MKR1163 Plastics Design and Processing

Design of Experiments (DOE)

Do engineer experiments?

- Not going to work in a lab nor interested in research?
- Plan to work as a designer or in production lines?
- Why should you be concerned with experimentation?

Experimental Analysis in Product Realization

DEVELOPMENT

Research

(properties, processes)

Design

(concepts, performance)

PRODUCTION

Validation

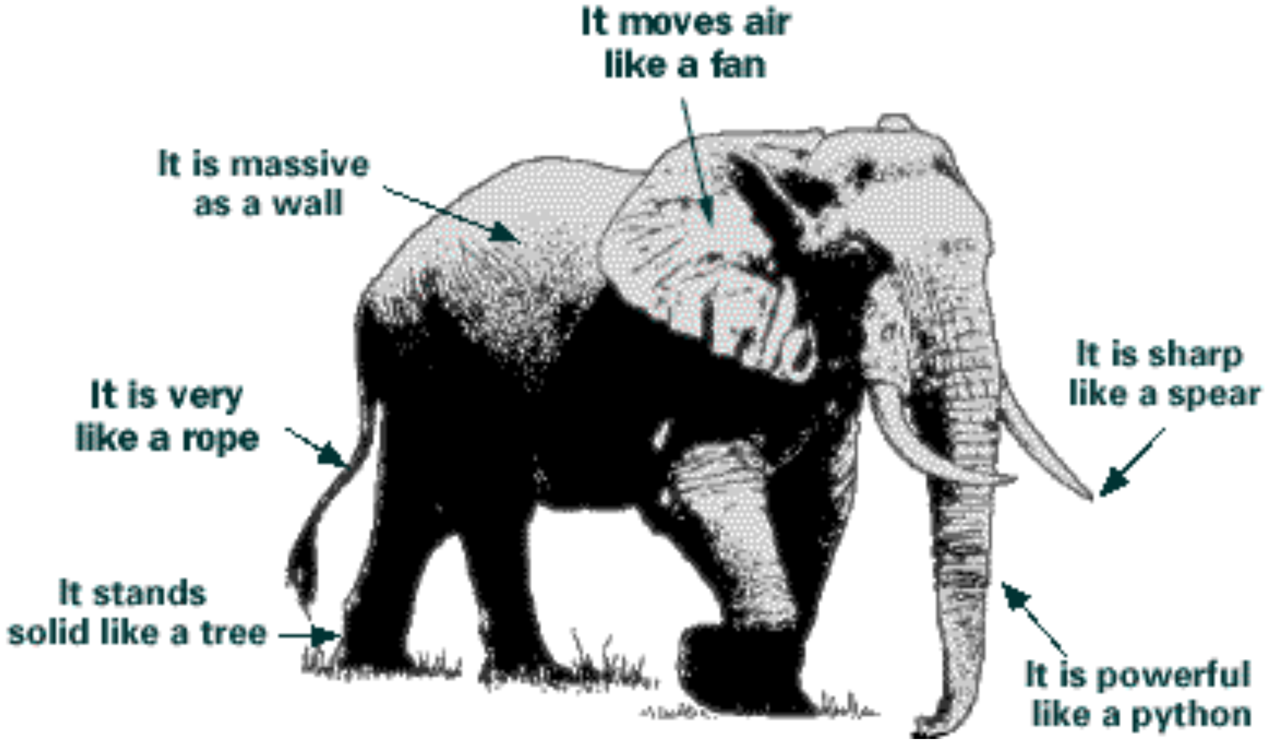
(processes, performance)

QA

(monitoring)

Experimentation

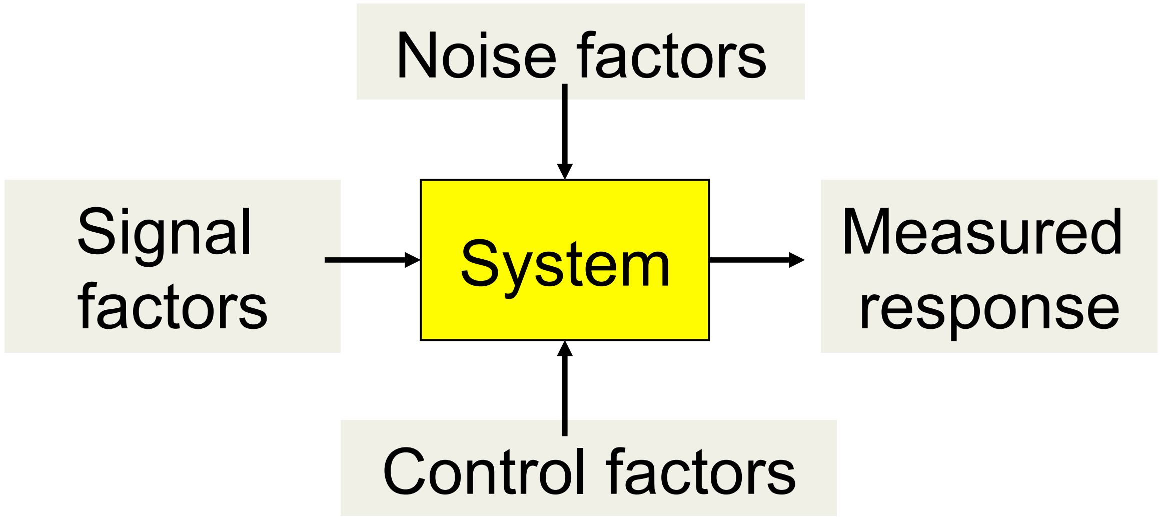
The Blind Man and the Elephant



What we learn from an experiment may depend on the scope of our view, i.e. where we look, how we look

Experimentation

- Experimenter's first goal-
  - Understand the process! How?
- Experiments are used to study effects of parameters as they are set at various levels



Cost of Experimentation

- Resources
  - people,
  - equipment, etc.
- Time
- Material
  - unprocessed or
  - unusable product
- Usable product that is not being produced

Approaches to Experimentation

1. Build-test-fix
2. One-factor-at-a-time (the classical approach)
3. Designed experiments (DOE)

Approaches to Experimentation: Build-Test-Fix

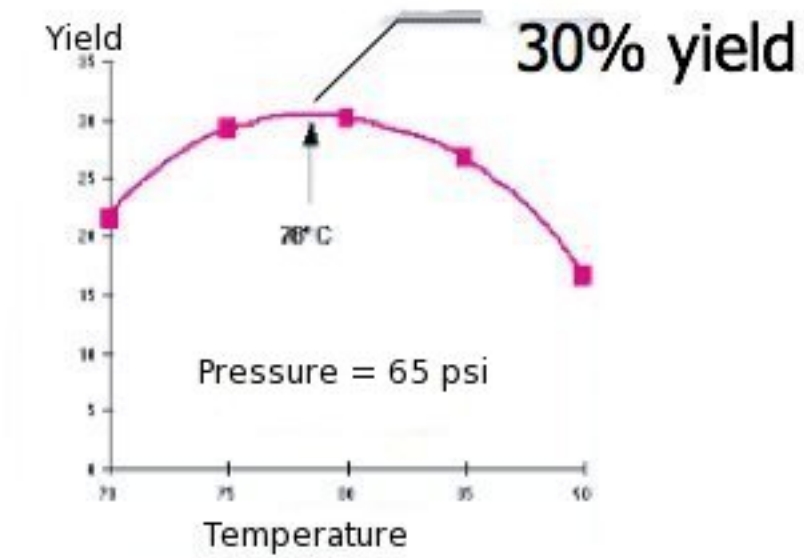
- Build-test-fix
  - the tinkerer's approach
  - pound it to fit, paint it to match
  - impossible to optimize
    - you quit when it works!
  - slow
    - requires intuition, luck, rework
    - Re-optimization and continual fire-fighting

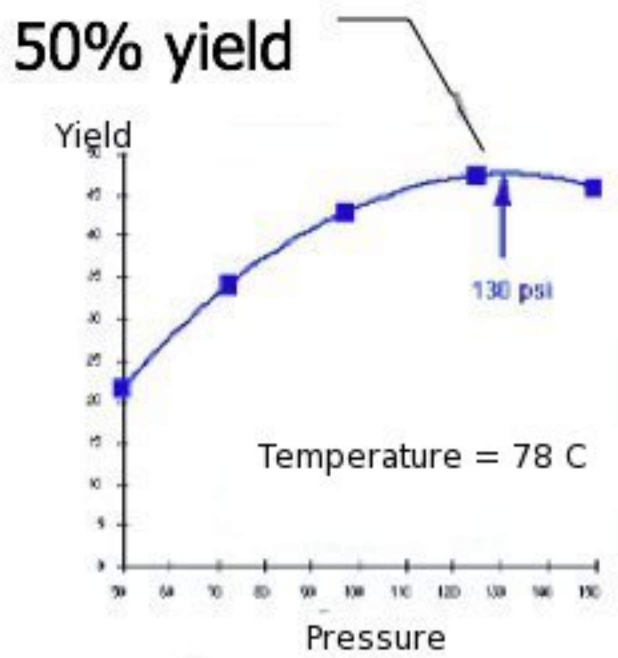
Approaches to Experimentation: One-Factor-at-a-Time

- One-factor-at-a-time
  - procedure (2 level example)
    - run all factors at one condition
    - repeat, changing condition of one factor
    - continuing to hold that factor at that condition, rerun with another factor at its second condition
    - repeat until all factors at their optimum conditions
  - slow, expensive: many tests
  - can miss interactions!

One-Factor-At-A-Time

Process: Yield = f (temperature, pressure)



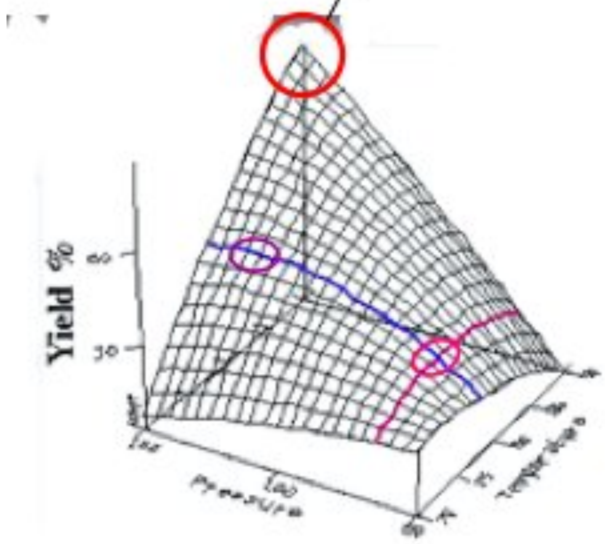


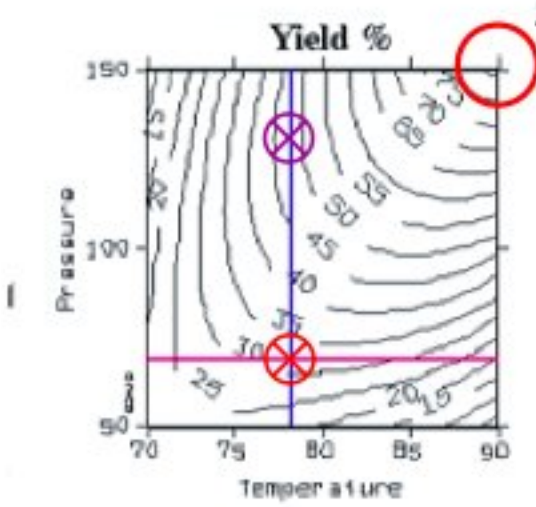
Max yield: 50% at 78°C, 130 psi?

One-Factor-At-A-Time

A better view of the maximum yield!

Optimized yield is over 85%





Process: Yield = f(temperature, pressure)

Approaches to Experimentation: DOE

- Design of Experiments (DOE)
  - A statistics-based approach to designed experiments
  - A methodology to achieve a predictive knowledge of a complex, multi-variable process with the fewest trials possible
  - An optimization of the experimental process itself

Major Approaches to DOE

- Factorial Design
- Taguchi Method
- Response Surface Design

DOE - Factorial Designs

- Full factorial
  - simplest design to create, but extremely inefficient
  - each factor tested at each condition of the factor
  - number of tests, N: $N = y^x$

    where y = number of conditions, x = number of factors
    - example: 8 factors, 2 conditions each,

      $N = 2^8 = 256$ tests
  - results analyzed with ANOVA
  - cost: resources, time, materials, …

DOE - Factorial Designs - 2^3

Trial	A	B	C
1	Lo	Lo	Lo
2	Lo	Lo	Hi
3	Lo	Hi	Lo
4	Lo	Hi	Hi
5	Hi	Lo	Lo
6	Hi	Lo	Hi
7	Hi	Hi	Lo
8	Hi	Hi	Hi

DOE - Factorial Designs

- Fractional factorial
  - "less than full"
  - condition combinations are chosen to provide sufficient information to determine the factor effect
  - more efficient, but risk missing interactions

DOE – Factorial Designs (Fractional: 7 factor, 2 level; 128 → 8)

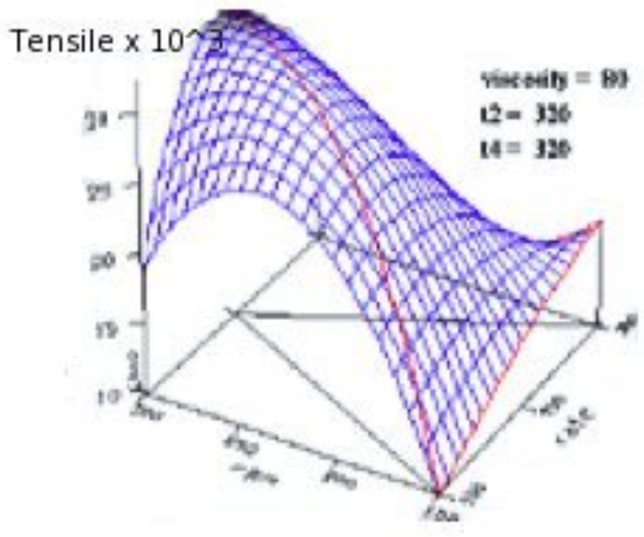
Trial	A	B	C	D	E	F	G
1	Lo	Lo	Lo	Lo	Lo	Lo	Lo
2	Lo	Lo	Lo	Hi	Hi	Hi	Hi
3	Lo	Hi	Hi	Lo	Lo	Hi	Hi
4	Lo	Hi	Hi	Hi	Hi	Lo	Lo
5	Hi	Lo	Hi	Lo	Hi	Lo	Hi
6	Hi	Lo	Hi	Hi	Lo	Hi	Lo
7	Hi	Hi	Lo	Lo	Hi	Hi	Lo
8	Hi	Hi	Lo	Hi	Lo	Lo	Hi

DOE - Taguchi Method

- Taguchi designs created before desktop computers were common
  - pre-created, cataloged designs intended to quickly find a set of conditions that meet the criteria of success
  - previous slide an example of an L8 template
- Designs cannot support response surface models and are limited to only predicting at the points where data was taken

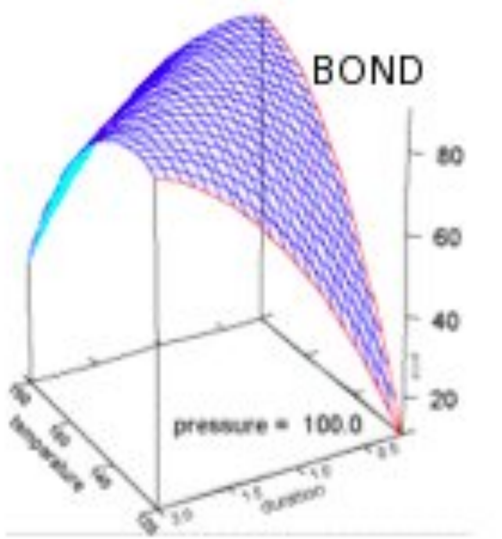
DOE - Response Surface: RSM

- Goal: develop a model that describes a continuous curve, or surface, that connects the measured data taken at strategically important places in the experimental window



DOE - Response Surface: RSM

- RSM uses a least-squares curve-fit (regression analysis) to:
  - calculate a system model *(what is the process?)*
  - test its validity *(does it fit?)*
  - analyze the model *(how does it behave?)*



Bond = f(temperature, pressure, duration)

$$
\begin{aligned}
Y = a_0 + a_1T + a_2P + a_3D \\
+ a_{11}T^2 + a_{22}P^2 + a_{33}D^2 \\
+ a_{12}TP + a_{13}TD + a_{23}PD
\end{aligned}
$$

Experimental Design Process

1. Determine the goals (measurable)
2. Define the factors of success
3. Estimate feasibility (roughly)
4. Design the experiment (precise estimate)
5. Run the experiment
6. Collect and analyze the data
7. Determine and verify the response
8. Act on the results

Experimental Design Process

1. Determine the goals

- doing so often leads to:
  - goals are too many to cover in a single study
  - goals that seemed concrete are actually very negotiable
- once consensus achieved, a valid experimentation strategy can be developed
- plan the action to be taken if the experiment is a success <u>or</u> a failure

Experimental Design Process

2. Define the factors of success

- once the goals are set, how do we know when we are meeting them?
- measures must be metric and refer to an intrinsic feature of the process or product
  - qualitative "good/bad" cannot be modeled
- including a large number of responses just to see how they change often diverts focus from the responses that are critical to meeting the goals

Experimental Design Process

3. Estimate feasibility (roughly)

- use a power calculation to determine whether any information can be found with a reasonable number of trials
  - a function of the amount of noise associated with a response
  - the more noise in the process, the more trials required to see a change in the desired parameter

Experimental Design Process

3. Estimate feasibility (roughly)

- example: how many runs needed to observe changes of 5,000 psi in the tensile strength of a plastic extruded part?

Resolution (psi)	Number of runs
10000	5
5000	22
2500	90
1250	362

Experimental Design Process

4. Design the experiment (precise estimate)
   - Identify the controls to be varied
   - Make the design
   - Determine whether the number of experiments is too large
     - If necessary, use a screening design to sift through to find the critical few

Experimental Design Process

5. Run the experiment
   - A task in resource management
   - Complete the work as efficiently and as effectively as possible

Experimental Design Process

6. Collect and analyze the data
   - Best to examine the data as a whole
   - Analysis of a set of data has significant advantage over contrasting the results between two data points
     - Ability to find suspect data is greatly enhanced
   - If there is a choice as to order, you may wish to obtain the most critical data first

Experimental Design Process

7. Determine and verify the response
   - A <u>Response Surface</u> gives you the ability to predict, with statistical limits, the behavior of the process at any point within the design window
   - Combining predictions from several responses allows you to simultaneously optimize for several key specifications

Experimental Design Process

8. Act on the results
   - Goals set earlier identified what was to be done if success obtained – do it!
     - If no action is taken, why was the experiment done?
   - Complete the documentation of the experiment

Summary

- Experimenter’s first goal: Understand the process!

Summary (cont.)

- The cost of experimentation
  - Resources (people, equipment, etc.)
  - Time
  - Material (unprocessed or unusable product)
  - Usable product that is not being produced

Summary (cont.)

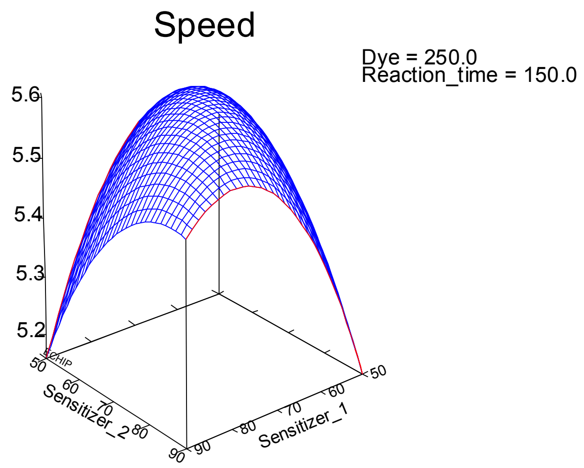
- Approaches to experimentation
  - Build-test-fix
  - One-factor-at-a-time (the classical approach)
  - Designed experiments (DOE)
- Major approaches to DOE
  - Factorial Design (full, fractional)
  - Taguchi Method
  - Response Surface Design

Summary (cont.)

- Full factorial
  - simplest design to create, but extremely inefficient
  - each factor tested at each condition of the factor
  - results analyzed with ANOVA
  - cost: resources, time, materials, …
- Taguchi Method
  - Taguchi designs created before desktop computers were common
  - Designs cannot support response surface models and are limited to only predicting at the points where data was taken

Summary (cont.)

- Response Surface Modeling
  - Goal: develop a continuous curve or surface that models the effects of parameters at different levels



Summary (cont.)

- Experimental Design process
  - Determine the goals
  - Define the measures of success
  - Verify feasibility (rough estimate)
  - Design the experiment (precise estimate)
  - Run the experiment
  - Collect and analyze the data
  - Determine and verify the response
  - Act on the results

Adapted from original Source: "What is DOE?", www.echip.com