Impact Force Identification on Steel Pipelines Using Deep Learning and Bayesian Inference with Minimal Sensing Elements

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ABSTRACT

Pipelines are crucial for various industries but are vulnerable to impact damage, making it essential to identify impact forces for maintaining structural integrity and preventing accidents. Traditional inverse methods for impact force identification can be expensive, time-consuming, and require pipeline shutdowns. To address these challenges, this study proposes a novel approach using deep learning and Bayesian inference techniques with minimal sensing. Four accelerometers were placed on a 6-meter-long steel pipeline, and data was collected, pre-processed, and split into training and testing sets. A 5-layered ANN model was trained, achieving 87.2% accuracy, which was then used as a surrogate model for the Bayesian inference. The proposed approach, based on Approximate Bayesian Computing with Subspace Simulation (ABC-SS), demonstrated a reliable and robust solution for identifying impact forces on pipelines.

Keywords: Pipelines, structural integrity, Bayesian inference, vibration data, ABC-SS.

INTRODUCTION

Impact force events can have significant consequences on the integrity of various structures, including pipelines, bridges, and buildings. These events can take various forms, such as bird strikes on aircraft, space debris collisions with satellites, or excavation damage to pipelines. It has been reported that bird strikes impose more than $1.2 billion in costs on the aviation industry annually [1]. Similarly, space debris poses a significant threat to satellites in orbit [2]. In the context of pipelines, excavation damage accounts for approximately 15% and 18% of incidents for hazardous liquid and natural gas transmission pipelines, respectively [3].

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The ability to detect and identify impact forces is crucial for maintaining the safety and operational efficiency of these critical infrastructures.

Traditional methods for impact force identification have relied on analytical techniques, such as the ones presented by [4, 5]. These techniques often involve multiple sensors, complex mathematical modeling, and signal processing techniques. Although successful to a certain extent, they are often expensive, time-consuming, and may require shutting down the pipeline for the duration of the analysis. In recent years, machine learning (ML) techniques, particularly deep learning, have emerged as promising tools for impact force identification, as demonstrated in studies by [6-8]. Deep learning models, such as artificial neural networks (ANNs), can automatically learn to extract relevant features from raw data and perform complex tasks with minimal human intervention [9].

In this paper, a novel approach for identifying impact forces on steel pipelines using deep learning and Bayesian inference techniques with minimal sensing is proposed. This approach combines a 5-layered ANN with Bayesian inference, a statistical method for updating the probability of a hypothesis based on new data and prior knowledge. By integrating these advanced techniques, the framework aims to develop a reliable, efficient, and robust solution for impact force identification and validate it using a pipeline.

The rest of the paper is organized as follows: Methodology describes the experimental setup and data collection process; Surrogate model and Bayesian Inference detail the deep learning model, its training and evaluation, and the integration of Bayesian inference methodology; Results present cases to evaluate the performance of the proposed framework; and finally, some concluding remakes and suggestion for future research directions.

METHODOLOGY

Experimental Setup and Data Collection

When it comes to using deep-learning models to identify impact forces, proper and enough data collection is essential to secure a well-descriptive dataset that can be utilized for training and testing the developed models. The traditional and most well-known method of impact testing involves utilizing a calibrated impact hammer, data acquisition system, data display, and a number of sensors. Figure 1 shows the setup of impact-response acquisition that was used in the current study. The flow chart of the entire methodology is shown in Figure 2.

Four single-axis accelerometers (352C34) by PCB Piezotronics are placed on each segment of the pipeline to capture the full information about the vibrational wave traveling through the pipeline. This will later help with accomplishing more accurate predictions of the impact force and its location. However, in this paper only one segment will be taken into consideration and the testing cases will be done on one accelerometer. The used pipeline and experimental setup are shown in

Figure 3.

The data collection process was conducted by connecting an impact hammer (086C04) by PCB Piezotronics and the accelerometers to a high-precision PXI system by national instruments (NI). The impact hammer is used to generate impact forces at specific nodes on the pipeline, simulating real-world impact events. The accelerometers, placed along the pipeline, measure the corresponding acceleration responses at different sensing locations.

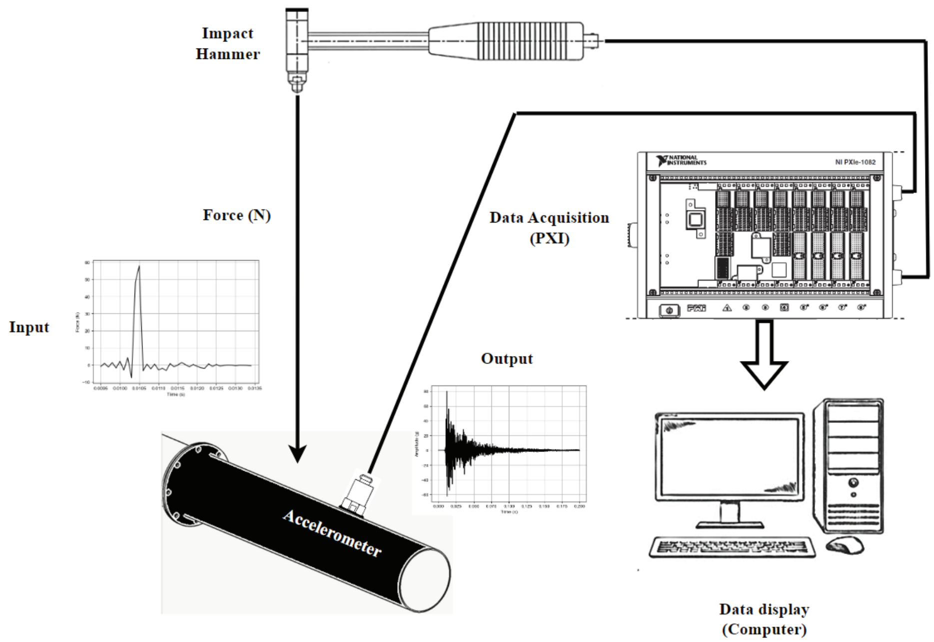

Figure 1. The schematic that will be used for data acquisition.

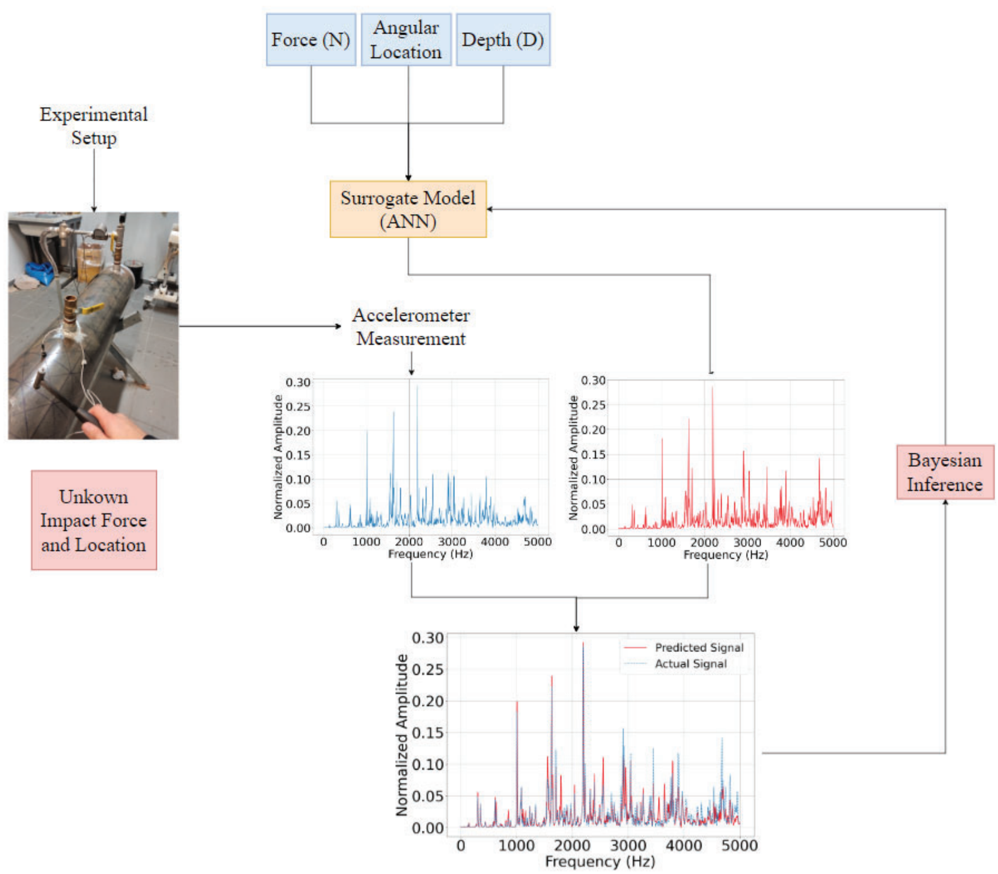

Figure 2. Flow chart of the proposed impact-force identification methodology

(a) (b)

Figure 3. The experimental setup: (a) is the entire pipeline, (b) a single sensing point using a single-axis accelerometer and impact hammer for excitation.

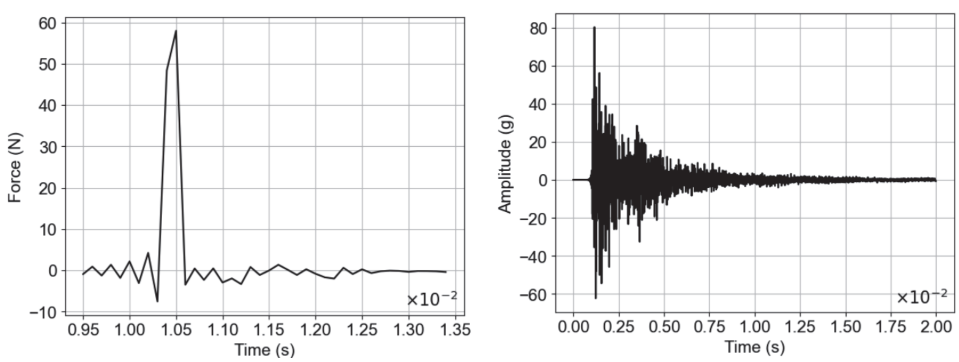

Figure 4. Impact force signal (left) and the acceleration signal (right).

For each impact event, the impact information such as the location of the impact, the magnitude of the force, and the time-domain signals of the event measured from the impact hammer and all the accelerometers are all saved in a dedicated file. Figure 4 shows a typical impact signal excited at a certain location and its response measured by one of the accelerometers.

Pre-processing the data involves identifying the most crucial features in the impact signal to be used as input for the deep learning model. The most significant feature for training the model is the maximum impact force, as it has the greatest influence on the acceleration signal. Additionally, the acceleration signal should be distilled to its essential features, which can be achieved by performing a Fast Fourier Transform (FFT) on the signal. By limiting the number of features in the output, the model can more easily learn the modes and patterns of the acceleration signal's FFT. Other input features include the pipeline's angular location and depth position.

Deep Learning Model

The deep learning model, consisting of six hidden layers as illustrated in Figure 5, was designed through an iterative process of evaluating the testing accuracy for various hyperparameter configurations. The optimal combination of neurons and other hyperparameters was selected to enhance the model's performance, ultimately achieving the highest possible testing accuracy. Before training the model, the dataset, comprising 4320 samples, is divided into an 80% training dataset and a 20% testing dataset. Within the training dataset, the model is used in conjunction with the k-fold cross-validation (CV) technique to create a validation dataset and determine the best split for training and validation. This approach, combining careful model optimization and well-balanced data division, results in a more robust and efficient model capable of generalizing well to unseen data.

Approximate Bayesian Computation by Subset Simulation (ABC-SS)

ABC-SubSim is a method that combines the Approximate Bayesian Computation (ABC) principle with Subset Simulation for sequential computational efficiency. This approach fuses the ABC algorithm with an efficient rare-event sampler, generating conditional samples from a series of nested sub-domains [10]. The algorithm begins by generating N random impact parameter samples (F, α, d) that meet the problem's constraints, denoted as Θ_{r}.

The trained deep model predicts N sensor measurements (in the frequency domain) based on Θ_r, with the distance ρ between predicted and actual sensor measurements calculated using the modified cosine distance as shown in Eq. (1) [10].

$$\rho = \left| 1 - \frac{uv'}{\sqrt{(uu')(vv')}} \right| \tag{1}$$

Θ_r is sorted by distance, and Np_0 samples with the lowest ρ values are chosen, serving as seeds for generating new samples closer to the actual sensor measurement. This constitutes one simulation level, and the process is repeated for up to m levels or until the stopping criterion is met. The Modified Metropolis Algorithm (MMA) is used

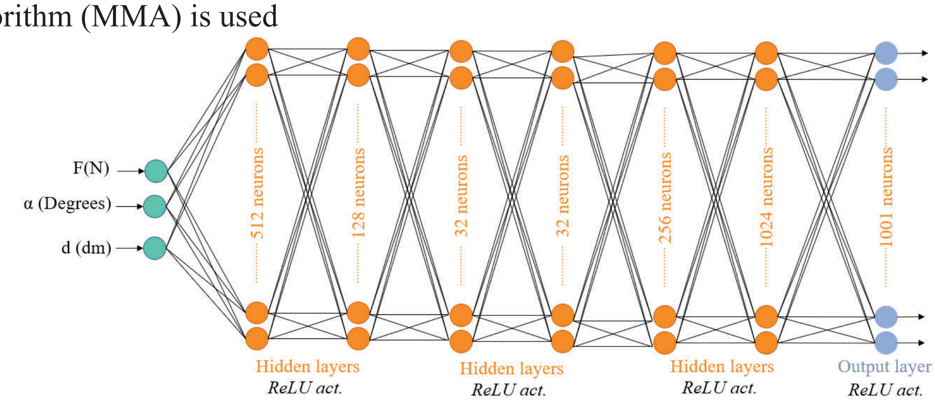

Figure 5. ANN architecture used for training the surrogate model.

to generate new samples in each chain, and the standard deviation (STD_{prop}) for each simulation is chosen based on parameter constraints and acceptance rate (R_{acc}) recommendations. The MMA is shown in Eq. (2) [10].

$$\theta_r(i,p) = \theta_r(i-1,p) + STD_{prop}(j-1,p) \times rand \quad (2)$$

RESULTS

The model was evaluated using two distinct test cases. Each of these cases was explicitly excluded from the training set to ensure an unbiased assessment. The cases are presented in Table I and are used in the surrogate model and the Bayesian inference.

Surrogate Model

Upon evaluation, the surrogate model demonstrated an accuracy using R^2 of 87.2% on testing, indicating its ability to predict the acceleration frequency signal with a high degree of precision. Figure 6 presents a comparison between the FFT of acceleration signals obtained from the experiments and the predicted FFT generated by the surrogate model.

This level of accuracy suggests that the surrogate model is well-suited for inferring the impact magnitude and location in the Bayesian inference framework with a high level of reliability.

Bayesian Inference Results

The visualization of the inference results consists of scatter plots that display the approximated posterior of the impact parameters (Θ_r) as determined by the ABC-SubSim algorithm. For instance, Figure 7 presents the impact force identification results for a pipeline segment for an accelerometer placed at the first segment of the pipeline for each simulation level. Each scatter plot in the figure represents a pair of impact parameters plotted together. The diagonal plots are probability histograms that show the probability density function (PDF) of each impact parameter: impact force in newtons (N), angular location (α), and depth (d).

The magnitude of the impact force is effectively inferred (1st column), but the scatter plots for the angular location (theta) and depth (d) parameters (2nd and 3rd columns) reveal some uncertainty regarding the exact location of the impact. This uncertainty is illustrated in the scatter plots, which display the range of potential impact locations based on the signal measured by the accelerometer.

Table I. Cases are taken for framework evaluation.

Case	F (N)	α (Degrees)	d (m)
1	66.81	176.5	0.25
2	26.75	0	0

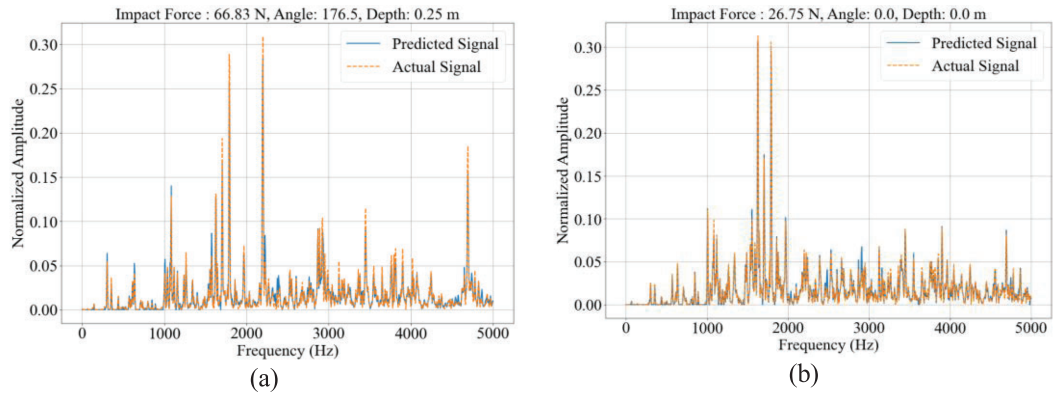

Figure 6. Different predicted and actual responses under different force and impact locations.

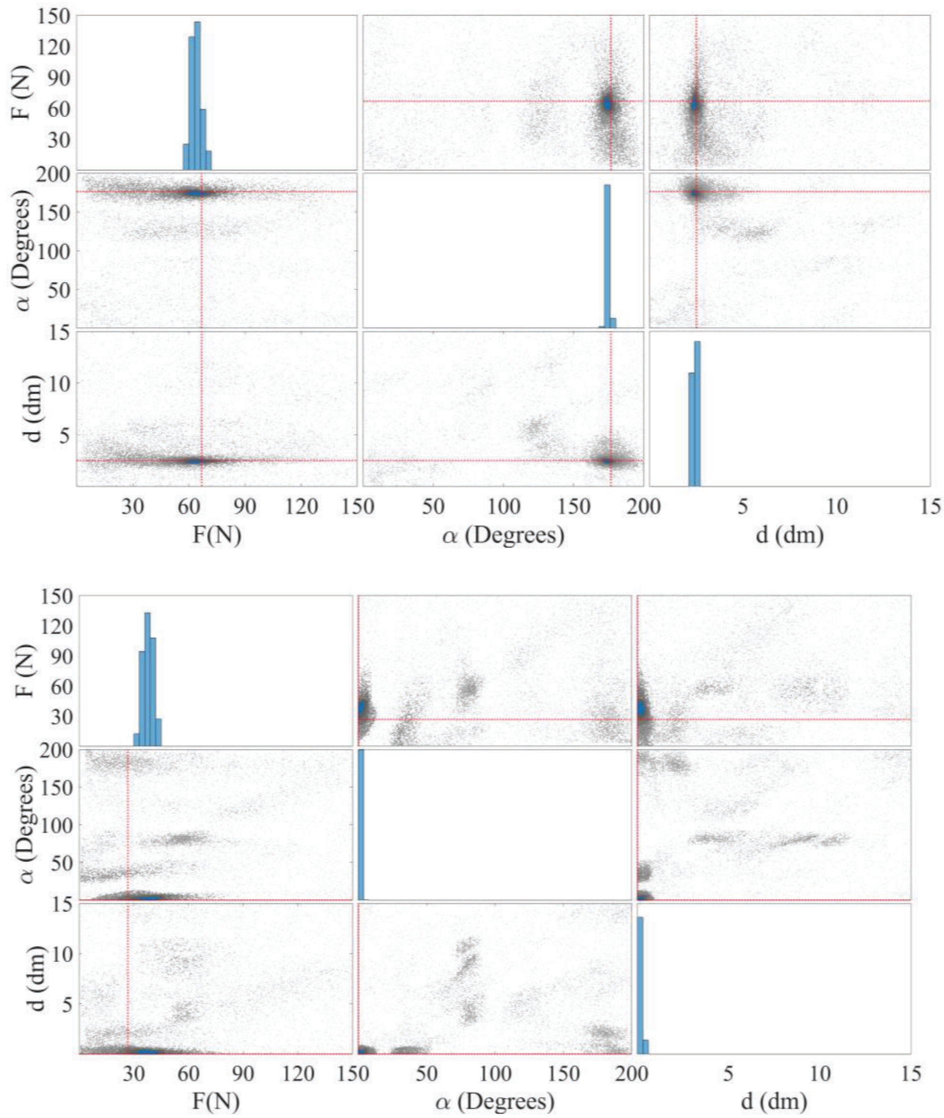

Figure 7. Bayesian Inference for the testing cases. (a) is the first testing case at medium impact force, and (b) is the second testing case.

CONCLUSIONS

The proposed methodology for predicting impact force and location has exhibited considerable promise in an array of test scenarios, as evidenced by the application of the ABC SubSim algorithm. This points to both its efficacy and its flexibility in adapting to different situations. However, for a comprehensive evaluation and further refinement of this framework, it's imperative that the dataset is augmented to include the pipeline under operation. Doing so will provide a more realistic context for fine-tuning the hyperparameters. Furthermore, careful consideration must be given to the control parameters that govern the convergence of the inference process for impact parameters. These necessary enhancements will lead to a more dependable and robust predictive model.

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