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RELIABILITY OF THE POWER SPECTRAL DENSITY METHOD IN PREDICTING STRUCTURAL INTEGRITY

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Abstract. *For any method to be adopted and deployed in engineering practice, its reliability should be fully understood. This paper addresses the reliability of the Power Spectral Density (PSD) method for damage detection. As a vibration-based approach, the method is classic, but its reliability and how the damage level affects the performance have not been discussed. We hypothesize that the accuracy of the method strongly depends on the damage level. We evaluate the reliability by using a large dataset involving 3500 cases with five levels of structural integrity. The dataset is produced by analyzing a seven degree-of-freedom system subjected to a concentrated dynamic force with random magnitude. A spring on the system is reduced in its stiffness to simulate damages. Our significant findings are the following: it is challenging for the PSD-based method to differentiate the healthy condition from the damaged conditions when the damage level is small. However, the reliability is high at 95% probability when the structural integrity has dropped by five percents.*
Keywords: Structural health monitoring, Power spectral density, Reliability, Damage prediction

1. **Introduction.** Catastrophic failures of engineering structure often lead to great material and non-material lost. Gunawan [1], for instance, reported Kutai Kartanegara bridge in Samarinda, Indonesia, that suddenly collapsed on Nov. 26, 2011, killed 24 people, injured 39 persons, and destroyed dozens of cars and motorbikes. The bridge construction cost nearly a million of the present dollar, taking the inflation rate into account.

To avoid catastrophic failures, engineering structures should be continuously monitored, manually or automatically. Manual monitoring is susceptible to human errors and often unreliable [2]. For the reason, automatic and continuous Structural Health Monitoring (SHM) is preferable. SHM has been a field of research for a few decades. One of the earliest publications regarding SHM was found in 1895 [3], and the number of publications on SHM has been increasing significantly for the last thirty years [4].

In the field of SHM, many developed detection and classification methods were based on vibration where one of the large classes is called statistical time series methods. In this class, the detection is performed by applying statistical analysis of structural vibration responses due to random excitation. This approach has many advantages. Mainly, damages on any part of structures can be inferred from data collected on a few measurement points. In the class of statistical time series, the methods can be categorized into the non-parametric method and the parametric method. Within the former category is the methods of the Power Spectral Density (PSD), Frequency Response Function (FRF),

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model residual variance, and sequential probability ratio test. Within the latter category is the methods of the AutoRegressive Moving Average (ARMA) models, the model parameter based method, state space models, and residual based methods.

Since the last decade, the trend of using machine learning or soft computing technique for SHM continues [5]. Khodabandehlou et al. [6] developed a convolution neural network model that classified the structural conditions into healthy, and minor, moderate, and extensive damages on the basis of the acceleration data recorded on many points on the structure. Chang et al. [7] developed a simple neural network model to estimate a class of the structural damage index on the basis of structural natural frequencies and mode shapes. Gomes et al. [8] used an artificial neural network that minimized an objective function governed by the ratio of the modal shape on the healthy and damaged conditions. The mode shapes were measured on some points that maximized the modal information. In addition to the broad adoption of the machine learning techniques, we also witness a genuine identification method proposed by [9] that the damage was detected by observing the change in the dynamic equilibrium equation on the steady state condition. The approach is simple and has excellent potential. We encourage more investigations on this approach.

The issue of reliability is critical and needs to be fully understood before prediction methods can be put into practice. Regarding the PSD method, its reliability has not been comprehensively discussed even though the method is classic.

To the best of our knowledge, the reliability of the PSD method has only been discussed by a few articles [10, 11, 12]. The discussion was limited by the type of the engineering structures, the number of the experimental data, and the damage scenarios and levels. In [12], the tested structure was a scaled aircraft skeleton. The number of data was 320 in total: 60 data for the healthy condition, and 40 data for each damage case. Six damage cases were studied. The damages were simulated by loosing the bolts connecting some structural members.

Kopsaftopoulos and Fassois [11] tested a simple truss structure hanging in the air by some strings. The number of data was 200 in total: 40 data for the healthy condition, and 32 data for each damage case. Five damage cases were also studied. Similarly, the damages were introduced by loosing some bolts.

Both references reported that the PSD method provided a 100%-reliability level. In general, any predictive model that achieves such a level of reliability is considered harmful [13]. We speculate that the scenario of inducing damages by loosing bolts may have significantly altered the structural stiffness. As a result, the structural responses were remarkably different from those of the healthy condition; hence, the prediction at 100% accuracy could be obtained. We do not rule out that the limitation in the number of data may also become a contributing factor. For evaluating the reliability of a method convincingly, datasets of large size are required.

We hypothesize that the damage size also influences the prediction reliability. Any predictive method faces challenges to differentiate healthy condition from conditions with small damages. Thus, in this paper, we seek to understand how the damage level affects the prediction reliability.

For SHM, it is essential to have a clear taxonomy about the scale of the imperfection of the structure: defect, damage, or fault. The defect is the material imperfection in the nano- or micro-scale level. All engineering materials contain defects. With the inherent existence of defects, engineering structures can still function satisfactorily. However, with a fault, the structures can no longer operate satisfactorily. The damage scales the imperfection between the defect and the fault. The damage is initiated from a defect and potentially develops becoming a fault. With damages, engineering structures may or may not function satisfactorily. SHM deals with imperfection in the damage scale [14].

The article is structured as the following. Section 2, Research Method, describes the data collection method and the computation of the damage sensitive F statistic. Section 3, Research Results, describes the F statistic reliability for structural damage monitoring and discussion. Finally, the article is completed with Section 4, Conclusions, that briefly summarized the most important insight obtained from the study and a potential future research.

2. **Research Method.** From many SHM publications, we have seen various SHM methodologies developed for various case studies involving actual or/and laboratory test structures. Some of them are the I-40 bridge [4], a lumped-mass system of eight freedom system [4], truss structures [11], and composite beams and plates [8]. In the present study, we utilize the lumped mass system due to its simplicity.

2.1. **Data collection method.** Data are produced by a numerical analysis of a seven-degree-of-freedom system (Figure 1). The system consists of seven lumped masses, 1 kg each, connected by eight similar linear elastic springs. Each has 1 N/m stiffness. A dynamic force having a random magnitude is applied to the center mass. The force magnitude is drawn from a normal probabilistic distribution with a mean of zero and a standard deviation of 0.09. Initially, the random force data have frequency contents up to 25 Hz. Then, the data are filtered with a Butterworth filter with a cutoff frequency of 20 Hz and an order of 12.

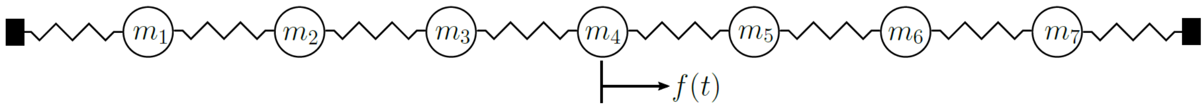

FIGURE 1. The model of the seven-degree-of-freedom system

The structural damage is assumed to occur on the spring connecting m_3 and m_4. It is also assumed to affect the spring and to degrade its stiffness only. The four levels of degradation are studied, namely, 1%, 5%, 10%, and 20%. This decision is made to understand how the damage level affects the accuracy of the classification. We hypothesize that the classification accuracy is low when the damage level is low, the relation between the classification accuracy and the damage level is not linear, and when the damage level is higher than a certain threshold, the classification accuracy is independent to the damage level.

The analysis results are the displacement of the seven masses. The data are sampled at a constant rate of 0.1 s and for a duration of 360 s. For each structural condition, the analysis is repeated for 500 times by varying the distribution of the dynamic force. The settings of the applied dynamic force and the sampling rate of the structural responses are determined by considering the structure natural frequencies: 0.62, 1.22, 1.77, 2.25, 2.65, 2.94, and 3.12 in Hz. The frequencies ω are determined by solving the eigenvalue problem of $(\mathbf{K} - \omega^2\mathbf{M})\mathbf{\Phi} = \mathbf{0}$, where $\mathbf{K}$ is the stiffness matrix, $\mathbf{M}$ is the mass matrix, and $\mathbf{\Phi}$ is the eigenvector.

2.2. **Power density spectrum by Barlett's method.** In this research, F statistic is used as the damage-sensitive feature. Its computation requires the Power Spectrum Density (PSD) data, which are computed by the following procedure by using Barlett's method [15].

We consider an analog, time-varying, and finite-length signal $x_a(t)$. In SHM, the signal may represent the historical data of the displacement at an observation point. The signal is assumed to be measured at a constant sampling rate of t_s such that

$$x_i = x_a(i \cdot t_s) \tag{1}$$

where $i = 0, 1, 2, \ldots, (N-1)$. We transform the discrete time-domain signal x_i into the frequency domain by applying the discrete Fourier transform with the formula:

$$X(f_k) = \sum_{i=0}^{N-1} x_i \cdot \exp(-\jmath i 2\pi f t_s) \tag{2}$$

where $f \in [0, f_s/2]$ and $f_s = 1/t_s$, which is called the sampling frequency, and f_k are discrete frequencies of $f_i = i \cdot f_s/N$. To shorten the expression, we use the symbol X_i to denote $X(f_i)$. We partition the signal into M-equal-length sub signals as illustrated by Figure 2. Barlett's method computes a signal PSD by averaging PSDs of the sub signals. The resulted PSD is more reliable and less sensitive to the signal noises. However, the method is only applicable for long signals. The Barlett's formula for computing PSD is:

$$S_i(f) = \frac{1}{LM} \sum_{m=0}^{M-1} \left| X_i^{(m)} \right|^2. \tag{3}$$

The signal length N and the number of sub signals M is related by $N = LM$, where L is the length of the sub signal (see Figure 2).

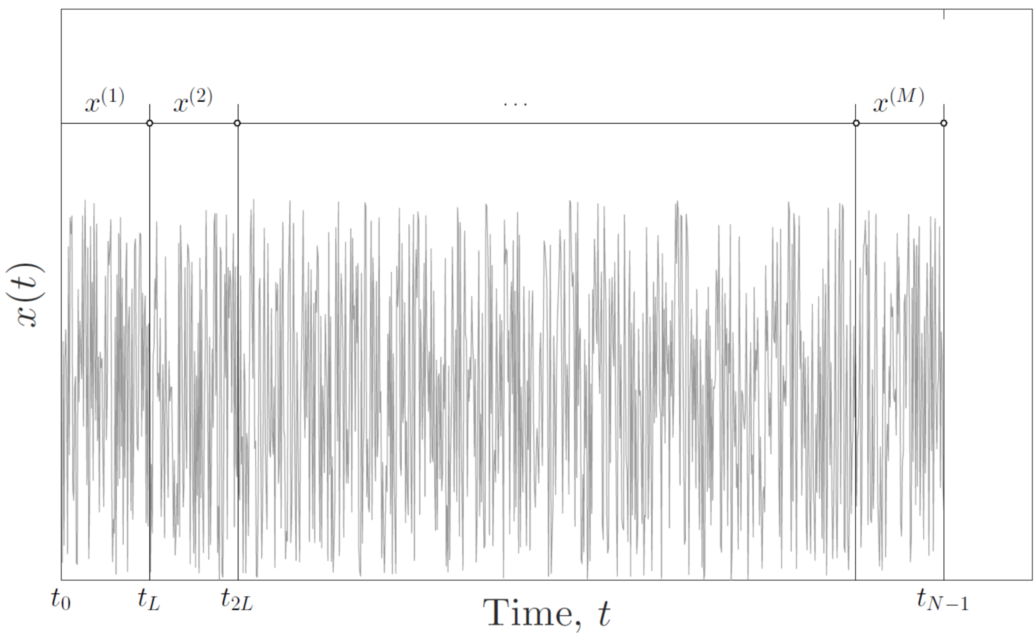

FIGURE 2. The partition of the signal $x(t)$ into M-equal-length sub signals

2.3. ***F* statistic for SHM.** The method is simple and practical, depending only on the data of structural responses, which can be collected on a few measurement points. It turns the damage monitoring problem into a direction-less hypothesis test that can be solved in three steps.

The first step is the statement of the null and alternative hypotheses, which for this case, are:

$$\text{H}_0 : S_h(\omega) = S_u(\omega) \quad \text{and} \quad \text{H}_\text{a} : S_h(\omega) \neq S_u(\omega). \tag{4}$$

The symbol $S(\omega)$ denotes PSD. The subscript h denotes the healthy condition, and u means the unknown-to-be-sought condition. The healthy condition is the reference condition, from which the other structural conditions are measured. It should be determined previously. The structure is assumed healthy if the null hypothesis, H_0, prevails. It is considered healthy if its PSD is very much similar to the PSD of a healthy condition. The degree of similarity is measured statistically. The structure is assumed to contain damage if the alternative hypothesis, H_a, prevails, which means that the PSD has changed significantly. The structure that is associated with $S_u(\omega)$ is considered damaged if $S_u(\omega)$ deviates significantly from $S_h(\omega)$.

The second step is to compute the relevant F statistic. This statistic is simply a comparison of two PSDs: $S_h(\omega)$ and $S_u(\omega)$. The statistic has the value of one when the two PSDs are identical. When the structure contains damages, some values of the F statistic may deviate from one to be very big or very small. The level of change in PSD determines the magnitude of the F statistic. The statistic is computed by: $F = \left[\hat{S}_h(\omega)/S_h(\omega)\right] \Big/ \left[\hat{S}_u(\omega)/S_u(\omega)\right]$. The hat denotes the estimated PSD. This expression can be made simpler. Under the condition of (4), it can be simplified to

$$F = \hat{S}_h(\omega)/\hat{S}_u(\omega). \tag{5}$$

The third state is to establish the upper and lower limits of the statistic from which the change of PSD can be categorized as significant or not. The lower limit is $F_{(1-\alpha/2,2K,2K)}$ and the upper limit is $F_{(\alpha/2,2K,2K)}$. The symbol α denotes the statistical significance, which represents the probability of rejecting the null hypothesis given that the structure condition is healthy. The symbol K denotes the degree of freedom, which represents the number of windows in Barlett's method (see Subsection 2.2).

An expression similar to Equation (5), as discussed by [16], is susceptible to perturbation, producing highly fluctuating statistic, and often exceeding the lower and upper limits on a healthy structural condition. The F statistic is unreliable and must be computed with great care.

2.4. **Performance indicator and evaluation method.** We adopt five performance measures from [17] to evaluate the classification performance. They are: True Positive Rate (TPR), True Negative Rate (TNR), False Positive Rate (FPR), False Negative Rate (FNR), and accuracy. They are computed by the following formulas: $\text{TPR} = \text{TP}/(\text{TP}+\text{FN})$, $\text{TNR} = \text{TN}/(\text{TN}+\text{FP})$, $\text{FPR} = \text{FP}/(\text{FP}+\text{TN})$, $\text{FNR} = \text{FN}/(\text{FN}+\text{TP})$, $\text{Accuracy} = (\text{TP}+\text{TN})/(\text{TP}+\text{TN}+\text{FP}+\text{FN})$ where TP is True Positive, TN is True Negative, FP is False Positive, and FN is False Negative. TPR is also called recall.

3. **Research Results.** In this article, we wish to provide a better and detail description regarding the reliability of a PSD-based method for structural health monitoring. Specifically, we focus on the use of the F statistic.

We structure this section as the following. We start by presenting the structural deformations as responses to a dynamic load having a random magnitude applied to the structure. Then, we present the deformations on various damage levels. Subsequently, we show the deformations in the form of the F statistic for structural health monitoring, followed by the statistic in misclassification cases. Finally, we present the roots of the misclassification.

The structural deformations of the seven nodes on the model are presented in Figure 3. The figure also shows the random magnitude of the associated dynamic load applied to the center node, Node 4. The deformations follow, to some extent, a pattern with a larger

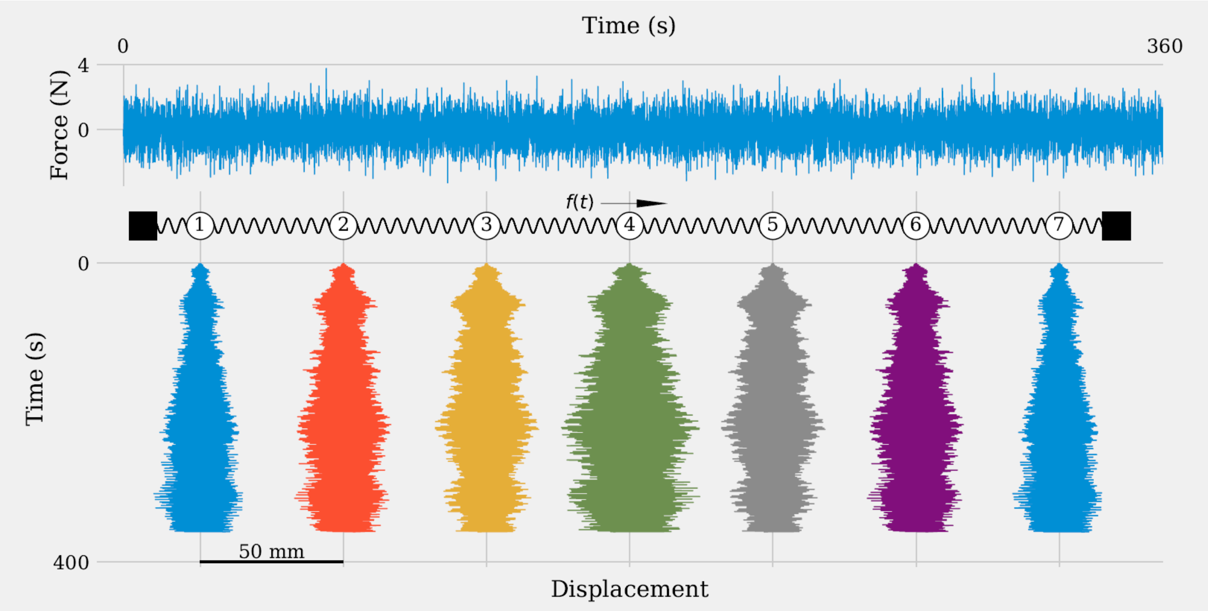

FIGURE 3. The seven-degree-of-freedom model, the typical applied force, and the typical responses on the healthy condition

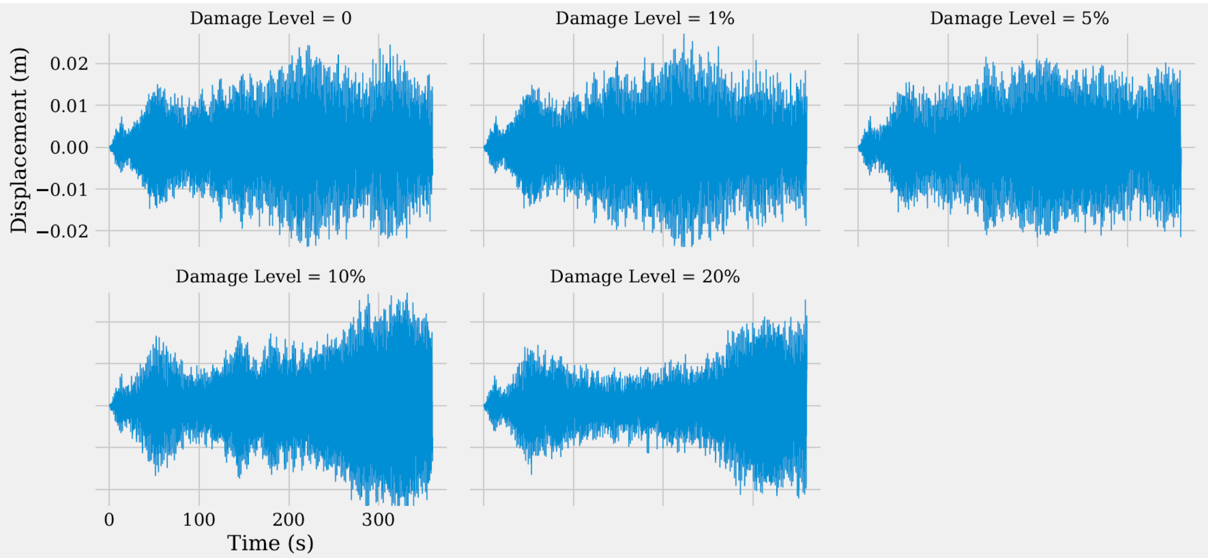

FIGURE 4. The model responses at Node 4 for healthy and damaged conditions with the damage levels of 1%, 5%, 10%, and 20%

magnitude on the center node and smaller magnitude on the nodes distancing from the center.

How the structural deformations affect the damage level is shown in Figure 4. We should note that the damage is assumed occurring on the spring connecting Node 3 and Node 4, the spring to the left of Node 4. It only affects the spring stiffness. We reduce the stiffness by factors of 1%, 5%, 10%, and 20% to simulate various damage levels.

The results are rather interesting. Generally, in the static loading condition, structures containing damage tend to become less stiff in comparison to that on healthy condition, resulting in a larger deformation on the same loading condition. However, in the dynamic loading condition, the phenomenon may be different, and may even be in the contrary. The figure shows that the deformation is larger on the healthy condition than on the damaged conditions. Particularly, the deformation of the case of 20% damage level is much smaller than that of the healthy condition. Generally, we conclude that the magnitude of the structural deformation due to dynamic loads may not be a reliable indicator of structural integrity.

Unlike the structural deformation, the F statistic is a good indicator of structural integrity. Theoretically, the F statistic should lie within the range of $F_{(\alpha/2,2K,2K)}$ and $F_{(1-\alpha/2,2K,2K)}$ when the structure is healthy. The variable α denotes the statistical significance and is usually assigned to a value of 1×10^{-6}. Figure 5 shows how the damage level affects the statistic. For a healthy condition, the statistic completely lies within the limits. For the damaged conditions, the F statistic at the frequency 1.7684 Hz exceeds the upper limit of 7.4014. For the cases of high damage levels, the F statistic crosses the critical statistic at several frequencies. The figure suggests that the F statistic associated with some natural frequencies are sensitive to the damage. The value of the F statistic tends to increase with the damage level.

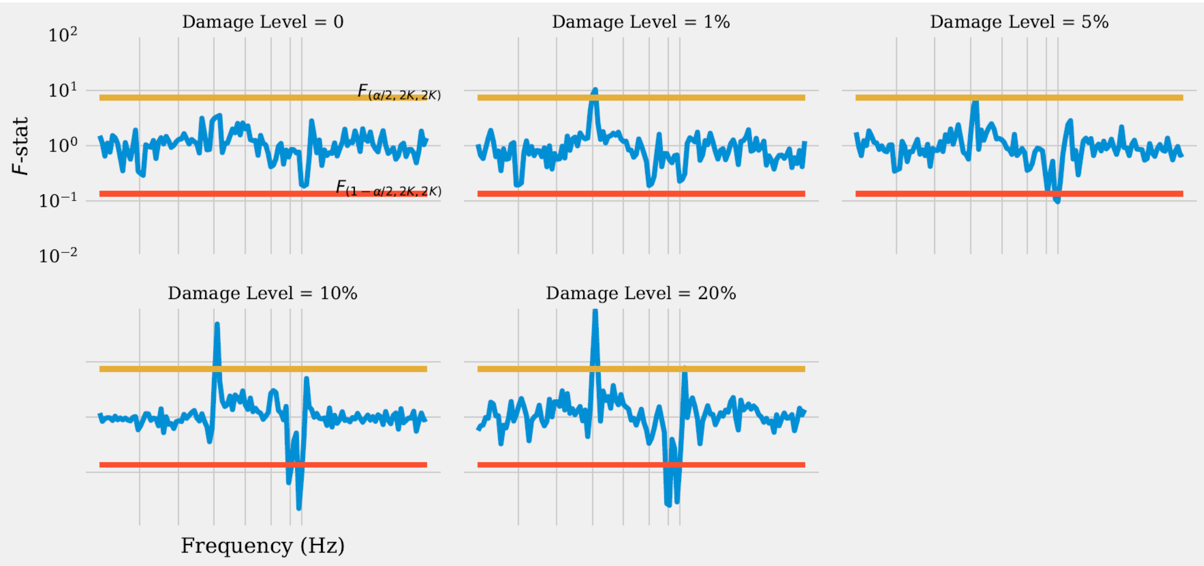

FIGURE 5. The F statistic on the center node for the cases of healthy condition and damaged conditions with the damage levels of 1%, 5%, 10%, and 20%. The vertical grid lines denote the natural frequencies of the structure obtained by a modal analysis. The natural frequencies, in Hz, are 0.62099, 1.2181, 1.7684, 2.2508, 2.6466, 2.9408, and 3.1219. The critical statistic $F_{(\alpha/2,2K,2K)}$ is 7.4014 and $F_{(1-\alpha/2,2K,2K)}$ is 0.1351.

Although the F statistic is a good indicator of damages, it is not entirely reliable. The use of the statistic may lead us to some erroneous classifications. We support this assessment with the facts presented in Figure 6. Theoretically, we know that a structure is considered damaged if $F > F_{(\alpha/2,2K,2K)}$ or $F < F_{(1-\alpha/2,2K,2K)}$. In these examples, we witness that F statistic exceeds the critical statistic although the structure is known to be healthy. On the contrary, we also witness that F statistic is within the range of the critical statistic although the structure is damaged. How accurate or reliable F statistic for structural health monitoring is a subject of discussion to follow.

The characteristics of the classification accuracy by the PSD method is shown in Figure 7. These results are obtained from analyzing 3500 cases involving the healthy condition and the damage conditions of four damage levels, 500 cases for each condition. In general,

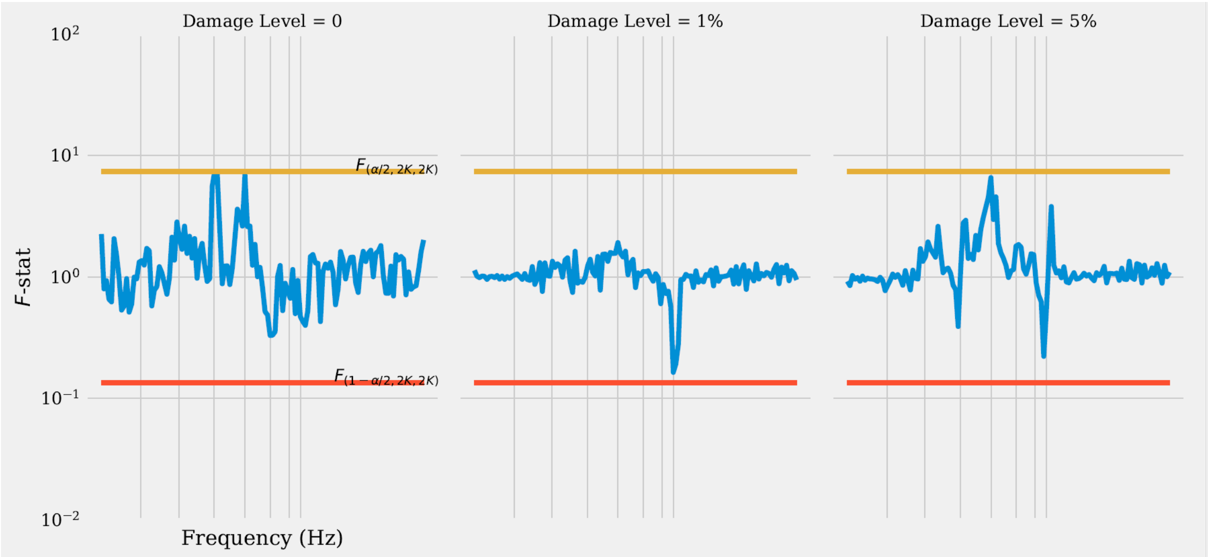

FIGURE 6. Three examples of misclassification. On the left panel, a healthy structure is classified to be damaged leading to a false negative classification. On the middle and right panels, a structure on two damaged states is classified to be healthy, leading to false positive classifications.

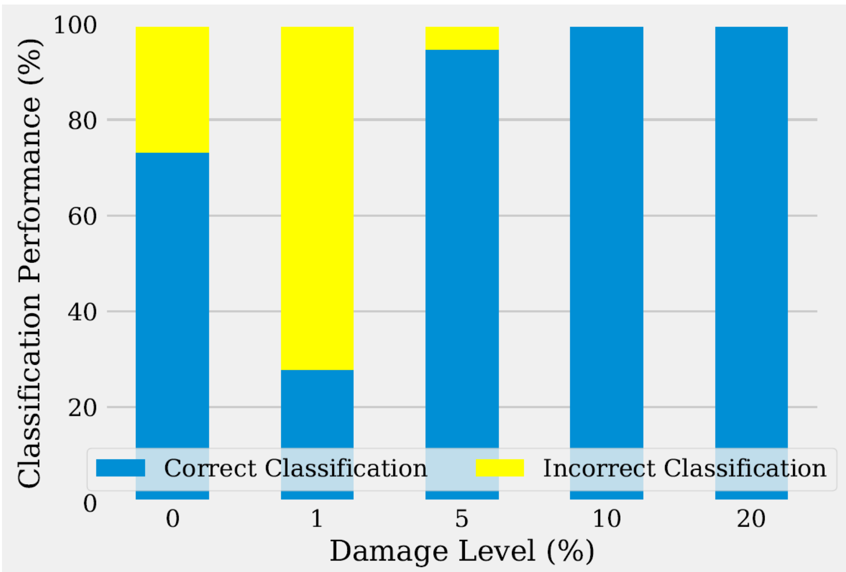

FIGURE 7. The classification performance of the power spectral density method. Respectively, the correct classification is 74%, 28%, 95%, 100%, and 100% for healthy condition, and damaged condition at the damage levels of 1%, 5%, 10%, and 20%.

the method works well, or it can detect the damages. The accuracy is very high when the structure contains the damage at high levels. In the current case, the classification accuracy is 100% when the structural stiffness has been degraded by 10% or higher. For the damage level of five percents, 95% cases of the damaged structure are accurately classified, suggesting one false positive classification for every 20 cases.

Alamdari [18] noted that: "Salawu [19] found that in order to reliably detect damage by monitoring natural frequency, a minimum of 5% change in the natural frequency is required." The present finding advises that 5% change of the structural integrity is required for the PSD-based method to detect damages reliably.

The classification accuracy is abysmal when the damage level is minimal. In this case, the classifier can hardly differentiate the healthy condition from the damage condition. Only 28% cases are accurately identified. More than 70% cases of the structure containing the damage at 1% level are considered healthy.

When the structural condition is healthy, the classifier produces about 25% false negative classification where the structure in good condition is classified as damaged. The proportion seems rather big. However, when we look into the detail, we begin to understand the issue better. The detail is presented in Table 1, which comprehensively summarizes the number of correct and incorrect classifications.

Table 1. The number of correct and incorrect classifications for the healthy condition and the damaged conditions at the levels of 1%, 5%, 10%, and 20%

		Damage level (%)				
		0	1	5	10	20
Damage level (%)	0	2586	949	0	0	0
	1	2529	971	0	0	0
	5	187	0	3313	0	0
	10	0	0	0	3500	0
	20	0	0	0	0	3500

From Table 1, the issue becomes clear. The false negative classification occurs due to the difficulty differentiating the healthy condition from the one-percent damage-level condition. The table reads nearly a thousand cases of the identified healthy condition contain the small damage. The majority of the cases of the damaged condition are considered healthy. The number of the false negative classifications is about 1000, and the number of the false positive classifications is about 2500. The rate of the false positive classification is prevalent in the rate of the false negative classification. For the case of five percents damage level, a small fraction of 187 cases are classified as healthy. However, if the data from the one-percent damage case are not considered, the classification accuracy of the healthy condition would be 100%.

The misclassification issues can be traced back to the features used for the classification: $F_{\max}$ and $F_{\min}$. The distribution of these statistic is depicted in Figure 8 for the healthy condition and the damage conditions with the damage levels of 1%, 5%, 10%, and 20%. The distribution of the statistic for the healthy condition greatly overlaps with the case of 1% damage level; thus, misclassification occurs frequently. The figure also suggests that the classification criterion $F_{(1-\alpha/2,2K,2K)} = 0.1351$ seems to pass through the boundary of the case of five-percent damage level, and the cases of healthy and one-percent damage level. Differentiating the five-percent damage cases from the healthy and one-percent damage cases is possible. Finally, when the damage level has significantly increased to the levels of 10% and 20%, the resulted F statistic completely lie on the left side of $F_{(1-\alpha/2,2K,2K)} = 0.1351$. Thus, the cases are predicted with high reliability.

4. **Conclusions.** The recent development of the methods for Structural Health Monitoring (SHM) tends to adopt and deploy computationally-extensive soft computing approach where damages are detected based on patterns extracted from large-size datasets. In the other side, the traditional methods detect damages from the understanding of the structural mechanics, for example, by monitoring the vibration modes. Generally speaking, the

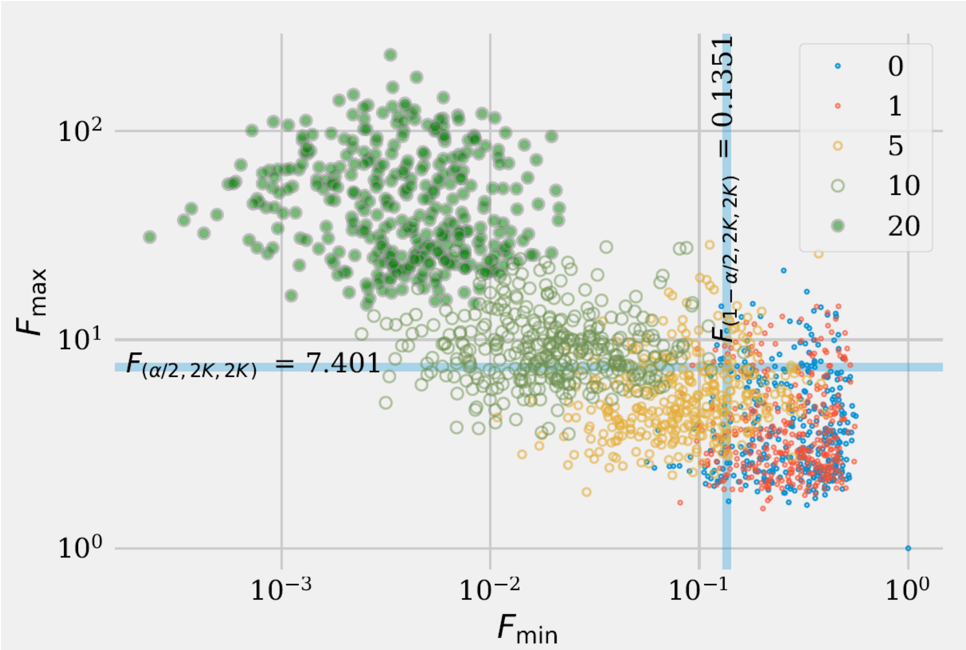

FIGURE 8. The distribution of the F_{max} and F_{min} statistic for the damage levels of 0, 1%, 5%, 10%, and 20%. The statistic tends to increase in line with the increase in the damage level. The distribution of the statistic for the healthy condition largely overlaps with that of one-percent damage level. The critical statistic $F_{(\alpha/2,2K,2K)}$ and $F_{(1-\alpha/2,2K,2K)}$ are for $\alpha = 1 \times 10^{-6}$ and $K = 14$.

traditional methods require much less computational resources than the soft computing approaches.

Although the computational power has increased tremendously in recent years, to bring those power into the vast and remote areas where engineering structures are situated is still a challenging issue. The safe use of soft computing approaches is also required training in advanced mathematics, which is inaccessible to many engineers. Therefore, developing easy-to-use detection methodologies from sound engineering principles is still crucial.

This article discusses further the use of F statistic for SHM. The statistic is easy to compute and understand to engineers trained with the structural dynamics. We compose this article to describe the reliability of F statistic, a PSD-based method, for structural health monitoring. Our finding suggests that the method works well when the damage has reached a size larger than a threshold, in this case, more extensive than 5% damage level. We are certain that this characteristic is general for all damage classification methods. Therefore, to use any method in practice successfully, we should first address the issue of what is the critical size of the damage of the structure and whether the deployed method can detect the damage before it reaches the critical size. The second is what is the remaining lifetime from the time the damage is detected to the time that the damage is critical.

For future work, we suggest to use the current dataset and use other classification methods from which a comparison regarding the reliability of the structural health monitoring methods can be made.

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