Available online at www.sciencedirect.com

ScienceDirect

Procedia Structural Integrity 75 (2025) 344–352

Structural Integrity Procedia

www.elsevier.com/locate/procedia

Fatigue Design 2025 (FatDes 2025)

Prediction of fatigue life for butt-welded joints using multi-fidelity surrogate modelling

Mahamudul Hasan Tanvir*, Marten Beiler, Phyo Myat Kyaw, Moritz Braun, Shojai Sulaiman

German Aerospace Center DLR, Institute of Maritime Energy Systems, Geesthacht, Germany.

Abstract

Welding is considered as one of the most efficient and reliable joining technologies in fabrications of metallic components for aerospace, maritime, and civil engineering applications. However, fatigue associated failures are inevitable in welded joints due to several aspects, such as local high-stress concentrations, high-residual stresses as well as material and geometry imperfections. Fatigue strength assessments are often performed experimentally or numerically. However, parameter uncertainties regarding geometry, experimental conditions and inadequate consideration of imperfections can lead to inaccurate evaluations. Recently, machine learning (ML) models have been developed for fatigue assessments in terms of computational efficiency for various engineering tasks. Despite the benefits brought by the ML based fatigue assessments, it is still challenging in prediction models as it requires large databases of experimental data for training and validation of models for accurate predictions. In this study, a multi-fidelity (MF) surrogate model which can predict the fatigue life of butt-welded joints is developed and validated. The MF model takes advantage of high-fidelity models which were developed from the 3D scan data of specimens, and simplified low-fidelity models for which less computational resources are needed for data generation. Additive-scaling function concept is employed for MF modelling, and surrogate and discrepancy models are built using Kernal Polynomial Least Square Kriging and eXtreme Gradient Boosting algorithms. The proposed MF model can provide predictions while keeping the balance between accuracy and computational efficiency with a small amount of sample points.

Peer-review under the responsibility of Dr Fabien Lefebvre with at least 2 reviewers per paper

Keywords: fatigue assessment; reverse engineering method; stress concentration factor; low-fidelity; high-fidelity.

* Corresponding author. Tel.: +49 4152 84881 61
E-mail address: mahamudul.tanvir@dlr.de

2452-3216
Peer-review under the responsibility of Dr Fabien Lefebvre with at least 2 reviewers per paper
10.1016/j.prostr.2025.11.035

1. Introduction

Welded joints are extensively used in aerospace, maritime, and civil engineering industries for their low deformation and high stiffness, light weight integration and efficient fabrication of complex components. However, fatigue damage remains one of the most threatening failures in the design and maintenance of welded components due to residual stresses induced by welding, stress concentrations at the weld toe, and potential material and geometry imperfections in combination with cyclic loading. Therefore, accurate fatigue assessments are crucial to ensure the structural integrity and durability of structural components while minimizing the cost of downtime and repairs.

Several studies have investigated fatigue behavior in welded joints using four different categories: empirical, theoretical, numerical, and data-driven methods which have been evolved one after another (Wang et al. 2023). To overcome the limitations in conventional fatigue assessment methods, ML-based approaches become an alternative solution to handle multivariate data and their correlations. They are shown to be effective when large amount of data exhibiting considerable statistical variance is available (Schubnell et al. 2025). In previous studies, different algorithms such as regression-based, random forest, support vector machine, and neural network-based methods are being used in predicting stress concentrations and fatigue life of structures.

Among them, artificial neural network (ANN) based-approaches are commonly used as they can provide good predictions where mathematical models cannot capture the actual behavior, and the dataset is incomplete and noisy. It has been indicated that good accuracy of fatigue life prediction can be achieved with backpropagation NN-based methods while capturing important features such as defect size, distance to surface, depth and build orientation (Heng et al. 2022; Chen et al. 2023). Yet, the ability to predict the values outside of the training dataset and the black box behind the algorithm are challenges with using ANN models. For this reason, Halamka et al. (2023) proposed a hybrid Physics-informed NN (PINN) model composed from Gated Recurrent Unit (GRU) and feed-forward NN where the power law relationship between predicted damage parameter and fatigue life can be established using the physics-informed model. Although some studies demonstrated conservative predictions from small amount of data using conventional ML method (Braun and Kellner 2022), the complexity of network increased as the likely accuracy increases (Lee et al. 1999). Due to lack of full understanding and control behind the algorithms of NN-based predictions, most scientists prefer supervised ML and explainable ML based assessments (Wang and Braun 2025).

All the above-mentioned studies require significant amount of HF data derived from experiments or simulations which still demanding financial resources and computational efforts. To address this, surrogate modelling can be employed as a solution where approximate models are used. Particularly, MF surrogate modelling combines data from different fidelity models–high-fidelity (HF) and low-fidelity (LF) data. This approach offers the balance between computational efficiency and prediction accuracy as the extrapolation of the given data can be performed rather than predicting the output based on statistics and classification of training data. To compare the performance of different MF surrogate models, Zhang et al. (2021) investigated three different Kriging based models where the additive scaling function (ASF) based surrogate models provided the best prediction of chosen fillet welded joints. Zhang et al. (2024) also claimed that prediction error of no more than 1% is obtained using data driven surrogate models. Reliability of prediction results and increased computational efficiency are also mentioned by Dong et al. (2020) where adaptive surrogate models are used to replace time-consuming fatigue crack propagation analyses. Furthermore, the benefit of using MF models in fatigue life prediction was demonstrated by Wang et al. (2025) where LF data grasps the physics-based weights and the high-fidelity data variance.

Although MF models and surrogate models show promising accuracy and efficiency in structural reliability analyses, their use for fatigue life prediction of welded joints remains limited due to large variance in local weld geometry-related stress concentration factors (SCF), coupled with a large variance for misalignment-related secondary bending stresses. This gap highlights the need to develop a robust MF surrogate model for the welded joints that can integrate the availability of different data sources while balancing computational cost. In this study, HF models are constructed from fatigue tests of butt-welded joints through reverse engineering approach in order to ensure the prediction accuracy contributed by HF models. In addition, simplified 2D butt-welded joints are used as sources for LF data where the models are also validated across HF ones. Fatigue life of HF and LF models are evaluated using effective notch stress method. The surrogate models are constructed with ASF concept based on Kernal Polynomial Least Square Kriging (KPLSK) (Bouhlel et al. 2016) and eXtreme Gradient Boosting (XGBoost) (Chen and Guestrin 2016) frameworks using HF and LF models' data.

Nomenclature

α	flank angle	ASF	Additive Scaling Function
R	weld toe radius	XGBoost	eXtreme Gradient Boosting
$\Delta\sigma_n$	nominal stress range	KPLSK	Kernal Polynomial Least Square
$\Delta\sigma_R$	reference fatigue strength at 2×10^6 cycles		Kriging
$\Delta\sigma_{en}$	effective notch stress range	LOO	Leave-one-out
$f(R)$	mean stress correction factor	GMM	Gaussian Mixture Model

2. Preparation of training data

2.1. High-fidelity (HF) model

HF models are constructed based on the fatigue experiments. The dataset consists of 7 butt-welded joints specimens under different stress ranges with a stress ratio of $R = 0.1$. Base plate's material is S355 ML and filler metal is EN ISO 14171-A: S3Si. Geometric configurations of the HF models are shown in Fig. 1 where flank angle and radius of the weld are described as α and R. HF models used in this study are constructed using three-dimensional (3D) scan data of specimens and the reverse engineering method, which ensures that the model represent the actual profile and surface geometry of the welds. The fatigue test and 3D scan data are referred from the work of Shojai et al. (2023).

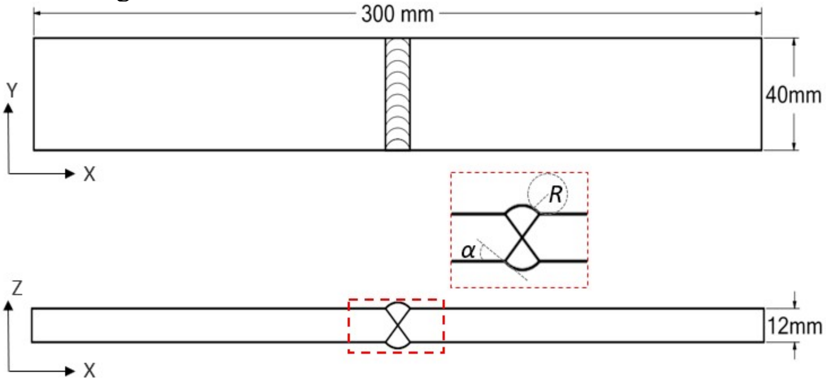

Fig. 1 Geometry of butt-welded joint used in fatigue testing (a) top view, (b) profile view.

Reverse engineering method is used to generate a solid model from scanned point cloud data. The constructed solid model based on reverse engineering concept consists of Non-Uniform Rational B-Spline (NURBS) surfaces which can capture more complex geometric features precisely compared to STL-formatted data. Pre-processing of finite element (FE) model and FE analysis are then conducted using Ansys 2022 R1. The procedures used from scanning to pre-processing of FE model are the same as in Shojai et al. (2024). Fig. 2 shows the FE model in which elements for global region have edge lengths of 2.0 mm while those in the weld zones are 0.4 mm and the non-smooth surface with 0.05 mm. The left end of the specimen has been constrained translational movements in x, y, and z directions, while the other end has been applied with unit distributed load. Structural steel is assigned as material property for FE analysis.

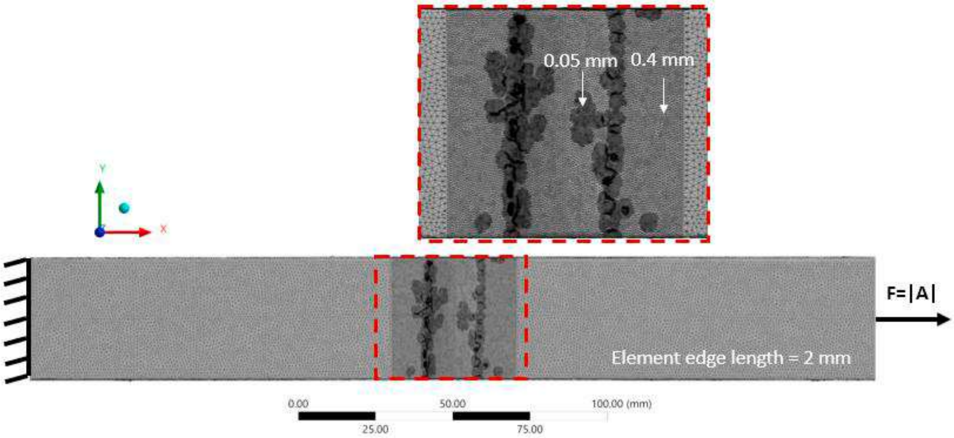

Fig. 2 FE model of Specimen No. 3 with boundary conditions.

The structural analysis using unit load provide the stress distribution including the location of maximum stress concentration as shown in Fig. 3. The SCF was determined using critical distance approach where the stress was determined at a fixed distance of 0.1 mm perpendicular to the notch root at the point of maximum stress (typically maximum principal stress). For fatigue assessments of welded joints with critical distance approach, FAT 160 curve was employed as a design SN curve as recommended in Baumgartner et al. (2015). The mean stress correction factor, $f(R)$ was calculated by applying the method proposed by Hensel (2020), using a measured residual stress of 230 MPa from Shojai et al. (2023). The fatigue life for each specimen was then evaluated using equation (1) and (2), and the results are shown in Table 1. Except specimen No. 2 with an outlier of fatigue life value given by experiment, the evaluated solutions using effective notch stress method are in acceptable agreement with the experiments with percentage differences ranging from 4.15 to 35.78.

$$N_f = 2 \times 10^6 \left(\frac{\Delta\sigma_n}{\Delta\sigma_R}\right)^{-m} \tag{1}$$

$$\Delta\sigma_{en} = (\Delta\sigma_n \times SCF)/f(R) \tag{2}$$

Table 1 Predicted fatigue life for HF models using effective notch stress method.

Specimen No.	Peak stress location Flank Angle (degree)	Radius (mm)	Stress range (MPa)	SCF	Fatigue life (Experiment) (cycles)	Fatigue life (Predicted by FEM) (cycles)
1	22.54	2.27	215.63	2.527	169,360	200,705
2	16.86	1.59	206.25	1.9766	1,711,744	479,447
3	18.53	1.46	225.00	1.855	487,616	447,147
4	23.03	1.30	243.75	1.858	365,274	349,766
5	30.27	1.37	309.38	1.772	149,586	197,233
6	21.76	2.42	262.50	2.344	206,491	139,468
7	42.74	0.66	281.25	1.981	203,244	187,822

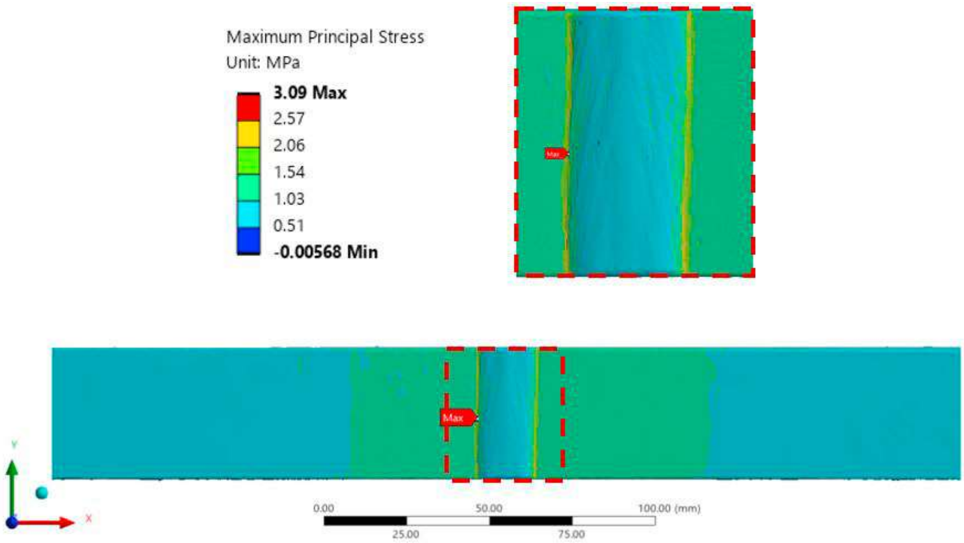

Fig. 3 Maximum principal stress distribution of HF model (Specimen No. 3) with location of peak stress.

2.2. Low-fidelity (LF) model

Although the number of initial sample points from HF and LF models influence the performance of MF surrogate model, there is no consensus regarding the selection of the number of initial sample points. Based on the previous studies, the recommendations are made in terms of computational resources, fidelity gap, and value of information. Some suggestions mention a typical ratio of 1 HF sample point per 3-10 LF points in Zhou (2023). The number of LF sample points in this study are chosen to be 42 which represents 1 HF per 6 LF points.

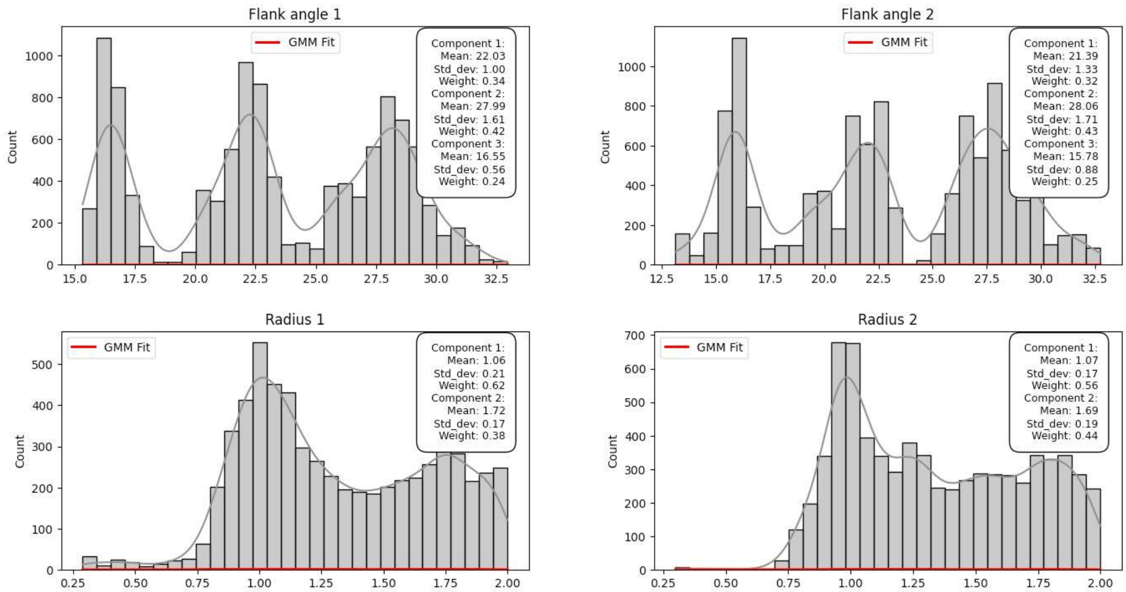

Fig. 4 Parameter distributions of scanned data from HF models.

The LF models are simplified and more computationally efficient ones compared to HF models. In this work, 2D FE models for butt-welded joints are used as LF model. To determine the geometry of these models, scanned data of HF models are firstly investigated to understand the parameter distributions. The scan data consists of flank angles and radii values on left and right sides noted by 1 and 2 in Fig. 4 from cut slices of 1789-1852 for each specimen. Tri-normal and bi-normal distributions are observed from the scanned flank angles and radius values of all specimens whose components are analyzed using Gaussian Mixture Model (GMM). The distribution parameters, means, standard deviations, and weights, are then defined in Monte Carlo simulations to generate random geometric parameters of LF models. The distributions shown in Fig. 4 are for weld-seams on the bottom surface, and same procedure is followed for the top surface. A total of 21 LF-FE models are then created using these generated parameters. 42 LF sample points are extracted from these 21 FE models which have combinations of flank angle and radius for top and bottom surfaces.

2D-FE models are created and the simplified geometry of butt-welded joint follows the work of Braun (2021) as shown in Fig. 5. FE models consist of quadratic elements with edge length of 0.04 mm in the weld toe region, and 0.4 mm globally (Fig. 5(b)). Symmetric boundary condition is applied on the left side of the model and unit distributed load on the other end. Same material properties are used as in HF models. The results obtained for specimen No. 1 can be seen in Fig. 5(b) with peak stress location on bottom surface. Fatigue life evaluations are carried out for both top and bottom surface of LF models following the procedures in Section 2.1. The results obtained by finite element method (FEM) are shown in Fig. 7 in comparison with predictions by ML approaches. The geometrical data, SCF, and fatigue life values from both LF and HF models are then used to train the surrogate models in Section 3.

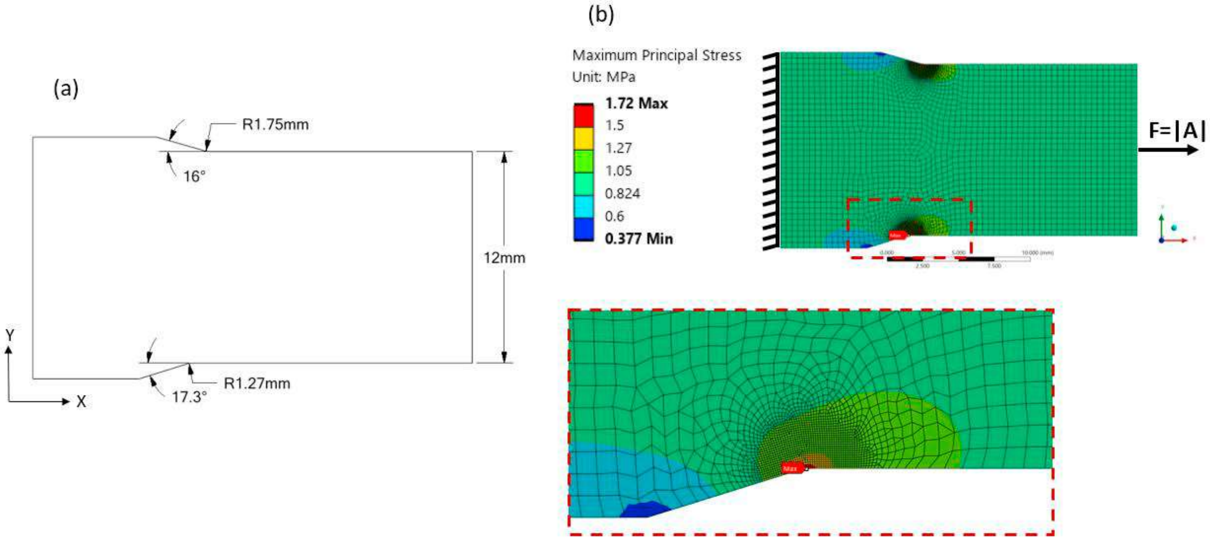

Fig. 5 Maximum principal stress distribution of LF model (Model No. 1).

3. Results and discussion

3.1. Construction of MF surrogate models

The MF-surrogate models are built using ASF method, and the Kriging models are constructed with KPLSK and XGBoost techniques. For surrogate modelling and high-dimensional inputs, KPLSK (Bouhlel et al. 2016) is one of the common choices due to its optimization ability, uncertainty quantification, and good prediction accuracy with small datasets. However, XGBoost model (Chen and Guestrin 2016) is also included as a reference of regression-based ML model to compare the prediction ability and computational efficiency of KPLSK. The sample data for LF and HF models are prepared as described in Section 2. The Leave-one-out (LOO) method is used for training the model at each step which is a typical choice to validate the Kriging models with limited dataset. The flow chart for each surrogate model used in predictions are shown in Fig. 6.

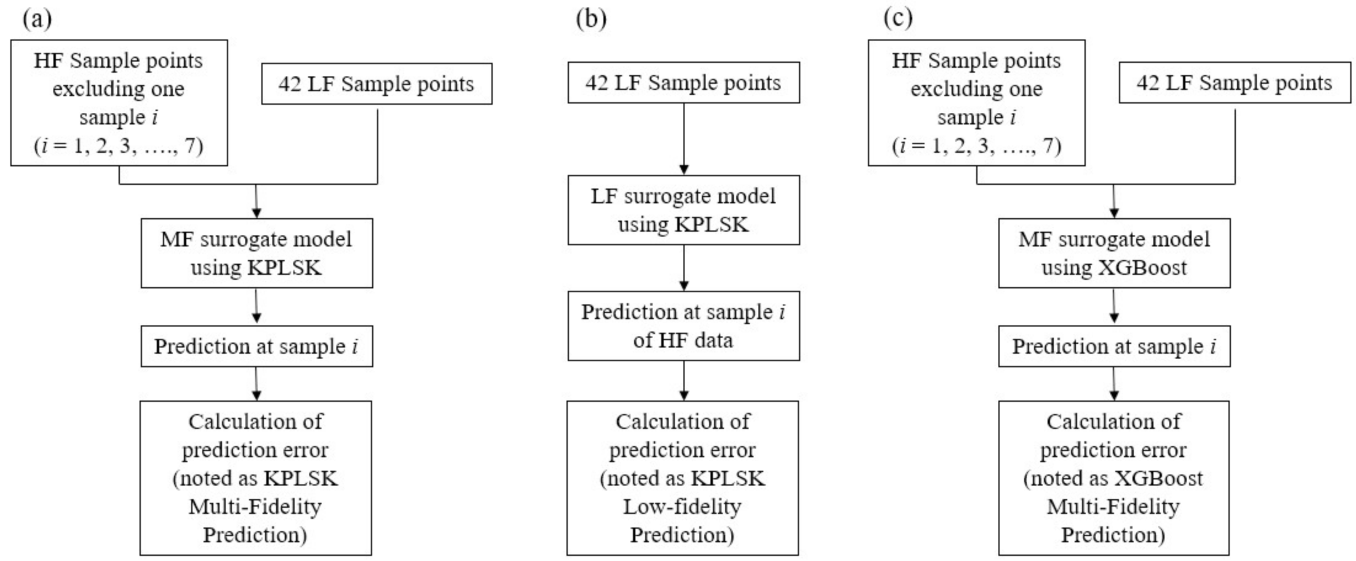

Fig. 6 Flow chart of construction of surrogate models used in this study. (a) KPLSK-based MF surrogate model, (b) KPLSK-LF kriging model, and (c) XGBoost-based MF model.

3.2. Prediction of fatigue life

In this section, the prediction of fatigue life given by different MF surrogate models are discussed. 7 HF samples and 42 LF samples are used as sample data using 4 features: stress range, flank angle, radius, and SCF at critical distance. Since there is an outlier in HF sample (specimen No. 2), predictions are made with and without specimen No. 2 to investigate the effect of outlier on the results (see Fig. 7(a) and (b)). The parity plots include prediction results obtained by KPLSK-based MF surrogate model, KPLSK-based LF surrogate model, and XGBoost-based MF model against the experiment values. The Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Root Mean Squared Logarithmic Error (RMSLE) are provided to compare the performance of each model. In addition to that, the fatigue life values obtained by finite element method (FEM) are also included to assess the accuracy of the output data.

As can be seen in the figure, all the predictions lie within the scatter band of 1:4 with most of them in 1:2. It is surprising to see the LF kriging model performing better than MF model. This phenomenon could happen when the data correlations between HF and LF are weak, leading to MF model not being able to outperform the LF model. This could also be because the LF data already have good accuracy compared to true values, and LF model capturing the trend well enough. In addition, LF model prediction and FEM predictions give almost the same values of MAE, RMSE, and RMSLE. The number of HF samples not being enough could also be another underlying solution for fatigue life prediction. Overall, XGBoost model is the worst performer among three models which was expected as it is mainly designed for handling large datasets and relies on decision trees and boosting. Another aspect is that XGBoost model do not provide prediction intervals and uncertainty estimates which are important of optimization tasks especially with small scale of dataset.

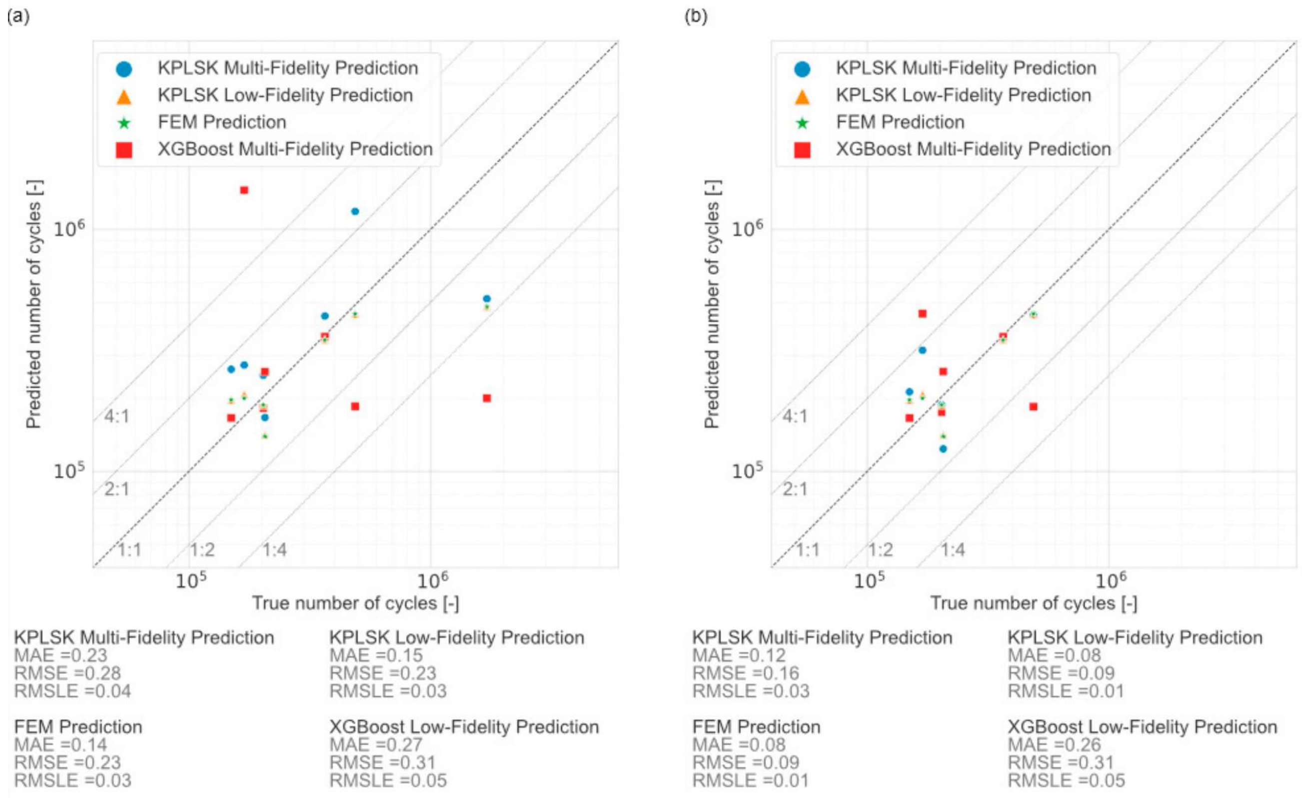

Fig. 7 Comparison of predicted fatigue life using different surrogate models. (a) With an outlier in the HF sample, (b) without outlier.

4. Conclusion

In this work, the purpose is to predict the fatigue life of butt-welded joints using MF surrogate modelling approach which can provide good accuracy with small amount of sample points of HF. The HF models are created based on the scanned data and reverse engineering method so that the results calculated by FEM could represent all the geometric features of the specimens used in the experiment. The LF models are then generated with the geometric parameters from distribution analysis of scanned profiles and Monte Carlo simulations. The LF models are simplified 2D FE models of butt-welded joints to facilitate the dataset for MF surrogate with less computational efficiency. Using these HF and LF dataset as samples, the MF surrogate models are developed with ASF approach where two different ML algorithms, KPLSK and XGBoost, are employed. The findings from this work are described as follows:

1) The HF-models based on reverse engineering method shows acceptable estimation of fatigue life using FEM.
2) The simplified LF models provide sufficient accuracy to be used as samples in MF surrogate model, and 2D FE models can estimate the fatigue life as good as HF models.
3) The MF surrogate models rely highly on data quality of HF samples rather than the number. When there is a good data correlation and continuity between HF and LF data, the MF surrogate performs with high accuracy.
4) The XGBoost-MF models show acceptable prediction accuracy compared to kriging-based MF surrogate models although only a small number of datasets was used for training and validation.

The results of this study indicate that the proposed MF surrogate modeling approach is effective for estimating the fatigue life of butt-welded joints. However, future investigations should focus on improving HF model accuracy through more precise calibration to experimental conditions and enhancing the LF modeling framework to better capture complex weld geometries. Additionally, further studies with different samples are needed to confirm the effectiveness of XGBoost as a surrogate model. These will contribute to further improving and extending the applicability of the proposed methodology.

References

Baumgartner, J., Schmidt, H., Ince, E., Melz, T., Dilger, K. 2015. Fatigue assessment of welded joints using stress averaging and critical distance approaches. Weld World 59 (5), 731–742. doi:10.1007/s40194-015-0248-x.

Bouhlel, M.A., Bartoli, N., Otsmane, A., Morlier, J. 2016. An Improved Approach for Estimating the Hyperparameters of the Kriging Model for High-Dimensional Problems through the Partial Least Squares Method. Mathematical Problems in Engineering 2016, 1–11. doi:10.1155/2016/6723410.

Braun, M. 2021. Assessment of fatigue strength of welded steel joints at sub-zero temperatures based on the micro-structural support effect hypothesis, 219 pp. doi:10.15480/882.3782

Braun, M., Kellner, L. 2022. Comparison of machine learning and stress concentration factors based fatigue failure prediction in small scale butt welded joints. Fatigue Fract Eng Mat Struct 45 (11), 3403–3417. doi:10.1111/ffe.13800.

Chen, D., Li, Y., Liu, K., Li, Y. 2023. A physics-informed neural network approach to fatigue life prediction using small quantity of samples. International Journal of Fatigue 166, 107270. doi:10.1016/j.ijfatigue.2022.107270.

Chen, T., Guestrin, C. 2016. XGBoost, in: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. KDD '16: The 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco California USA. 13 08 2016 17 08 2016. ACM, New York, NY, USA, pp. 785–794.

Dong, Y., Teixeira, A.P., Guedes Soares, C. 2020. Application of adaptive surrogate models in time-variant fatigue reliability assessment of welded joints with surface cracks. Reliability Engineering & System Safety 195, 106730. doi:10.1016/j.ress.2019.106730.

Halamka, J., Bartošák, M., Španiel, M. 2023. Using hybrid physics-informed neural networks to predict lifetime under multiaxial fatigue loading. Engineering Fracture Mechanics 289, 109351. doi:10.1016/j.engfracmech.2023.109351.

Heng, J., Zheng, K., Feng, X., Veljkovic, M., Zhou, Z. 2022. Machine Learning-Assisted probabilistic fatigue evaluation of Rib-to-Deck joints in orthotropic steel decks. Engineering Structures 265, 114496. doi:10.1016/j.engstruct.2022.114496.

Hensel, J. 2020. Mean stress correction in fatigue design under consideration of welding residual stress. Weld World 64 (3), 535–544. doi:10.1007/s40194-020-00852-z.

Lee, J., Almond, D., Harris, B. 1999. The use of neural networks for the prediction of fatigue lives of composite materials. Composites Part A: Applied Science and Manufacturing 30 (10), 1159–1169. doi:10.1016/S1359-835X(99)00027-5.

Schubnell, J., Fliegener, S., Rosenberger, J., Feth, S., Braun, M., Beiler, M., Baumgartner, J. 2025. Data-driven fatigue assessment of welded steel joints based on transfer learning. Weld World. doi:10.1007/s40194-025-01967-x.

Shojai, S., Brömer, T., Ghafoori, E., Schaumann, P. 2024. Application of local fatigue approaches on corroded welded joints with consideration of weld geometry and residual stresses. Theoretical and Applied Fracture Mechanics 129, 104215. doi:10.1016/j.tafmec.2023.104215.

Shojai, S., Brömer, T., Ghafoori, E., Woitzik, C., Braun, M., Köhler, M., Schaumann, P. 2023. Assessment of corrosion fatigue in welded joints using 3D surface scans, digital image correlation, hardness measurements, and residual stress analysis. International Journal of Fatigue 176, 107866. doi:10.1016/j.ijfatigue.2023.107866.

Wang, H., Li, B., Gong, J., Xuan, F.-Z. 2023. Machine learning-based fatigue life prediction of metal materials: Perspectives of physics-informed and data-driven hybrid methods. Engineering Fracture Mechanics 284, 109242. doi:10.1016/j.engfracmech.2023.109242.

Wang, L., Zhu, S.-P., Wu, B., Xu, Z., Luo, C., Wang, Q. 2025. Multi-fidelity physics-informed machine learning framework for fatigue life prediction of additive manufactured materials. Computer Methods in Applied Mechanics and Engineering 439, 117924. doi:10.1016/j.cma.2025.117924.

Wang, X., Braun, M. 2025. Explainable machine learning-based fatigue assessment of 316L stainless steel fabricated by laser-powder bed fusion. International Journal of Fatigue 190, 108588. doi:10.1016/j.ijfatigue.2024.108588.

Zhang, L., Choi, S.-K., Xie, T., Jiang, P., Hu, J., Koo, J. 2021. Multi-fidelity surrogate model-assisted fatigue analysis of welded joints. Struct Multidisc Optim 63 (6), 2771–2787. doi:10.1007/s00158-020-02840-9.

Zhang, W., Su, Y., Jiang, Y., Hu, Z., Bi, J., He, W. 2024. Data-driven fatigue crack propagation and life prediction of tubular T-joint: A fracture mechanics based machine learning surrogate model. Engineering Fracture Mechanics 311, 110556. doi:10.1016/j.engfracmech.2024.110556.

Zhou, Q. 2023. Multi-Fidelity Surrogates: Modeling, Optimization and Applications, 1st ed. Springer, Singapore, 1461 pp.