

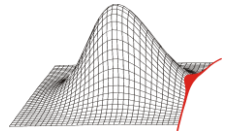
# Meta-model-based Quality Assessment of Sample Estimates

Andriy Prots, Lars Högner, Matthias Voigt, Ronald Mailach

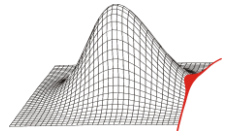
[Andriy.Prots@tu-dresden.de](mailto:Andriy.Prots@tu-dresden.de)

Dresden, October 10, 2019

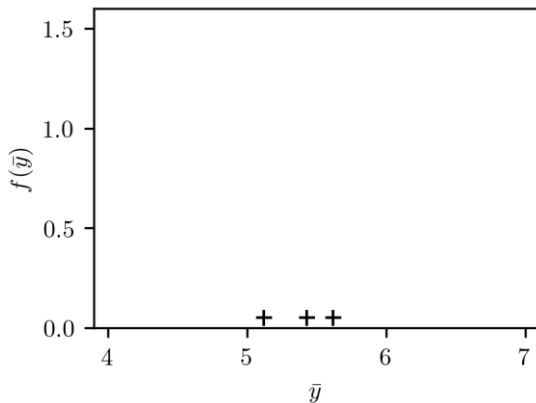




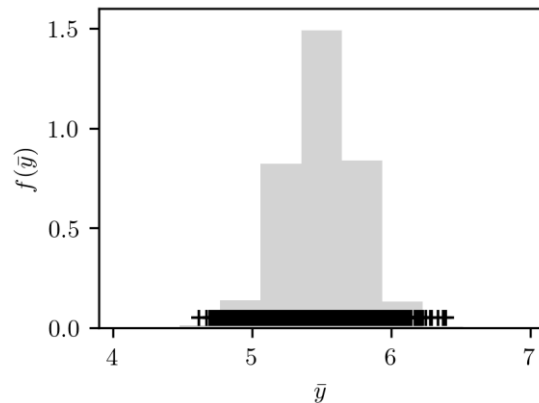
1. Motivation
2. Theoretical Foundation
3. Presentation of the new Methods
4. VMCS – A Framework for Application
5. Summary



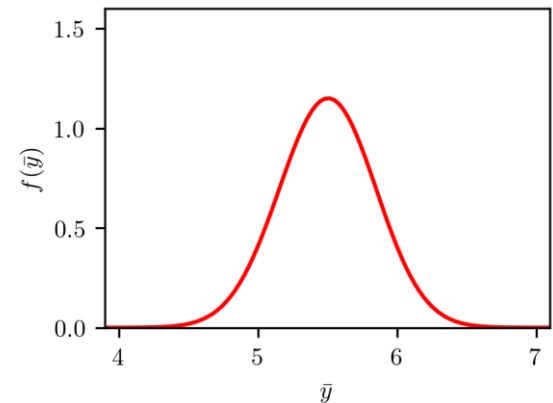
- Probabilistic Methods are gaining in importance
- Monte Carlo simulation (MCS):
  - Sample of representative realizations (e. g. with Simple Random Sampling (SRS))
  - Calculation of the sample with deterministic methods
  - Statistical evaluation of the results (Mean, Variance, Quantile value, Correlation Coefficient)
- Sample is generated randomly → Result of a MCS is also random



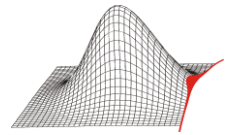
Andriy Prots



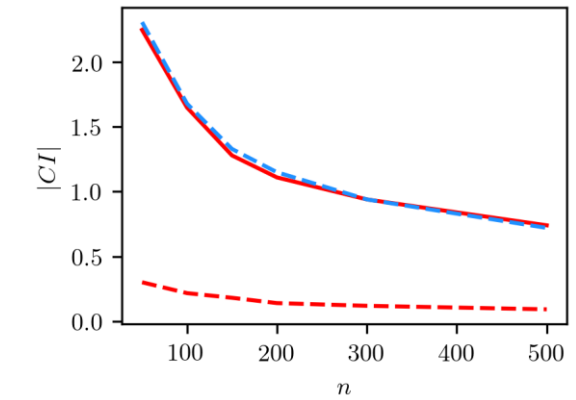
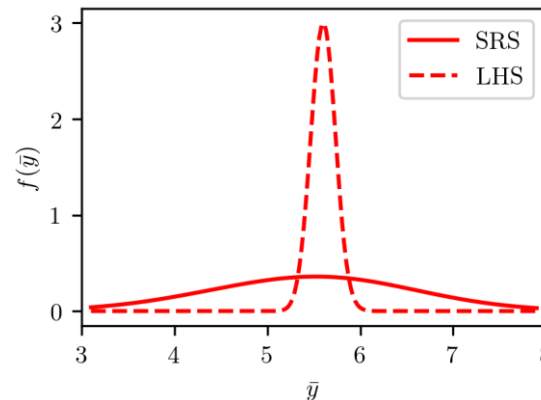
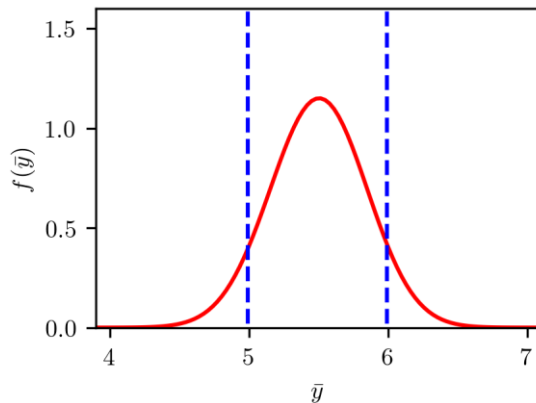
Meta-model-based Quality Assessment of Sample Estimates



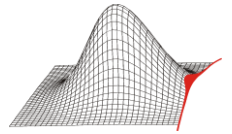
Slide 3



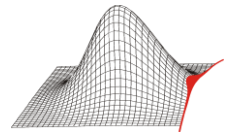
- Value to describe the variance of the result: Confidence Interval (CI)
- Real CI: repetitions of MCS required
- Determinable by analytical formulas or bootstrapping
  
- Latin Hypercube Sampling is used to reduce variance of result
  
- Problem 1: Known methods cannot describe the variance reduction
- Problem 2: Factor of variance reduction is unknown



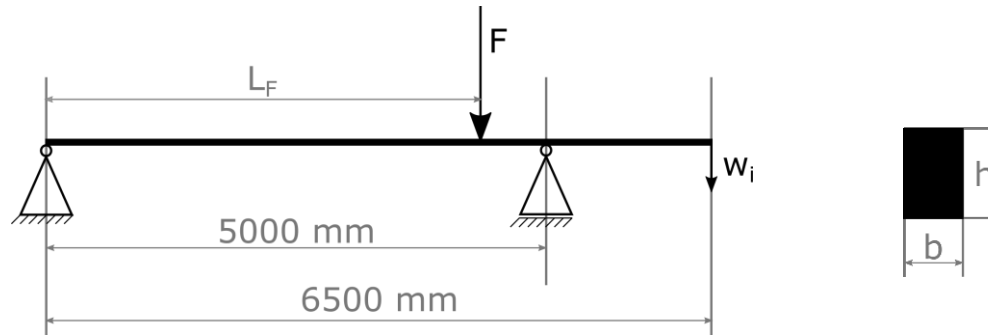
— SRS    - - - LHS    - - - analytical formulas  
 Slide 4



- Goal:
  - Predicting the size of CI more precisely, when using LHS
  - Reduce required sample size to reach a target size of CI
  
- Idea:
  - Approximate system behavior with meta model (MM)
  - Simulate MCS with help of MM
  - Evaluate virtual MCS
  
- Assumption:
  - Good description of system behavior with MM
  - Real MCS can be approximated with virtual MCS



➤ Beam system:

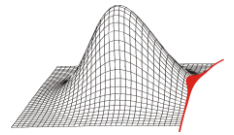


➤ Input values:

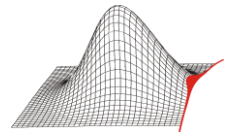
- Height  $h$  (uniform in [95 mm; 105 mm])
- Width  $b$  (uniform in [45 mm, 55 mm])
- Young's module  $E$  (normal with  $\mu = 210\,000\text{ GPa}$  und  $\sigma = 10\,000\text{ GPa}$ )
- Force  $F$  (normal with  $\mu = 2\,500\text{ N}$  und  $\sigma = 300\text{ N}$ )
- Position of the Force  $L_F$  (uniform in [0 mm, 6 500 mm])

➤ Output value:

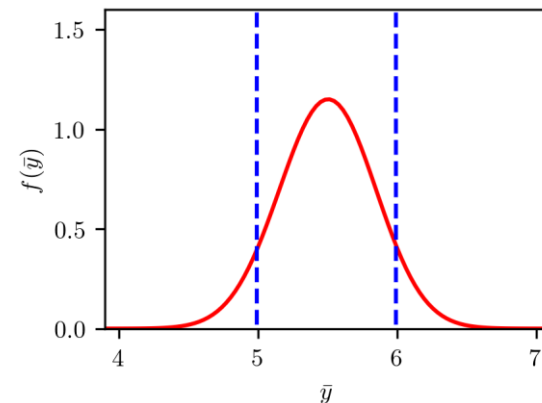
- Deflection  $w_i$  at the end (calculated by beam theory)



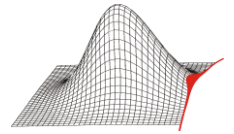
- MCS: description of system behavior based on a random sample
  
- Required steps:
  - Generate samples
  - Evaluate sample with deterministic models
  - Evaluate the results statistically
  
- Possible result values:
  - Mean
  - Variance / Standard deviation
  - Quantile values
  - Correlation coefficient



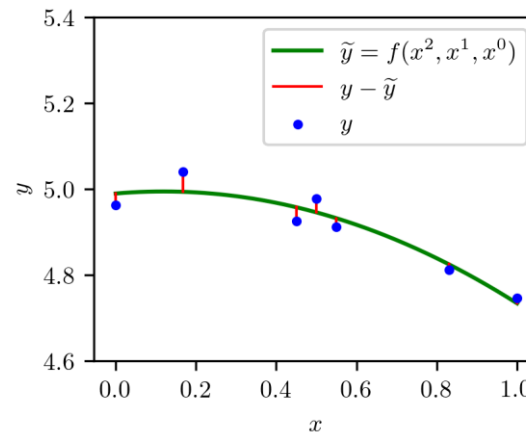
- Confidence Intervals (CI): describes the variance of a result value of MCS
- Significance level  $\alpha$ : CI contains the real value in  $(1 - \alpha) * 100\%$  of the cases
- Smaller CI  $\rightarrow$  result can be more trusted
- Possibilities of determining the CI
  - Repetition of MCS (not practical)
  - Analytical formulas
    - E. g. for mean:  $\bar{y} \pm z_{1-\frac{\alpha}{2}} \sigma/\sqrt{n}$
  - Bootstrapping
- Assumption: realization within sample are independent
- Reduction of variance from LHS is not considered!





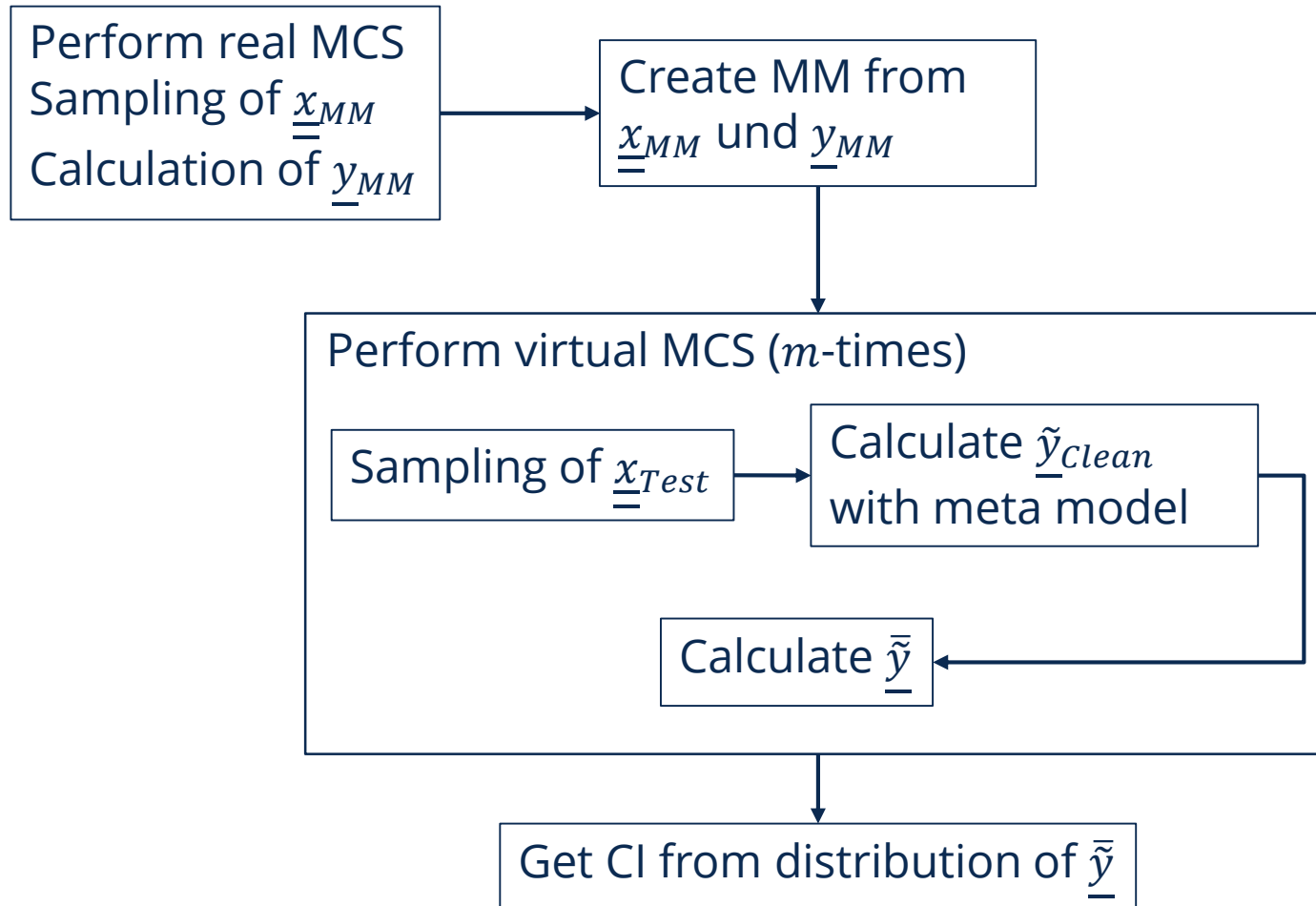
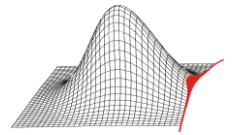


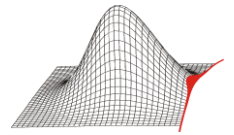
- Meta model (MM): description of system behavior with simple approach
- E. g. polynomial meta model:
  - $\tilde{y} = c_0 + c_1 x_1 + c_2 x_2 + c_3 x_1^2 + c_4 x_2^2$
- Determination of coefficients: least square approach



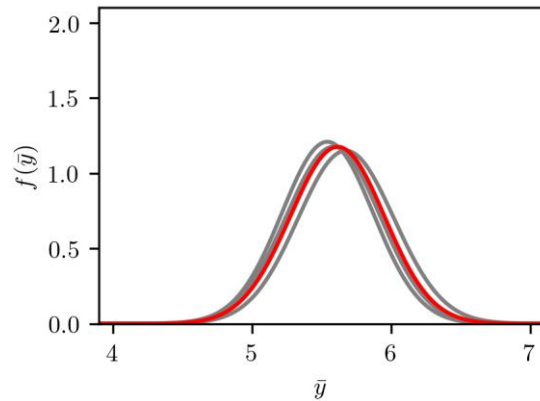
- Quality Assessment:

- Coefficient of Determination  $R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \tilde{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$
- Cross validation

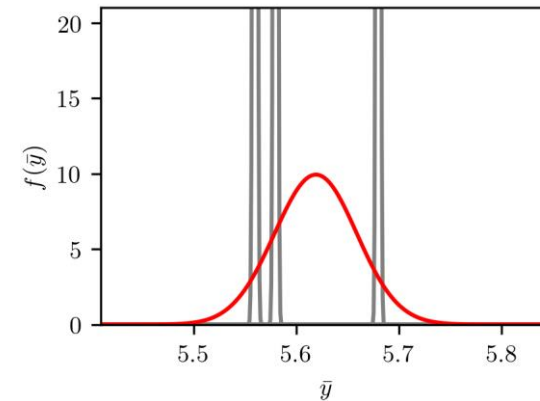




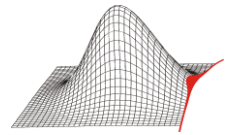
➤ SRS:



LHS:



- Works only for SRS
- Variance of mean heavily underestimated for LHS
- Reason: Error of the meta model  $\varepsilon = y - \tilde{y}$



- Impact of  $\varepsilon = y - \tilde{y}$ :

$$y = \tilde{y} + \varepsilon$$

$$\bar{y} = \tilde{y} + \bar{\varepsilon}$$

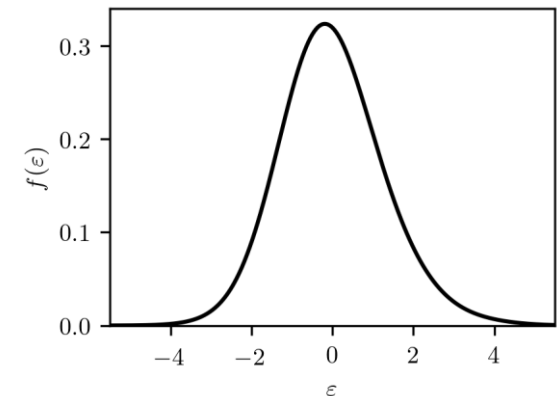
$$Var(\bar{y}) = Var(\tilde{y} + \bar{\varepsilon}) = Var(\tilde{y}) + 2Cov(\tilde{y}; \bar{\varepsilon}) + Var(\bar{\varepsilon})$$

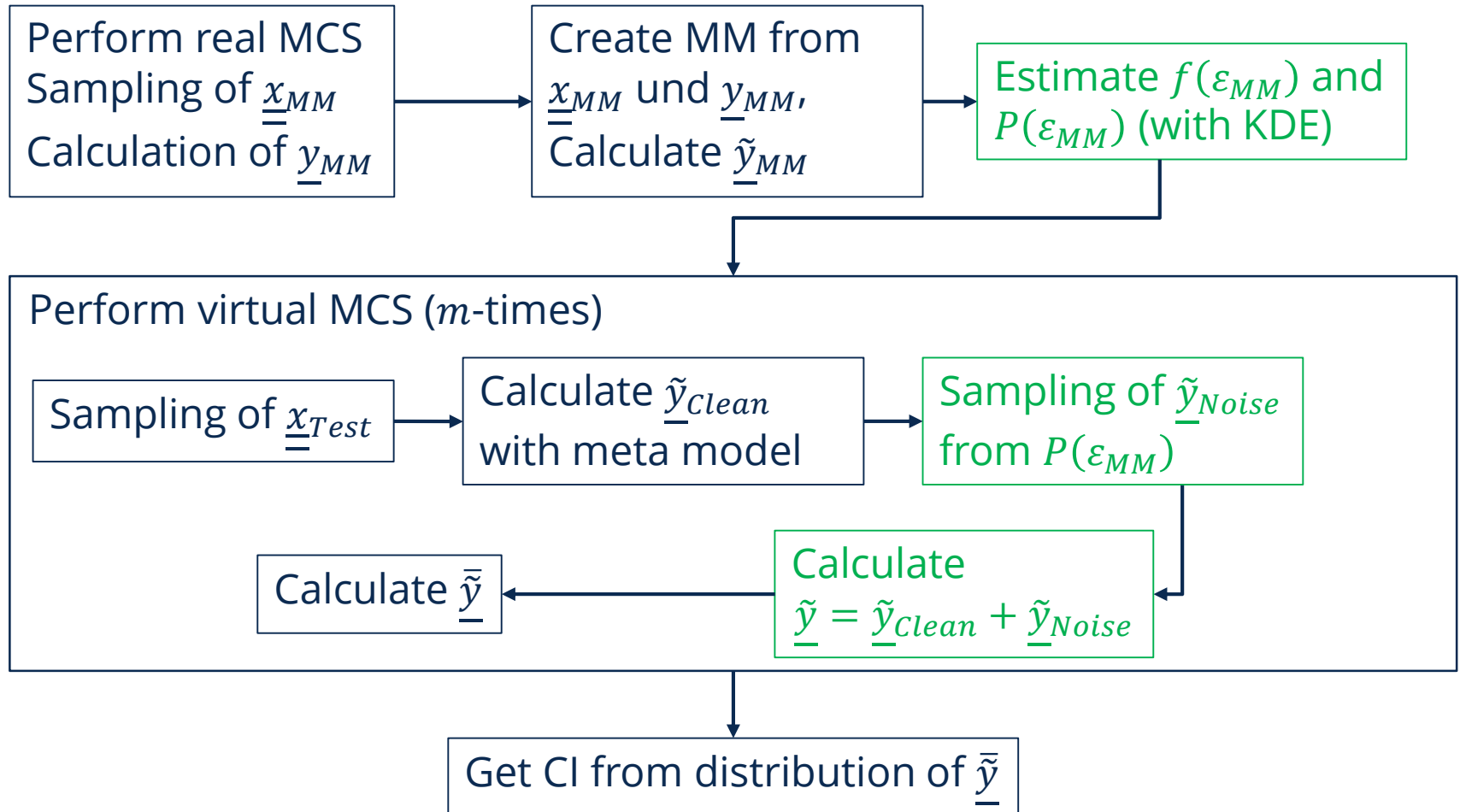
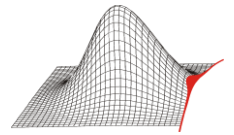
- Assumption: Independence between  $\tilde{y}$  and  $\varepsilon \Rightarrow Cov(\tilde{y}; \bar{\varepsilon}) = 0$   
 $Var(\bar{y}) = Var(\tilde{y}) + Var(\bar{\varepsilon})$

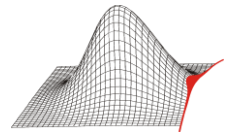
- Problem: for LHS often  $Var(\bar{\varepsilon}) \gg Var(\tilde{y})$

- Solution: generate additional sample for  $\varepsilon$
- Since independence between  $\tilde{y}$  and  $\varepsilon$  is assumed: only  $P(\varepsilon)$  is required

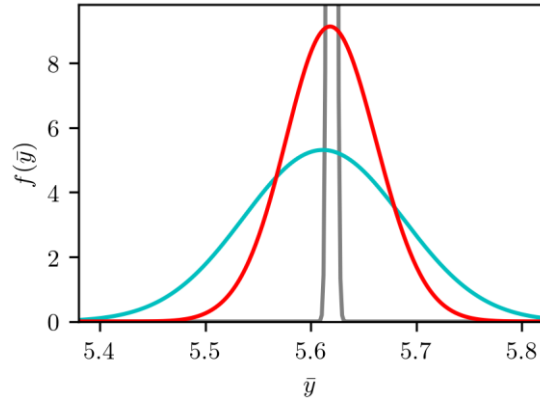
- Approximation of  $f(\varepsilon)$  with kernel density estimation (KDE),  
 Approximation of  $P(\varepsilon)$  with numerical integration



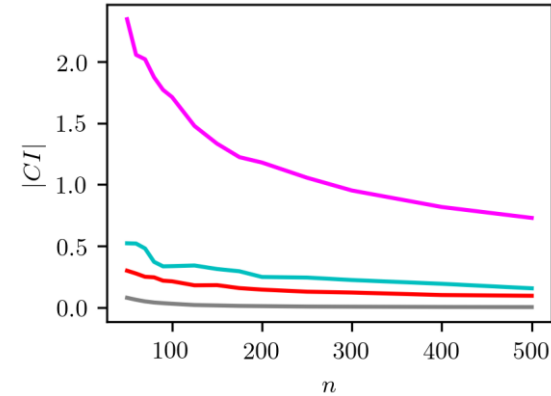




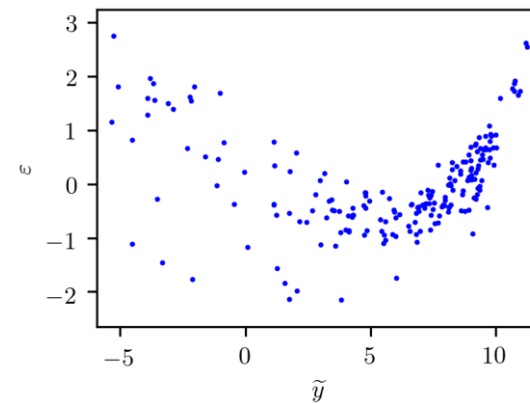
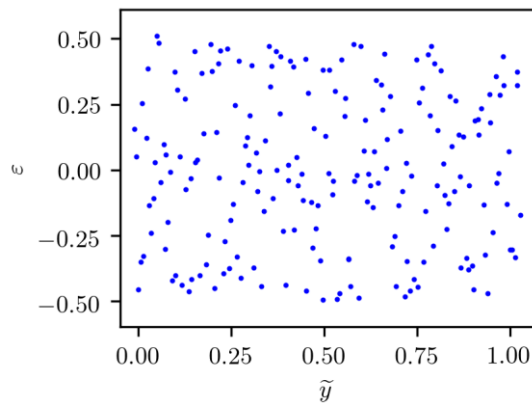
➤ LHS

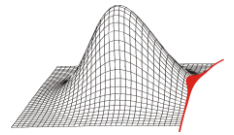


— real — M1 — M2 — analytische Formeln

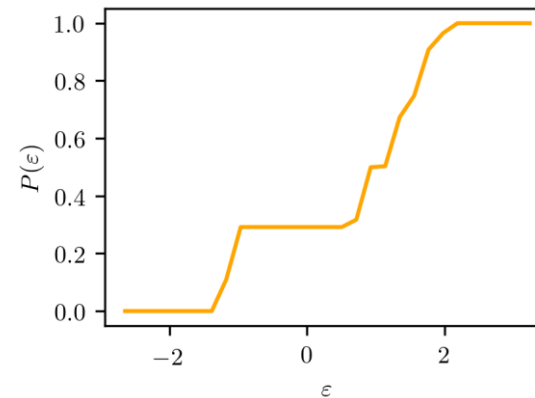
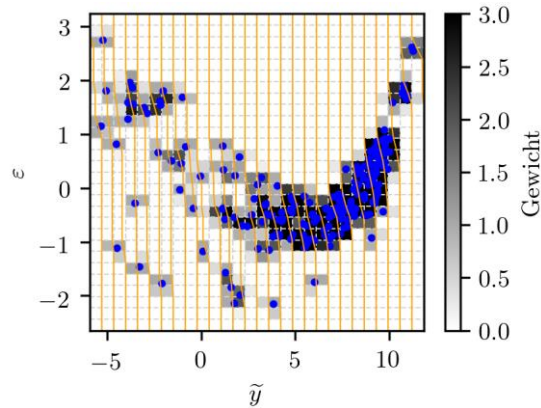


- Prediction of variance is better
- But: is the assumption correct?

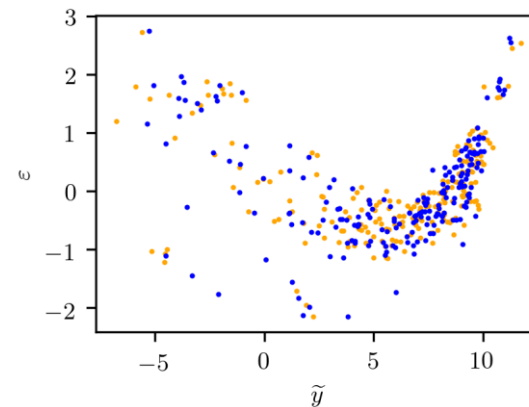
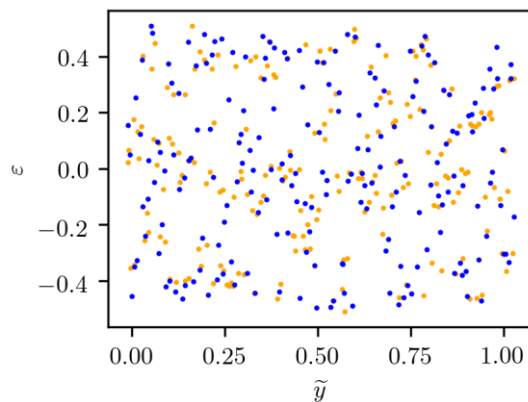


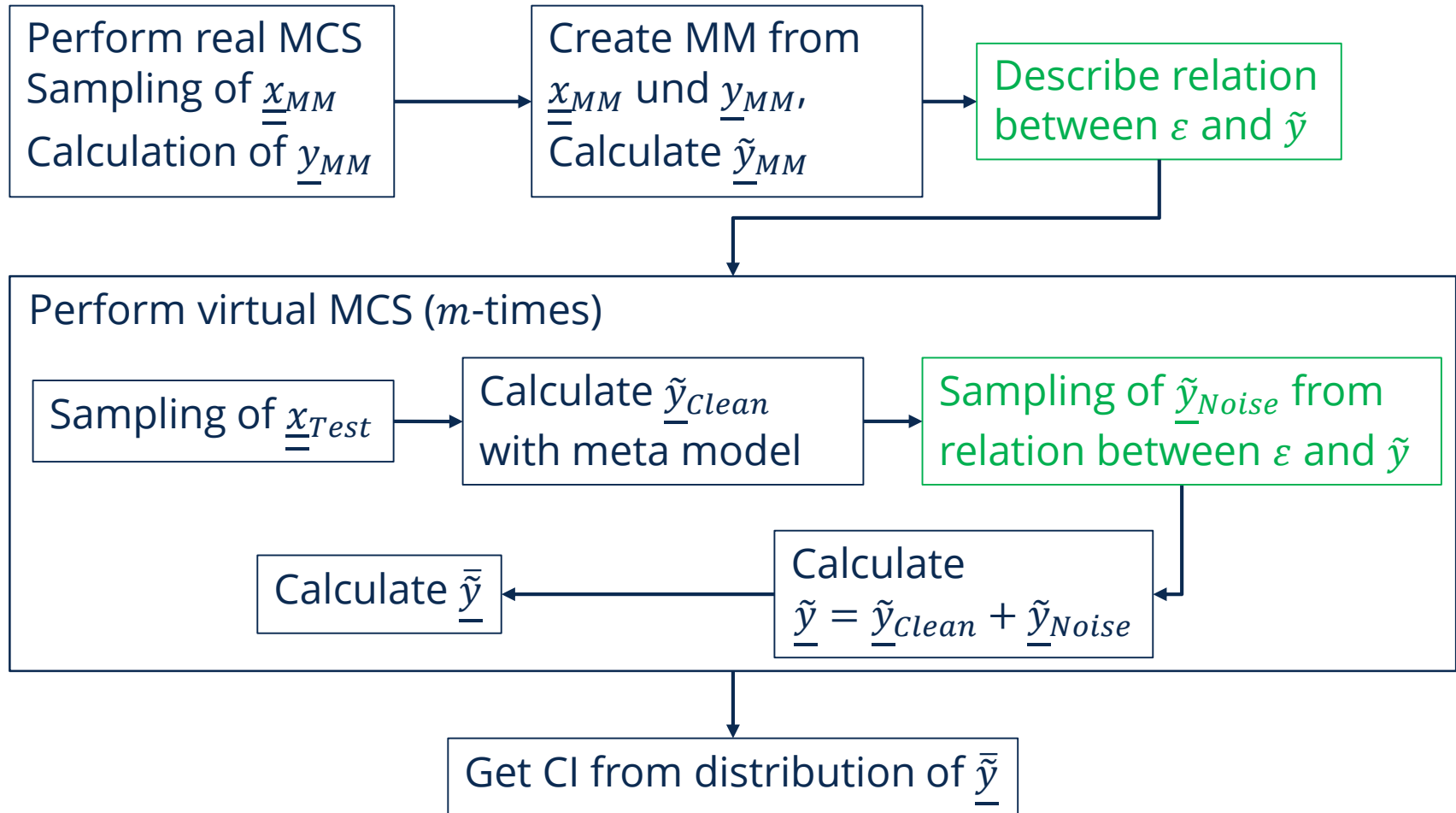
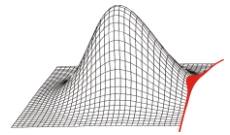


➤ Idea: local cumulative density functions

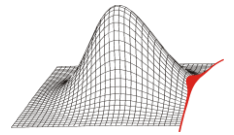


➤ Comparison:

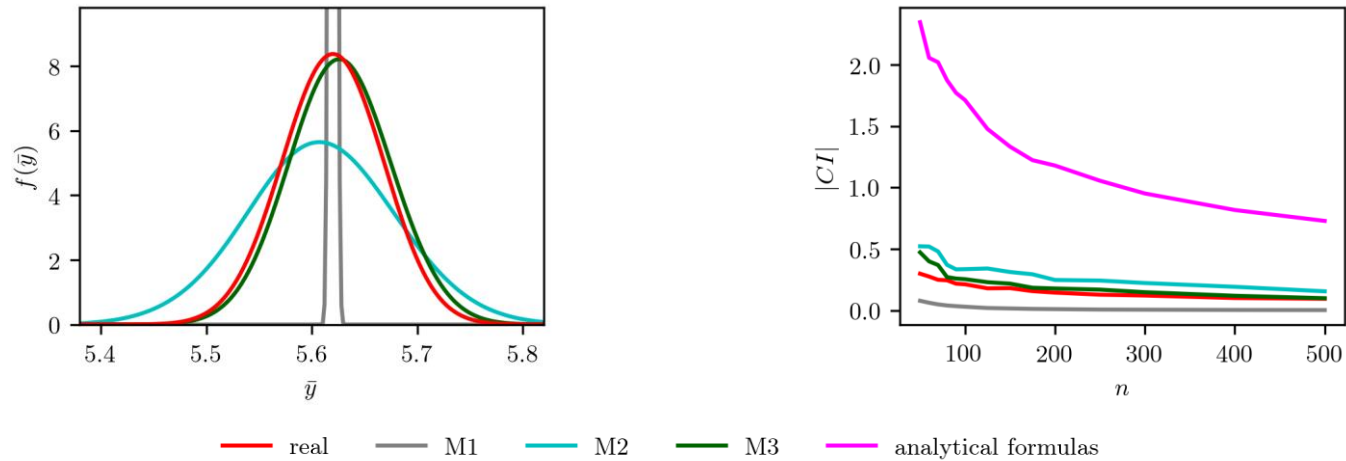


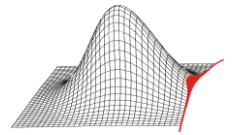




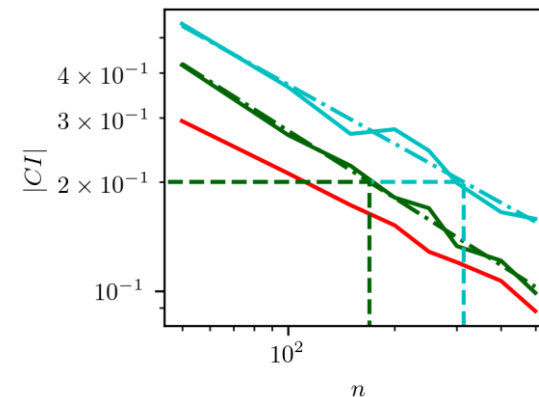
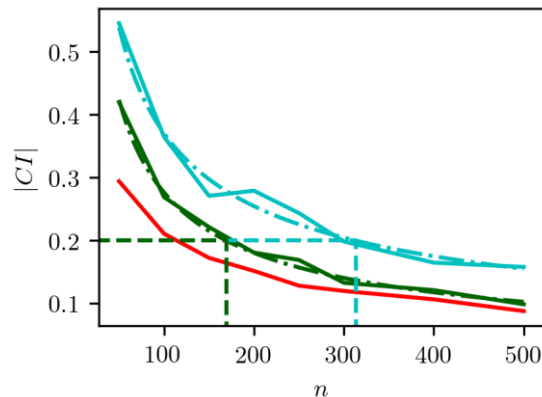


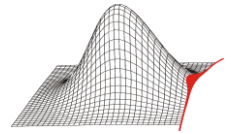
➤ LHS:



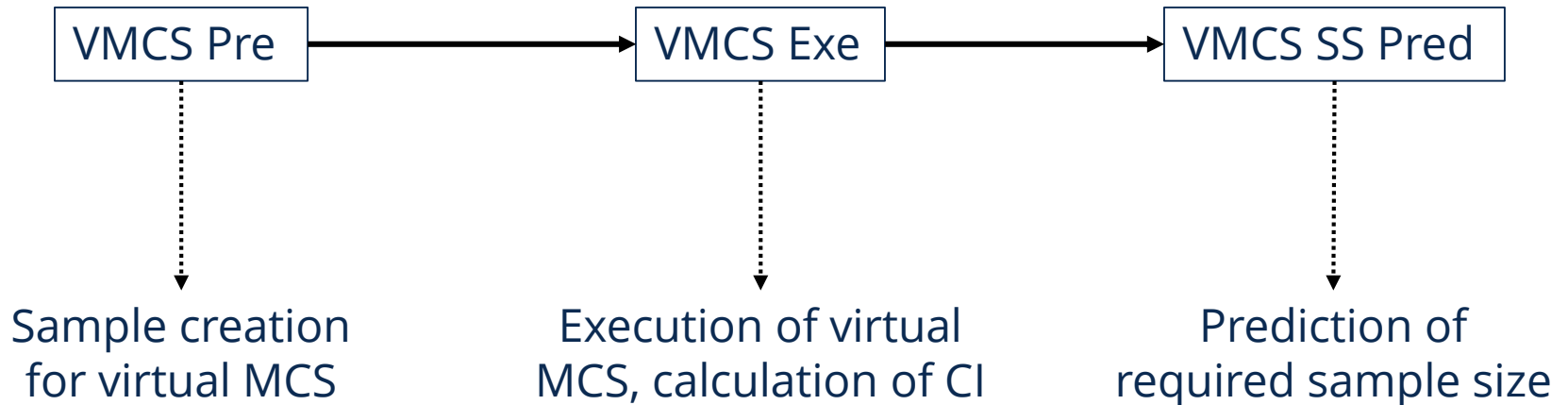


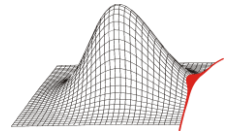
- Certain size of CI must be achieved
- Size of CI known after MCS
  
- Methods can be used to predict required sample size
  
- Steps:
  - Create MM, perform virtual MCS at different sample sizes
  - Determine size of CI at different sample sizes
  - Approximate evolution of CI size
  - Calculate required sample size



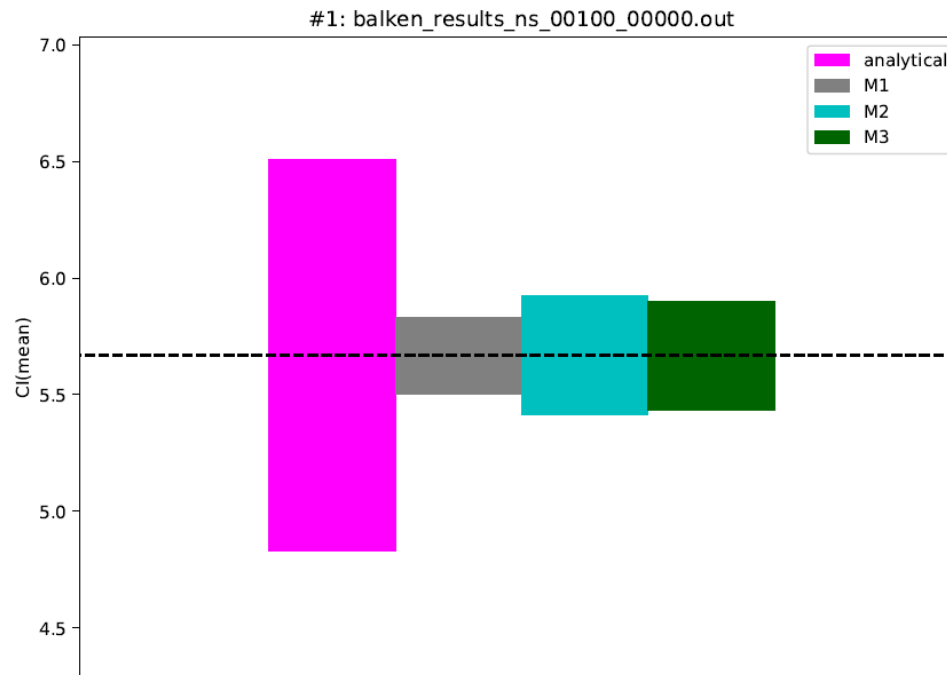


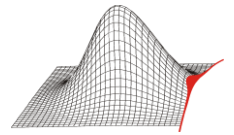
- Framework to calculate CI from given MCS
- Easy to handle, flexible usage
- Basis: MCS from ProSi



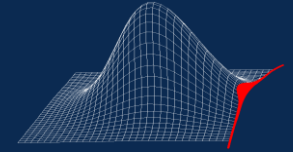


➤ Output: xml-Format or visualization





- Goal: Predict confidence interval of MCS with LHS more precisely
- Idea:
  - Approximate system behavior with meta model
  - Simulate MCS
- 3 Methods:
  - M1: Meta model
  - M2: Meta model +  $\varepsilon$  from PDF / CDF
  - M3: Meta model +  $\varepsilon$  from relation between  $\tilde{y}$  and  $\varepsilon$
- **SRS:** M1, M2, M3, **LHS:** M2, M3
- CI is predicted more precisely
- Framework for application was developed
  
- Outlook:
  - Application of methods on turbomachinery example
  - Use of other meta model types
  - Performing of further tests



# Thank you for your attention!

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