

Full paper

Digital Visual Testing and Machine Learning-Based Prediction of Fatigue Strength in Circumferential Welded Joints of Offshore Monopiles

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Abstract

Circumferential welded joints in offshore monopiles are critical structural elements subjected to cyclic loading. Thus, robust inspection and fatigue life prediction methods are required to ensure structural integrity and to optimize structural design. This study presents a digital visual testing (D-VT) methodology for the assessment of weld quality in these joints, combined with machine learning (ML) models to predict their fatigue strength. High-resolution optical surface geometry measurements are employed to characterize weld seam geometries and to detect surface-level discontinuities in welds. Extracted features were used to train multiple ML algorithms, including artificial neural networks and extreme gradient boosting models, with input from both visual inspection data such as weld geometry but also loading conditions. The predictive models were validated against experimental fatigue test data. Results demonstrate that D-VT, when integrated with ML-based analysis, can effectively identify fatigue-prone locations along weld seams and provide reliable estimates of fatigue strength. The methodology offers a robust, non-destructive testing solution for weld quality assessment. It both saves time and resources and can be applied to various industries and weld types.

Keywords

3D-scanning, weld geometry, welding irregularities, non-destructive testing, weld imperfections, fatigue life prediction

1 Introduction

Wind energy production has become a cornerstone of the global transition toward sustainable power generation, with monopile foundations serving as the primary support structure for increasingly large and powerful turbines offshore. As turbine ratings exceed 15 MW and monopile diameters surpass 10 meters, the structural integrity of circumferential welded joints—critical load-transfer interfaces between individual segments—has become one of the main concerns in fatigue design [1]. These joints are subjected to severe, long-term cyclic loading from wind, wave, and current forces, compounded by environmental degradation and complex stress concentrations at the weld toe. Consequently, accurate prediction of fatigue strength is essential to ensure safety, reliability, and cost-effective design throughout the lifetime and for possible life extensions.

Traditional fatigue assessment methodologies rely on standardized stress life (S-N) curves derived from laboratory tests, often based on nominal stress approaches or hot-spot structural stress analysis. While codes such as DNV-ST-0126 [2], DNV-RP-C203 [3], and IEC 61400-3-1 [4] provide robust guidance, they frequently incorporate conservative assumptions due to uncertainties in weld geometry, residual stresses, and microstructural variability. Moreover, the reliance on visual inspection and manual measurement tools—prone to subjectivity, low repeatability, and limited spatial resolution—has hindered the accurate characterization of weld quality, particularly in large-scale circumferential joints. The current quality classification systems, such as ISO 5817 [5], while widely adopted, lack a direct, quantitative link to actual fatigue performance, leading to potential over-design or underestimation of fatigue life [6].

Recent advances in digitalization and non-destructive evaluation have opened new ways for improving fatigue assessment. Digital Visual Testing (D-VT) [7], leveraging high-resolution 3D scanning via laser triangulation or structured light projection (e.g., fringe light projection (FLP) sensors), enables precise, automated, and repeatable characterization of weld geometry. By converting discrete point cloud data into continuous surface models through Poisson reconstruction and aligning scans using, e.g., RANSAC algorithms [8], this approach facilitates the extraction of critical geometric parameters—such as weld toe radius, undercut depth, and misalignment—with sub-millimeter accuracy [9]. Furthermore, the ability to slice the 3D weld profile into multiple 2D cross-sections allows for a comprehensive statistical analysis of geometric variability along the joint, revealing that extreme values (e.g., high quantiles) often correlate more strongly with fatigue life than mean parameters [10].

Complementing geometric data, modern non-destructive techniques such as X-ray diffraction (XRD) enable the in-situ, non-destructive assessment of microstructural features and residual stresses. By analyzing the full width at half maximum (FWHM) of diffraction peaks, XRD provides indirect yet reliable estimates of grain size, dislocation density, and hardness—key factors influencing crack initiation in the heat-affected zone (HAZ). Similarly, automated XRD measurements along the weld seam offer detailed spatial maps of residual stress distribution, capturing local variations that significantly impact fatigue behavior.

Building on these rich, multi-scale datasets, machine learning (ML) offers a fast opportunity to model the complex, non-linear interactions between weld geometry, microstructure, residual stresses, and fatigue performance. Unlike conventional empirical or finite element analysis (FEA)-based methods, ML models (e.g., ensemble algorithms like XGBoost or deep neural networks) can learn intricate patterns from high-dimensional data, enabling accurate predictions. By integrating geometric descriptors (e.g., median and quantile-based features), residual stress distributions, and microstructural indicators into a unified feature space, ML models can predict fatigue strength with significantly reduced conservatism and improved generalizability.

This study presents a comprehensive methodology for the DV-T and ML-based prediction of fatigue strength in circumferential welded joints of offshore monopiles. It describes the development of a high-fidelity 3D scanning and data processing pipeline for weld geometry characterization, the integration of XRD-derived microstructural and residual stress data, and the construction of predictive ML models trained on a dataset of over 400 butt-weld specimens. This study demonstrates that a holistic, data-driven approach—combining digital inspection, multi-scale material characterization, and advanced analytics—can significantly enhance the accuracy and reliability of fatigue life prediction. Our work aims to help optimizing design and to warrant life extension strategies in offshore wind infrastructure.

2 State-of-the-art fatigue design of monopiles

The fatigue design of offshore wind monopiles has become a critical aspect of structural integrity assessment as turbines grow in size and are deployed in increasingly challenging environments. Modern methodologies aim to balance safety, reliability, and cost-effectiveness while addressing complex dynamic interactions between environmental loads, structural response, and material behavior [11]. The state-of-the-art approach integrates advanced simulation techniques, refined fatigue assessment procedures, and probabilistic design principles.

Fatigue design begins with accurate characterization of site-specific environmental conditions. This includes long-term statistical data on wind, waves, currents, and water levels. State-of-the-art practice employs coupled aero-hydro-servo-elastic simulations to capture the interaction between the wind turbine rotor, tower, monopile, and soil foundation. These simulations consider operational states such as power production, idling, and fault conditions, as well as transient events like emergency stops. Tools such as OpenFAST and Bladed are widely used to generate representative load time histories, incorporating aerodynamic damping and control system effects. Additionally, directional wave spectra and joint probability distributions of wind and wave conditions are applied to ensure realistic fatigue load combinations.

Monopiles are slender structures with dynamic properties that significantly influence fatigue behavior. Modern design methodologies utilize high-fidelity finite element models that include nonlinear soil-structure interaction through soil resistance-lateral deflection (p-y) curves or 3D continuum models. These models improve predictions of natural frequencies and dynamic amplification factors, which are essential for accurate fatigue assessment. Secondary effects such as scour development, soil stiffness degradation, and grouted connection flexibility are increasingly considered [12]. Modal superposition techniques combined with rainflow counting algorithms are applied to extract stress ranges from simulated time histories, ensuring that fatigue-relevant cycles are accurately captured.

Fatigue damage evaluation traditionally relies on S-N curves derived from experimental data for welded steel joints, as monopiles are fabricated primarily from tubular steel sections. Current standards such as DNV-ST-0126 [2], DNV-RP-C203 [3], and IEC 61400-3-1 [4] provide baseline guidance, but refinements are introduced for offshore wind applications. These include hot-spot stress analysis and local weld detail modelling to reduce conservatism and improve accuracy. Damage accumulation is typically calculated using Miner's rule, but probabilistic approaches are gaining traction to account for uncertainties in load predictions [13, 14], material properties [15], and inspection intervals [16]. Furthermore, corrosion-fatigue interaction is increasingly recognized as a critical factor, prompting the integration of protective coatings and cathodic protection strategies into fatigue life predictions [17].

Recent trends emphasize optimization of monopile

geometry and wall thickness to achieve cost-effective designs without compromising fatigue life. Advanced design frameworks integrate fatigue assessment into iterative design loops, supported by surrogate modeling and ML techniques for rapid evaluation of design alternatives. Digitalization plays a key role in modern fatigue design: structural health monitoring systems equipped with strain gauges and accelerometers provide real-time data on in-service performance. These data streams feed into digital twin models, enabling predictive maintenance and life extension strategies. Such approaches allow operators to move from conservative design margins toward condition-based maintenance, reducing lifecycle costs.

The next generation of fatigue design methodologies will likely incorporate fully probabilistic design codes, leveraging real-time monitoring data and advanced uncertainty quantification techniques. As turbines scale beyond 15 MW and monopile diameters exceed 10 meters, new challenges arise related to fabrication tolerances, residual stresses, and welding quality. Integration of AI-driven predictive models and cloud-based simulation platforms will further enhance the ability to manage fatigue risks throughout the asset lifecycle.

3 Characterization of butt joints at monopiles

3.1 Weld geometry characterization based on digital visual testing

Following the recently proposed guidelines of the IIW Document XIII-3153-2025 [7], D-VT was used to evaluate the geometrical parameters, as shown in Figure 1. For the digitalization of the surface 3D-scanning technique were used.

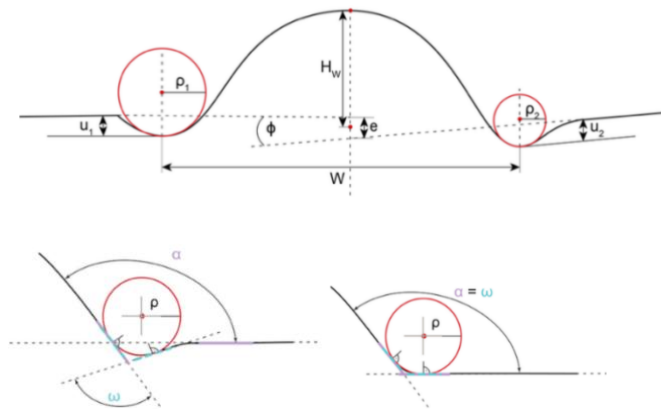


Figure 1. Definition of geometrical parameters of welding joints according to [7]

The data processing pipeline according to Wang et. al. [18] was used to translate the discrete point cloud data into a continuous surface model and then, in single 2D-cross sections, see Figure 2. The specimen surfaces were coated with a white coating and digitized using an SC3500-120 stripe light projection sensor with a scanning area of 120×80 mm and a dot pitch of 25 μm. The dot pitch varied slightly depending on how the FLP was generated. Larger dot pitches were generated in areas with small geometric changes (e.g., flat substrates). The open-source software

MESHLAB© was used to align the scan data in different directions. The next step was to align the model due to the randomness of the scanning direction. The alignment was performed using the Random Sample Consensus (RANSAC) algorithm [19]. The next step was to convert the discrete 3D surface model defined by a point cloud into a continuous surface model by Poisson reconstruction, as described by Kazhdan [20]. This study used the open-source Poisson surface reconstruction algorithm (PoissonRecon) in Python (Adaptive Multigrid Solvers (Version 18.74)).

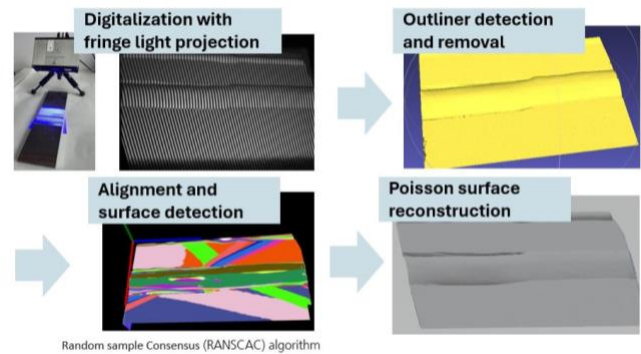


Figure 2. Processing of 3D-scan data.

Geometrical parameters were evaluated according to IIW Document XIII-3153-2025 [7] using curvature-based and RANSAC based algorithms on single 2D-cross sections. Weld toe radius ρ and weld toe angle α were evaluated in a distance of 0.2 mm.

3.2 Weld quality assessment based on digital visual testing

Circumferential weld seams in offshore monopiles foundations are among the most critical structural joints, as they are subjected to high-amplitude cyclic loading and severe environmental damage throughout their lifetime. Design standards such as DNV-RP-C203 [3] and Eurocode 3 [21] require, through associated standards, strict fabrication and inspection criteria for these welds, specifying ISO 5817 [5] Quality Level B and complete visual inspection to ensure their reliability. Recently, the new F.16 Appendix of DNV-RP-C203 introduced S-N curves specifically developed to better represent the behavior of the thick plates used in offshore monopile foundations [22]. To apply the benefits of these enhanced S-N curves in design, the appendix requires welded joints to meet quality level B90 (as defined in ISO 5817 [5] Annex B). Therefore, weld quality control is an integral part for the development of optimization of welded structures subjected for fatigue loading in order to comply with the mandatory requirements and to achieve an increase in durability for cost-effective production.

Traditionally visual quality control and inspection measurement tools used in welding production are handheld gauges, resulting in measurements with large unreliable scatters with low repeatability and user dependance. Moreover, the quality levels in ISO 5817 were defined in terms of workmanship without a clear relation with their structural properties. For this reason, the Annex B from ISO 5817 was implemented based on

the works of Hobbacher and Kassner [23]. It proposes the geometrical weld seam requirements of three quality levels C65, B90 and B125 with their corresponding fatigue design classes (FAT) of 65 MPa, 90 MPa and 125 MPa; however, recent studies have found weak relations between the proposed fatigue resistance and the quality levels. Mouradian et al. [24] showed that imperfections assigned to the same quality level do not have uniform effects on fatigue resistance. For example, in butt welds, a lack of penetration rated as Level D influences fatigue performance differently than a Level D misalignment. Consequently, current applications of weld quality criteria in monopile design are challenged by unreliable visual inspections and poor correlation with the final mechanical properties.

In recent years, researchers and industry have introduced digital scanning techniques to enable more efficient and traceable assessment of weld geometry [25–27]. These methods typically generate 2D weld profiles that are compared directly with quality limits. Renken et al. observed that increasing the number of slices per millimeters lowers the assessed ISO 5817 quality, as the likelihood of detecting a worse slice increases, until reaching a plateau at 1.25 slices/mm [25]. Stenberg et al. [27] further demonstrated that laser-scanning technologies and associated algorithms can provide automated, unbiased weld quality assurance suitable for production environments. More recently, Glienke et al. [28] estimated the fatigue resistance of large circumferential welds in monopile sections using imperfections extracted from 3D scan data, finding that higher-quality butt welds (per ISO 5817) exhibit fatigue strengths exceeding the FAT-90 class. These findings indicate that D-VT can effectively address the first major challenge by reliably capturing weld geometry in circumferential joints.

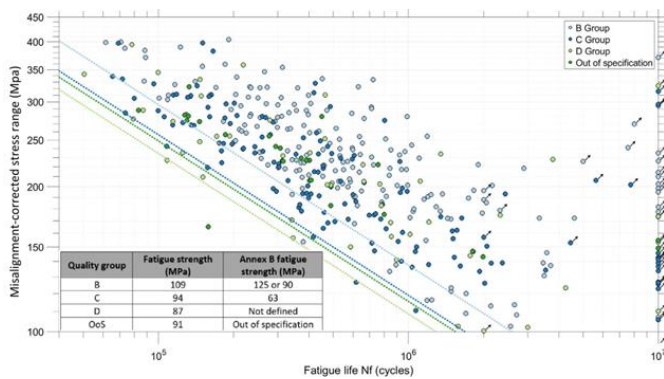


Figure 3. Fatigue strength for different ISO 5817 qualities [6].

Slicing the digitally scanned weld seam into 2D profiles yields a distribution of geometric feature values, due to their variation along the joint. In this work, more than 400 digitally scanned butt-weld specimens (following the methodology of Renken et al. [25]) were assigned an ISO 5817 quality level based on the worst value observed in any slice. The classification considered weld overfill, undercut depth, and axial and angular misalignment. As shown in Figure 3, a two-level weld quality grouping would provide a clearer distinction in the resulting fatigue performance, and for welds free of internal defects. For the presented data, ISO 5817 underestimates the fatigue

strength of low-quality joints.

These measurements can be used not only to verify compliance with standard acceptance criteria but also to construct statistical distributions that capture the variability of the welding process, c.f., [29, 30]. Analyzing these distributions offers a more complete representation of weld quality by incorporating both central tendencies and quantiles of the geometric features that influence mechanical performance. The relationship between geometric parameters and fatigue life was assessed through residual analysis of the fitted S–N curves. These residuals were then correlated with statistical descriptors of each geometric feature distribution, following the workflow shown in Figure 4. The main observations can be summarized as:

- Overfill was the only geometric parameter consistently correlated with fatigue life across all welding methods.
- The strongest correlations appeared in low or high quantiles rather than in mean values, accentuating the value of analyzing full distributions.

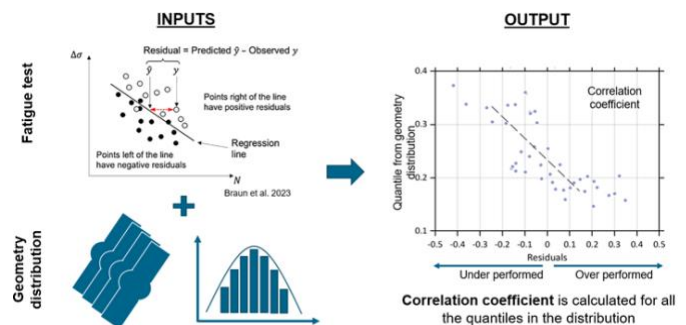


Figure 4. Workflow of the statistical descriptor selection (Based on Braun [31]).

The workflow allows to identify the most representative statistical metrics for each geometric parameter and then used them in newly developed quality assessment or as input for a machine learning algorithm to determine the expected fatigue life of each welded joint. A continuation of the work is planned to repeat the process with high quality and thick butt-welded joints, which are typical for offshore monopiles.

3.3 Microstructure

It is known that a coarse-grained microstructure, as typically found in the heat-affected zone of structural steels, promotes crack propagation [32]. This is especially true in the early phase of fatigue for microstructural and physically short cracks [33]. It has long been known that microscopic residual stresses of type II and III [34], which are in equilibrium within a grain or over several interatomic spacings, as well as grain size, affect crack initiation [35]. In addition to the shift of diffraction lines or X-ray interference lines used to determine residual stresses, X-ray diffraction measurements also determine the width of the diffraction lines (e.g., full width at half maximum), see Figure 5. This correlates with microstructural residual stresses and dislocation density as well as with grain size [36] and is thus an indirect measure of the material's hardening state [37]. An indirect

consideration of microstructure based on X-ray interference lines for fatigue-life assessment of welded joints has not yet been considered or published.

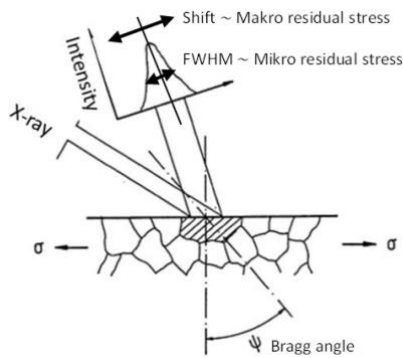


Figure 5. Correlation between hardness and FWHM determined for the HAZ of submerged arc welding of S355 according to [36]

Destructive hardness measurements are usually used for the characterization of the HAZ. In this investigated case, however, it is not possible to determine the hardness of an individual specimen at each individual position along the weld toe. For this reason, the mentioned correlation of FWHM determined by XRD and the microstructural residual stresses is used to determine the hardness indirectly and non-destructive by XRD. For this, Gleeble experiments are used to thermophilically simulate the microstructure of the HAZ for a range of t_8-5 time from 0.1 s to 200 s. The range of the t_8-5 time was estimated according to German CCT-Atlas [38]. The results are shown in Figure 6. A nearly linear correlation between FWHM and hardness was determined. In this way, both residual stresses and hardness can be derived from XRD experiments.

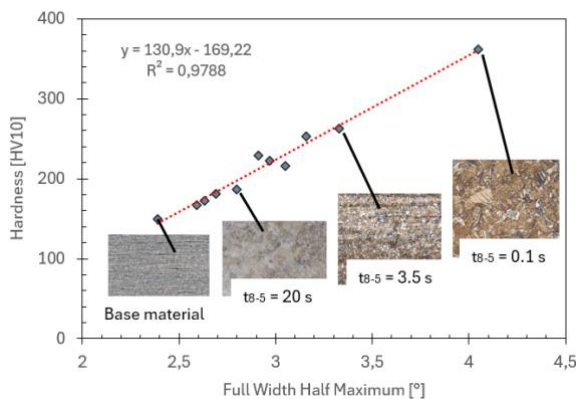


Figure 6. Correlation between hardness and FWHM determined for the HAZ of submerged arc welding of S355

3.4 Residual stresses

Residual stresses strongly influence the fatigue strength and life of welded joints in structural steels [39]. Welding induces macroscopic residual stresses (RS) through heterogeneous plastic deformation caused by thermal expansion/shrinkage, quenching, uneven temperature fields, and phase transformations. A distinction is made between local residual stresses (short/medium range, typically weld-induced) and global residual stresses (structure-wide, often from restraint) [40, 41]. In this work, only short range residual stresses are considered.

The RS were determined by X-ray diffraction using a 2D-detector Pulstec μ -360 and the evaluation according to the $\cos\alpha$ -method [42, 43]. The process of RS determination of XRD was automated using an industrial robot, see Figure 7. In a step distance of 1 mm the RS were in this way measured along the weld seam. As shown, no high tensile residual stresses were determined at the weld toe, while the variability of the residual stresses in the investigated case was high. Thus, no high influence of the residual stresses in as-welded condition is assumed.

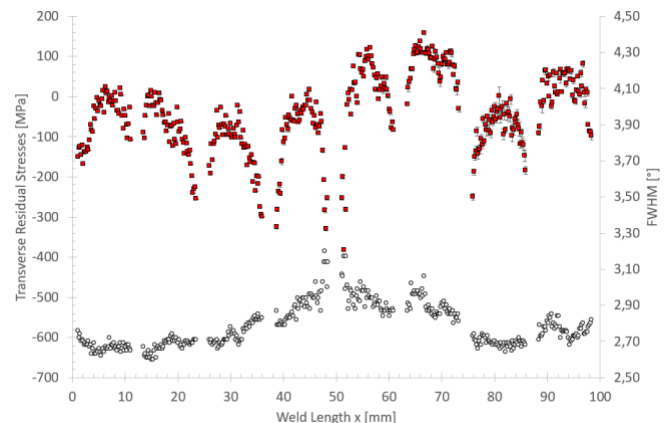
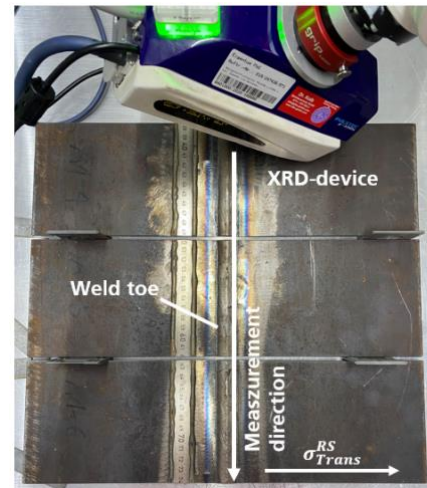


Figure 7. Set-up for automated RS determination by XRD (upper) and distribution of welding RS and FWHM along the weld seam of a single specimen

The information about RS and Hardness/FWHM are processed in the same way for fatigue analysis by ML.

4 Machine learning-based prediction of fatigue strength

The fatigue behavior of welds is influenced by numerous interacting effects, making ML algorithms particularly suitable for modelling these complex relationships. Traditional approaches such as the nominal stress approach lack accuracy, while FEA-based effective stress methods are computationally too slow for holistic and precise fatigue strength estimation.

To develop ML models for fatigue strength prediction of welded joints, the fatigue-driving mechanisms must be represented appropriately within the feature space. In practice, this means that—next to the local loading conditions at the weld—additional measurable parameters

such as surface geometry, microstructure, and residual stresses need to be included. Previous work by Braun and Kellner [44] incorporated the influence of the surface geometry of butt-welded joints into a data-driven fatigue assessment approach. The required geometric parameters, specifically notch radius, undercut depth and opening angle, were extracted from 2D slices of a 3D point cloud using the curvature-based method proposed by Renken et al. [25]. To reduce data complexity, the locally computed values were aggregated over a 40 mm weld section using the median and were then combined with load parameters such as stress amplitude, maximum stress, and stress ratio as features for training an XGBoost model. The resulting fatigue-life predictions mostly fell within an error band of ± 2 compared to the experimental results (Figure 6).

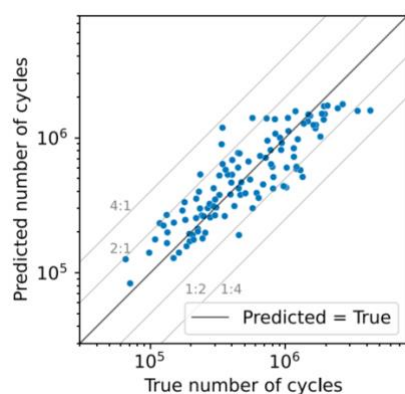


Figure 8. Predicted number of stress cycles from the XGBoost-model trained on load and geometry parameters over the experimental investigated true number of stress cycles [44].

In practice, weld imperfections cannot be completely avoided due to inherent variations in the welding process. Because the training data cannot fully represent all weld types and geometric deviations encountered in real applications, the generalizability of the ML model is of central importance. Anomalous weld geometries can be addressed by designing the feature space to capture fundamental physical relationships and by selecting ML algorithms capable of learning such relationships robustly. In a study by Beiler et al. [45], a comparison of the transferability of Artificial Neural Networks (ANN) and XGBoost was performed. The results showed that ANNs are generally better suited to learn these relationships and to predict reliably beyond the domain represented in the training data; however, XGBoost models are significantly faster to train and can be interpreted more easily using Explainable AI methods such as SHapley Additive exPlanations (SHAP) [46]. With a sufficiently comprehensive and representative database that covers a wide range of fatigue-influencing effects, the performance of XGBoost can approach that of ANN models. Achieving this, however, requires clean and representative data. For example, it has been shown that the median value of geometric parameters along the weld is not suitable when local undercuts occur [47]. In such cases, more advanced feature-engineering strategies are required.

Transferring the ML-based fatigue strength prediction from small-scale butt joints to real circumferential monopile welds requires exactly this ability to generalize beyond the training data domain. The decisive factor for the practical

success of such methods lies in the adequate representation of the weld transition geometry. When this geometric information is combined with measurements of residual stresses and microstructural characteristics, a holistic description of the fatigue-relevant state can be established within the feature space. This ensures that both the initial stress condition (external loading plus residual stresses) and the stress-raising effects caused by local notches and microstructural variations are properly captured.

5 Discussion

The integration of digital visual testing, material characterization, and machine learning represents a paradigm shift in the fatigue assessment of offshore monopile welds. The results demonstrate that traditional quality classification systems—such as ISO 5817 [5]—while useful for acceptance criteria in production, are insufficient as standalone predictors of fatigue performance. Our analysis reveals that geometric imperfections, particularly overfill and undercut, exhibit strong correlations with fatigue life, but only when assessed through full statistical distributions rather than mean values. This highlights the importance of capturing spatial variability along the weld seam, as extreme local features (e.g., deep undercuts or sharp notches) are often the dominant drivers of crack initiation. The finding that high quantiles of geometric parameters correlate more strongly with fatigue life than central tendencies supports the need for a shift from deterministic, average-based assessments to probabilistic, distribution-aware methodologies.

Furthermore, the non-destructive assessment of microstructure and residual stresses via XRD provides critical insights into the material's fatigue-relevant state. The observed linear correlation between FWHM and hardness enables indirect, spatially resolved estimation of material hardening in the HAZ—without destructive testing—thereby supporting continuous monitoring and quality assurance. Notably, the absence of high tensile residual stresses at the weld toe in the as-welded condition of monopile-like circumferential butt welds suggests that, for the investigated welding process, residual stress effects may be less dominant than geometric stress concentrations; nevertheless, this does not diminish their importance in other welding scenarios or under post-weld treatments (e.g., stress relief), highlighting the need for context-specific modeling.

The performance of machine learning models—particularly XGBoost and ANNs—demonstrates the feasibility of predictive fatigue assessment at scale. XGBoost offers a favorable trade-off between interpretability and accuracy, enabling the use of SHAP to identify key drivers of fatigue strength (e.g., weld toe radius, undercut depth, and residual stress gradients). While ANNs show superior generalization potential, their "black-box" nature remains a barrier to industrial adoption. The success of the ML models relies on the quality and representativeness of the input data, particularly the accurate representation of geometric features. Our findings confirm that simple aggregation (e.g., median values) can mask critical local defects, which emphasizes the need for advanced feature

engineering (such as quantile-based descriptors and spatial clustering) to ensure robustness.

A key challenge remains the transferability of models from small-scale laboratory specimens to full-scale monopile joints. While the current dataset includes a large number of butt-weld specimens, real-world circumferential welds exhibit greater complexity due to access limitations, variable welding sequences, and environmental influences during fabrication. Future work must expand the training data to include thicker plates, multiple weld beads, real-world fabrication variations and more imperfection types.

6 Conclusions

The following conclusions are drawn from this study:

- Digital visual testing enables high-resolution, automated, and repeatable characterization of weld geometries in circumferential monopile joints, which overcomes the limitations of traditional manual inspection methods.
- Statistical analysis of geometric features across multiple 2D cross-sections reveals that extreme values (e.g., high quantiles) of parameters like undercut depth and overfill are more strongly correlated with fatigue life than mean values, highlighting the importance of spatial variability.
- The integration of X-ray diffraction allows for non-destructive, spatially resolved assessment of microstructural properties (e.g., grain size, dislocation density) and hardness via FWHM measurements, which enables indirect material characterization.
- Residual stress measurements show no significant high tensile stresses at the weld toe in the as-welded condition of monopile circumferential butt joints, suggesting that geometric stress concentrations may dominate fatigue initiation over residual stress effects in this specific welding scenario.
- Machine learning models, particularly XGBoost, successfully predict fatigue strength by combining geometric, residual stress, and microstructural features, achieving high accuracy and interpretability through Explainable AI techniques like SHAP.
- The use of quantile-based and spatially resolved geometric descriptors significantly improves model robustness compared to simple aggregation methods, enhancing generalization to unseen weld geometries.
- The methodology demonstrates strong potential for real-world application, supporting a shift from conservative, code-based design toward condition-based fatigue management and life extension strategies.
- Future work must expand the dataset to include thicker plates, multiple weld beads, real-world fabrication variations and more imperfection types to ensure model transferability to full-scale offshore monopiles.

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