Auto-Extraction of Modelica Code from Finite-Element-Analysis or Measurement Data

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Outline

1. Objective
2. Theoretical Basics
   - Gaussian Process / Kriging
   - Visualization
3. Auto-Extraction with OptiY®
4. Practical FEA Example
   - Electromagnetic Actuator
   - System Simulation

Objective

Modeling of a real Product

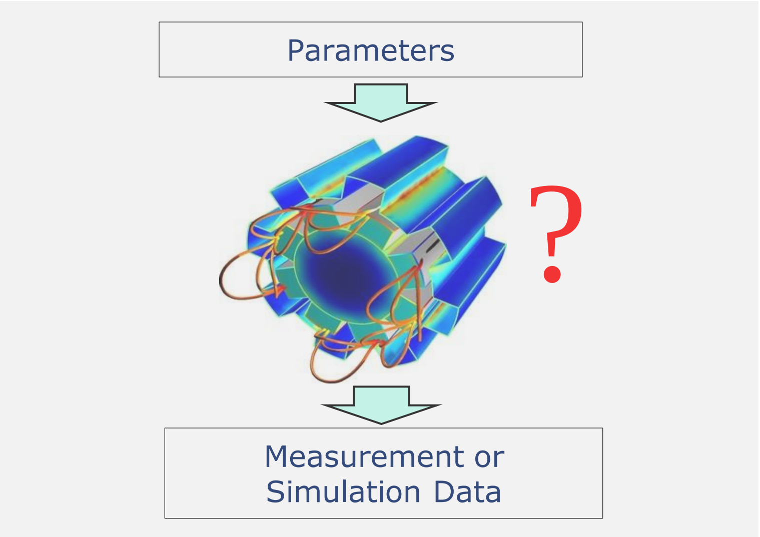
- Relationships or work principles are unknown
- Only existing measurement data of prototypes

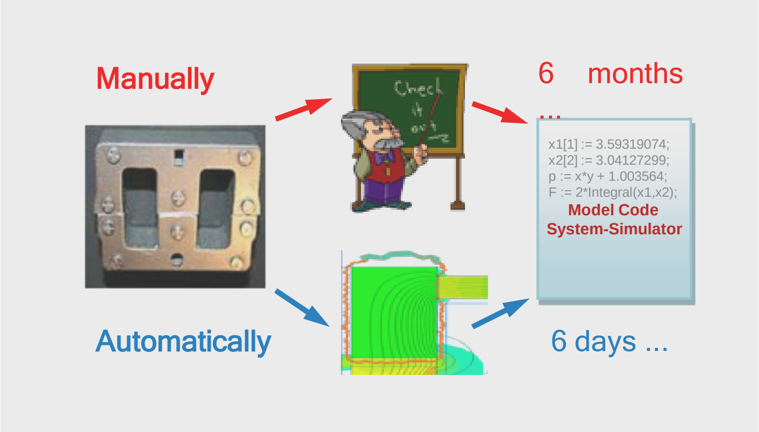
Complex Finite Element Analysis

- Detailed component behaviors
- Long computing time: hours or days
- Technical feasibility for system simulation.

Current Solution

- Model reduction using network elements
- Only mathematically describable relationships
- Find suitable model structures
- Model parameter validation required
- Time-consuming and cost-intensive



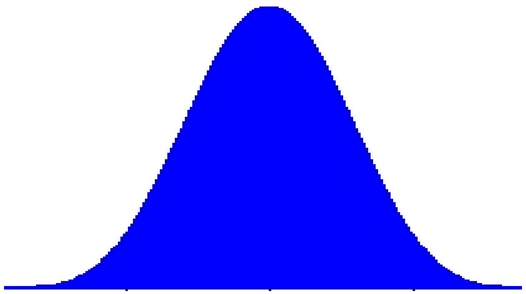


Gaussian Process or Kriging

- Polynomial f(**x**) of p^{th} order for global adaptation
- Stochastic process Z(**x**) for local adaptation as multivariate Gaussian distribution

$$Y(\mathbf{x}) = \sum_{i=1}^{p} \beta_i \cdot f_i(\mathbf{x}) + Z(\mathbf{x})$$

$$\begin{pmatrix} Y_0 \\ \mathbf{Y}^n \end{pmatrix} \approx N_{n+1}\left[\begin{pmatrix} \mathbf{f}_0^T \\ \mathbf{F} \end{pmatrix}\boldsymbol{\beta}\,, \quad \sigma_z^2 \begin{pmatrix} 1 & \mathbf{r}_0^T \\ \mathbf{r}_0 & \mathbf{R} \end{pmatrix}\right]$$



Correlation Function R

- Interpolation between sampled points
- Interaction between input parameters
- Crucial ingredient in Gaussian predictor
- Encode the assumptions about the function be predicted
- Different well-known types for wide range

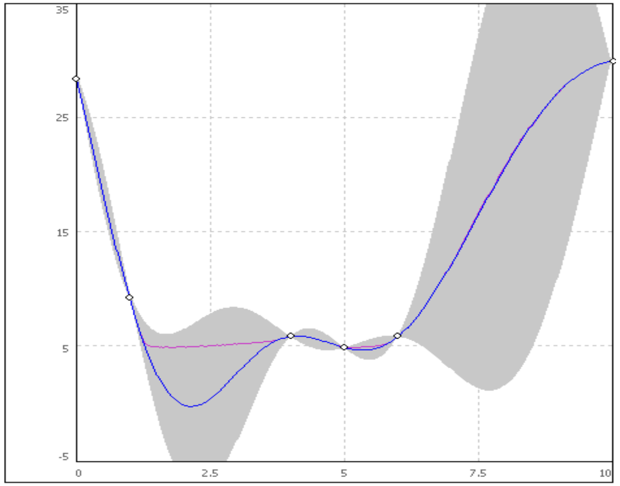
$$R(\mathbf{x}_1, \mathbf{x}_2) = \exp\left\{-\sum_{i=1}^{m} w_i^{\gamma} \cdot \left|\mathbf{x}_1 - \mathbf{x}_2\right|^{\gamma}\right\}$$ Gamma-Exponential

$$R(\mathbf{x}_1, \mathbf{x}_2) = \frac{1}{\Gamma(\upsilon)2^{\upsilon-1}}\left(\frac{2\sqrt{\upsilon}\left|\mathbf{x}_1 - \mathbf{x}_2\right|}{\theta}\right)^{\upsilon} K_{\upsilon}\left(\frac{2\sqrt{\upsilon}\left|\mathbf{x}_1 - \mathbf{x}_2\right|}{\theta}\right)$$ Matérn Class

$$R(\mathbf{x}_1, \mathbf{x}_2) = \left(1 + \frac{w^2 \cdot \left|\mathbf{x}_1 - \mathbf{x}_2\right|^2}{\alpha}\right)^{-\alpha}$$ Rational Quadratic

Predictor and Uncertainty of the Gaussian Process

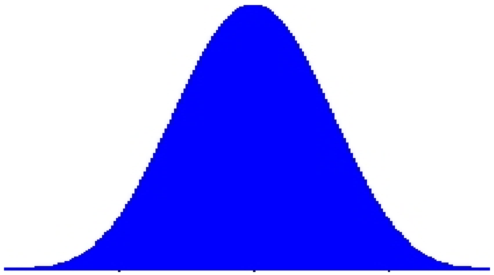
the best linear unbiased predictor for Y(x0) is the mean value of the multivariate Gaussian distribution



$$\widehat{Y}(\mathbf{x}_0) = \mathbf{f}_0^T \boldsymbol{\beta} + \mathbf{r}_0^T \mathbf{R}^{-1}(\mathbf{Y}^n - \mathbf{F}\boldsymbol{\beta})$$

The uncertainty of the predicted value is characterized by the variance of the multivariate distribution

$$\sigma^2 = \sigma_z^2\left(1 - \mathbf{r}_0^T \mathbf{R}^{-1}\mathbf{r}_0 + (\mathbf{f}_0 - \mathbf{F}^T\mathbf{R}^{-1}\mathbf{r}_0)^T(\mathbf{F}^T\mathbf{R}^{-1}\mathbf{F})^{-1}(\mathbf{f}_0 - \mathbf{F}^T\mathbf{R}^{-1}\mathbf{r}_0)\right)$$



Adaptive Gaussian Process

- Minimize the uncertainty of the predictor:
- Find the max. point of the variance and replace by a sampling point

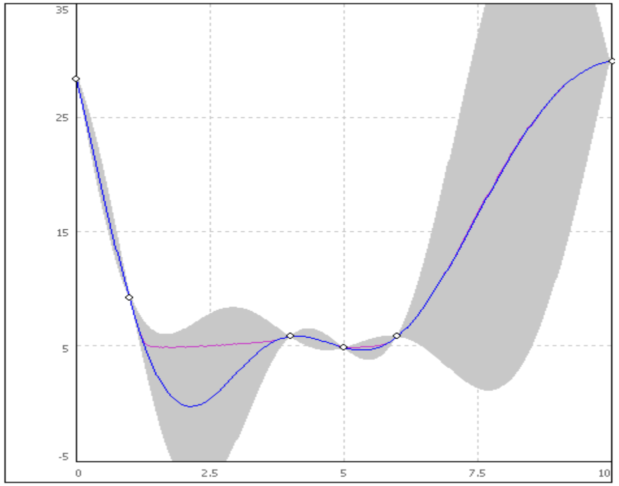
$$\sigma^2 = \sigma_z^2\left(1 - \mathbf{r}_0^T\mathbf{R}^{-1}\mathbf{r}_0 + (\mathbf{f}_0 - \mathbf{F}^T\mathbf{R}^{-1}\mathbf{r}_0)^T(\mathbf{F}^T\mathbf{R}^{-1}\mathbf{F})^{-1}(\mathbf{f}_0 - \mathbf{F}^T\mathbf{R}^{-1}\mathbf{r}_0)\right)$$

- The expected improvement EI = potential for substantial improvement by investigation of parameter
- Minimize the expected improvement EI
- Find the max. point of the EI and replace by a sampling point

$$EI = \sigma\left\{\frac{Y_{\min} - \widehat{Y}}{\sigma}\Phi\left(\frac{Y_{\min} - \widehat{Y}}{\sigma}\right) + \Psi\left(\frac{Y_{\min} - \widehat{Y}}{\sigma}\right)\right\}$$

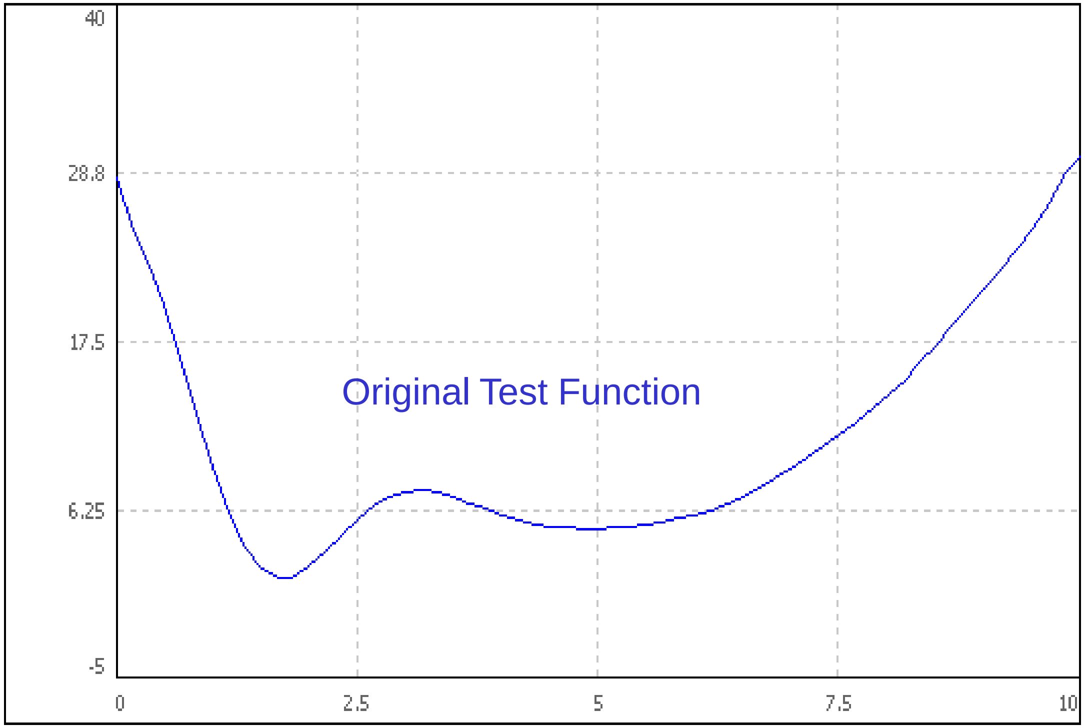
- Statistical low boundary k =1, 3, 5 …
- Find the min. point of the SLB and replace by a sampling point

$$SLB = \widehat{Y} - k \cdot \sigma$$



Visualization of the Adaptive Gaussian Process

$$Y = (X-5)^2 - 15 \cdot e^{-(X-1.5)^2} + 5$$



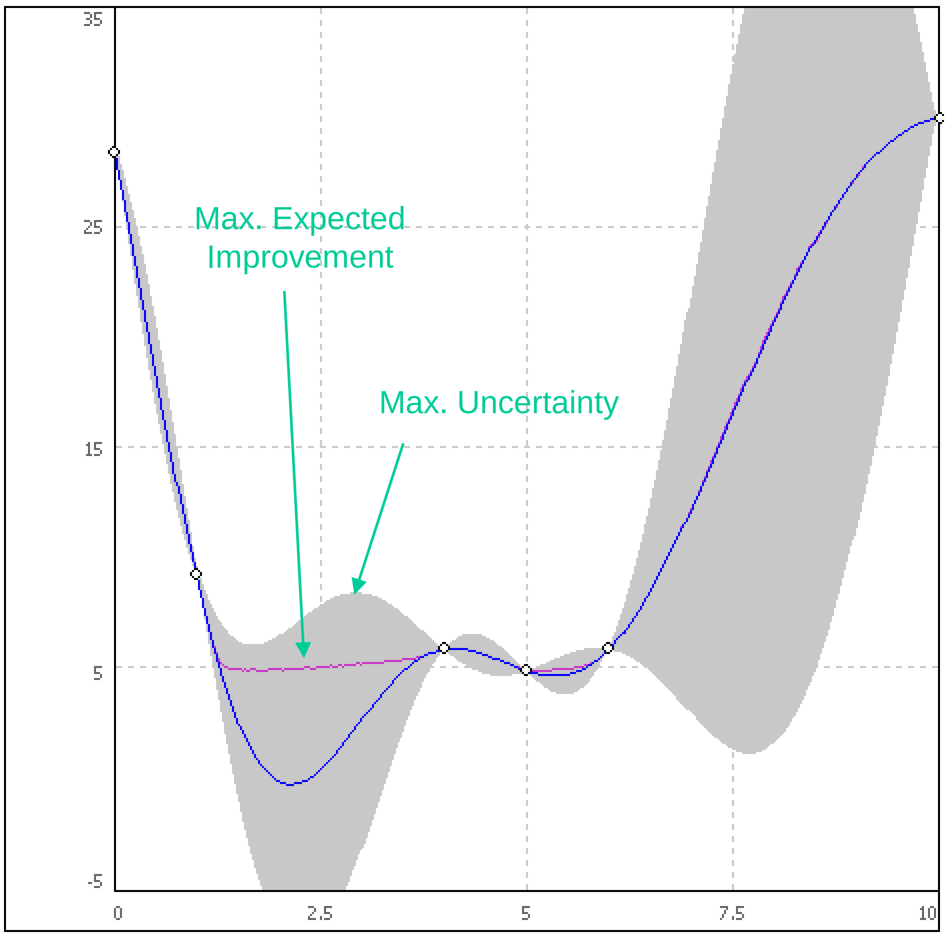
Approximation Loops

Response Surface

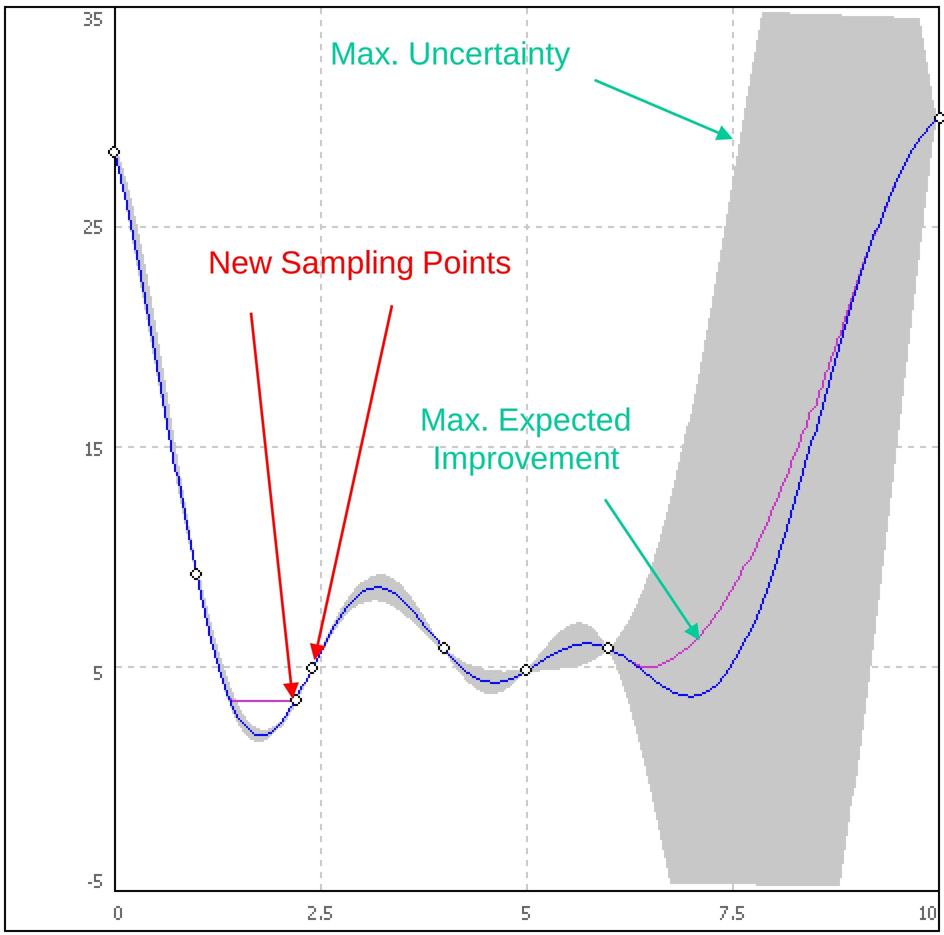
Expected Improvement EI

95% Confidence Interval

Start: 6 Sampling Points



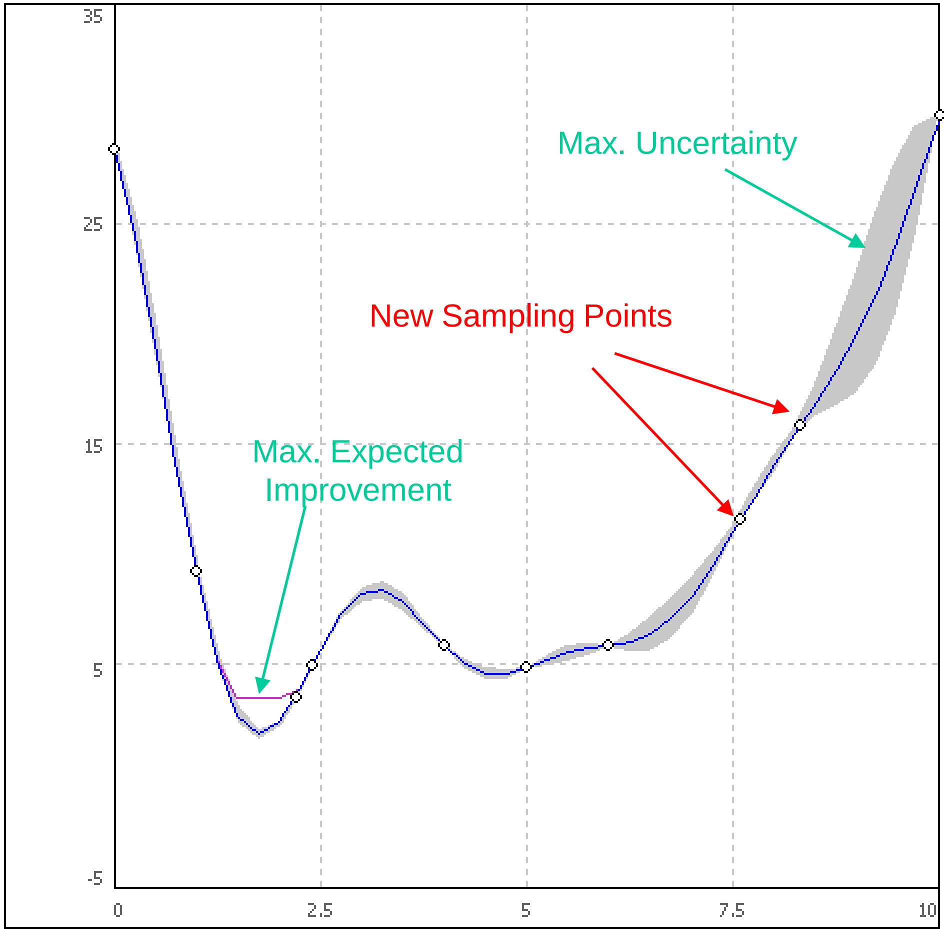
Loop 1



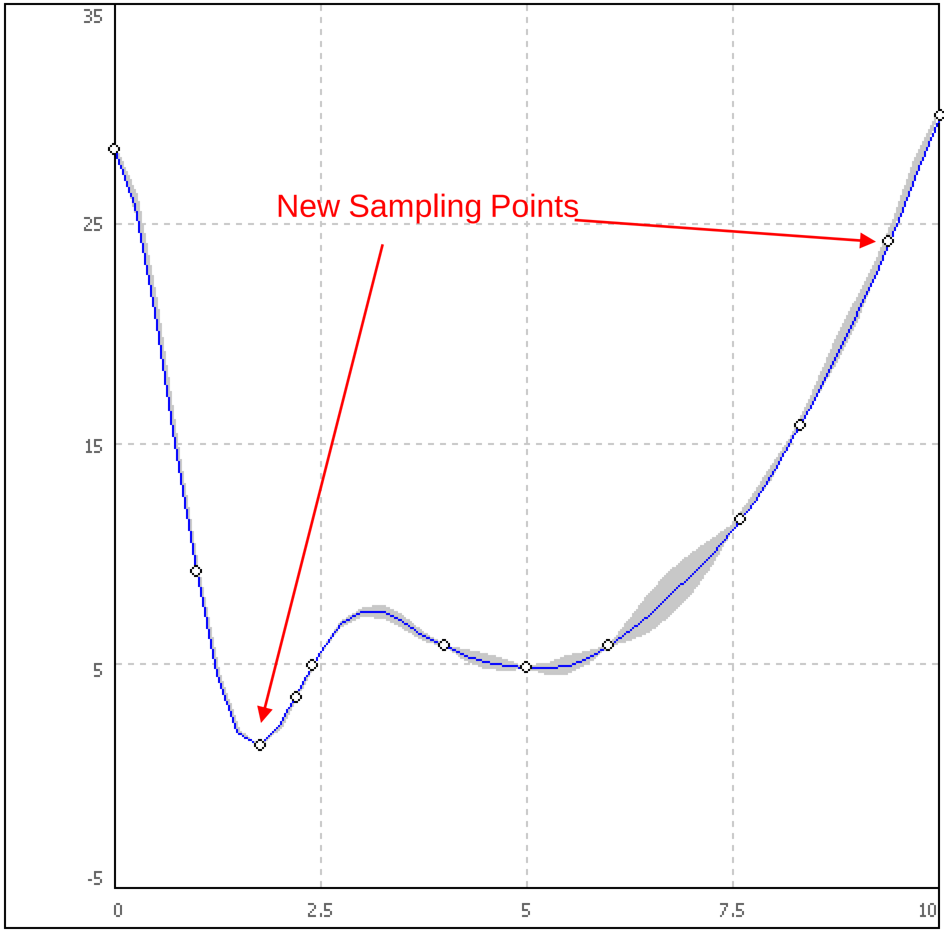
Approximation Loops

Required number of sampling points depends on:
- Number of input parameters
- Degree of response nonlinearity
- Correlation between design parameters

Loop 2



Loop 3: Automatic Stop

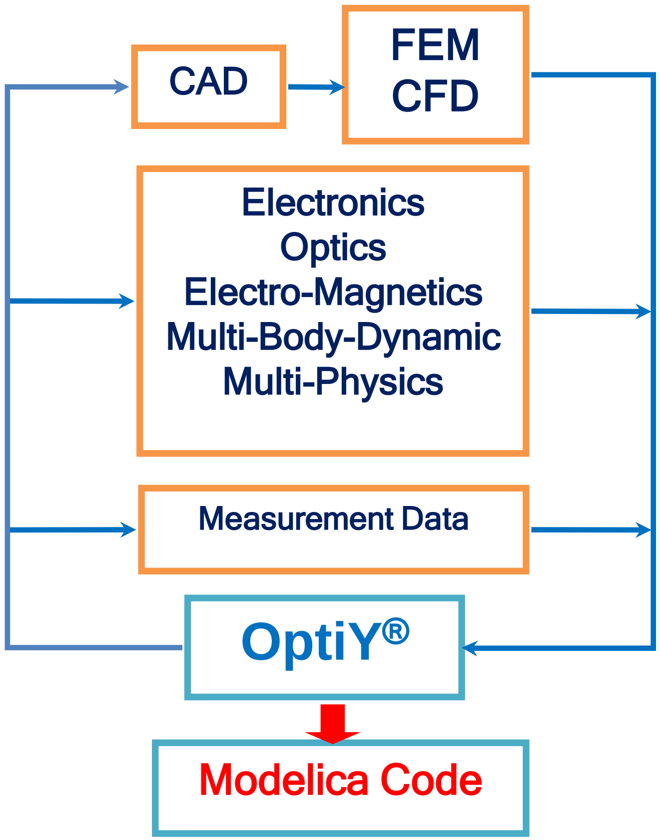


Auto-Extraction of Modelica code with OptiY®

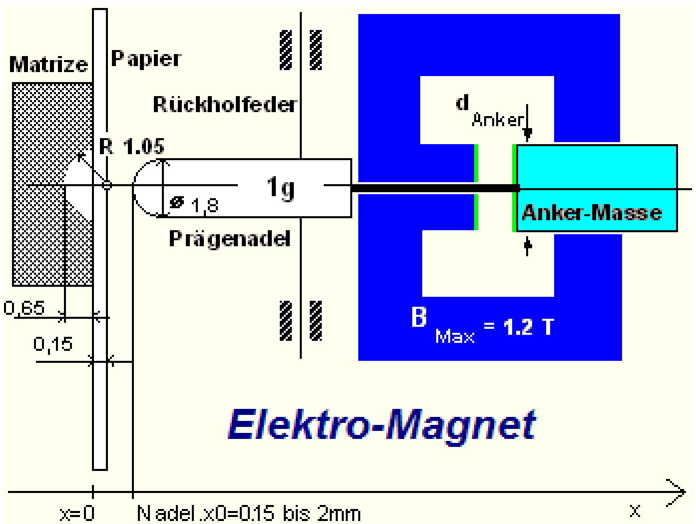
- Numerical algorithms implemented in OptiY
- Interfaces to many commercial CAD/CAE-software systems or in-house code
- Auto-extraction of Modelica from these simulation

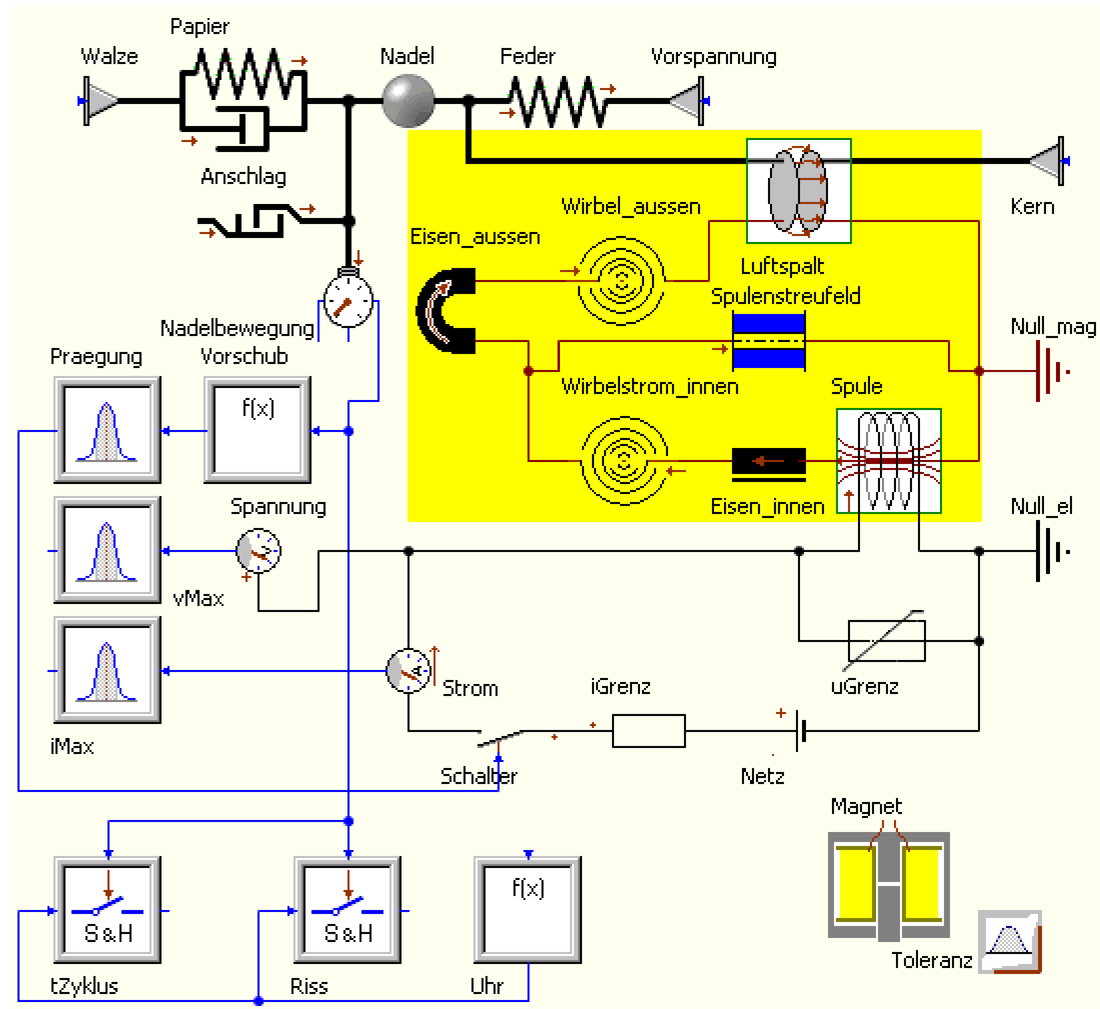
Advantages:

- Easy usage and quick handling of the software,
- Availability of expert knowledge,
- Detailed and accurate component behavior modeling,
- Small number of model parameters, which have to be identified



Practical Example: Electromagnetic Actuator

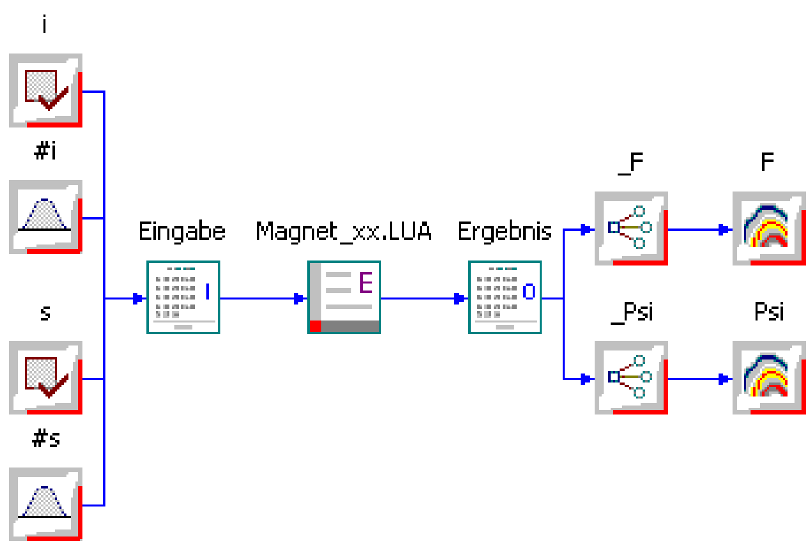


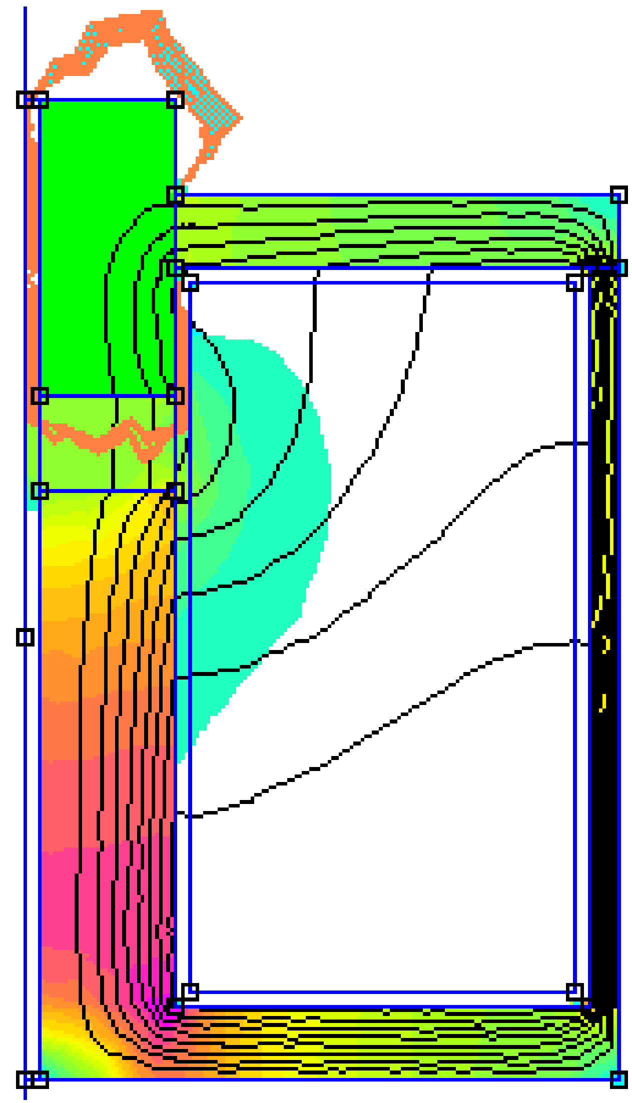


- Braille-Printer with known working principles
- System-Simulation by network elements using ready-to-use library in SimulationX

Meta-Modeling with OptiY and FEMM

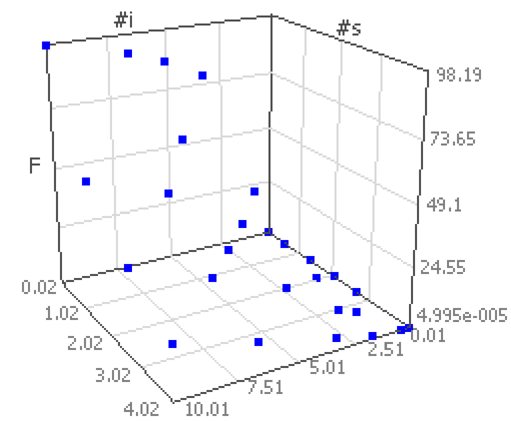
- Using the FEM-program FEMM to model and parameterize the electro-magnetic actuator in 2D-axisymmetric.
- The characteristics as magnetic force ***F*** and linkage flux ***Psi*** in dependence of the parameters current ***i*** and air gap ***s*** are treated.
- OptiY starts several loops:
  - ✓ Set Parameter
  - ✓ Start FE-Simulation
  - ✓ Collect Results

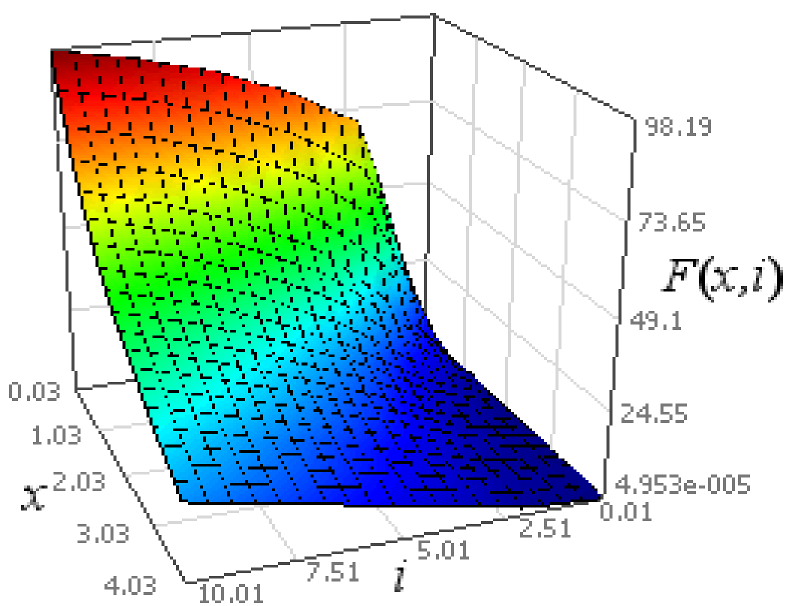


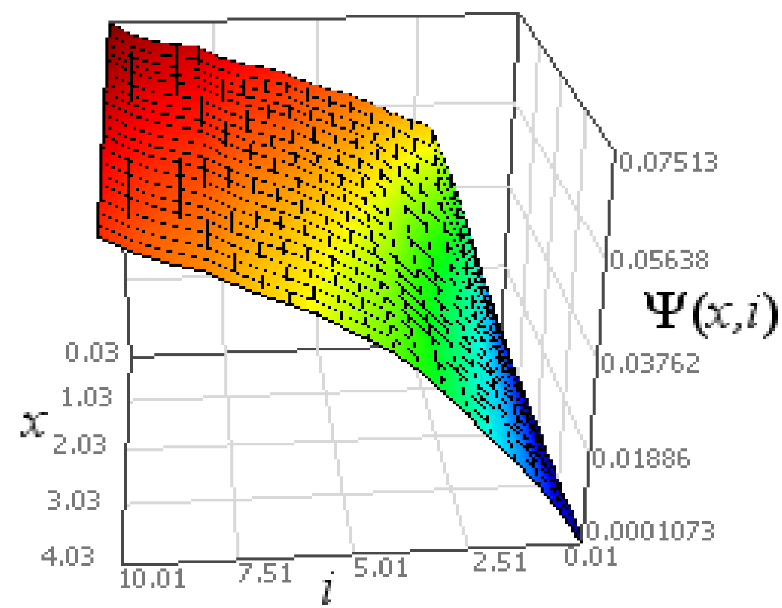


Identify the Characteristics using Adaptive Gaussian Process

- Based on the sampled points by original FEA-model
- Surrogate Models of magnetic force F and linkage flux Psi
- Code-Export as Modelica-codes for system simulation

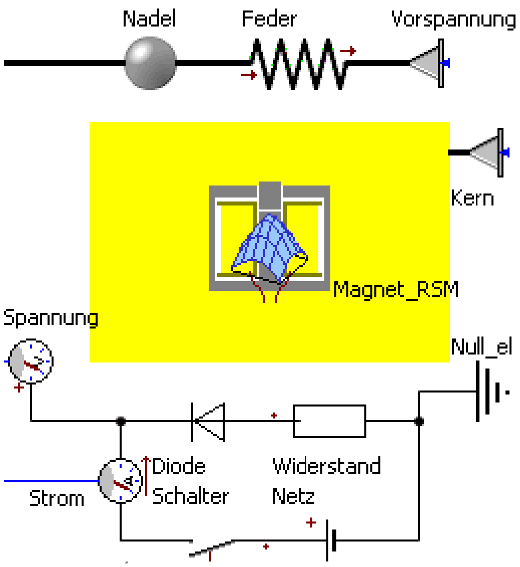


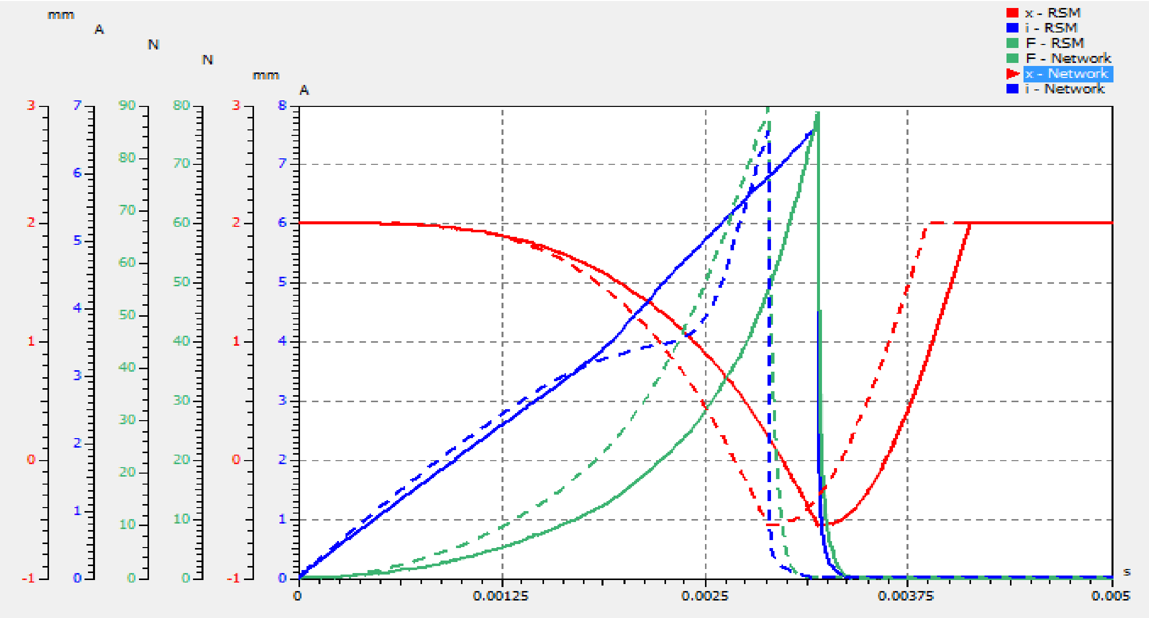




System-Simulation with Surrogate Models

- The surrogate models replace network elements in system model.
- Comparing between network and surrogate models reveals slightly differences
- The network model is more idealized
- The component behaviors of surrogate model is detailed and accurately because of spatial modeling for the magnet geometry.





Conclusion

- Modeling of a real product or process is infeasible or difficult because of unknown relationships or time-consuming computations. Current solutions for solving this problem apply model reduction to network elements, which is very time- and cost-intensive

- The adaptive Gaussian process is an approach that allows an efficient and automatic generation of precise component models for system simulation. . It requires only few support points of the black box system.

- The amount of identified parameters is smaller in comparison to the network model. The system behavior is more accurate

- The algorithms are implemented in the multidisciplinary design software OptiY® providing generic and direct interfaces to many specialized commercial CAD/CAE-software tools and also in-house codes. Within, user can easily create fast surrogate models and export them as Modelica code automatically.

- The advantages of network-based system simulation can be combined with the advantages of the FEA and the measurement of real objects throughout the design process.