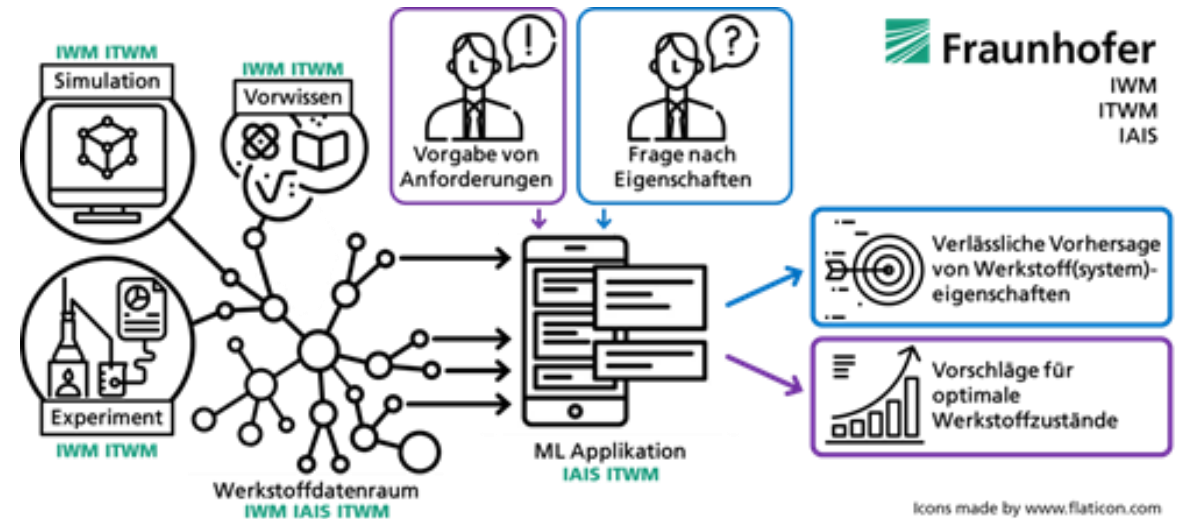


Design of Experiments in R&D

Abschlusskolloquium des Fraunhofer-Konsortiums »UrWerk« zur Entwicklung von unternehmensspezifischen Werkstoff(system)-Datenräumen

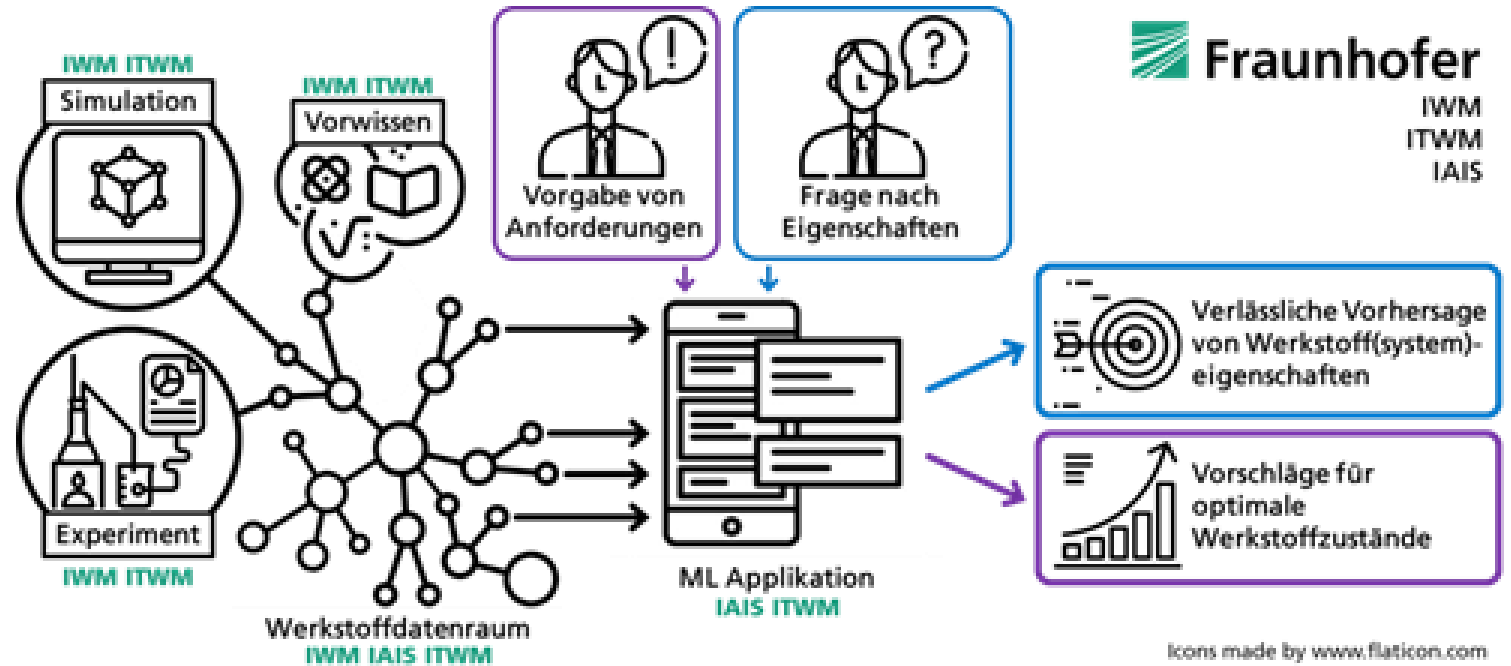
Moderation Dr. Michael Luke
Projektleiter »UrWerk«
Geschäftsfeldleiter »Bauteilsicherheit und Leichtbau«
am Fraunhofer-Institut für Werkstoffmechanik IWM

24.November 2022



Design of Experiments in R&D

Unternehmensspezifische Werkstoff(system)-Datenräume zur beschleunigten Produktentwicklung

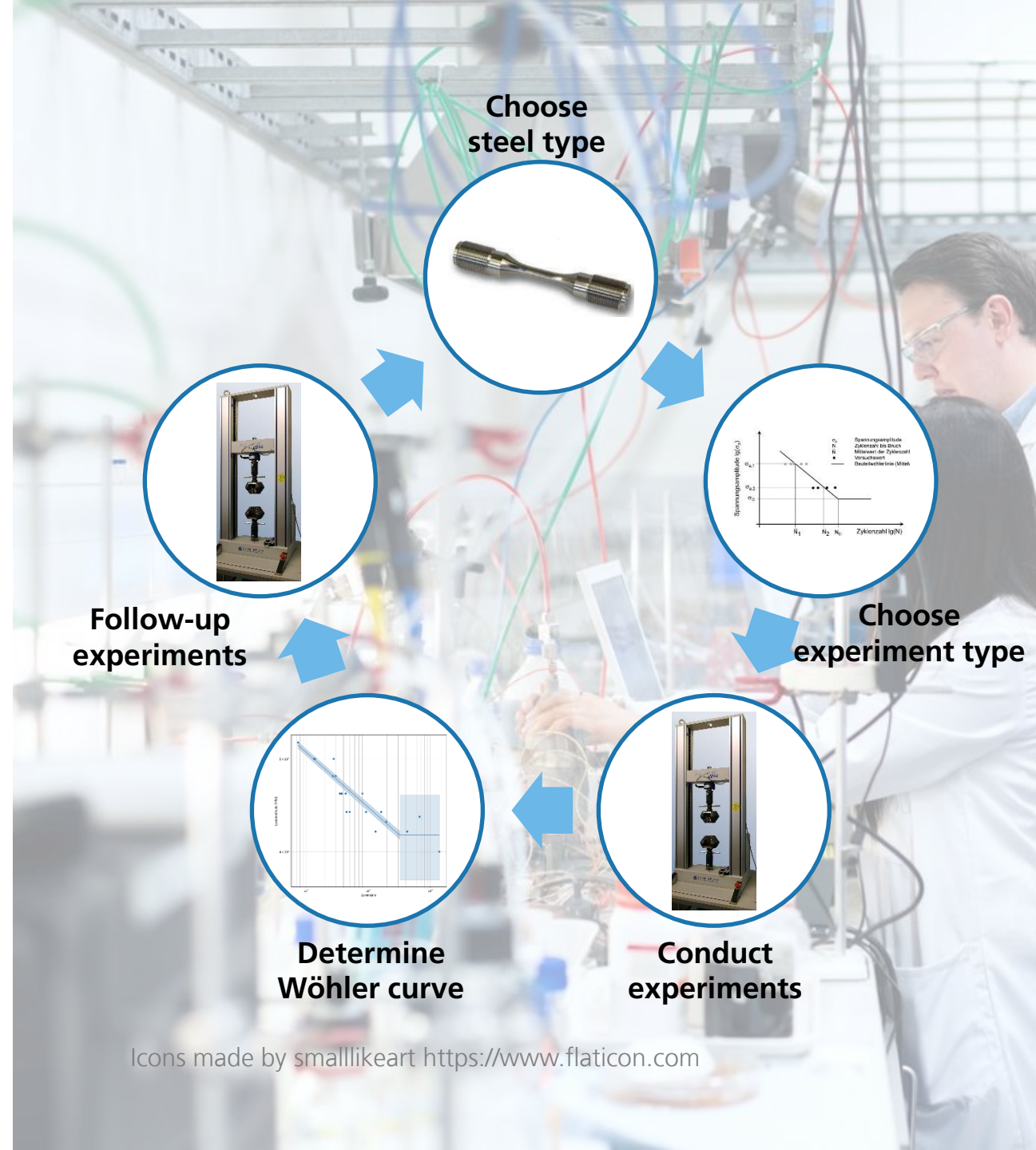


Dr. Gunar Ernis

Dr. Hans-Ulrich Kobialka

Challenges in technical product development

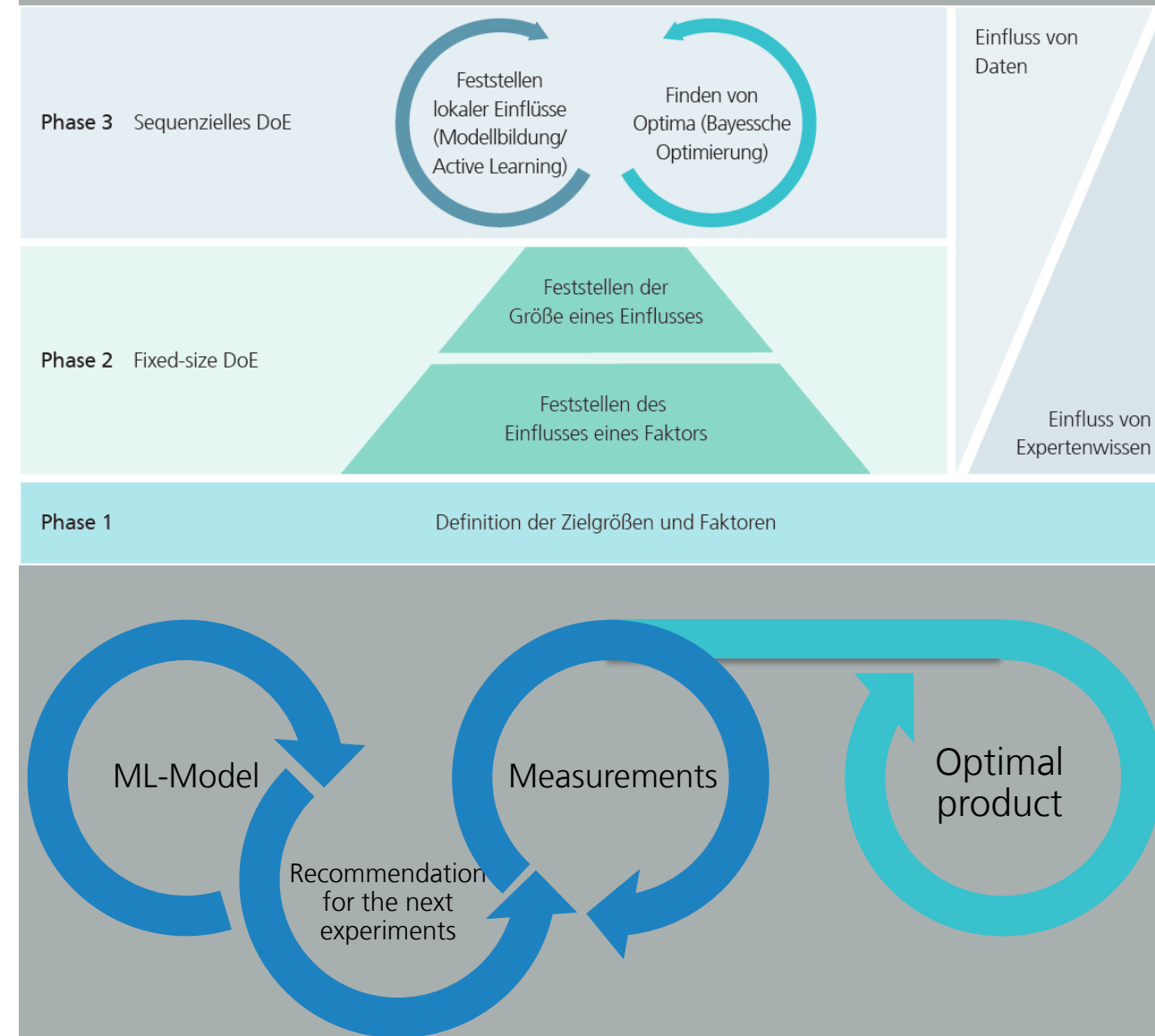
- ▶ Product development cycles often consist of several manual and time consuming steps
 - ▶ Formulation of the product
 - ▶ Designing experiments
 - ▶ Conducting the experiments
 - ▶ Evaluating the experiments
 - ▶ Follow-up of the experiments
- ▶ Often a very large number of experiments is needed to determine the optimal formulation
- ▶ Many experiments cause high costs and tie up resources



Design of Experiments

Supported by AI methods

- › Design of Experiments (DoE) is an integral part of engineering and product development
- › **Goal:** Apply different (statistical, ML,...) methods to minimise the number of experiments needed to find optimal parameter settings for a product
- › Approaches:
 - › **Classical:** Experiments are independent of each other, we do not use information from previous experiments
 - › **AI-supported:** We use data from previous experiments to learn probabilistic informed ML-models, which help to predict future experimental points
- › You can find our Whitepaper here:
<https://www.iais.fraunhofer.de/de/geschaeftsfelder/industrial-analytics/optimale-versuchsplanung-mit-ki.html>

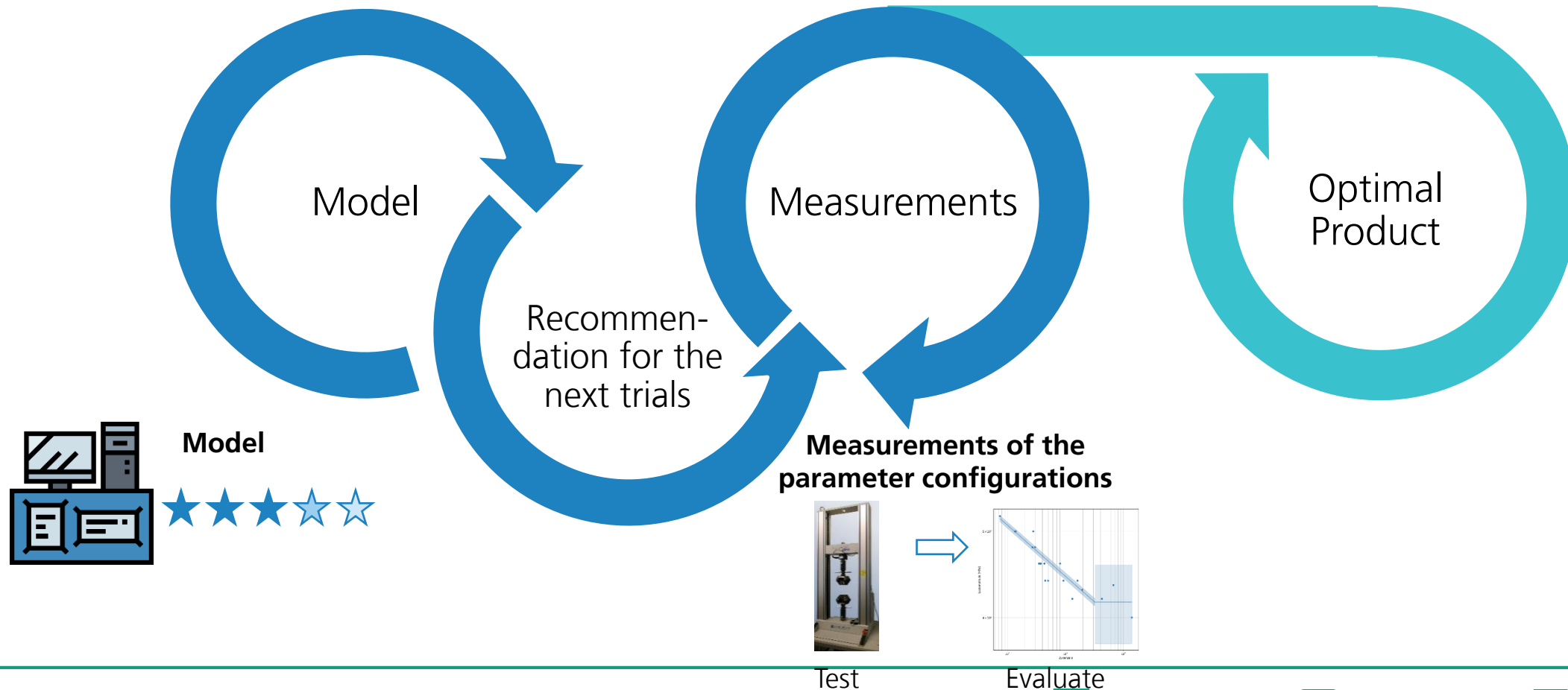


Our Approach: Sequential Experiments

For optimal Product configurations

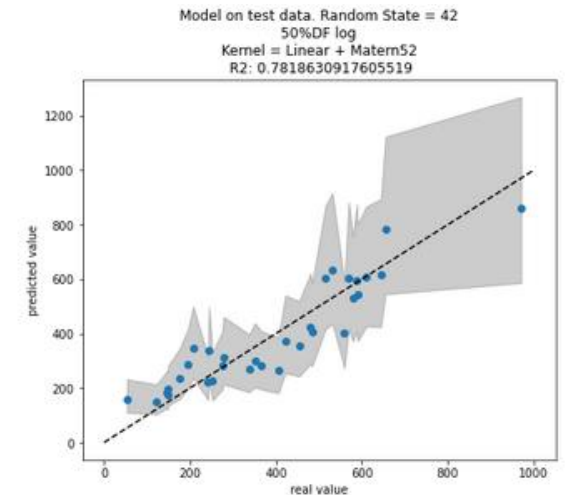
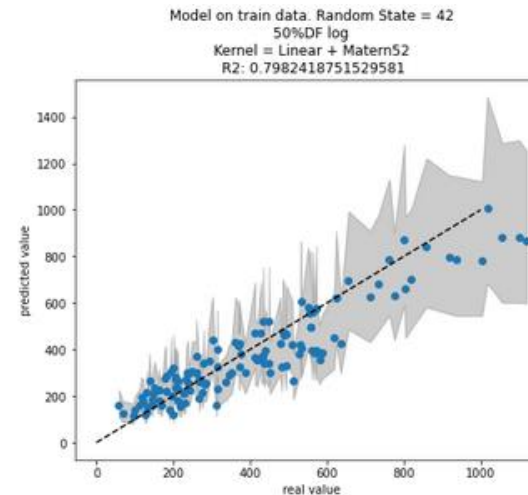
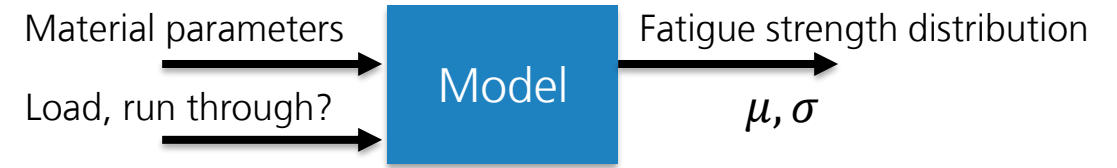
Recommendation for the upcoming measurements:

- Unknown distributions
- Good distributions



Application to fatigue experiments

- Initial idea:
 - Create a ML-Model which predicts the fatigue distribution
 - Improve the model by adding more experiments
- We use Gaussian processes to estimate the fatigue strength distribution
 - Low feature dimensionality
 - Inherent measure of variation
 - Kernel engineering allows the integration of prior knowledge



Application to fatigue experiments II

- Construction of the posterior distribution:
 - Prior: Gaussian Process Model
 - Likelihood: Probability of number of run throughs/failures given load
- Fit (Log-)Normal distributed fatigue strength
- Determine the trial with largest influence on fatigue strength

Distribution of trials:

$$\begin{aligned}g(\mu) &= p(\mu) \cdot l(s_i, s_j | \mu) \\ &= N(\mu_m, \sigma_m) \cdot \prod_i \Phi_{\mu, \sigma}(s_i) \prod_j (1 - \Phi_{\mu, \sigma}(s_j))\end{aligned}$$

Estimate for fatigue strength and load for the next trial:

$$\arg \max_{\mu} g(\mu)$$

Results on fatigue data

Prototypical application & Publication of scientific results

Application Prototype



Lade DoE Lade Modell Führe Experimente... Hole neues Experim... Ergebnisse speichern

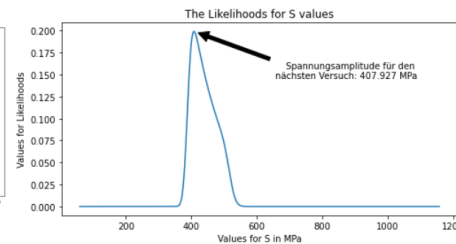
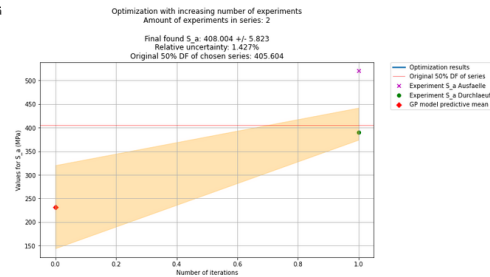
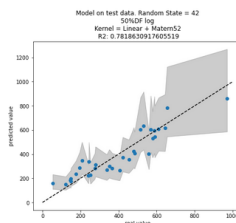
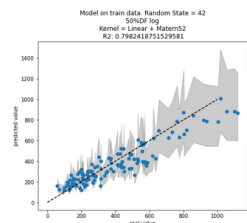
R-Verhältnis : -1.0
Härte Probenrand: 237.0

S_a (MPa)	Lastwechsel	Durchläufer
1	520.0	123000.0
2	390.0	2120000.0
3	410.0	

Used features for model training: Härte_Probenrand (HV) [berechnet], R-Verhältnis, Belastungsart_Axialbelastung, Belastungsart_Biegung

Model: GP regression
Objective: 163.23617928716158
Number of Parameters: 10
Number of Optimization Parameters: 10
Updates: True

GP_regression	value	constraints	priors
sum.linear.variance	(4,)	+ve	
sum.Mat52.variance	0.16586096507378267	+ve	
sum.Mat52.lengthsca	(4,)	+ve	
Gaussian_noise.var	0.27501398275833955	+ve	



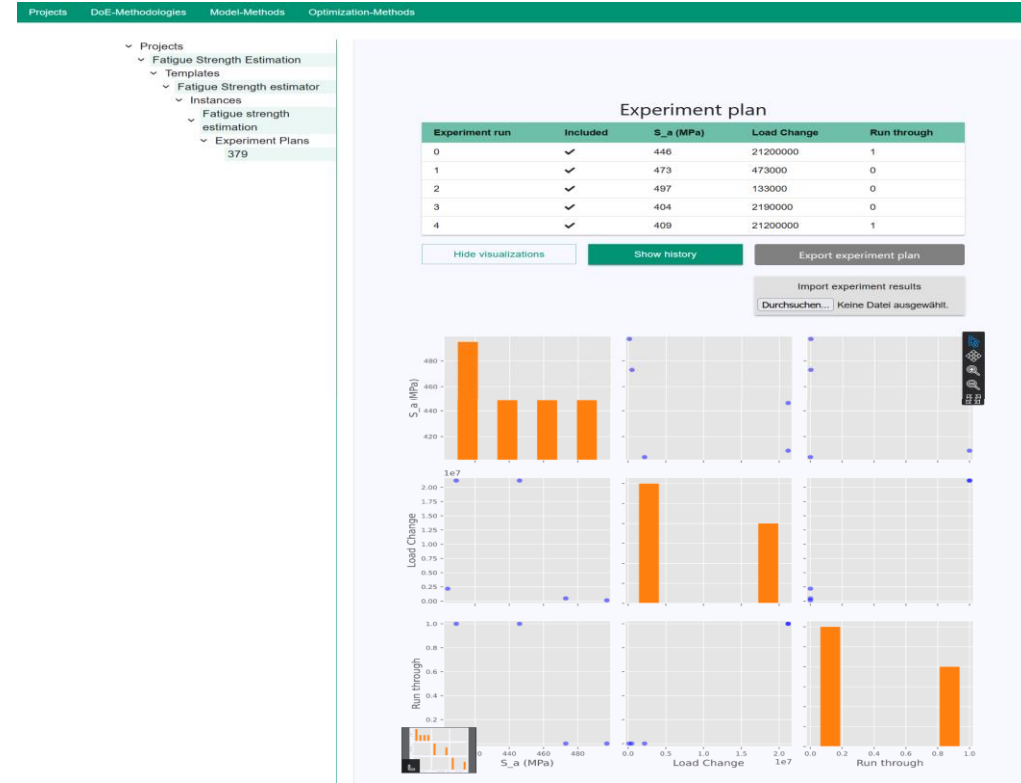
Publication of Scientific results

- Accepted as Workshop Paper at AAAI 2023
- Submitted as contribution to an anthology on Informed Machine Learning

Strategic Development

Tooling for iterative Design of Experiments

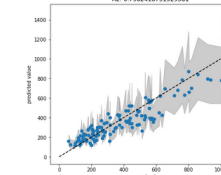
- Development of a Tool for the creation of sequential DoE
- Few competitors:
 - Statistic Tools: Design Expert, Statistica, Minitab...
 - DoE: GlobalOptimize, GaussML, S-Matrix...
- High demand:
 - Every product development can benefit from targeted experiments
 - First appointments with possible customers have taken place
- Working on a Web-Service:
 - API Design with Swagger/OpenAPI
 - Python Backend
 - JavaScript Frontend:
 - React UI
 - Node.js Backend



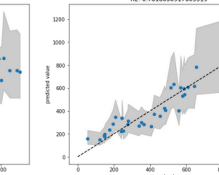
Used features for model training: Härte_Probenrand (HV) [berechnet], R-Verhältnis, Belastungsart_Axialbelastung, Belastungsart_Biegung
Model: GP regression
Objective: 163.23617928716158
Number of Parameters: 10
Number of Optimization Parameters: 10
Updates: True

GP_regression	value	constraints	priors
sum.linear.variance	(4,)	+ve	
sum.Mat52.variance	0.16586096507378267	+ve	
sum.Mat52.lengthscale	(4,)	+ve	
Gaussian_noise.vari	0.27501398275833955	+ve	

Model on train data, Random State = 42
 R Squared = 0.9997
 Kernel = Linear + Matern52
 R2 = 0.78544415125941



Model on test data, Random State = 42
 R Squared = 0.9997
 Kernel = Linear + Matern52
 R2 = 0.781862051605513



Optimization with increasing number of experiments
 Amount of experiments in series: 2
 Final found S_a: 408.004 +/- 5.823
 Relative uncertainty: 1.427%
 Original 50% QP of chosen series: 405.604

