Design of Simulation Experiments

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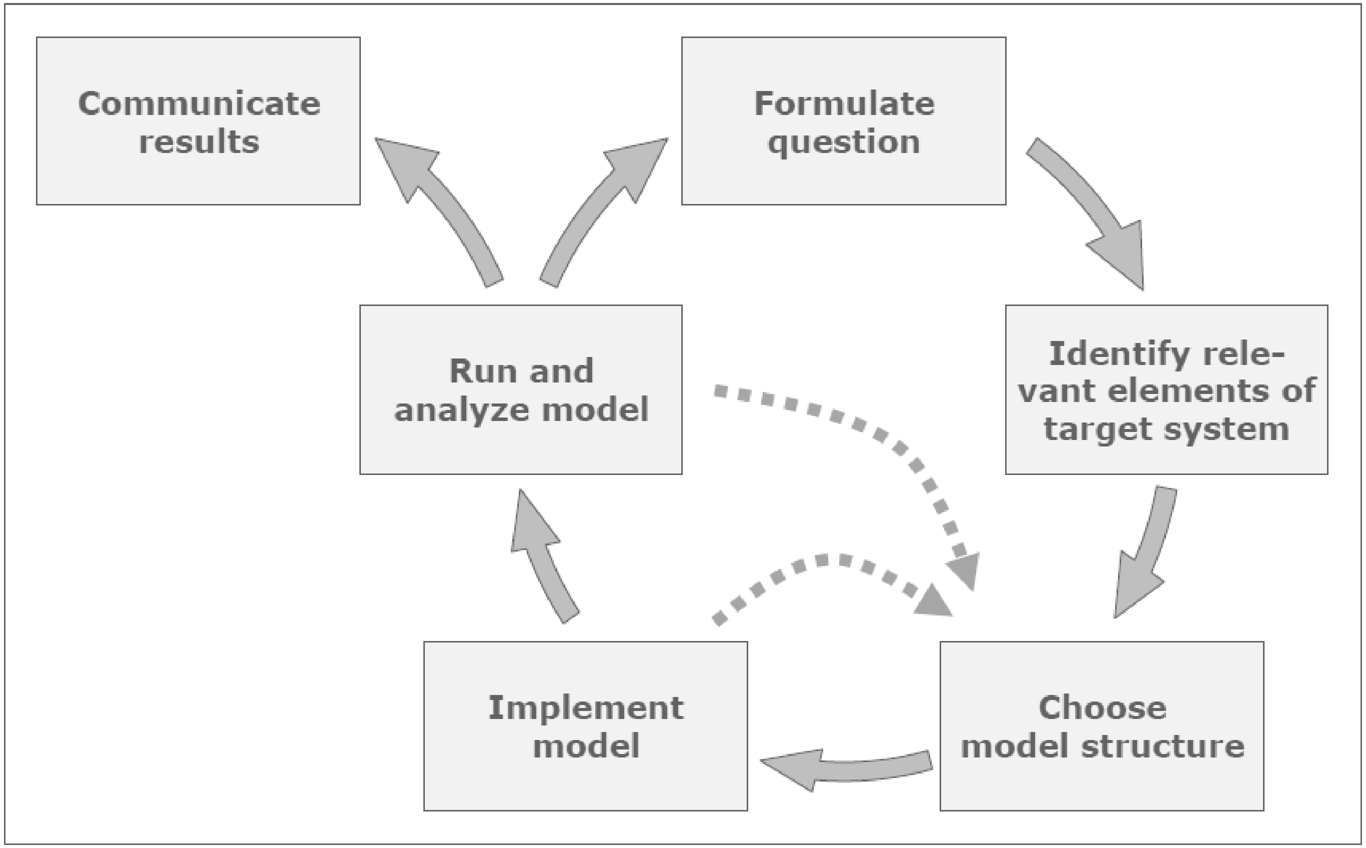
Research Process of Simulation



See Barth/Meyer/Spitzner (2012): Typical Pitfalls of Simulation Modeling – Lessons learned from Business and Military, in: JASSS, 15, 2. Adpated from Railsback/Grimm (2012): Agent-based and individual-based modeling: A practical introduction.

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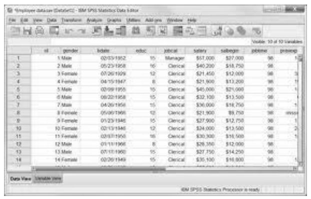
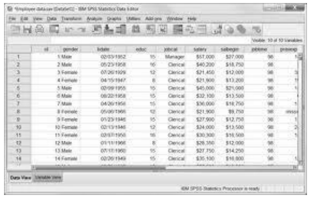
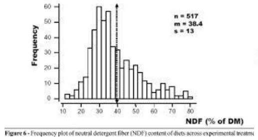
What is it about?

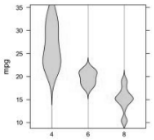
A. Producing simulated data



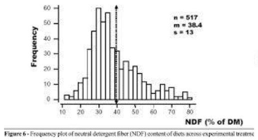
B. Analyzing simulated data

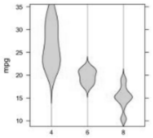






C. Communicating results





What needs to be done?

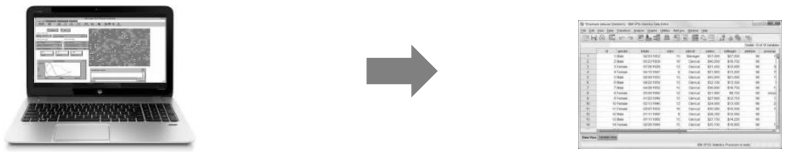
A. Producing simulated data	Defining parameter combinations to run the simulation (experimental design) Determining the number of runs per setting
B. Analyzing simulated data	Finding methods and tools to analyze the simulated data Choosing relevant perspectives on data (level of detail, course of runs, avg,…)
C. Communicating results	Creating an condensed overview of relevant results Using output templates and graphical representations

What are challenges along the way?

A. Producing simulated data	Complexity Focus on the research objective
B. Analyzing simulated data	Stochasticity Non-linearities
C. Communicating results	Presentation of complex results

Focus of this talk on design of simulation experiments

A. Producing simulated data



Research objective
Classification of Variables
Factors and Output measures
Experimental design
Error variance analysis

B. Analyzing simulated data

Effect analysis

C. Communicating results

Effect matrix

Step (1) Objective of the Simulation Experiment

Problem

- Clear reference to the research goal is needed for the experimental setup in order to produce the ‚right data'.

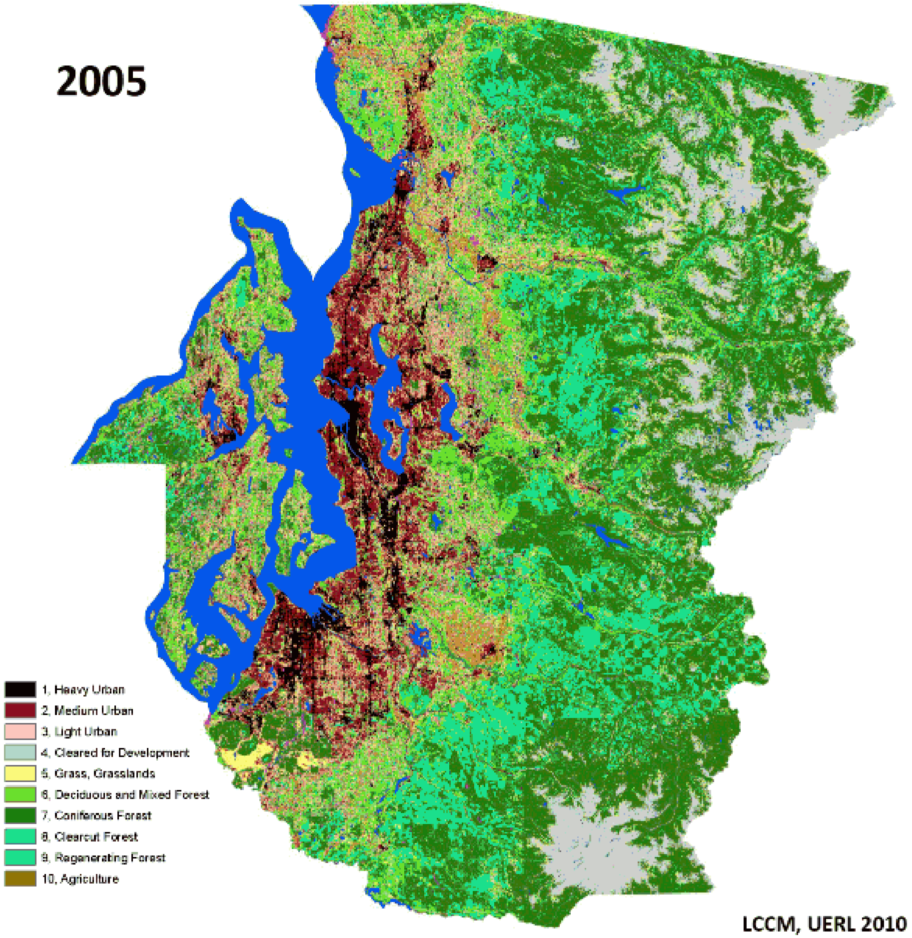
Steps

- Check potential **objectives.**
- Check whether results will provide **data to answer the research question.**

Output

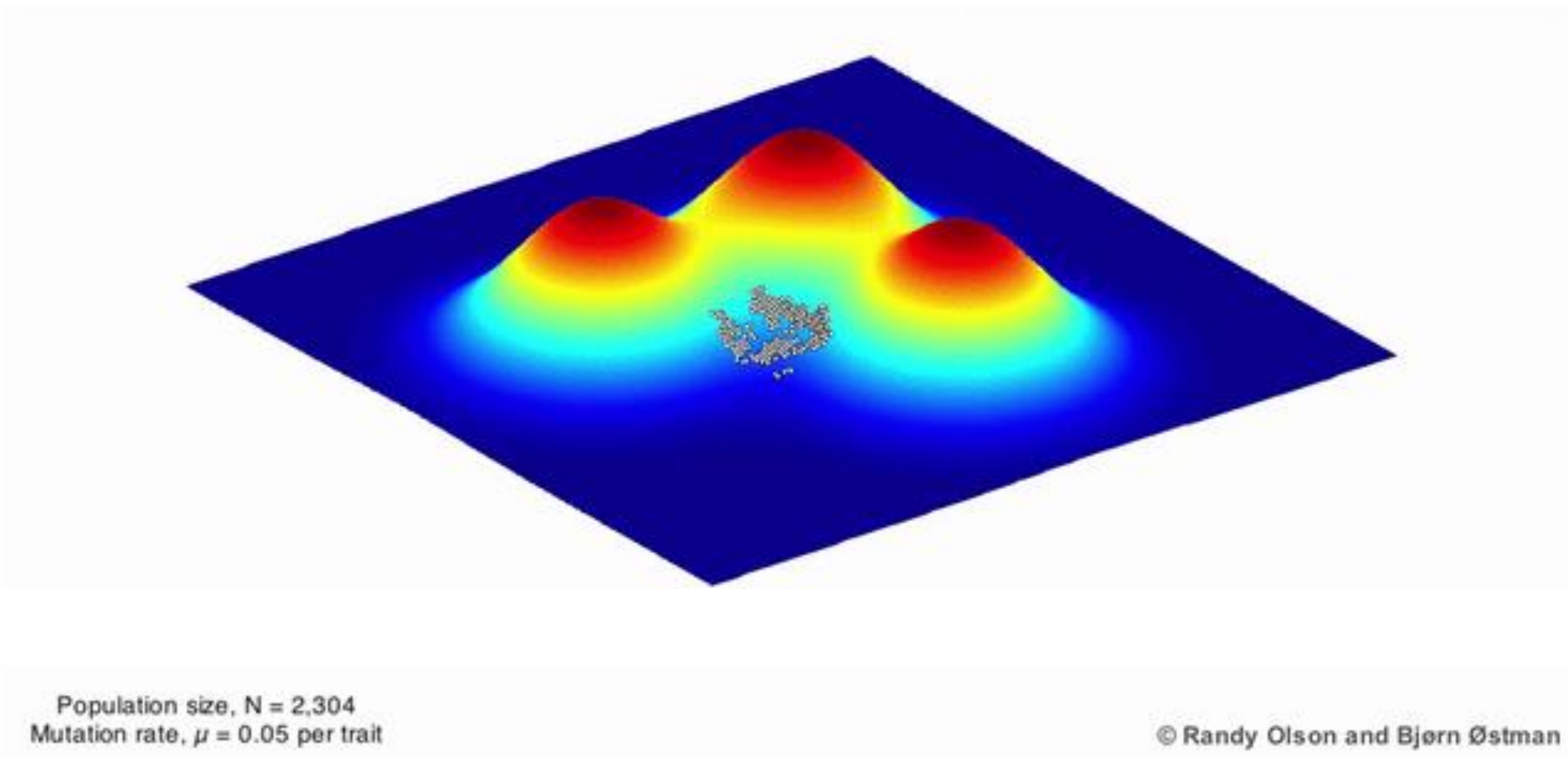
Objective of simulation experiment

First association with simulation models: Prediction as the objective



Source: UrbanSim Model - Modeling Land Cover Change In Central Puget Sound: The LCCM Model (urbaneco.washington.edu)- Pudget Sound, US-State: Washington

Objective: Analyzing the fitness landscape of simulation outputs



Source: http://en.wikipedia.org/wiki/Fitness_landscape

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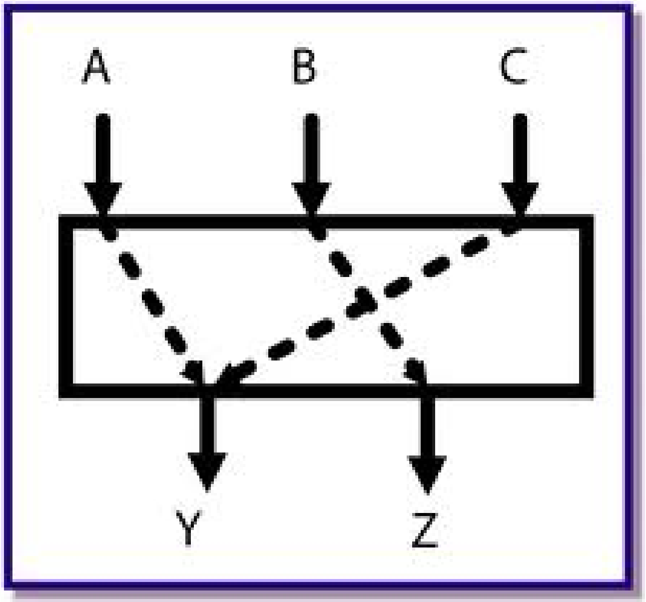
Often in the focus: The input-output relation of variables



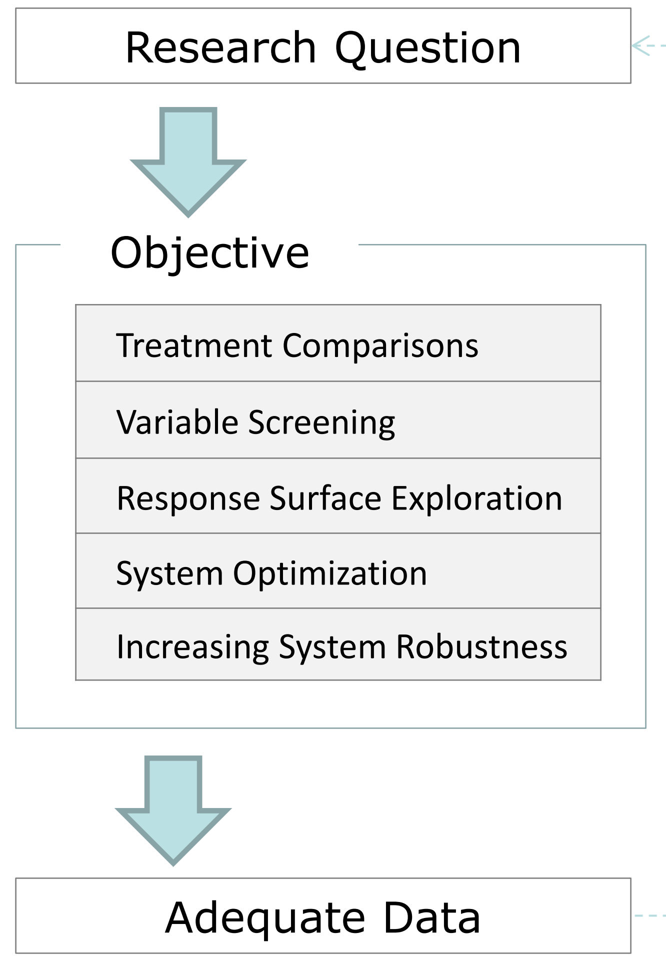
What are the forces?

How are the effects of factors?

How do they interact?

Given the research question, the objective of the simulation experiment needs to be formulated to produce adequate data

- A simulation can be used for **many different issues**, for example for the characterization or optimization of models.
- The research question can only be answered if the simulation experiment produces **adequate data**.
- Two major objectives are typically stressed (Law 2007):
    1. Relative comparison of alternative simulation configurations, e.g. <u>identifying important factors and their effects on the response</u>.
    2. Performance assessment of different simulation configurations, e.g. <u>finding the optimal parameter settings</u>.



Step (2) Classification of Variables

Problem

- Typically, simulation models have a **large number of variables** that influence the model behavior. An overview is needed.
- What are the **important ones** for the given research question?

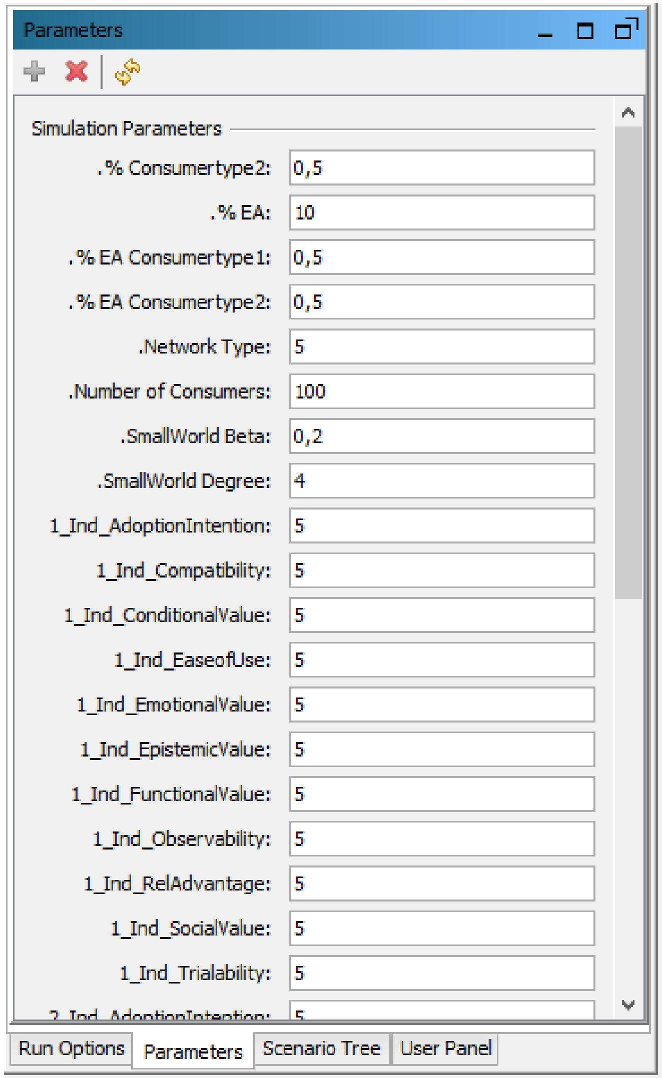
Steps

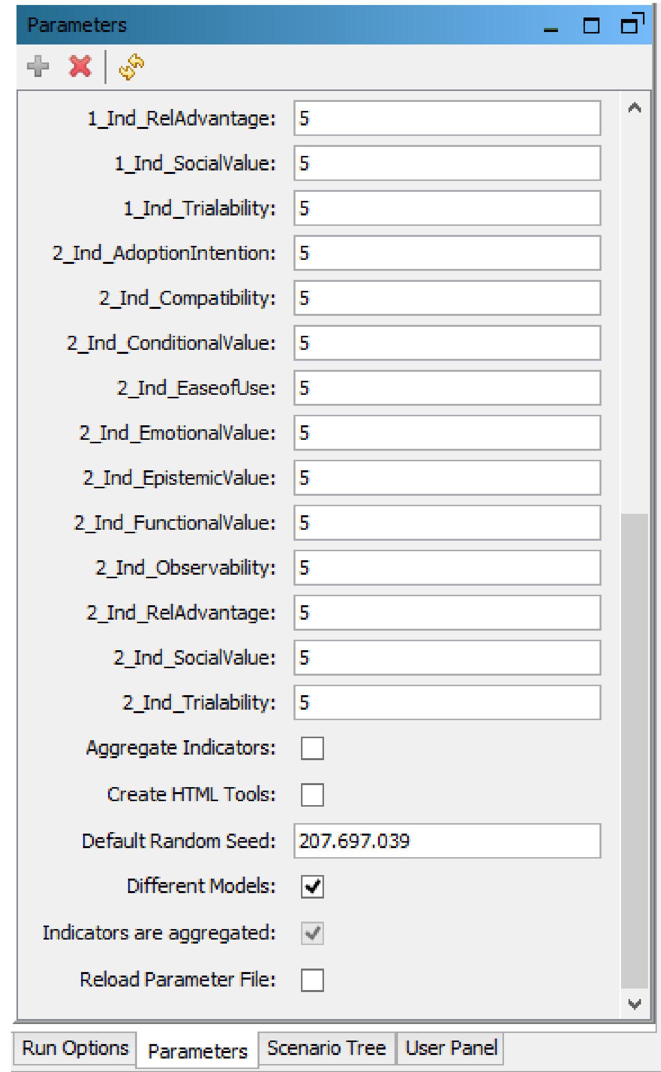
- Variables are assigned to one of three groups:
  - independent variables
  - dependent variables
  - control variables

Output

Classification of variables

What are the relevant parameters to answer the research question?





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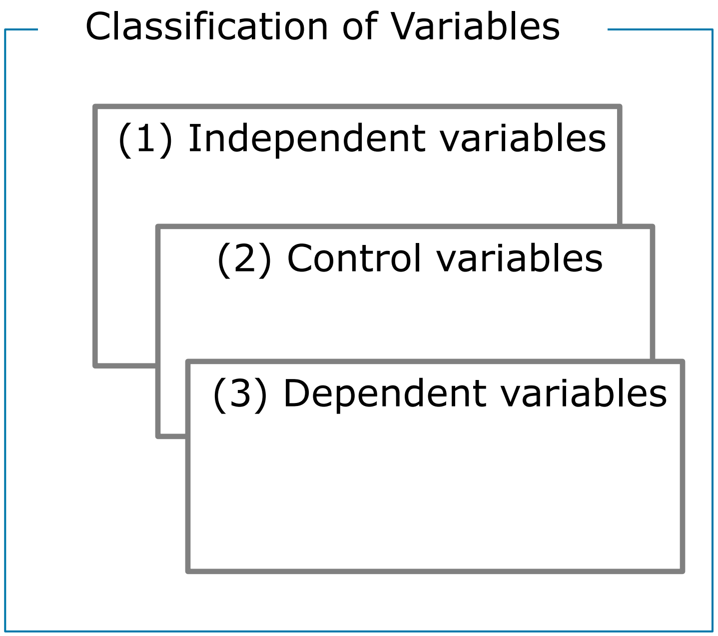
The classification of model variables allows for an overview of the different types of variables based on their roles with respect to the model and its analysis

- The set of variables has to be divided into
  - the ones that are **important for the given research question** and
  - the ones that are **not important but could affect the model behavior** as well.

- Above, the **variables measuring simulation performance** have to be identified to be able to evaluate the model behavior.



Basic aspects of the research question can be easily communicated using the table of variables

- Based on this table one can easily read
  - **which relationships** are in the focus of research and
  - major questions under investigations **in a standardized and condensed way**
- Advantageous in an interdisciplinary context, where the relationships of interest are expressed in the "**universal language**" of variables and their relationships.
- Using variables might make the simulation experiment **more accessible**, particularly for non-experts.

Classification of Variables

Independent variables	Control variables	Dependent variables	
(1) Learning algorithm	(2) Length of equilibrium	(7) Quality,	… of learning truthful reporting
	(3) Strategy set	(8) Speed,	
	(4) Real productivity	(9) Stability	
	(5) Report of opponent		
	(6) Number of ticks		

Preparation of the simulation experiment by defining
- *factors* (independent variables and control variables)
- *response variables* (dependent variables)

Transformation of variables into factors and response variables

- For the simulation experiment, quantitative or qualitative factor level value ranges, and discrete or continuous response variables have to be established.
- Potential control variables can be included as additional factors to understand their effects as well.
- Check of factors with parameters in the program code (main class parameters) assures a comprehensive list of influencing factors.

Simulation parameter (main class)	DOE		Other parameters
`double lamda`	✓	Factor	
`double T`	✓	Response Variable	
`double T_i`	-		Support parameter to calculate T (per i)
`double T_max`	-		Support parameter to calculate T (basis)
`double[] strategies`	✓	Control Variable	
`double pi`	-		Simulation output (report)
(…)			

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Important complication: Complex factors may have many different configurations in their substructure.

- Some factors are **complex**, having a substructure that determines their qualitative or quantitative value
- Different configurations may cause **varying responses**
- To make the effects of complex factors comparable, a **benchmark level for each factor level** has to be established

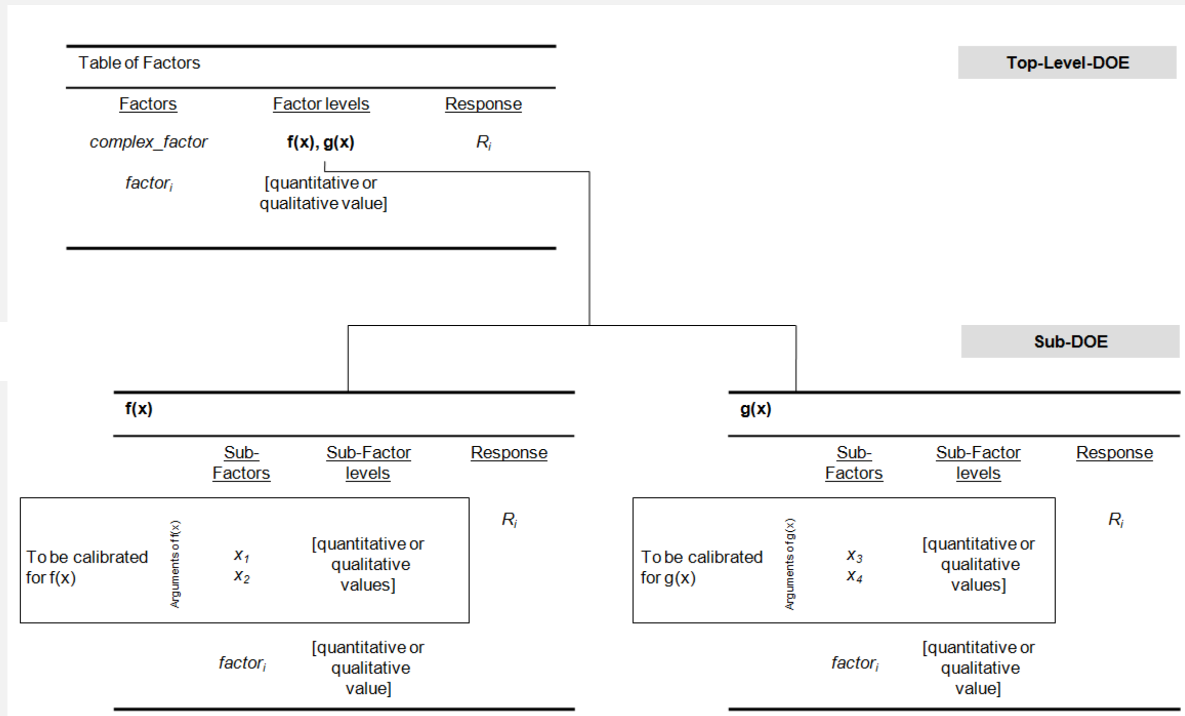
"Cascaded DOE" as solution

Cascaded DOE allows to identify appropriate configurations of complex factors.

In the cascaded concept we distinguish **two different DOE-Types**:

- The **Top-Level-DOE** is to analyze the overall research question, containing complex variables as factors

- The **subordinated DOEs** aim at optimal factor configurations on the level of the substructure of the complex factor



Optimized learning algorithms performance for treatment comparison

Cascaded DOE allows to identify appropriate configurations of complex factors

Table of Factors - Top-Level DOE, Research Question "Complexity of Groves Mechanism"

Factors	Factor Level Ranges	Responses	
Learning Algorithms	Zero Intelligence	R - Quality	... of learning truthful reporting
	Reinforcement Learning	T - Speed	
	Experience Weighted Attraction	E - Stability	
ticks	N		

Sub-DOE Zero Intelligence

Sub-Factors	Sub-Factor Level Ranges	Responses	
ticks	N	R - Quality	... of learning truthful reporting
		T - Speed	
		E - Stability	

Sub-DOE Reinforcement Learning

Sub-Factors	Sub-Factor Level Ranges	Responses	
φ_1	Є [0,1]	R - Quality	... of learning truthful reporting
ticks	N	T - Speed	
		E - Stability	

Sub-DOE Experience Weighted Attraction

Sub-Factors	Sub-Factor Level Ranges	Responses	
ρ	Є [0,1]	R - Quality	... of learning truthful reporting
σ	Є [0,1]	T - Speed	
φ_2	Є [0,1]	E - Stability	
λ	Є [0,1]		
ticks	N		

Step (4) Select appropriate factorial design

Problem

- Blessing and curse: „Playing around"
- How to **produce** simulation data **systematically**?

Steps

- Selecting an **appropriate factorial design.**

Output

Design point matrix

Alternative Strategies to Factorial Design

Strategies	
Buest-gess approach	(1) Arbitrary combination of factors (2) Outcome (3) Switching one (or two) factor levels (depending on the outcome).
One-factor-at-a-time approach	(1) Baseline (starting point) (2) Varying each factor over its range (3) Result: Effects on response value for each factor, while other factors are fixed.
Factorial experiment	***Factors are varied together.***

reveals interaction effects

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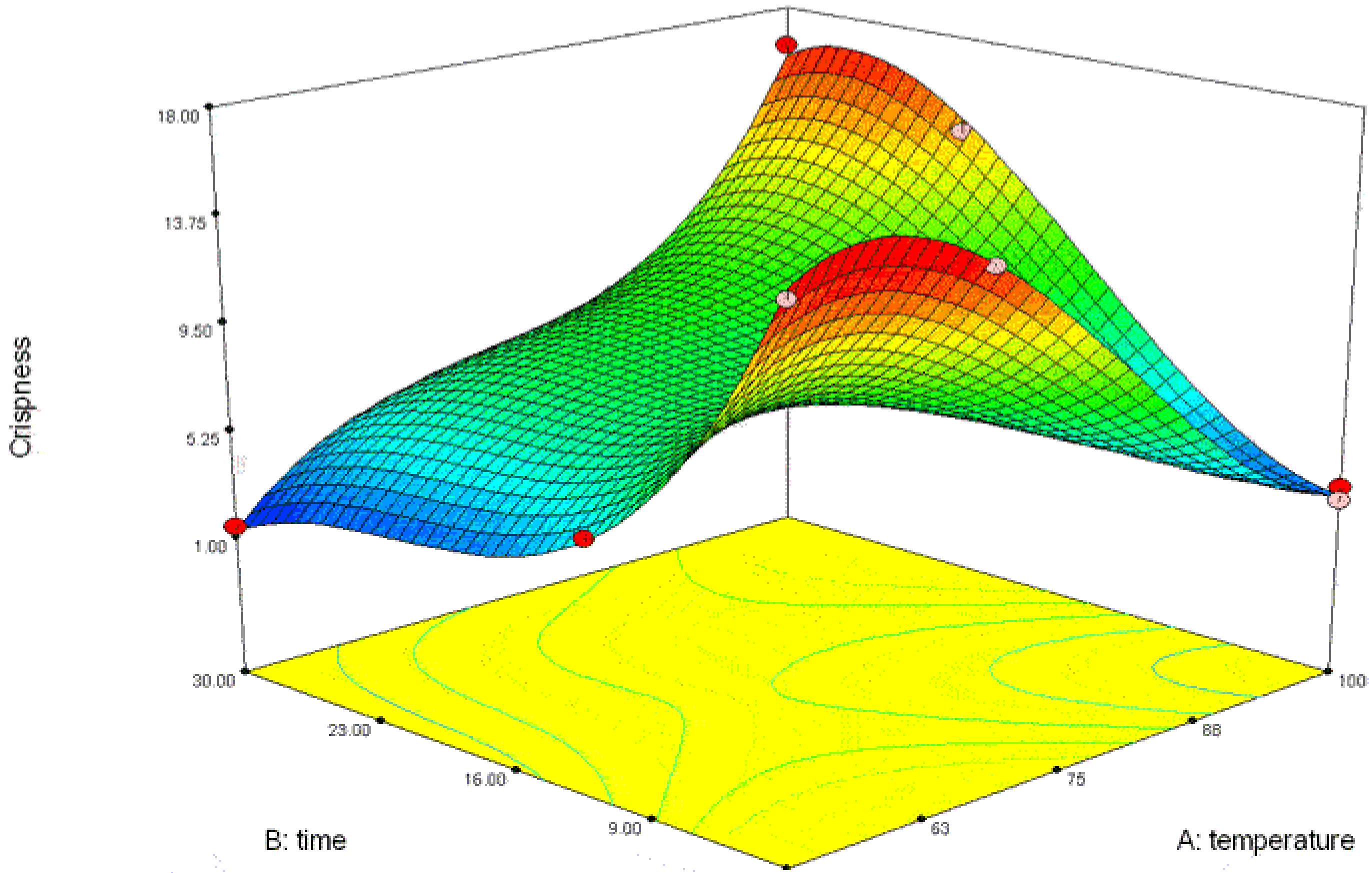
Task: To define points in the surface by which we may learn about the nature of the model.



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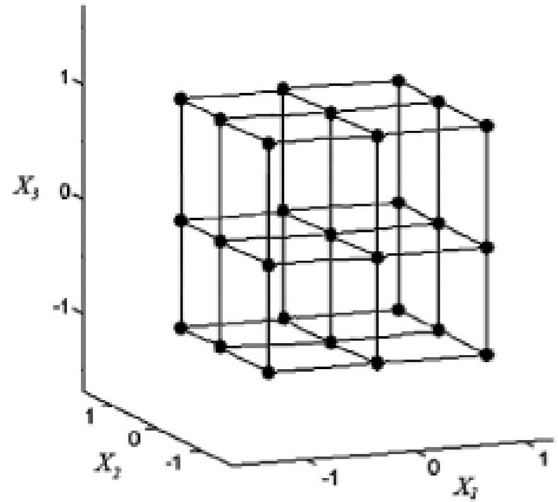
Factorial design can deal efficiently with a large number of factors and factor level ranges

- Factorial design assures a **systematic analysis** of factor level combinations, so that valid and objective results are produced and interactions between factors are identified.

- The choice for the right factorial design depends on the **number** of factors, the **factor level ranges,** and the **objective** of the simulation experiment.



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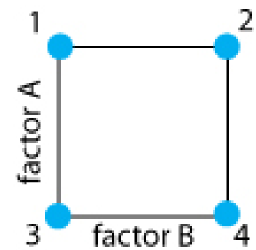
For a 2^k-factorial design only two factor levels per factor are defined. Typically one high and one low value per factor

2^k factorial Design:
k number of factors
with **2** factor levels each.
Here: k=5



factor levels

trial	A	B
1	+	–
2	+	+
3	–	–
4	–	+

2k Design

Factors	Factor Level Range	Factor Levels	Respresentation
ρ	∈ [0,1]	{0.15, 0.85}	{-, +}
σ	∈ [0,1]	{0.15, 0.85}	{-, +}
φ_2	∈ [0,1]	{0.15, 0.85}	{-, +}
λ	∈ [0,1]	{0.15, 0.85}	{-, +}
ticks	*N*	{1000, 5000}	{-, +}

For a 2^k-factorial design only two factor levels per factor are defined. Typically one high and one low value per factor.

2k Design

Factors	Factor Level Range	Factor Levels	Respresentation
ρ	∈ [0,1]	{0.15, 0.85}	{-, +}
σ	∈ [0,1]	{0.15, 0.85}	{-, +}
φ_2	∈ [0,1]	{0.15, 0.85}	{-, +}
λ	∈ [0,1]	{0.15, 0.85}	{-, +}
ticks	*N*	{1000, 5000}	{-, +}

This leads to
2^5 = 32 design points in the design matrix to be run as simulation settings within the simulation experiment.

Based on the recorded (average) resonse values in the design matrix, the factor effects are calculated.

Design matrix Sub-DOE EWA

	Factors				
DP	*ticks*	*ρ*	*σ*	*φ2*	*λ*
1	-	-	-	-	-
2	-	-	-	-	+
3	-	-	-	+	-
4	-	-	-	+	+
5	-	-	+	-	-
6	-	-	+	-	+
7	-	-	+	+	-
8	-	-	+	+	+
9	-	+	-	-	-
10	-	+	-	-	+
11	-	+	-	+	-
12	-	+	-	+	+
13	-	+	+	-	-
14	-	+	+	-	+
15	-	+	+	+	-
16	-	+	+	+	+
17	+	-	-	-	-
18	+	-	-	-	+
19	+	-	-	+	-
20	+	-	-	+	+
21	+	-	+	-	-
22	+	-	+	-	+
23	+	-	+	+	-
24	+	-	+	+	+
25	+	+	-	-	-
26	+	+	-	-	+
27	+	+	-	+	-
28	+	+	-	+	+
29	+	+	+	-	-
30	+	+	+	-	+
31	+	+	+	+	-
32	+	+	+	+	+

Step (5) Estimation of experimental error variance

Problem

- Often, simulation produce non-deterministic simulation responses, due to stochastic elements in the model. **How many runs per settings are needed to come to meaningful results?**

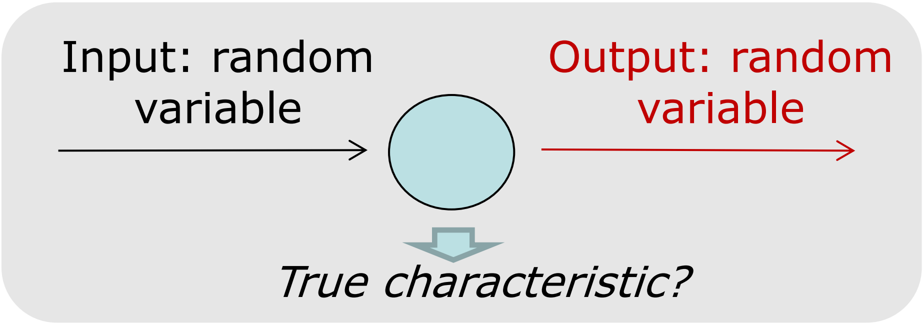
Steps

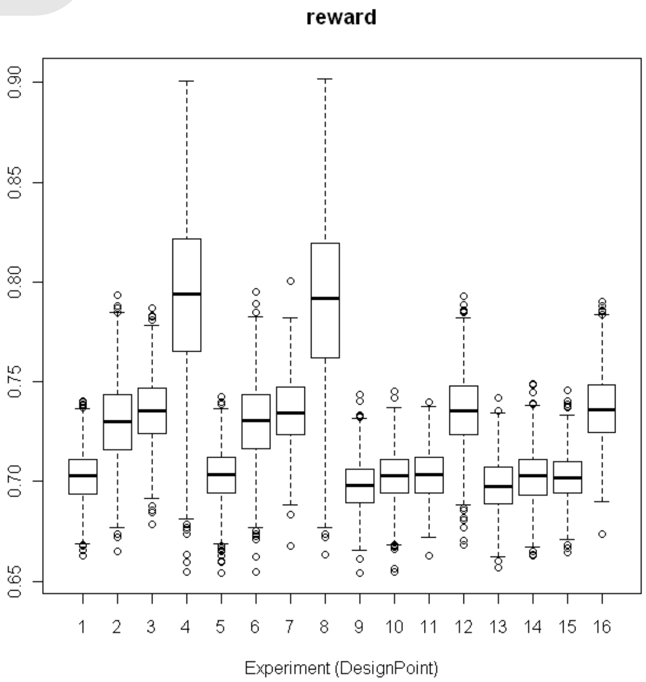
- Estimation of error variance to define the **needed number of runs per setting** by pre-experimental simulation runs.
- Check: **Stochastic stable results?**

Output

Variance Matrix (Number of Runs)

Stochastic elements in simulation models cause a variance in the simulation output.





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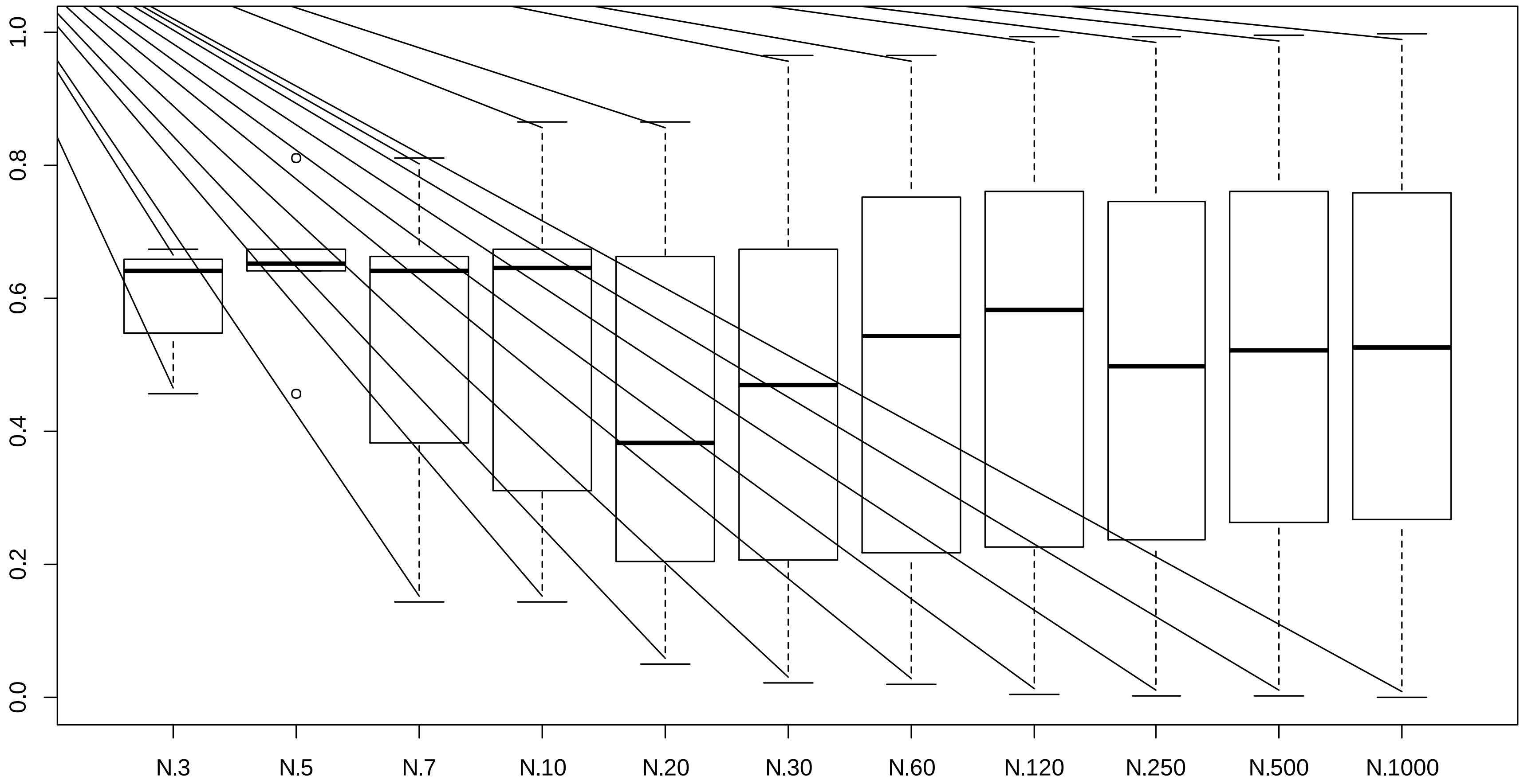
For an initial estimation of the number of simulation runs required per simulation setting, the size of the experimental error needs to be analyzed

- Simulation models often contain **stochastic elements**, resulting in **non-deterministic simulation responses.**
- The fluctuation would **distort the analysis of outcome differences** between simulation settings.
- In order to obtain **meaningful results**, the mean and variance over **several simulation runs per setting** must be analyzed (Gilbert 2008).
- As a first approximation of the needed number of runs per setting, the **experimental error analysis** is performed.

Toy Model: Error variance analysis for normal distributed random numbers ∈ [0,1]



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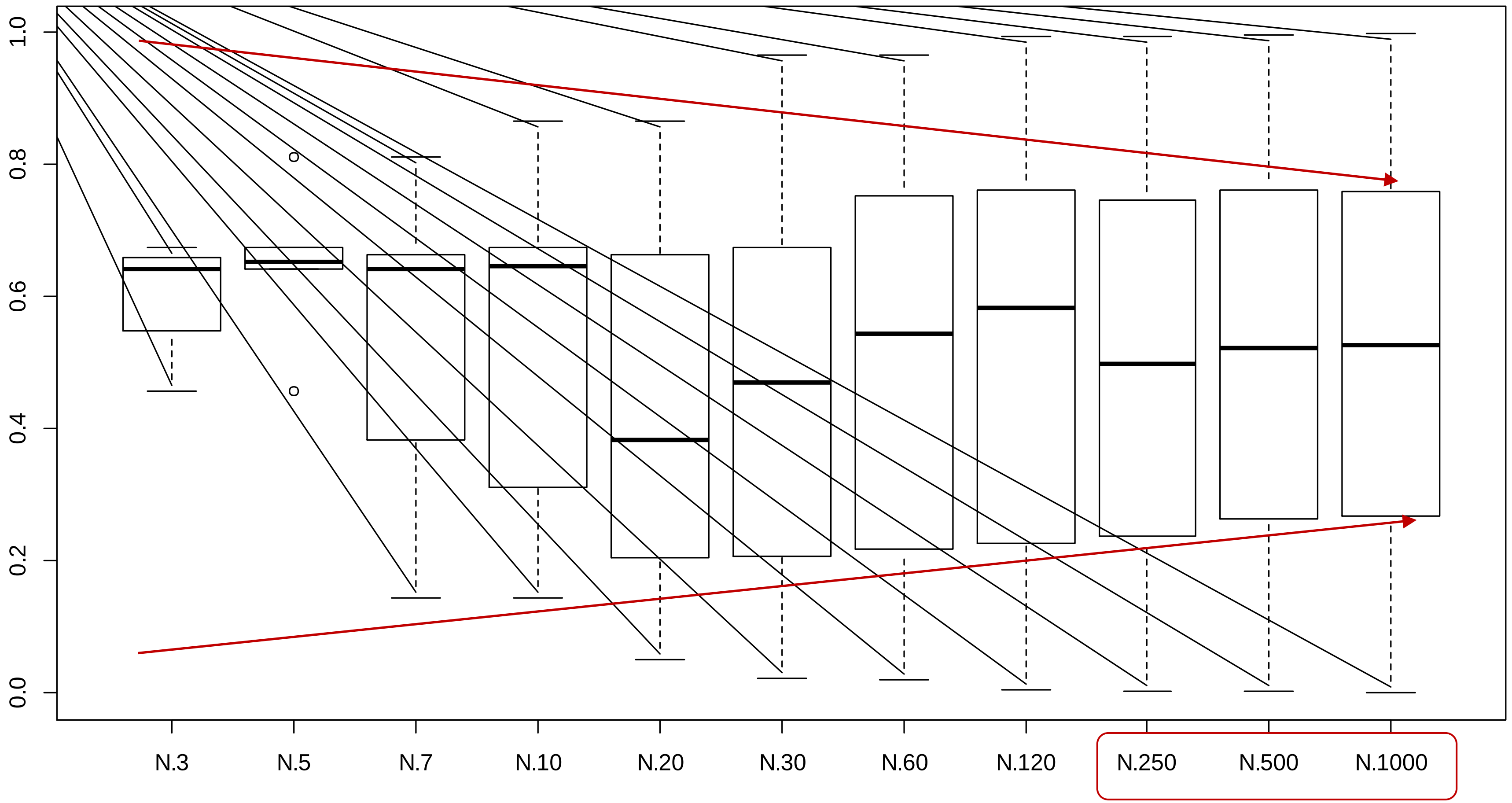
Error Variance Analysis



Task:Finding N with **stable variance** and the **respresentative mean**,
Knowing more about the **error (here: deviation from 0.5)**

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Error Variance Matrix

responses

number of runs per setting (N)

Design Point	dep. Variables		Number of Runs									
			10	100	500	1000	5000	10000	20000	40000	60000	80000
1.VA	R	MEAN	0.70	0.70	0.70	0.70	0.70	0.70	0.70	0.70	0.70	0.70
		VARIANCECOEFF	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**
	T	MEAN	361.90	524.01	500.26	498.88	502.03	503.25	503.94	502.71	503.11	502.25
		VARIANCECOEFF	**0.28**	**0.34**	**0.38**	**0.37**	**0.38**	**0.37**	**0.37**	**0.37**	**0.37**	**0.37**
	E	MEAN	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
		VARIANCECOEFF	**0.67**	**0.93**	**0.93**	**0.94**	**0.95**	**0.95**	**0.95**	**0.95**	**0.95**	**0.95**

design point for error variance analysis

mean and coefficient of variance of the response variable over N runs.

coefficient of variance

Providing a dimensionless and nomalized measure of variance. Allows for comparing different data sets to sundry units and means.

$$c_v = \frac{s}{\mu}$$

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Increasing the number of repetitions typically stabilizes the variability of the response to a point when c_v with increasing N does not change any more

Error Variance Matrix

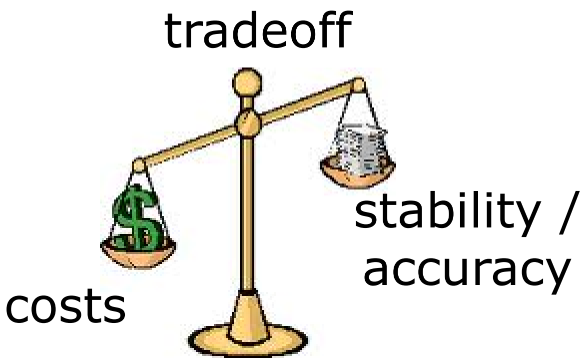
Design Point	dep. Variables		Number of Runs									
			10	100	500	1000	5000	10000	20000	40000	60000	80000
1.VA	R	MEAN	0.70	0.70	0.70	0.70	0.70	0.70	0.70	0.70	0.70	0.70
		VARIANCECOEFF	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**
	T	MEAN	361.90	524.01	500.26	498.88	502.03	503.25	503.94	502.71	503.11	502.25
		VARIANCECOEFF	**0.28**	**0.34**	**0.38**	**0.37**	**0.38**	**0.37**	**0.37**	**0.37**	**0.37**	**0.37**
	E	MEAN	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
		VARIANCECOEFF	**0.67**	**0.93**	**0.93**	**0.94**	**0.95**	**0.95**	**0.95**	**0.95**	**0.95**	**0.95**

Design Point	dep. Variables		Number of Runs									
			10	100	500	1000	5000	10000	20000	40000	60000	80000
2. VA	R	MEAN	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66	0.66
		VARIANCECOEFF	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**
	T	MEAN	400.30	522.90	525.89	517.81	513.88	516.75	517.92	515.27	515.70	518.83
		VARIANCECOEFF	**0.33**	**0.37**	**0.37**	**0.38**	**0.38**	**0.37**	**0.37**	**0.37**	**0.37**	**0.37**
	E	MEAN	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
		VARIANCECOEFF	**0.73**	**0.94**	**1.09**	**1.03**	**1.01**	**1.01**	**1.01**	**1.01**	**1.01**	**1.02**

Design Point	dep. Variables		Number of Runs									
			10	100	500	1000	5000	10000	20000	40000	60000	80000
3.VA	R	MEAN	0.66	0.67	0.66	0.67	0.67	0.67	0.70	0.67	0.66	0.66
		VARIANCECOEFF	**0.03**	**0.02**	**0.03**	**0.03**	**0.03**	**0.03**	**0.02**	**0.03**	**0.03**	**0.03**
	T	MEAN	514.70	513.45	488.99	515.62	515.46	513.27	503.94	515.90	516.46	515.71
		VARIANCECOEFF	**0.25**	**0.32**	**0.40**	**0.37**	**0.37**	**0.37**	**0.37**	**0.37**	**0.37**	**0.37**
	E	MEAN	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
		VARIANCECOEFF	**1.00**	**0.96**	**0.91**	**0.97**	**1.01**	**1.02**	**0.96**	**1.01**	**1.01**	**1.01**

Limitations of the error variance analysis

- The experimental error needs **to be interpreted with respect to the respective model**.
- General criteria **might not be applicable** to the given model, e.g. the variability of the response variables does not stabilize over an affordable number of runs.
- Definition of number of runs required is a **tradeoff between stability and costs**. As in empirical research, more points of observations bring accuracy, but produce cost.
- Error variance analysis should result in **a first impression of the error variance** and in the ability to approximate the required number of runs per setting for the simulation experiment.
- It should provide a tool for determining the number of runs and thus for **communication and transparency of the criteria**.



Filling the *design point matrix* with response variable values

- The simulation experiment is performed to produce the simulation data.
- The factor level combinations are given from the factorial design (4.).
- For every design point, N simulation runs are performed, as given from the analysis of error variance (5.).
- The response values are recorded as average values over N runs.

Design matrix Sub-DOE EWA

	Factors					Responses		
DP	*ticks*	*ρ*	*σ*	*φ2*	*λ*	*R*	*T*	*E*
1	-	-	-	-	-	0.705	456.487	0.012
2	-	-	-	-	+	0.731	181.767	0.052
3	-	-	-	+	-	0.734	364.125	0.022
4	-	-	-	+	+	0.783	207.305	0.104
5	-	-	+	-	-	0.705	457.304	0.012
6	-	-	+	-	+	0.731	181.033	0.052
7	-	-	+	+	-	0.734	367.212	0.022
8	-	-	+	+	+	0.784	206.150	0.105
9	-	+	-	-	-	0.699	512.463	0.009
10	-	+	-	-	+	0.706	461.628	0.012
11	-	+	-	+	-	0.705	484.552	0.011
12	-	+	-	+	+	0.735	362.173	0.022
13	-	+	+	-	-	0.699	509.315	0.009
14	-	+	+	-	+	0.705	461.081	0.012
15	-	+	+	+	-	0.705	484.614	0.010
16	-	+	+	+	+	0.735	361.748	0.022
17	+	-	-	-	-	0.705	462.672	0.018
18	+	-	-	-	+	0.732	182.305	0.053
19	+	-	-	+	-	0.737	368.752	0.025
20	+	-	-	+	+	0.800	222.256	0.109
21	+	-	+	-	-	0.705	458.574	0.018
22	+	-	+	-	+	0.732	180.379	0.053
23	+	-	+	+	-	0.737	367.273	0.025
24	+	-	+	+	+	0.799	226.051	0.109
25	+	+	-	-	-	0.699	512.191	0.016
26	+	+	-	-	+	0.705	459.364	0.018
27	+	+	-	+	-	0.705	483.745	0.017
28	+	+	-	+	+	0.737	361.640	0.025
29	+	+	+	-	-	0.699	517.674	0.016
30	+	+	+	-	+	0.706	459.273	0.018
31	+	+	+	+	-	0.705	490.982	0.017
32	+	+	+	+	+	0.737	358.334	0.025

Basis for data analysis

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Step (7) Analyzing effects

Problem

- How to **analyze** the produced data?
- **Which** factors are **important**?
- **How** do the factors **influence** the simulation response?

Steps

- **Effect strength** calculation to specify their strength and direction.

Output

Effect Matrix

Within the effect analysis we determine factor effects, interaction effects and control variables as major results

- Basis for the effect analysis is the design matrix, as defined by the **factorial design**.
- Within the **effect analysis**, we determine the simulation results by
  - the **effect of every factor** on all response values in strength and direction,
  - check for possible **interaction effects** between factors, and
  - fix potential **control variables**, if they have no or a nominal effect on the response (result for sensitivity analysis)

Basis for analysis: Design point matrix

Design matrix Sub-DOE EWA

	Factors					Responses		
DP	*ticks*	*ρ*	*σ*	*φ2*	*λ*	*R*	*T*	*E*
1	-	-	-	-	-	0.705	456.487	0.012
2	-	-	-	-	+	0.731	181.767	0.052
3	-	-	-	+	-	0.734	364.125	0.022
4	-	-	-	+	+	0.783	207.305	0.104
5	-	-	+	-	-	0.705	457.304	0.012
6	-	-	+	-	+	0.731	181.033	0.052
7	-	-	+	+	-	0.734	367.212	0.022
8	-	-	+	+	+	0.784	206.150	0.105
9	-	+	-	-	-	0.699	512.463	0.009
10	-	+	-	-	+	0.706	461.628	0.012
11	-	+	-	+	-	0.705	484.552	0.011
12	-	+	-	+	+	0.735	362.173	0.022
13	-	+	+	-	-	0.699	509.315	0.009
14	-	+	+	-	+	0.705	461.081	0.012
15	-	+	+	+	-	0.705	484.614	0.010
16	-	+	+	+	+	0.735	361.748	0.022
17	+	-	-	-	-	0.705	462.672	0.018
18	+	-	-	-	+	0.732	182.305	0.053
19	+	-	-	+	-	0.737	368.752	0.025
20	+	-	-	+	+	0.800	222.256	0.109
21	+	-	+	-	-	0.705	458.574	0.018
22	+	-	+	-	+	0.732	180.379	0.053
23	+	-	+	+	-	0.737	367.273	0.025
24	+	-	+	+	+	0.799	226.051	0.109
25	+	+	-	-	-	0.699	512.191	0.016
26	+	+	-	-	+	0.705	459.364	0.018
27	+	+	-	+	-	0.705	483.745	0.017
28	+	+	-	+	+	0.737	361.640	0.025
29	+	+	+	-	-	0.699	517.674	0.016
30	+	+	+	-	+	0.706	459.273	0.018
31	+	+	+	+	-	0.705	490.982	0.017
32	+	+	+	+	+	0.737	358.334	0.025

Calculation of Effect Sizes

Design matrix Sub-DOE EWA

	Factors					Responses		
DP	*ticks*	*ρ*	*σ*	*φ2*	*λ*	*R*	*T*	*E*
1	-	-	-	-	-	0.705	456.487	0.012
2	-	-	-	-	+	0.731	181.767	0.052
3	-	-	-	+	-	0.734	364.125	0.022
4	-	-	-	+	+	0.783	207.305	0.104
5	-	-	+	-	-	0.705	457.304	0.012
6	-	-	+	-	+	0.731	181.033	0.052
7	-	-	+	+	-	0.734	367.212	0.022
8	-	-	+	+	+	0.784	206.150	0.105
9	-	+	-	-	-	0.699	512.463	0.009
10	-	+	-	-	+	0.706	461.628	0.012
11	-	+	-	+	-	0.705	484.552	0.011
12	-	+	-	+	+	0.735	362.173	0.022
13	-	+	+	-	-	0.699	509.315	0.009
14	-	+	+	-	+	0.705	461.081	0.012
15	-	+	+	+	-	0.705	484.614	0.010
16	-	+	+	+	+	0.735	361.748	0.022
17	+	-	-	-	-	0.705	462.672	0.018
18	+	-	-	-	+	0.732	182.305	0.053
19	+	-	-	+	-	0.737	368.752	0.025
20	+	-	-	+	+	0.800	222.256	0.109
21	+	-	+	-	-	0.705	458.574	0.018
22	+	-	+	-	+	0.732	180.379	0.053
23	+	-	+	+	-	0.737	367.273	0.025
24	+	-	+	+	+	0.799	226.051	0.109
25	+	+	-	-	-	0.699	512.191	0.016
26	+	+	-	-	+	0.705	459.364	0.018
27	+	+	-	+	-	0.705	483.745	0.017
28	+	+	-	+	+	0.737	361.640	0.025
29	+	+	+	-	-	0.699	517.674	0.016
30	+	+	+	-	+	0.706	459.273	0.018
31	+	+	+	+	-	0.705	490.982	0.017
32	+	+	+	+	+	0.737	358.334	0.025

λ	*R*	*response values of R*
-	0.699	
-	0.699	
-	0.699	
-	0.699	
-	0.705	
-	0.705	
-	0.705	
-	0.705	0.711 *avg response low λ*
-	0.705	
-	0.705	
-	0.705	
-	0.705	
-	0.734	
-	0.734	
-	0.737	
-	0.737	
+	0.705	
+	0.705	
+	0.706	
+	0.706	
+	0.731	
+	0.731	
+	0.732	
+	0.732	0.741 *avg response high λ*
+	0.735	
+	0.735	
+	0.737	
+	0.737	
+	0.783	
+	0.784	
+	0.799	
+	0.800	

λ	*R*	*avg effect of λ on R*
-	0.711	**0.030**
+	0.741	

Interaction Effect Size

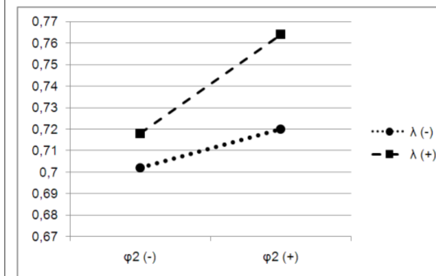
Design matrix Sub-DOE EWA

	Factors					Responses		
DP	*ticks*	*ρ*	*σ*	*φ2*	*λ*	*R*	*T*	*E*
1	-	-	-	-	-	0.705	456.487	0.012
2	-	-	-	-	+	0.731	181.767	0.052
3	-	-	-	+	-	0.734	364.125	0.022
4	-	-	-	+	+	0.783	207.305	0.104
5	-	-	+	-	-	0.705	457.304	0.012
6	-	-	+	-	+	0.731	181.033	0.052
7	-	-	+	+	-	0.734	367.212	0.022
8	-	-	+	+	+	0.784	206.150	0.105
9	-	+	-	-	-	0.699	512.463	0.009
10	-	+	-	-	+	0.706	461.628	0.012
11	-	+	-	+	-	0.705	484.552	0.011
12	-	+	-	+	+	0.735	362.173	0.022
13	-	+	+	-	-	0.699	509.315	0.009
14	-	+	+	-	+	0.705	461.081	0.012
15	-	+	+	+	-	0.705	484.614	0.010
16	-	+	+	+	+	0.735	361.748	0.022
17	+	-	-	-	-	0.705	462.672	0.018
18	+	-	-	-	+	0.732	182.305	0.053
19	+	-	-	+	-	0.737	368.752	0.025
20	+	-	-	+	+	0.800	222.256	0.109
21	+	-	+	-	-	0.705	458.574	0.018
22	+	-	+	-	+	0.732	180.379	0.053
23	+	-	+	+	-	0.737	367.273	0.025
24	+	-	+	+	+	0.799	226.051	0.109
25	+	+	-	-	-	0.699	512.191	0.016
26	+	+	-	-	+	0.705	459.364	0.018
27	+	+	-	+	-	0.705	483.745	0.017
28	+	+	-	+	+	0.737	361.640	0.025
29	+	+	+	-	-	0.699	517.674	0.016
30	+	+	+	-	+	0.706	459.273	0.018
31	+	+	+	+	-	0.705	490.982	0.017
32	+	+	+	+	+	0.737	358.334	0.025

φ2	*λ*	*R*	*response values of R*
-	-	0.705	0.702
-	-	0.705	
-	-	0.699	
-	-	0.699	
-	-	0.705	
-	-	0.705	
-	-	0.699	
-	-	0.699	
-	+	0.731	0.718
-	+	0.731	
-	+	0.706	
-	+	0.705	
-	+	0.732	
-	+	0.732	
-	+	0.705	
-	+	0.706	
+	-	0.734	0.720
+	-	0.734	
+	-	0.705	
+	-	0.705	
+	-	0.737	
+	-	0.737	
+	-	0.705	
+	-	0.705	
+	+	0.783	0.764
+	+	0.784	
+	+	0.735	
+	+	0.735	
+	+	0.800	
+	+	0.799	
+	+	0.737	
+	+	0.737	

2-factor interaction effect

	φ2 (-)	φ2 (+)
λ (-)	0.702	0.72
λ (+)	0.718	0.764
IAE	0.014	



φ2	*λ*	*avg response values of R*	*effects of λ on R*		*2-factor Interaction Effect φ2 on λ*
-	-	0.702	0.016	*with low φ2*	**0.014**
-	+	0.718			
+	-	0.720	0.043	*with high φ2*	
+	+	0.764			

*Difference of effects * **1/2***
(convention)

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The effect matrix allows for a condensed representation of simulation results in a standardized way

To structure the results we fill an **effect matrix for every response value,** containing the factor effects of each factor and all interaction effects between factor pairs.

Effect Matrix

response variable R_i	factor x_1	factor x_2	factor x_3	factor x_4	factor x_5
factor x_1	*main effect* x_1	*interaction effect* (x_1, x_2)	*interaction effect* (x_1, x_3)	*interaction effect* (x_1, x_4)	*interaction effect* (x_1, x_5)
factor x_2		*main effect* x_2	*interaction effect* (x_2, x_3)	*interaction effect* (x_2, x_4)	*interaction effect* (x_2, x_5)
factor x_3			*main effect* x_3	*interaction effect* (x_3, x_4)	*interaction effect* (x_3, x_5)
factor x_4				*main effect* x_4	*interaction effect* (x_4, x_5)
factor x_5					*main effect* x_5

Example for a filled effect matrix (mean differences)

Table 7.5.: Effect matrix - LAMDA I (mean differences)

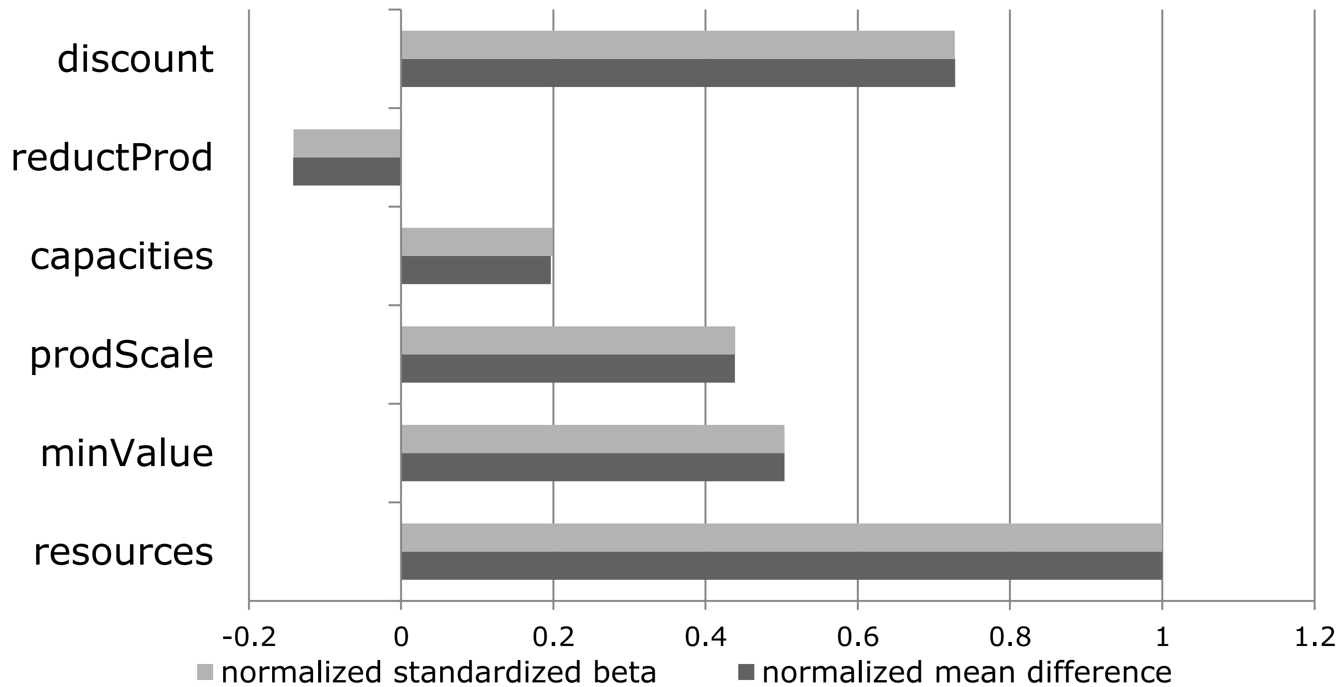
	resources	minValue	prodScale	capacities	reductProd	discount
resources	21.5 (21.53, 21.47)	9.93	8.65	3.88	-2.78	14.35
minValue	-	10.83 (10.83, 10.83)	0.03	-0.01	0.01	7.23
prodScale	-	-	9.43 (9.36, 9.51)	0.03	-0.34	6.32
capacities	-	-	-	4.23 (5.38, 3.08)	2.52	2.84
reductProd	-	-	-	-	-3.05 (-3.24, -2.86)	-2.03
discount	-	-	-	-	-	15.65 (15.6, 15.69)

Example for a filled effect matrix (regression analysis)

Table 7.6.: Effect matrix - LAMDA I (standardized β from regression analysis, $R^2 = 0.865$, adjusted $R^2 = 0.865$, Signif. codes: p<0.001='***', p<0.01='**', p<0.05='*', N=729.000)

	resources	minValue	prodScale	capacities	reductProd	discount
resources	0.558*** (p=0.000)	-0.211*** (p=0.000)	0.183*** (p=0.000)	0.083*** (p=0.000)	-0.059*** (p=0.000)	0.304*** (p=0.000)
minValue	-	0.281*** (p=0.000)	0.001 (p=0.137)	0.000 (p=0.816)	0.000 (p=0.483)	0.153*** (p=0.000)
prodScale	-	-	0.245*** (p=0.000)	0.001* (p=0.034)	-0.007*** (p=0.000)	0.134*** (p=0.000)
capacities	-	-	-	0.111*** (p=0.000)	0.054*** (p=0.000)	0.061*** (p=0.000)
reductProd	-	-	-	-	-0.079*** (p=0.000)	-0.043*** (p=0.000)
discount	-	-	-	-	-	0.406*** (p=0.000)

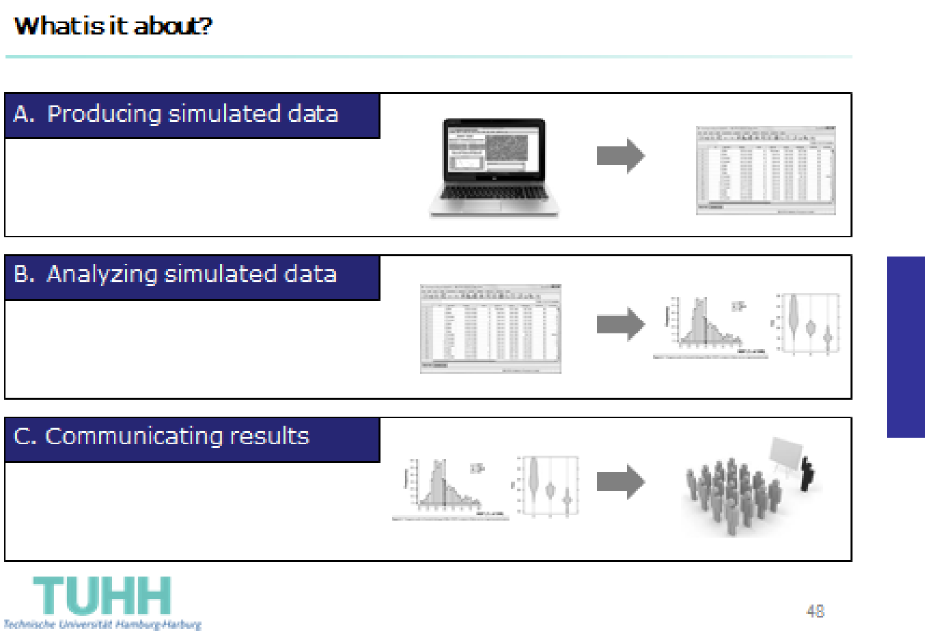
Mean difference vs. standardized beta (regression analysis)



„Detective Work" vs. Design of Experiments

- Often, simulation models are **too complex** for a full factorial design.
- DOE provides techniques to **reduce** the simulation analysis **complexity** (see *fractional factorial design*).
- Still, **other techniques above systematic DOE** might be used to reduce the model complexity. As there are:
  - switching certain mechanisms on/off,
  - simplifying scenarios,
  - making environment constant/homogeneous,
  - using zero intelligence agents.
- These techniques are proposed to be defined at the beginning of the analysis process and can be used **as benchmark** for increasing model complexity.
- **Iterative analyses** based on the DOE process can be conducted for these scenarios.

The issues presented are addressed in a systematic procedure to apply DOE principles for simulation experiments.



Lorscheid, Iris, Bernd-Oliver Heine und Matthias Meyer. (2012) **Opening the 'black box' of simulations: increased transparency and effective communication through the systematic design of experiments.** *Computational and Mathematical Organization Theory*. 18(1):22-62 -- DOI: 10.1007/s10588-011-9097-3

(1) Formulate objective of simulation experiment

(2) Classification of variables

(3) Definition of response variables and factors

(4) Select appropriate factorial design

(5) Estimation of experimental error variance

(6) Performing simulation experiment

(7) Analyzing effects

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