# Unsupervised Damage Diagnostics with Data Normalization Using Experimental Data

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## ABSTRACT

Environmental temperature variations can significantly affect modal parameters, complicating damage detection in vibration-based structural health monitoring (SHM) approaches. To mitigate these challenges, this study proposes a novel approach to transform temperature-variant data into a temperature-invariant domain for more effective data normalization and thus more accurate damage detection when the labeled data under temperature variation is unavailable. Experimental acceleration data collected from different structural health states are first categorized into temperature-variant and temperature-invariant domains, and modal parameters (modal eigenfrequencies, eigenforms, and damping ratios) are extracted accordingly. An adversarial domain adaptation technique is then employed to enhance the algorithm's ability to generalize across domains while accurately distinguishing between damage states. The proposed approach is validated on a real field engineering structure realized as a 9 m high lattice mast under real environmental conditions. The approach consists of three main components: a general feature extractor, a classifier, and a domain discerner. The modal parameters are processed through the feature extractor to obtain domain-independent features, which are subsequently mapped to the corresponding damage states. Meanwhile, the domain discerner competes with the feature extractor by attempting to identify the domain origin of the features, ensuring robust feature extraction. The results demonstrate the potential of this approach to overcome temperature-induced challenges in SHM and improve damage detection accuracy.

## INTRODUCTION

Data normalization in structural health monitoring (SHM) refers to the process of distinguishing changes in measured system responses caused by benign operational and environmental variability from those caused by structural damage [1, 2]. A variety of normalization techniques have been proposed, ranging from statistical methods to advanced machine learning-based approaches [3]. Traditional strategies often rely on ex-

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plicit compensation using measured environmental parameters—for example, adjusting vibration features based on temperature or other contextual inputs [4]. However, reliably separating damage-induced changes from environmentally driven fluctuations remains a significant challenge. Environmental factors such as temperature, humidity, and traffic loading can mimic or obscure damage signatures, making robust normalization essential for accurate diagnostics [5].

As structural systems grow more complex, so too do the effects of operational and environmental variability on measured responses [6]. Recent approaches employ data-driven methods to automatically suppress environmental effects—for instance, unsupervised techniques such as principal component analysis or deep autoencoders, which can remove dominant environmental trends without requiring explicit temperature data [7–9]. Rather than explicitly modeling or removing environmental effects, an alternative strategy is to extract invariant features from system responses that are insensitive to operational and environmental variability, yet still sensitive to structural damage. A notable advantage of this approach is its independence from labeled data capturing operational and environmental conditions, significantly simplifying the data normalization process and enhancing practical applicability.

In this study, we focus on temperature as the sole environmental variable influencing the measurements, as a first step toward broader normalization. We propose a novel framework that leverages the adversarial training concept to achieve dual objectives: detecting damage and generalizing across domains. Two auxiliary networks are used to guide a shared feature extractor in learning temperature-invariant features relevant for damage diagnosis. The proposed method is validated on real structural data collected under varying temperature conditions, demonstrating its effectiveness in extracting robust diagnostic features.

## EXPERIMENTAL SETUP AND SYSTEM IDENTIFICATION

To validate the proposed concept, a real structure was used whose dynamic behavior was identified through acceleration measurements. Simultaneously, ambient air temperatures were recorded using a nearby weather station. The test structure is shown in Fig. 1. Figure 1 (**a**) presents a photo of the 9-meter-high steel lattice mast; Fig. 1 (**b**) shows a side view and cross-section including the SHM system and the location of the applied structural damage.

The structure and data acquisition were conducted by the Institute of Statics and Dynamics at Leibniz University Hannover, Germany. A detailed description of the setup and dataset can be found in [10] and [11]. The test structure is located approximately 20 km south of Hannover and consists of a 9-meter-high steel lattice mast mounted on a reinforced concrete foundation. It comprises three identical 3 m segments with tubular legs forming an isosceles triangular cross-section. The mast weighs approximately 90 kg and is equipped with an accelerometer-based SHM system. Each segment includes seven bracing levels and is assembled using M10 bolts. The base plate is anchored with 12 M12 bolts to ensure a rigid connection between the mast and the 1.50 x 1.50 x 0.80 $m^3$ reinforced concrete foundation.

To simulate damage, diagonals of one plane in segment DAM 3 were removed, as shown in Fig. 1 (**b**). Ambient conditions such as temperature, humidity, and wind were

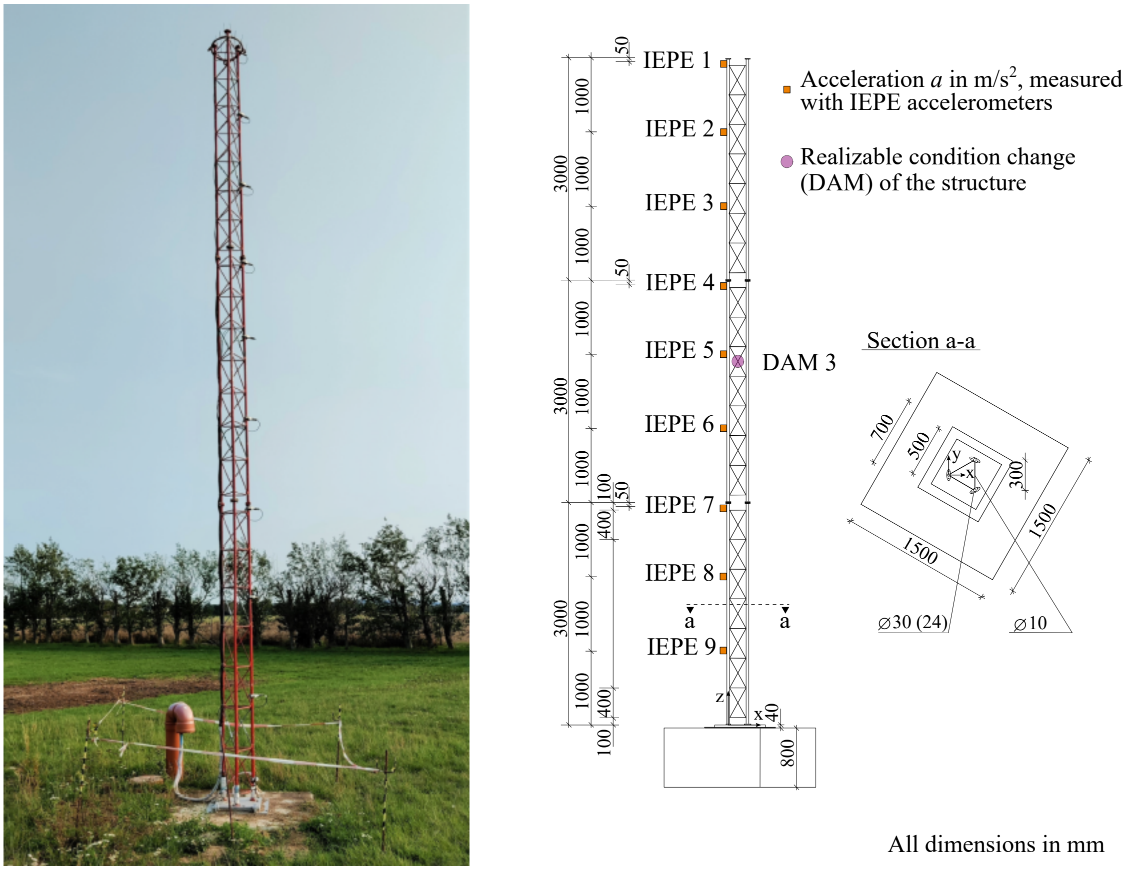


Figure 1. Validation structure based on Wernitz et al. [10]. (**a**) Photo of the steel lattice mast; (**b**) View and cross-section drawing with SHM system and realized structural damage of the lattice mast.

monitored, with the temperature data being utilized for further analysis in this study.

To extract modal parameters – eigenfrequencies, eigenforms, and damping ratios – Operational Modal Analysis (OMA) was performed using the covariance-driven Stochastic Subspace Identification (SSI-COV) method [12]. OMA is a widely used technique in SHM because it relies solely on structural responses and does not require knowledge of the excitation. The SSI-COV algorithm uses time-domain covariance of the measured responses to identify a state-space model of the structure. This method helps mitigate harmonic interferences and noise. In this study, the open-source Python toolbox PyOMA-GUI [13] was used for SSI-COV-based OMA. For theoretical background, refer to Rainieri (2014) [14] and Van Overschee (2012) [15].

For damage diagnosis using domain adversarial neural networks (DANN), system identification was carried out for two domains: a source domain and a target domain. In the source domain, modal parameters for both undamaged and damaged states were calculated using data recorded under nearly stationary temperature conditions. Specifically, measurements taken at temperatures between 19 °C and 22 °C were selected to ensure a sufficient number of samples for training the network.

In contrast, the target domain includes modal parameters for healthy and damaged states recorded under varying temperature. This allows the model to generalize across

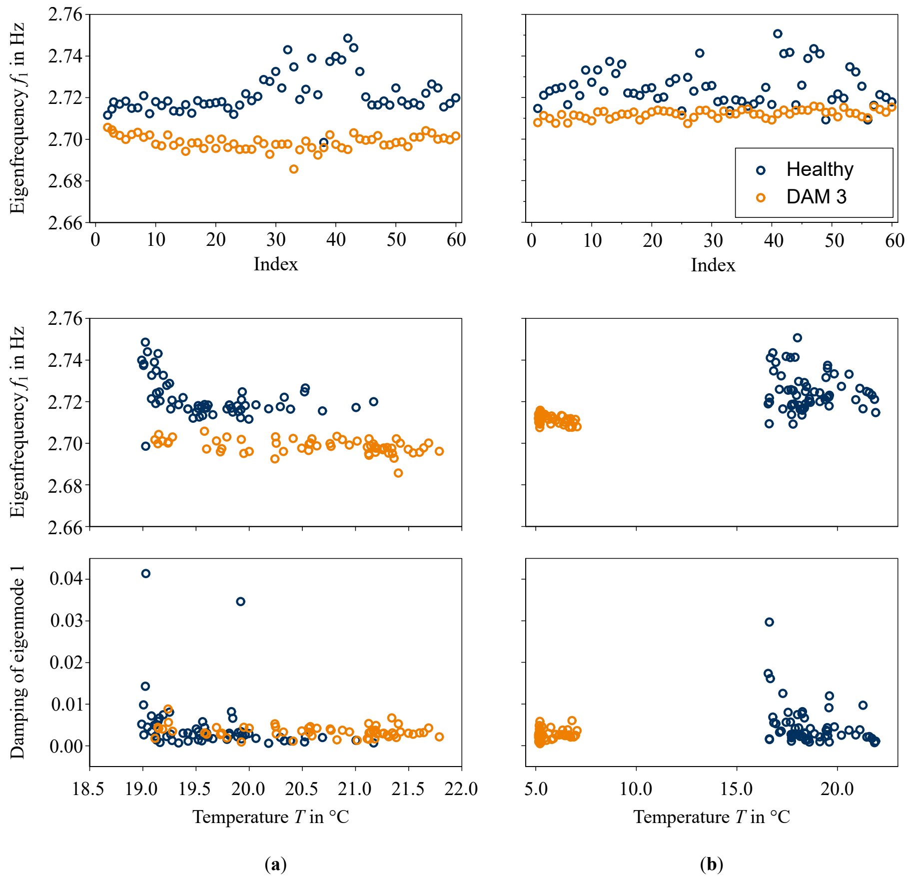


Figure 2. Operational Modal Analysis (OMA) on the lattice tower structure for the parameters of the first bending eigenfrequency over the instances considered, as a function of temperature and the damping ratio of the first eigenform as a function of temperature. (**a**) Source domain; (**b**) target domain.

different environmental influences, which is crucial for robust damage detection.

The results of the OMA for the first bending eigenfrequency, the corresponding eigenform, and the damping ratio are presented in Fig. 2. Modal parameters for the source domain are shown in Fig. 2 (**a**), while those for the target domain are displayed in Fig. 2 (**b**).

In the source domain, a separation between the healthy and damaged structural states is observed based on the first bending eigenfrequency. The healthy state exhibits eigenfrequencies between 2.72 Hz and 2.75 Hz, whereas the damaged structure (with diagonals removed at DAM 3) shows values below 2.71 Hz. This simulated damage DAM 3 would be serious for the real use of a supporting structure. Nevertheless, the first bending eigenfrequencies only show a change in the parameters of less than 1 %. This makes a reliable damage diagnosis difficult. In addition, the damping ratio as a function of temperature shows less pronounced differences between the healthy and damaged states. Except for two outliers in the healthy state, the damping values remain below 0.01 and do not provide a clear distinction.

In the target domain, shown in Fig. 2 (**b**), stronger temperature variations are present, but no significant shift of the first bending eigenfrequencies is observed between the healthy and damaged states. The healthy state data points also show stronger scattering of the first bending eigenfrequency with larger temperature variations. This highlights a key challenge in modal parameter-based damage diagnosis: individual modal indicators may be insensitive to significant damage when confounded by environmental variability, making damage diagnosis difficult.

To overcome this limitation and improve diagnostic performance, an unsupervised learning approach based on adversarial network is employed. In the following section, this method is described in detail and applied to the previously analyzed modal datasets to assess its damage detection capabilities.

## DAMAGE DIAGNOSIS WITH DATA NORMALIZATION THROUGH DOMAIN ADVERSARIAL NEURAL NETWORK

As illustrated in Fig. 3, the aim of this study is to leverage measurement data without temperature variations, denoted as $M^I$, and their corresponding damage status $D^I$, to enhance damage diagnosis accuracy ($D^T$) for measurement data with temperature variations ($M^T$), particularly when $D^T$ labels are unavailable. The damage status with temperature variations is exclusively used for validation purposes. The fundamental strategy involves capturing diagnostic similarities through identifying common features between the two domains (with and without temperature changes). These commonalities represent generalized features capable of indicating damage status across both domains.

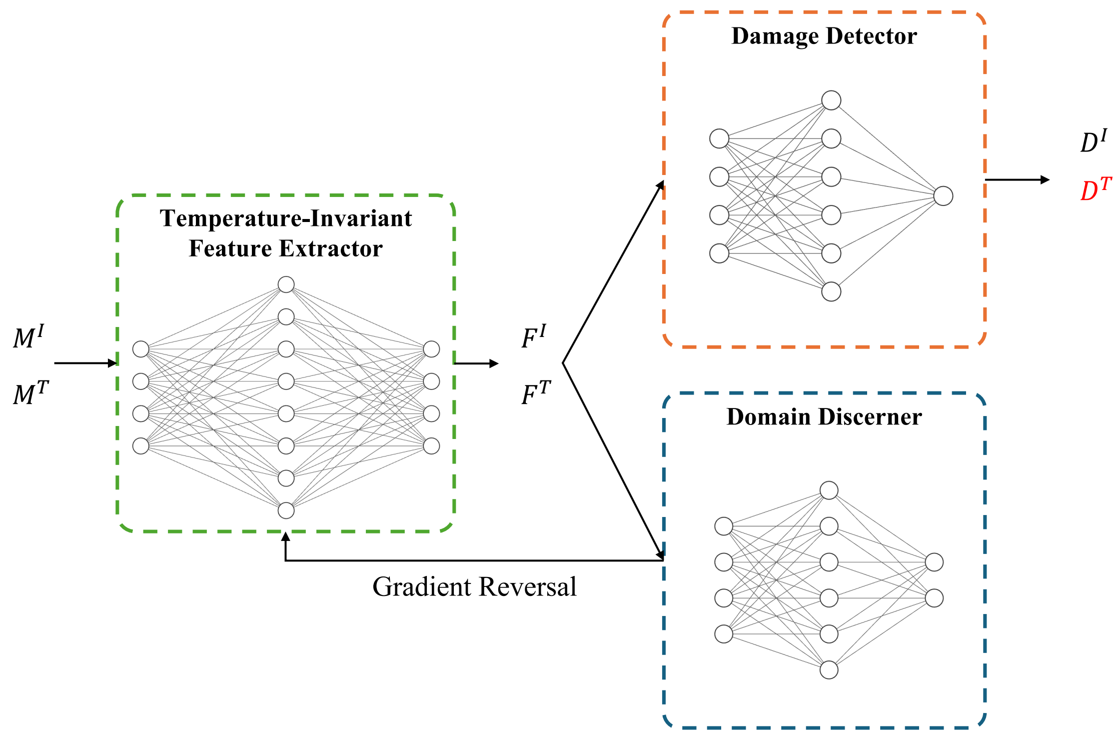


Figure 3. The architecture of the proposed diagnostics network with data normalization.

To generalize the feature extractor for these domains, we employ two guiding networks designed to produce temperature-invariant features ($F^I$ and $F^T$) while preserving sufficient diagnostic information. First, a damage detection network diagnoses the structural damage status $D$ based on extracted features $F$. This network ensures that essential diagnostic information is retained in both $F^I$ and $F^T$. Notably, the damage detection network is trained exclusively on data without temperature variations ($F^I$, $D^I$), due to the absence of $D^T$.

Second, rather than explicitly normalizing the temperature effect, we adopt a domain discerner network to implicitly learn temperature-invariant features. As shown in Fig. 3, a gradient reversal layer is inserted between the feature extractor and the domain discerner to encourage the extractor to learn features that are invariant across domains with and without temperature variations. The domain discerner attempts to classify whether the extracted features originate from the temperature-variant domain ($F^T$) or the temperature-invariant domain ($F^I$). Inspired by the generative adversarial network (GAN) framework [16] and domain adversarial neural networks (DANN) [17], this setup introduces an adversarial dynamic between the feature extractor and domain discerner to promote the extraction of shared, temperature-invariant features. All the parameters in these three networks are updated jointly during training.

## DAMAGE DIAGNOSIS RESULTS

The total input dimension is 11. Modal parameters – including eigenfrequency, damping ratio, and eigenform of the first mode – are used as the input. The output is a single Boolean value indicating whether the structure is damaged. This study focuses on damage existence detection; damage localization will be explored in future work as more data become available.

For the domain without temperature change, we collected 120 data samples within a controlled temperature range of 19–22 °C. Similarly, for the domain with temperature change, another 120 samples were collected under temperature conditions outside of this range. In both datasets, 60 samples correspond to a healthy structure and 60 to a damaged one.

TABLE I. Diagnosis accuracy with and without proposed network.

| **Training Method** | **Test Prediction Accuracy (%)** |
| --- | --- |
| $M^I$ and $D^I$ only without normalization | $M^I$ (labeled): 97.22<br>$M^T$ (unlabeled): 61.11 |
| $M^I$, $M^T$ and $D^I$ with proposed normalization | $M^I$ (labeled): 97.22<br>$M^T$ (unlabeled): 83.33 |

Table I presents the diagnosis results comparing the proposed network with a baseline model that does not account for temperature normalization. When only the feature extractor and damage detector are trained using data from the domain without temperature variation ($M^I$ and $D^I$), the accuracy on $M^I$ reaches 97.22%. However, the performance drops significantly on $M^T$, achieving only 61.11% accuracy, as the model fails to account for temperature-induced variability.

In contrast, when the full framework—including the feature extractor, damage detector, and domain discerner—is trained using $M^I$, $M^T$, and $D^I$, the accuracy on $M^I$ remains at 97.22%. This consistency is expected, as $M^T$ provides no additional information about $D^I$. Importantly, the diagnosis accuracy on $M^T$ improves markedly to 83.33%, demonstrating that the proposed normalization mechanism effectively enhances generalization across domains. These results indicate that the proposed method can significantly improve diagnostic performance in scenarios where temperature influence is poorly understood or when labeled data under temperature variation is unavailable.

## CONCLUDING REMARKS

The primary objective of this study is to improve diagnostic accuracy for measurement data collected under temperature variations using an adversarial neural network architecture. This approach is particularly useful when the influence of temperature is not well understood and labeled data under varying temperature conditions is limited or unavailable. The proposed architecture achieves both damage detection and feature generalization through the adversarial interplay between the feature extractor and domain discerner. The method is validated using real measurement data affected by temperature variation, demonstrating its effectiveness in enhancing diagnostic robustness. Future work will extend this framework from binary damage detection to damage localization as additional data become available.

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