Optimizing Thermographic Fatigue-Limit Estimation: GPR, SVR, and Stacking Ensembles within the Two Curves Method for C45 Steel

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Optimizing Thermographic Fatigue-Limit Estimation: GPR, SVR, and Stacking Ensembles within the Two Curves Method for C45 Steel

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1 Abstract

Passive Infrared Thermography provides an approach to estimate fatigue limits rapidly by extracting thermal parameters during loading. However, the application of the Two Curves Method (TCM) during the fatigue resistance computation may result in sparse measurements of the thermal parameter and approximating curves adopted for analysis. Based on thermal emissions measurements of C45 steel, the current study suggests a TCM-machine-learning model enhancing continuity of the approximating curves and minimizing scatters by training continuous surrogates of the experimental thermal behavior. Three other regressors are used to model thermal parameters: (i) Gaussian Process Regression (GPR), (ii) Support Vector Regression (SVR), and (iii) a stacking ensemble combinig the use of both kernel and tree learners through a regularized meta-model. The ML-augmented thermal curves are extrapolated into TCM by use of Linear-Linear and Parabola-Power-law estimates and the fatigue-limit estimates obtained are compared to Staircase references at 50 and 1 percent failure probability. Findings indicate that the suggested surrogates reduce the between strategies variation and narrow agreement between ΔT- and A-based intersections on a regular occasion, whereas uncertainty in GPR offers a viable confidence mark of the end estimate.

Keywords: passive thermography; fatigue limit; Two Curves Method; Gaussian process regression; uncertainty quantification.

2 Introduction

This The use of IR thermography dates back to the year of around 1930, the Passive Thermography (PT) was the first IR technology to be realized through early IR cameras and was initially used in remote sensing of forest-fires but later diversified to other applications [1]. PT was used in mechanical engineering to measure the temperature of the processes in hot steel rolling and subsequently became entrenched in production and maintenance in line with the condition monitoring practices [1,2]. Since the 1970s the use of PT to fatigue testing to evaluate crack and damage has been extended, leading to the development of faster methods of estimating fatigue limits such as the One Curve Method as an alternative to traditional methods such as the Staircase Method, and subsequent iterative methods such as the Two Curves Method (TCM) [3,4,5].

More broadly, materials science increasingly benefits from datasets of material

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properties, and integrating these resources with regression machine learning models can accelerate development and improve efficiency [6]. Gaussian Process Regression (GPR), Support Vector Regression (SVR) and stacking ensemble models are particularly suited to modelling complex non-linear relationships by learning patterns from prior observations, which supports their use across engineering and other application areas [7]. Figure 1 shows the flowchart of a sample stacking ensemble process.

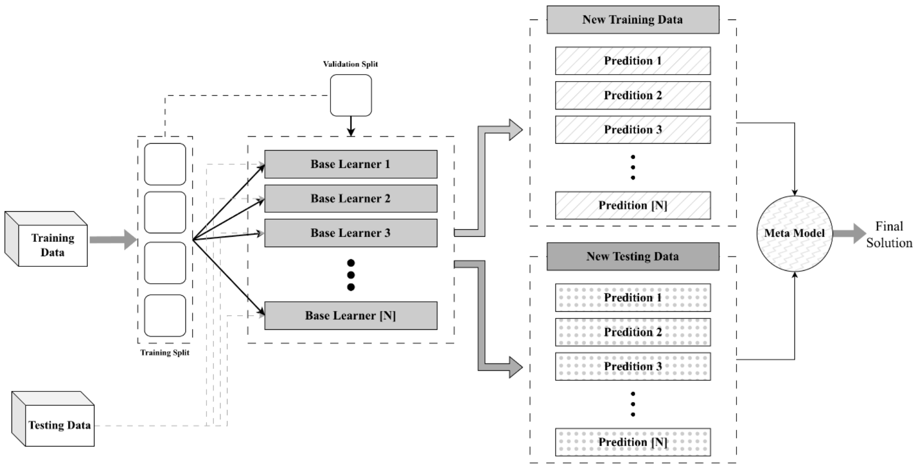

Fig. 1. Flowchart of a sample stacking ensemble process.

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