t)+k_2u_2(t)=p_1(t). \tag{2}$$

Transforming Equation 2 into the frequency domain (e.g. via fast Fourier transform [14]) results in:

$$m_1\ddot{U}_1(\omega)+(c_1+c_2)\dot{U}_1(\omega)+(k_1+k_2)U_1(\omega)-c_2\dot{U}_2(\omega)+k_2U_2(\omega)=P_1(\omega). \tag{3}$$

In Equation 2, ω is the natural frequency, and $\ddot{U}$, $\dot{U}$ and U are the frequency-domain representations of the acceleration, the velocity and the displacement, respectively. In the frequency domain, the accelerations, velocities and displacements are related to each other with the following expressions:

$$\dot{U}(\omega)=\frac{\ddot{U}(\omega)}{\omega i} \qquad U_1(\omega)=-\frac{\ddot{U}(\omega)}{\omega^2}, \tag{4}$$

with the help of which, Equation 3 becomes:

$$\ddot{U}_2(\omega)=\frac{P_1(\omega)+\left(\frac{k_1+k_2}{\omega^2}-\frac{c_1+c_2}{\omega i}-m_1\right)\ddot{U}_1(\omega)}{\frac{k_2}{\omega^2}-\frac{c_2}{\omega i}}. \tag{5}$$

Considering that for broadband quasi-white-noise excitation the contribution of $\ddot{U}_1(\omega)$ is much larger than the contribution of the load $P_1(\omega)$ around frequencies that dominate the structural response, Equation 5 serves essentially as a transfer function between the internal DOF of substructure 1 and the interface DOF 2. Following the exact same reasoning, the equation of motion of DOF 3 (substructure 2) may be written as:

$$\ddot{U}_2(\omega) = \frac{P_3(\omega) + \left(\frac{k_3+k_4}{\omega^2} - \frac{c_3+c_4}{\omega i} - m_3\right)\ddot{U}_3(\omega) + \left(\frac{c_4}{\omega i} - \frac{k_4}{\omega^2}\right)\ddot{U}_4(\omega)}{\frac{k_2}{\omega^2} - \frac{c_2}{\omega i}}. \tag{6}$$

From Equations 5 and 6, it is evident that two independent estimates can be obtained for the acceleration response of interface DOF 2, which, by extension, entails that two independent estimates can be obtained for every interface of the oscillator. Subsequently, the estimates can be compared to the actual acceleration responses of interface DOF 2, and, in case of discrepancies, the partial model that is no longer capable of describing the structural condition is detected. In the next section, simulations on a 4-DOF oscillator are performed to showcase the validity of the proposed concept using acceleration response data.

3 Simulations on a 4-DOF oscillator

The proposed embedded physics-based modeling concept is validated through simulations on a 4-DOF oscillator. The simulations involve two scenarios: scenario 1, with the oscillator intact, and scenario 2, with slight damage induced as a small change in stiffness. The oscillator comprises four lumped masses on 4 beam elements, as shown in Figure 3a. The dynamic behavior of the oscillator is assumed to be characterized by translational degrees of freedom solely, i.e. following the “stick” model paradigm. The oscillator is segmented into two substructures with one interface, as shown in Figure 3b. For scenario 1 (no damage), the oscillator is subjected to white-noise excitation $P_n(t)$ ($n = 1\ldots4$), and its acceleration response data are calculated through time-history analysis, using the Newmark-β integration algorithm:

$$\begin{aligned} \dot{u}_{m+1} &= \dot{u}_m + (1-\gamma)\Delta t \cdot \ddot{u}_m + \gamma \Delta t \cdot \ddot{u}_{m+1} \\ u_{m+1} &= u_m + \Delta t \cdot \dot{u}_m + \tfrac{1}{2}(\Delta t)^2 \left[(1-2\beta)\cdot \ddot{u}_m + 2\beta \cdot \ddot{u}_{m+1}\right]. \end{aligned} \tag{7}$$

In Equation 7, subscript m represents the mth time interval of the time-history analysis, and γ and β are integration coefficients, whose values in this study are set equal to $\gamma = 0.5$ and $\beta = 0.25$. The duration of the time interval is denoted as Δt. The total duration of the time-history analysis is $3{,}600$ s, and the acceleration response data is calculated with a sampling rate equal to $f_s = 100$ Hz.

Following the substructuring, the partial model of substructure 1 and the partial model of substructure 2 will be used to estimate the acceleration response $\ddot{U}_2$ of interface DOF 2, using Equations 5 and 6. The acceleration response data is split into 21 windows of 16,384 points length, and for each window, Equations 5 and 6 are applied for each substructure, yielding estimates $\ddot{U}_{2,1}(\omega_j)$, from substructure 1, and $\ddot{U}_{2,2}(\omega_j)$, from substructure 2, respectively, over a range of 20 dominant natural frequencies ($j = 1\ldots20$). Finally, the root mean squared error (RMSE) values (ε) between estimates $\ddot{U}_{2,1}(\omega_j)$, $\ddot{U}_{2,2}(\omega_j)$ and $\ddot{U}_2(\omega_j)$ are computed over the range of the 20 natural frequencies. The RMSE values for the 21 windows are plotted in Figure 4; since responses in the frequency domain are complex numbers, the errors are plotted separately for the real parts and the imaginary parts of $\ddot{U}_{2,1}(\omega_j)$, $\ddot{U}_{2,2}(\omega_j)$ and $\ddot{U}_2(\omega_j)$.

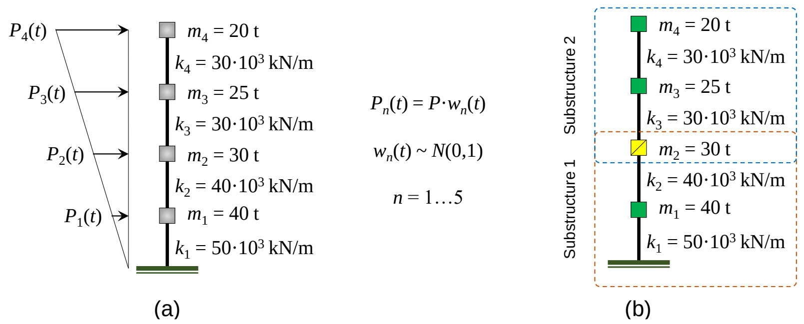

Figure 3: 4-DOF oscillator used for the simulations.

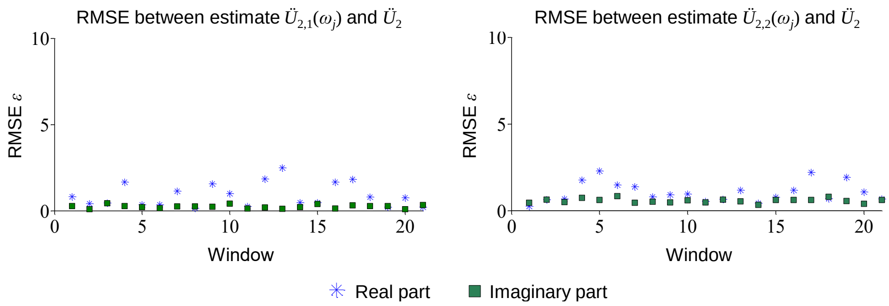

Figure 4: RMSE between estimates $\ddot{U}_{2,1}(\omega_j)$, $\ddot{U}_{2,2}(\omega_j)$ and responses $\ddot{U}_2(\omega_j)$ (Scenario 1).

As shown in Figure 4, the RMSE values between the estimates yielded by the substructures and the actual acceleration responses at the interface are relatively low, showcasing the capability of the partial models to provide information on the structural behavior. To highlight the sensitivity of the estimates to damage, scenario 2 involves a second time-history analysis with a slight change in stiffness k_1, which is reduced to $k_1' = 45\cdot10^3$ kN/m. Upon completing the second time-history analysis, the estimates are calculated anew using the original model parameters (i.e. with $k_1 = 50\cdot10^3$ kN/m), as shown in Figure 5.

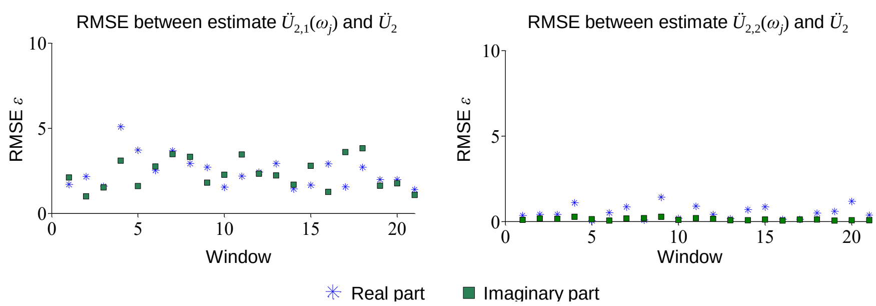

Figure 5: RMSE between estimates $\ddot{U}_{2,1}(\omega_j)$, $\ddot{U}_{2,2}(\omega_j)$ and responses $\ddot{U}_2(\omega_j)$ (Scenario 2).

The significant error values in the left plot of Figure 5 are indicative of the capability of the embedded physics-based modeling concept to yield richer information about damage on the monitored structure than global data-driven methods. Specifically, the inability of the partial model corresponding to substructure 1 to provide correct estimates of the acceleration response of interface DOF 2 indicate the location where changes in structural stiffness have occurred. By contrast, the estimates obtained from substructure 2 for scenario 2 are low, thus indicating that the model parameters of substructure 2 have remained unaffected.

4 Summary and conclusions

This paper has reported on an embedded physics-based modeling concept for wireless structural health monitoring, to enable wireless sensor nodes to analyze data locally with physics-based models. Using substructuring, the embedded physics-based modeling concept foresees the segmentation of an overall physics-based model of the monitored structure into partial models, each corresponding to one substructure, which comprises internal degrees of freedom and interfaces with neighboring substructures. Thereupon, functioning as transfer function, each partial model is used to obtain estimates of acceleration responses in the frequency domain at the interfaces of the corresponding substructure, using equations of motion at internal degrees of freedom. By comparing the estimates of the acceleration responses to the actual acceleration responses at the interfaces, conclusions are drawn on the structural condition, and, particularly, on the capability of the partial models (and, by extension, of the overall physics-based model) to describe the structural condition. The embedded physics-based modeling concept has been validated through simulations on a 4-DOF oscillator showcasing the capability of the concept to accurately describe the current structural condition both in the presence and in the absence of damage. Future work will focus on considering more elaborate physics-based models as well as applying the concept to real-world SHM systems.

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