Data Analysis with optiSLang

Dynardo GmbH
1. Introduction to optiSLang

2. Data Import

3. Sensitivity Analysis

4. Optimization

5. Application

6. Training
Dynardo

- Founded: 2001 (Will, Bucher, CADFEM International)
- More than 50 employees, offices at Weimar and Vienna
- Leading technology companies Daimler, Bosch, E.ON, Nokia, Siemens, BMW are supported

Software Development

Dynardo is engineering specialist for CAE-based sensitivity analysis, optimization, robustness evaluation and robust design optimization

CAE-Consulting

- Mechanical engineering
- Civil engineering & Geomechanics
- Automotive industry
- Consumer goods industry
- Power generation
Excellence of optiSLang

- optiSLang is an algorithmic toolbox for
  - sensitivity analysis,
  - optimization,
  - robustness evaluation,
  - reliability analysis
  - robust design optimization (RDO)
- functionality of stochastic analysis to run real world industrial applications
- advantages:
  - predefined workflows,
  - algorithmic wizards and
  - robust default settings
Sensitivity Analysis of External Data

- optiSLang can be used to evaluate external data
- Univariate and multi-variate statistics are available
- Results of a global sensitivity study are:
  - **Sensitivities** of inputs with respect to important responses
  - **Estimate** the variation of responses
  - **Estimate** the noise of experimental measurements
  - **Better understanding** and verification of dependences between input and response variation
1. Introduction to optiSLang
2. Data Import
3. Sensitivity analysis
4. Parametric Optimization
5. Robustness analysis
6. Training
External Data

Generate optiSLang design table
- From Excel
- Importing CSV files
- Through Python interface

Export results
- To Excel
- To Text file

Export postprocessing results
- Pictures (jpg, bmp, png, pdf, …)
- Tables (Excel, CSV, Text)
# Excel Plugin: Export Data to optiSLang Format

<table>
<thead>
<tr>
<th>Details</th>
<th>Parameters</th>
<th>Responses</th>
</tr>
</thead>
<tbody>
<tr>
<td>x1</td>
<td>x2</td>
<td>x3</td>
</tr>
<tr>
<td>-2.36E+00</td>
<td>-2.61E+00</td>
<td>3.11E+00</td>
</tr>
<tr>
<td>5.10E+00</td>
<td>3.97E-01</td>
<td>-2.23E+00</td>
</tr>
<tr>
<td>-1.29E-01</td>
<td>-9.42E-02</td>
<td>9.11E-01</td>
</tr>
</tbody>
</table>

- **Inputs**
  - Bitte geben Sie in diesem Schritt den Excel-Bereich an, der die Inputs enthält!
  - Wenn sich die Inputs in mehreren, nicht zusammenhängenden Excel-Bereichen befinden, können Sie mit der untenstehenden Schaltfläche eine Liste anzeigen.
  - Die Daten befinden sich in folgendem Bereich:
    - [coupled_function.xml]\Design Overview\1SDs2:SH$102

- **Outputs**
  - **horizontal Anordnung (weitere Designs in neuen Zeilen)**
  - **vertikale Anordnung (weitere Designs in neuen Spalten)**
  - **die erste Zeile enthält die Parameternamen**
  - **die Parameternamen befinden sich in folgendem Bereich**

- **Hinweise**
  - Bereich mit 5 Parametern für 10 Designs.
Example: Analytical Nonlinear Function

\[
Y = 0.5X_1 + X_2 + 0.5X_1X_2 + 5.0 \sin(X_3) + 0.2X_4 + 0.1X_5 \\
-\pi \leq X_i \leq \pi
\]
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**Anthill Plots**

**Additive linear**

\[ Y = 2 \cdot X_1 + X_2 \]

**Additive nonlinear**

\[ Y = 2 \cdot \sin(\pi X_1) + X_2 \]

- Two-dimensional scatter-plots of two sample vectors of any input variable or response
- Reveals both linear and nonlinear dependencies
**Anthill Plots**

**Bilinear interactions**

\[ Y = X_1 \cdot X_2 \]

**Nonlinear interactions**

\[ Y = \sin(\pi X_1) \cdot X_2 \]

- Even strongly nonlinear dependence and interactions may become visible
- No quantification of variable importance is possible
- For larger number of important inputs and interaction of mechanisms the interpretation becomes more difficult
- Anthill plots may be used only as proof for other methods
Coefficient of Correlation

\[ \rho(X, Y) = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y} \approx \frac{1}{N - 1} \sum_{i=1}^{N} (x_i - \hat{\mu}_X)(y_i - \hat{\mu}_Y) \hat{\sigma}_X \hat{\sigma}_Y \]

- Defined as standardized covariance of two variables
- Coefficient of correlation is always between -1 and 1
- Defines degree of linear dependence
Correlation Matrix

- Symmetric matrix:
  \[ \rho_{ij} = \rho_{ji} \]
  \[-1 \leq \rho_{ij} \leq 1 \]

- One at diagonal:
  \[ \rho_{ii} = 1 \]

- Significant deviation from the target correlation of the input parameters indicates failed designs, or that the number of samples is too small.
Response Surface Method

- Approximation of response variables as explicit function of all input variables
- Approximation function can be used for sensitivity analysis and/or optimization
- Global methods (Polynomial regression, Neural Networks, ...)
- Local methods (Spline interpolation, Moving Least Squares, Radial Basis Functions, Kriging, ...)
- Approximation quality decreases with increasing input dimension
- Successful application requires objective measures of the prognosis quality
Metamodel of Optimal Prognosis (MOP)

- Approximation of solver output by fast surrogate model
- Reduction of input space to get best compromise between available information (samples) and model representation (number of inputs)
- Determination of optimal approximation model
- Assessment of approximation quality
- Evaluation of variable sensitivities
### Summary - optiSLang Sensitivity Methods

<table>
<thead>
<tr>
<th>Correlations</th>
<th>MOP/CoP</th>
</tr>
</thead>
<tbody>
<tr>
<td>• One-dimensional linear or quadratic dependencies</td>
<td>• Multi-dimensional nonlinear dependencies with automatic identification of important input variables</td>
</tr>
<tr>
<td>• No error measure</td>
<td>• CoP as error measure (Prognosis quality)</td>
</tr>
<tr>
<td>• Independent and dependent inputs</td>
<td>• Independent and weakly correlated inputs</td>
</tr>
</tbody>
</table>

#### Diagrams:
- **Correlations Diagram**: One-dimensional linear or quadratic dependencies with a red line indicating the correlation.
- **MOP/CoP Diagram**: Multi-dimensional nonlinear dependencies with a complex surface representing CoP as an error measure, indicating the quality of prediction.
Perform Sensitivity Analysis for External Data

- Use Excel plugin to transform data in optiSLang binary file:

\[\text{External DoE} \rightarrow \text{Excel plugin} \rightarrow \text{MOP}\]

- MOP uses external DoE to perform sensitivity analysis:

![Metamodel of Optimal Prognosis (MOP)](image-url)
Example: Analytical Nonlinear Function

- Prediction quality is almost perfect with MOP on 100 data samples
- Optimal subspace contains only $X_1$, $X_2$ and $X_3$
- Highly nonlinear function of $X_3$ and coupling term $X_1X_2$ are represented by the MOP approximation and its sensitivity measures
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Optimization on External Data using the MOP

- Approximation function of MOP can be used for further optimization
- Optimization criteria can be formulated using approximated responses
- Optimizer uses reduced subset of important variables
- Obtained optimum may be validated with following experiment
- The data can be updated and the procedure may be repeated, if the requirements are not fulfilled
optiSLang Optimization Algorithms

Gradient-based Methods
- Most efficient method if gradients are accurate enough
- Consider its restrictions like local optima, only continuous variables and noise

Adaptive Response Surface Method
- Attractive method for a small set of continuous variables (<20)
- Adaptive RSM with default settings is the method of choice

Nature inspired Optimization
- GA/EA/PSO imitate mechanisms of nature to improve individuals
- Method of choice if gradient or ARSM fails
- Very robust against numerical noise, non-linearity, number of variables,...
Definition of the Objective and Constraints

- All design parameters, responses and help variables can be used within mathematical formulations for objectives and constraints
- Minimization and maximization tasks with constraints are possible
Optimization Wizard

- Optimization on the MOP assumes no solver noise
- Gradient-based optimizer is recommended
- Use best design of the data as start design for the optimizer
Body Fat Content
Estimation with Respect to Simple Body Measurements

- Percentage of body fat, age, weight, height, and ten body circumference measurements (e.g., abdomen) are recorded for 252 men
- Body fat is estimated through an underwater weighing technique
- Fitting body fat to the other measurements using multiple regression provides a simple way of estimating the body fat content

Body Fat Content
Data Export
• Data are available in EXCEL
• EXCEL Addin to write optiSLang Binary File
• MOP approach can be applied on external data
Body Fat Content
Input Correlations

• 11 body measures, weight and the age as input variables
• Inputs correlations up to 90%
Body Fat Content
Input/Output Correlations

- BMI and density are correlated
- BMI can explain only 50% of the variance of the density
- Height and weight are weakly correlated
Body Fat Content
MOP Results

- Variance of density can be explained by body measures with 73%
- Important input parameters are highly correlated
Body Fat Content

MOP Results

• Input correlation filters detects important variables with minimum dependence to each other.
• Again three important inputs but less correlations are detected.

Polynomial regression of Density
Coefficient of Prognosis = 73 %
Further Training

**optiSLang 4 Basics** 3 day introduction to process integration, sensitivity, optimization, calibration and robustness analysis

**optiSLang inside ANSYS Workbench** 2 day introduction seminar to parameterization in ANSYS Workbench, sensitivity analysis and optimization

**optiSLang 4 and ANSYS Workbench** 1 day introduction to the integration of ANSYS Workbench projects in a optiSLang 4 solver chain, parameterization of signals via APDL output

**Parameter Identification** 1 day seminar on basics of model calibration, application of sensitivity analysis and optimization to calibration problems

**Robust Design and Reliability Analysis** 1 day seminar on basics of probability, robustness and reliability analysis, robust design optimization

12th Weimar Optimization and Stochastic Days 2015

November 5-6
cc neue weimarhalle

Conference for CAE-based parametric optimization, stochastic analysis and Robust Design Optimization

Registration and Info: www.dynardo.de/en/wost
Thanks for your attention!