presented at the 17th Weimar Optimization and Stochastic Days 2020 |
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Simulation based Digital Twins

for Predictive Maintenance, Optimal Operation & New Business Models

Teresa Alberts, Christof Gebhardt, CADFEM Group & ITficient
June 26th 2020, WOST

CADFEM GmbH

Christof Gebhardt

ITficient AG

Teresa Alberts

CADFEM® GROUP

20+
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500+
EMPLOYEES

17+
COUNTRIES

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Shareholdings in

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- CADFEM (Suisse), Switzerland
- CADFEM (Austria), Austria
- CADFEM UK CAE, UK
- CADFEM Ireland, Ireland
- MESco, Poland
- SVS FEM, Czech Republic, Slovakia
- CADFEM CIS, Russia
- CADFEM Ukraine, Ukraine
- CADFEM Afrique du Nord, Tunisia, Morocco, Algeria
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  Robust Design Optimization
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  Digital Cities
- ITficient, Switzerland
  Digital Twin & Big Data Analytics

TechNetAlliance

- Worldwide Network of CAE-Specialists
- 80+ Members
- 25+ Countries

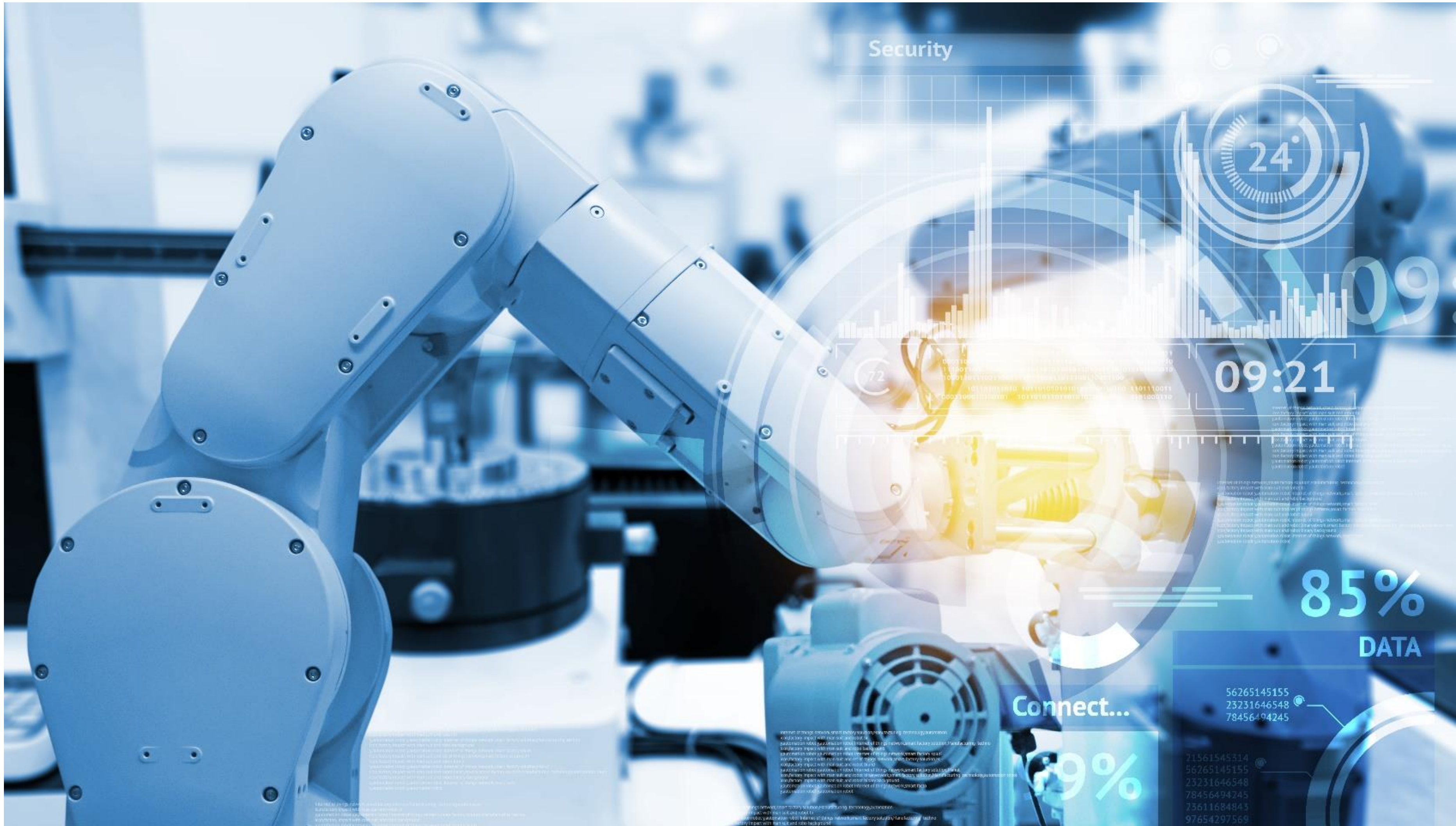
www.cadfemgroup.com

Overview ITfficient

Digitale Service Models

Digital Twins

Analytics



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Active poll

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What do you understand by a Digital Twin?

014

Simplied simulation model
behaviour model
Find useful life
replica
magic
Data models
Big Data
system model
physikalisches abbild
Digital Factory
a copy of a full system
Mathematical modelling

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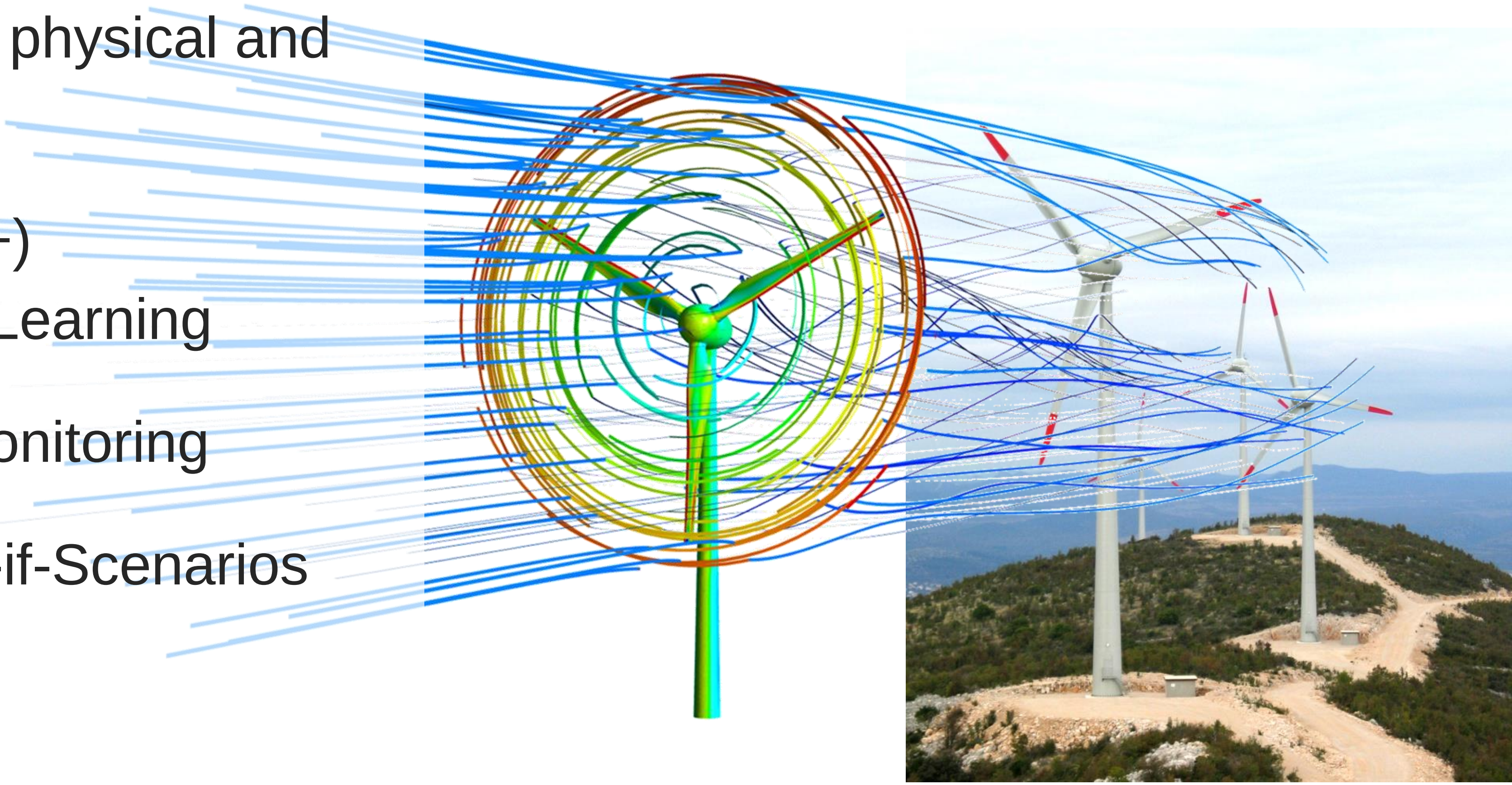
Digital Twin

Connection between the physical and digital world

- Sensors + Analytics (+) Simulation / Machine Learning
- Realtime Condition Monitoring
- Predictions and What-if-Scenarios



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Optimal operation

Smart Products / Services

Optimal operation

- Secured availability
  - Condition based monitoring
  - Cost reduction by optimized service and spare parts
- Balancing of operation time, performance & operation costs

New revenue streams

- New business models
  - Maintenance as a Service
  - Recommendations as a Service
  - Machine as a Service
- Customer specific solution sales
  - Configuration as a Service

Customer loyalty

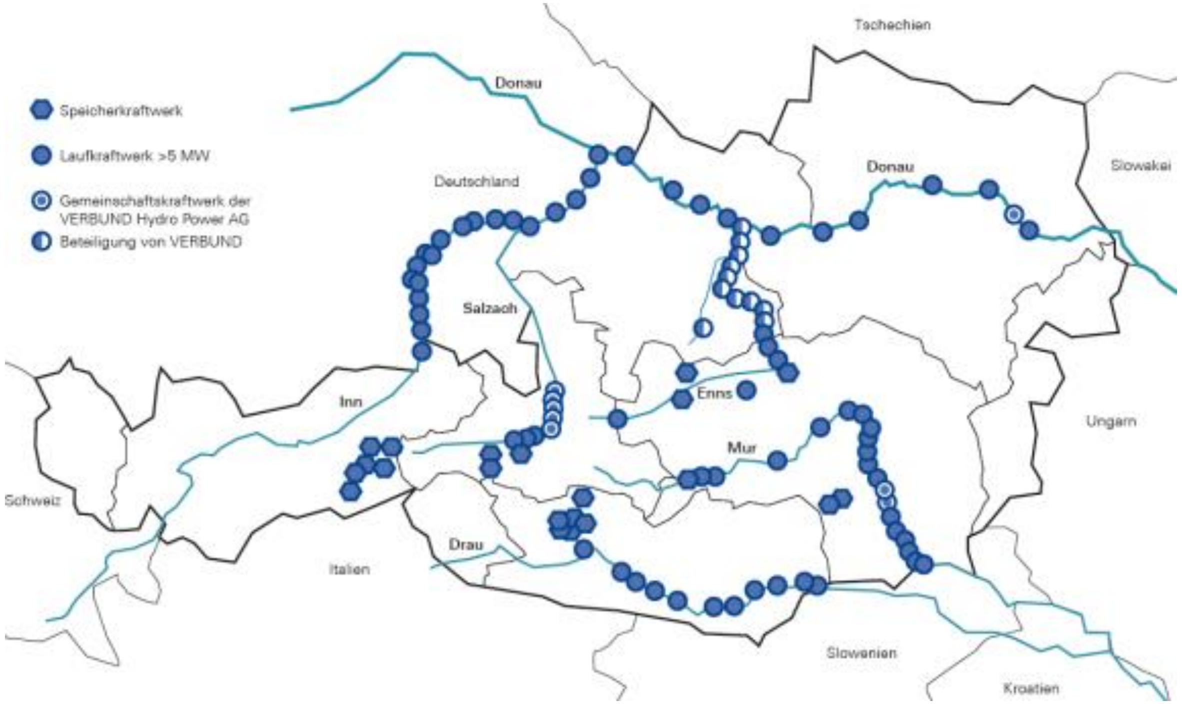
- Competitive positioning
- Customer satisfaction
- Trust
- Innovation power

Digital Twin Use Case
Verbund Hydro Power

Verbund

Verbund Hydro Power

- Austria's leading electricity company
- Gain 90% of generation in 130 hydropower plants
- Regulation controlled via 7 central bases



Verbund

Motivation: Fatigue fracture of control rod of turbine blades of vertical Kaplan runner

Challenges

Downtimes

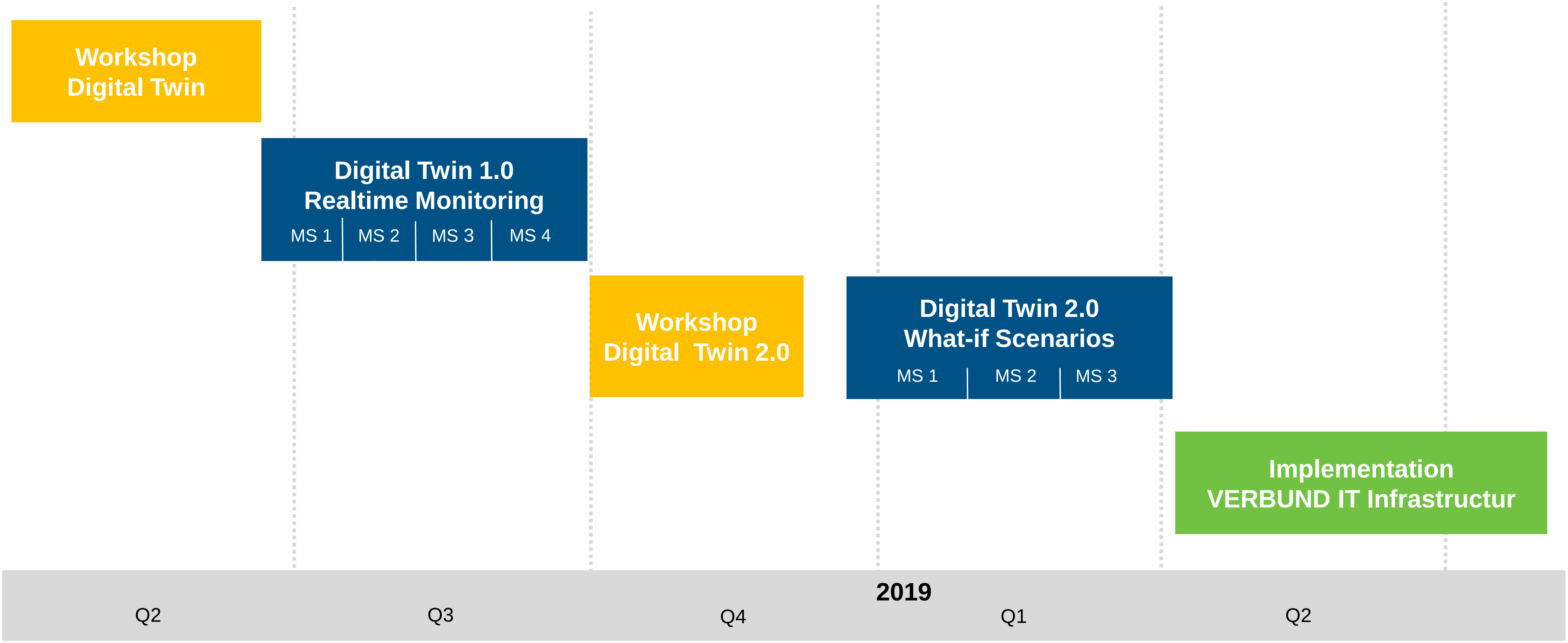
- Loss of production
- Procurement service and spare parts
- High cost
- Maintenance at fixed defined intervals

High operating costs

- Risk minimization (quality, contracts, ...)

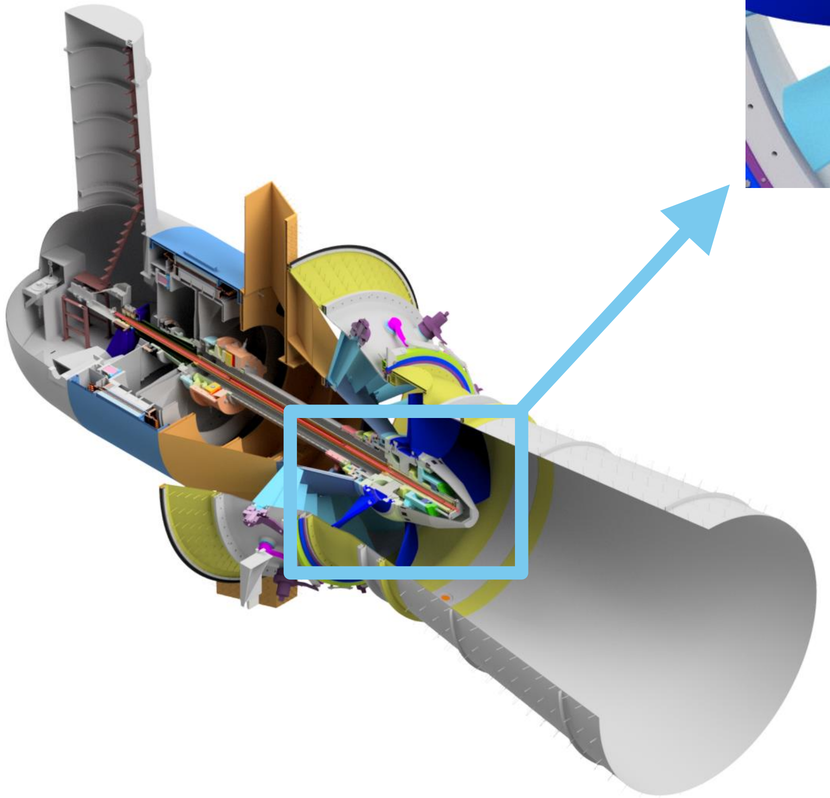

Verbund
„Our goal are transparent power stations („gläsernes Kraftwerk“) for which we know the exact current status of all components, to avoid downtimes by unpredicted failures.“
Karl Heinz Gruber
CEO, VERBUND Hydro Power GmbH

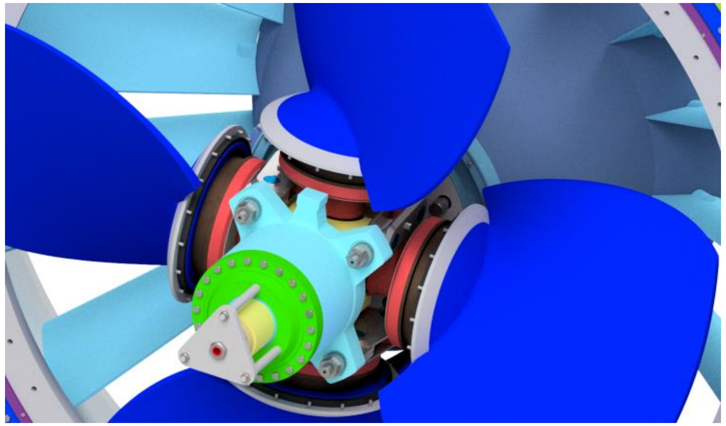
Project Approach

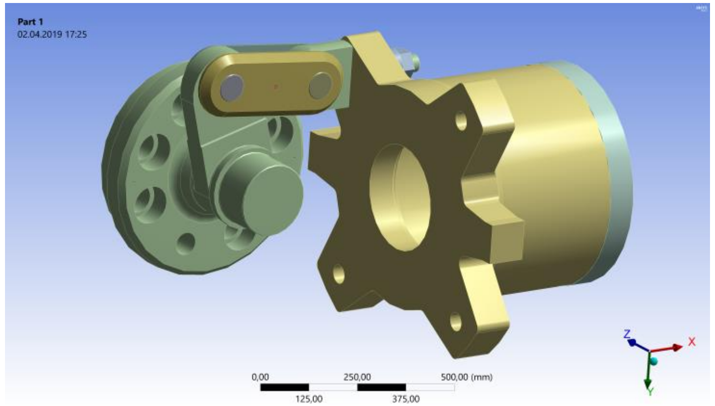


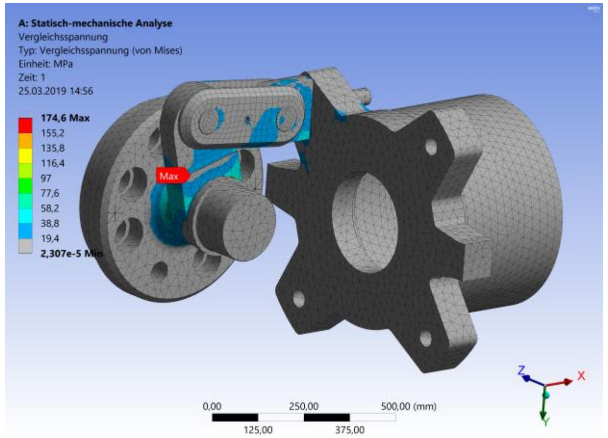
Real-time Monitoring of Remaining Service Life

Digital Twin Generation









3D-Geometry → **Finite Element Analysis**

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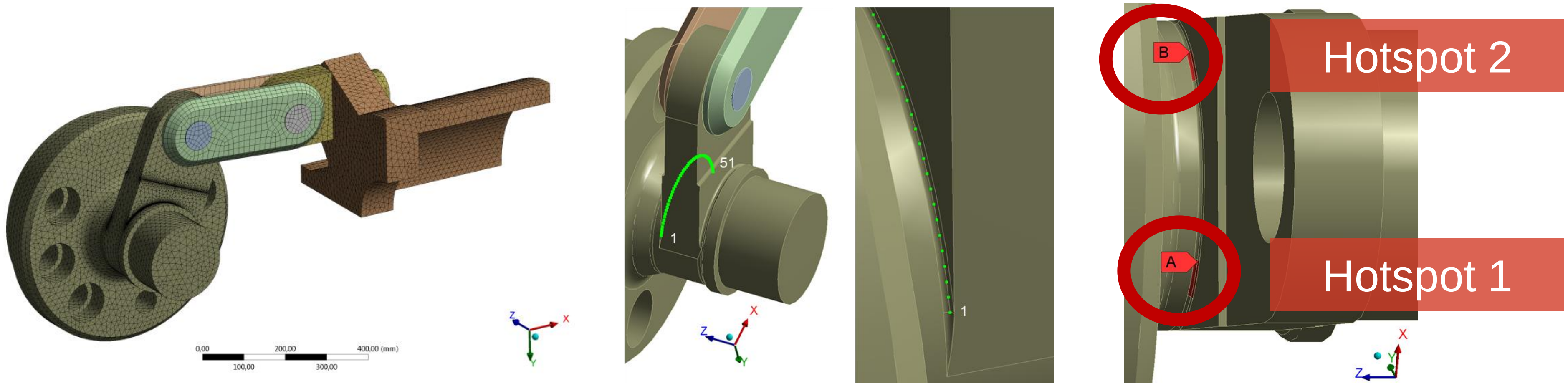
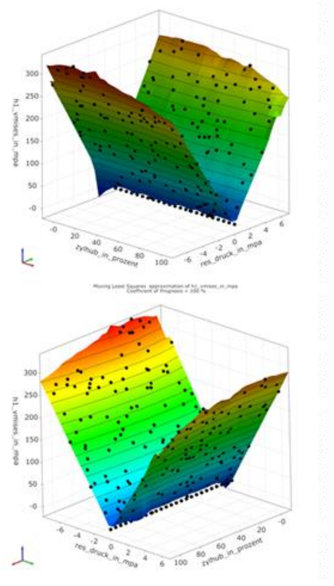
Real-time Monitoring of Remaining Service Life

Digital Twin Generation



dynardo optiSLang

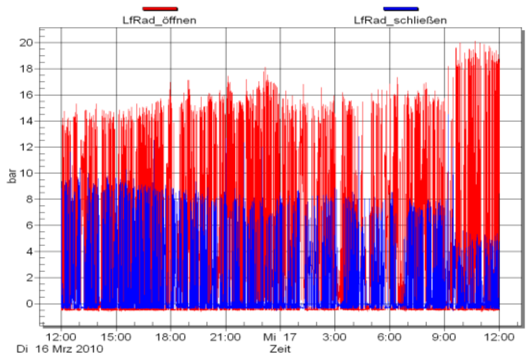


Finite Element Analysis: Determination of the hotspots

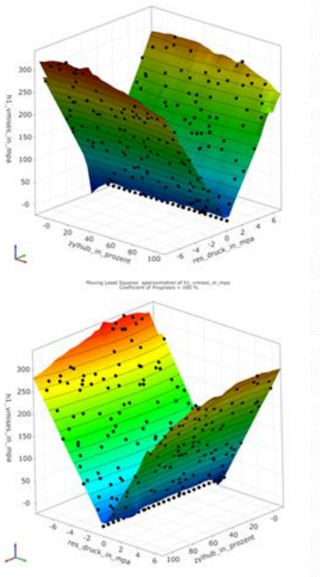
Reduced Order Model (ROM)

Real-time Monitoring of Remaining Service Life

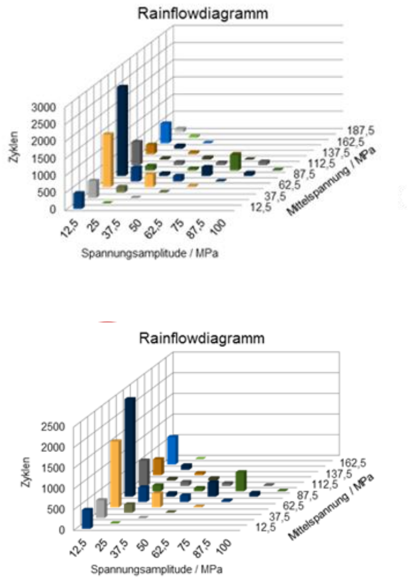
Digital Twin in Operation



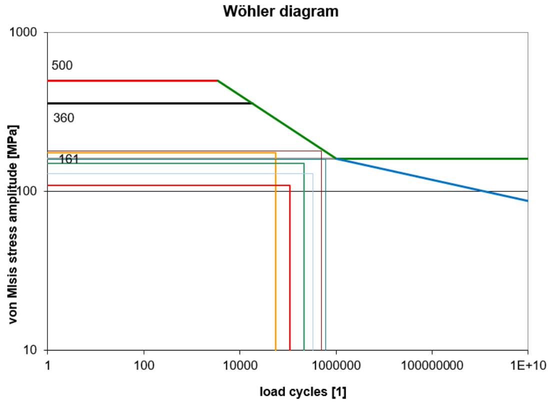
Online measurement data



ROM



Rainflow counting



Fatigue analysis

Technical Implementation of the Prototype

Sensors

Physical Sensors

- eg. Speed, flow rate, power

Import Sensor Data in IoT-Platform

IoT Platform

Device Management & Security

Transfer Sensor Data to Simulation Model (ANSYS TwinBuilder)

Simulation

Virtual Sensors & Lifetime Analysis

Generation of the simulation model in ANSYS TwinBuilder

Determination of the hotspots

Reduced Order Model (ROM)

Integration of Fatigue Analysis trough sensors and virtual sensors

Analytics

Visualization of sensors, virtual sensors and remaining lifetime in Verbund Dashboard

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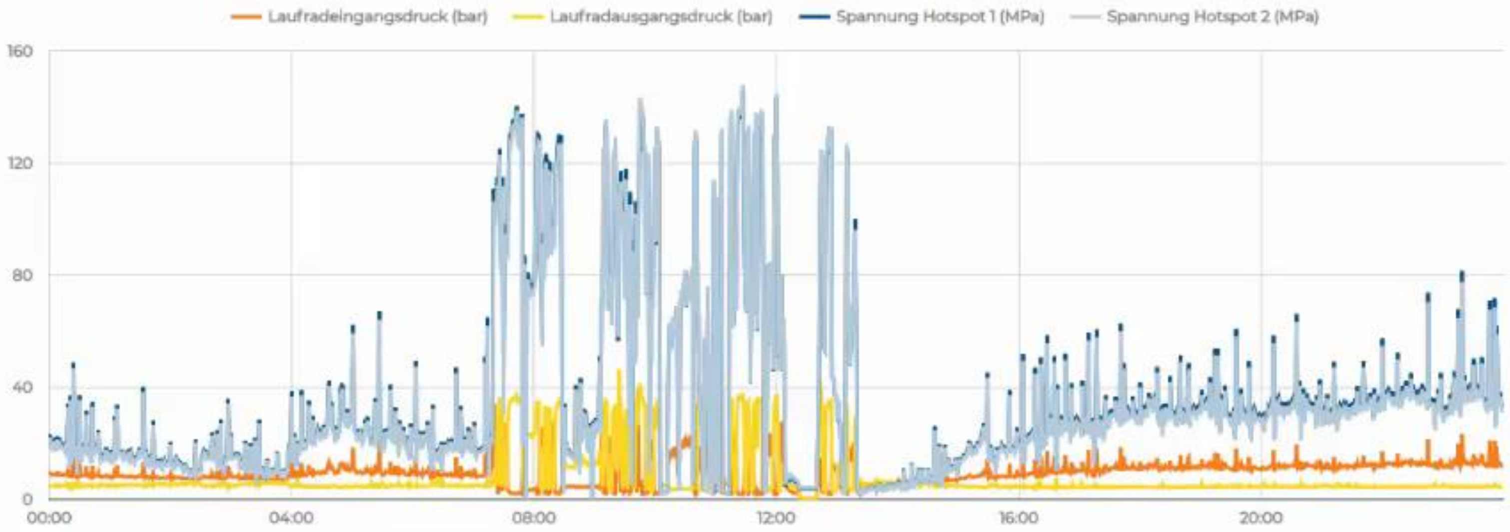
ITficient > Rabenstein Turbine 1 > Dashboard

FILTER Datum 12. März 2019

FESTIGKEITSNACHWEIS	HOTSPOT 1	HOTSPOT 2	LAUFRADSTELLUNG	LEISTUNG
✓	26.233 Jahre	15.584 Jahre	88,82 %	6,80 MW

SENSORDATEN



LAUFKRAFTWERK RABENSTEIN

Verbund

Eigentümer:	VERBUND Hydro Power GmbH
Inbetriebnahme:	1987
Region:	Österreich, Steiermark
Gewässer:	Mur
Leistung:	13,9 MW
Jahreserzeugung:	65.981,1 MWh
Turbinenart:	Kaplan
Turbine:	Turbine 1

SENSORDATEN

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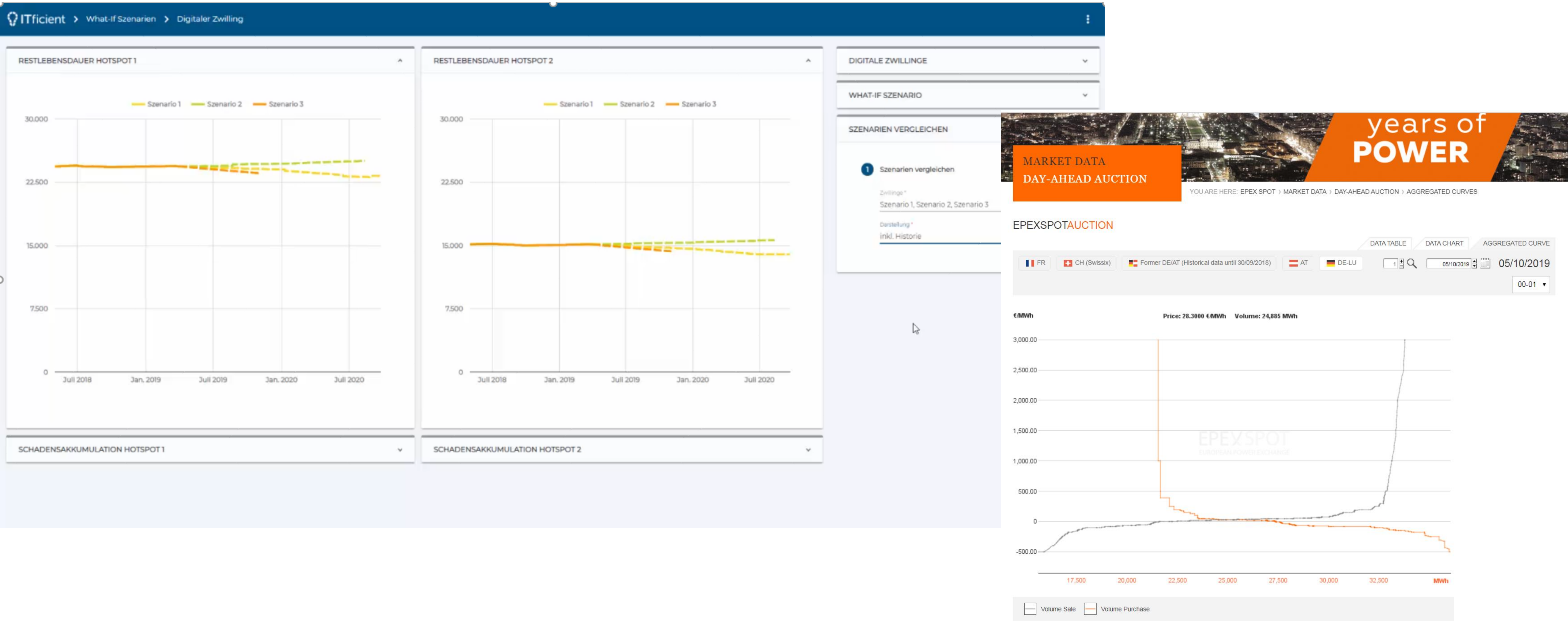
Prototype Development: What-if Scenarios

- Provide greater insight into how to operate the system **in a system-friendly way**
- Provide insights what it means for the **lifetime** if the system is operated under **very high or low loads** (synthetic load spectrum)

What-if Scenarios: Balance of Plant Performance & Degradation



Benefits for Verbund

"In addition to achieving the highest possible **availability** of hydropower plants, we also aim to get a more well-founded forecast of their remaining service lives. We also expect benefits in terms of the **condition-based servicing** and the avoidance of expensive repairs.“

Dipl.-Ing. Dr. Bernd Hollauf
Project Manager Digital Hydro Power Plant at Verbund Hydro Power

„This process of asking ‘what if X happens’ can provide us with greater **insight into how to operate the system** in a system-friendly way or what it means for the service life if the system is operated under very high loads.”

Dipl.-Ing. Michael Artmann
Project Manager Digital Twin at Verbund Hydro Power

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Use Case
Oil & Gas Safety Valve
Condition based Operation
• Evaluation of plant operation
• Fulfill GHG regulations
• Minimize losses
• New service by valve OEM

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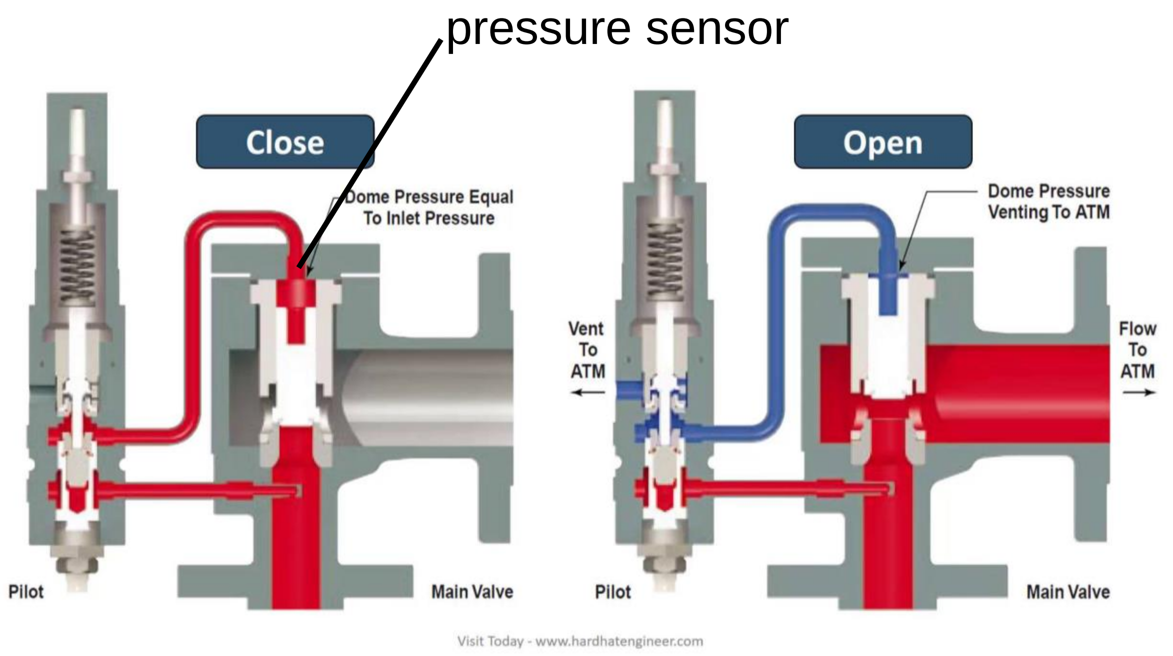
Virtual Sensor for Medium Released

- Equip safety valve with additional pressure sensor
- Engineering knowledge and simulation model from OEM development process
- Track pressure over time → quantify medium released
- Virtual sensor as digital service for operator, managed by valve OEM



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- Customer satisfaction
- Trust
- Innovation power

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Which of these Topics are relevant for you and your Company? 012

Development of smart Products and smart Services — 83%

Predictive Maintenance for your End Customer — 67%

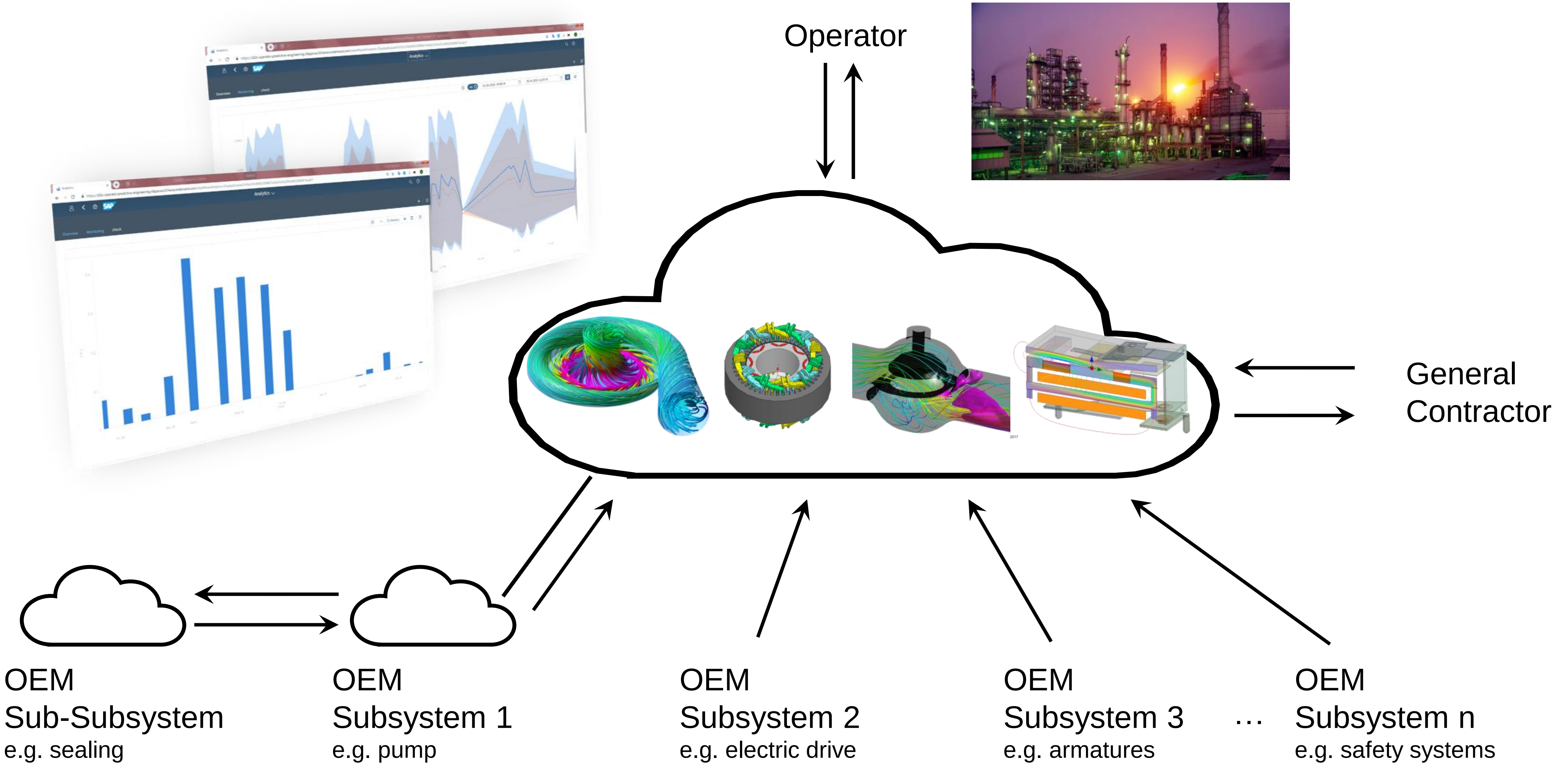
Condition Monitoring for your End Customer — 50%

Condition Monitoring for your Production — 8%

Predictive Maintenance for your Production — 8%

Ecosystem

How arises an ecosystem right now?



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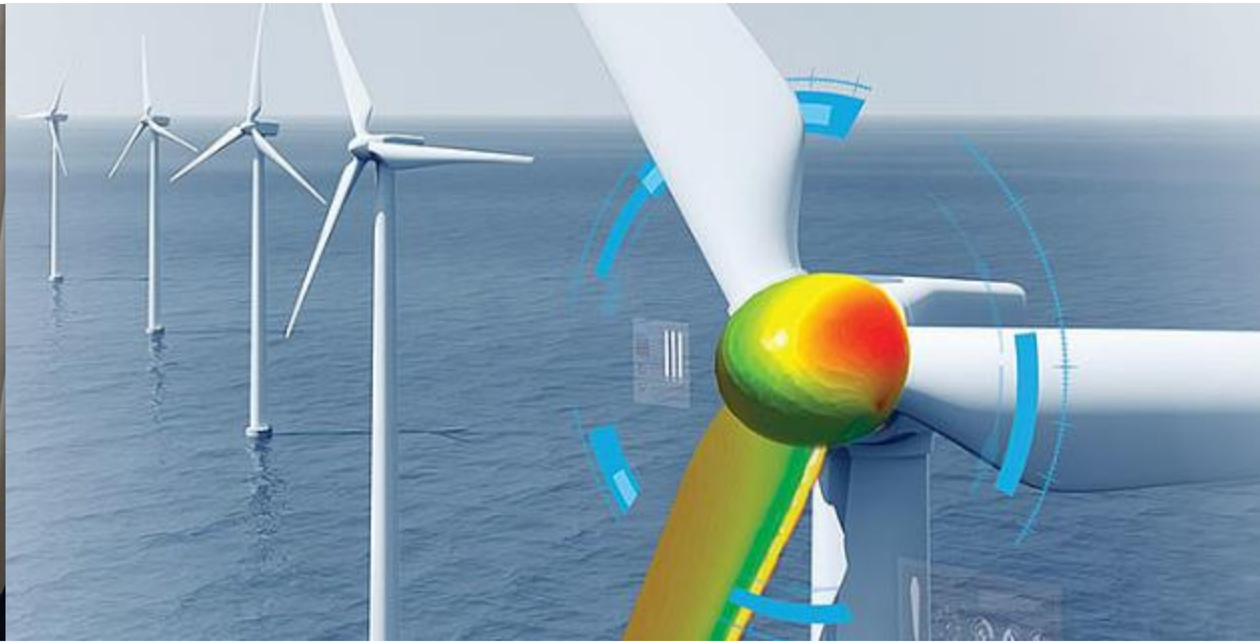

Supporting your customers in the development of new digital service models

Technical support for the creation of your digital twin

Contact

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WOST 2020
Workshop: Digital Twin

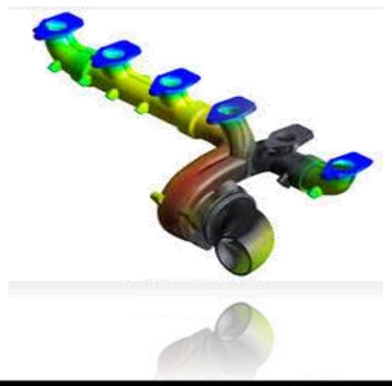
Teresa Alberts (ITficient AG)
Christof Gebhardt (CADFEM GmbH)
Sebastian Wolff (Ansys Austria)
David Schneider (Ansys Dynardo)

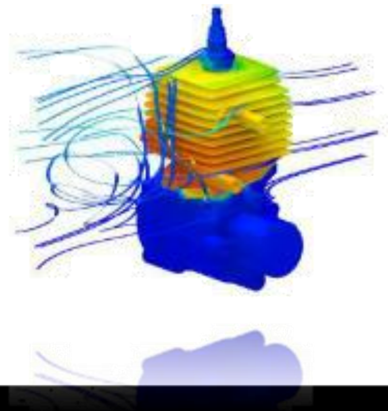
Ansys

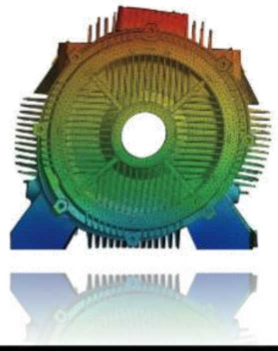
What is a Simulation Based Digital Twin?

- Connected, virtual replica of an in-service physical asset, in the form of an integrated multi-domain simulation, that mirrors the life and experience of the asset

- Enables system design and optimization, predictive maintenance and optimize industrial asset management







Ansys

How Digital Twins help our customers

Increase topline revenue

Manage bottom-line costs

Gain/retain Competitive Edge

Implementing A Digital Twin Presents Significant Challenges

1.65BN Assets under condition monitoring by 2025[1]

$80BN/Yr Investments in IIoT[1]

Over 90% of executives say they are willing to digitally reinvent their industry and business……yet less than 10% have fully integrated digital threads[2,3]

To enhance adoption of digital twins, they must be:

- Predictive
- Accurate
- Real-Time

1. Forbes
2. Accenture: Seizing the Digital Opportunity in Aerospace & Defense 2018
3. Accenture: The Digital Thread Imperative 2017

Ansys

Yet The Benefits Are Clear

15%
Revenue Gain[1]

- New business models
- Improved productivity and accelerated new product introduction
- Competitive advantage

10%
Cost Reduction[1]

- Warranty cost reduction
- Operational efficiency
- Shortened design and development cycles

30%
Maintenance Cycle Time Improvement[2]

- Improved maintenance efficiency

1. McKinsey & Company: Five Keys to Digitizing Aerospace and Defense
2. Companies Aviation Week MRO

Customers are putting simulation at the center of their Digital Twin implementations

Ansys
Simulation-based Digital Twins

+

IIoT and Data Analytics

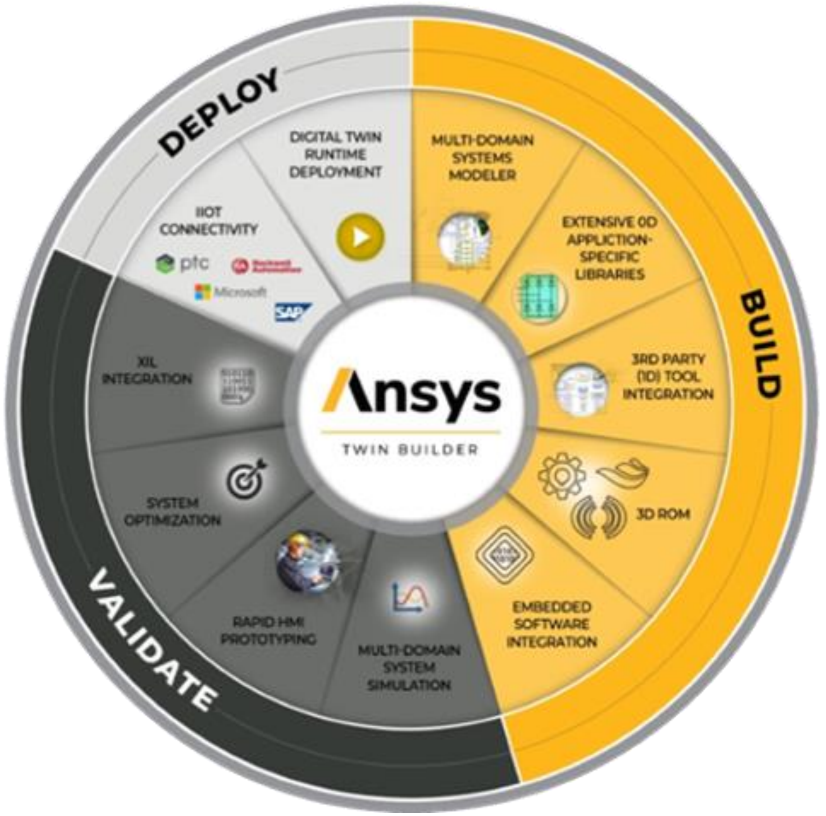
Virtual Sensors to Simulate Critical Quantities

Perform What-ifs before applying a solution

Physics Based Accuracy, Improved ROI

Generate baseline and failure data using Physics

Solution Capabilities Required To Deliver These Benefits



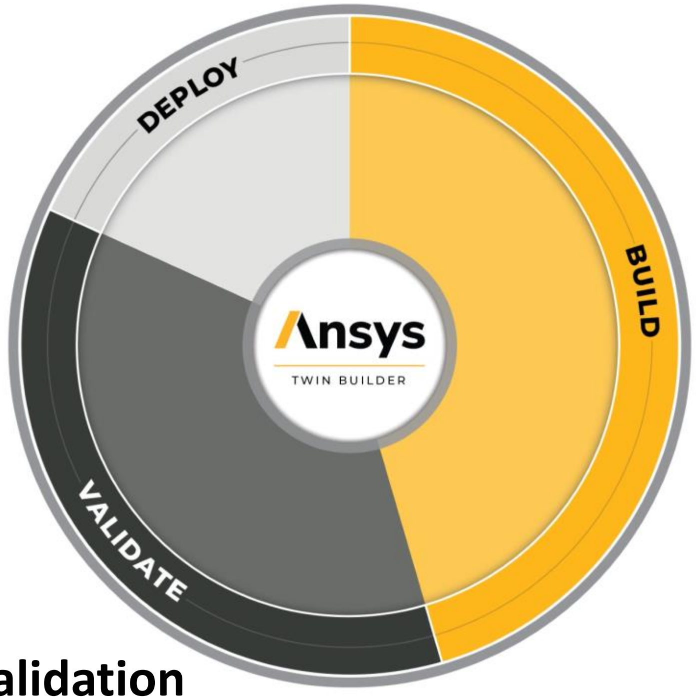
- Build an Accurate, Physics-Based Digital Twin
- Validate and Optimize the Twin
- Connect Twins to IIoT Platforms and Deploy Runtimes in Operation

Simulation based Digital Twin

Deploy

System Predictive Maintenance

Connect the Twins to IIoT Platforms and Deploy Run times in operation



Build

Simulation

Build an accurate Physics-based Digital Twin in record time

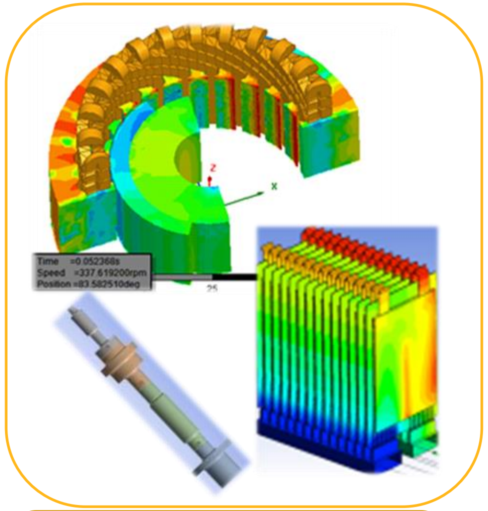
Validate

System Validation and Optimization

Validate and Optimize the Twin

3D Reduced-Order Modeling Interfaces
Transforms 3D simulation results into system-level models

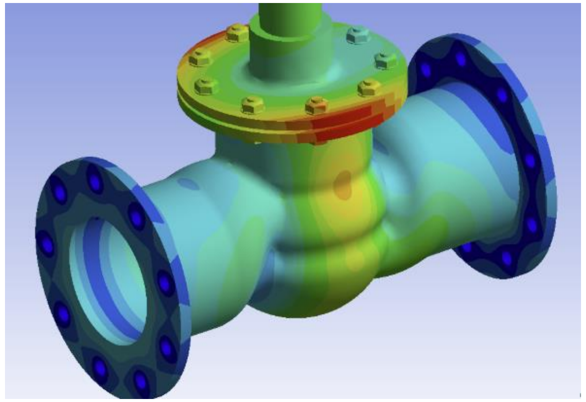
- Use Reduced-Order Modeling (ROM) interfaces to generate accurate, compact models from detailed 2D and 3D physics simulations.
- Simulates in a fraction of the time required by 3D Techniques for all ANSYS physics
- Link to a variety of ANSYS tools to create high performing models.



Connections with 3D Physics

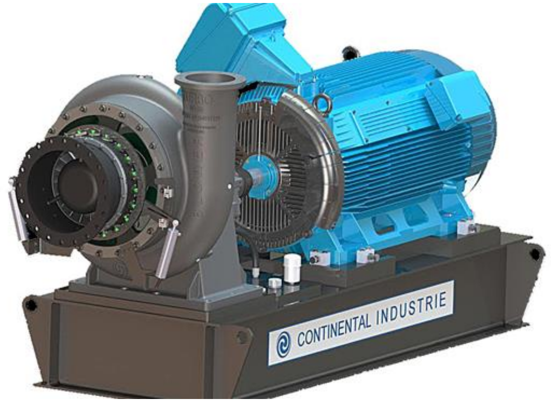
Application Examples of Digital Twins with Twin Builder

Battery/Electrification

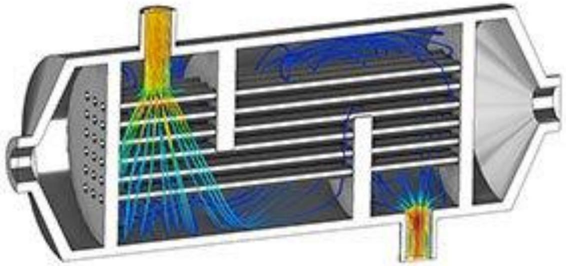


Structural

Industrial Automation



Electric Motors and Machines



Heat Exchangers

Rotating Machinery

Ansys

Ansys / DYNARDO
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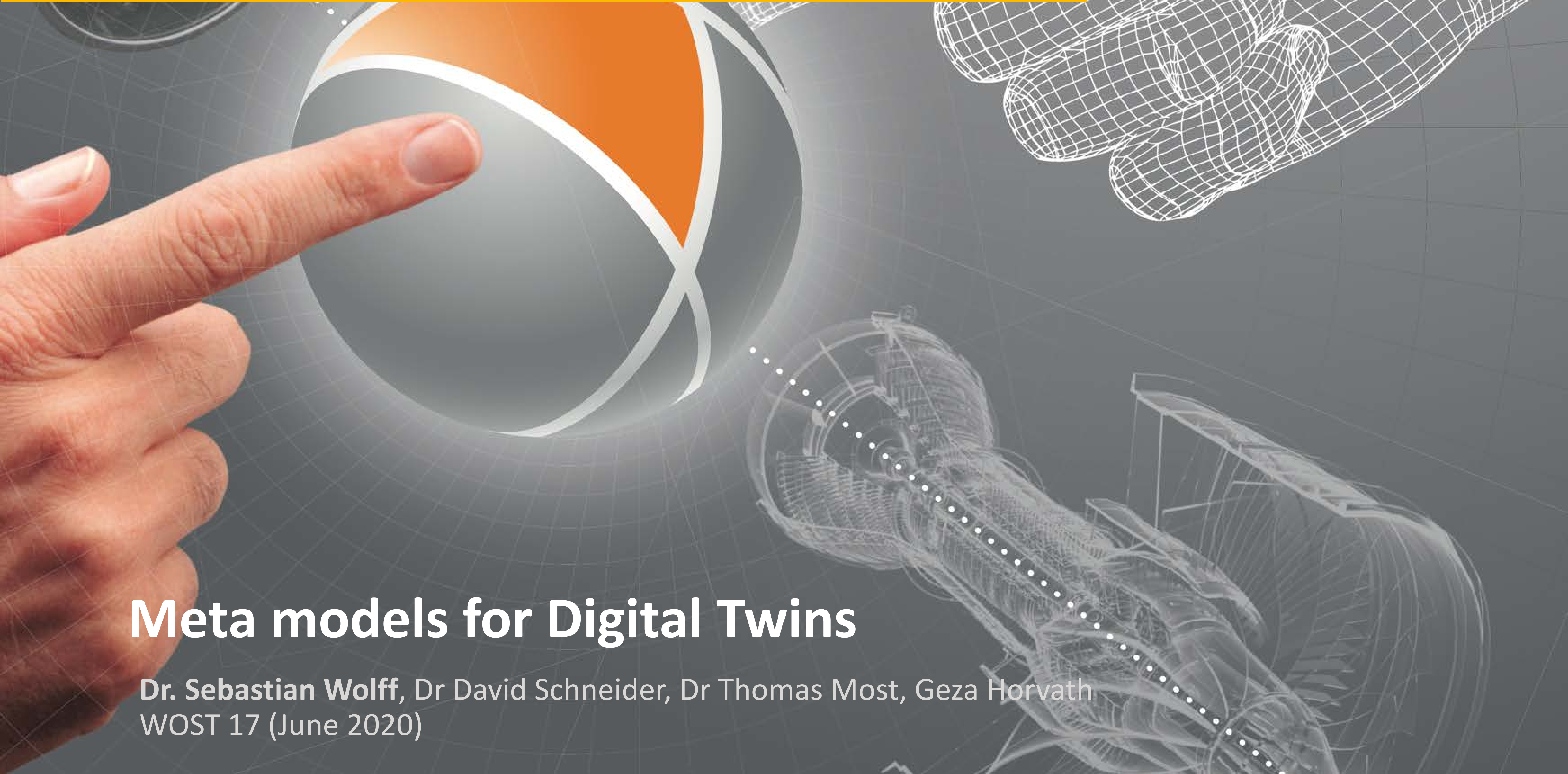
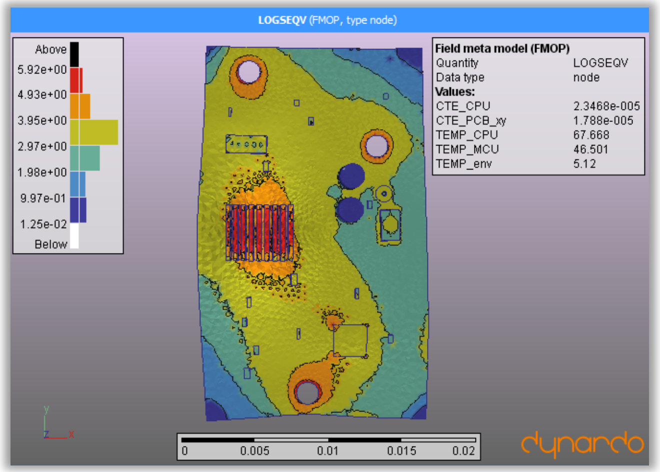


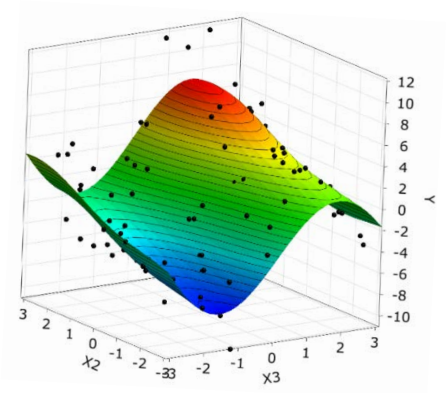
Meta models for Digital Twins

Dr. Sebastian Wolff, Dr David Schneider, Dr Thomas Most, Geza Horvath
WOST 17 (June 2020)

optiSLang Reduced Order modelling (ROMs)

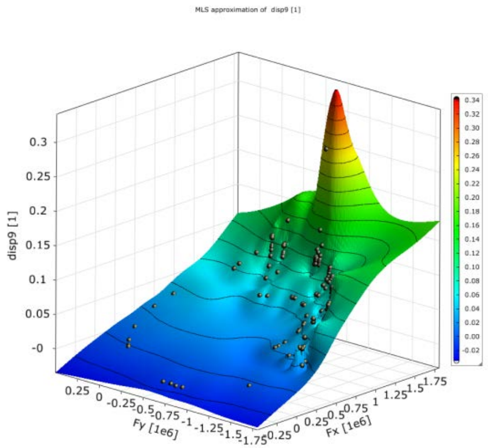


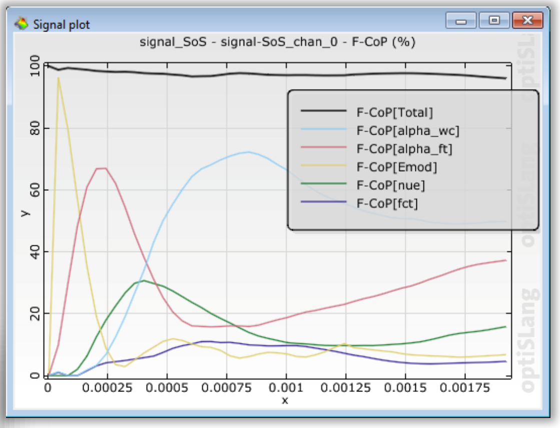
- **ROM's replace a higher-dimensional model by a simplification**
  - **Physical ROMs:** solve a physical system of equation with less variables; fast and flexible, but often only linear
  - **Data based ROMs:** Based on data analysis, nonlinear
- **Databased – physics agnostic**
- **Real time surrogate models**
  0D-3D Field data (e.g. FEM, CFD, signals)
- **Automatic (spatial) parameterization**
  based on measurements or simulations
- **3D Robust Design**
  detect hotspots, failure locations, sensor positions
- **Data & Solver agnostic**
  Supports CAE solver formats
  Analysis of measurements (CSV,STL, images)
  …

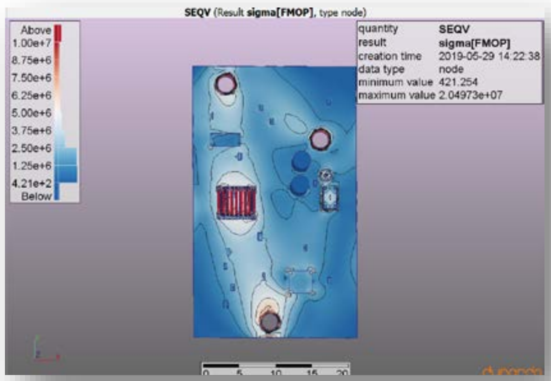


Overview on of optiSLang meta models (parameter based)

- MOP (for scalars)
  - Part of optiSLang
  - Build: license needed
  - Usage: no license needed
- Field MOP for curves (Signal MOP)
  - Part of optiSLang capability SoS
  - Build: license needed
  - Usage: license needed
- Field MOP for 2D/3D (mesh, grid, point cloud, image,…)
  - Part of optiSLang capability SoS
  - Build: license needed
  - Usage: license needed; no license for FMU



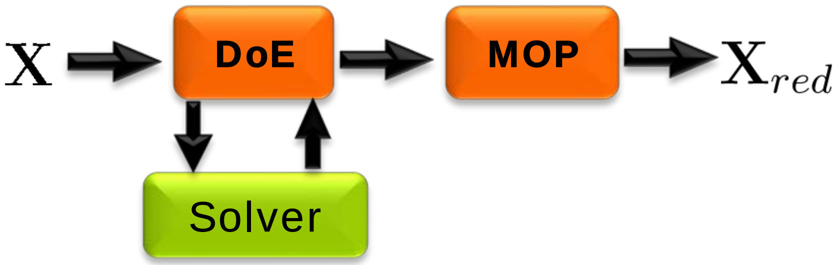


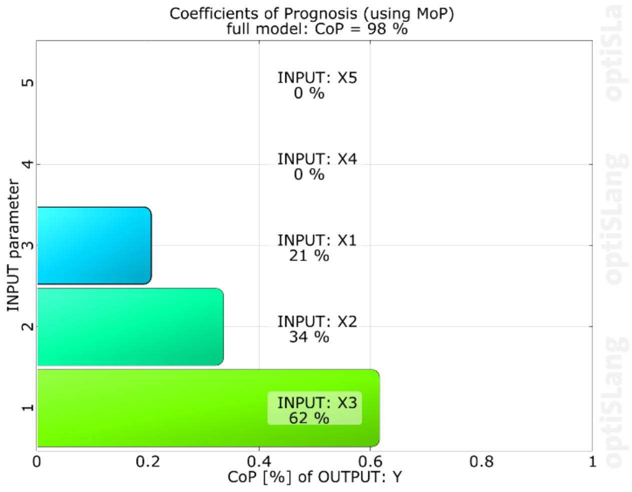


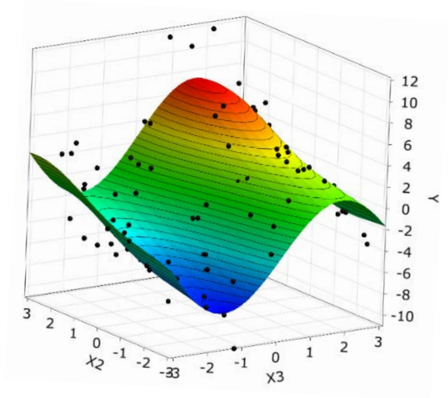
Metamodel of Optimal Prognosis (MOP)

- A fully automatic workflow identifies the subspace of important parameter with the best possible meta-model (MOP) of every response variable resulting in the best possible forecast quality towards result variation
- Include multi-dimensional nonlinear dependencies with automatic identification + ranking of important input variables

•MOP Solves 3 Important Tasks:
1st Best Input Variable Subspace
2nd Best Meta-model
3rd Estimation of Prediction Quality



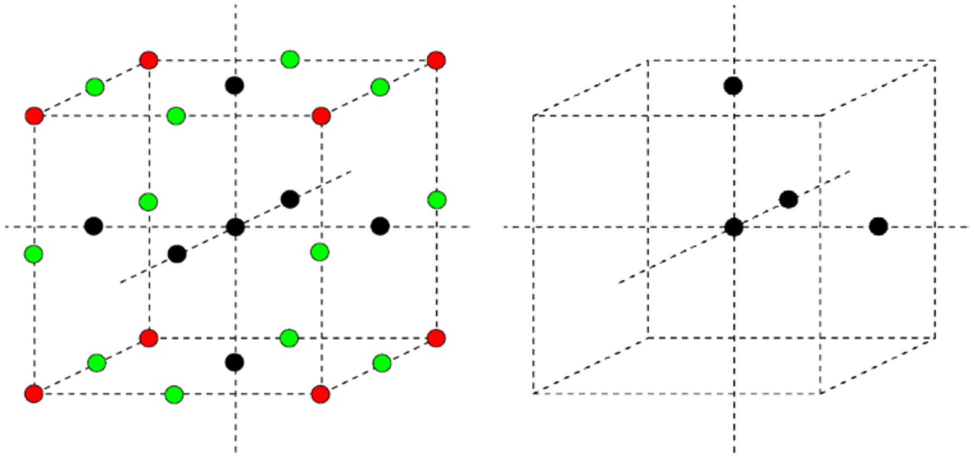




How to generate Design of Experiments

Deterministic DoE

- Complex scheme required to detect multivariate dependencies
- Exponential growth with dimension

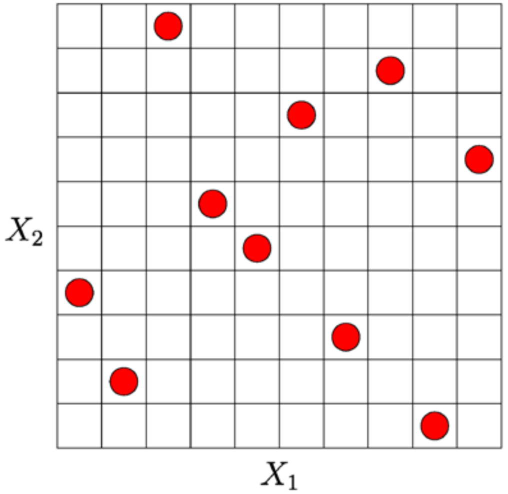


Full factorial: $N = 2^k, 3^k, \ldots$

Koshal linear: $N = k + 1$

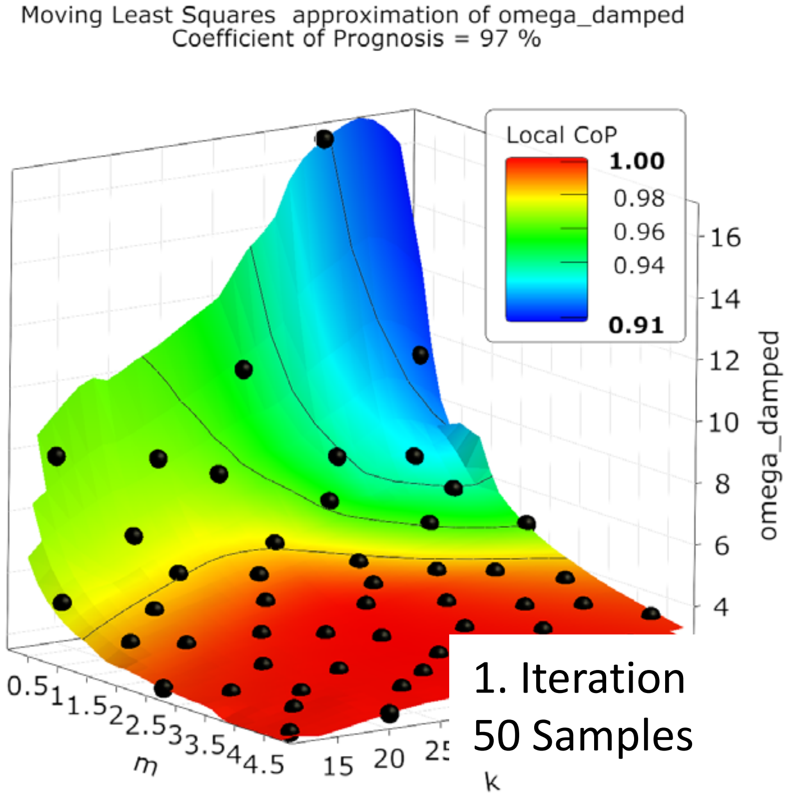
Advanced Latin Hypercube Sampling

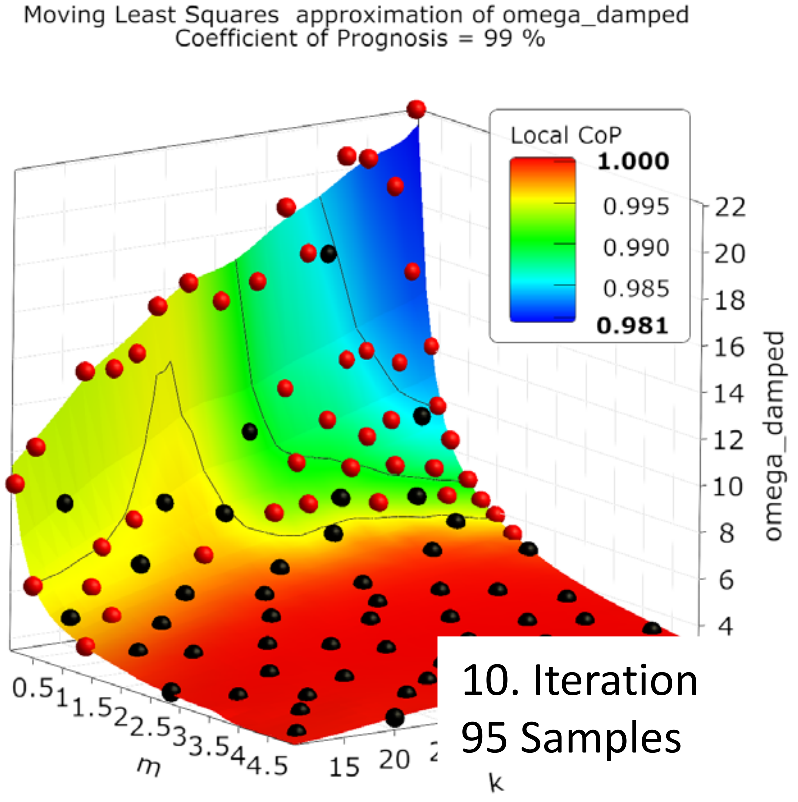
- Reduced sample size for statistical estimates compared to plain Monte Carlo
- Reduces unwanted input correlation



Optimizing Design of Experiments: Adaptive MOP

- New points are placed in region with large gradients
- Local CoP is improved significantly with small number of additional designs



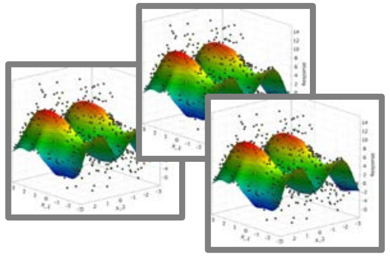


MOP – Metamodel of Optimal Prognosis

MOP for scalar values:

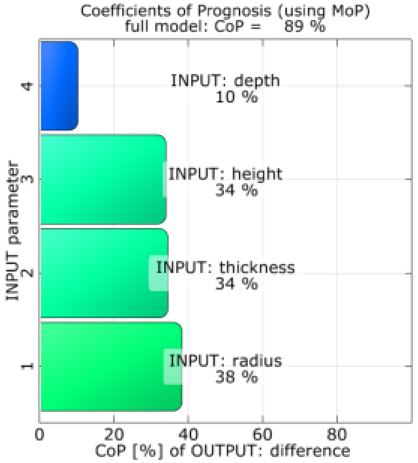
- Objective measure of prognosis quality = **CoP**
- Determination of **relevant parameter subspace**
- Determination of **optimal approximation model**
- Approximation of solver output by fast surrogate model **without over-fitting**
- Evaluation of **variable sensitivities**

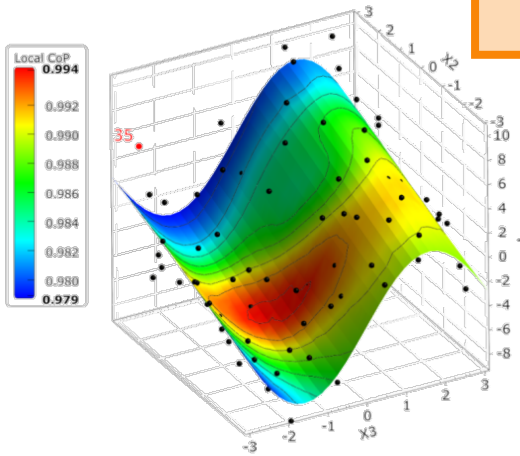
investigate response by response based on LHS sampling



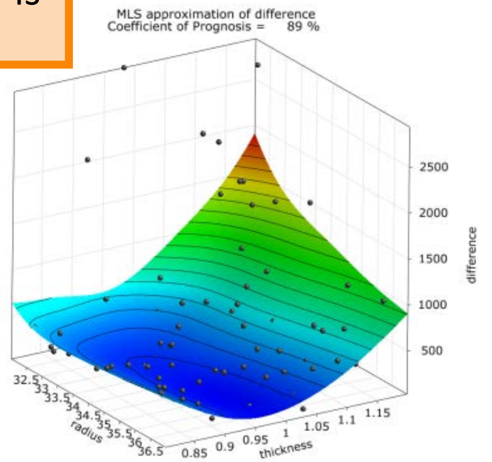
generate competing meta-models

calculate forecast quality using **CoP** (**C**oefficient **o**f **P**rognosis)





The winner is … **MOP**



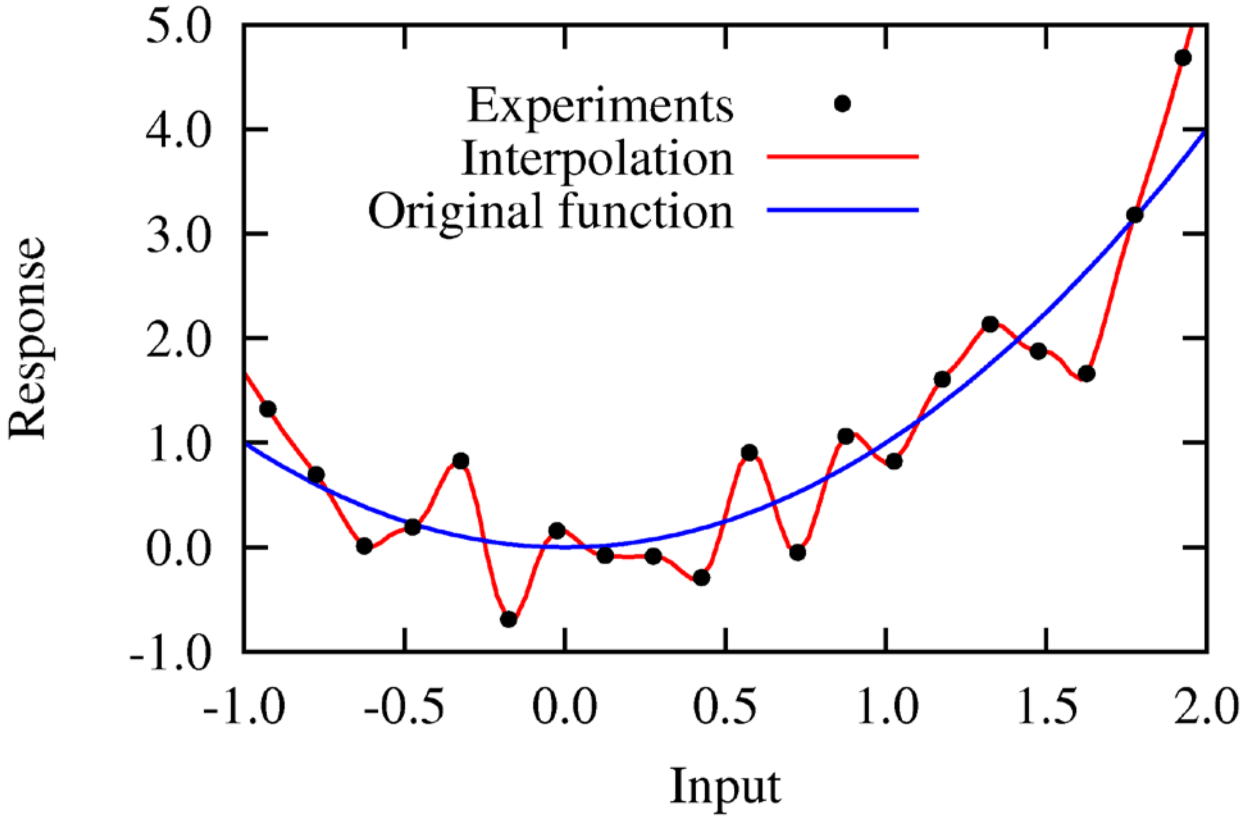
Measure Goodness of Fit = Coefficient of Determination (CoD)

- Coefficient of Determination quantifies merely the Goodness of Fit.
- Interpolation models (e.g. MLS, Kriging) can reach CoD of 1.00
- **But perfect fit does not mean perfect forecast quality!**

$$R^2 = \frac{SS_R}{SS_T} = 1 - \frac{SS_E}{SS_T}$$

$$SS_E = \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$$

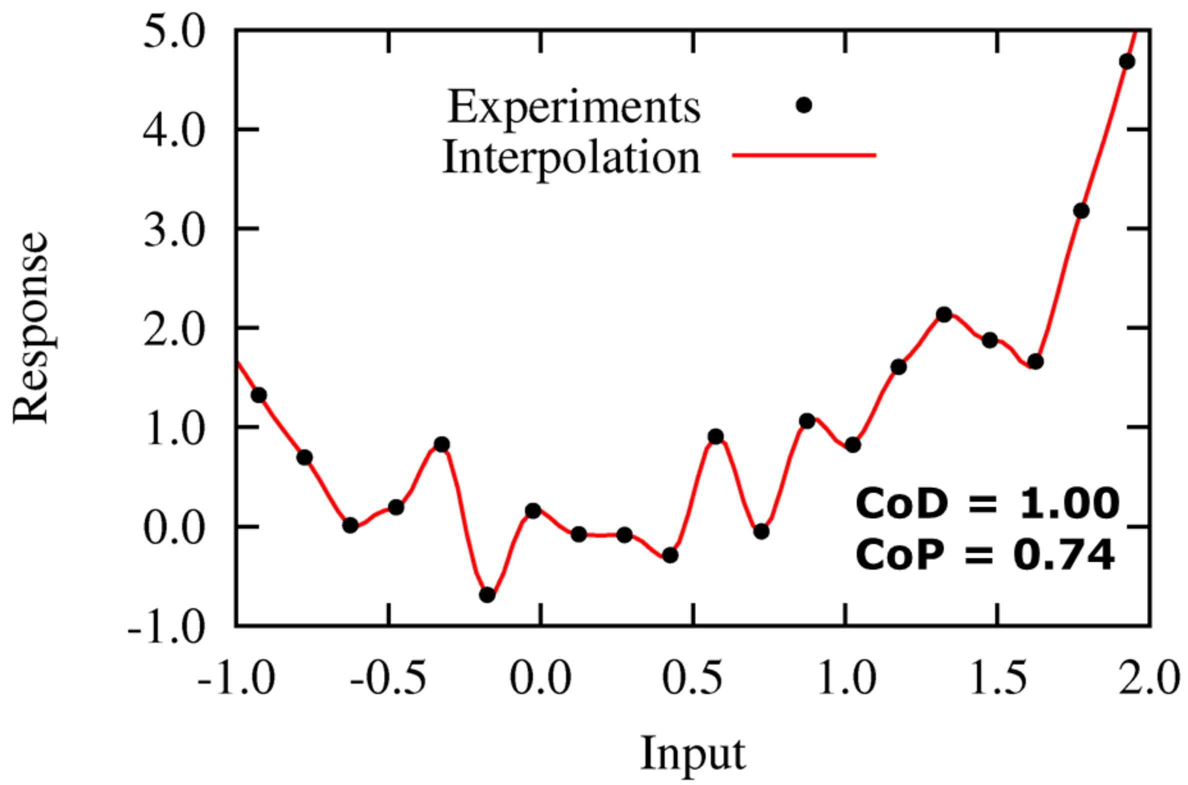
$$SS_T = \sum_{i=1}^{N} (y_i - \mu_Y)^2$$



Measure forecast quality = Coefficient of Prognosis (CoP)

- Coefficient of Prognosis sums up the errors from both cross validation cases:
- **CoP is an objective measure of forecast quality.**

$$CoP = 1 - \frac{SS_E^{Prediction}}{SS_T}$$



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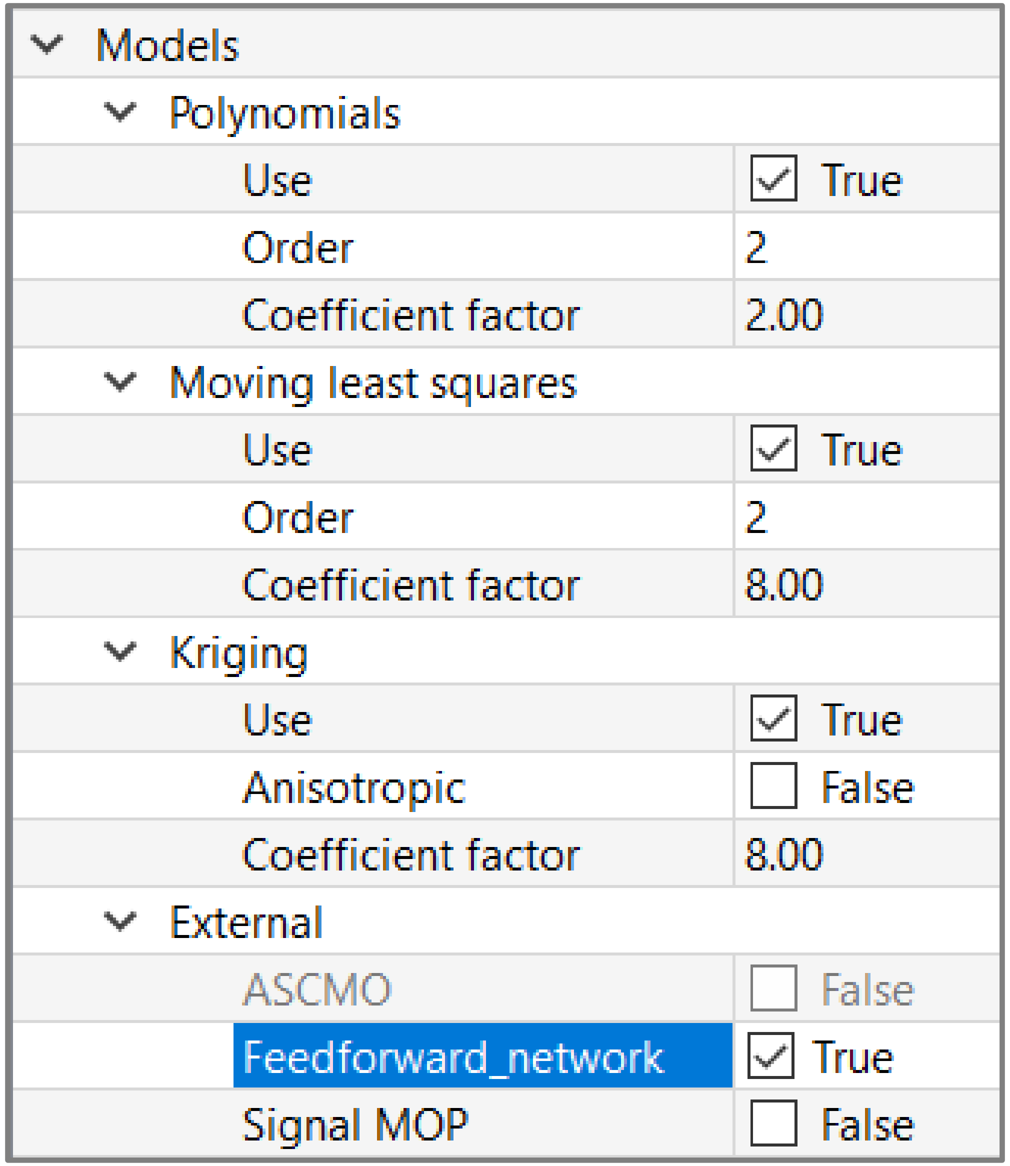
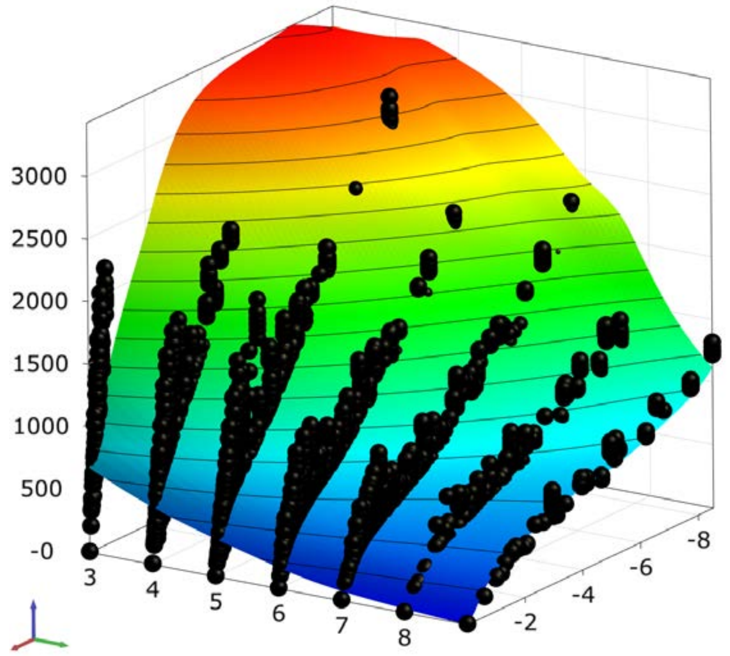
Approximation Models

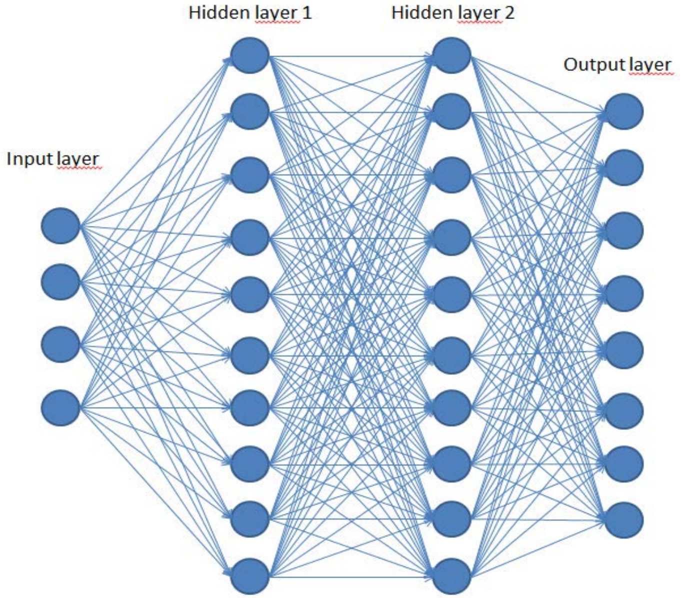
- **Polynomials - Linear Regression**
  - Linear & quadratic with/without mixed terms
- **Moving Least Squares**
  - Linear and quadratic basis
  - Exponential or regularized kernel
- **Kriging**
  - Isotropic & anisotropic kernel
- **Externals**
  - ASCMO
  - Neural networks (Tensorflow)
  - DX meta models (GARS, Support Vector Regression)



Deep Learning Extension

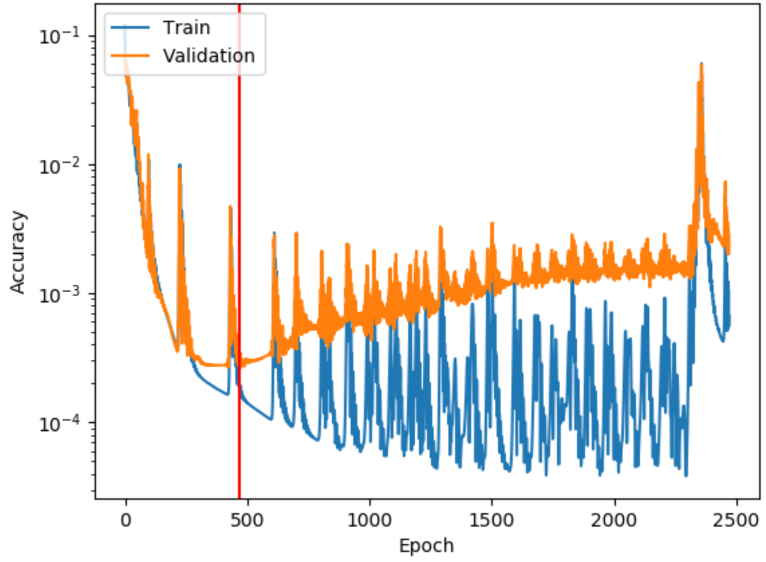
- Automatic configuration of neurons and layers
- Cross validation to estimate Coefficient of Prognosis
- Available as external python environment
- Neural networks are treated as one of a library of approximation models
- Competition is done in the MOP framework based on the CoP





Deep Learning

K + TensorFlow



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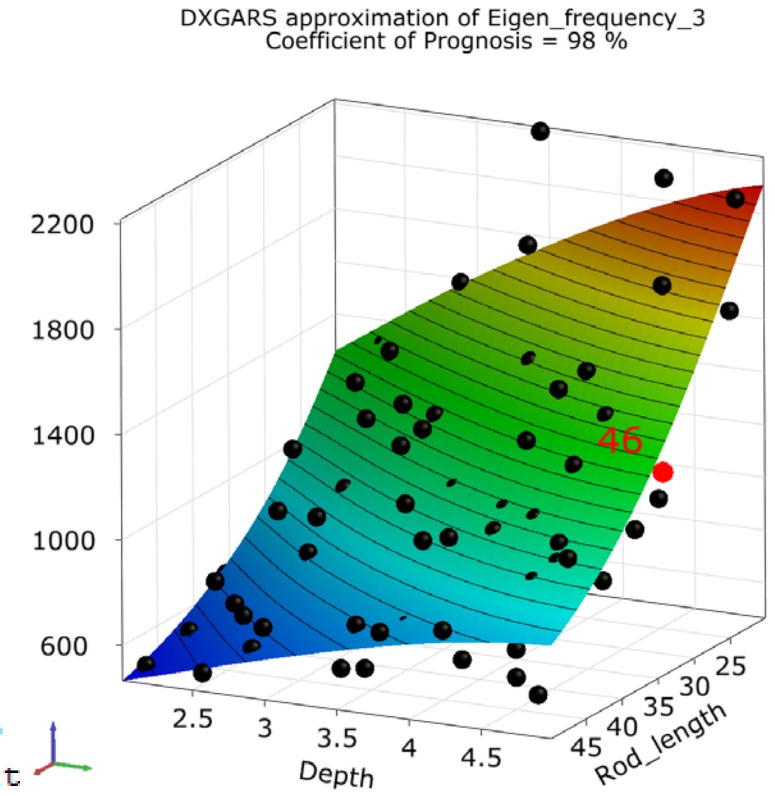
Integration of DX meta-models (2020 R2)



- Implementation of Python wrapper within custom surrogate
- Cross validation estimates have been verified

➢ DX models can be considered in the MOP competition

Response	CoD adjusted	CoP	Model
Eigen_frequency_1	0.841747	0.836	Linear Regression of order 1 (no
Eigen_frequency_1	0.955115	0.945973	Linear Regression of order 1 (wit
Eigen_frequency_1	0.984982	0.983589	Linear Regression of order 2 (with mixed terms, BoxCox)
Eigen_frequency_1	0.998362	0.973476	Moving Least Squares of order 1 (e
Eigen_frequency_1	0.999582	0.979185	Moving Least Squares of order 2 (e
Eigen_frequency_1	0.997524	0.988275	Kriging (isotropic kernel, BoxCox)
Eigen_frequency_1	0.998804	0.987579	Kriging (anisotropic kernel)
Eigen_frequency_1	1	0.980692	DXGARS
Eigen_frequency_1	1	0.980452	DXKriging
Eigen_frequency_1	1	0.921952	DXNPR
Eigen_frequency_1	0.998672	0.991904	Feedforward_network

External	
ASCMO	☐ False
DXGARS	☑ True
DXKriging	☑ True
DXNPR	☑ True
DXPoly	☐ False
Feedforward_network	☐ False

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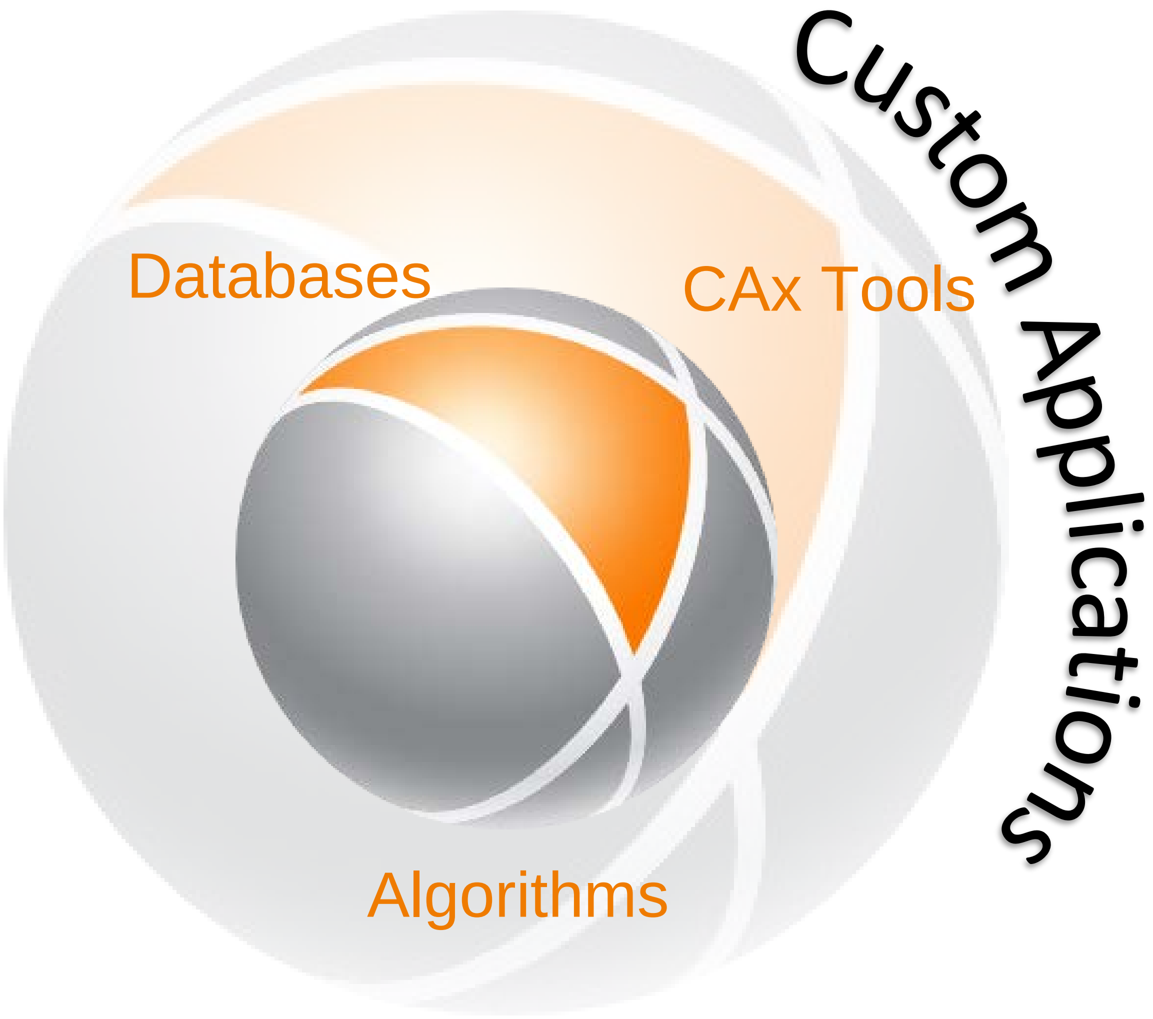
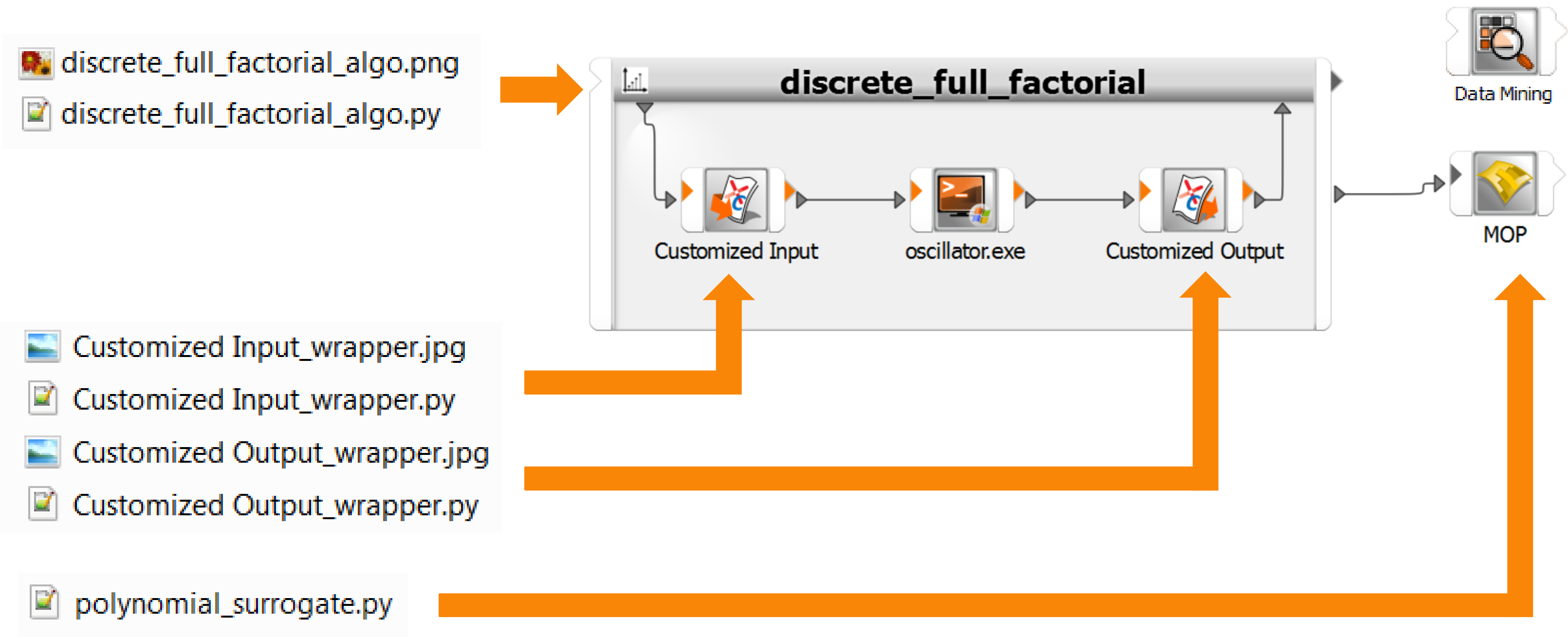
Openness – open and programmable architecture

- Plugins
  - CAx tool integrations
  - Algorithms
  - (PLM-) Databases
- Interfaces
  - Batch
  - Scriptable (.py, .opx)
  - Shared libraries (.dll, .so)
  - Remote control (TCP/IP)



Customization overview

- optiSLang provides plugin mechanisms via Python scripting
  - Define own **integration nodes**
  - Implement own **algorithms**
  - Customize **Solver Wizard** and **Postprocessing**
  - Extend MOP algorithm with own **surrogates** (beta)
  - Implement **Data Mining** functions



Use case

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Reduced order modelling for Digital Twins

Training

Create suitable training data (e.g. through DOE) and create a real-time approximation model (ROM)

Deploy

Connect ROM with online sensors and deploy to ECUs (e.g. by TwinBuilder)

1. Simulation
2. Training
3. Validate
4. Deploy

Simulation

Create a simulation model predicting the performance. Parameterize model with virtual sensors

Validate

Check prognosis quality of simulation and meta model.

Training of field meta models

1. Simulation
2. Training
3. Validate
4. Deploy

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Software demonstration

- ANSYS Mechanical model
- optiSLang DOE
- Create Field MOP

Validation of meta model

1. Simulation | 2. Training | **3. Validate** | 4. Deploy

Ansys

Software demonstration

- Analyse Field MOP:
  - Stddev and hot spots
  - Field CoP and sensitivity
  - Variation patterns
  - OSL PP for interpolation functions
- Outlook: Measurements
  - Filter noise (separate example)
  - Identify outliers (Random field; optiSLang CV)

Export and consume Field Meta Models

1. Simulation
2. Training
3. Validate
4. Deploy

1. “Brute force”: Direct export and consumption of data

- Export any data from Field MOP database as CSV to Excel, optiSLang etc.
- Connect Field MOP consumpton with 3rd party software through shared libraries:
  - Solve Field MOP and retrieve complete data vectors (3D fields, signals, etc.)
  - Access mesh connectivity
  - Use embedded scripting for full SoS capability including Field Mop creation and I/O
  - ANSI C API and examples for Matlab, C++, Python …

```c

DYNARDO_FMOP_API fmop_error_t FMOP_getModelIdents
    ( const fmop_db_handle_t database, fmop_dataobject_types data_ty
DYNARDO_FMOP_API fmop_error_t FMOP_getModelParamIdents
    ( const fmop_handle_t fmop, char *** const param_idents, size_t
DYNARDO_FMOP_API fmop_error_t FMOP_getParamLowerBounds ( const fmop_
DYNARDO_FMOP_API fmop_error_t FMOP_getParamUpperBounds ( const fmop_
DYNARDO_FMOP_API fmop_error_t FMOP_getModelTotalAvgFCoP ( const fmop
DYNARDO_FMOP_API fmop_error_t FMOP_getModelAvgFCoP ( const fmop_hand
DYNARDO_FMOP_API fmop_error_t FMOP_getModelDim ( const fmop_handle_t
DYNARDO_FMOP_API fmop_error_t FMOP_getDataPointIndizes ( fmop_handle
DYNARDO_FMOP_API fmop_error_t FMOP_getDataPointCoors (fmop_handle_t


/*****************************************/

DYNARDO_FMOP_API fmop_error_t FMOP_approxField
    ( const fmop_handle_t fmop, const double * param_values, double

```

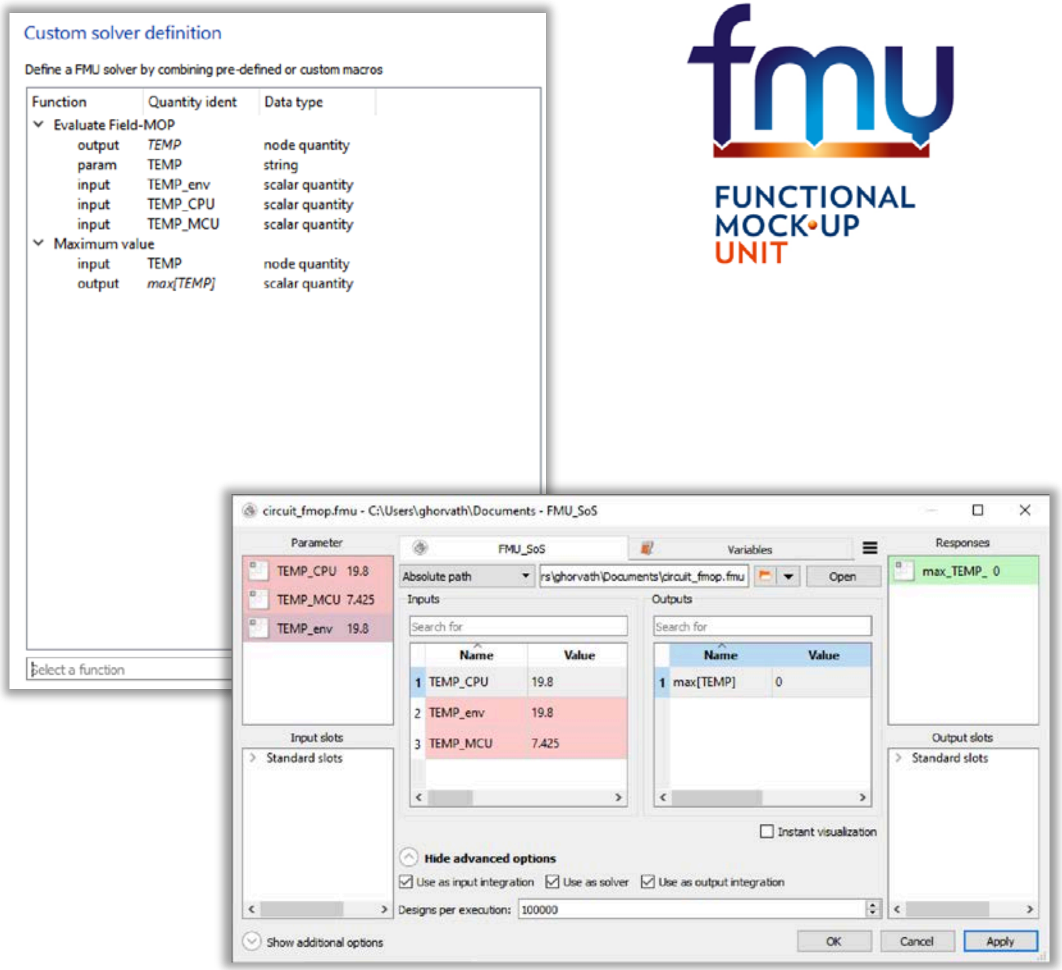
ANSI C/C++

```python
param_idents = ctypes.POINTER( ctypes.c_char_p )()
num_idents = ctypes.c_ulonglong(0)
sos.FMOP_getModelParamIdents ( fmop, ctypes.byref( param_idents ), ctypes.

num_mesh_items = ctypes.c_ulonglong(0)
sos.FMOP_getModelDim ( fmop, ctypes.byref ( num_mesh_items ) )

param_values = ( ctypes.c_double * num_idents ) ( 1., 2., 3., 4., 5., 6. )
approx_field = ( ctypes.c_double * num_mesh_items.value ) ()
sos.FMOP_approxField ( fmop, param_values, ctypes.byref( approx_field ) )
```

Python example

2. Innovation: Export FMU 2.0 (Functional Mockup Unit)

- User can write his own analysis macros
- Combine macros into a single automated analysis
- Export workflows to FMU 2.0 (model exchange)
- Consume FMU in optiSLang or TB
- Visualize all 3D fields afterwards in SoS post prociessing



FUNCTIONAL MOCK-UP UNIT

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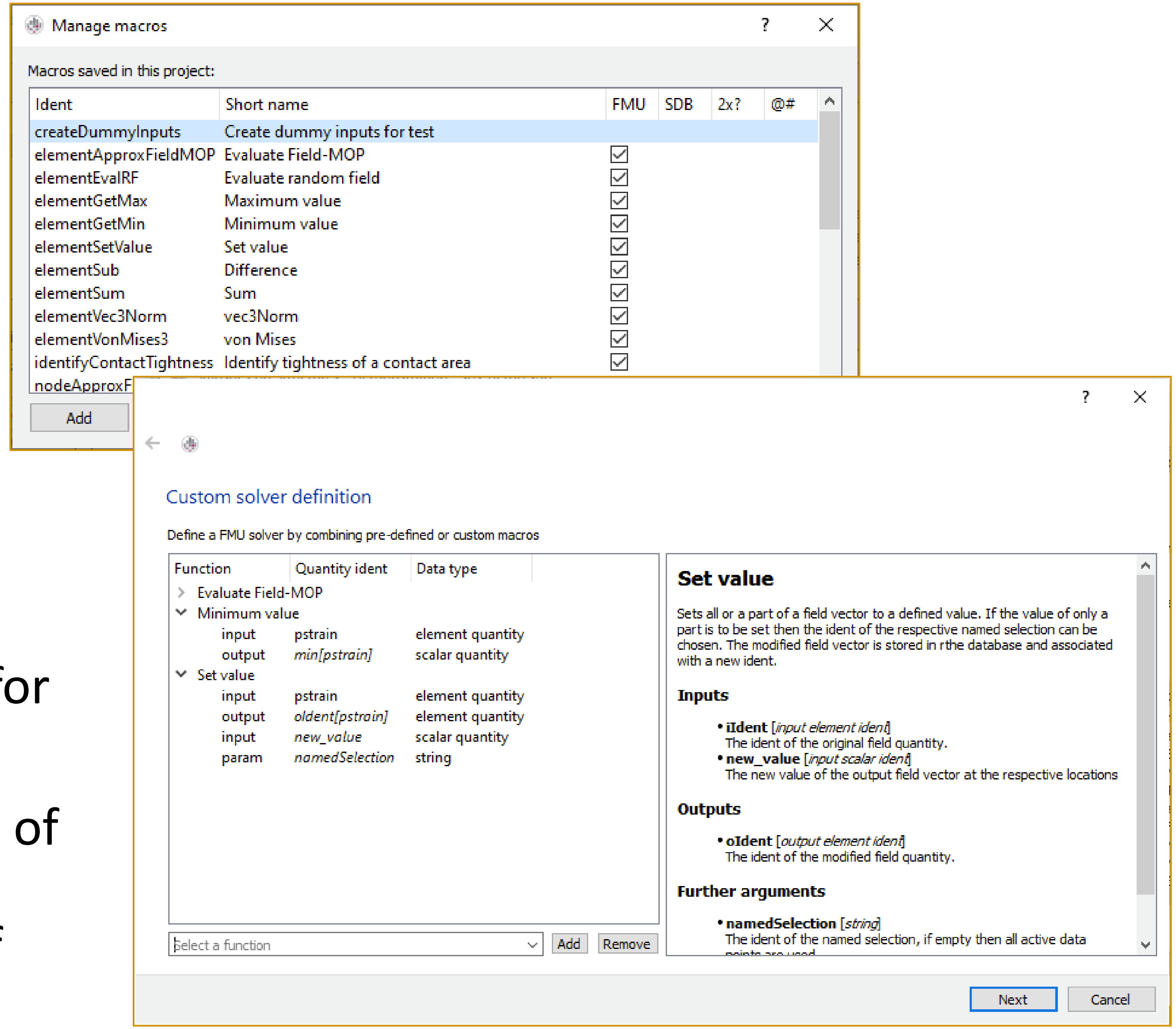
2. Innovation: User macros

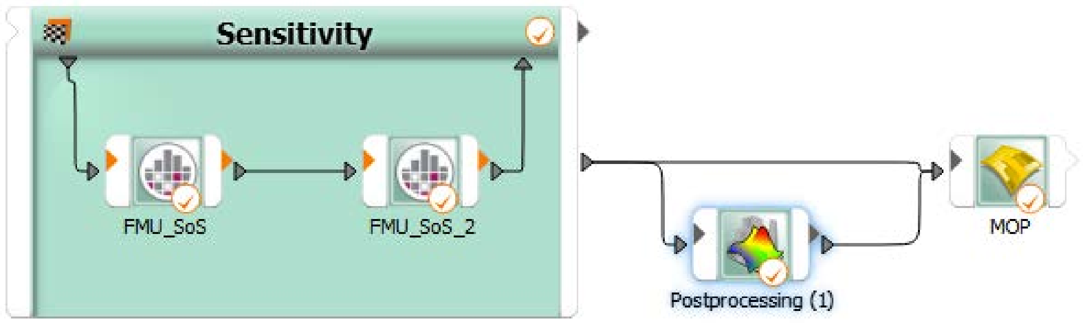
Macros may include

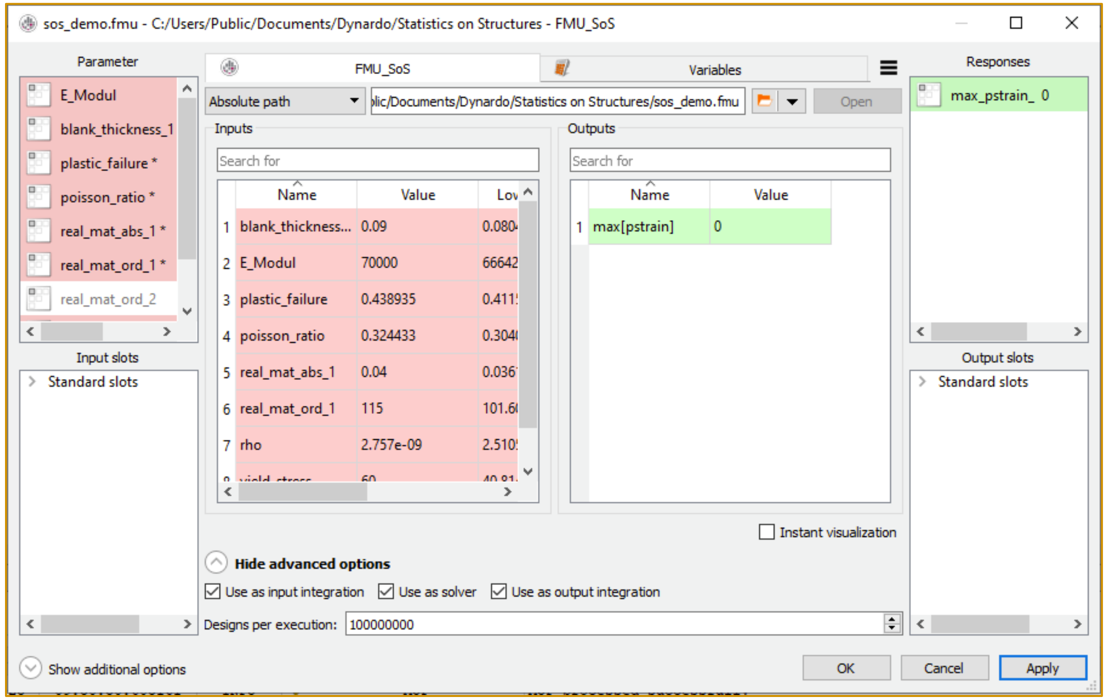
- Simple analysis macros (e.g. extract maximum along an edge)
- Post processors (e.g. Log, Exp, von Mises stress from tensor, vector norms)
- Statistical analysis over all designs (for Robustness, Reliability or Fatigue)
- Complex analysis (e.g. identification of tightness of contact areas in high pressure valves; see presentation of Tamasi et al)



2. Innovation: Consumption of FMUs in optiSLang workflows

- Use Field MOP FMU for simulation in optiSLang
- FMU solver node (Beta option)
  - Autoregister inputs and responses
  - Runs in optimized mode
  - Visualize all 3D fields afterwards in SoS post prociessing
  - Entirely implemented using optiSLang's powerful customization features (Python 3)





FUNCTIONAL MOCK-UP UNIT

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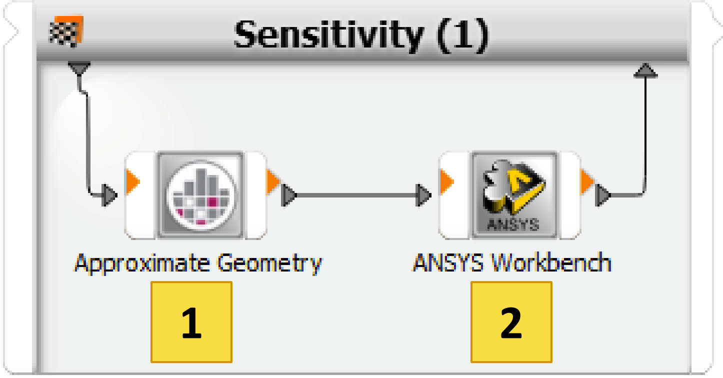
3. Process automation for field data in optiSLang
Innovation: Improved process nodes (**output** fields)

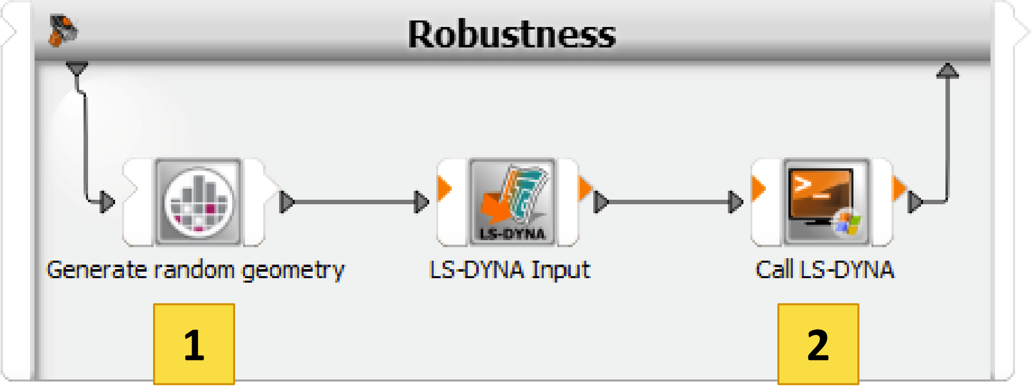
How does it work ?

- User prepares CAE solver
- User prepares SoS model for export (to CSV ? To mesh file ? To ANSYS Mechanical, LS-DYNA, Abaqus, Nastran?)

For each design:

1. optiSLang calls SoS to modify the CAE input deck based on scalar parameters
2. optiSLang calls CAE to run with modified mesh





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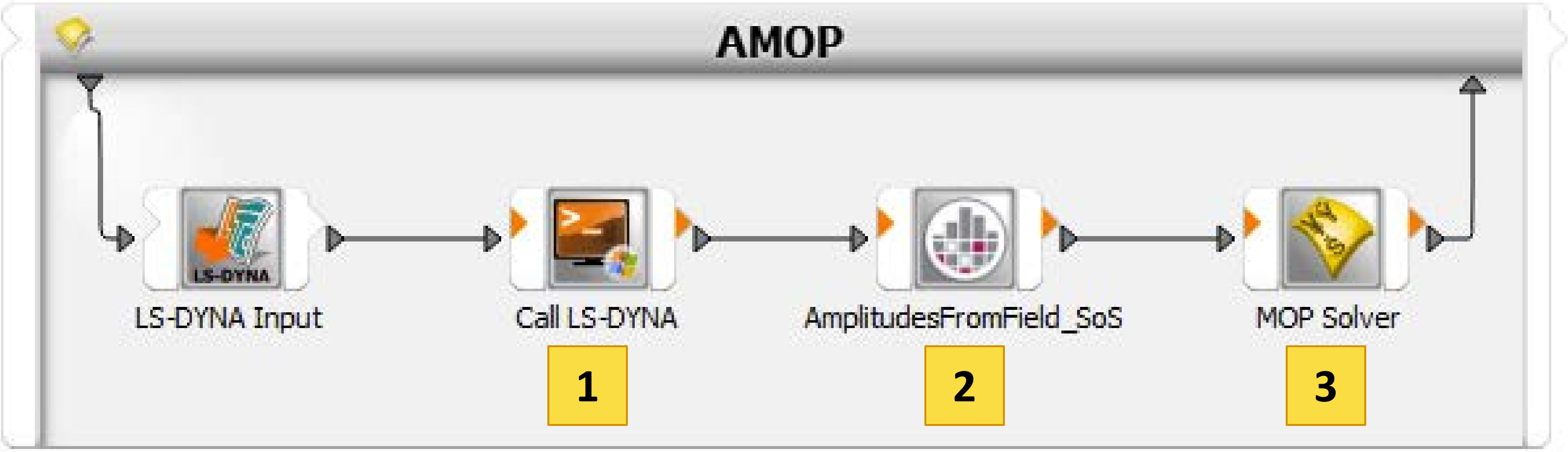
3. Process automation for field data in optiSLang Innovation: Improved process nodes (**input** fields)

How does it work ?

- User prepares CAE solver or measurement that produces field output (e.g. a modified FEM mesh, a STL 3D measurement, a signal)
- User prepares SoS model that imports the file and projects the field data into scalar "parameters"

For each design:

1. optiSLang calls the CAE solver
2. optiSLang calls SoS to read CAE result and gets the scalar parameters
3. optiSLang uses the scalars, e.g. in (Field)MOP, as inputs to CAE solvers or in optimization goals



Software demonstration

- Export FMU
  - Workflow with max. stress and max. temperature
- Consume FMU in optiSLang
  - Minimize max stress
  - Show 3d fields afterwards in SoS

Reduced order modelling for Digital Twins

1. Simulation
2. Training
3. Validate
4. Deploy

Simulation

Create a simulation model predicting the performance. Parameterize model with virtual sensors

Training

Create suitable training data (e.g. through DOE) and create a real-time approximation model (ROM)

Validate

Check prognosis quality of simulation and meta model.

Deploy

Connect ROM with online sensors and deploy to ECUs (e.g. by TwinBuilder)

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