Design Experiment

Bayreuth Summer School

22 – 26 August 2013

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MANAGEMENT SCHOOL

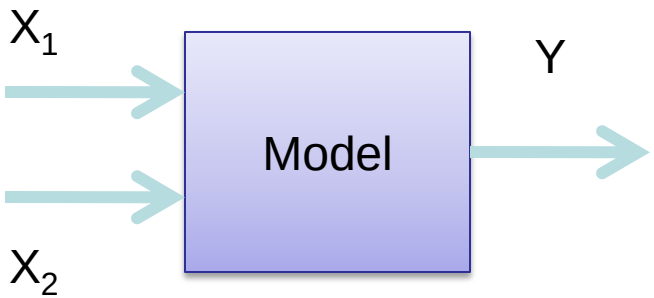
Experimental validation

- Ensure experimental procedures provide sufficiently accurate results
- Issues:
  - Warm-up: to remove the bias of initial states
  - Run length: to ensure enough samples are collected
  - Replications: to build the confidence interval
  - Variance reduction: reduce the number of replications
  - Experimental design: metamodelling and optimization

Experimentation

- Many simulation compares alternative decisions
- Usually focus on decision variables
  - In simulation, it can also be done on the uncontrollable variables
- Usually experiment on a black box, but knowing what is inside the box offers more advantages
- Experimental design
  - Fair comparison
  - Valid conclusion

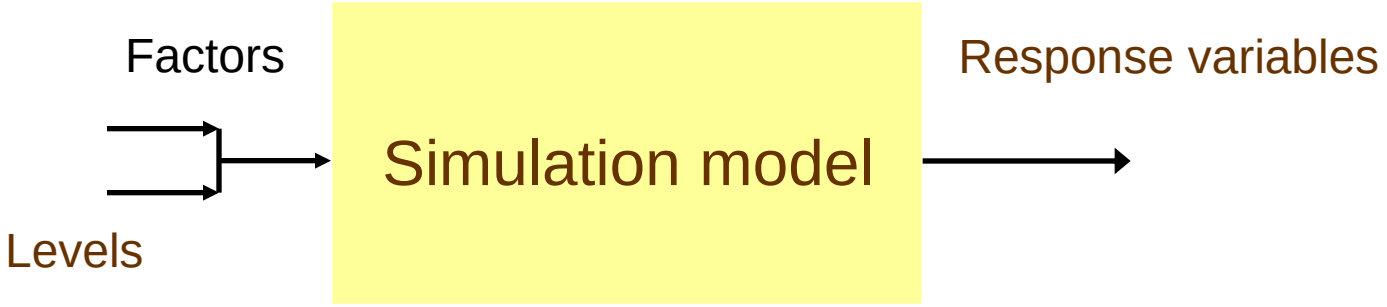
Experimentation

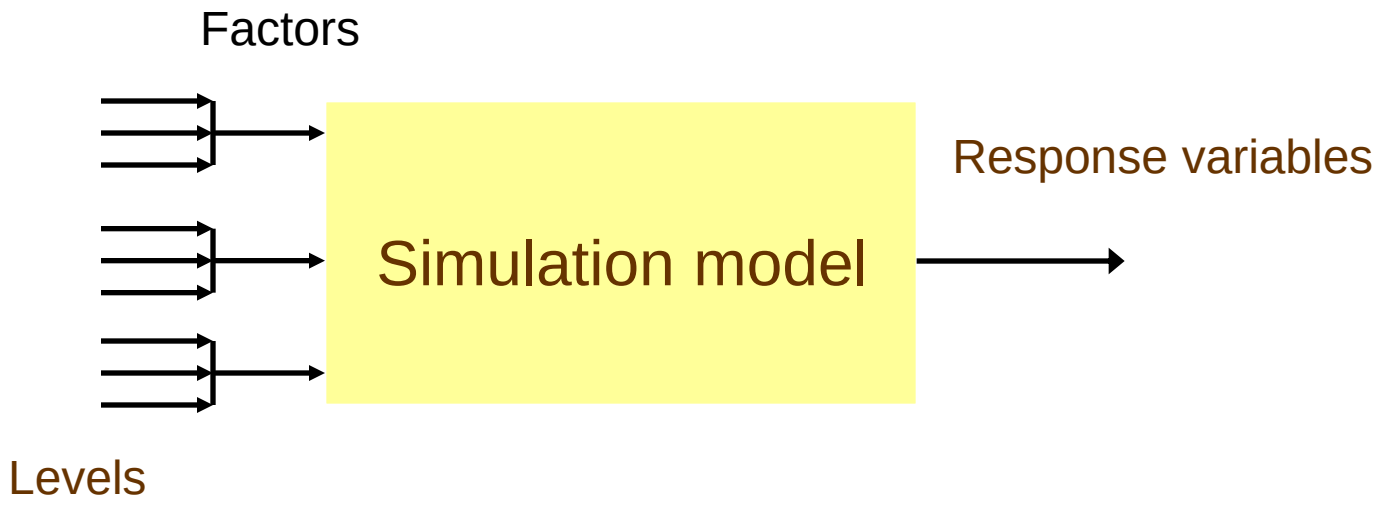


X_1	X_2	Y
Low	Low	Low
High	High	High

X_1	X_2	Y
Low	Low	Low
High	Low	Low
Low	High	Low

Experimentation





Factorial Experiments

- For *K* factors, each has *M* levels and *N* replications, number of experiments: $M^K.N$

- Suppose, we have 3 factors, experiment would aim to uncover
  - Main effects: due to solely on X_1, X_2 or X_3 (keeping all the same)
  - Interaction effects: due to simultaneous change in two or more of the X_1, X_2 and X_3

- ANOVA and plots can be useful

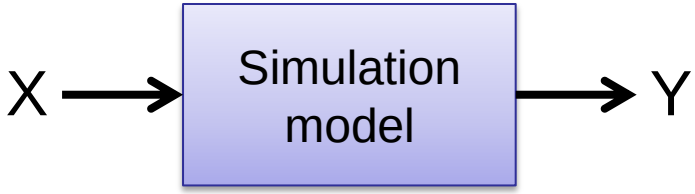
Other experimental designs

- 2^K Factorial design
  - Use 2 levels for each factor
- 2^{K-P} Factorial design
  - Choose a subset of all the 2^K Factorial design points
  - Larger p results in less information
- Latin hypercube design
  - Quantitative factors with $M \geq K$

Simulation Metamodel

- A simplified model of a simulation model
- Why?
  - Significant computation time
  - Needs to run multiple sets of parameters
    - Comparing significant number of designs
    - Optimization
- Prerequisite
  - A validated simulation model
  - Known operating regions

Principles



$$Y = f(X, \theta) + \varepsilon$$

f = a parametric function
θ = the parameters that we need to estimate
ε = the error term

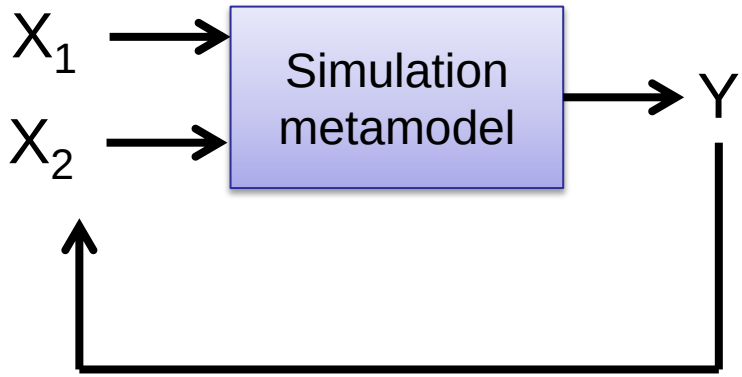
Many techniques

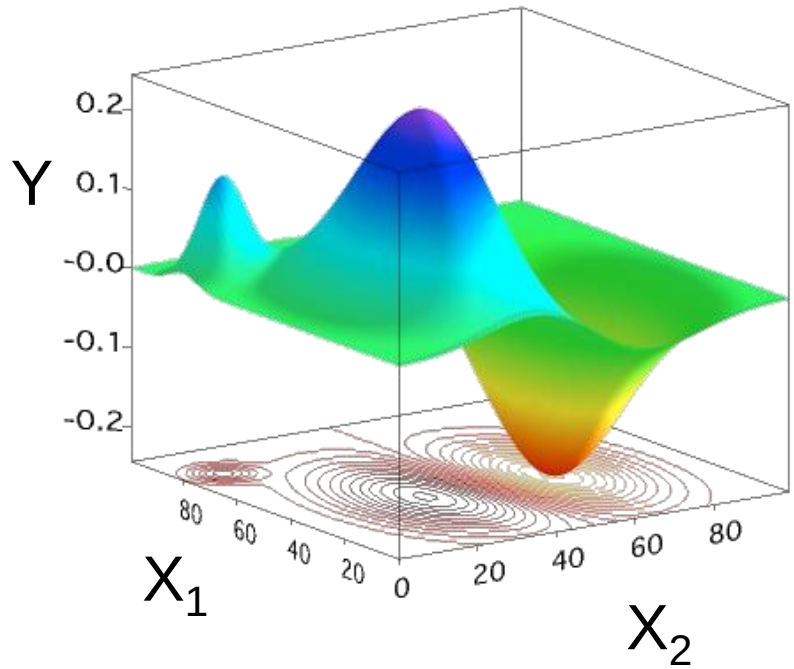
1. Bootstrapping (Cheng 2001)
2. Kriging (Kleijnen and van Beers 2005)
3. Nonlinear regression metamodel (Santos and Nova 1999)
4. Neural network (Sabuncuoglu and Touhami 2002)
5. Response surface method (Myers et al. 2009)

RSM

- Design experiment phase
  - Determine factors, their operating region and response variables
  - Run simulation using suitable design experiment method
  - Determine significant factors (screening)
- Metamodelling phase
  - Fit a regression model to represent the input-output relationship
  - Validate the regression model

Simulation Optimisation





Now, we can use this for optimisation
Many methods such as the steepest ascent method, tabu search, simulated annealing, …

Further reading

- Pidd (2004) Chapter 11

- Law (2010). Statistical analysis of simulation output data: The practical state of the art. *Proceedings of the 2010 Winter Simulation Conference.*