Sequential Experiments: Introduction

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- Collect data
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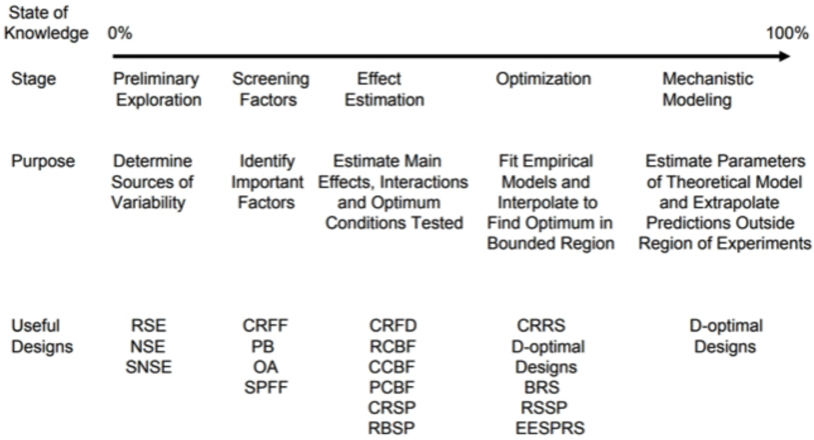
The exception was RSM, which allowed two blocks of experiments and included an optimization that presumably led to additional experiments.

RSM is one example of strategies for increasing knowledge by **sequential experimentation**.

Why sequential experimentation?

There is an inherent tradeoff between the breath and width of our experimental designs. This tradeoff is described by the *knowledge line*.

Figure 13.1 *The State of Knowledge Line*



State of Knowledge	0%				100%
Stage	Preliminary Exploration	Screening Factors	Effect Estimation	Optimization	Mechanistic Modeling
Purpose	Determine Sources of Variability	Identify Important Factors	Estimate Main Effects, Interactions and Optimum Conditions Tested	Fit Empirical Models and Interpolate to Find Optimum in Bounded Region	Estimate Parameters of Theoretical Model and Extrapolate Predictions Outside Region of Experiments
Useful Designs	RSE NSE SNSE	CRFF PB OA SPFF	CRFD RCBF CCBF PCBF CRSP RBSP	CRRS D-optimal Designs BRS RSSP EESPRS	D-optimal Designs

Stage 1: Preliminary Exploration

- What factors could possibly matter for my system?
- Overlaps with needs assessment from design.
- We did not cover this stage.

Stage 2: Screening Factors

- What factors actually matter?
- Resolution III fractional factorial designs.
- Estimate main effects only; interactions are usually confounded.

Stage 3: Effect Estimation

- How much do the factors affect the response?
- Full factorial, resolution IV and V fractional designs.
- Often the last stage for science, the beginning stage for engineering.

Stage 4: Optimization

- What are the optimal operating conditions?
- RSM
- All factors must be important since designs are expensive.

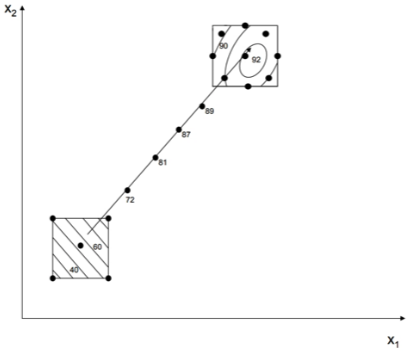
Stage 5: Mechanistic modeling

- A mechanistic model contains only important factors and allows effect estimation and optimization.
- Experiments are only needed to fit parameter values.
- Often the best at extrapolating beyond the region of experimentation.

Early sequential experiments: Box & Wilson (1951)

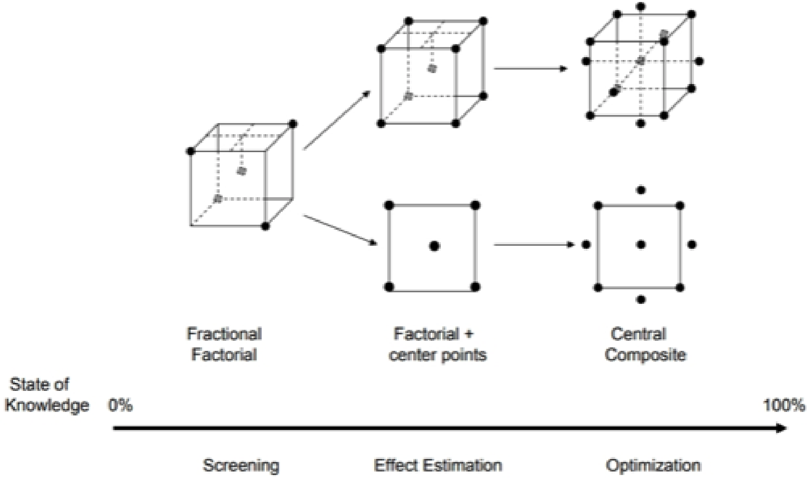
- A full/fractional design identified the direction of steepest ascent for process improvement.
- Experiments were run one-at-a-time in this direction until improvement stopped.
- An RSM-like procedure was run at the endpoint to assess the curvature and declare a maximum.

Figure 13.2 *The Method of Steepest Ascent*



RSM with a CCD allows sequential experimentation

Figure 13.3 *Blocked Response Surface*



Online learning

Process improvement is often at odds with the goals of production.

The goals of production are:

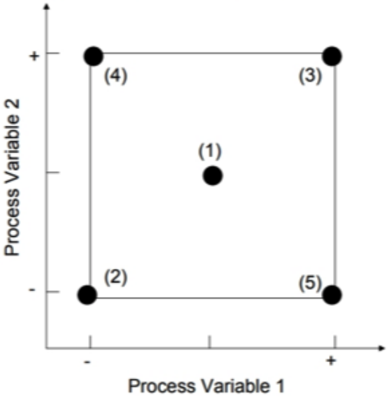
- Quality products
- High output
- Low costs
- Low variability

Our experimental designs require runs with multiple changes and large perturbations. This strategy cannot be implemented online.

How do we balance learning with production?

In 1957 Box invented Evolutionary Operation (EVOP) to learn from an active production line.

Figure 13.6 *A 2^2 Plan for EVOP*



EVOP example: 2^2 full factorial

- Rotate the production through cycles of five runs:
  - y_{00} is the current operating conditions
  - y_{--}, y_{++}, y_{-+}, y_{+-}
- After every cycle, estimate the effects:
  - $\beta_1 = \text{mean}(y_{+\cdot}) - \text{mean}(y_{-\cdot})$
  - $\beta_2 = \text{mean}(y_{\cdot+}) - \text{mean}(y_{\cdot-})$
  - $\beta_{12} = [\text{mean}(y_{++}) - \text{mean}(y_{--})] - [\text{mean}(y_{+-}) - \text{mean}(y_{-+})]$
- Test for significant effects using s.e. $= 2\sigma/\sqrt{4r}$ where r is the cycle number.

Since r increases over time, any truly nonzero effect will become significant over time *regardless of the effect size*. These data can be used to modify the process.

Next steps: Reinforcement Learning

Optimal online learning is the goal of a branch of artificial intelligence called *reinforcement learning (RL)*.

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Examples of RL systems:

- Computer chess
- Chatbots
- Self-driving cars
- Humans