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Optimization of the Surrogate Model for Acoustic Wave Propagation: Defect Detection

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1. Introduction

Non-destructive testing (NDT) plays a vital role in ensuring the safety and integrity of structures across various industries, including the nuclear sector [1, 2]. Among the various techniques used for NDT, ultrasonic testing (UT) effectively detects defects without causing damage. The effectiveness of UT depends on the precise analysis of acoustic wave propagation phenomena, which reveals essential information about the presence, nature, and dimensions of defects.

A major challenge in UT is estimating the dimensions of defects, particularly their location (depth) and size (width). Typically, UT is performed through scanning the target under inspection by exciting and receiving acoustic waves and analyzing the measured signal by ultrasonic reception. Defect depth is estimated by calculating the time of flight (ToF), and defect width is estimated using dB drop methods for ultrasonic visualization, such as B-mode imaging and the synthetic aperture focusing technique (SAFT) [3].

However, conventional methods necessitate constant algorithmic adjustments to adapt to varying material properties, geometrical factors, and noise conditions. This iterative adjustment process significantly undermines the efficiency and cost-effectiveness of UT practices. Moreover, the reliance on fixed parameters for the defect detection algorithms often leads to inaccuracies in defect characterization under less-than-ideal conditions. These challenges highlight the need for a more adaptive and precise approach to enhance the efficiency, accuracy, and reliability of defect dimension estimation through acoustic wave analysis.

This research presents an artificial intelligence-powered strategy that integrates surrogate modeling and Bayesian optimization to enhance the efficiency and adaptability of defect detection based on acoustic waves. Surrogate models are computationally efficient approximations of physical phenomena, ideally suited for simulating the dynamics of acoustic wave propagation in materials. These models facilitate a more resource-friendly approach to exploring the extensive parameter space associated with acoustic wave initiation and propagation, including variations in excitation width [4, 5]. Defect detection can be achieved by finding the optimal input parameters that enable the surrogate model to output the wave propagation corresponding to the target received signals reflected by the defect [6]. Bayesian optimization provides a reliable technique for optimizing input parameters for the surrogate model [7], specifically defect depth and width. This streamlines the UT process by eliminating the need for developing and adjusting target-specific algorithms. The proposed approach aims to enhance the efficiency and practicality of defect detection while allowing for a greater adaptability to the variability in target conditions.

2. Methods and Results

2.1 Surrogate Model for Acoustic Wave Propagation

We employed a symmetry-informed surrogate model [4] to accurately simulate acoustic wave propagation as shown in Fig. 1, the choice motivated by several key attributes: computational efficiency, the capability to closely approximate wave propagation phenomena, and the flexibility to adjust model parameters such as the excitation width. The surrogate model takes receiver location (x), defect depth (y), time (t), and defect width (w) as input and outputs the corresponding von Mises stress (σ). The development of this surrogate model was initiated with the collection of a comprehensive dataset of wave propagation derived from finite element method (FEM) simulations conducted in COMSOL Multiphysics, a platform renowned for its precision in modeling and simulating physical systems. Details of the surrogate model and dataset are presented in [4]. Fig. 1 shows the symmetry-informed surrogate model for acoustic wave propagation.

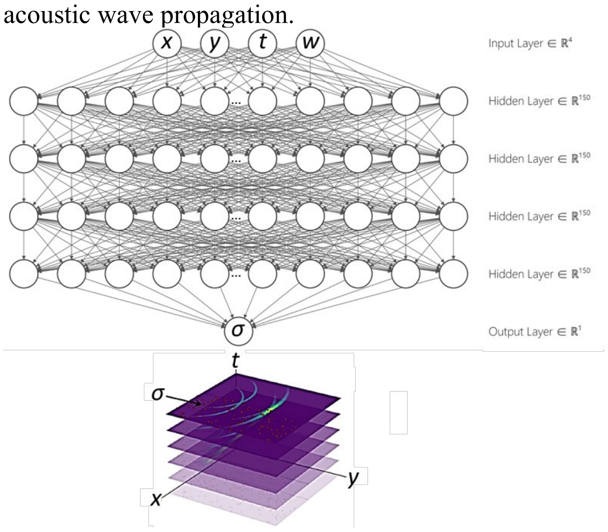

Fig. 1. Symmetry-informed surrogate model for acoustic wave propagation.

2.2 Bayesian Optimization to find Optimal Model Inputs

Bayesian optimization was used to systematically explore the input space of the surrogate model, precisely the estimated defect depth (y_B) and defect width (w_B), to identify the optimal input that produces the output with best agreement with the target acoustic signals (σ_T) that can obtained in actual measurements. The estimated defect depth (y_B) and width (w_B) are iteratively updated through optimization to maximize the cosine similarity between the target signals (σ_T) and the surrogate model outputs (σ_S).

2.3 Defect Detection by Model Input Optimization

The proposed strategy focused on maximizing the similarity between the target signals (σ_T) and the simulated signals (σ_S) from the surrogate model, indicating the presence and characteristics of defects (depth and width, y_B and w_B, respectively). Following the flowchart illustrated in Fig. 2, the defect depth and width are estimated by optimization of the surrogate model input from the initial random to the optimal input as shown in Fig. 3. After the optimization, the estimated defect depth and width have the errors of 0.0 mm and 0.3 mm, respectively.

3. Conclusions

This research demonstrates the integration of surrogate modeling and Bayesian optimization to enhance the efficiency and adaptability of UT for defect detection. By employing symmetry-informed surrogate models, the study addresses the conventional challenges of UT, such as the need for constant algorithmic adjustments and inflexibility in defect characterization, by providing a computationally efficient optimization method based on simulating acoustic wave propagation without signal or image processing. Using Bayesian optimization to refine the model inputs systematically ensures optimal alignment with target signals, thereby estimating defect dimensions precisely. The results, evidenced by the small error in the estimation of defect depth and width, underscore the potential of this approach to revolutionize NDT practices by offering a more reliable, efficient, and adaptable method for defect detection. However, it needs to be validated to ensure that its performance is maintained when noise, such as the fields, is included in signals to be used in practice.

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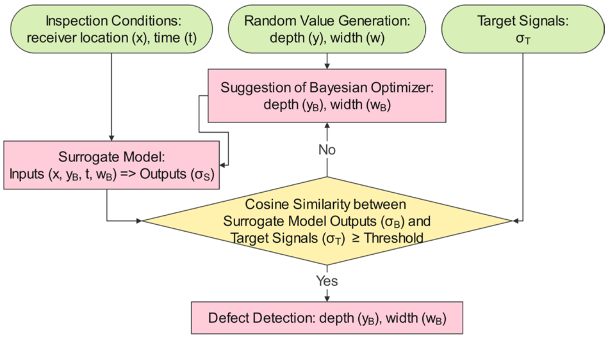

Fig. 2. Flowchart of defect detection based on surrogate model optimization.

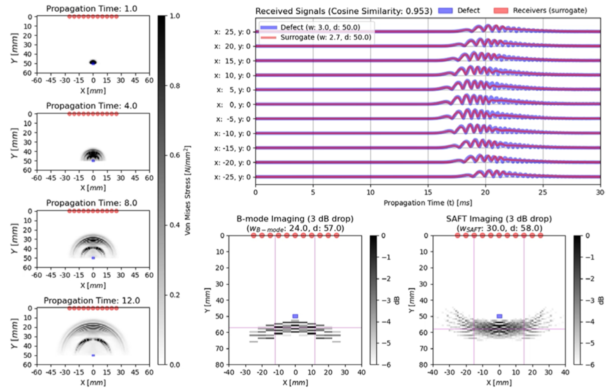

Fig. 3. Estimation of defect depth and width via optimization.

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