

Robust statistical feature extraction and deep learning surrogates for highly accurate guided wave-based determination of global corrosion parameters in metallic plates

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ABSTRACT

Accurate evaluation of corrosion in metal plates is essential across many industries, particularly in shipbuilding. Among available techniques, non-destructive testing (NDT) is especially valuable, as it enables the assessment of material degradation without compromising structural integrity. Within this domain, guided ultrasonic waves have attracted increasing attention in recent years due to their potential for estimating statistical corrosion parameters, such as mean thickness loss and its standard deviation. However, practical application of these methods remains challenging because of the complex interaction between wave propagation and spatially varying thickness profiles. This study presents an advanced methodology for precise estimation of corrosion parameters using deep learning-based inverse models. The corrosion morphology is modeled as a stochastic field, while guided wave responses, obtained through numerical simulations and recorded by a sensor network, are postprocessed to extract statistical descriptors. In particular, the mean vector and covariance matrix of sensor signals, including wave packet location, width, and amplitude, are computed. To ensure robustness, feature scaling and elliptic envelope-based covariance estimation are employed, effectively mitigating the influence of outliers, which are especially pronounced at higher levels of thickness loss and surface roughness. The inverse model establishes a mapping between extracted feature vectors and the corresponding corrosion parameters, enabling their direct prediction. This framework addresses the intrinsic non-uniqueness of the problem, where identical statistical descriptors may arise from infinitely many realizations of the stochastic corrosion field. Extensive numerical investigations demonstrate that reliable feature extraction, particularly robust handling of outliers, combined with the ability of deep neural networks to capture nonlinear relationships, is critical for accurate parameter estimation. Prediction performance is further improved by aggregating responses from multiple independent realizations of the stochastic corrosion field. Overall, the results demonstrate that the proposed framework, combining robust statistical feature extraction, covariance-based feature representation and nonlinear inverse modeling, provides improved prediction accuracy compared with the previously developed feature-based linear regression model and the conventional time-of-flight approach under the considered numerical simulation conditions.

1. Introduction

Accurate assessment of corrosion in metallic structures, particularly plate-like components, is essential for maintaining safety and structural integrity in sectors such as shipbuilding, oil, and energy [1]. Corrosion can lead to material loss as well as microstructural changes, both of which may significantly alter mechanical properties [2–4]. Broadly,

corrosion can be classified into two categories: localized forms, confined to small regions (e.g., pitting), and global forms, which typically affect large portions of a structure [5,6]. The latter is especially critical due to the cumulative loss of material over extended areas, yet it remains difficult to quantify accurately. A key challenge lies in the inherently inhomogeneous nature of global corrosion, characterized by spatially varying thickness distributions in which overall material loss is

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accompanied by local irregularities [7]. Consequently, effective characterization requires estimation of both the mean thickness reduction and its spatial variability (or surface roughness), as these factors directly influence stress concentrations and overall structural reliability [8,9].

Guided ultrasonic waves have emerged as a powerful tool within the broader class of nondestructive evaluation methods, primarily due to their capacity to cover large inspection areas with relatively sparse sensor networks and their pronounced sensitivity to both material characteristics and geometric changes [10–13]. A key advantage of these waves lies in their dispersive behavior, which makes their propagation highly dependent on structural thickness. This property renders them particularly well suited for detecting and quantifying corrosion in plate-like structures, where thickness variations play a central role [14,15]. Over the past decade, guided-wave-based techniques have been increasingly employed to assess global corrosion, including estimation of average thickness loss and, in some cases, its spatial variability [16–18]. Early approaches largely relied on time-of-flight measurements and dispersion curve analysis, linking effective wave velocities to plate thickness [15,19,20]. Although such methods perform well for structures with uniform or mildly varying geometry, their effectiveness diminishes in the presence of more complex, spatially distributed corrosion patterns. Another important group of approaches is based on guided-wave imaging and local or instantaneous wavenumber analysis, which enables quantitative reconstruction of corrosion profiles and thickness maps from densely sampled ultrasonic wavefields [21–26]. These methods have demonstrated excellent capabilities for quantitative damage characterization; however, they typically require full-wavefield acquisition using laser scanning systems or other dense measurement techniques, resulting in substantial data acquisition effort and specialized experimental equipment.

To overcome these limitations, more sophisticated frameworks based on sparse guided-wave measurements have been developed. These include parametric models that approximate thickness variations, as well as stochastic descriptions of corrosion morphology that better reflect its inherent randomness and heterogeneity. More recently, there has been a shift toward data-driven methodologies and inverse modeling strategies, which aim to directly relate features extracted from guided wave responses to underlying corrosion parameters, offering increased flexibility and improved performance in complex scenarios.

Notwithstanding recent progress, extracting reliable information from guided wave measurements in the presence of distributed corrosion remains inherently difficult. Spatial variations in thickness give rise to intricate propagation effects, such as scattering, mode conversion, and energy attenuation, that collectively distort the recorded signals [17,27,28]. These phenomena introduce nonlinearity into the relationship between measured responses and the underlying corrosion state. Moreover, the problem is fundamentally ill-posed: corrosion patterns sharing identical global statistical characteristics can still generate markedly different wave signatures. This ambiguity significantly complicates the development of robust and generalizable inverse modeling strategies [29].

To enable the use of guided wave data in corrosion assessment, measured signals are commonly reduced to a set of descriptive features, such as wave packet arrival time, temporal width, and amplitude [18,30]. These features are then used as inputs to inverse or data-driven models that relate signal characteristics to corrosion parameters. While this representation is computationally efficient, it is often based on the implicit assumption that the features are statistically independent. In reality, this assumption is inconsistent with wave propagation physics. Thickness variations influence local wave velocity, dispersion, and attenuation simultaneously, leading to coupled changes in arrival time, packet width, and amplitude [31,32]. As these features originate from the same wave packet and are affected by the same structural irregularities, they exhibit inherent statistical dependencies. Ignoring these relationships may result in a loss of important information contained in their joint variability and, consequently, limit the predictive

performance of inverse models. This issue is particularly critical when estimating parameters related to spatial variability, such as the standard deviation of thickness reduction, which depends on higher-order characteristics of the signal and is therefore more sensitive to its statistical structure.

To overcome the challenges mentioned, this study proposes a novel framework for estimating global corrosion parameters based on robust statistical feature representation and nonlinear inverse modeling. The corrosion morphology is represented as a stochastic field, and guided wave responses are generated through numerical simulations and recorded by a distributed sensor network. These signals are subsequently processed to extract statistical descriptors, specifically the mean vector and covariance matrix of key features such as wave packet arrival time, width, and amplitude. A central aspect of the methodology is the use of robust preprocessing techniques, including feature scaling and covariance estimation via elliptic envelopes, which effectively suppress the influence of outliers, particularly at higher levels of thickness loss and surface roughness. The resulting feature representation is subsequently used to construct a nonlinear inverse model implemented using a deep neural network. This feature-based formulation preserves the physical interpretability of the learning process, substantially reduces the dimensionality of the regression problem, and enables robust statistical preprocessing prior to nonlinear mapping between guided-wave responses and the corrosion parameters. Extensive numerical investigations demonstrate that the proposed integrated framework, combining statistical feature extraction, covariance-based descriptors and nonlinear inverse modeling, provides improved prediction accuracy for estimating global corrosion parameters within the considered numerical simulation framework. Performance is further improved by incorporating data from multiple independent realizations of the stochastic corrosion field. Overall, the proposed methodology consistently outperforms the previously developed feature-based linear regression model and the conventional time-of-flight approach under the considered numerical simulation conditions.

2. Corrosion parameter prediction using statistical features and deep learning

This section presents the proposed methodology for estimating global corrosion parameters based on statistical features of guided wave responses and deep learning-based inverse surrogate models. Section 2.1 describes the numerical representation of the corrosion profile, while Section 2.2 formulates the underlying problem. The initial processing of guided wave signals and extraction of their key characteristics are detailed in Section 2.3. Section 2.4 introduces alternative feature vector definitions, with particular emphasis on robust covariance matrix estimation and outlier handling. Strategies for constructing inverse surrogate models and addressing the nonlinear relationship between feature vectors and corrosion parameters are discussed in Section 2.5. Finally, Section 2.6 presents the benchmark approach based on the time-of-flight methodology.

2.1. Corroded metal plate modelling. Computational model

For this research, the metal plate corrosion is represented as a stochastically determined thickness field. This approach enables capturing the overall material loss and localized irregularities corresponding to surface deterioration. Let Ω be the spatial domain of interest. The plate thickness at $\mathbf{x} \in \Omega$ will be denoted as $d(\mathbf{x})$, which, in our model, is a combination of a deterministic component and a stochastic fluctuation term, i.e.,

$$d(\mathbf{x}) = h_0 - h + s \cdot Z(\mathbf{x}) \quad (1)$$

where h_0 is the nominal undamaged plate thickness, h is the mean thickness reduction, and s is the standard deviation determining the

spatial variability. The function $Z(x)$ is a zero-mean, Gaussian random field of unity variance describing normalized thickness fluctuations [33].

The spatial correlation structure determined by $Z(x)$ is defined using a covariance function that is a function of the distance between spatial locations. This study adopts an isotropic Gaussian covariance model, with a correlation length parameter l controlling the characteristic size of corrosion features. Here, $l = 1$ mm is assumed. Smaller l corresponds to rapidly varying, highly irregular surfaces, whereas larger l is associated with smoother and more spatially coherent thickness distributions.

In this work, stochastic field is generated using a truncated Karhunen–Loève (KL) expansion, which allows for achieving an efficient representation of spatial variability regarding a finite set of uncorrelated random variables [34]. The truncation level determines the effective model dimensionality and is chosen to ensure accurate reproduction of the prescribed statistical properties [28]. In particular, it is selected so that a prescribed percentage (e.g., 95–99%) of the total field variance is retained. The generated field is discretized on a regular grid and interpolated onto the finite element mesh. The nodal coordinates are subsequently adjusted in the direction of thickness to create a three-dimensional plate geometry. The three-dimensional geometry generated from the stochastic corrosion field (described above) requires the use of solid finite elements rather than simplified 2D plate formulations. This modelling strategy inevitably increases the number of degrees of freedom and the computational cost of the transient analyses. Therefore, reduced-integration C3D8R elements were deliberately adopted to improve computational efficiency while preserving the accuracy required for guided wave propagation simulations. Although reduced integration may potentially introduce zero-energy (hourglass) modes, Abaqus/Explicit employs an automatic hourglass control algorithm to suppress these spurious deformation patterns. Furthermore, the present analyses involve linear elastic material behavior, small displacement

amplitudes and no large deformation or contact nonlinearities, i.e., conditions under which hourglass effects are generally not expected to become significant. Fig. 1 graphically summarizes the process of generating the computational model.

Propagation of guided waves in the corroded metal plate is simulated by means of a finite element model under a transient dynamic framework. The main components of the computational model have been outlined in Table 1. The model is applied to produce datasets for selected combinations of the corrosion parameters h and s and for multiple realizations of the stochastic field corresponding to each parameter pair (used as training and testing samples for inverse model construction and validation).

It is worth mentioning that the adopted stochastic corrosion model is not intended to represent all possible corrosion morphologies encountered in engineering practice. Instead, it provides a physically motivated representation of globally distributed corrosion. Importantly, the adopted stochastic field is not an arbitrary mathematical construction introduced solely for numerical convenience. Rather, its statistical description was developed on the basis of experimental investigations of naturally corroded steel specimens, from which the characteristic levels of mean thickness reduction, spatial variability, and surface roughness were identified. These experimentally observed characteristics were subsequently used to define the parameter ranges and statistical properties of the stochastic corrosion fields employed throughout the present study.

Consequently, the generated numerical realizations should be regarded as physically plausible representations of a specific class of globally distributed corrosion rather than synthetic surfaces generated without experimental justification. Although individual realizations differ, they all satisfy statistical characteristics consistent with experimentally observed corrosion morphologies and therefore provide a realistic numerical representation of the investigated degradation

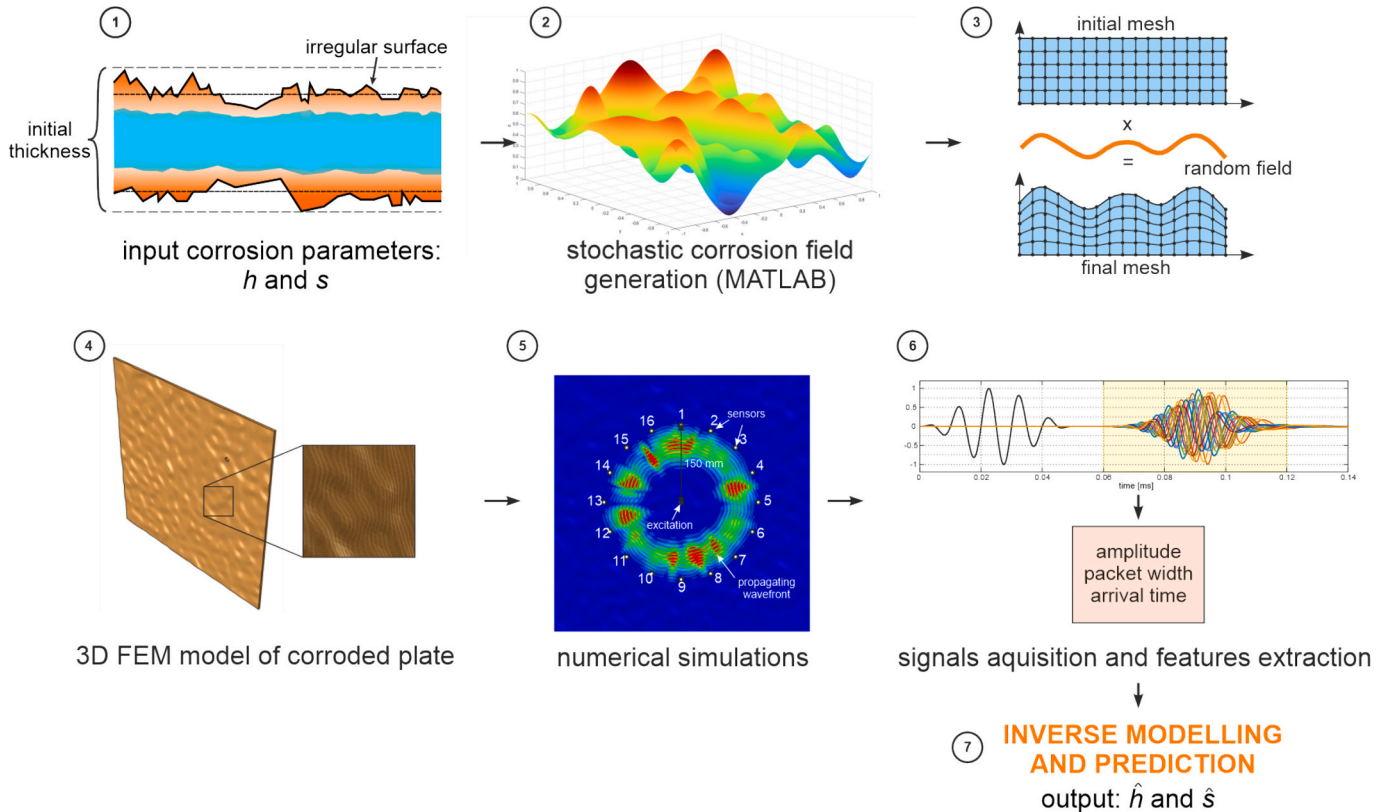


Fig. 1. Schematic overview of the proposed framework for global corrosion parameter estimation. Stages (1)–(6) illustrate the generation of the computational dataset and statistical feature extraction, whereas Stage (7) summarizes the inverse modeling framework used for prediction of the mean thickness reduction h and its standard deviation s . The individual components of the inverse modeling procedure are presented in detail in Sections 2.3–2.5.

Table 1
Computational model setup.

Component	Description
Metal plate	Three-dimensional isotropic solid of lateral dimensions 500 mm × 500 mm and the nominal thickness of $h_0 = 4$ mm.
Material	Steel (density $\rho = 7850$ kg/m ³ , Young's modulus $E = 210$ GPa, Poisson's ratio $\nu = 0.3$)
Mesh	Linear hexahedral elements with reduced integration (C3D8R). The element size is selected to ensure appropriate resolution of the propagating wave (~10–15 elements per wavelength at the excitation frequency) [35]. The plate was discretized using 5 solid elements through the thickness.
Simulation	Time integration using an explicit scheme; time step equal to 10^{-8} (chosen according to the Courant–Friedrichs–Lewy stability condition) [36] The total simulation time of 0.5 ms (sufficient for the primary wave packet to reach all sensing locations without contamination from boundary reflections)
Source signal	Wave excitation at the center of the plate in the form of time-dependent force (a tone-burst signal with a central frequency of 100 kHz, modulated by a Hann window)
Guided wave responses	Out-of-plane displacements recorded at $N_s = 16$ sensing points uniformly distributed along a circular path with a radius of 150 mm from the source. For the adopted transverse excitation and response component, the dominant incident packet is predominantly associated with the flexural A0 mode; however, no explicit modal filtering or assumption of perfect modal purity is imposed.

mechanism.

The purpose of the stochastic field is therefore not to reproduce the exact morphology of a particular corroded specimen, but rather to generate statistically equivalent corrosion states sharing prescribed global descriptors, namely the mean thickness reduction and the spatial variability of thickness. This enables systematic investigation of the inverse identification problem while maintaining physical consistency with experimentally observed corrosion characteristics.

The present study intentionally focuses on this particular class of corrosion in order to establish and validate the proposed inverse modeling framework for estimating global corrosion descriptors. Such an approach is consistent with the development of structural health monitoring methodologies, which are typically developed and assessed with respect to a well-defined damage mechanism before being extended to additional degradation scenarios.

2.2. Problem statement

The objective of this study is to estimate global corrosion parameters, namely the mean thickness reduction h and its standard deviation s . The parameter h represents the average extent of material loss, while s serves as a scalar measure of surface roughness. Within the proposed framework, these parameters are inferred from guided ultrasonic wave responses recorded by $N_s = 16$ sensors uniformly arranged along a circular path around the excitation source. The excitation frequency is set to 100 kHz. Wave propagation characteristics depend on the underlying corrosion morphology, influencing key signal attributes such as arrival time, wave packet width, and amplitude at each sensor. These attributes are therefore utilized as primary features for assessing the corrosion state. The relationship between corrosion morphology and measured wave responses is captured through a data-driven inverse surrogate model, introduced in subsequent sections, which enables direct prediction of both h and s . Thus, the adopted sensing configuration and excitation frequency are intentionally kept fixed throughout the study in order to isolate the performance of the proposed inverse modeling framework from the influence of the measurement setup, whereas their initial selection follows established physics-based design principles reported in the guided-wave literature [13].

To ensure versatility, the parameter estimation should work over large ranges of h and s . In this research, the parameter space C is defined

as an interval $C = [h_{\min} h_{\max}] \times [s_{\min} s_{\max}]$. The lower and upper bounds are set to $h_{\min} = 20\%$, $h_{\max} = 50\%$, $s_{\min} = 4\%$, and $s_{\max} = 20\%$, which covers most real-world scenarios. In particular, $h > 40\%$ and $s > 15\%$ corresponds to a significant degradation of the plate. The inverse surrogate $S(\mathbf{y})$: $Y \rightarrow C$ will be identified to map the sensor response space Y into C . The specifics of space Y and response vector $\mathbf{y}$ will be given in Section 2.3. Note that $\mathbf{c}(\mathbf{y}) = [h(\mathbf{y}) s(\mathbf{y})] = S(\mathbf{y})$ represents a prediction of the corrosion parameters produced by the inverse model for the guided wave response vector $\mathbf{y} \in Y$. To enable reliability, the inverse model must be of sufficient quality. In Section 3, it will be assessed using diverse metrics such as the Mean Absolute Error (MAE), Relative MAE (RMAE), and Pearson correlation coefficient R .

In practice, the primary challenge in constructing the inverse model arises from the inherent non-uniqueness of the relationship between guided wave responses and corrosion parameters. Specifically, infinitely many corrosion morphologies can correspond to a given pair of parameters h and s . Within the computational framework described in Section 2.1, this translates to an infinite number of stochastic field realizations yielding identical values of h and s . Consequently, the predictive accuracy of the inverse model is fundamentally constrained, as any practical measurement corresponds to only a single realization of the corrosion profile.

To alleviate this limitation, several strategies can be employed: enhanced feature extraction that captures complex dependencies between wave responses and corrosion parameters, incorporation of data from multiple independent realizations of the stochastic field, and the use of modeling techniques capable of representing nonlinear relationships between the feature space Y and the parameter space C . All three approaches are investigated in this study, as detailed in Sections 2.3–2.5.

2.3. Initial signal processing. Fundamental response features

The guided wave responses are waveforms $f_k(t)$, $k = 1, \dots, N_s$, where t stands for time, and N_s is the number of sensors. Because the finite element model solves the full three-dimensional elastodynamic problem, the simulated responses may contain contributions from multiple guided-wave modes, as well as components associated with scattering and boundary reflections. No modal filtering or single-mode constraint is imposed in the numerical formulation.

In the present study, a transverse time-dependent force is applied to the plate, and the out-of-plane displacement component is recorded at the sensing locations. This excitation–reception configuration predominantly emphasizes the flexural A0 contribution, whereas the fundamental S0 mode is primarily associated with in-plane extensional motion. Nevertheless, complete suppression of the S0 mode is neither assumed nor claimed. Any residual contribution from S0 or other guided-wave components remains intrinsically included in the simulated response.

The feature extraction procedure is therefore applied to the dominant incident packet observed in the out-of-plane displacement signal rather than to an analytically isolated or perfectly pure A0 mode. The packet is selected as the dominant response component within the analysis interval corresponding to the direct source-to-sensor propagation. The methodology requires consistent identification of this packet across the considered corrosion cases, but it does not require complete modal separation.

During propagation, the incident packet is affected by the dispersive characteristics of the plate. Consequently, its waveform is not assumed to be a simple time-shifted copy of the excitation signal $e(t)$. Frequency-dependent phase and group velocities may lead to temporal broadening, waveform distortion, and amplitude variation. These propagation effects are explicitly reflected in the three fundamental response descriptors considered in this work: the temporal location of the packet, its width, and its amplitude.

For the purpose of extracting these descriptors, the envelope formed by the local maxima $(t_{k,j}, y_{k,j})$, $j = 1, \dots, K_k$, of $|f_k(t)|$ within the selected

packet is approximated by a Gaussian function. The fitted parameters are interpreted as the packet center μ , packet width σ and amplitude A . The Gaussian function is therefore used as a compact parametric approximation of the selected packet envelope and does not imply that the propagated waveform preserves the shape of the excitation signal. The extraction process by least square regression has been explained in Fig. 3. A graphical illustration is provided in Fig. 2(b).

2.4. Feature vectors: statistical properties of fundamental features

The set of fundamental features of Section 2.3 extracted for all sensor responses constitute the baseline $3N_s \times 1$ feature vector $\mathbf{v}_f = [A_1 \dots A_{N_s} \mu_1 \dots \mu_{N_s} \sigma_1 \dots \sigma_{N_s}]^T$. As shown in [18] direct application of the vector $\mathbf{v}_f$ to construct the inverse model is not recommended because of exacerbating the non-uniqueness problem mentioned earlier. The reason is that when used independently, the $3N_s$ entries of $\mathbf{v}_f$ represent one specific realization of the stochastic corrosion field. An alternative is to use statistical moments of the fundamental features with respect to the sensor set (vector $\mathbf{v}_s$) as defined in Fig. 4, which smoothens out the field-related fluctuations. In this approach, the fundamental features are treated as statistically independent, which is a simplification.

Yet another alternative is to approximate the set of fundamental features using a multivariate normal distribution within the three-dimensional feature space. This is justified by the fact that the probability distributions used to generate corrosion field are normal, whereas the relations between guided wave responses and corrosion parameters are close to linear. Consequently, the distribution of response features is expected to be comparable to multivariate normal. This is confirmed in Fig. 5(a), showing a typical distribution of fundamental features aggregated for several realizations of the stochastic corrosion field, all corresponding to $h = 20\%$ and $s = 5\%$. The resulting feature vector $\mathbf{v}_m$ contains nine entries (the mean vector and six entries of the covariance matrix), as explained in Fig. 5(b). Using these extra features is expected to improve the estimation of the second corrosion parameters (standard deviation s of the thickness reduction). As additional demonstration of the relevance of this approach, Fig. 6 compares the actual distribution of the fundamental features obtained for multiple independent realizations of the stochastic corrosion field (i.e., the outcome of the computational model) and the synthetic features generated using the multivariate normal distribution extracted from these features. Note that the datasets are in close resemblance concerning the ensemble shape.

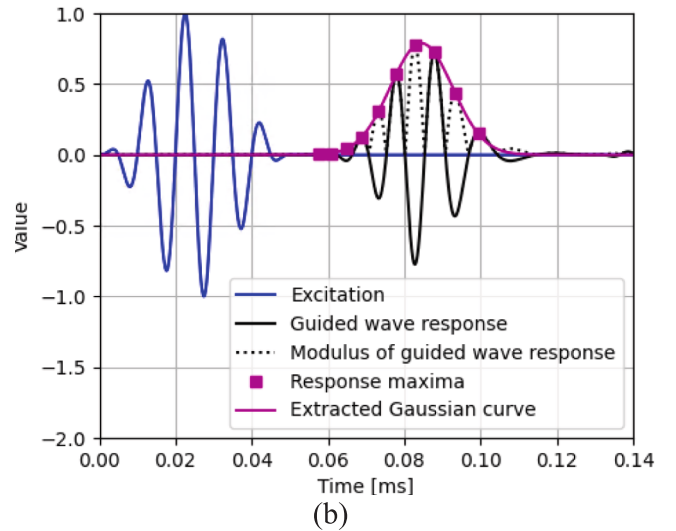
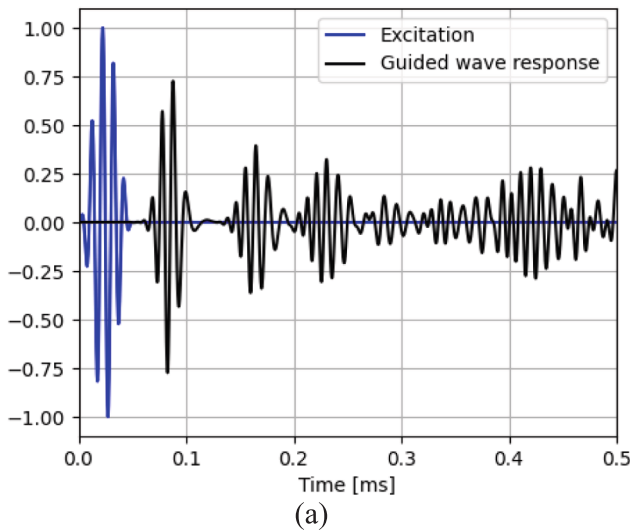


Fig. 2. Fundamental features of guided-wave responses: (a) excitation signal and a representative out-of-plane displacement response containing the dominant incident packet together with additional components associated with modal contributions, scattering, and reflections; (b) fundamental features assigned to be the mean μ , variance σ , and the amplitude A of the Gaussian curve extracted to fit the local maxima of $|f_k(t)|$.

Extracting multivariate distribution parameters using conventional means, i.e., the Maximum Likelihood Estimation (MLE) as indicated in Fig. 5(b), is associated with some practical difficulties. While the relationship between response features and corrosion parameters is nearly linear for low values of h and s , it becomes nonlinear for higher h , s , which has significant consequences for the fundamental feature distribution. As illustrated in Fig. 7(a), the distribution shape resembles Gaussian (see also Fig. 6) even for medium h . However, an increasing number of outliers start to occur for higher h , especially beyond 40%, cf. Fig. 7(b). In this region, say, for $h > 30\%$ and $s > 15\%$, which covers a good deal of practical scenarios, MLE-based estimation leads to excessively large values of covariance matrix entries, as illustrated in Fig. 8. For most entries, especially σ_{11} , σ_{33} , σ_{12} , and σ_{13} , a rapid increase is observed near the high-value domain corner.

To address the problems mentioned, we employ two algorithmic tools. The first one is robust scaling of the features, which uses the median and interquartile range, neither influenced by the extreme values (or outliers). The scaled values are obtained as $x_{scaled} = (x - \text{median}) / (Q_3 - Q_1)$, where median (or Q_2) is the middle value of the data, whereas $Q_3 - Q_1$ is the range between the 1st quartile (or 25th percentile) and the 3rd quartile (or 75th percentile).

The second tool is a robust covariance matrix estimation using elliptic envelope [37], which fits an ellipse around the central data points and excludes outliers during covariance matrix estimation as the points that fall outside the fitted shape. Initial experiments indicated that this approach leads to improved inverse modeling accuracy compared to an alternative approach, i.e., the minimum covariance determinant (MCD) method [38]. Fig. 9 provides a graphical illustration of the feature vector extracted using the above tools. On the one hand, the uncontrolled growth of the covariance matrix entries has been effectively contained. On the other hand, the overall dependencies between the corrosion parameters and the feature vector are much less nonlinear than that shown in Fig. 8. Notwithstanding, to further improve the inverse model performance, the linear model employed in [18] will be replaced by a deep neural network (DNN), as elaborated in Section 2.5.

2.5. Inverse model using deep neural networks

The training data for constructing the inverse model will be denoted as $\mathbf{c}_B^{(k)} = [h_B^{(k)} s_B^{(k)}]^T \in C$, $k = 1, \dots, N_B$. Due to low dimensionality of the

Fundamental response features: mean μ , variance σ , and amplitude A of the Gaussian curve $G(t)$ approximating the local maxima $(t_{k,j}, y_{k,j}), j = 1, \dots, K_k$, of $|f_k(t)|$. We have

$$G(t) = A \exp\left(-\left(\frac{t - \mu}{\sigma}\right)^2\right) \quad (\text{F1})$$

Feature extraction: Solve least square regression problem

$$[A_k^*, \mu_k^*, \sigma_k^*] = \arg \min_{A, \mu, \sigma} \left\| \begin{bmatrix} G(t_{k,1}; A, \mu, \sigma) \\ \vdots \\ G(t_{k,K_k}; A, \mu, \sigma) \end{bmatrix} - \begin{bmatrix} y_{k,1} \\ \vdots \\ y_{k,K_k} \end{bmatrix} \right\| \quad (\text{F2})$$

Fig. 3. Fundamental guided wave response features: wave packet center μ , width σ , and amplitude A .

Feature vector defined as arithmetic means and standard deviations of individual sensor features A_k, μ_k , and $\sigma_k, k = 1, \dots, N_s$ (in this approach fundamental features are treated as statistically independent):

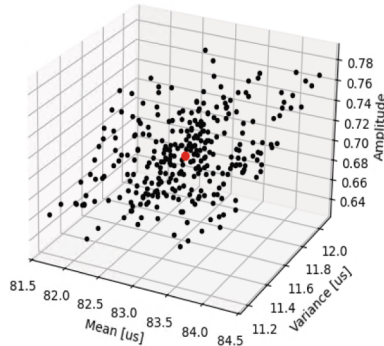
$$\mathbf{v}_s = [\bar{A} \ \bar{\mu} \ \bar{\sigma} \ \text{std}(A) \ \text{std}(\mu) \ \text{std}(\sigma)]^T \quad (\text{F3})$$

where

$$\bar{A} = \frac{\sum_k^{N_s} A_k^*}{N_s}, \quad \bar{\mu} = \frac{\sum_k^{N_s} \mu_k^*}{N_s}, \quad \bar{\sigma} = \frac{\sum_k^{N_s} \sigma_k^*}{N_s} \quad (\text{F4})$$

$$\text{std}(A) = \sqrt{\frac{\sum_k^{N_s} (A_k^* - \bar{A})^2}{N_s - 1}}, \quad \text{std}(\mu) = \sqrt{\frac{\sum_k^{N_s} (\mu_k^* - \bar{\mu})^2}{N_s - 1}}, \quad \text{std}(\sigma) = \sqrt{\frac{\sum_k^{N_s} (\sigma_k^* - \bar{\sigma})^2}{N_s - 1}} \quad (\text{F5})$$

Fig. 4. Feature extraction of sensor responses $f_k(t)$ as recommended in [18]. The vector $\mathbf{v}_s$ consists of statistical moments of the fundamental sensor features, which is equivalent to treating them as statistically independent.



Feature vector defined using the mean and covariance matrix of multivariate Gaussian distribution of fundamental features A_k, μ_k , and $\sigma_k, k = 1, \dots, N_s$:

$$\mathbf{v}_m = [\mu_1 \ \mu_2 \ \mu_3 \ \sigma_{11} \ \sigma_{22} \ \sigma_{33} \ \sigma_{12} \ \sigma_{13} \ \sigma_{23}]^T \quad (\text{F6})$$

where

$$\boldsymbol{\mu} = [\mu_1 \ \mu_2 \ \mu_3]^T, \quad \boldsymbol{\Sigma} = [\sigma_{jk}]_{j,k=1,2,3} \quad (\text{F7})$$

are mean vector and covariance matrix of $N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ with the probability density function given as

$$p(\mathbf{x}; \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{1}{(2\pi)^{3/2} \|\boldsymbol{\Sigma}\|^{1/2}} \exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})\right) \quad (\text{F8})$$

Here, the parameters of $p(\mathbf{x}; \boldsymbol{\mu}, \boldsymbol{\Sigma})$ are obtained using Maximum Likelihood Estimation (MLE), which provides an unbiased estimated for $\boldsymbol{\mu}$ and a biased estimate for $\boldsymbol{\Sigma}$. Note that $\boldsymbol{\Sigma}$ is symmetric, i.e., $\sigma_{kj} = \sigma_{jk}$ for $j, k = 1, 2, 3$.

Fig. 5. Feature vector using multivariate normal distribution: (a) distribution of the fundamental features corresponding to different realizations of stochastic corrosion field for the same global corrosion parameters $h = 20\%$ and $s = 5\%$. The red circle denotes the mean value of the distribution, which is approximately equal to $[\bar{A} \ \bar{\mu} \ \bar{\sigma}]^T$; (b) feature vector definition using the mean vector and covariance matrix of extracted multivariate normal distribution of the fundamental features.

corrosion parameter space, the training samples are distributed on a rectangular grid defined in Section 3.1. The dataset is arranged to uniformly cover the space $C = [h_{\min} \ h_{\max}] \times [s_{\min} \ s_{\max}]$. For each sample, the guided wave responses are obtained through numerical simulation, and the corresponding feature vectors $\mathbf{v}_{m,B}^{(k)}$ are extracted. For validation, a separate set of testing samples is used, denoted as $\mathbf{c}_t^{(k)} = [h_t^{(k)} \ s_t^{(k)}]^T, k = 1, \dots, N_t$. These points are also distributed on a rectangular grid that interleaves with that for the training data (cf. Section 3.1).

As the dependence between the mean propagation velocity and corrosion-induced thickness reduction of the plate is nearly linear in the considered frequency range, at least for relatively small values of h , linear inverse model seems to be an appropriate choice as demonstrated in [18]. At the same time, using linear regression (also with second-order basic functions) helps smooth out fluctuations of the response features caused by the non-uniqueness problem discussed earlier. However, the relationships between covariance matrix entries and

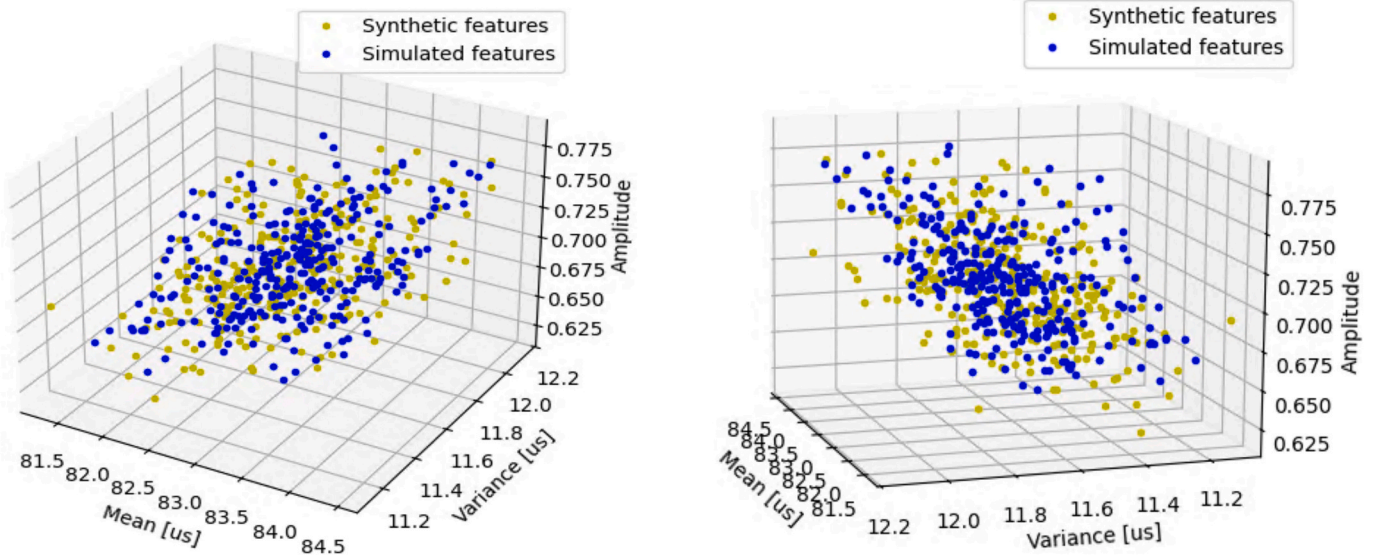


Fig. 6. Fundamental feature distribution obtained for 20 independent realizations of the stochastic corrosion field (by simulating the computational model, here, for $h = 20\%$ and $s = 4\%$) and the synthetic features generated using the multivariate normal distribution extracted from these features. Observe the similarity of the two datasets regarding the sample shape (here, shown from two different view angles).

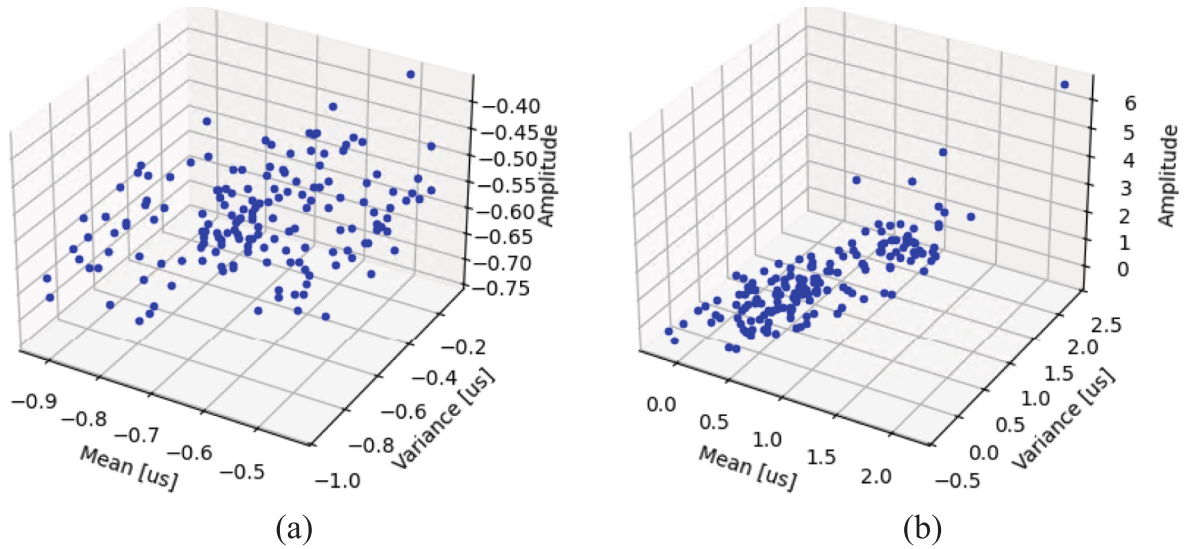


Fig. 7. Fundamental feature distribution for different corrosion parameters: (a) $h = 22\%$, $s = 4\%$, (b) $h = 44\%$, $s = 18\%$. In both cases, aggregated distributions obtained for ten realizations of the stochastic corrosion field are shown. Note that in the case of larger h and s , the distribution contains multiple outliers, which is problematic for covariance matrix estimation using MLE (i.e., leads to excessively large entries).

corrosion parameters are considerably more nonlinear (cf. Fig. 9). Therefore, in this research, the model is implemented using a deep neural network (DNN). The purpose of employing the DNN is to provide a sufficiently flexible nonlinear regression model for the proposed statistical feature representation, rather than to investigate the performance of a particular machine learning algorithm. The network architecture has been shown in Fig. 10. The model contains five fully connected layers of sizes 256, 128, 64, 32, and 16 neurons, and a two-dimensional output regression layer. The model outputs are the estimated thickness reduction h and its standard deviation s . The activation function is ReLU [39]. The network is trained using the ADAM algorithm [39], which is a version of a stochastic gradient descent routine. The learning rate is 10^{-5} , and the maximum number of epochs is 5000. The loss function is Mean Squared Error (MSE). The specific architecture of the network has been established through ablation studies, where three different architectures were tested: (i) decreasing number of neurons per

layer, (ii) increasing number of neurons per layer, (iii) and fixed number of neurons (from 32 to 512). For each architecture, we tested several options with different layer numbers. These experiments indicated that a decreasing pyramidal structure with five layers is the most advantageous. Simpler architectures (lower numbers of neurons/layers) could not capture the nonlinear dependencies between the input and output spaces, whereas more involved networks tend to overfit.

Apart from the algorithmic mechanisms already mentioned (robust feature scaling, and elliptic envelope-based covariance matrix estimation), we also consider additional enhancement of the surrogate, which involves utilization of multiple realizations of the stochastic corrosion field corresponding to the same pairs of parameters h and s . More specifically, for each pair $h_B^{(k)}$ and $s_B^{(k)}$, we generate N_f random fields and their corresponding feature vectors are extracted as $\mathbf{v}_{m,B,j}^{(k)}$, $j = 1, \dots, N_f$. The averaged feature vectors are then assigned as $\mathbf{v}_{m,B}^{(k)} = N_f^{-1} \sum_j \mathbf{v}_{m,B,j}^{(k)}$. A practical meaning of this approach is the following. When using a

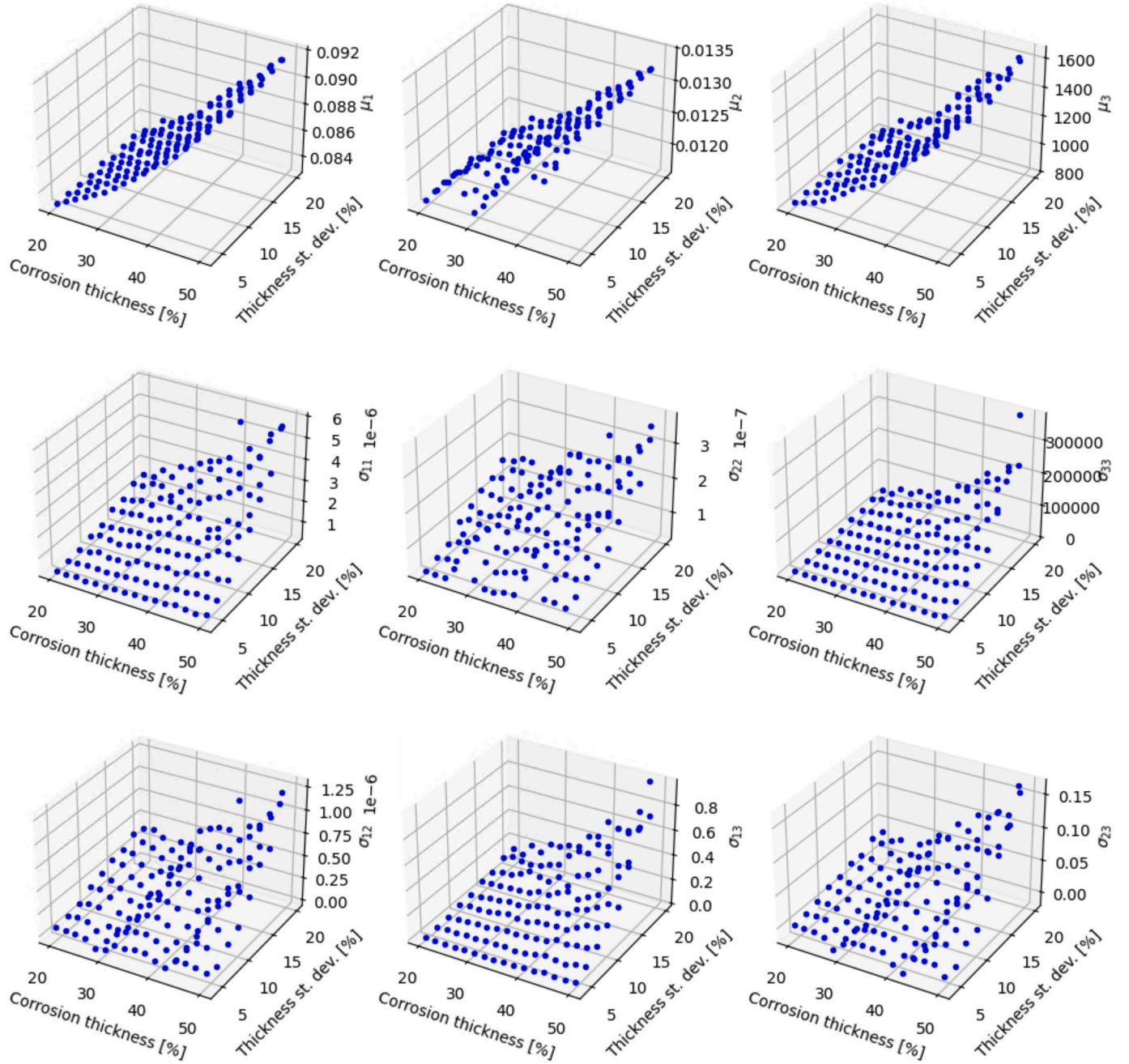


Fig. 8. Multivariate distribution extraction using MLE. Shown are the mean vectors and covariance matrices (vectors $\mathbf{v}_m$) for different corrosion parameters h and s . As observed, extracting μ and Σ using MLE, which is extremely sensitive to outliers, leads to excessively large values of the covariance matrix entries, especially for higher values of h and s . As a result, building an inverse model representing this data becomes problematic.

single realization (e.g., as in [18]), the feature vector represents one point in a distribution similar to that shown in Fig. 5(a). Using multiple realizations is equivalent to estimating the distribution center, which has an effect of regularizing the problem as illustrated in Fig. 11.

2.6. Benchmark algorithm

The corrosion parameter estimation approach proposed in this research will be compared to several inverse modeling-based approaches but also to the conventional identification procedure involving the time-of-flight (ToF) analysis of guided wave signals. This is to underscore the limitations of analytically rooted methods and to emphasize the benefits of data-driven methodologies.

The ToF algorithm is based on the determination of the propagation

time of the primary wave packet between the excitation source and individual sensors, denoted as T_k , $k = 1, \dots, N_s$. In practice, T_k is simply extracted from the temporal position of the recorded guided wave response. The associated effective group velocity is then computed as

$$c_{g,k} = \frac{L}{T_k}, \quad k = 1, \dots, N_s \quad (2)$$

where L is the source-to-sensor distance. These velocities are employed to obtain directional thickness estimates based on a precomputed dispersion relation for the selected guided wave mode and excitation frequency

$$h_k^{\text{eff}} = d(c_{g,k}), \quad k = 1, \dots, N_s \quad (3)$$

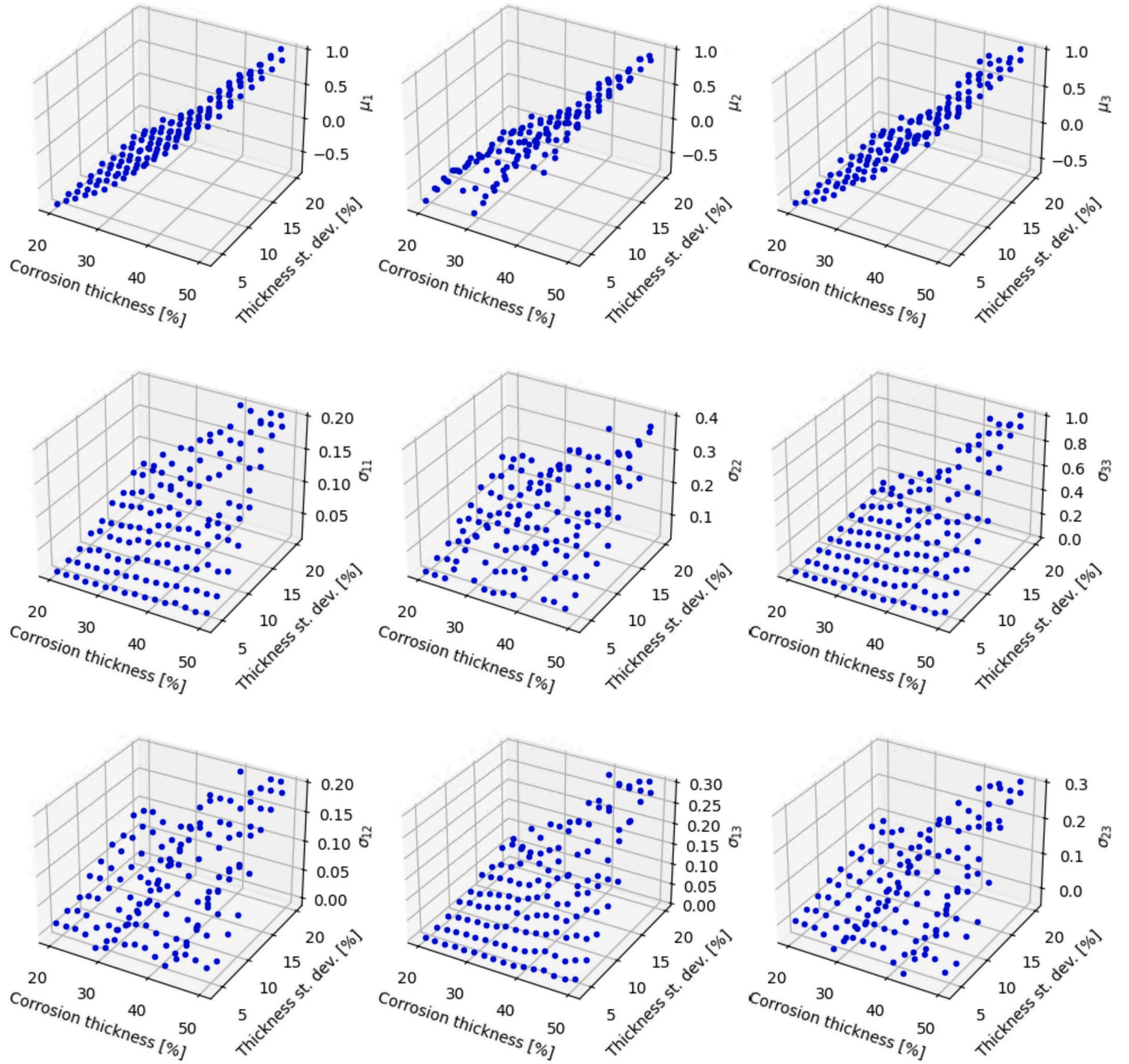


Fig. 9. Multivariate distribution extraction using robust feature scaling and robust covariance matrix estimation through elliptical envelopes. Shown are the mean vectors and covariance matrices (vectors $\mathbf{v}_m$) for different corrosion parameters h and s . Note that the relationship between covariance matrix entries and the corrosion parameters is much more regular than for MLE (cf. Fig. 8), making the construction of reliable inverse model considerably easier.

in which $d(\cdot)$ stands for the mentioned inverse relation.

The ToF-based estimate of the global thickness reduction is then determined as the average value of the directional thickness estimates

$$h^{\text{bench}} = h_0 - \frac{1}{N_s} \sum_{k=1}^{N_s} h_k^{\text{eff}} \quad (4)$$

where h_0 is the nominal undamaged plate thickness. Meanwhile, the thickness variability indicator is computed as the standard deviation of h_k^{eff} as

$$s^{\text{bench}} = \text{std}(h_1^{\text{eff}}, \dots, h_{N_s}^{\text{eff}}) \quad (5)$$

Fig. 12 summarizes the operating flow of the benchmark procedure.

Note that the methodology discussed here merely leverages the propagation delay data but does not exploit other response features, in particular, the temporal width of the wave packet nor its amplitude. In addition, the velocity-thickness relation is derived for the metal plate of uniform thickness. Under practical scenarios, especially the presence of distributed corrosion, where the plate geometry is inhomogeneous along the wave propagation path, the said assumption is just an approximation. As a result, the thickness parameters determined using ToF should be viewed as path-averaged quantities rather than precise descriptors of the corrosion morphology.

3. Results

The corrosion parameter identification framework is demonstrated

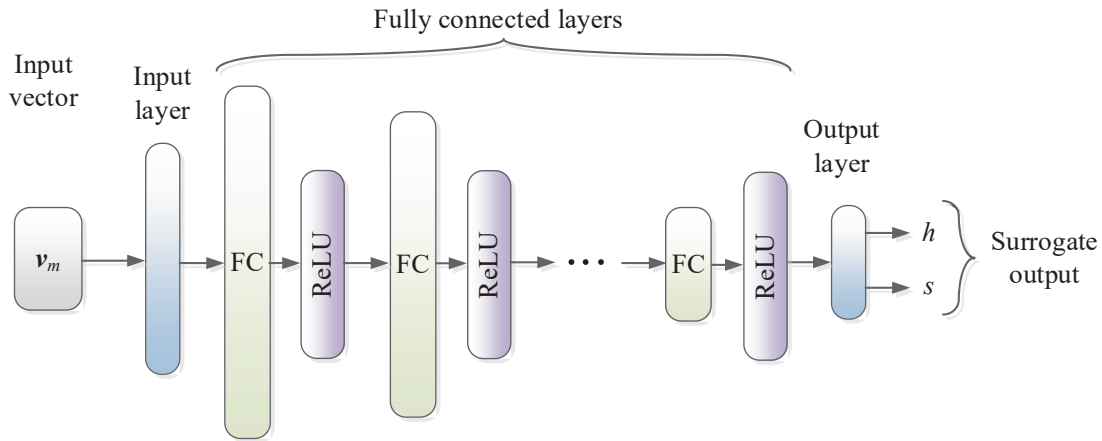


Fig. 10. Architecture of the inverse surrogate for estimating the global corrosion parameters as a function of the feature vector v_m . The network contains five fully connected layers of sizes 256, 128, 64, 32, and 16 neurons. The activation function of ReLU [39]. The network is trained using ADAM algorithm [39] with the learning rate of 10^{-5} , the maximum number of epochs 5000, and the loss function being Mean Squared Error (MSE).

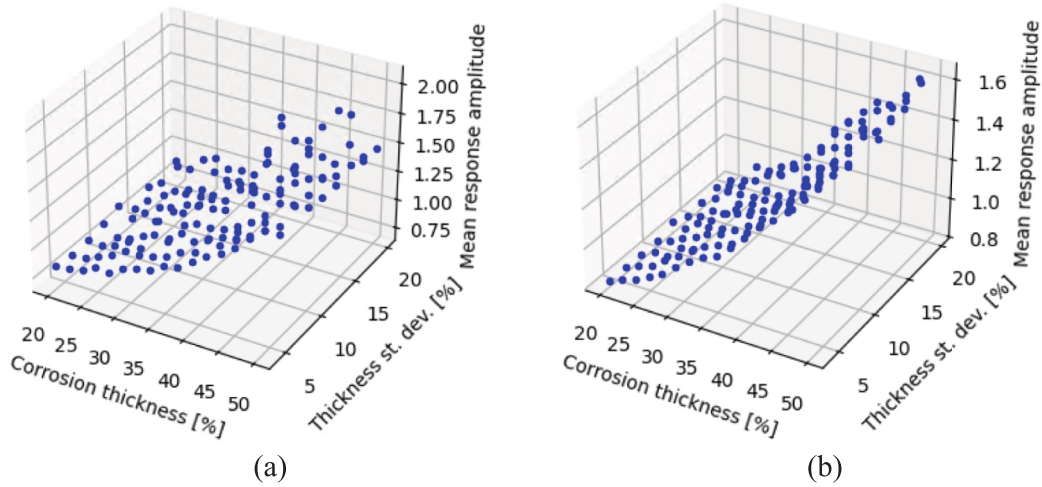


Fig. 11. One of response features, specifically the mean response amplitude, as a function of corrosion parameters: (a) the plot for one random realization of the stochastic corrosion field, (b) average of ten random field realizations. Note that using multiple realizations smoothens the surface, which makes the modeling process simpler and improves accuracy.

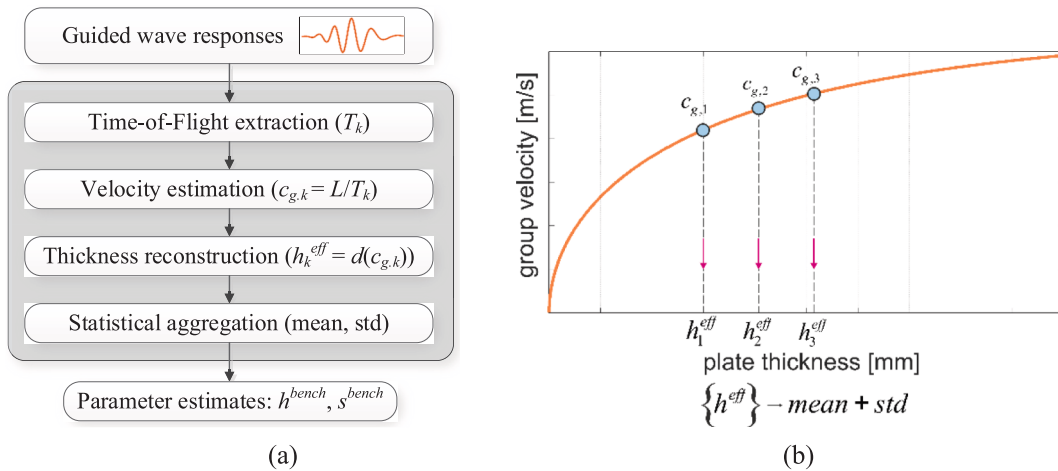


Fig. 12. Time-of-flight-based procedure for corrosion parameter estimation: (a) operational flow of the algorithm, including time-of-flight extraction, velocity estimation, and statistical aggregation, (b) physical interpretation, emphasizing the conversion of directional velocity estimates obtained along different propagation paths into effective thickness values using the inverse dispersion relation.

here and compared to several alternative approaches. These include the conventional time-of-flight method, and several feature-oriented strategies involving different extraction schemes as outlined in Section 2.4. In addition, we also study augmented methods integrating multiple realizations of the stochastic corrosion field, corresponding to different values of N_f as elucidated in Section 2.5. The quality of parameter estimation is quantified using several error metrics, including the relative and absolute errors and the correlation coefficient.

The material of this section is arranged into three parts. The design of experiments and acquisition of the training and testing data is explained in Section 3.1. Section 3.2 puts together the numerical results. Section 3.3 summarizes the key observations and findings.

3.1. Training and testing data. Design of experiments and data acquisition

The training and testing samples are denoted as $c_B^{(k)} = [h_B^{(k)} s_B^{(k)}]^T$, $k = 1, \dots, N_B$, and $c_t^{(k)} = [h_t^{(k)} s_t^{(k)}]^T$, $k = 1, \dots, N_t$, respectively. Both sets are arranged as subsets of a rectangular 16×9 grid M_g , incorporating all combinations of $h \in \{20\%, 22\%, \dots, 48\%, 50\%\}$, and $s \in \{4\%, 6\%, \dots, 18\%, 20\%\}$. The details are explained in Fig. 13(a). Fig. 13(b) shows a graphical illustration of the training and testing sample allocation.

The accuracy of corrosion parameter prediction is assessed using RMAE, MAE, and the correlation coefficient, all defined in Table 2. Among these, MAE is convenient in quantifying typical (absolute) discrepancies between the predicted and true values of h and s .

3.2. Results and comparative studies

In this section, we put together the numerical results obtained using the corrosion parameter estimation approach proposed in this research, and several alternative methods, including diverse feature-based techniques and the conventional time-of-flight algorithm. Recall that the proposed procedure employs feature vectors $\mathbf{v}_m$ based on multivariate probability distribution estimation of the fundamental features, robust feature scaling, and elliptic envelope-based covariance matrix extraction oriented towards handling outliers. Furthermore, multiple realizations of the stochastic corrosion field are incorporated. Benchmark feature-based approaches utilize the feature vectors $\mathbf{v}_s$ of [18] as well as different number of stochastic field realizations $N_f = 1, 3$, and 10. The results are collected in Table 3 and include the error metrics (RMAE, MAE, R) for thickness reduction h and standard deviation s . For supplementary illustration, Figs. 14–17 show the scatter plots for selected techniques.

Table 2

Error metrics employed to validate the prediction accuracy of the inverse models.

Error metric	Formula	Explanations
Relative Mean Absolute Error (RMAE)	$RMAE = \frac{1}{n} \sum_{k=1}^n \frac{ x_k - y_k }{x_k}$	In all formulas, x_k and y_k are predicted and actual values, whereas $\bar{x}$ and $\bar{y}$ are their mean values
Mean Absolute Error (MAE)	$MAE = \frac{1}{n} \sum_{k=1}^n x_k - y_k $	
Pearson correlation coefficient (R)	$R = \frac{\sum_{k=1}^n (x_k - \bar{x})(y_k - \bar{y})}{\sqrt{\sum_{k=1}^n (x_k - \bar{x})^2 \sum_{k=1}^n (y_k - \bar{y})^2}}$	

3.3. Summary of findings

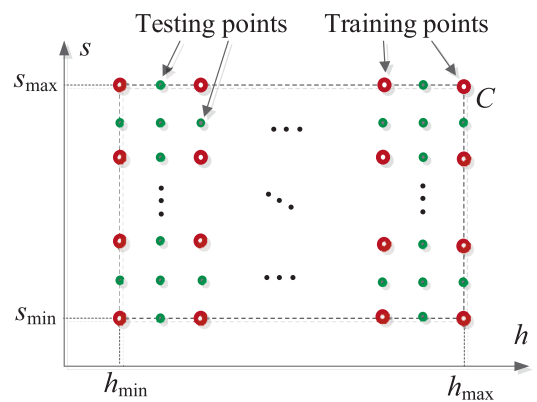
The results in Table 3 provide comprehensive assessment of the predictive accuracy of the proposed procedure and diverse alternative algorithms, including the time-of-flight identification technique. The first key observation is significant difference between ToF and all inverse-modeling-based approaches. The predictive power of the simplest feature-based approach using single realization of the stochastic corrosion field and rudimentary feature vector $\mathbf{v}_s$ [18] provides considerably lower prediction errors than the ToF approach yielding about five times smaller RMAE for h (3.7% vs. 18.1%) and over twice as small RMAE for s (17.5% vs. 38.4%). The improvements regarding MAE are comparable. Similarly, the inverse modeling method [18] substantially improves the correlation coefficient (0.983 vs 0.732 for h and 0.844 vs. 0.447 for s). These numbers corroborate the benefits of exploiting additional information, especially temporal width of the guided wave packet and its amplitude in contrast to solely using the effective wave velocity.

The employment of multiple corrosion field realizations ($N_f > 1$) leads to further enhancement of the predictive accuracy. The data in Table 3 compares three multiplicity levels, the baseline ($N_f = 1$), the middle value ($N_f = 3$), and the higher value ($N_f = 10$). As observed, the error metrics decrease significantly even for $N_f = 3$, in which case the correlation coefficient reaches 0.993 for h and starts exceeding 0.9 for s . Increasing N_f to 10 brings additional improvements with the errors (both RMAE and MAE) reaching about half of their values for $N_f = 1$. These results are consistent with the expected behavior because utilization of multiple field realizations regularizes the modeling problem and addresses the fundamental non-uniqueness problem. More specifically, instead of making the model represent individual corrosion profile realizations whose corresponding features might fluctuate considerably even for small changes of h and s , the surrogate needs to follow the

Design of experiments:

- **Primary grid M_g :** a 16×9 grid encapsulating all combinations of $h \in \{20\%, 22\%, \dots, 48\%, 50\%\}$, and $s \in \{4\%, 6\%, \dots, 18\%, 20\%\}$,
- **Testing samples:** The remaining M_g points, i.e., $M_t = M_g \setminus M_B$ (the total of 114 points).

(a)



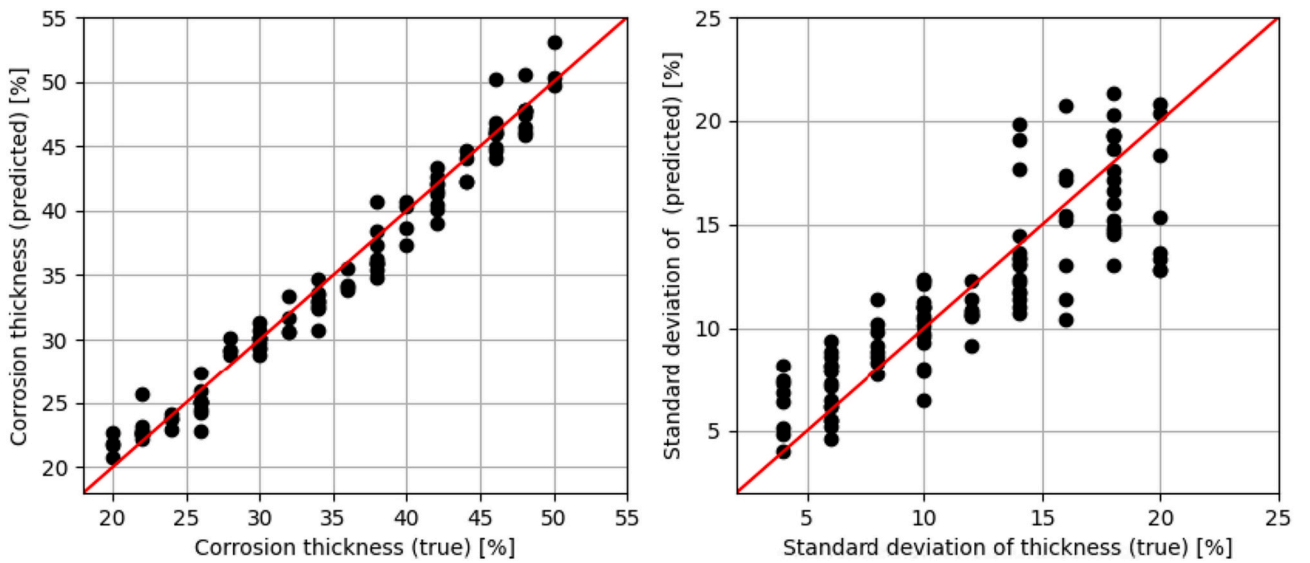
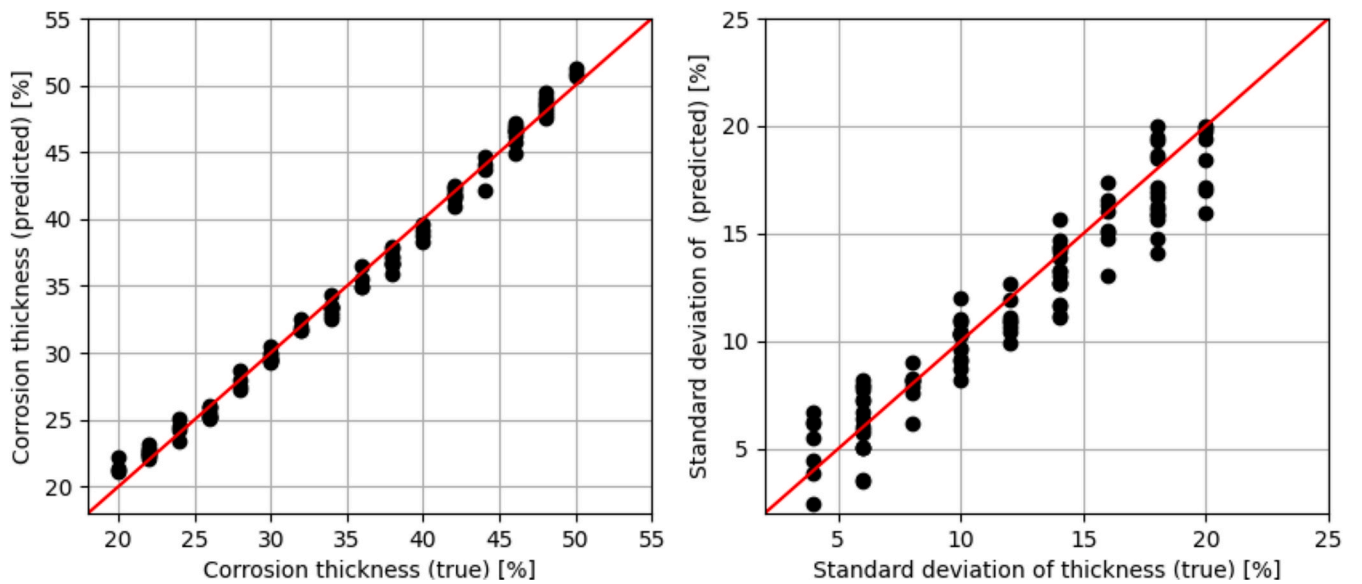
(b)

Fig. 13. Distribution of the training and testing points for inverse model construction and validation: (a) sample set description, (b) graphical illustration. Both datasets are assigned to rectangular grids, with the testing points interleaved the training ones.

Table 3

Corrosion parameter prediction using the proposed technique and benchmark methods.

Model	Accuracy metric					
	Thickness reduction h			Standard deviation s		
	RMAE [#]	MAE	R	RMAE [#]	MAE	R
Benchmark (time-of-flight-based identification)	18.1%	6.3%	0.732	38.4%	4.6%	0.447
Linear inverse model						
Single-random-field $N_f = 1$, feature vector $\mathbf{v}_s$	3.7%	1.3%	0.983	17.5%	2.1%	0.844
Multi-random-field $N_f = 3$, feature vector $\mathbf{v}_s$	2.5%	0.9%	0.993	13.0%	1.6%	0.928
Multi-random-field $N_f = 10$, feature vector $\mathbf{v}_s$	1.9%	0.7%	0.996	10.2%	1.2%	0.955
Multi-random-field $N_f = 3$, feature vector $\mathbf{v}_m$	2.5%	0.9%	0.992	9.6%	1.0%	0.955
Multi-random-field $N_f = 10$, feature vector $\mathbf{v}_m$	1.7%	0.6%	0.996	8.3%	1.0%	0.966
Multi-random-field $N_f = 10$, feature vector $\mathbf{v}_m$, feature scaling and robust covariance matrix extraction, DNN surrogate (this work)	1.3%	0.4%	0.998	5.4%	0.6%	0.989

**Fig. 14.** Scatter plots for the corrosion parameter prediction technique based on inverse model using baseline feature vector $\mathbf{v}_s$ of [18] ($N_f = 1$). The identity function is marked using the solid line.**Fig. 15.** Scatter plots for the corrosion parameter prediction technique based on inverse model using baseline feature vector $\mathbf{v}_s$ of [18] ($N_f = 10$). The identity function is marked using the solid line.

estimated mean values thereof, which behave much more consistently.

Another observation pertains to the benefits of using the feature

vector $\mathbf{v}_m$ incorporating multivariate Gaussian distribution approximation of the fundamental features. It should be stressed that relying on $\mathbf{v}_m$ has almost no effect on the accuracy of estimating the thickness reduction parameter h . The reason is that h depends mainly on the zero-order statistical moments of the fundamental features (i.e., their mean values), and these are essentially the same for $\mathbf{v}_s$ and $\mathbf{v}_m$. However, employing $\mathbf{v}_m$ noticeably improves the accuracy of determining the standard deviation parameter s . This can be attributed to the fact that the covariance matrix of the fundamental features (mean, variance, amplitude) encodes their essential interactions controlled by the surface roughness. These interactions are neglected then the features are treated as statistically independent, as in $\mathbf{v}_s$. Quantitatively, replacing $\mathbf{v}_s$ by $\mathbf{v}_m$ reduces RMAE from 13.0% to 9.6%, and MAE from 1.6% to 1.0% for $N_f = 3$. Meanwhile, the correlation coefficient is increased from 0.928 to 0.955. These enhancements are significant, yet they are further improved for $N_f = 10$. Notwithstanding, a saturation effect is observed, meaning that the additional benefits due to further increase in N_f would rather be marginal.

Now, as indicated in Table 3, the incorporation of robust feature scaling and robust covariance matrix extraction through elliptic envelopes proposed in this study results in further improvements in prediction accuracy, despite the already high performance of the inverse model using the multivariate feature vector $\mathbf{v}_m$. As shown both RMAE and MAE drop down significantly compared to the best benchmark method (feature vector $\mathbf{v}_m$ with $N_f = 10$), from 1.7% to 1.3% for h and from 8.3% to 5.4% for s (RMAE), and from 0.6% to 0.4% for h and from 1.0% to 0.6% for s (MAE). At the same time, the correlation coefficient reaches nearly perfect value of 0.998 for h and 0.989 for s . These improvements are clearly visible in the scatter plots illustrated in Figs. 14–17, where the distribution of points for h (Fig. 17) is almost indistinguishable from the identity function.

From physical perspective, the predictive accuracy gains obtained for $N_f > 1$ can be explained by the random nature of the computational corrosion model. There exist infinitely many realizations of the stochastic corrosion fields that result in the same values of h and s . Each of these realizations leads to diverse guided wave outcomes owing to variations in local propagation conditions (different wave velocity, dispersion, and scattering). Thus, the fundamental features extracted from these signals exhibit fluctuations, which may be significant even for closely spaced pairs (h, s) if based on a single field realization. Using multiple realizations reduces these fluctuations and enables a more consistent feature extraction and enhanced inverse model performance.

It should be emphasized that multiple stochastic field realizations are employed in the present study as a controlled numerical tool for investigating the influence of observation diversity on the inverse estimation process. In practical applications, analogous diversity of guided-wave information may be achieved by acquiring measurements corresponding to different propagation paths or sensing configurations. Although these measurement configurations are not mathematically equivalent to independent stochastic field realizations, they provide complementary observations of the same underlying corrosion state, thereby increasing the amount of statistical information available for estimating the global corrosion descriptors.

4. Conclusion

This study presents a novel methodology for estimating of global corrosion parameters in metal plates. The proposed approach utilizes guided wave responses and their statistical features, extracted from multiple sensors distributed around the excitation source. These features capture statistical moments associated with the temporal position of the recorded wave packets, as well as their width and amplitude, together with their mutual dependencies represented through the covariance matrix of a multivariate Gaussian approximation. Corrosion parameters are then inferred using an inverse model designed to accommodate a wide range of thickness reductions and surface roughness levels.

The proposed technique combines several algorithmic components that are essential for achieving high prediction accuracy. These include robust feature scaling and covariance matrix estimation based on elliptic envelopes, both of which effectively mitigate the influence of outliers in the feature space and enhance the reliability of multivariate distribution characterization. In addition, incorporating multiple realizations of the stochastic corrosion field helps address the intrinsic non-uniqueness of the inverse modeling problem.

The numerical results demonstrate improved prediction performance of the proposed approach, showing clear advantages over the conventional time-of-flight identification method as well as a range of feature-based inverse modeling techniques relying on alternative feature definitions. In particular, it is shown that robust feature extraction, combined with modeling the interdependence of response characteristics, namely arrival time, wave packet width, and amplitude, consistently yields higher predictive accuracy than approaches that treat these features as statistically independent.

In summary, the proposed technique constitutes a promising

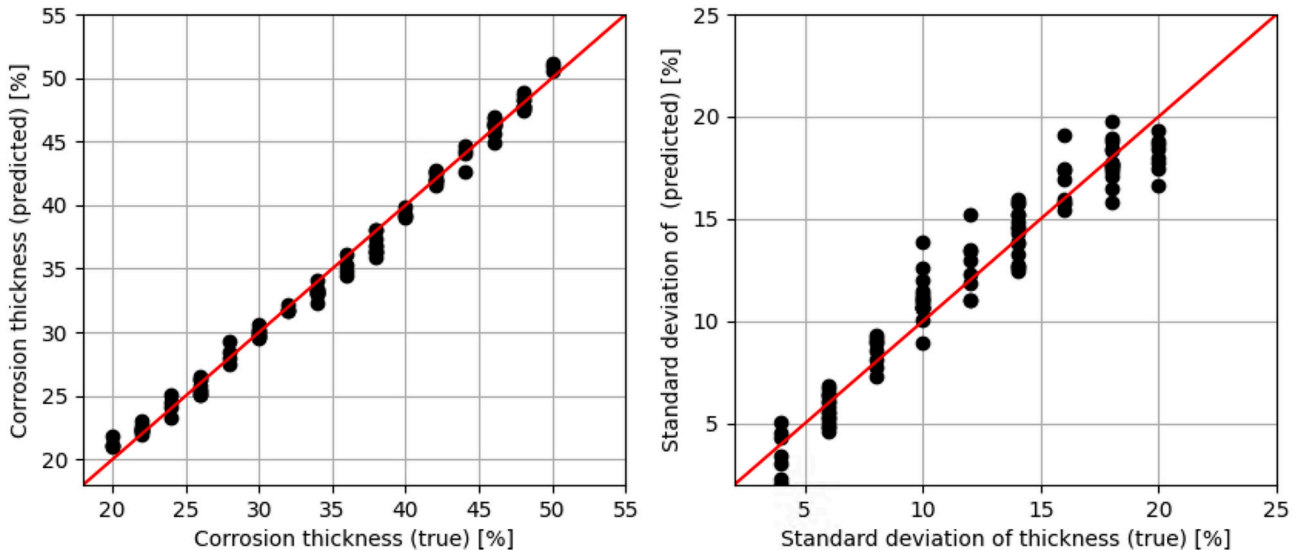


Fig. 16. Scatter plots for the corrosion parameter prediction technique based on inverse model using multivariate-based feature vector $\mathbf{v}_m$ ($N_f = 10$). The identity function is marked using the solid line.

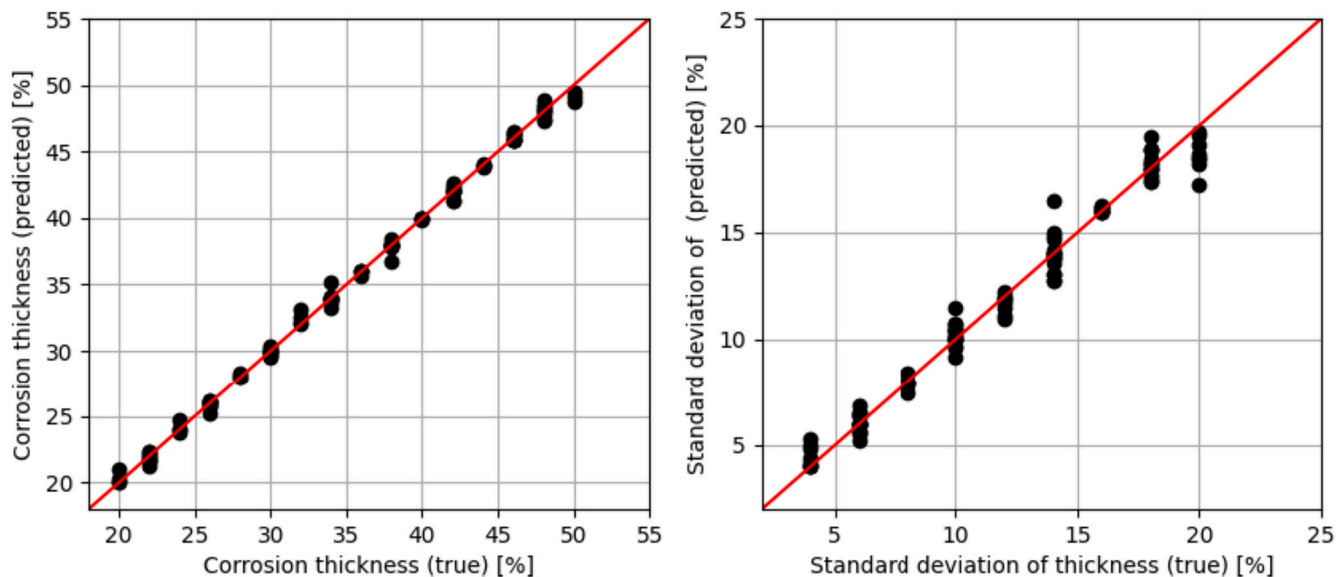


Fig. 17. Scatter plots for the corrosion parameter prediction technique based on inverse model using multivariate-based feature vector $\mathbf{v}_m$ ($N_f = 10$) and the improved multivariate distribution extraction with robust feature scaling and elliptical-envelope covariance matrix extraction. The identity function is marked using the solid line.

alternative to existing methods for the nondestructive evaluation of global corrosion parameters in metallic plates. Within the considered numerical simulation framework, it delivers competitive accuracy in estimating both mean thickness loss and its spatial variability based on guided-wave measurements and derived response features. The present study should be regarded as a numerical proof-of-concept of the proposed inverse modeling framework for globally distributed corrosion represented by experimentally informed stochastic fields. Consequently, the conclusions are limited to the considered numerical simulation conditions and the adopted class of corrosion morphology.

The primary objective of the present work is to evaluate the proposed multivariate feature representation and nonlinear inverse modeling strategy independently of uncertainties associated with the measurement system. Practical aspects related to sensing-system imperfections, including source-to-sensor distance uncertainty, sensor positioning tolerances, sensor layout, and installation-related effects, constitute a separate research problem and are being investigated in complementary studies. They are therefore intentionally not reproduced here in order to maintain the methodological focus of the present contribution.

Comprehensive experimental validation under realistic inspection conditions, including measurement noise, sensor coupling variability, installation tolerances, finite transducer effects, and environmental influences, remains an essential next step before practical engineering deployment of the proposed methodology.

Future developments will also include investigation of different structural configurations, including varying plate thicknesses and geometries, together with extension of the methodology towards identification of localized defects, such as cracks, within a unified inverse modeling framework.

Ethical statement

The authors state that the research was conducted according to ethical standards.

CRediT authorship contribution statement

Slawomir Koziel: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Conceptualization. **Beata Zima:** Writing – review & editing, Writing –

original draft, Visualization, Software, Methodology, Investigation, Conceptualization. **Anna Pietrenko-Dabrowska:** Writing – review & editing, Writing – original draft, Validation, Project administration, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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