## Extreme-Value Analysis of Corrosion Data

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## Outline

Motivation

Objective of the Thesis

Methods used

Data declustering

Examples of application

Framework for modelling extremes of corrosion

Conclusions and recommendations





## Motivation

- in the oil industry, hundreds of kilometres of pipes and other equipment can be affected by corrosion
- ▶ it is extreme defect depth/wall loss that influences the system reliability ⇒ extreme-value methods are sensible for application
- ▶ only part of the system can be subjected to inspection ⇒ results extrapolation is needed



## Motivation

▶ defects/wall losses caused by corrosion are likely to be locally dependent ⇒ independence assumption questionable









# Objective of the Thesis

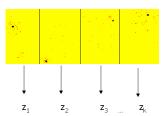
- present statistical methods to model extremes of corrosion data, taking into account local defect dependence
- spatial extrapolation of the results
- examples of application
- framework/guideline for modelling extreme-values of corrosion





### Methods used

The Generalised Extreme-Value (GEV) distribution (block maxima data)

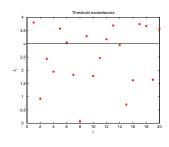


$$G(z) = egin{cases} \exp\left\{-\left[1+\xi\left(rac{z-\mu}{\sigma}
ight)
ight]_+^{-rac{1}{\xi}}
ight\}, & \xi 
eq 0 \ \exp\left\{-\exp\left[-\left(rac{z-\mu}{\sigma}
ight)
ight]
ight\}, & \xi = 0, & aguruputus \ \end{bmatrix}$$

## Methods used

The Generalised-Pareto (GP) distribution (excess over threshold data)

$$Y_i = X_i - u$$
, for  $X > u$ ,  $i = 1, \ldots, n_u$ 



$$H(y) = \begin{cases} 1 - \left[1 + \frac{\xi y}{\bar{\sigma}}\right]_{+}^{-1/\xi}, & \xi \neq 0 \\ 1 - \exp\left(-\frac{y}{\bar{\sigma}}\right), & \xi = 0 \end{cases}$$

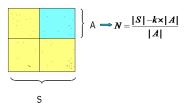




# Methods used (extrapolation-GEV)

return-level method

$$G(z_p) = 1 - p \Leftrightarrow Pr\{M > z_p\} = p = \frac{1}{N}$$



implied distribution of the maximum corresponding to the not inspected area

$$Pr\{X_N \le z\} = G_N(z) = G(z)^N$$



# Methods used (extrapolation-GP)

based on Poisson frequency of threshold exceedances (Poisson-GP model)



return-level method

$$H(y_p) = 1 - p \Leftrightarrow Pr\{Y > y_p\} = p = \frac{1}{N_F}$$

 $N_E = \lambda_{GEV} \times (|S| - k \times |A|)$  - expected number of exceedances on the not inspected area

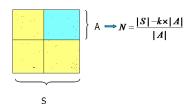




## Methods used (extrapolation-GP)

implied distribution of the maximum corresponding to the not inspected area

$$Pr\{X_N \le x\} = \exp\left\{-\lambda_{GEV} \left(1 + \xi \frac{x - u}{\bar{\sigma}}\right)_+^{-1/\xi}\right\}^N$$







## Methods used-summary

- two methods for statistical inference about extreme-values of corrosion
  - the GEV distribution (block maxima)
  - the GP distribution (excess over threshold data)
- two methods for spatial results extrapolation
  - return-level
  - distribution of the maximum corresponding to the not inspected area
- ▶ the GEV and GP distributions are closely related and theoretically, should give the same results





# Modelling extremes of dependent data

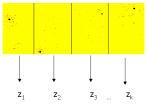
- ▶ for the stationary data characterised by the limited extend of long-range dependence at extreme levels, the extreme-value methods can be still applied
- ▶ in corrosion application it is reasonable to assume that pit depths are locally dependent ⇒ extreme-value methods are applicable





# Modelling extremes of dependent data with the **GEV** distribution

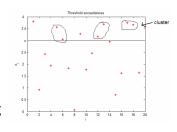
- assuming local data dependence, block maxima of stationary data (for sufficiently large block sizes) can be considered as approximately independent
- the GEV distribution is used in its standard form





# Modelling extremes of dependent data with the **GP** distribution

- neighbouring exceedances may be dependent, therefore the change of practise is needed
- one of the most widely adopted method is data declustering filtering out dependent observations such that remaining exceedances can be considered as approximately independent

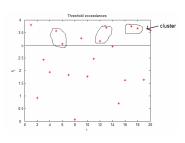






# Modelling extremes of dependent data with the **GP** distribution-approach

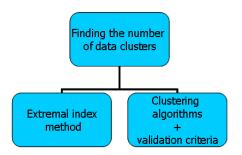
- define clusters of exceedances
- identify maximum excess within each cluster
- assuming that cluster maxima are independent fit the GP distribution







Estimation of the number of data clusters







#### Extremal index method:

 the extent of short-range dependence of extreme events is captured by the parameter θ, called extremal index

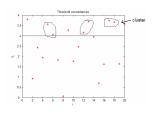
$$heta = rac{1}{ ext{limiting mean cluster size}}$$

 extremal index measures the degree of clustering of the process at extreme levels





#### Extremal index method



$$\theta = \frac{1}{\text{limiting mean cluster size}} \Rightarrow N_c = \theta \times N_e$$

where  $N_c$  - number of clusters,  $N_{\rm e}$  - number of exceedances above threshold u

 $\theta$  is estimated by the intervals estimator



Finding number of clusters using clustering algorithm

- define a validity criteria for the number  $N_c$  of found clusters
- $\triangleright$  run the clustering algorithm for a range of  $N_c$
- as proper number of clusters choose the one for which the validity criteria are optimised





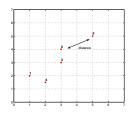
# Agglomerative hierarchical clustering algorithm

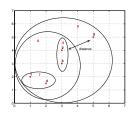
- starts with single points as clusters
- at each step the two closest clusters are merged
- stops when only one cluster remains

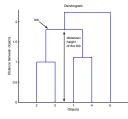




# Agglomerative hierarchical clustering algorithm











Validation criteria, that we used, aim at identifying clusters that are compact and well isolated:

- silhouette plot maximum value indicates optimum
- Davies-Bouldin index minimum indicates optimum





## Data declustering-summary

- two methods to estimate the number of data clusters
  - the extremal index method
  - clustering algorithm + validation criteria (Davies-Bouldin index, silhouette plot)
- prior to data declustering perform clustering tendency test



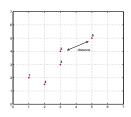


## Simulated corroded surface

- application of the gamma-process model
- dependence in terms of the product moment correlation

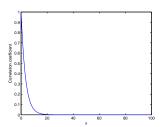
$$\rho(X_k, X_l) = \exp\left\{-d\left(\sum_{i=1}^2 |dist_i|^p\right)^{q/p}\right\}$$

$$X_k = (x_k, y_k), X_l = (x_l, y_l),$$
  
 $dist_1 = |x_k - x_l|, dist_2 = |y_k - y_l|,$   
 $d = 0.3, p = 2, q = 1$ 





## Simulated corroded surface

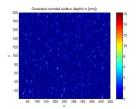


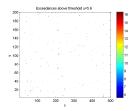
Matrix 1	Matrix 2	Matrix 3	Matrix 4	Matrix 5
Matrix 6	Matrix 7	Matrix 8	Matrix 9	Matrix 10
Matrix 11	Matrix 12	Matrix 13	Matrix 14	Matrix 15
Matrix 16	Matrix 17	Matrix 18	Matrix 19	Matrix 20

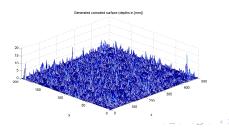




## Simulated corroded surface

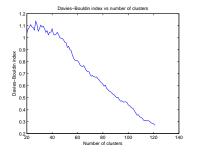


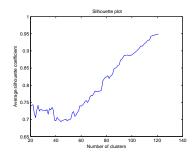






# Simulated corroded surface - clustering algorithm









## Simulated corroded surface - results

$\hat{ heta}$	nc	$n_{c_{alg}}$
0.544	107	121

Table: The estimate of extremal index and determined number of clusters

Number of clusters	$AD_{up}^2 p - v$ .	KS p - v.
107	0.376	0.204
121	0.549	0.493

Table: Goodness-of-fit test results for different number of clusters





ξ	$\hat{\overline{\sigma}}$	$AD_{up}^2 p - v$ .	KS p - v.
0.065	1.341	0.647	0.488

Table: GP fit to excess of dependent data

ξ̂	$\hat{ar{\sigma}}$	$AD_{up}^2 p - v$ .	KS p - v.
-0.0137	1.6839	0.555	0.493

Table: GP fit to excess of declustered data

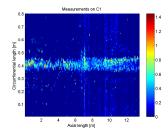
	$\hat{\xi}$	ô	$\hat{\mu}$	$AD_{up}^2 p - v$ .	KS p - v.
I	-0.007	1.627	5.637	0.621	0.899

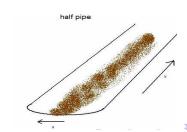
Table: GEV fit to block maxima data





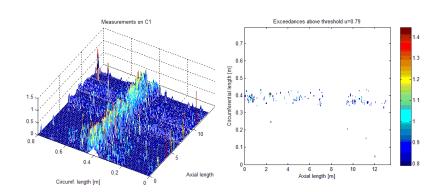
## Real data example







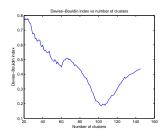
## Real data example

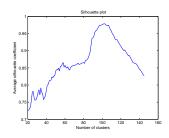






## Real data example









ξ	$\hat{\sigma}$	$\hat{\mu}$	$AD_{up}^2 p - v$ .	KS p - v.
-0.082	0.182	0.757	0.713	0.986

Table: GEV fit to block maxima data

ξ	$\hat{ar{\sigma}}$	$AD_{up}^2 p - v$ .	KS p - v.
-0.008	0.133	0.616	0.074

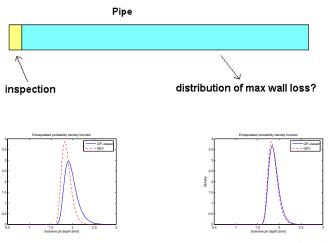
Table: GP fit to excess of dependent data

ξ	$\hat{\sigma}$	$AD_{up}^2 p - v$ .	KS p - v.
-0.069	0.172	0.717	0.654

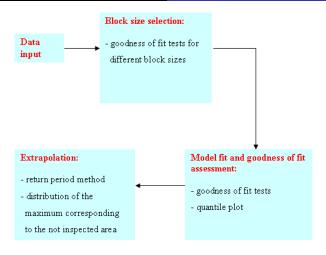
Table: GP fit to excess of declustered data





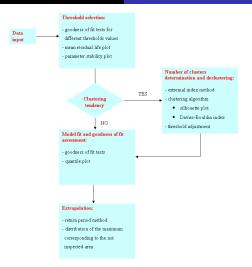






Framework for modelling extremes of corrosion with the GEV distribution







### Conclusions and recommendations

- ▶ the two applied distributions are closely related and lead to the consistent inference about extreme-values of corrosion
- data declustering improves the results given by the GP distribution
- the performance of other clustering algorithms could be checked
- in order to take into account corrosion nonstationarity due to space-varying environmental conditions, covariate-dependent extreme-value models with trends could be considered



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## THANK YOU FOR ATTENTION

Questions???



