

Damage Localization in Mechanical Structures Based on a Virtual Sensor Approach

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Summary:

This paper introduces a new methodology for localizing damages in mechanical structures thanks to a Virtual Sensor approach. We combine physics-based models, finite element methods, real-time data and data-driven models using machine-learning algorithms to determine in real-time the “damage localization” on real-world mechanical structures with a reduced number of strain sensors. By leveraging finite elements, we have built synthetic database gathering the normal physical behavior of the mechanical structures under various force applications and abnormal behaviors induced by notches in the material. Machine-learning algorithms have been trained on synthetic data coming from simulations. The notches have been effectively localized in real-time on the real-world mechanical structure with a reduced number of strain sensors, validating the approach.

Keywords: Virtual sensor, Digital twin, Data driven models, Finite element method, Neural Networks.

Introduction

In mechanical engineering, maintaining the structural integrity of systems is crucial for their safe and efficient operation. Damages, manifesting as notches, cracks, or various forms of material degradation, can drastically affect a system's performance and reliability. Structural Health Monitoring (SHM) techniques, including both traditional and advanced sensor-based methods, are essential for detecting and evaluating such damages [1]. However, the application of SHM techniques often hindered by challenges like the requirement for extensive sensor networks and the complexities involved in optimizing sensor placement. Recent developments in digital twin technology present new opportunities for improving damage localization with a reduced number of well-chosen sensors [2]. A digital twin is a virtual model that mirrors a physical system, enabling real-time monitoring and predictions through a continuous flow of data between the physical and virtual entities [3]. In this paper, we propose a new refined Virtual Sensor framework that integrates comprehensive aspects of digital twin technology, from its conceptualization to practical deployment at a systemic level. Applied to a well-chosen case study, this framework demonstrates its effectiveness in localizing notches in mechanical structures in real-time, highlighting the potential of digital twins in predictive maintenance.

Methodology

The proposed Virtual Sensor framework detailed in the Fig. 1 provides a comprehensive method for creating a digital twin of a physical system.

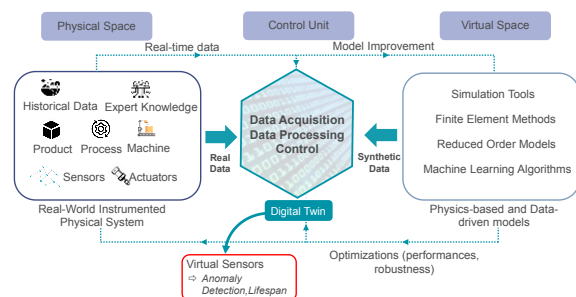


Fig. 1. Proposed Virtual Sensor Framework

It consists of three interconnected elements to achieve this. The physical space representing the real-world entity such as product, machine, or process [4]. Embedded in the physical space, sensor and actuators networks are actively involved in collecting data and executing actions based on instructions, respectively. The virtual space employs two types of models, Physics-based and Data-driven models. Physics-based models use Finite Element (FE) analysis and simulations to provide a deeper understanding of the system. Meanwhile, Data-driven models handle complex data efficiently using reduced order-modeling techniques, and analyze sensor data in order to predict potential issues or estimate system's lifespan. The control unit serves as the core entity of the digital twin, with

communication protocols allowing for wired and wireless data transfer. This unit manages the information flow and potentially controls the system based on the model's prediction. It is also responsible for generating visual outputs and issuing alerts, alongside a data storage component for maintaining a historical record of information.

Case Study: Damage Localization

The proposed framework (Fig. 1) is applied to construct a digital twin of a mechanical structure in order to predict damage localization. Tests are performed on steel beams subjected to bending forces, including one undamaged specimen and four with notches. Each beam is equipped with four strain gauges positioned along its length. As detailed in the workflow (Fig. 2), two FE models were developed. The first model represents undamaged beam's normal behavior, while the second simulates the beams with localized notches. Data from these simulations were then used to build two separate data-driven models: (i) A Reduced-Order Model (ROM), trained on virtual strain sensor data from the undamaged beam simulations to predict strain based on the applied force. (ii) A Convolutional Neural Network (CNN) model, trained on virtual strain sensor data from the damaged beams simulations to predict the location of damage along the beam. The combined approach of these models consists of detecting first, deviations between ROM predictions and real strain data measured by the gauges. If significant deviations arise, the CNN is activated to localize the damage.

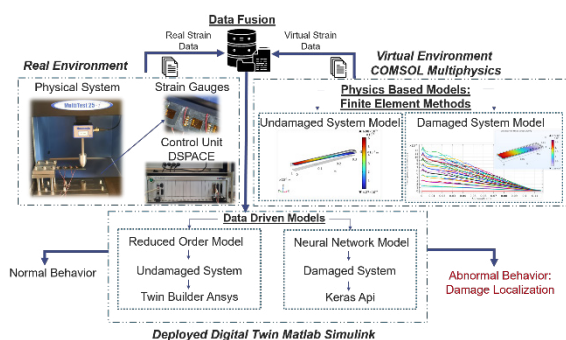


Fig. 2. Virtual Sensor Framework for Damage Localization

Reduced-Order Model for Strain Prediction

We employed ANSYS Static ROM Builder to create a ROM for real-time prediction of beam strain under various applied forces and Young's modulus values. This ROM efficiently approximates the strain response obtained from a high-fidelity FE model of the structure, previously built in COMSOL Multiphysics. The ROM creation method uses Singular Value Decomposition (SVD) for solution compression,

coupled with an interpolation technique to predict strain within the defined force and Young's modulus ranges [5]. The performance of the ROM is evaluated based on two metrics: relative error and the maximum absolute error between the ROM-predicted strain field and the corresponding field obtained from the full-order FE model [5]. Our ROM achieved a maximum relative error of 0.008798%.

Convolutional Neural Network for Damage Localization

To predict the location of damage along the beam structure based on strain gauge data from four specific positions, a CNN was employed. The CNN architecture consisted of an input layer followed by three convolutional layers with 64 filters each. These convolutional layers employed ReLU (Rectified Linear Unit) activation functions and incorporated batch normalization to enhance learning stability. The Adam optimizer was chosen to efficiently train the model on a dataset of 380 strain value samples generated from simulations of various damage scenarios in COMSOL Multiphysics. The Mean Absolute Error (MAE) served as the loss function during training. The evaluation of the model's performance on a separate test set of 80 data points demonstrated a Mean Squared Error (MSE) of $5.2705e-07$ and a MAE of $5.8641e-04$.

The "damage localization" virtual sensor was finally validated on the real-world mechanical structure. The various notches localization have been found by using the real-time strain sensor data and the CNN with a precision quantified by a MAE of 3.92mm. This validates the good operation of the digital twin developed here and the opportunity of virtual sensors for damage localization on mechanical structures with a reduced number of sensors.

References

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