Machine Learning for predicting the Fatigue strength of steels

Project Proposal for Course ME 793- 2022

Stage 1 Presentation

Team ID: 09

Latika Jitendrakumar Patel

Moitreyee Sarkar

Polamreddy Mithun Balram

CONTENT

Background

Where did we find it?

We wanted to apply Data-driven and Machine Learning techniques to predict material property. One with great significance and challenge in materials science was accurate prediction of fatigue strength of steels. We found only a few papers in this domain which predicted fatigue strength of steel.

Background

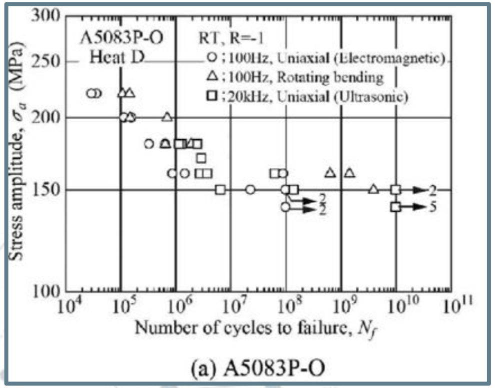
Why it's important?

- *Fatigue* strength is the most important and basic data required for design and failure analysis of a material. It is reported that fatigue accounts for over 90% of all mechanical failures of structural components.
- Here, we have selected *Steel* as the subject as it is a crucial metal from construction and transportation point of view.
- Accurate *prediction* of fatigue strength of steels is of particular significance in materials science because of the extremely high cost and time of fatigue testing and often debilitating consequences of fatigue failures.

Current Solutions

1. *Fatigue Testing Machine*

- Measures the force put onto the sample over many, many cycles until the sample fails.
- Help to determine a test sample's life expectancy under actual service loads.
- Repeated Fatigue tests conducted for similar samples at varying loads to determine the S-N curves.



(a) A5083P-O

2. *Handbooks*

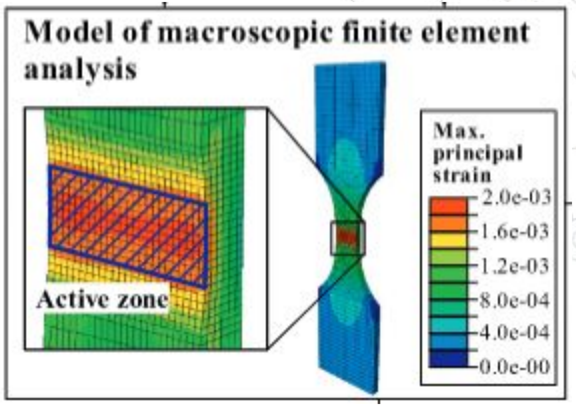
- Comprise a huge database of fatigue properties of structural materials.
- Compiled from the results of a number of tests conducted on standard commonly used materials.
- Can be referred to obtain the fatigue properties.

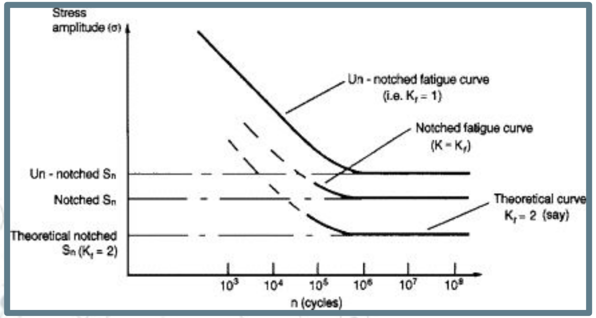
Current Solutions

3. *Finite Element Model*

- ➢ Efforts have been made to model the specimens using FEM methods utilising the microstructural information, tensile properties and test conditions.

- ➢ Simulate and determine the S\N curves and small crack behaviors.





4. *Empirical Models*

- ➢ Effects of surface integrity of specimen considered by correcting the endurance limit by an appropriate factor.
- ➢ Empirical relationships to determine these factors have been determined.
- ➢ However, Surface integrity itself is influenced by each individual manufacturing process, its parameters, the process order and the process combination.

Limitations

- The fatigue properties of components are **multi-parameter sets,** strongly influenced by surface integrity.
- Surface integrity is influenced by **each individual manufacturing process**, its parameters, the process order and the process combination.
- The current solutions are **unable to capture** the effect of parameters like constituents, processing parameters and structure due to the complicated nature of these relationships.
- A new test for changes in different parameters are difficult to conduct since they require significant experimental **effort and time**.

Limitations

- Specimens used in Fatigue test itself are costly and the machine is **not adaptive** to different specimen types.
- Relations between Microstructures and processing parameters are complex and not yet fully understood.
- We have a lot of data available collected in the handbooks and data sheets, but we haven't been able to **tap its potential**.
- Informatics techniques allows one to investigate complex multivariate information in an accelerated and physically meaningful manner.

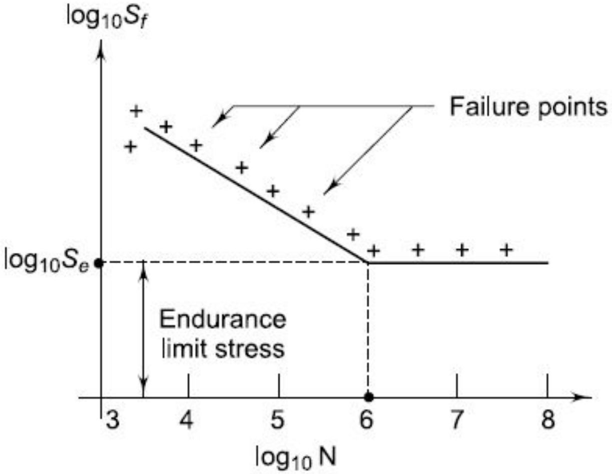
MOTIVATION

Motivation:

- In arriving at extreme value properties such as cyclic fatigue, the current state-of-the-art physics based models have severe *limitations*.
- We will try to build a framework by establishing highly reliable causal linkages between process variables in a class of steels, their chemical compositions, and their fatigue strengths.

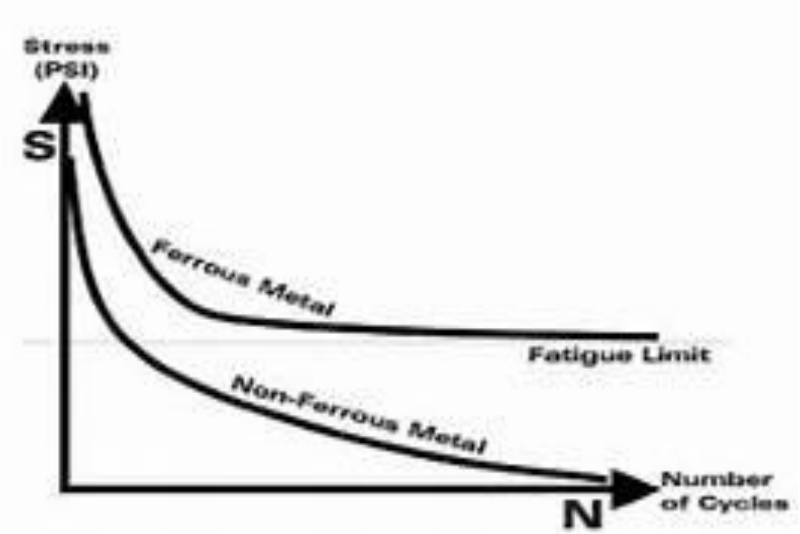
OBJECTIVES

1) Predicting the fatigue endurance limit from auxiliary data
2) Estimating the S-N graph from the endurance limit



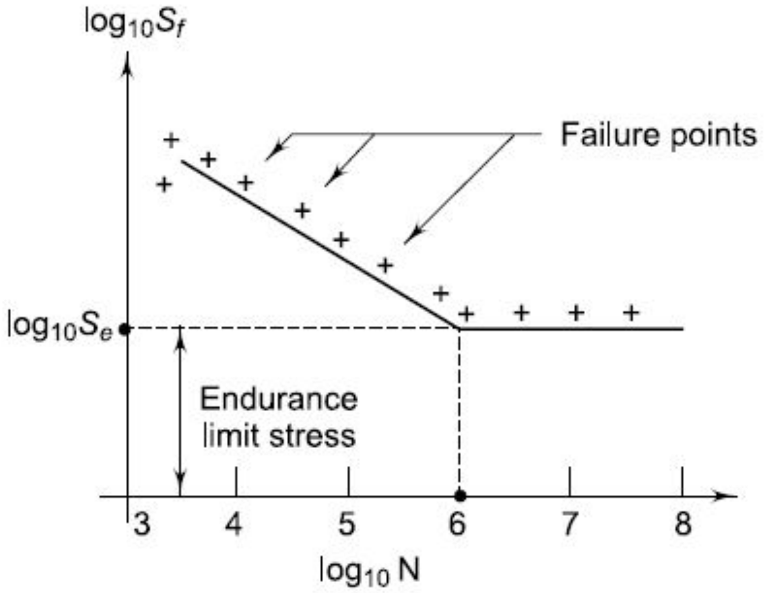
Predicting the Fatigue Endurance limit from auxiliary data

1) The data includes chemical composition of steel, processing, heat treatment conditions & some mechanical properties like hardness, charpy impact value etc.
2) We will train a regression to predict the endurance limit i.e. the threshold stress below which the material will have infinite life.



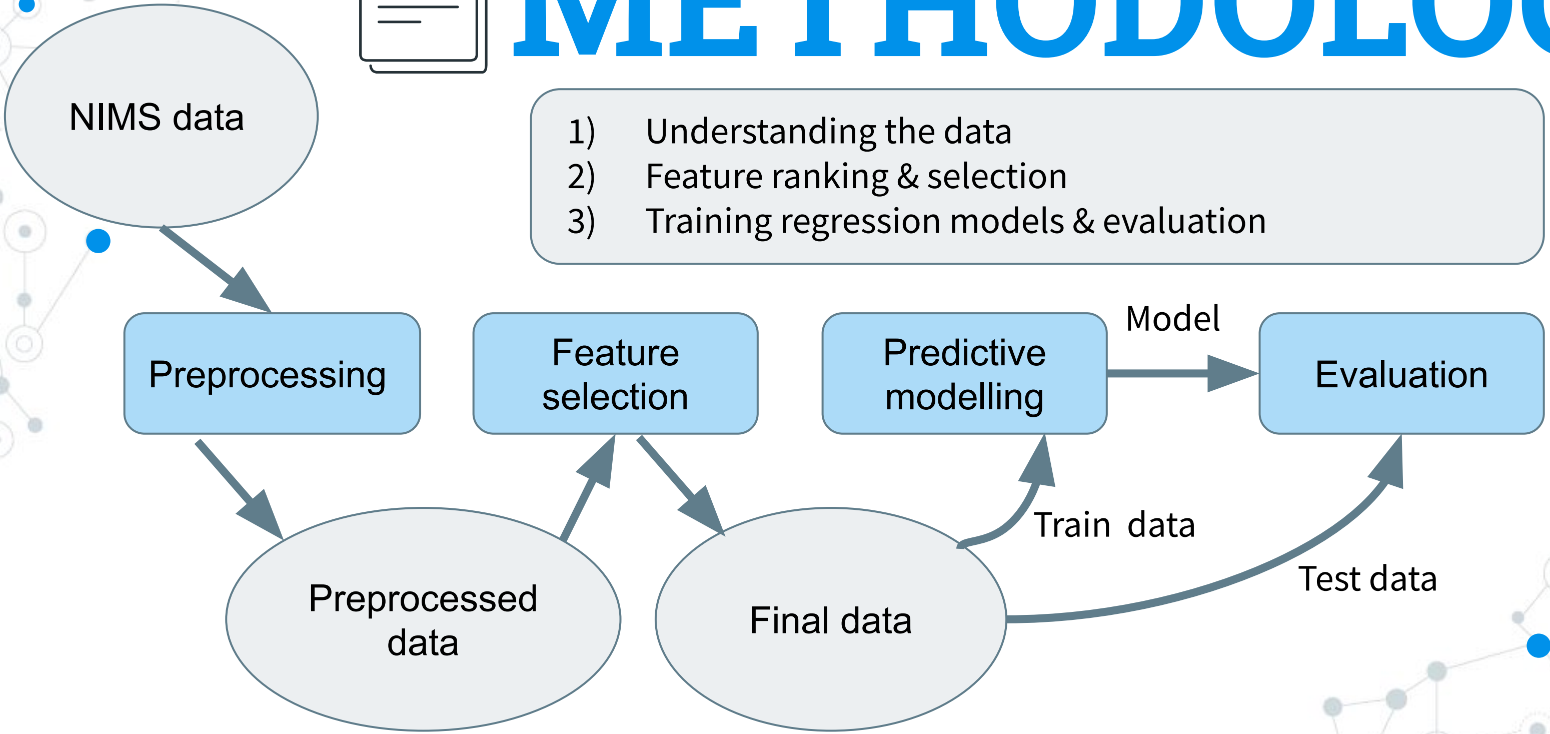
Estimating the S-N curve from the Endurance limit

1) The S-N curve of steel can be modelled using 2 straight lines
2) We directly get the second line from the endurance limit.
3) For the first line, we can get its y-intercept i.e. yield strength by performing a uniaxial tensile test & intersect it with the endurance limit at 10^6 cycles.
4) This is much easier than performing the much more complex fatigue tests for different values of N



METHODOLOGY

1) Understanding the data
2) Feature ranking & selection
3) Training regression models & evaluation



Understanding the data

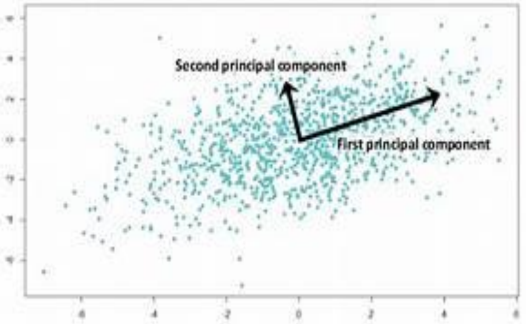
Fatigue Dataset for Steel from National Institute of Material Science (NIMS)

- ➢ Chemical composition - %C, %Si, %Mn, %P, %S, %Ni, %Cr, %Cu, %Mo (all in wt. %)
- ➢ Upstream processing details - ingot size, reduction ratio, non-metallic inclusions
- ➢ Heat treatment conditions - temperature, time and other process conditions for normalizing, through-hardening, carburizing-quenching and tempering processes
- ➢ Mechanical properties - YS, UTS, %EL, %RA, hardness, Charpy impact value (J/cm2), fatigue strength
- ➢ Corresponding endurance limit stress

Feature ranking & selection

1) ***Using correlation & information gain metrics***
We can compute correlations, information gain for each feature individually with respect to the endurance limit & rank the available features. We can discard some features with very less information gain to avoid overfitting the data.

2) ***Using Principal component analysis***
We can perform PCA on the features in the dataset to get most critical features & their contribution in explaining the variance in the data. We can discard useless features which contribute less than 1% to the variance as they have a low signal-noise ratio.

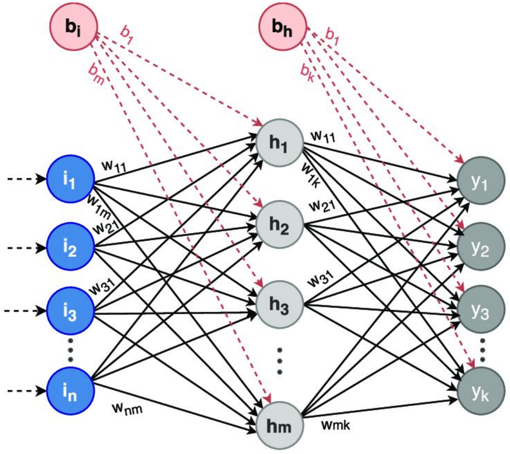


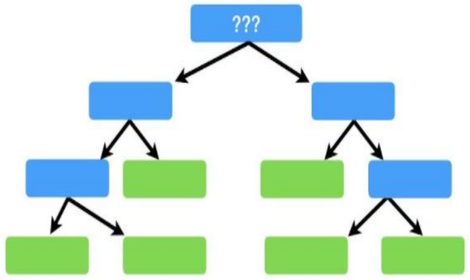
Training regression models & Evaluation

The main task is to train a predictive regression model to predict the endurance limit stress. For this we will be training multiple models including Multilinear regression, K-nearest neighbours, Decision Trees, Artificial neural networks.

We will evaluate with K-fold cross-validation over the standard error metrics like mean-squared error,mean absolute error, model fit i.e. R^2.

We will also evaluate it on other open source datasets to check if the models generalize well for different types of steels based on alloy composition & heat treatment .





CHALLENGES

1) Susceptible to overfitting, thus can give over-optimistic accuracy numbers.
2) Would require more data to further validate the results and/or make the model more robust
3) Significantly different number of data instances corresponding to the different types of steels. Hence the predictive models, which will be developed over the entire data may or may not be highly accurate for all steel types

References

1. Lei He, ZhiLei Wang, Hiroyuki Akebono, Atsushi Sugeta, Machine learning-based predictions of fatigue life and fatigue limit for steels, Journal of Materials Science & Technology, Volume 90, 2021, Pages 9-19, ISSN 1005-0302, https://doi.org/10.1016/j.jmst.2021.02.021
2. Agrawal, A., Deshpande, P.D., Cecen, A. et al. Exploration of data science techniques to predict fatigue strength of steel from composition and processing parameters. Integr Mater Manuf Innov 3, 90–108 (2014). https://doi.org/10.1186/2193-9772-3-8
3. Shibanuma, K., Ueda, K., Ito, H., Nemoto, Y., Kinefuchi, M., Suzuki, K., & Enoki, M. (2018). Model for predicting fatigue life and limit of steels based on micromechanics of small crack growth. *Materials & Design*, *139*, 269-282. https://www.sciencedirect.com/science/article/pii/S0264127517310122
4. Furuya, Y., Nishikawa, H., Hirukawa, H., Nagashima, N., & Takeuchi, E. (2019). Catalogue of NIMS fatigue data sheets. *Science and Technology of Advanced Materials*, *20*(1), 1055-1072.https://www.tandfonline.com/doi/full/10.1080/14686996.2019.1680574

“

Thank You