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CENTRE DES MATERIAUX
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Modelling the influence of clustered defects on HCF properties of Ni-based superalloys

02/02/2023

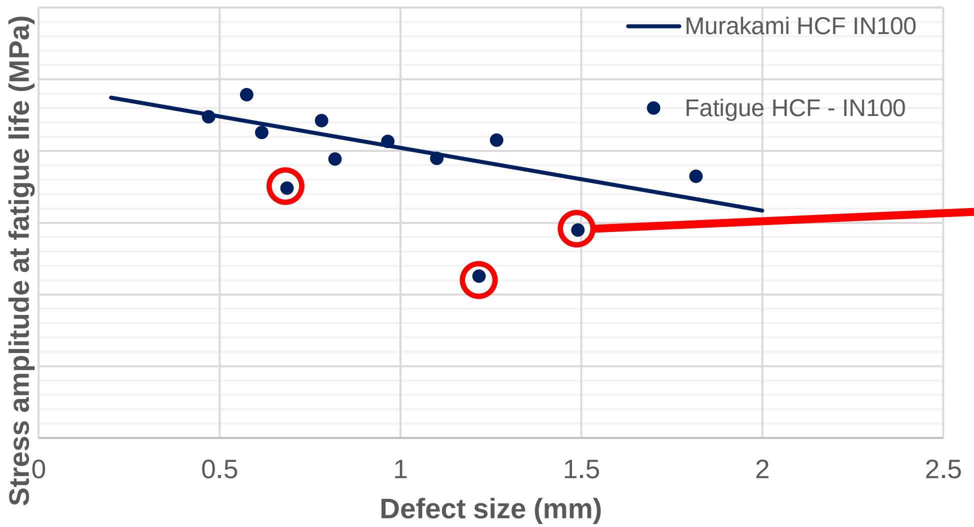
Arjun Kalkur MATPADI RAGHAVENDRA

Under the supervision of,

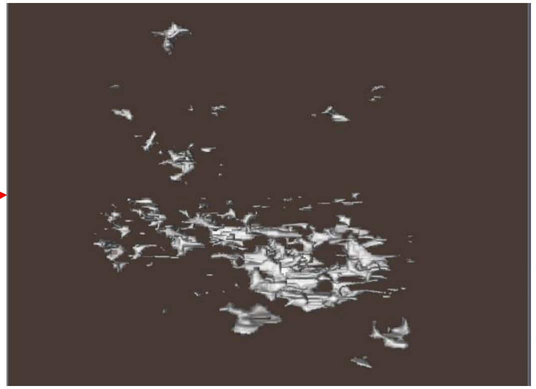
Henry PROUDHON,	Centre des Matériaux
Vincent MAUREL,	Centre des Matériaux
Lionel MARCIN,	Safran Aircraft Engines

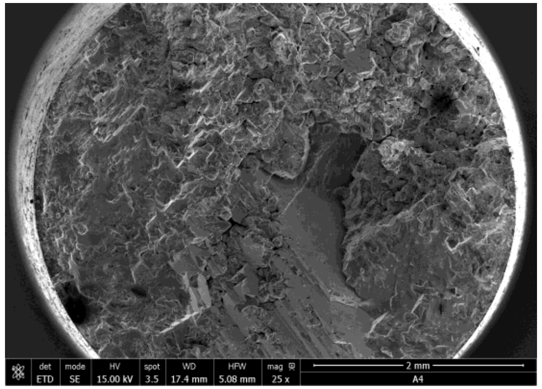
Introduction

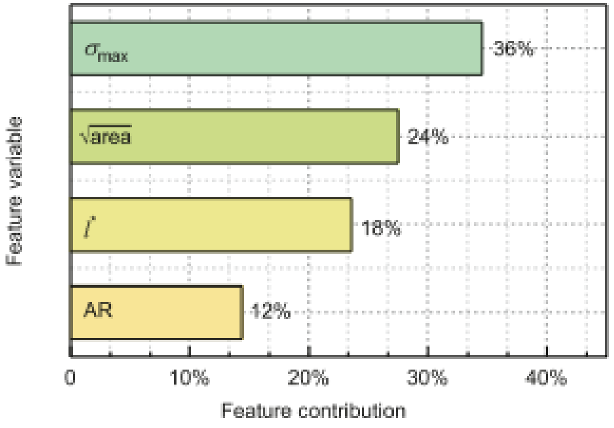
Kitagawa- Takahashi diagram: Fatigue life vs defect size



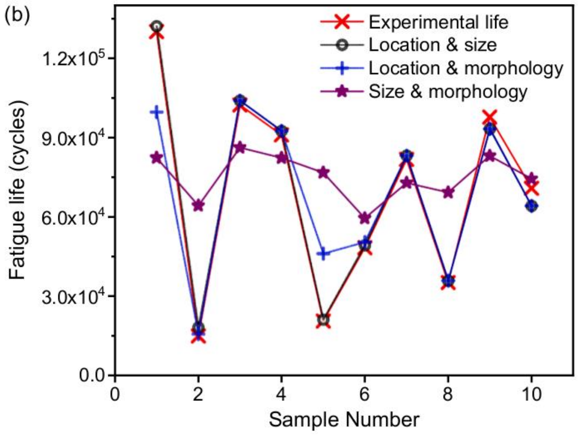
Clustered defects







Ref: Peng et al (2022)



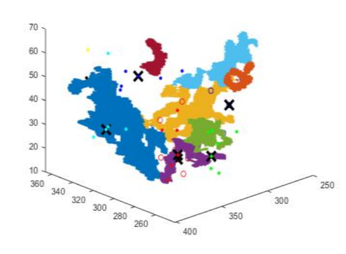
Ref: Bao et al (2021)

Influence of other defect characteristics ?

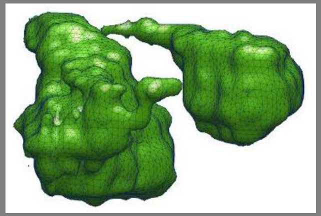
Estimate contributions of features for a better calibrated model

Introduction: Global strategy

Synthetic Microstructures

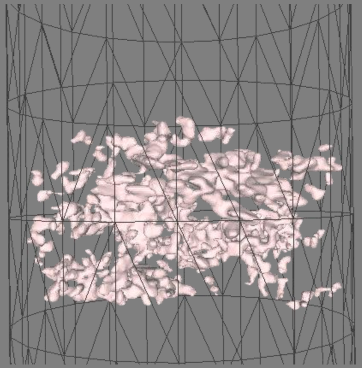


Spatial point pattern analysis

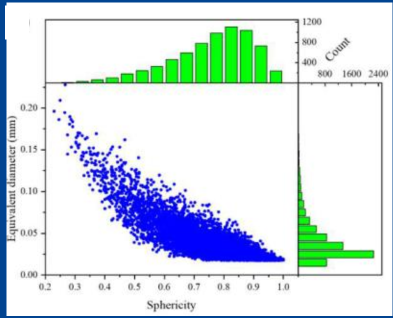


Generative Adversarial Networks

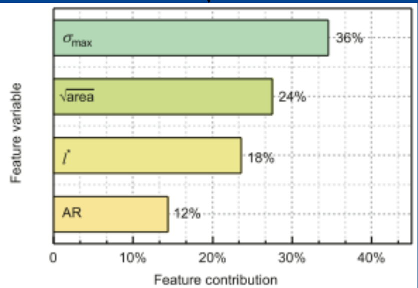
Synthetic microstructure



Monte-Carlo Approach

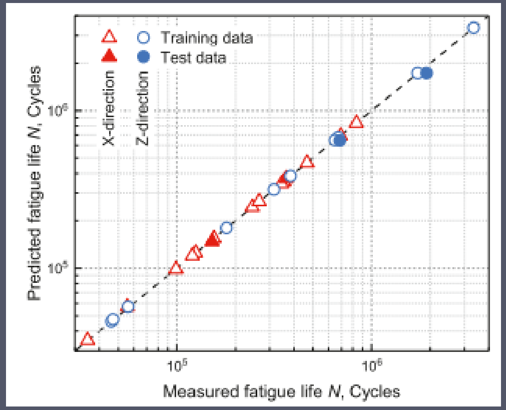


Numerical simulations followed by statistical analysis



Estimate influence of defect characteristics on HCF

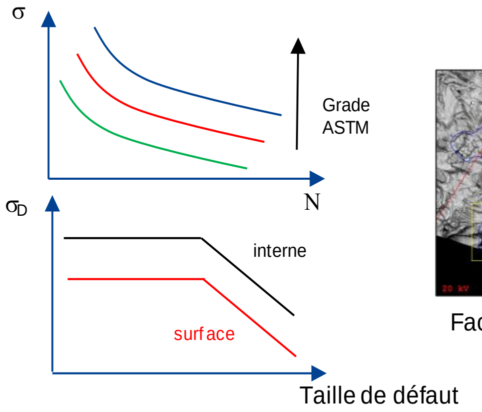
Fatigue Model

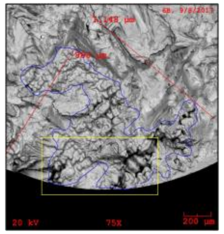


Develop a model on the basis of statistics of defects, CND criterions via a probabilistic approach

Image-based FE model to estimate fatigue life

Experimental campaign

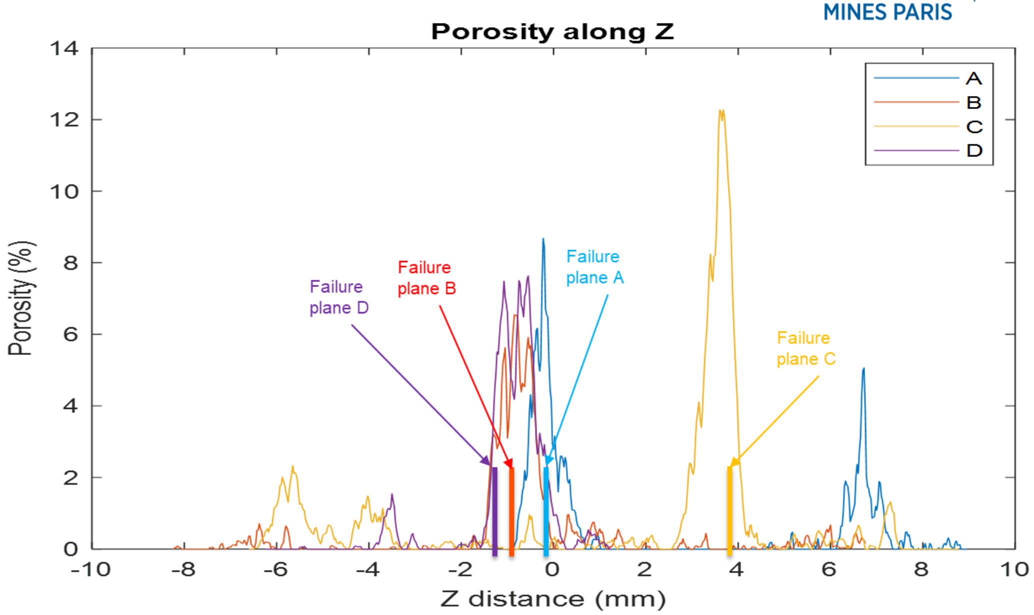




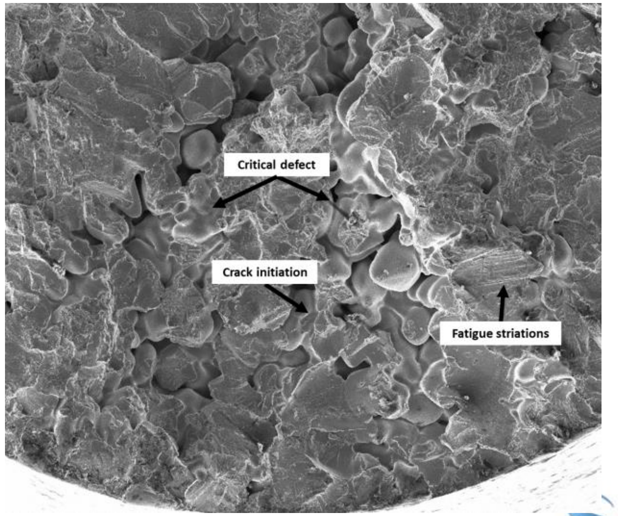
Faciès de rupture

Material: Inconel 100
Test temperature: 750 ºC
Load ratio: R = 0
Grains: Equiaxed

N°	Grade	Classe ressuage	Cycles	Crack-intiation site
A	Grade 5	Classe <10	8 096	Interne
B	Grade 5	Classe <10	77 155	Interne
C	Grade 6	Classe <10	39 638	Subsurfacique
D	Grade 6	Classe 20	31 343	Débouchante



All samples failed in the zone of clustered defects due to one critical defect



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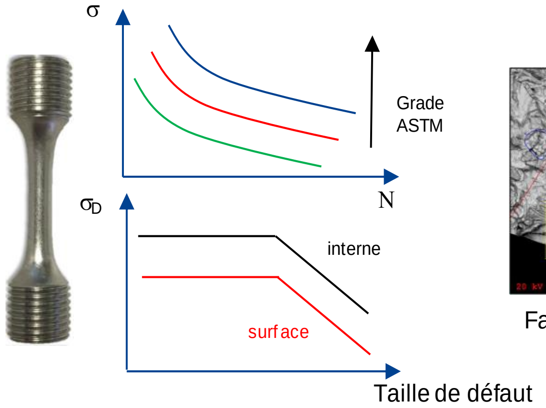

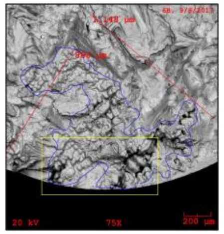

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Numerical campaign

Clustered defects

X-Ray Computed Tomography

Image-based FE model

- Numerical simulations at same conditions as experiments
- EVP behavior law with kinematic hardening
- Fatigue loads of 20 cycles until hysteresis loop stabilizes

Introduction

Synthetic Microstructures

Preliminary results

Perspectives

Generative Adversarial Networks

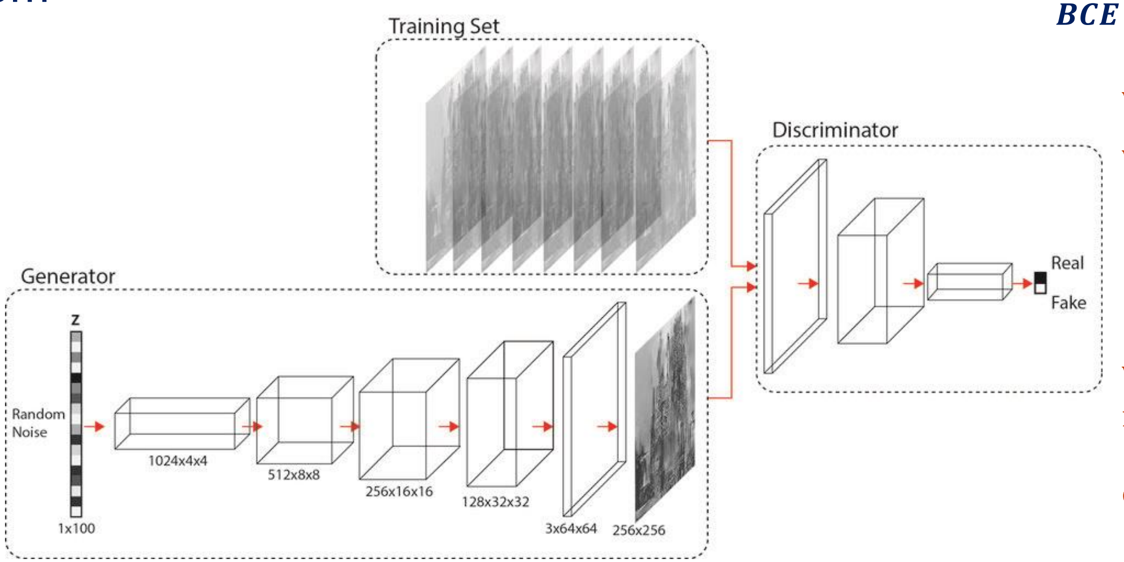
Functionalities

- Generation of data that resembles the real data
- Image transformation from one dimension to other

$$\boldsymbol{BCE\ loss = y * \log(y_{pred}) + (1 - y)\log(1 - y\_pred)}$$

When y==1, for real data → $L = \log(D(x))$

When y==0, for fake data → $L = \log(1 - D(G(z)))$



$$L^{(G)} = \min_{G}[\log(D(x)) + \log\left(1 - D(G(z))\right)]$$

$$L^{(D)} = \max_{D}[\log(D(x)) + \log\left(1 - D(G(z))\right)]$$

Where D(x) → Discriminator's prediction of real data

D(G(z)) → Discriminator's prediction of generated data

Z → distribution range of noise

Generative Adversarial Networks

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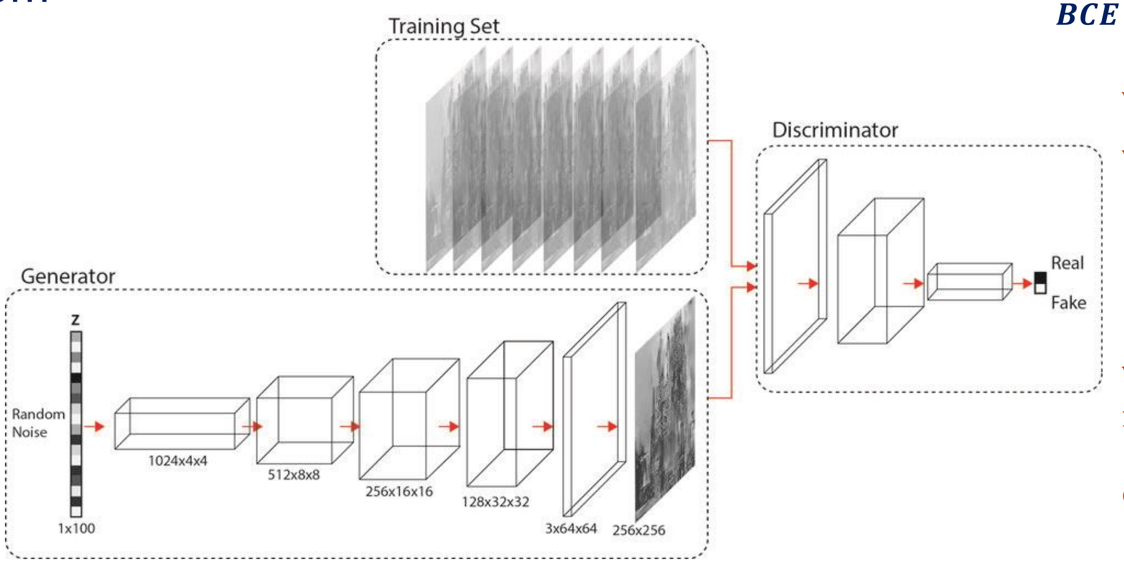

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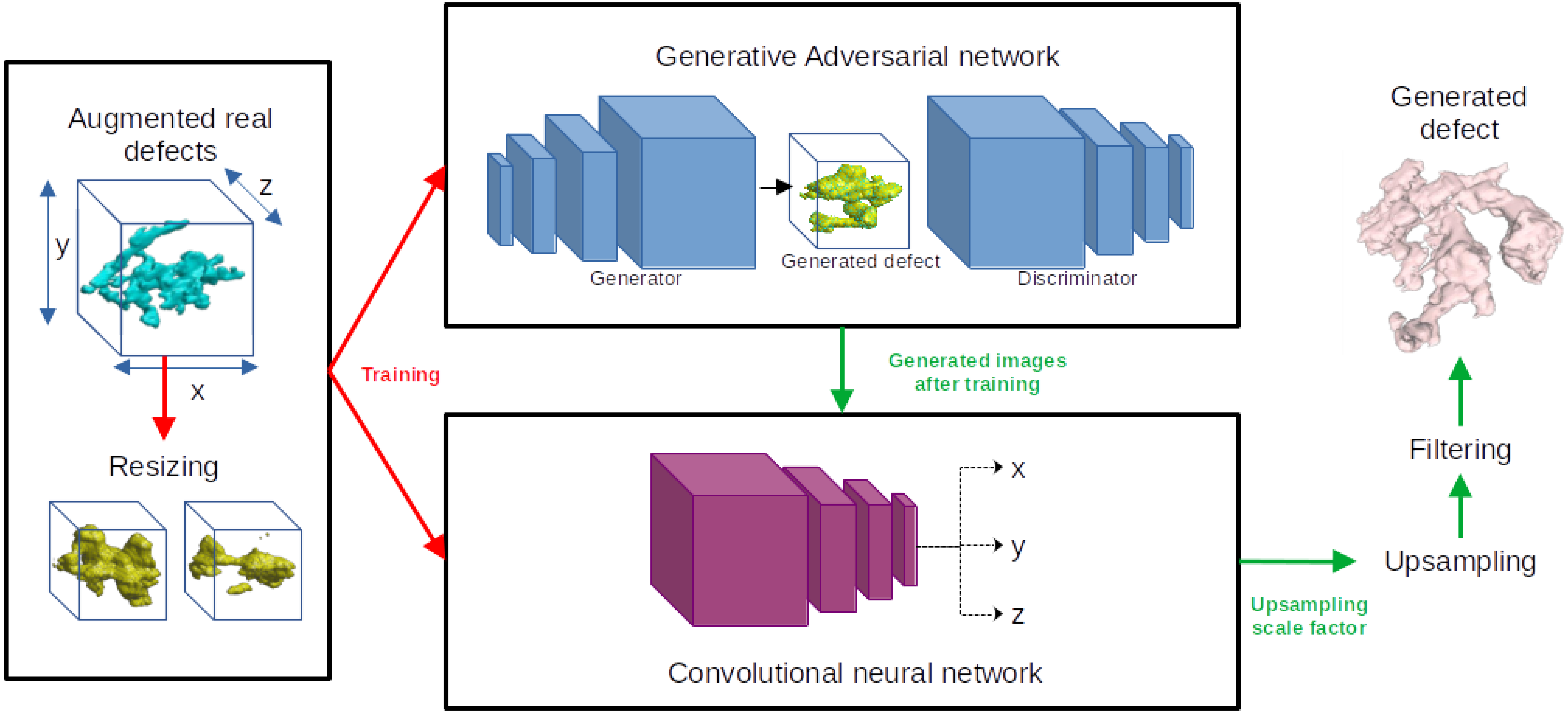
Where D(x) → Discriminator's prediction of real data

D(G(z)) → Discriminator's prediction of generated data

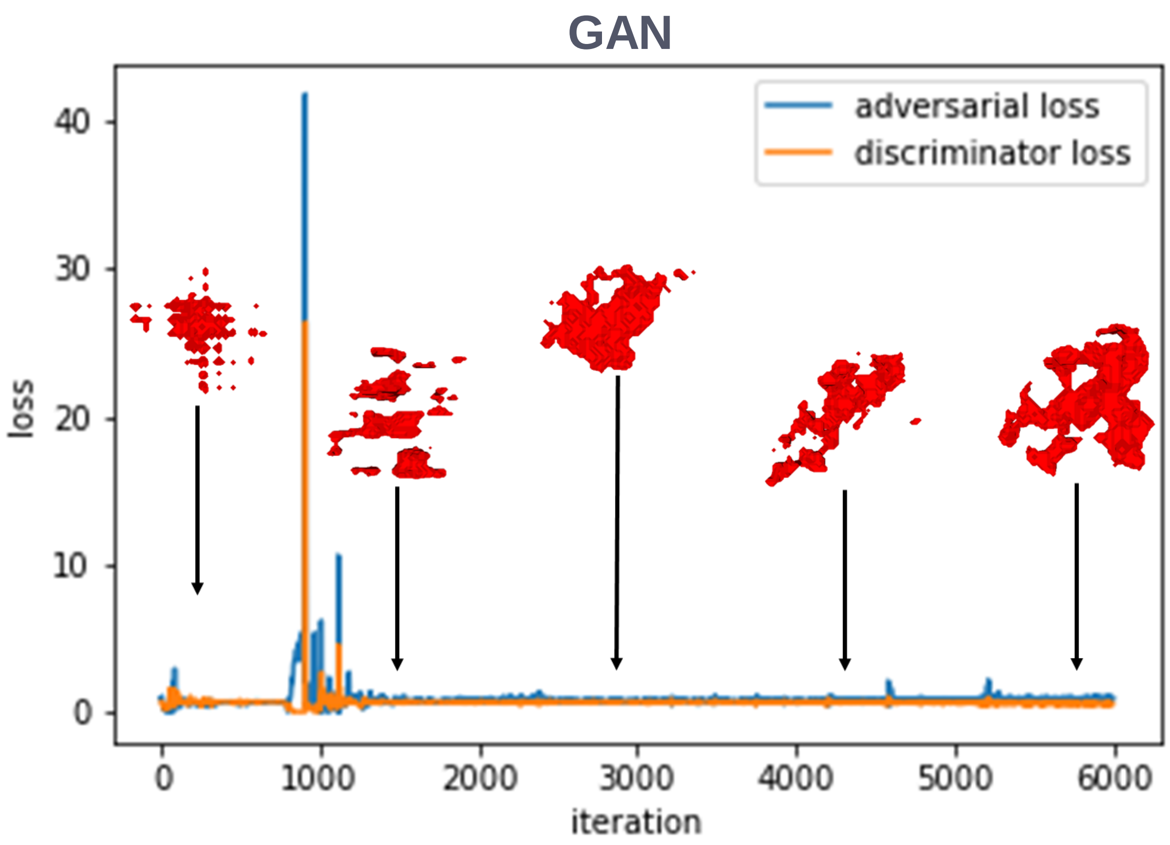
Z → distribution range of noise

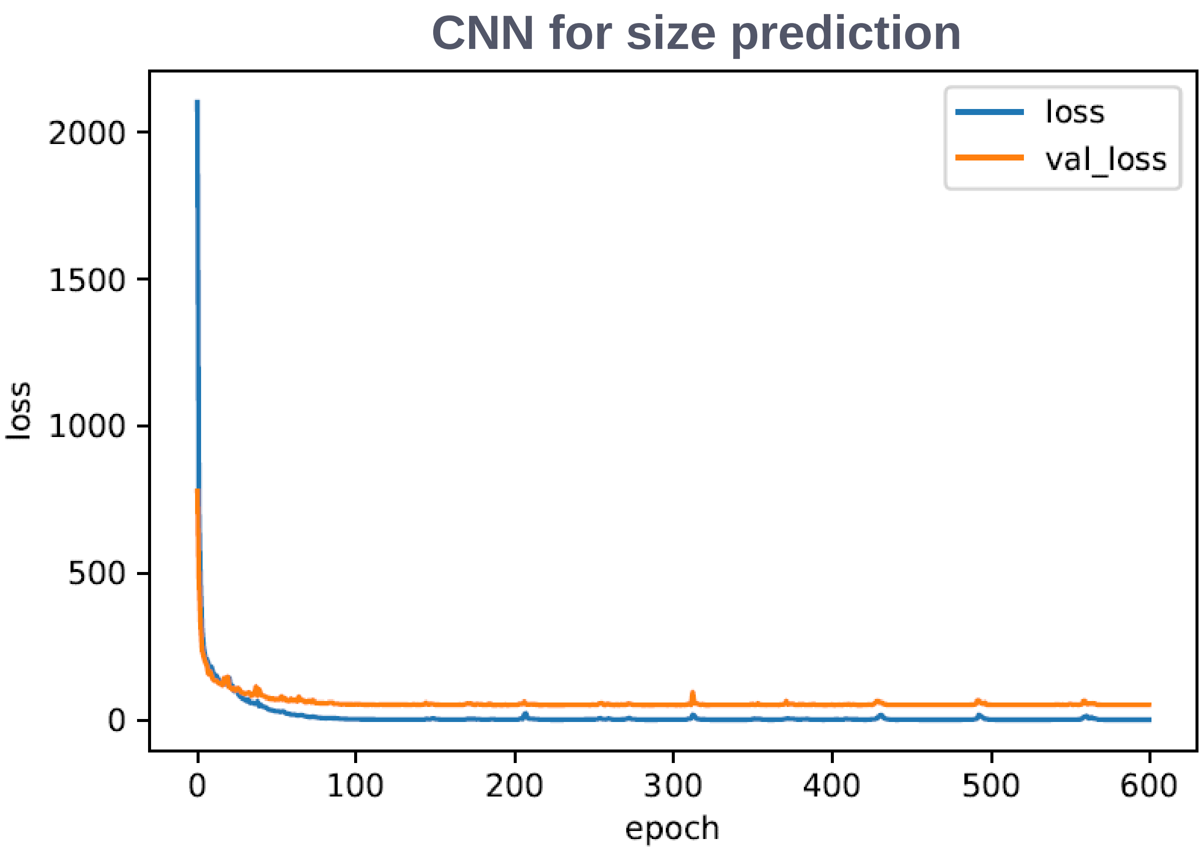
$$\min_{G}\max_{D} V(D, G) = \min_{G}\max_{D}(\mathbb{E}_x[\log(D(x))] + \mathbb{E}_z[\log\left(1 - D(G(z))\right)])$$

Generative Adversarial Networks



Generative Adversarial Networks: Loss history

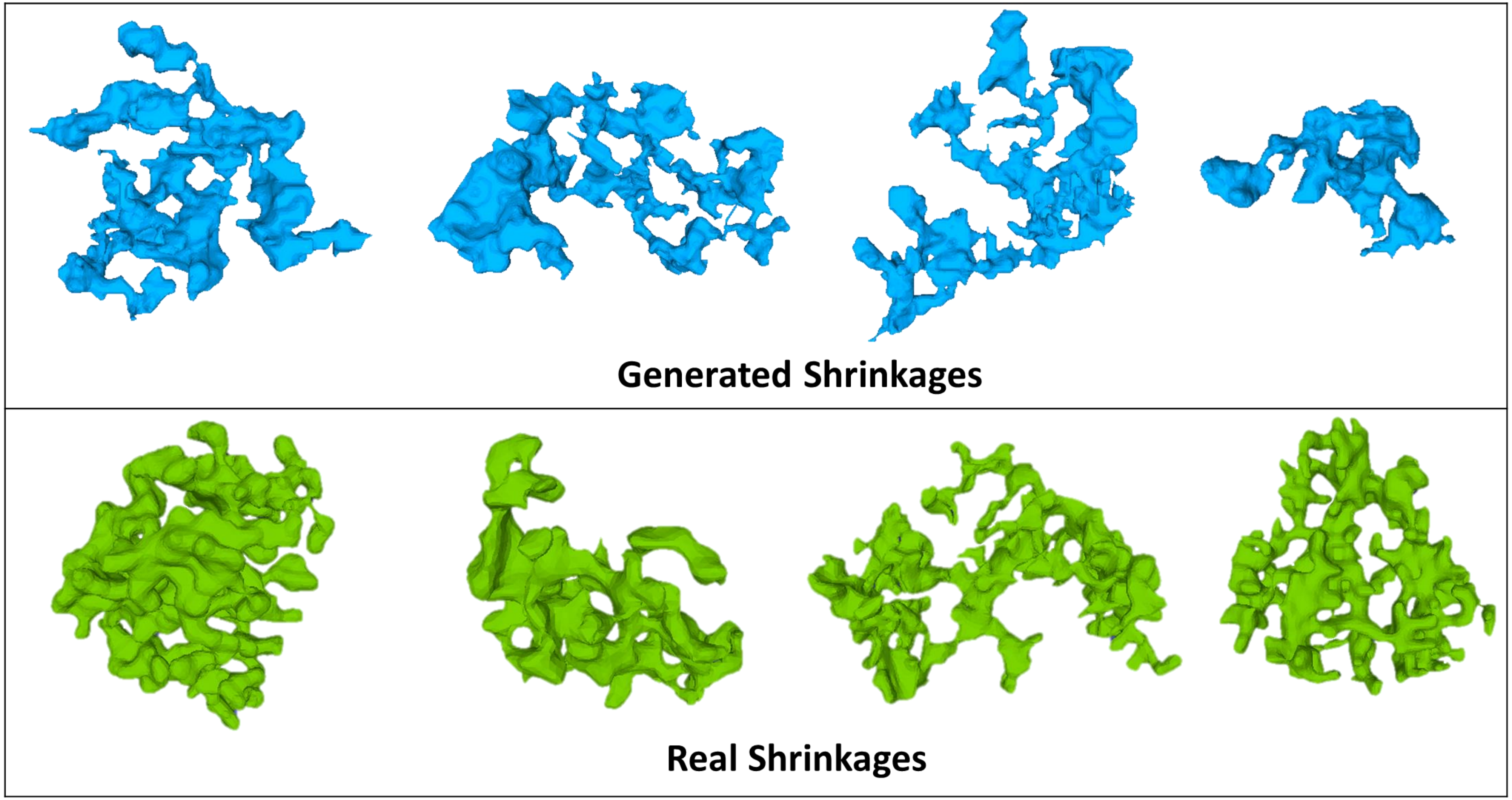




Modifications – GAN :-

- One sided label smoothing – addition of noise to labels
- Generator trained k times than discriminator to maintain balance between D and G

Generative Adversarial Networks: Examples



Spatial point pattern (SPP) Analysis

Compare spatial pattern analysis with poisson process to investigate local clustering

Ripley's K-function :-

Second order moment function that includes all distance pairs in a spatial pattern

$$K(d) = \lambda^{-1} E(number\ of\ points\ within\ distance\ d\ of\ a\ single\ arbitrary\ event)$$

Where λ → intensity or mean number of events in unit space
In 3-D λ = Number of points / Volume
E → Expected number of events in a length r
K(d) → K-function

Equation :-

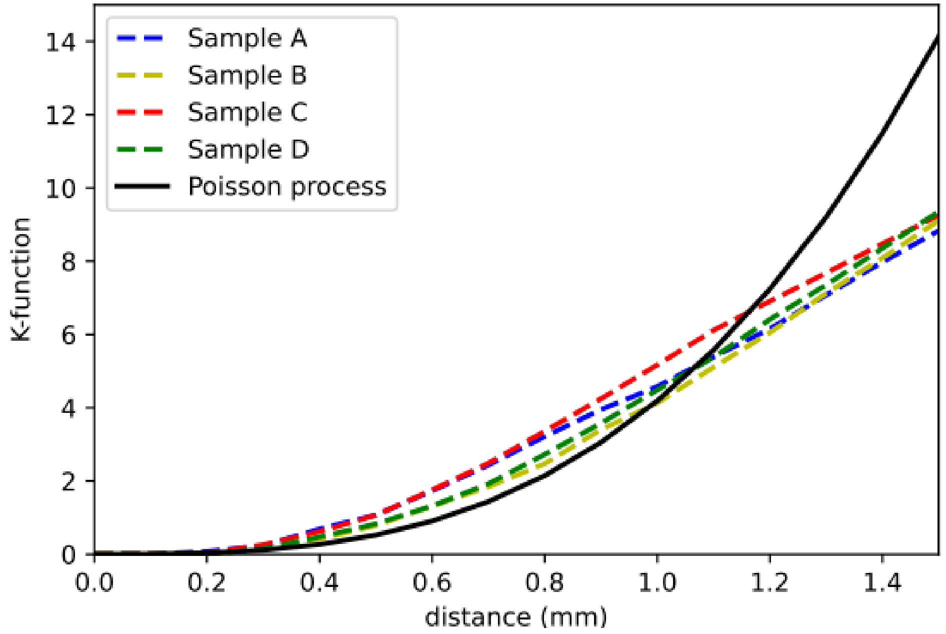
$$K(d) = \frac{V}{N} \sum_{i=1}^{N} \sum_{i \neq j}^{N} \frac{I(r_{ij} < d)}{N}$$

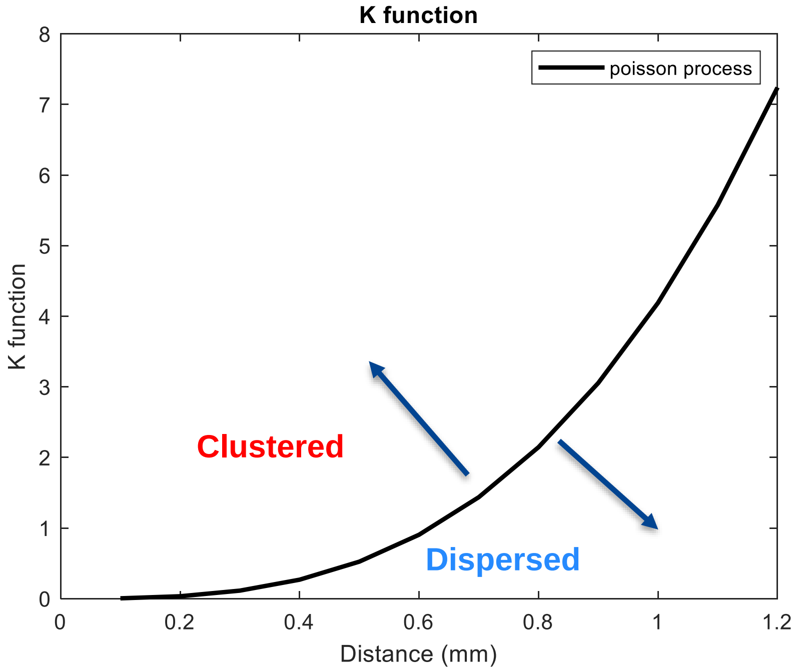
Where, N → Number of points

$$I \rightarrow \begin{cases} 1\,, & if\ r_{ij} < d \\ 0\,, & otherwise \end{cases}$$

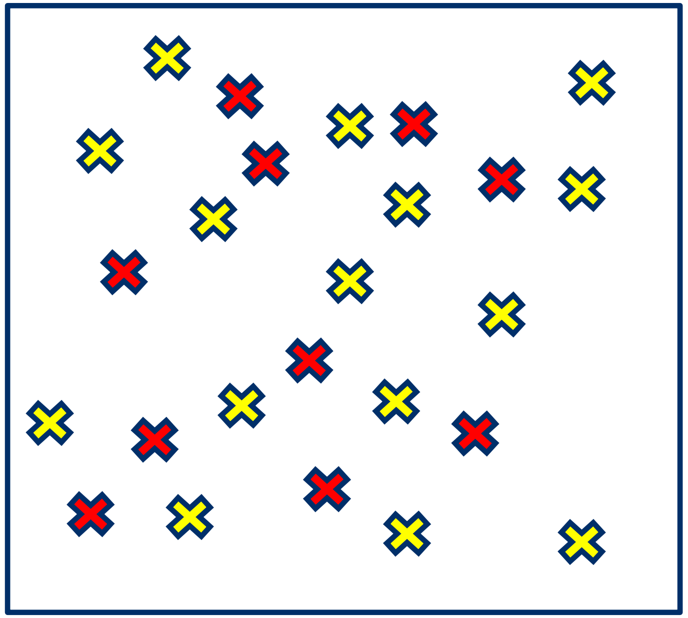
$\frac{V}{N}$ → 1 / (Intensity)

Double sum → Expected number of points





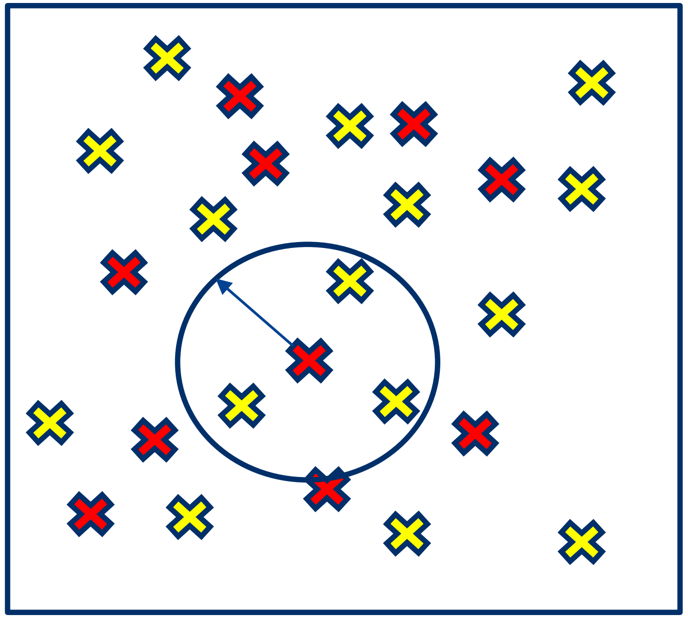
SPP Analysis: Neyman Scott Process



→ Parent defect (type 1)

→ Child defect (type 2)

SPP Analysis: Neyman Scott Process



→ Parent defect (type 1)

→ Child defect (type 2)

Splitting the defects into two categories assumes that both are different SPP process

Ripley's K function for two types of defect given as $\boldsymbol{K_{11}}$ and $\boldsymbol{K_{22}}$

Interaction between two processes : Cross K-function

$$K_{12}(d) = (\lambda_1 \lambda_2 V)^{-1} \sum_{i=1}^{N_1} \sum_{j=1}^{N_2} I(r_{ij} < d)$$

Where, $\boldsymbol{\lambda_1}$ and $\boldsymbol{\lambda_2}$ are intensities of type 1 and 2
N1 and N2 are number of points of type 1 and 2

↓

Bivariate K-function

$$K(r) = \begin{bmatrix} K_{11} & K_{12} \\ K_{21} & K_{22} \end{bmatrix}$$

Introduction of parameter $\boldsymbol{\theta}$

- θ corresponds to defect size.
- Defects are classified with respect to θ as either type 1 or type 2
- For e.g., if θ == 0.6 mm, all defects with size below θ belongs to type 1 and the rest type 2.

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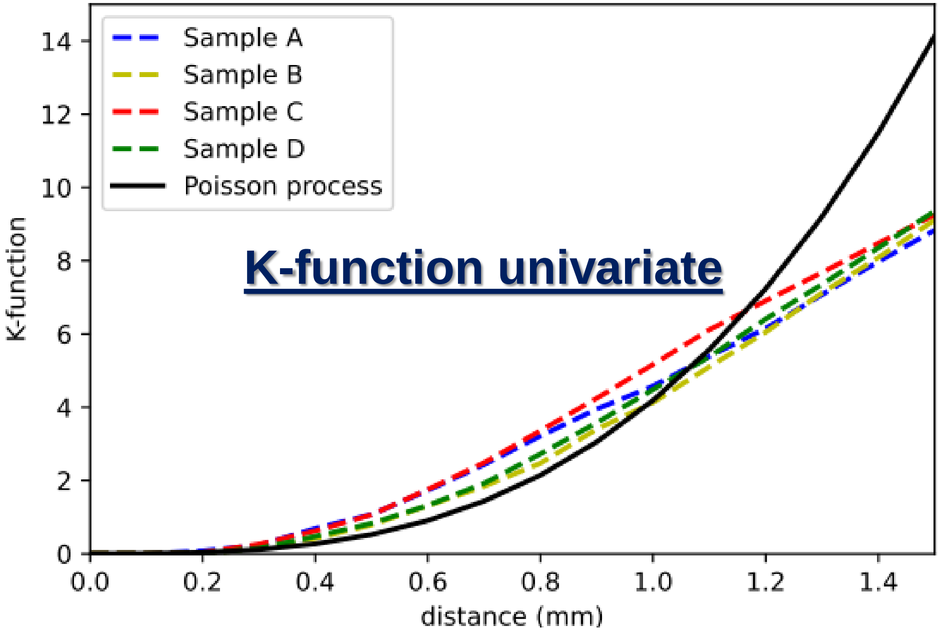
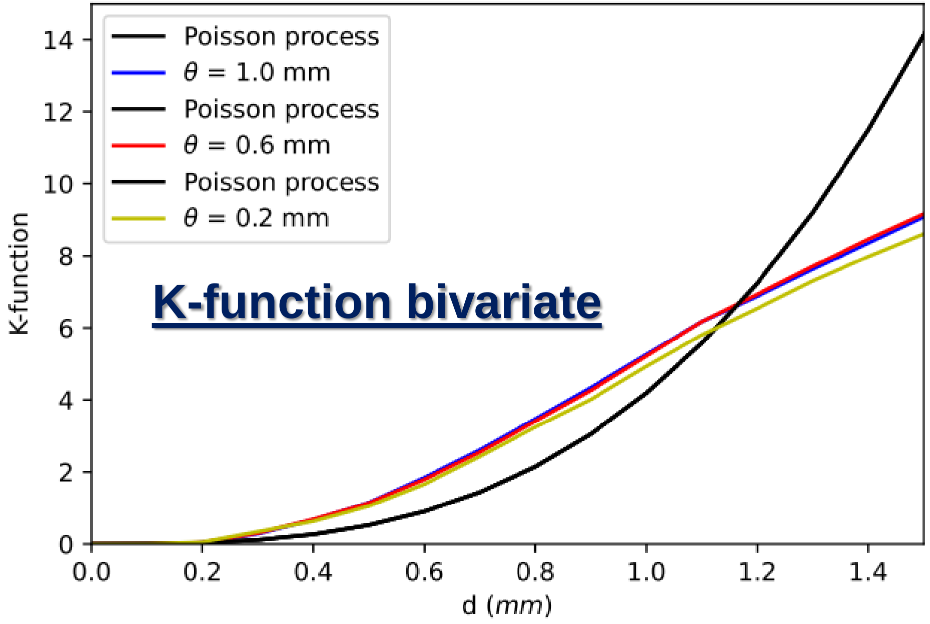
Spatial point pattern Analysis





- Clustering pattern observed in all samples
- In-homogenous process required for generation

- Defects larger than 0.6 mm are added first
- Defects smaller than 0.6 mm are added around larger defects – **Neyman-Scott process**

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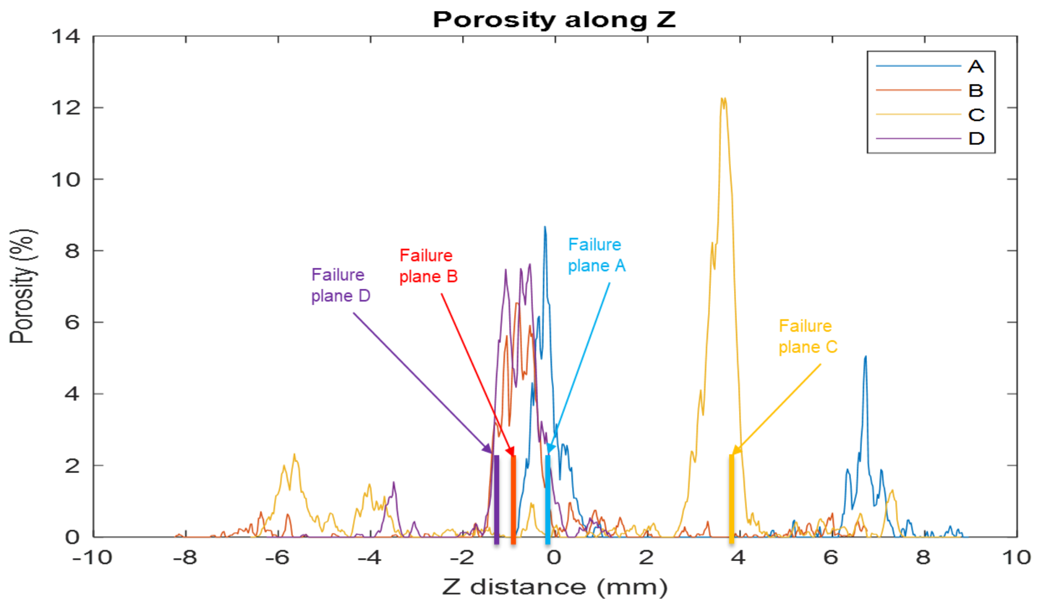
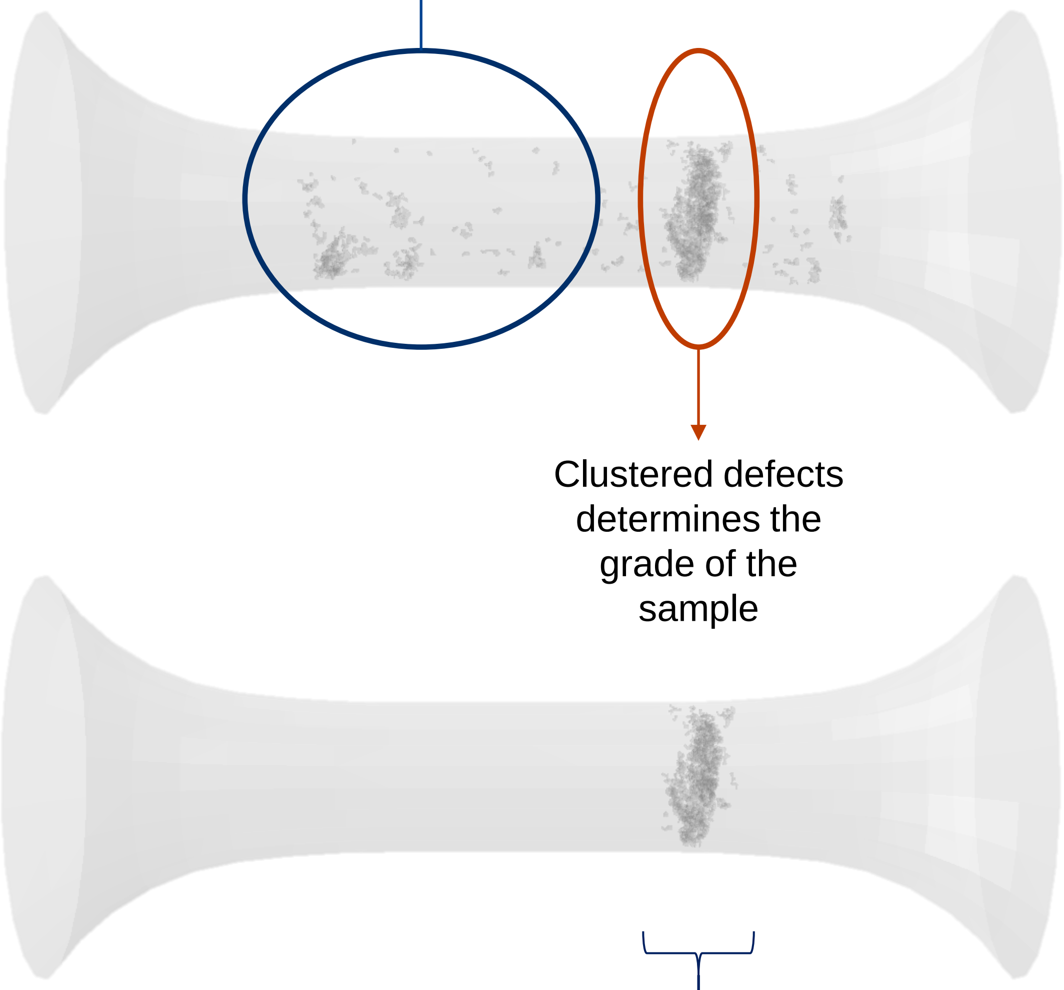
Material Space



Other defects have no influence on crack-initiation life



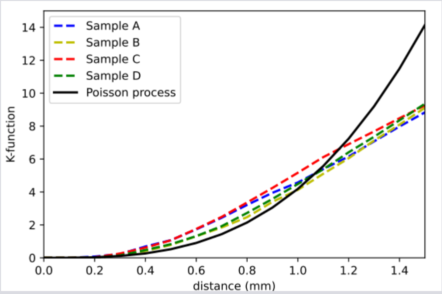
Clustered defects determines the grade of the sample

Generation of only clustered region : **Material space**

COMPLETE CHAIN

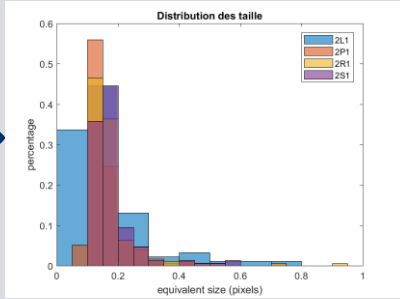
Create material space

Spatial point pattern analysis



K- function

Respecting



Size distribution

Synthetic sample along with statistics

Neyman Scott process

Parent defect

Number of shrinkages = poisson (Average no. shrinkages in samples)

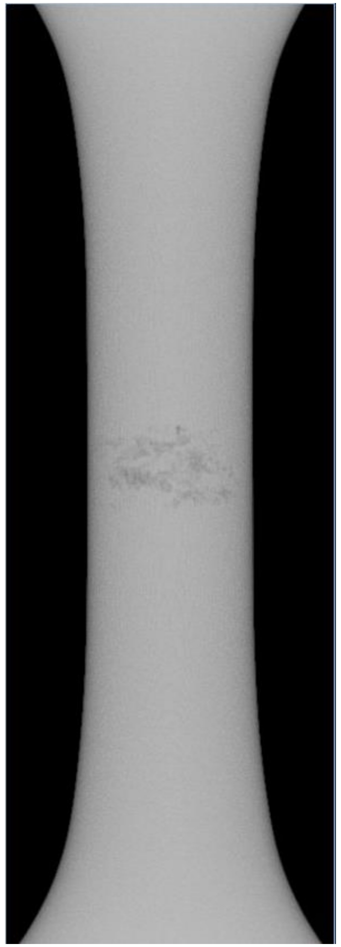
GAN → CNN – size prediction → Image resizing → Image post-process → Statistics

Child defect

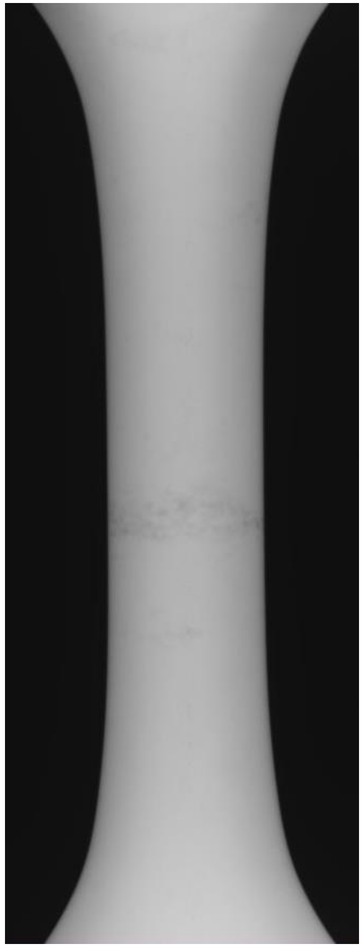
Number of pores = poisson (expected no. defects within a distance ‘d’ – K function)

GAN → CNN – size prediction → Image resizing → Image post-process → Statistics

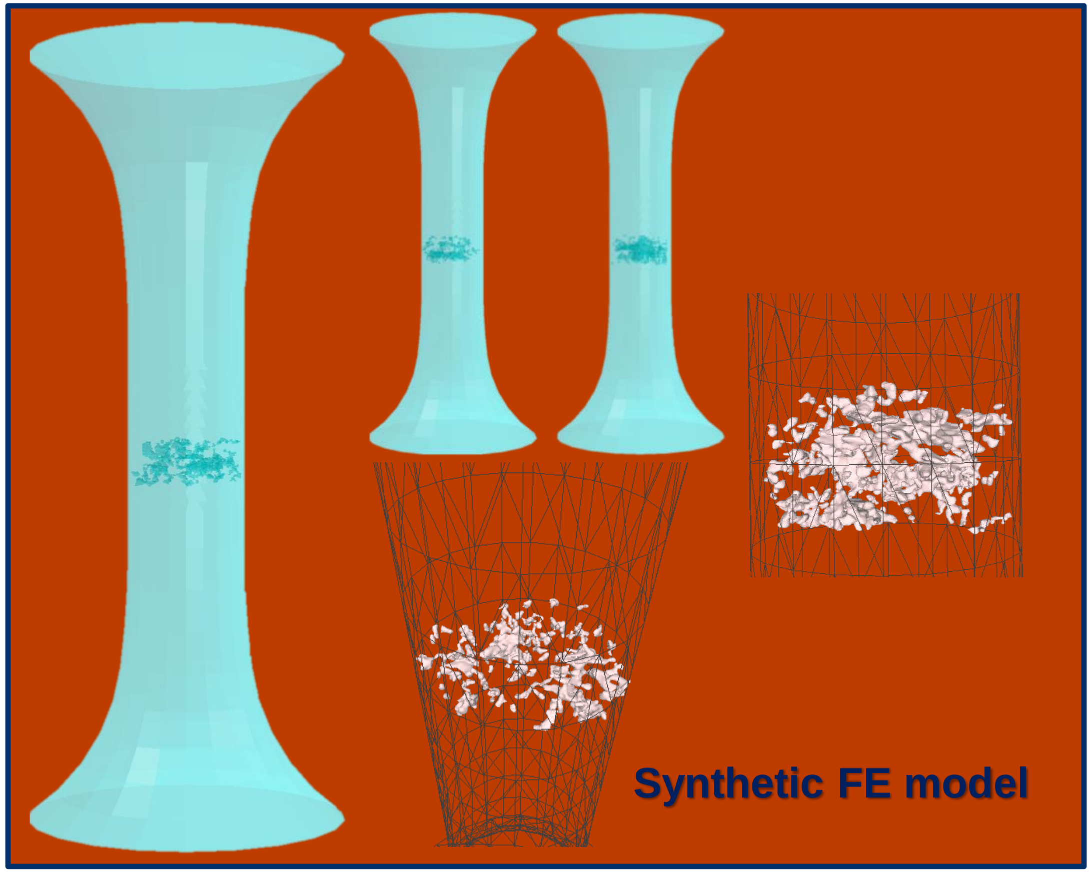
Examples

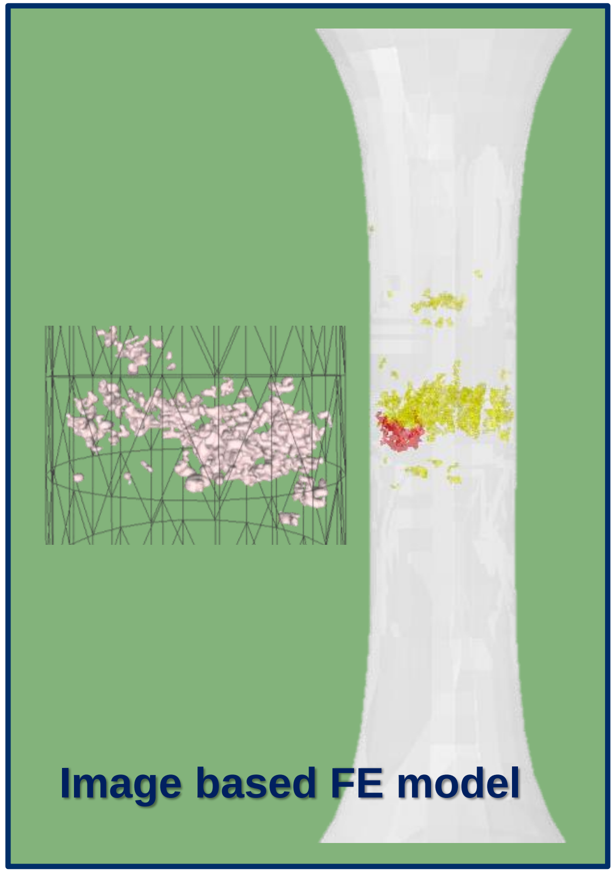


a) Synthetic microstructure



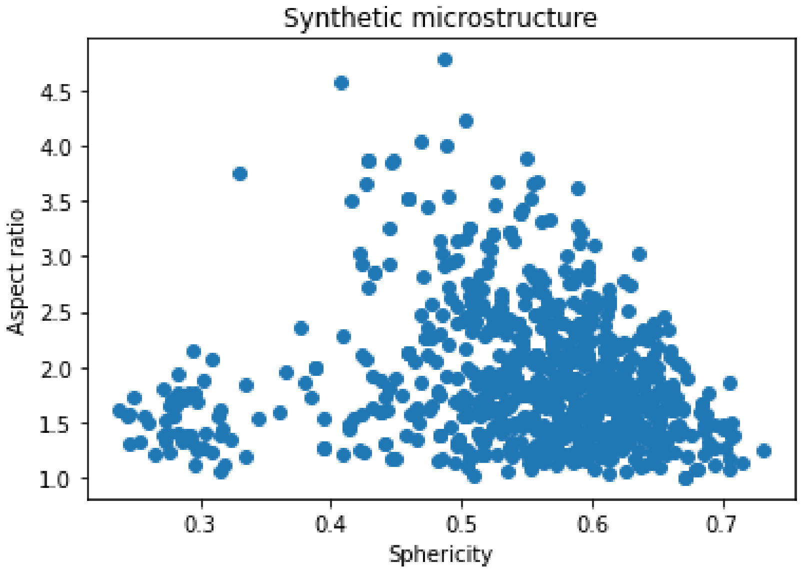
b) Real microstructure

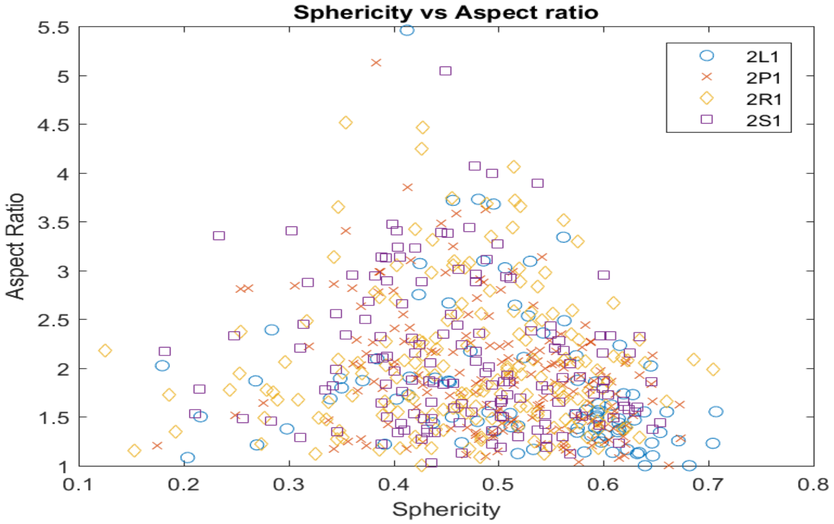




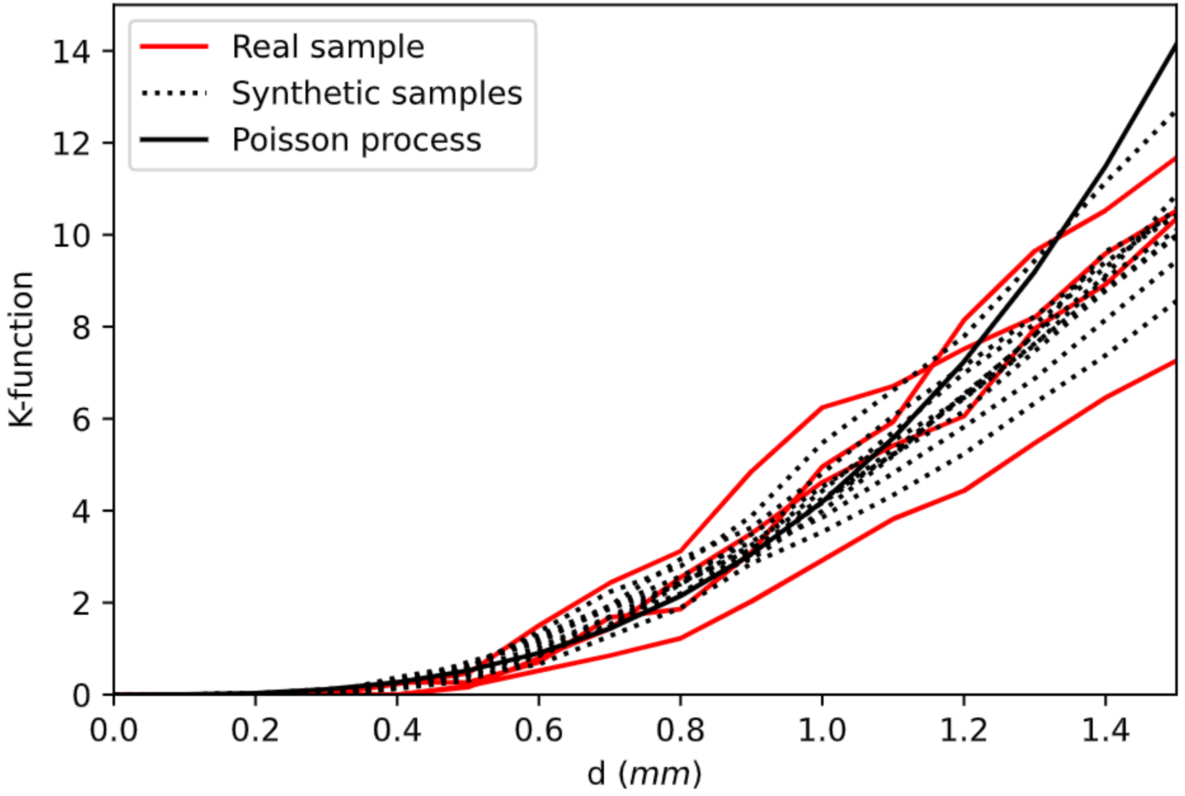
Synthetic microstructure – Global statistical validation and comparison

Sphericity vs Aspect ratio



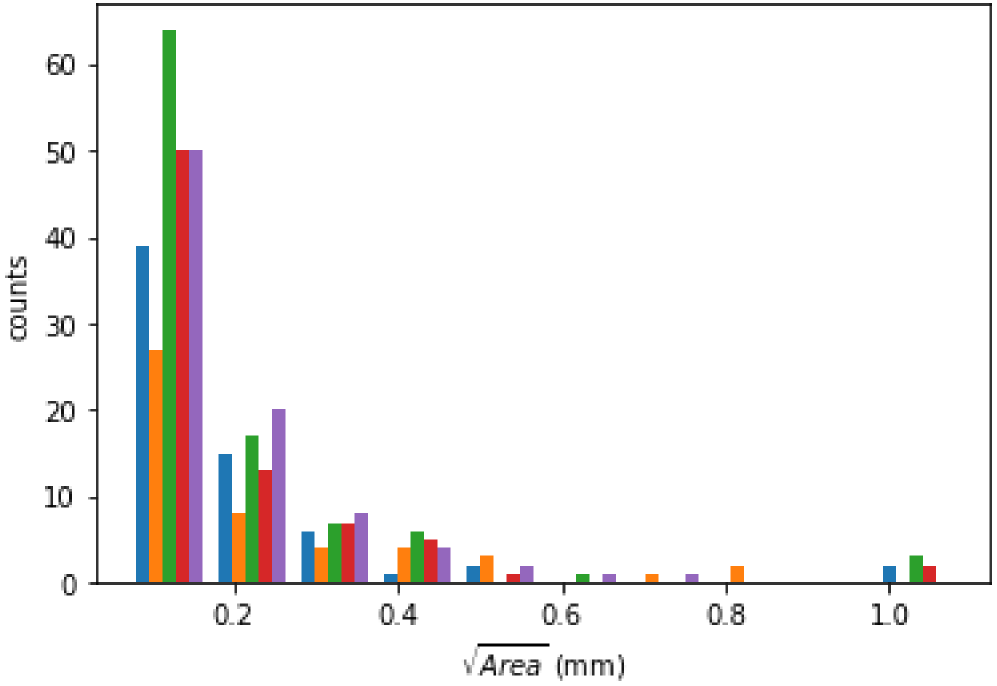


Spatial point pattern : cross K-function

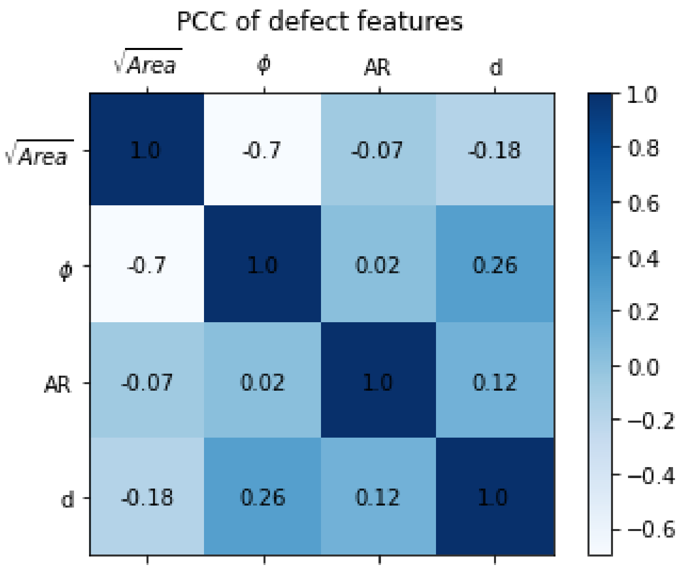


Synthetic microstructure – Global statistical validation and comparison

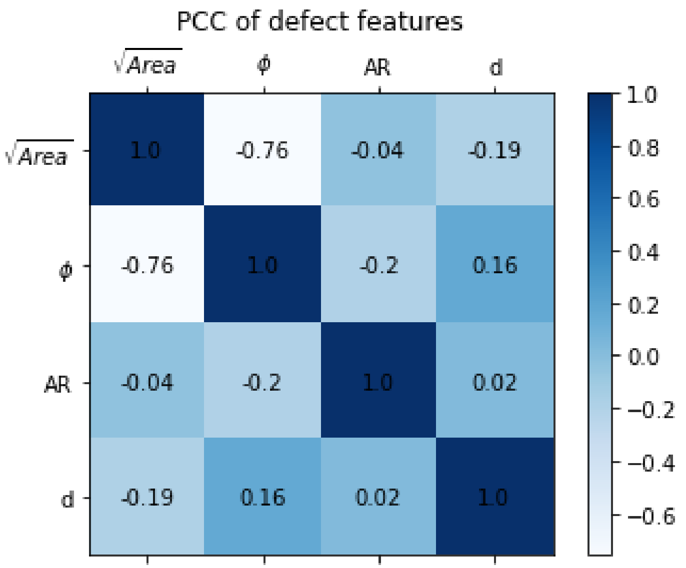
Defect size distribution for 5 synthetic microstructure



PCC of synthetic and real microstructure

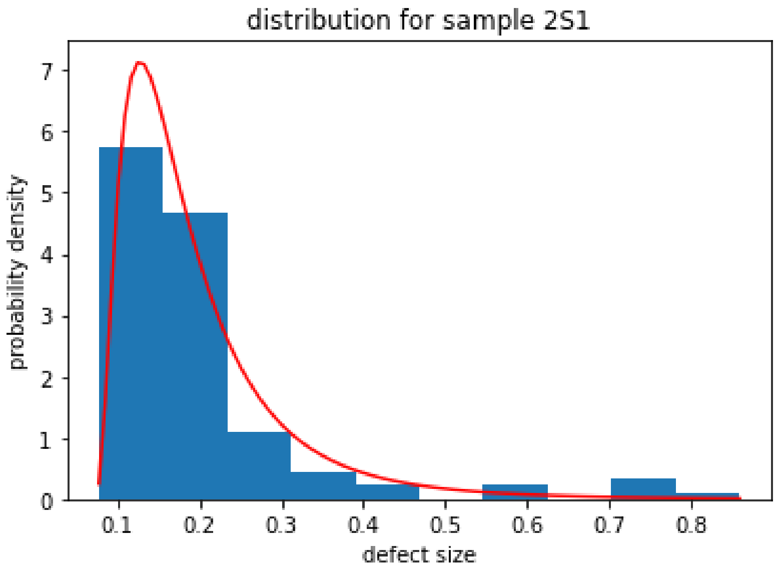


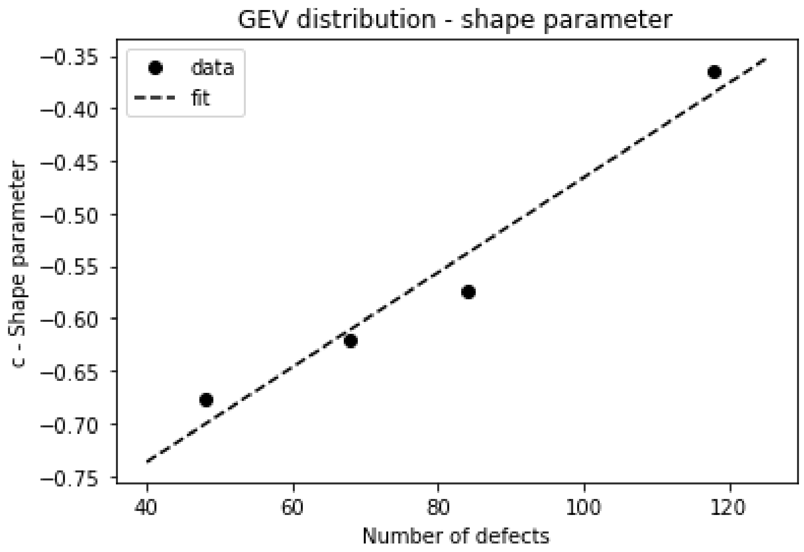
Real



Synthetic

Synthetic samples – selon ASTM





For each synthetic sample, the defect size distribution changes as per shape parameter

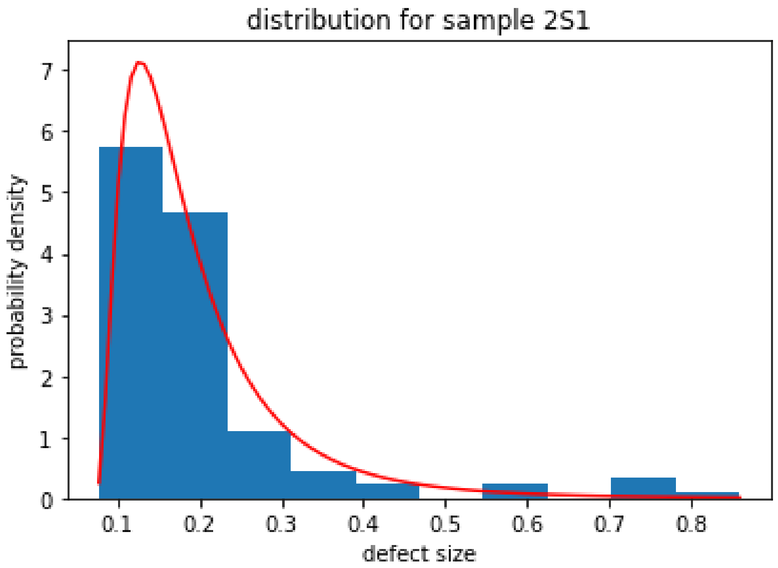
Generalized extreme value distribution:

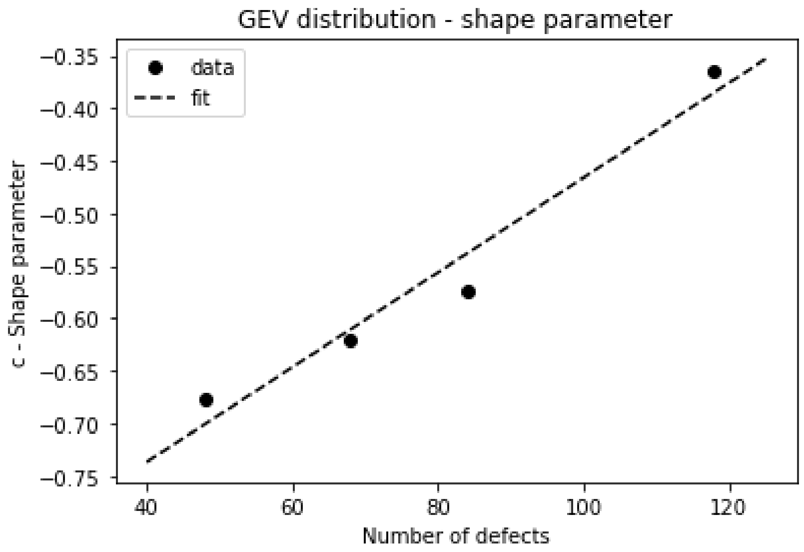
$$Gev = e^{-(1-cx)^{1/c}}(1-cx)^{1/(c-1)}$$

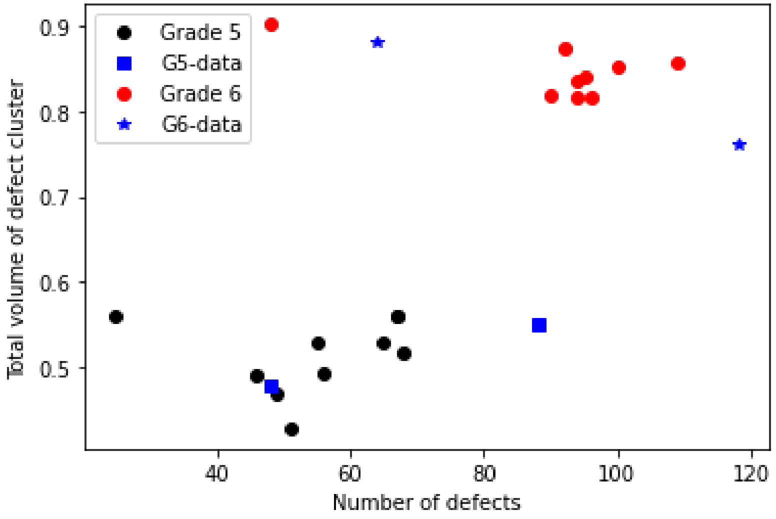
c → Shape parameter

C depends on number of defects of respective sample

Synthetic samples – selon ASTM







For each synthetic sample, the defect size distribution changes as per shape parameter

Total volume of cluster of generated samples

o → Synthetic samples

Generalized extreme value distribution:

$$Gev = e^{-(1-cx)^{1/c}}(1-cx)^{1/(c-1)}$$

c → Shape parameter

C depends on number of defects of respective sample

Introduction

Synthetic Microstructures

Preliminary numerical results

Perspectives

Number of cycles to failure: Numerical vs experimental correlation

Dissipated plastic strain energy per cycle

$$\Delta W_p = A(N)^k$$

where A and k are constants.

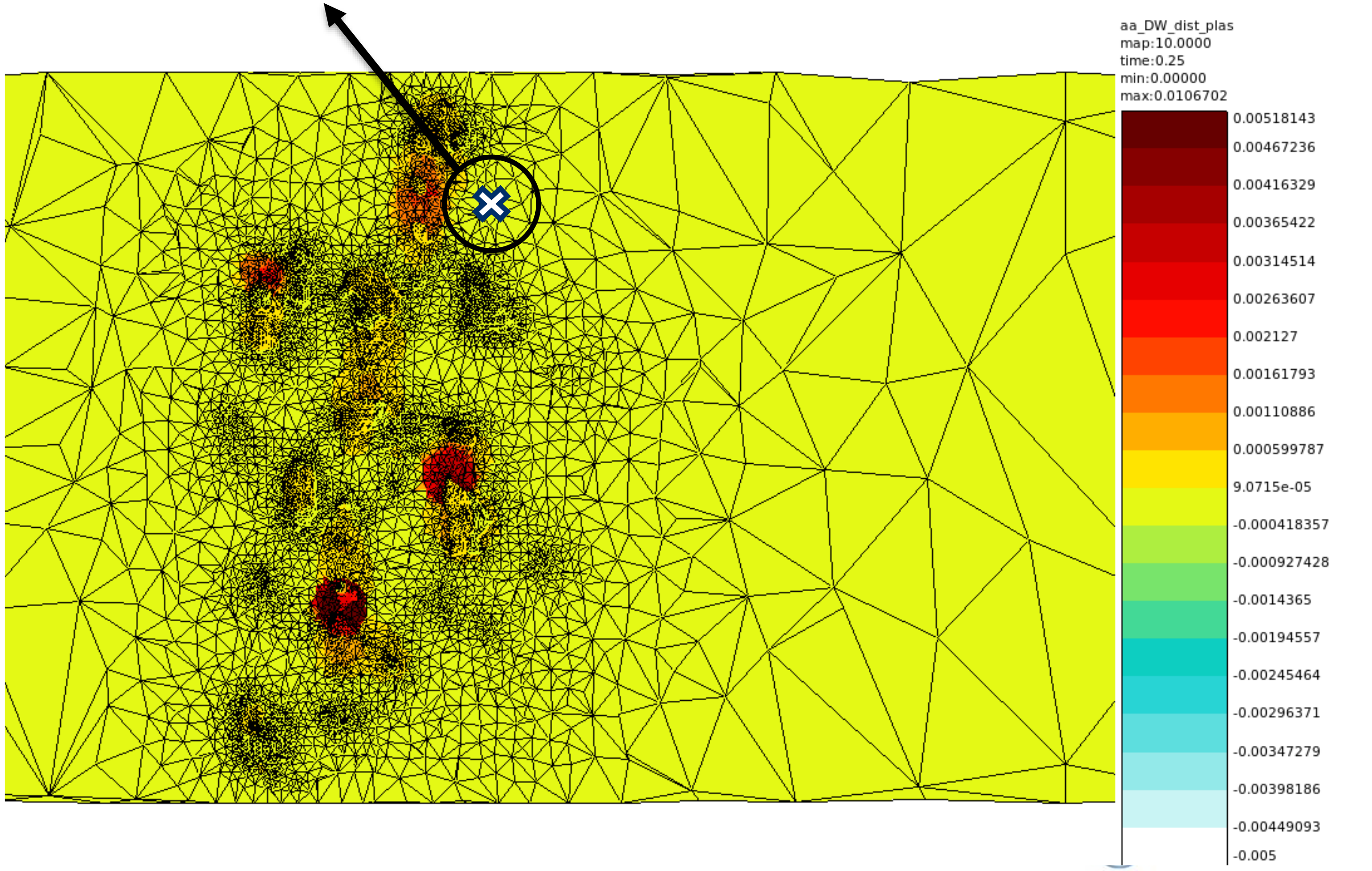
Underlying assumptions of the criteria being:
The crack is initiated on a defect with maximum dissipation at stabilized stress loop
Ref: V. Maurel et al (2009)

Volumetric homogenization

$$\Delta W_{p,avg} = \frac{1}{V}\int_V \Delta W_p . dV$$

Field homogenization for each element is done over a sphere of radius ‘R’ whose center lies on the element

$$R \in \{100\mu m, 150\mu m, 200\mu m\}$$



Number of cycles to failure: Numerical vs experimental correlation

Dissipated plastic strain energy per cycle

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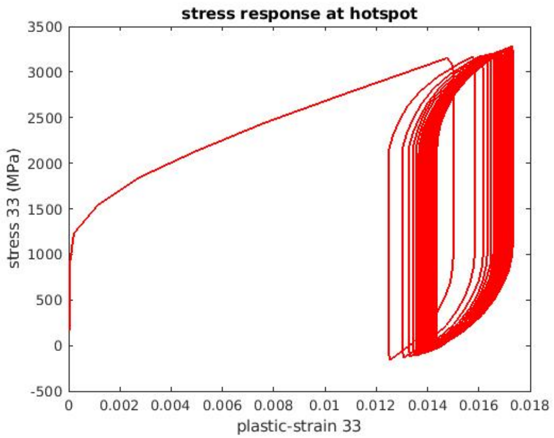
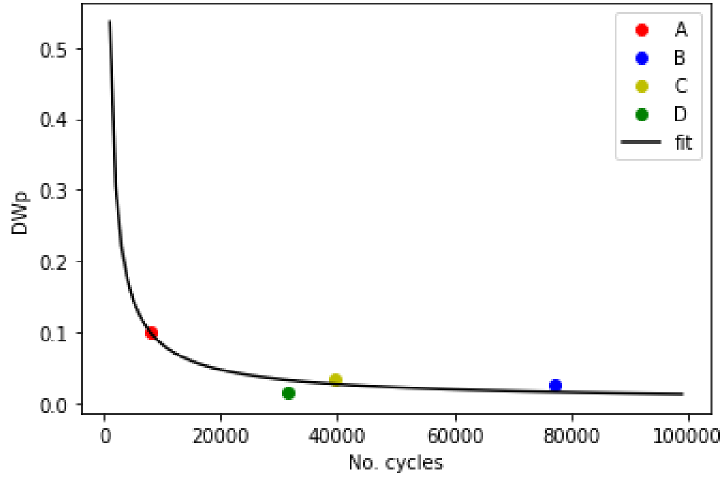
where A and k are constants.

Underlying assumptions of the criteria being:
The crack is initiated on a defect with maximum dissipation at stabilized stress loop

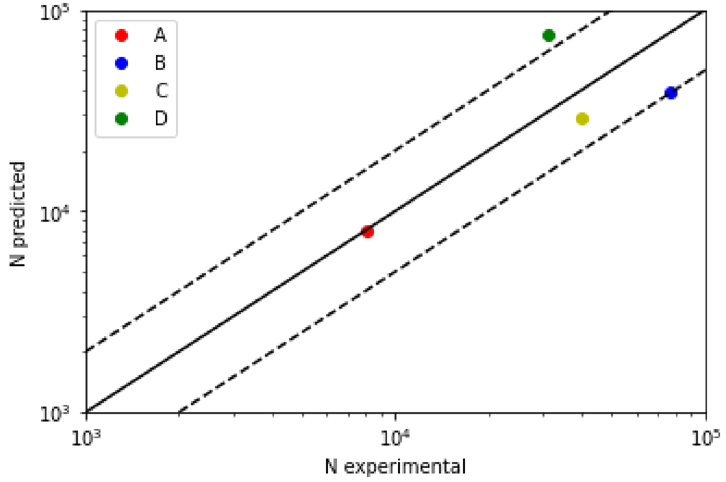
Radius of 150 µm was chosen for stress homogenization after comparison with experimental results





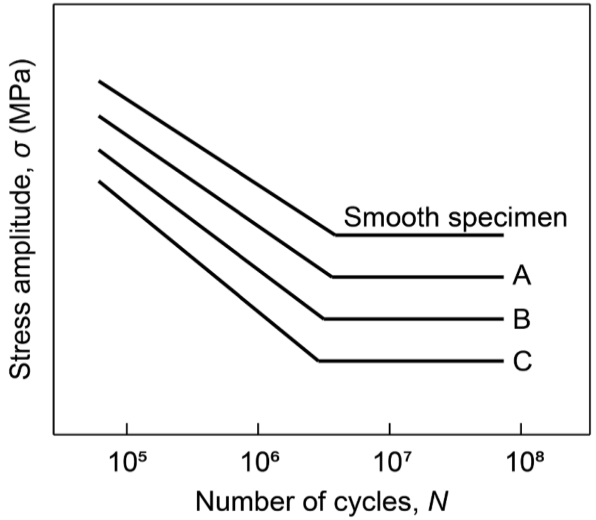
Fit to experimental results to find parameters A and k

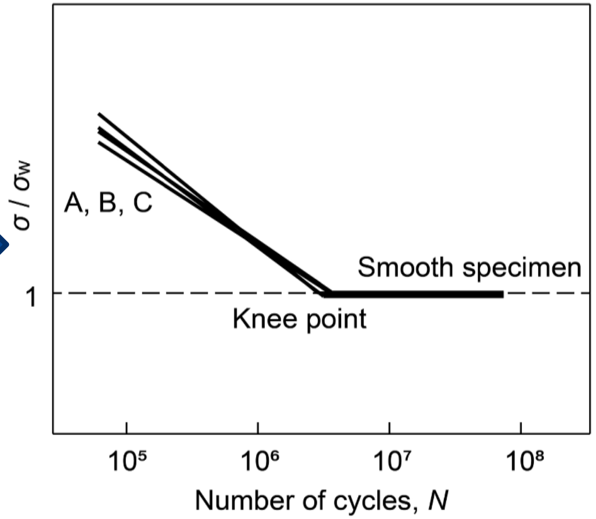
A	k
147.49	-0.813



Prediction of number of cycles to failure

Failure criterion - Estimations





Wohler curve for different defect sizes

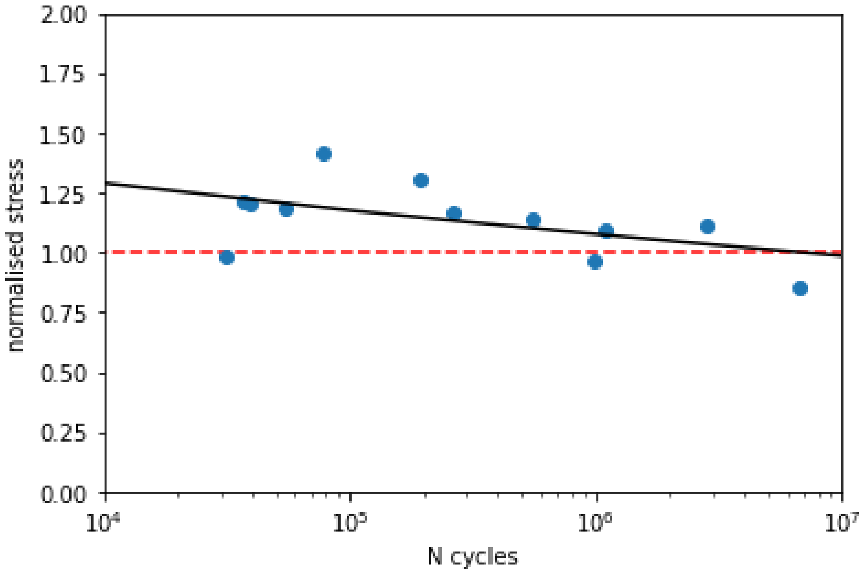
Defect size C > B > A i.e., fatigue limit decreases with respect to defect size

Relationship between fatigue limit and defect size:-

$$\sigma_D = \frac{C(H_v + 120)}{\sqrt{Area}^{1/6}} \left(\frac{1-R}{2}\right)^{\alpha}$$

Where, Hv is the Vickers hardness, R the load ratio, $\sqrt{Area}$ size of defect and σ_D, the fatigue limit

C = 1.56 for internal defect and 1.43 for surface defect.



Synthetic samples – Simulations

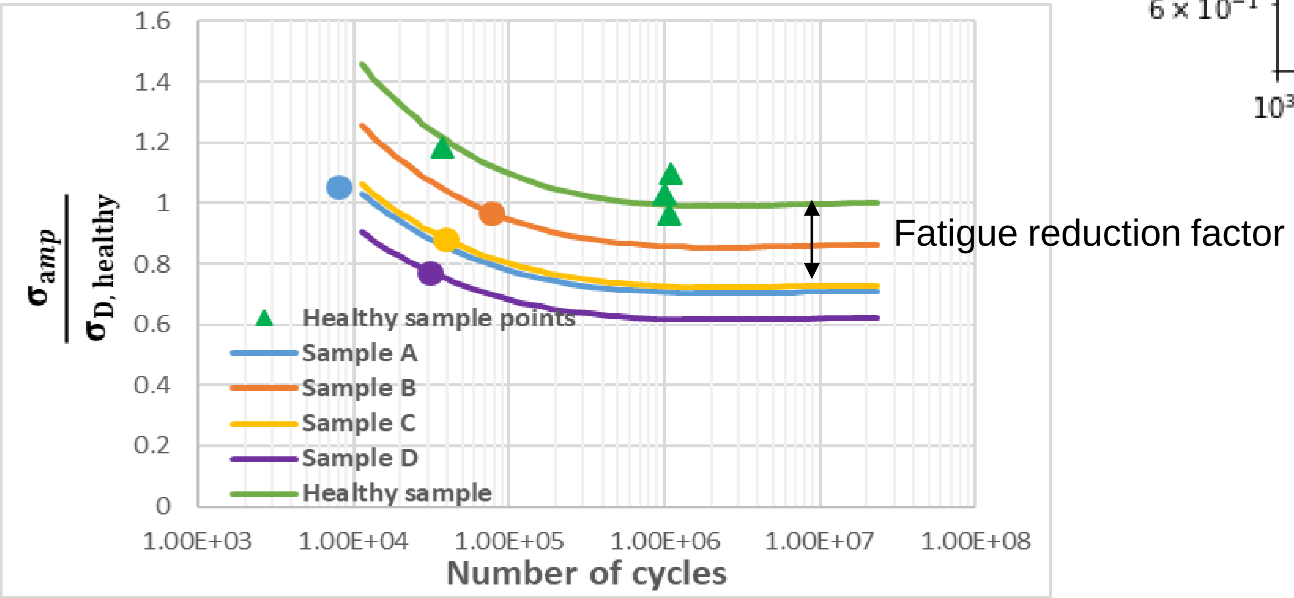
From fatigue reduction factor like SCF:

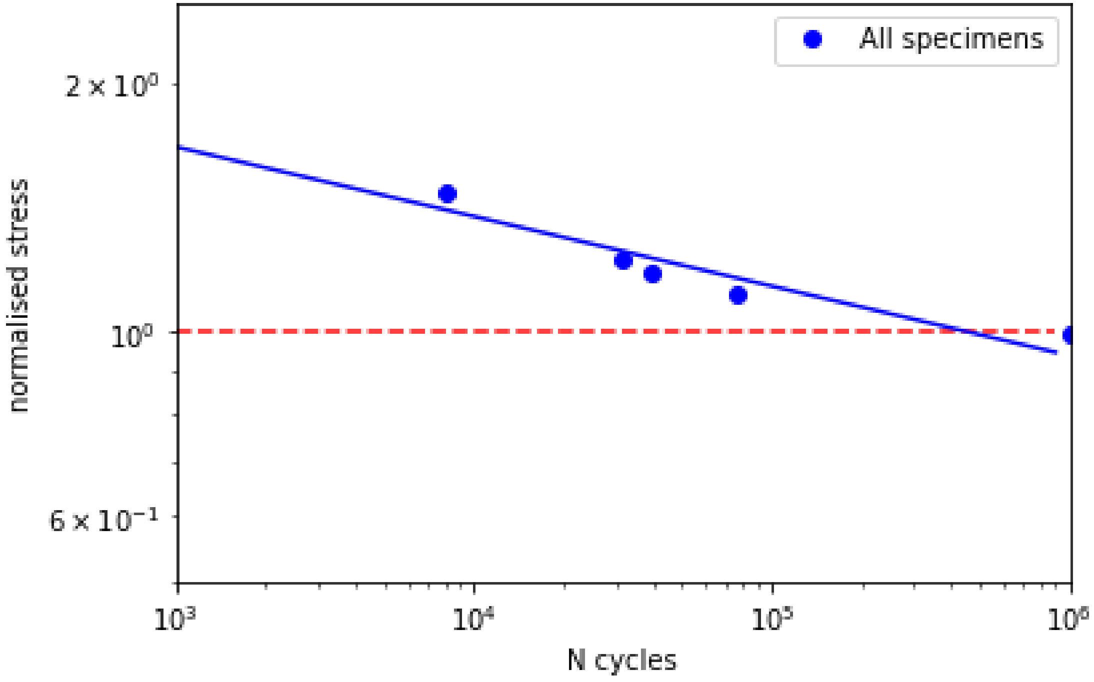
- Fatigue reduction factors from the experiments can be defined as,

$$k_f = \frac{\sigma_{amp,healthy}|@\ N\ cycles}{\sigma_{amp,samples}|@\ N\ cycles}$$

$$\sigma_D = \frac{\sigma_{D,healthy}}{K_f}$$

- **Fatigue limit reduces as much as k_f**



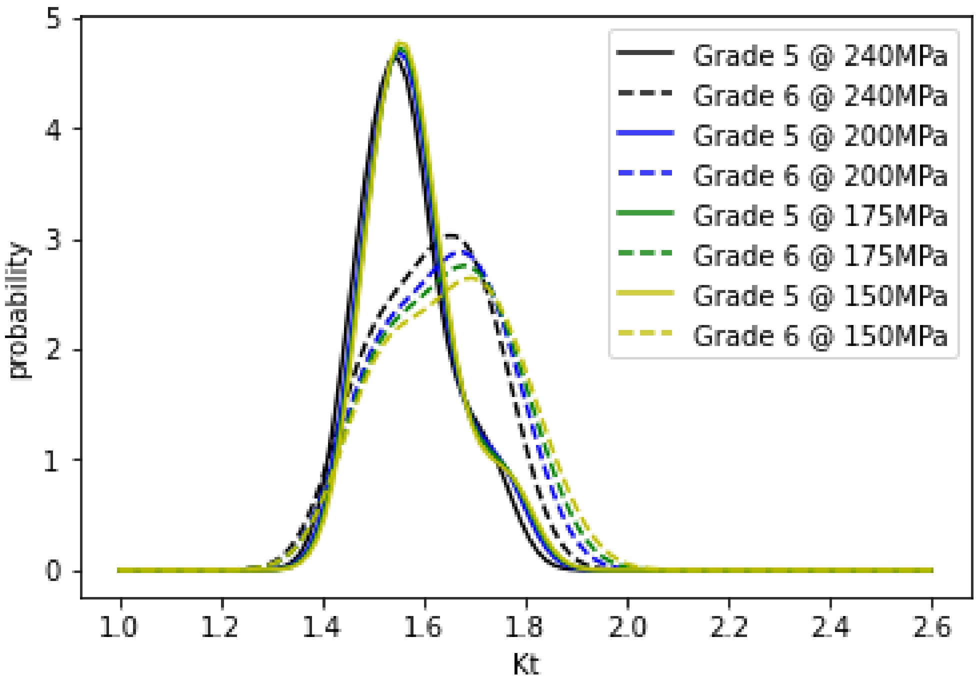


Fit an exponential law for number of cycles to failure – **Basquin law**

$$\frac{\sigma}{\sigma_D} = C * (N)^b$$

Synthetic samples – Simulations

Assuming Fatigue reduction factor == Stress concentration factor,
As in the case of notches



Stress concentration factor measured as,

$$K_t = \frac{\sigma_{local}}{\sigma_{nominal}}$$

Fatigue limit (10e+6 cycles) reduces as much as SCF

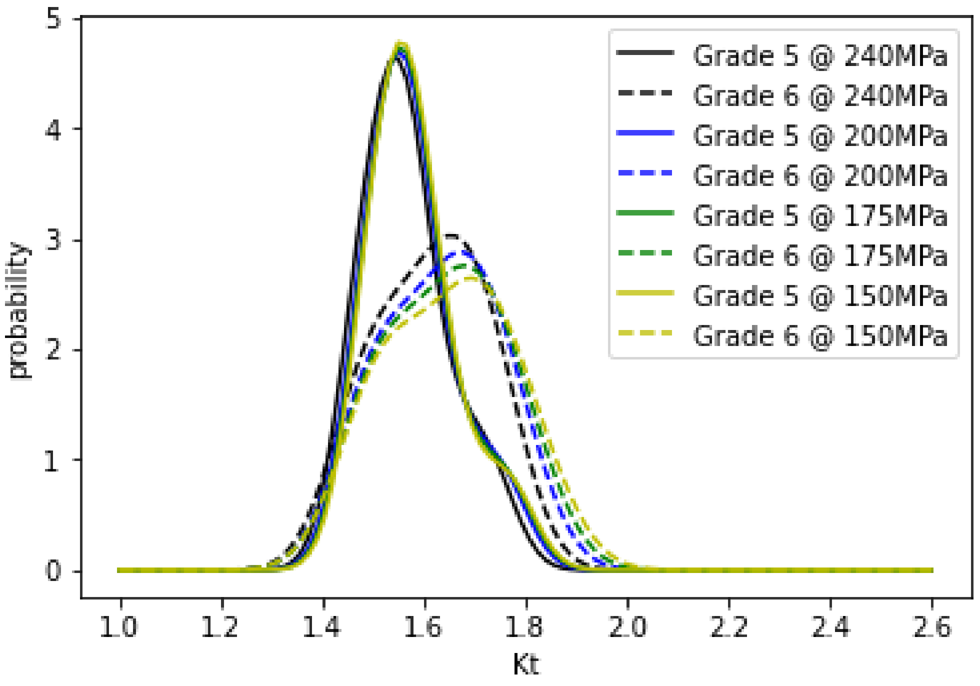
$$\sigma_D = \frac{\sigma_{D,healthy}}{K_t} = \frac{\sigma_{D,healthy} * \sigma_{nominal}}{\sigma_{local}}$$

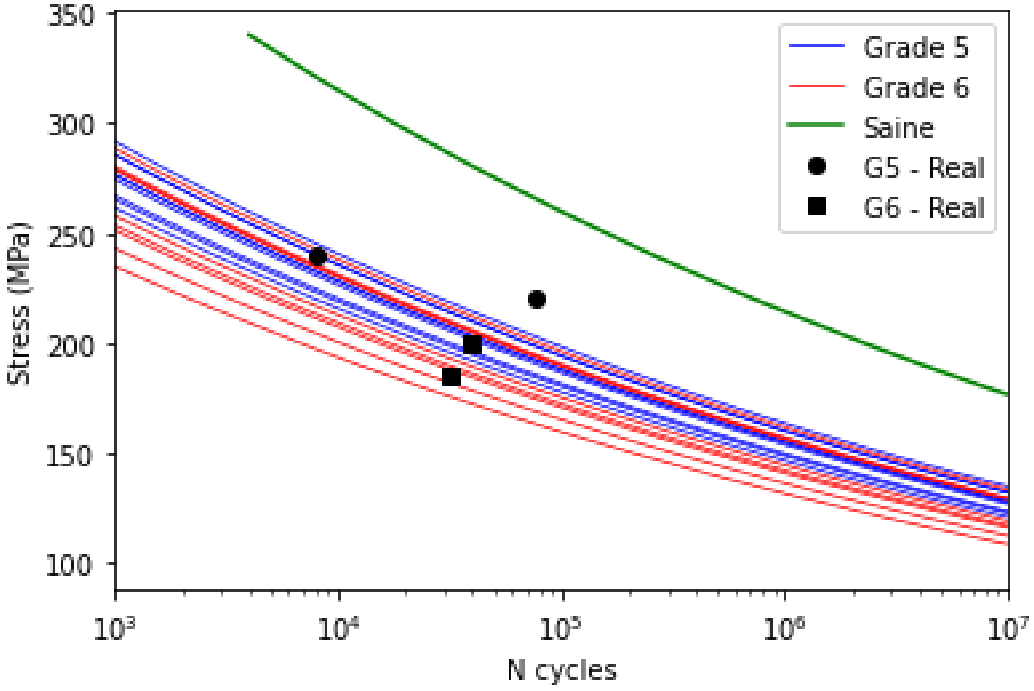
Substituting for σ_D,

$$\frac{\sigma_{nom}}{\sigma_D} = \frac{\sigma_{local}}{\sigma_{D,healthy}} = C * (N)^b$$

Synthetic samples – Simulations

Assuming Fatigue reduction factor == Stress concentration factor,
As in the case of notches





Introduction

Synthetic Microstructures

Preliminary numerical results

Perspectives

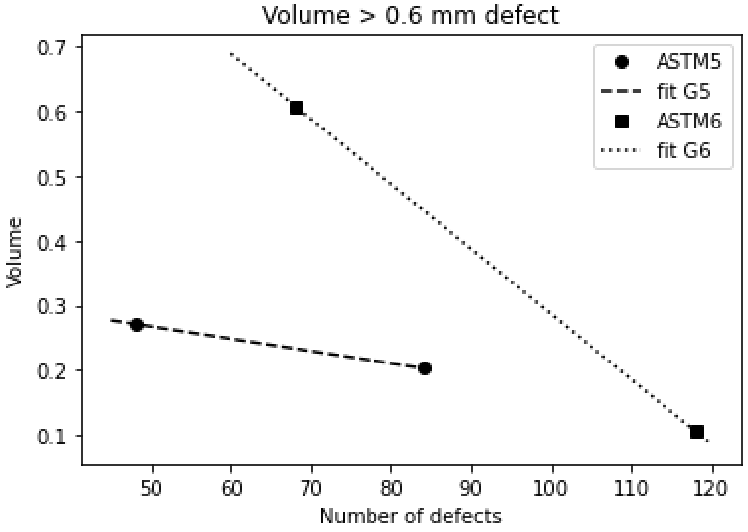
Conclusions and perspectives

- Samples of IN100 fail at the zone of clustered defects
- Synthetic microstructures can exactly mimic real samples and can be used to create a large database of mechanical response
- It is possible to generate synthetic microstructure of particular ASTM grade
- The cluster volume has a direct influence on fatigue due to high probability of large defects in the cluster
- An analysis similar to sensitivity analysis can be done using synthetic microstructure to estimate influence of cluster volume, thickness etc on stress gradients
- Monte carlo kind of approach to predict probable fatigue life based on cluster characteristics
- Experimental tests of more samples to estimate crack initiation

Merci!! Thank you for your attention

Back-ups

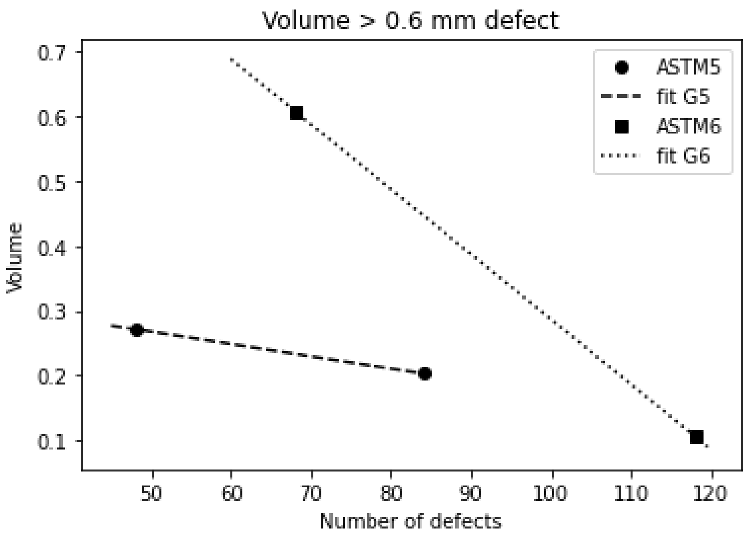
Synthetic samples – selon ASTM



Volume of defects larger than 0.6mm is specific to ASTM grade.

Hence a fit is constrained here on the volume of defects

Synthetic samples – selon ASTM



Volume of defects larger than 0.6mm is specific to ASTM grade.

Hence a fit is constrained here on the volume of defects

Choose no. defects

↓

Fit defect size distribution as per the fit

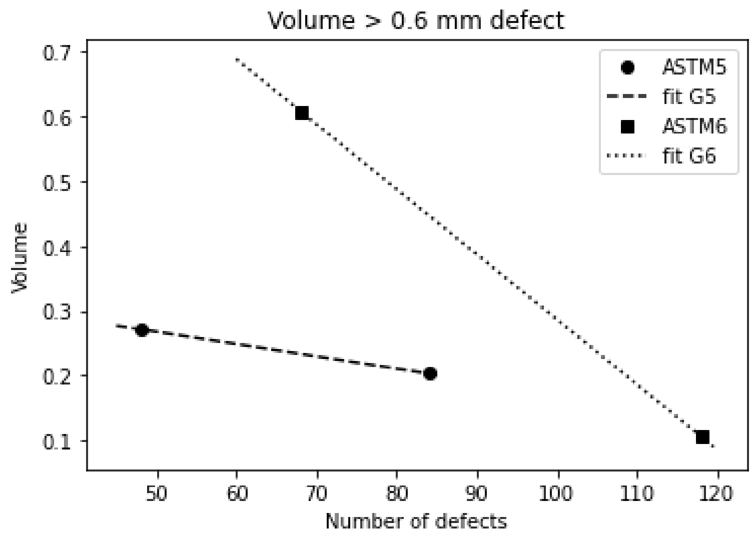
↓

Constrain volume of defects > 0.6mm as per ASTM grade

↓

Fit the maximum size as per the volume of defects > 0.6mm

Synthetic samples – selon ASTM



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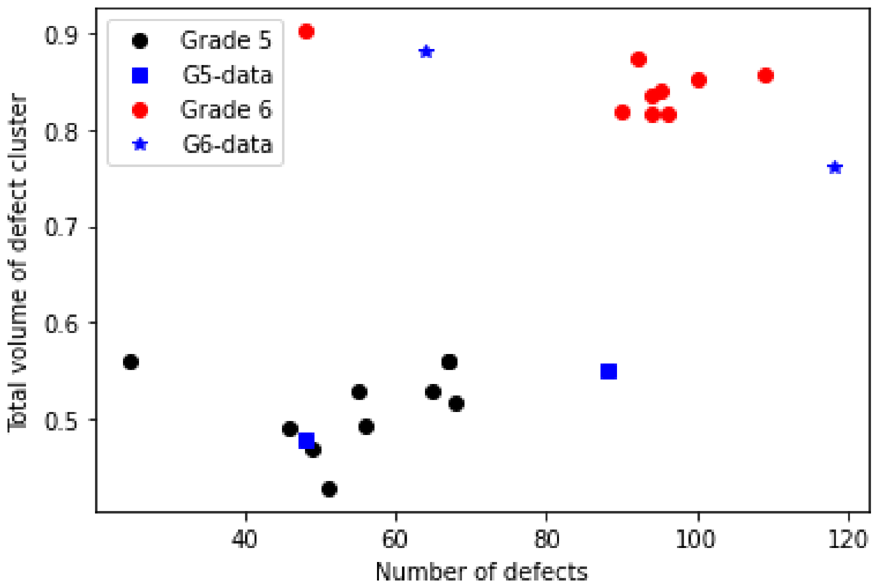


Total volume of cluster of generated samples

o → Synthetic samples

ASTM Grade – Synthetic samples

Sample	Area (in mm2)	Volume of defects in cluster	Number of defects
Grade 5	**1.47**		
2L1	1.0	0.48	48
2P1	1.2	0.55	88
Grade 6	**2.21**		
2R1	2.99	0.88	64
2S1	1.98	0.76	118

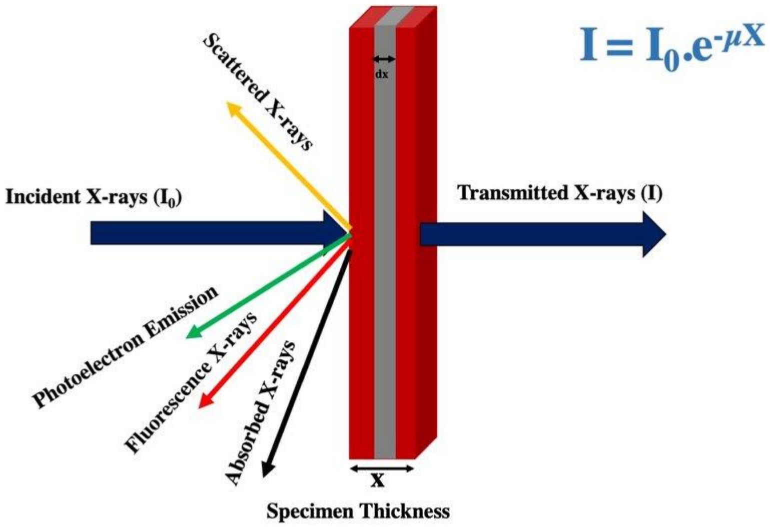
Less number of defects but more larger defects

More number of defects but less larger defects

- **Two different distributions for each grade**
- **By constraining volume and using respective distribution of ASTM grade, synthetic samples respecting grades are generated**

Virtual Radiography

Beer-Lambert Law of X-ray intensity :



For small discretized thickness dx,

$$I = constant \, * \int_0^L dx$$

L → Length of the material

I → Intensity

$$I = constant * \sum_0^L dx$$

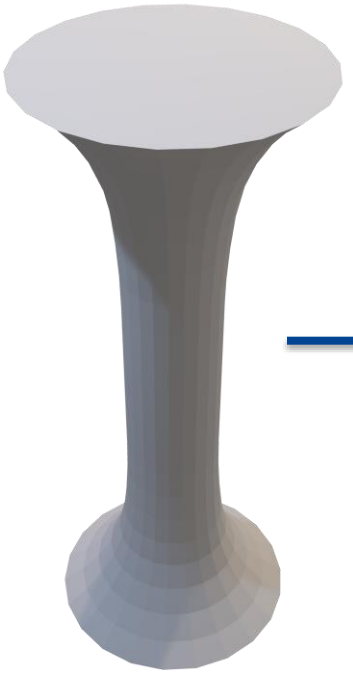
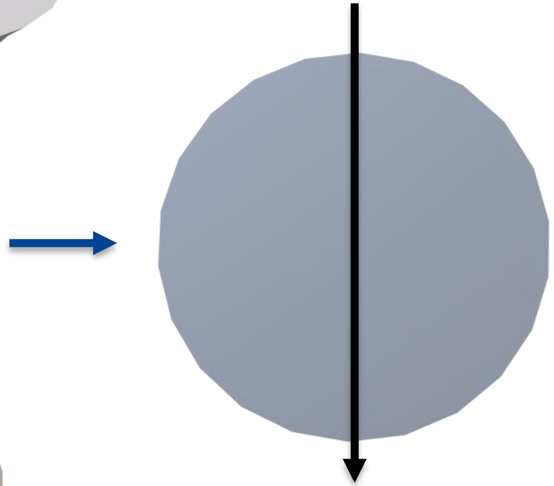
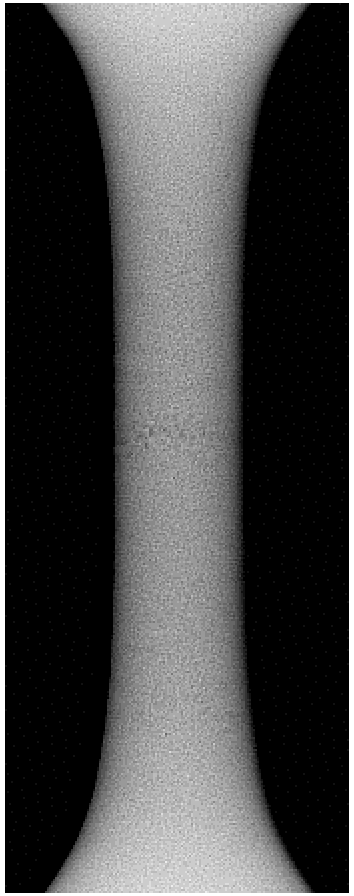


Image of sample



Summation in direction perpendicular to axis for Radiography

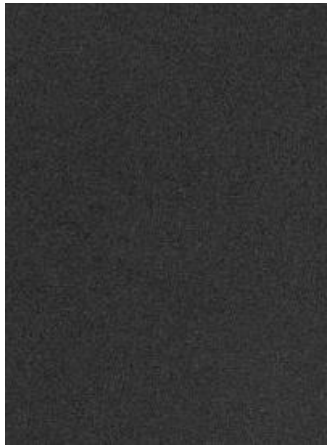


Virtual Radiography

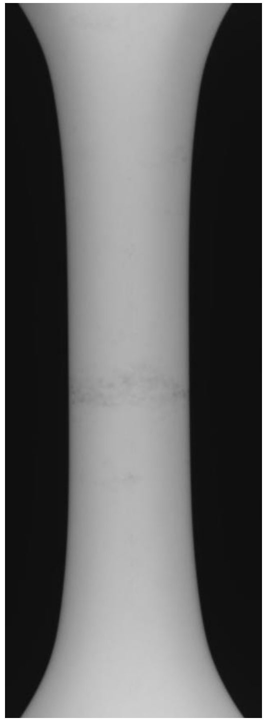
Virtual RX - Preprocess

ASTM norm 1/8 in (3mm) – Spongeous Shrinkage

- Homogeneous Radiography examples for a thickness of 3mm and can be applied for a thickness of upto 6mm
- Image resolution of 100µm
- Different greyscale intensity



Example



- Apply correction factor to transfer cylinder into a plate
- Resize as per the resolution of ASTM examples
- Greyscale intensity matching by Boolean operations

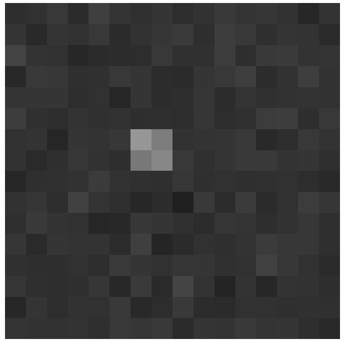
ASTM grade - Prediction

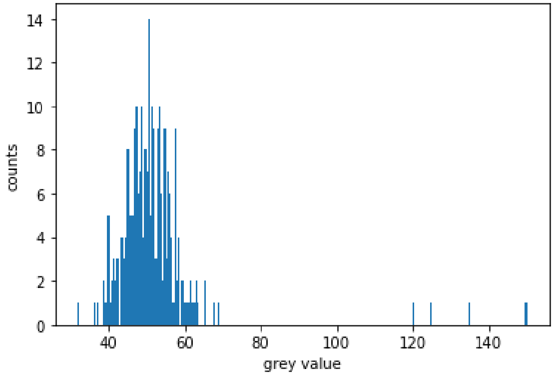
Shannon entropy: -

$$H(X) = -\sum_{x \epsilon X} p(x) log_b(x)$$

X → Image

x → each greyscale value between 0-255

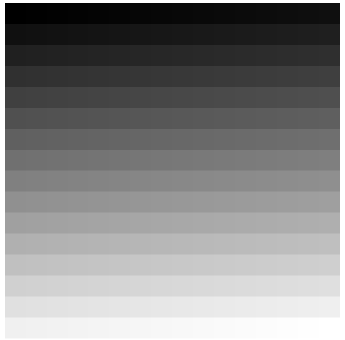


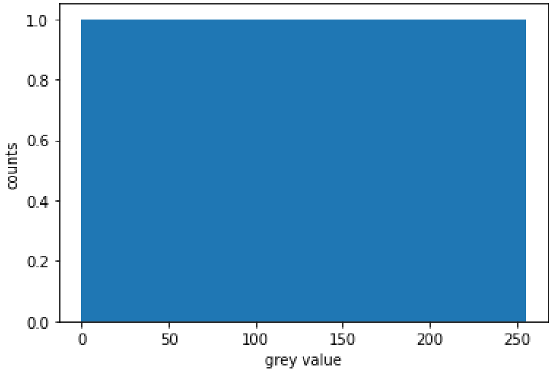


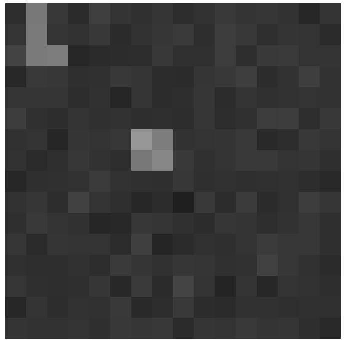
Entropy = 5.3

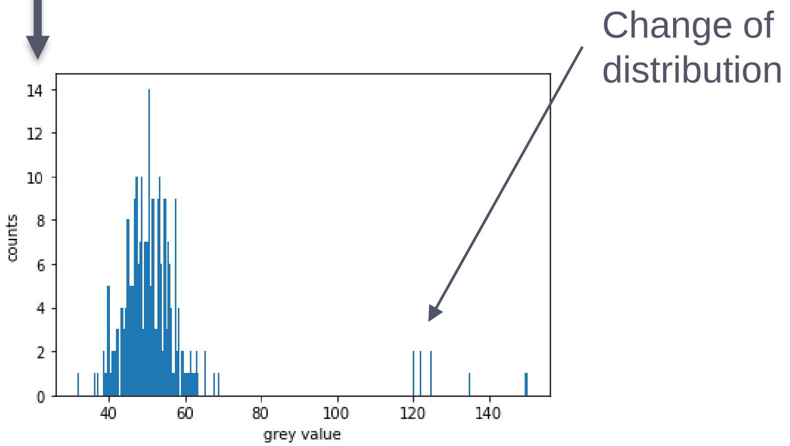
Entropy considers the intensity of **Defect indication** and its size

Add a defect





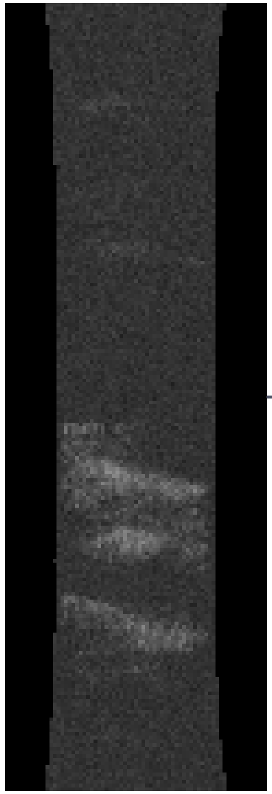




Entropy = 5.5

Max entropy @ uniform distribution = 8.0

ASTM grade - Prediction

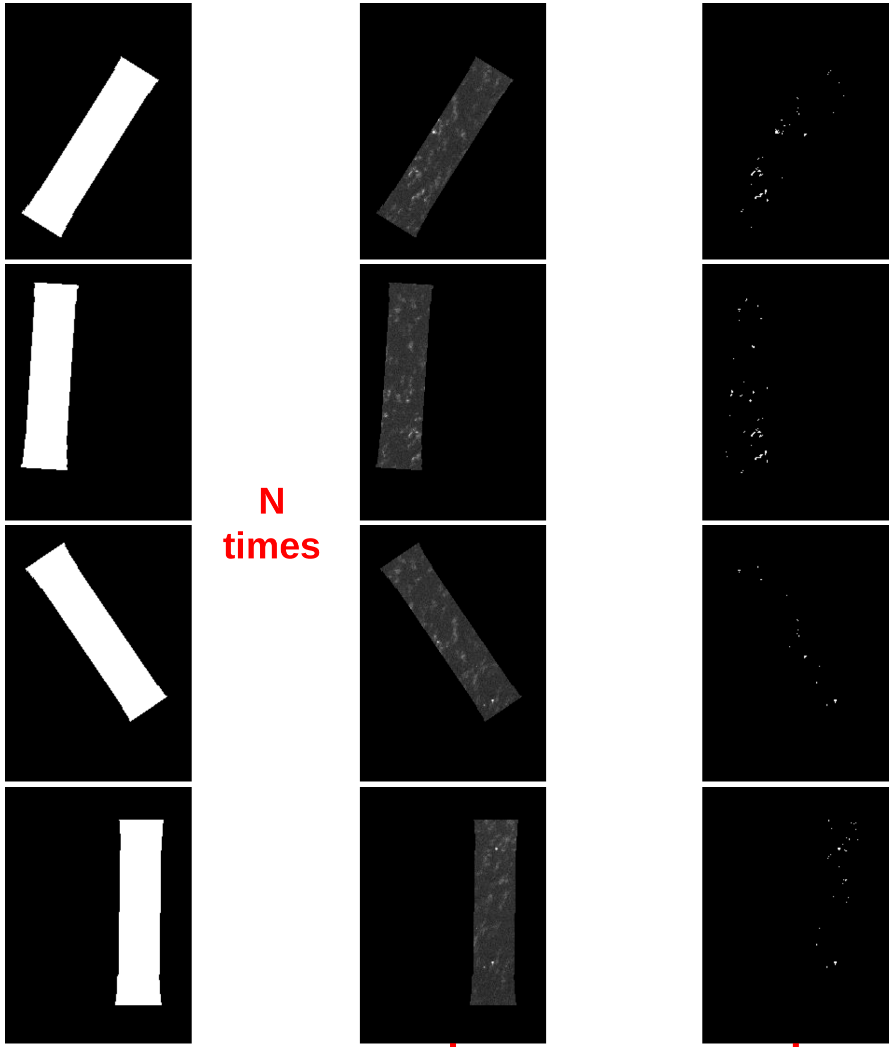


Reference Image G1

Reference Image G2

Reference Image G8

Create Mask of Virtual RX



N times

Measure entropy

Measure area of defect indication

Mean entropy

Mean Area

$$Metric = [\mu(Entropy_{Ref}) - (Entropy_{RX})] * f_E + [\mu(Area_{ref}) - (Area_{RX}]) * f_A$$

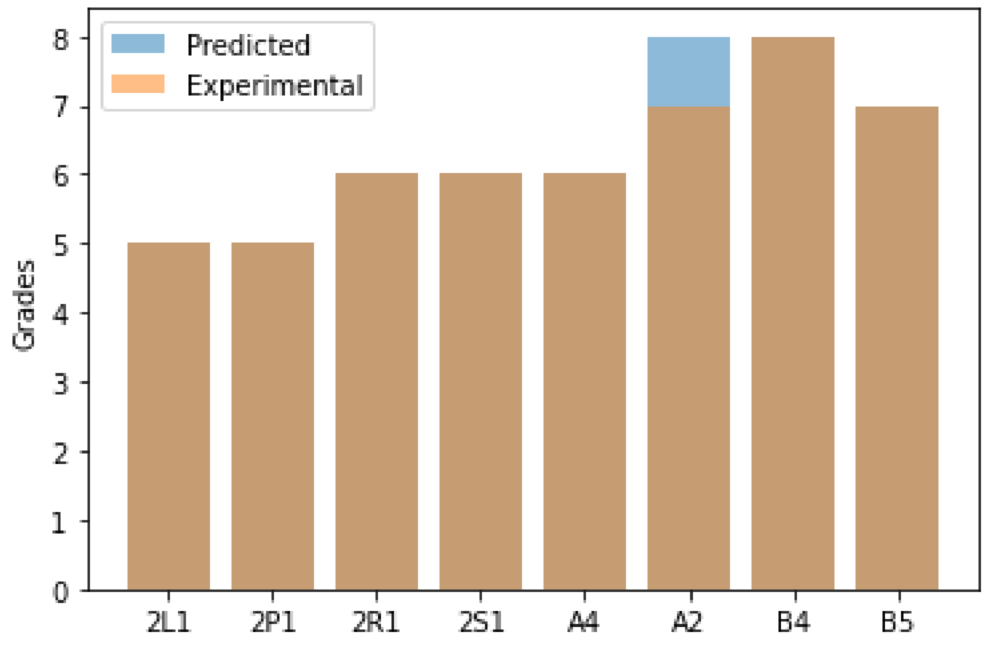
Ref→ Reference images of ASTM

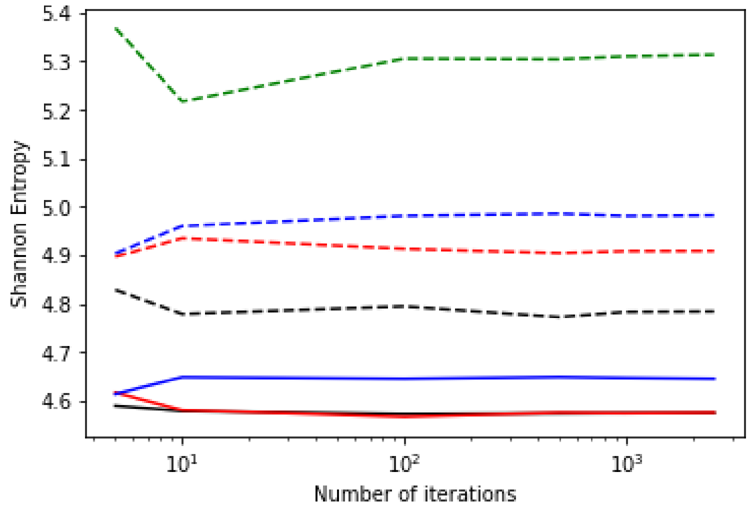
RX → Calibrated Virtual RX images of samples

f_E = factor to control contribution of entropy

f_A = factor to control contribution of Area

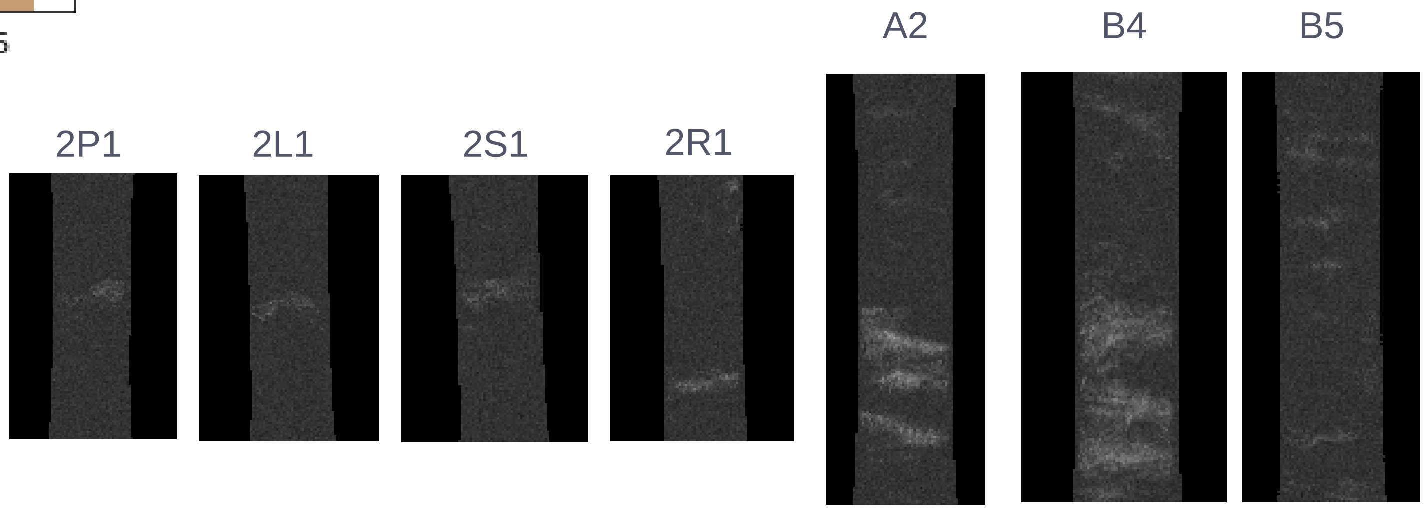
ASTM grade - Prediction





Multiple iterations needed so that the measurements are constant

Perfect predictions for all samples except one

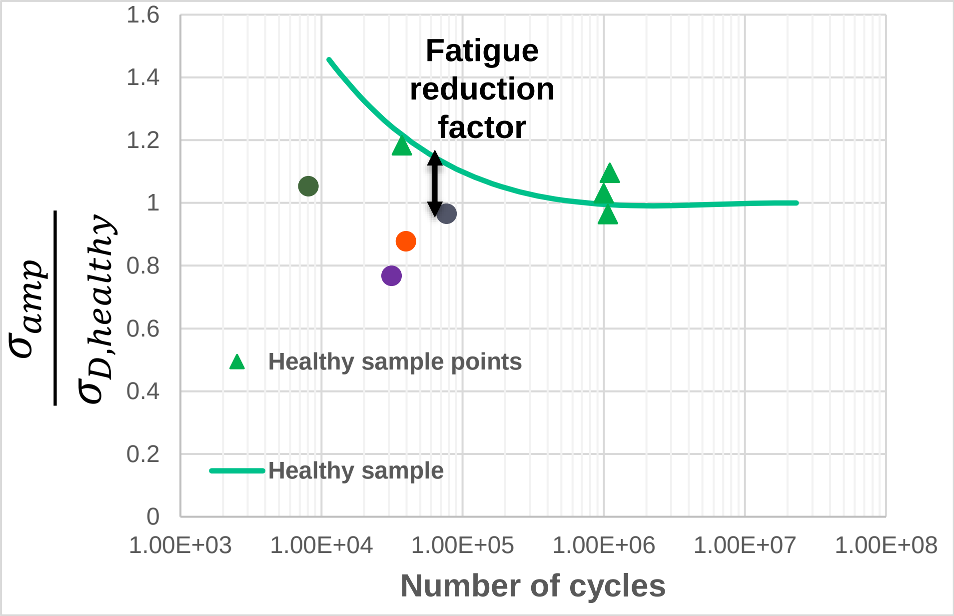


Fatigue Reduction factor

- Fatigue reduction factors from the experiments can be defined as,

$$k_f = \frac{\sigma_{amp,healthy}|@\ N\ cycles}{\sigma_{amp,samples}|@\ N\ cycles}$$

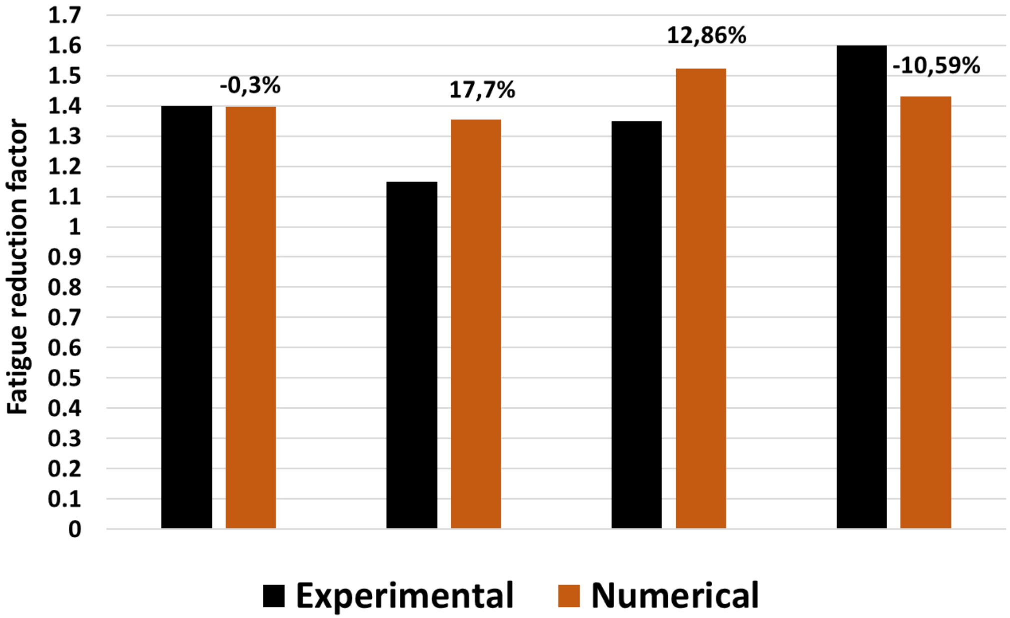
- **Fatigue limit reduces as much as k_f**



- By numerical approach, stress concentration factors are the fatigue reduction factors such that,

$$\sigma_D = \frac{\sigma_{D,healthy}}{k_{t,critical}}$$

With the assumption that, $k_t = k_f$



Ref: Matpadi Raghavendra et al (2022)