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Reliability-based robust design of smart sensing systems for failure diagnostics using piezoelectric materials

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ABSTRACT

This paper presents a reliability-based robust design approach to develop piezoelectric materials based structural sensing systems for failure diagnostics and prognostics. A detectability measure is defined to evaluate the performance of any given sensing system, and the sensing system design problem can be formulated to maximize detectability for different failure modes by optimally allocating piezoelectric materials into a target structure. This formulation can be conveniently solved within a reliability-based robust design framework to ensure design robustness while considering the uncertainties such as those from structure properties and operation conditions. Two case studies, that design sensor networks for an aircraft wing panel and a power transformer structure, are employed to demonstrate the effectiveness of the proposed methodology in developing multifunctional material sensing systems.

1. Introduction

With a growing complexity of engineered systems, failure diagnostics techniques have been prevalently employed to prevent potential catastrophic failures and improve system reliability and safety. Real-time health diagnostics interpret data acquired by smart sensors, and utilize these data streams in making critical operation and maintenance decisions [1]. Enormous benefits can be provided by effective health diagnostics activities, such as improved system safety, reliability, and reduced costs for the operation and maintenance of complex engineered systems. Structure maintenance and life-cycle management is an area that can significantly benefit from diagnostics and improved maintenance practices, as unexpected system breakdowns could be prohibitively expensive [2]. Thus to reduce and possibly eliminate such problems, it is important to accurately assess the health condition of an operating system in real time through effective health diagnostics. Researches on condition monitoring address these challenges by assessing system health states utilizing sensory information from the functioning system [3–5]. Monitoring of system health state (HS) changes over time provides valuable information about the performance degradation of system components for critical maintenance decision makings, and has been successfully applied to many engineering systems such as bearings [6–9], machine tools [10], power transformers [11], engines [12], aircraft wings [13], and turbines [14]. In the literature, there are two categories of approaches in general that are often employed for health diagnostics, machine learning techniques and statistical inference techniques. The machine learning-based health diagnostics approaches can further be divided into supervised learning, unsupervised learning and semi-supervised learning techniques. In addition to the aforementioned machine learning-based algorithms, statistical inference-based algorithms can also be used to classify system HSs based on statistical distances such as Mahalanobis distance [15], k-nearest neighbor method [16] and k-mean clustering [17]. Significant advancements in diagnostics area have been achieved by applying classification techniques based on machine learning or statistical inferences, resulting in a number of classification methods, such as back-propagation neural networks [18–21], deep belief networks [22,23], support vector machines [24–28], self-organizing maps [29], and Mahalanobis distance (MD) [15]. Some researchers combined two or more existing techniques to form hybrid models to achieve better diagnostic performance. Zhang et al. [9] proposed a bearing fault diagnosis methodology using multi-scale entropy (MSE) and adaptive neuro-fuzzy inference system. Saimurugan et al. [24] presented a multi-component fault diagnosis of a rotational mechanical system based on decision trees and support vector machines.

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Nomenclature

R	reliability	$f_x(x)$	probability density function
Φ	standard Gaussian cumulative distribution function	$f_{(\cdot\|\cdot)}$	conditional probability density function or likelihood function
β_t	target reliability index	p_{fs}	probability of system failure
C_L	user-defined confidence level	G_i	function of the ith constraint
$F(x)$	cumulative distribution function	C	cost function
$F^{-1}(x)$	inverse cumulative distribution function		

Despite a variety of numerical diagnostics algorithms being developed and a broad range of successful applications in various engineering fields being reported in the literature, one of the key challenges in structural health diagnostics lies in the fact that health relevant sensory data must be collected effectively so that enough evidences can be provided for diagnostics algorithms to conduct health state identification and damage detection. However, implicit relationship between sensory signals and system health states as well as sensor noise and uncertainties related to system operating conditions render a grand challenge in developing an effective sensor network so that system health states can be accordingly diagnosed accurately with sensory data collected from the sensor network. To overcome this challenge, a sensor network must be developed with sensors nodes being optimally placed so that the differences between different system health states can be reflected clearly on sensory signals. In addition, the sensor network must be designed to ensure the robustness of health diagnostics given the aforementioned uncertainties and variability involved in sensing and diagnosing processes. In the literature, sensor placement optimization under uncertainties has been studied for structural health monitoring applications [30,31], and further optimal location of sensors has been presented for parametric identification of linear structural systems [32]. A methodology for optimally locating sensors in a dynamic system [33,34] was developed as a probabilistic approach in structural health monitoring system. The study in [35] developed a Bayesian approach to optimize sensor placement for structural health monitoring. In [36], an optimal sensor location methodology for structural identification and damage detection has been studied. Most of these methods were settled for allocating a number of sensors to distinguish a specific health state of structural damage, and their applications were limited by the type of health state failure mechanisms. Although reported studies on sensor placement optimization have showed improvements on health diagnostics performance, there are two fundamental challenges that hinder the broad applications of this technique. First, the sensing capability of the sensor nodes used in sensor placement studies have been mostly assumed to be independent to the target systems, which is generally not true for practical structural applications; Second, there is no quantitative measure for the diagnostics performance related based upon a given sensor network design, thus, the performance robustness cannot be ensured in the sensor network design process.

To address the aforementioned sensor network design challenges for structural diagnostics applications, this paper presents a novel reliability-based robust design optimization (RBRDO) framework for structural sensing function design using multifunctional materials. The RBRDO technique has been developed to ensure the performance robustness thus improve quality and reliability in product and process design, while considering uncertainties involved in different stages of a system's life cycle [37–42]. In detail, design optimization of piezoelectric embedded sensor patches is considered to realize structural sensing function [43–48]. First, a generic detectability measure is defined in this study to quantify the performance of a given sensing system for diagnostics under uncertainty. A novel detectability analysis approach based on Mahalanobis distance classifier is then developed to carry out the detectability analysis for a given sensing system design. Second, with the defined detectability measure and developed detectability analysis approach, a novel reliability-based robust design optimization (RBRDO) framework is presented for sensing system design in order to minimize the system development costs while maintaining the predefined detectability target. The rest of the paper is organized as follows. First, smart sensing with piezoelectric materials is introduced in Section 2. In Section 3, a detectability measure is defined in a probabilistic form as a unified quantitative measure for the performance of any given sensing system used for the structural health diagnostics. A general approach for detectability evaluation is also introduced based on health state classification. In Section 4, a generic RBRDO framework is developed to design smart material systems for the structural health diagnostics and prognostics. Two case studies are used in Section 5 to demonstrate the effectiveness of the proposed methodology in developing structural sensing systems.

2. Smart sensing with piezoelectric materials

Piezoelectric materials can be potentially applied in both sensing and actuating applications [49–53]. In sensing applications the PZT sensor is attached to a structure and exposed to a stress field that creates electric charges (direct piezoelectric effect). In actuating applications the PZT actuator is attached to a structure and an external electric source is applied to the actuator that induce strain field (reverse piezoelectric effect). In both cases the constitutive relationship can be mathematically formulated as follows:

$$\varepsilon_i = S^E_{ij}\sigma_j + d_{mi}E_m \tag{1}$$

$$D_m = d_{mi}\sigma_i + e^{\sigma}_{ik}E_k \tag{2}$$

where the indexes $i, j = 1, 2, \ldots, 6$ and $m, k = 1, 2, 3$ refer to different directions within the material coordinate system [51], σ is a vector of the stress (N/m^2) and ε is a vector of the strain, d is a matrix of the piezoelectric strain constants that defines strain per unit at constant stress (m/V), E is a vector of the electric field (V/m), S^E is a matrix of the elastic compliance (m^2/N), D is a vector of the electric

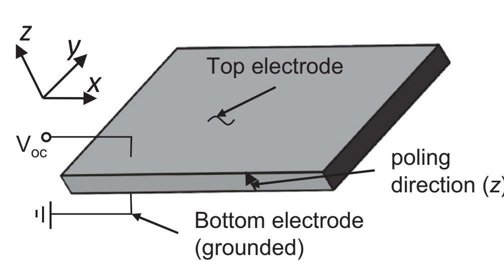

Fig. 1. Schematic of a piezoelectric ceramic sheet.