Continuous Improvement Toolkit

Design of Experiment

(Introduction)


Managing Risk
PDPC
FMEA
RAID Logs
Fault Tree Analysis
Risk Assessment*
Traffic Light Assessment
Deciding & Selecting
Pros and Cons
Importance-Urgency Mapping
Break-even Analysis
Cost -Benefit Analysis
Force Field Analysis
Voting
SWOT
Pugh Matrix
Decision Tree
TPN Analysis
QFD
Matrix Diagram
Prioritization Matrix
Kano Analysis
Paired Comparison
Critical-to Tree
Planning & Project Management*
RACI Matrix
Stakeholders Analysis
PEST
PERT/CPM
Activity Diagram
Roadmaps
Project Charter
Gantt Chart
PDCA
Control Planning
Gap Analysis
Hoshin Kanri
Kaizen
How-How Diagram
Tree Diagram**
Standard work
Identifying & Implementing Solutions***
Simulation
TPM
Mistake Proofing
Pull Systems
JIT
Ergonomics
Work Balancing
Automation
Bottleneck Analysis
Visual Management
Flow
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SMED
Understanding Cause & Effect
Cause & Effect Matrix
Pareto Analysis
Confidence Intervals
ANOVA
Probability Distributions
Design of Experiments
Hypothesis Testing
Graphical Analysis
Scatter Plot
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Multi-Vari Charts
Relations Mapping*
Fishbone Diagram
Understanding Performance
Lean Measures
KPIs
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Cost of Quality
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Run Charts
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Benchmarking
Sampling
Data Collection
Focus groups
Interviews
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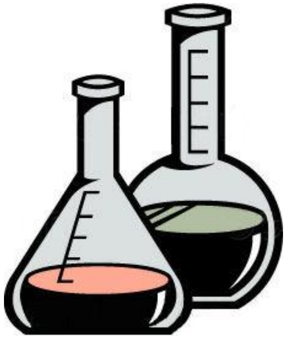
Check Sheets
Measles Charts
Surveys
Critical Incident Technique
Observations
Creating Ideas**
TRIZ***
Brainstorming
Analogy
SCAMPER***
Nominal Group Technique
Mind Mapping*
Affinity Diagram
Attribute Analysis
Lateral Thinking
Visioning
Designing & Analyzing Processes
Time Value Map
Process Redesign
IDEF0
Value Stream Mapping
SIPOC
Flow Process Chart
Process Mapping
Flowcharting
Service Blueprints

- Design of Experiment

Experimentation:

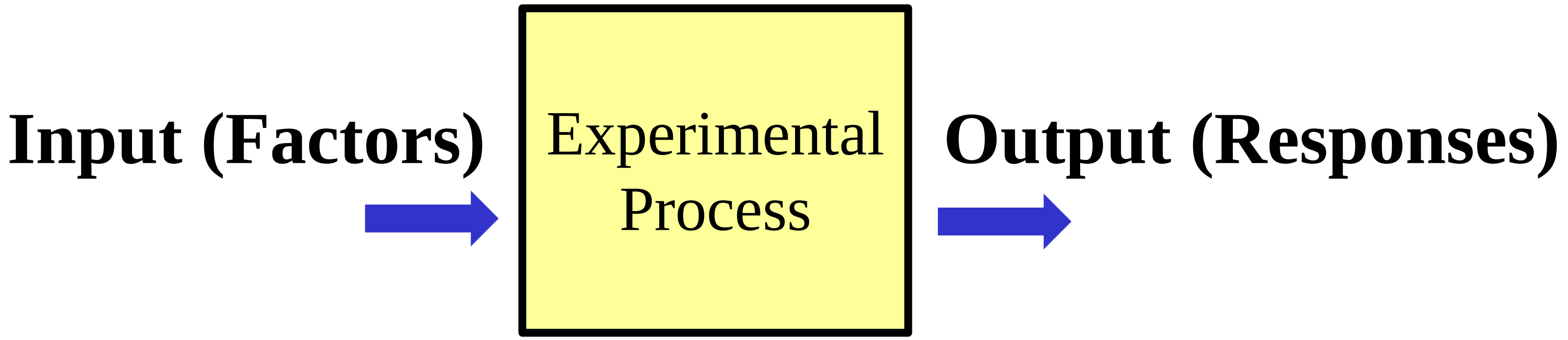
- An **experiment** is an act carried out under conditions determined by the experimenter in order to discover an unknown effect, to test or establish a hypothesis, or to illustrate a known effect.



- **Designed Experiment** - A formal practice for effectively exploring the causal relationship between input factors and output variables.
- It provides a range of efficient structured experiments which enable all the factors to be investigated at the same time, with minimum of trials.

- Design of Experiment

- **When analyzing a process, experiments are often used to:**
  - Evaluate which process inputs have a significant impact on the process output.
  - Decide what the target level of those inputs should be to achieve a desired output.



Input (Factors)

- People
- Material
- Equipment
- Policies
- Procedures
- Methods
- Environment

Experimental Process

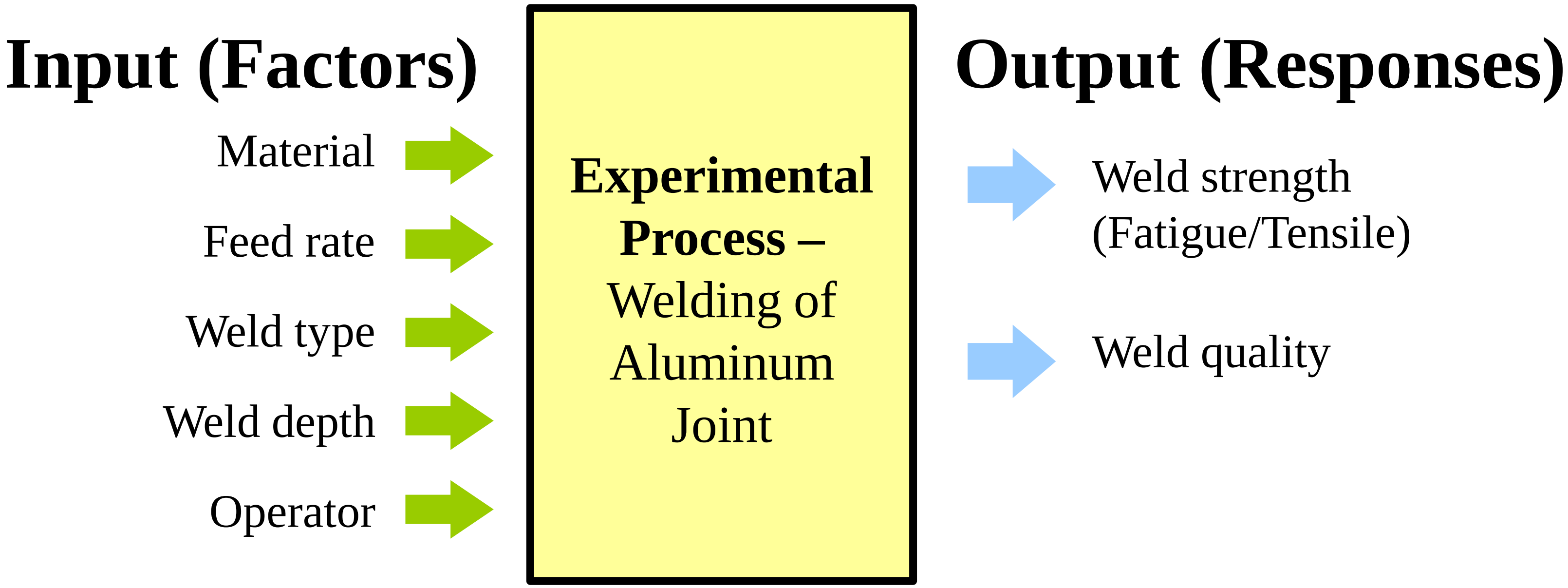
A Controlled Blending of Inputs Which Generates Corresponding Measurable Outputs

Output (Responses)

- Responses Related to Producing a Product
- Responses Related to Completing a Task
- Responses Related to Performing a Service

- Design of Experiment

Example - Welding of Aluminum Joint:



Regression vs. DOE:

- Regression are used to analyze historical data that is taken from the process in its normal mode.
- Designed experiments are used to create and analyze real time data that is taken in an experimental mode.
- The math behind DOE is similar to that for Regression.

$$Y=f(x)$$

- Design of Experiment

Benefits:

- **It identifies the significant inputs affecting an output to reduce the variability of the process and to achieve an optimal process output.**
- Allows to make an informed decision that evaluates both quality, cost and delivery.
- Achieves manufacturing cost savings.
- Reduces rework, scrap, and the need for inspection.
- Improve process or product "**Robustness**" or fitness for use under varying conditions.
- Compares alternatives.

- Design of Experiment

Where is DOE Used:

- DOE are more widespread in projects that are technically oriented such as manufacturing projects.
- The principles are relevant to transactional projects but the ability to control an experiment in an office environment tend to be limited.

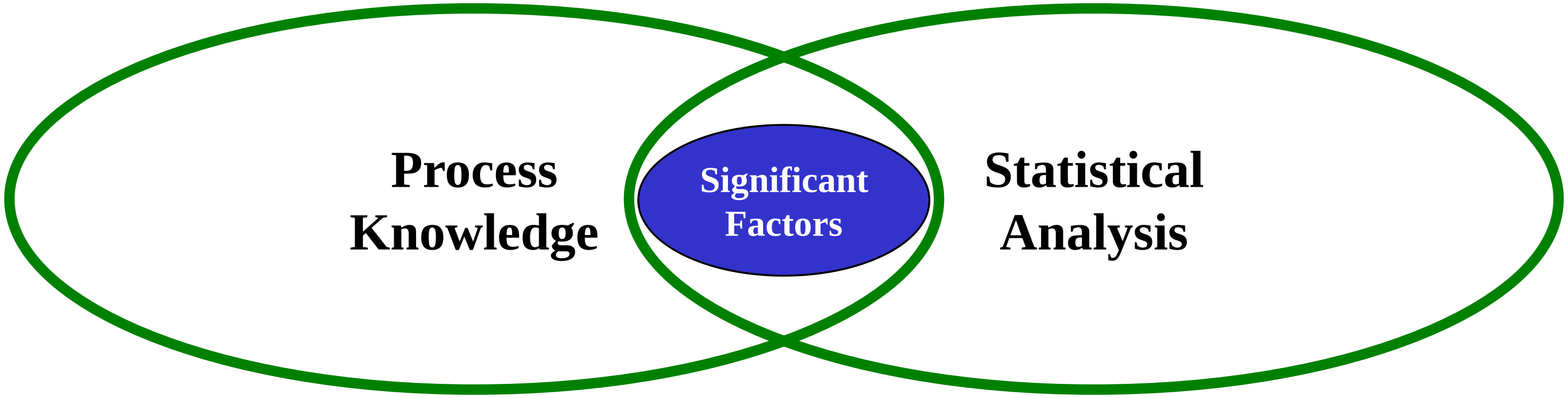
Why DOE is Not More Widely Used ?

- It is generally seen as heavy statistical technique, regarded as time consuming and expensive.
- Its value is often not well understood.

- Design of Experiment

Methods of Experimentation:

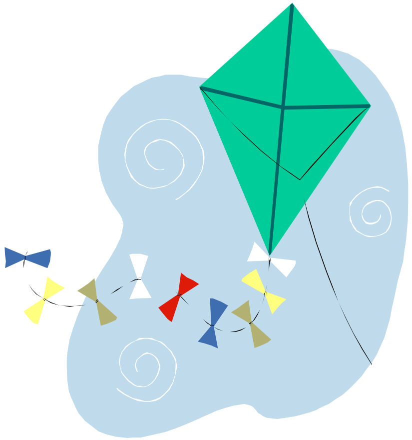
- Trial and Error.
- One Factor at a Time (OFAT).
- Designed Experiments (DOE).



Neither OTAF nor Trial and Error models can provide prediction equations

- Design of Experiment

Trial and Error:



- A method of reaching a correct solution or satisfactory result by trying experimentations until error is sufficiently reduced or eliminated.
- Perhaps the most widely used type of experimentation.
- Provides a "Quick Fix" to a specific problem.
- Random changes to process parameters.
- One selects a possible solution, applies it to the problem and, if it is not successful, selects another possible solution is subsequently tried until the right solution is found.

- Design of Experiment

Trial and Error:

- Attempt to find a solution, not all solutions, and not the best solution.
- This approach is most successful with simple problems when no apparent rule applies.
- Often used by people who have little knowledge about the problem.
- Symptoms may disappear but root cause of problem would still be undetected.
- Knowledge would not be expanded.

- Design of Experiment

One Factor at a Time (OFAT):

- One factor is tested while holding everything else constant, then another factor is tested, etc.
- Done in order to estimate the effect of a single variable on selected fixed conditions of other variables.
- This can be time consuming (very costly).

- What about interactions?
- Can we find the optimum process?
- Can we establish a Y=f (X) equation?

- Design of Experiment

Designed Experiments:

- Planned experiments that allow for the statistical analysis of several X's to determine their effects on any output (Y's).
- A more proactive way to learn about the process is to change it in a structured way.
- It provides the most efficient method for screening the vital few X's from the trivial many.
- It allows varying several factors "simultaneously".
- More efficient when studying two or more factors.

	A	B	C
1	1	1	1
2	1	2	2
3	2	1	2

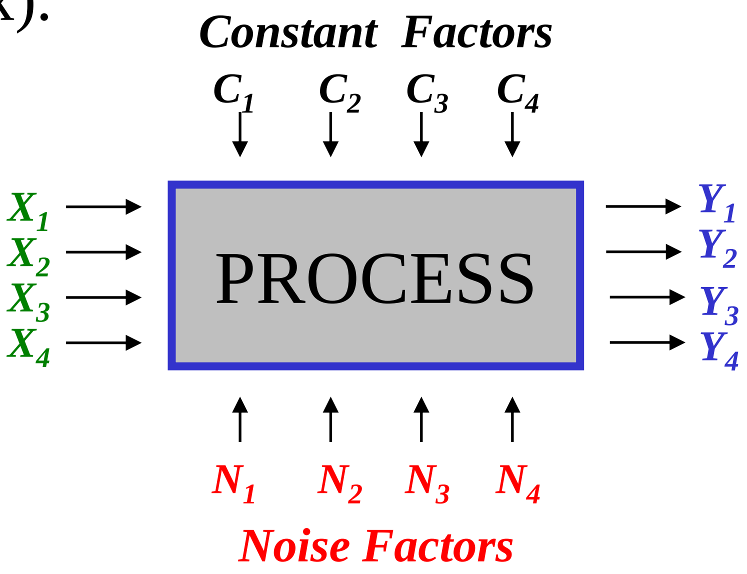
- Design of Experiment

Why Designed Experiments?

- Normally we have many Inputs, Outputs and possible settings.
- DOE explores the effects of different process inputs and combination of inputs on the output(s).
- DOE Enables us to establish: Y = f(x).

A well-performed DoE provide answers to:

- What are the key factors in a process?
- What are the best settings for our process?



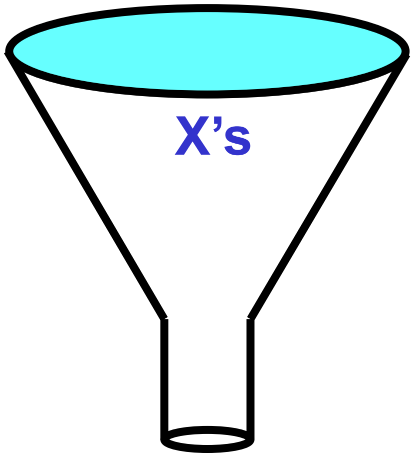
- Design of Experiment

Designed Experiments:

- In DOE, input variables are called **factors** and output variables are called **responses**.
- Each experimental condition is called a **run** and the response measurement is called an **observation**.
- The entire set of runs is called a **design**.
- **A well-performed DOE provide answers to:**
  - What are the key factors in a process?
  - At what **settings** would the process deliver acceptable performance or less variation in the output?

- Design of Experiment

- We need to determine which factors to evaluate in an experiment
- The critical variables or the “Vital Few”.
- **This requires:**
  - Process knowledge.
  - Statistical results.
- Next, we need to determine at which levels we want to set the factors in the experiment.
- Proper planning is the most critical step in conducting a successful DOE.



- Design of Experiment

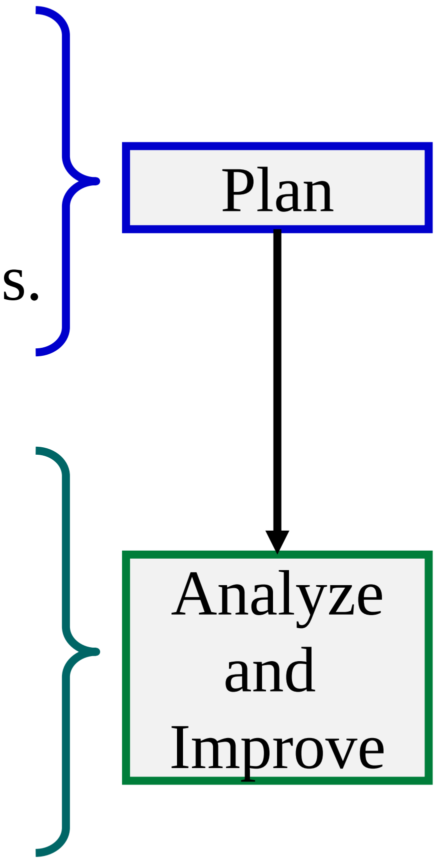
Three Aspects Analyzed by a DOE:

- **Factors:**
  - Controlled independent variables.
  - Potential factors can be obtained by the Fishbone diagram.
  - Ideally 2 to 4 factors
- **Response (Output):**
  - The output of the experiment (Single or Multiple).
- **Levels:**
  - Settings of a factor that are tested in an experiment.
  - The values here should be chosen with care and within the normal operating range.
  - Example: Oven temperature (high or low).

- Design of Experiment

Approach:

- Determine objectives and the key responses.
- Identify potential causes and factors.
- Identify potential levels and interactions.
- Choose appropriate design & the sequence of trials.
- **Run the experiment and collect the data.**
- Analyze data to determine interactions and best factor levels to optimize the process (evaluate the data).
- Verify the results and make recommendations.
- Implement the optimum factors.



- Design of Experiment

DOE Structure and Layout:

- The order in which the trials of an experiment are performed.
- **Randomization:**
  - Helps eliminate effects of **unknown** or **uncontrolled** variables.
  - Allows controlling the unknown source of variation that may affect the result.
  - Minimizes the possibility that other environmental factors will affect the test results.

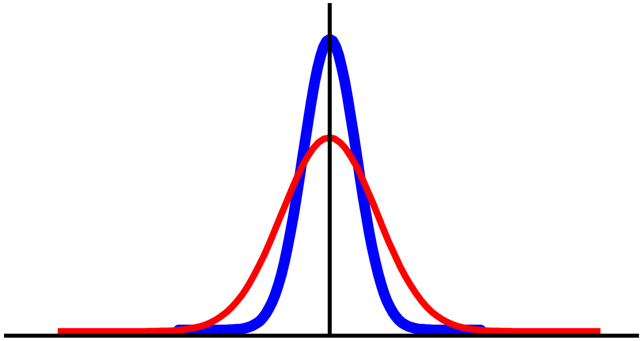
DOE Structure and Layout:

- **Blocking:**
  - An experimental technique that groups runs into logical collections of experimental units with a blocking variable to account for unavoidable process variation.
  - Used to reduce the unwanted variation in an experiment and increase the precision of the experiment.
  - In an experiment that contains a blocking variable, the runs are not completely randomized.
  - They are assigned to a logical collection (block) and then randomized within the block.

- Design of Experiment

DOE Structure and Layout:

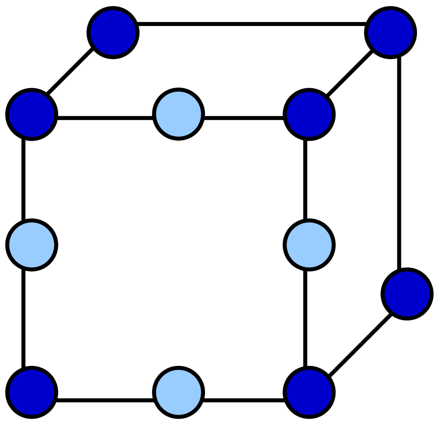
- **Replication:**
  - Uncontrollable factors (Noise factors) cause variation under normal conditions and could lead to measurement error.
  - By replicating the runs, the team will be able to estimate pure replication error which provides the best estimate of experimental variability (to gain statistical confidence).
  - **Sources of variability:**
    - Setting up equipment.
    - Resetting factors.
    - Natural variation in the process.



- Design of Experiment

Factorial Design:

- Allows to simultaneously evaluate the effect of several factors on a process.
- Varying the levels of the factors simultaneously rather than individually:
  - Saves time and expense.
  - Reveals the interaction between the factors.
- Helps identifying the optimal settings for factors.



- Design of Experiment

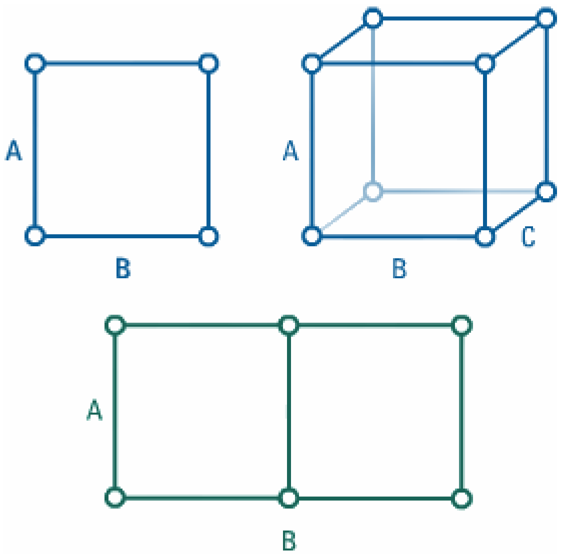
- **Full Factorial Experiment:**
  - Responses are measured at all combinations of the experimental factor levels.
  - With 2 factors at two levels, the full factorial design requires four runs.

No. of Factors	No. of Runs
2	4
3	8
4	16
5	32
6	64

- **Fractional Factorial Experiment:**
  - Are a good choice when resources are limited or the number of factors in the design is large.

- Design of Experiment

- **2-level factorial designs (2^K design).**
  - Each experimental factor has only 2 levels.



$$2^K$$

Number of Factors

Number of Levels

- **General factorial designs:**
  - Used when experimental factor has more than 2 levels.

- Design of Experiment

Example:

- Miss Marple wants to get her tea to the right sweetness.
- She has a teaspoon and sugar and wants you to explain how to do it.

	Low	High
Stirring	**None**	**20 seconds**
Sugar	**None**	**2 teaspoons**

Run Order	Stirring	Sugar
1	**Low**	**Low**
2	**Low**	**High**
3	**High**	**Low**
4	**High**	**High**

- Does just Stirring satisfy Miss Marple?
- Does just Sugar produce the desired effect?
- Is the interaction of stirring and adding sugar significant?

2-Level Full Factorial Design:

- It is the basic building block of designed experiments.
- **Factorial →** The input factors are changed simultaneously during the experiment.
- **2-level →** Every input factor is set at 2 different levels.
- **Full →** Every possible combination of the input factors is used during the experiment.

Run Order	Pressure	Type
1	310	One
2	380	One
3	310	Two
4	380	Two

- Design of Experiment

- The random order provides a random sequence in which the experiment should be completed.

Std. Order	Run Order	Pressure	Type	Thickness
1	1	310	One	4.25
2	5	380	One	4.41
3	7	310	Two	4.16
4	3	380	Two	4.63
5	4	310	One	5.15
6	6	380	One	4.80
7	2	310	Two	4.89
8	8	380	Two	4.29

Replication (Std. Order 5–8)

- Design of Experiment

Fractional Factorial Designs:

- Having fewer trials will lead to reduce the **resolution** of the experiment.
- This means that some of the interactions will not be visible because they will be confounded with other effects.
- Fractional factorial experiment can be and effective tool if this reduced resolution is understood and managed.

Available Factorial Designs (with Resolution)

	Factors													
Run	2	3	4	5	6	7	8	9	10	11	12	13	14	15
4	Full	III												
8		Full	IV	III	III	III								
16			Full	V	IV	IV	IV	III	III	III	III	III	III	III
32				Full	VI	IV	IV	IV	IV	IV	IV	IV	IV	IV
64					Full	VII	V	IV	IV	IV	IV	IV	IV	IV
128						Full	VIII	VI	V	V	IV	IV	IV	IV

- Design of Experiment

3 Factors (Pressure, Temperature, Type)

Fractional Factorial

Std. Order	Run Order	Pressure	Temperature	Type	Thickness
1	1	310	63	One	4.25
2	5	380	63	Two	4.41
3	7	310	68	Two	4.16
4	3	380	68	One	4.63
5	4	310	63	One	5.15
6	6	380	63	Two	4.80
7	2	310	68	Two	4.89
8	8	380	68	One	4.29
9	9	Mid	Mid	Mid	4.19

Center Points can be used to detect non-linear effects.

- Design of Experiment

To evaluate the data (Process Optimization):

- ❑ Determine whether the effects are significant.
- ❑ Determine the most contribution to the response variability.
- ❑ Fit the experimental data to a model.
- ❑ Check the model assumptions using residual plot.
- ❑ Determine process settings that optimize the response (using Response Surface Design).

- Design of Experiment

Determine Whether the Effects are Significant:

- In a designed experiment, we evaluate the p-value to determine if the effects are significant (ANOVA).
- The null hypothesis for each term in the model is that the effect is equal to zero.

Estimated Effects and Coefficients for Adhesion (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant		4.64313	0.02739	169.53	0.000
Pressure	-0.19375	-0.09687	0.02739	-3.54	0.004
Primer Type	0.41375	0.20687	0.02739	7.55	0.000
Pressure*Primer Type	-0.12125	-0.06062	0.02739	-2.21	0.047

Analysis of Variance for Adhesion (coded units)

Estimated Coefficients for Adhesion using data in uncoded units

Term	Coef
Constant	5.59804
Pressure	-0.00276786
Primer Type	0.804464
Pressure*Primer Type	-0.00173214

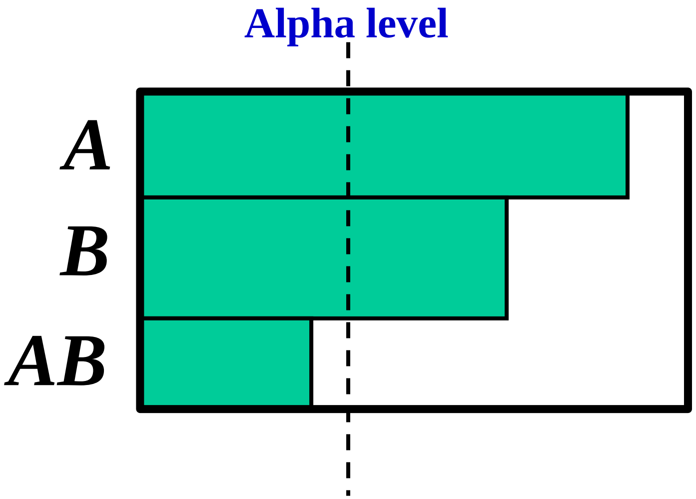
$$Y = 5.5980 - 0.0028*A + 0.8045*B - 0.0017*A*B + Error$$

- Design of Experiment

Determine the Most Contribution to the Response Variability:

- Which terms contribute the most to the variability of the response (use the Pareto chart).
- Any bar extending beyond the significance level reference line indicates that the effect is significant.

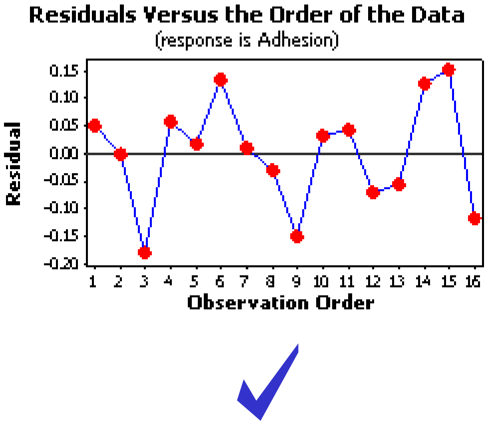
- The Pareto chart shows that both factors significantly affect the response.
- The interaction between the factors is not significant.

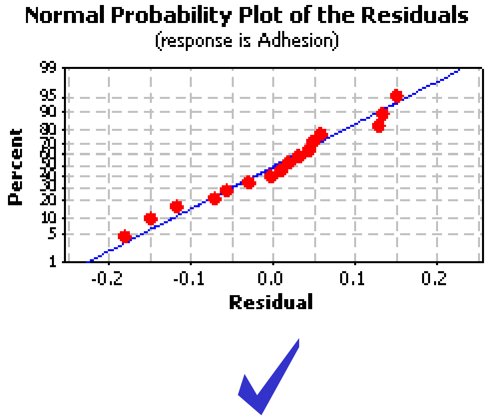


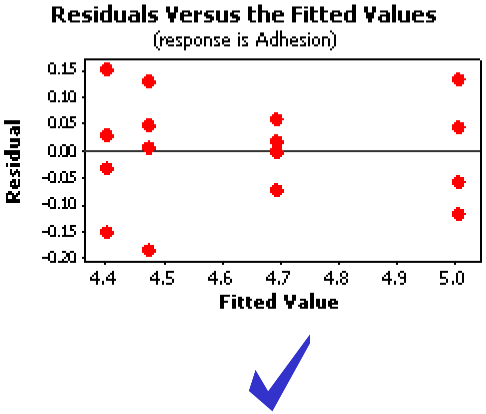
- Design of Experiment

Fit the experimental data to a model:

- It is a good practice to check the model assumptions before use the model to determine the optimal factor:
  - The errors are random and independent.
  - The errors are normally distributed.
  - Errors have constant variance across all factor levels.



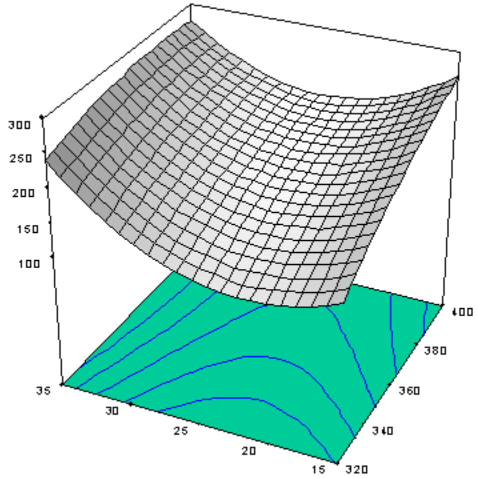




- Design of Experiment

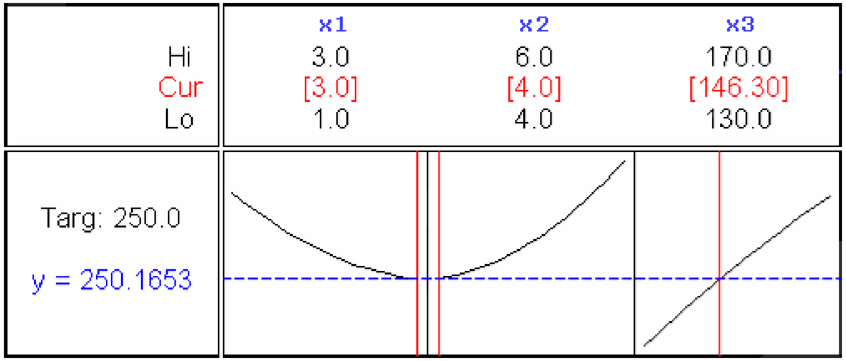
Determine Process Settings that Optimize the Response:

- We will use the Response Surface Design to determine the optimum settings of the X's that will optimize the response.
- The goal is to find the settings of the factors where the results are consistently close to the optimum.
- It investigates curvature of the response surface.
- Used usually following the factorial design because there will then be a higher level of knowledge about the key X's and their interactions needed to optimize the response.



Response Surface Designs are Used to:

- Find the optimal process settings that will influence the response.
- Troubleshoot process problems and weak points.
- Make a product or process more robust against external and non-controllable influences.
- Find the settings of the variables that will yield a maximum (or minimum) response.



- Design of Experiment

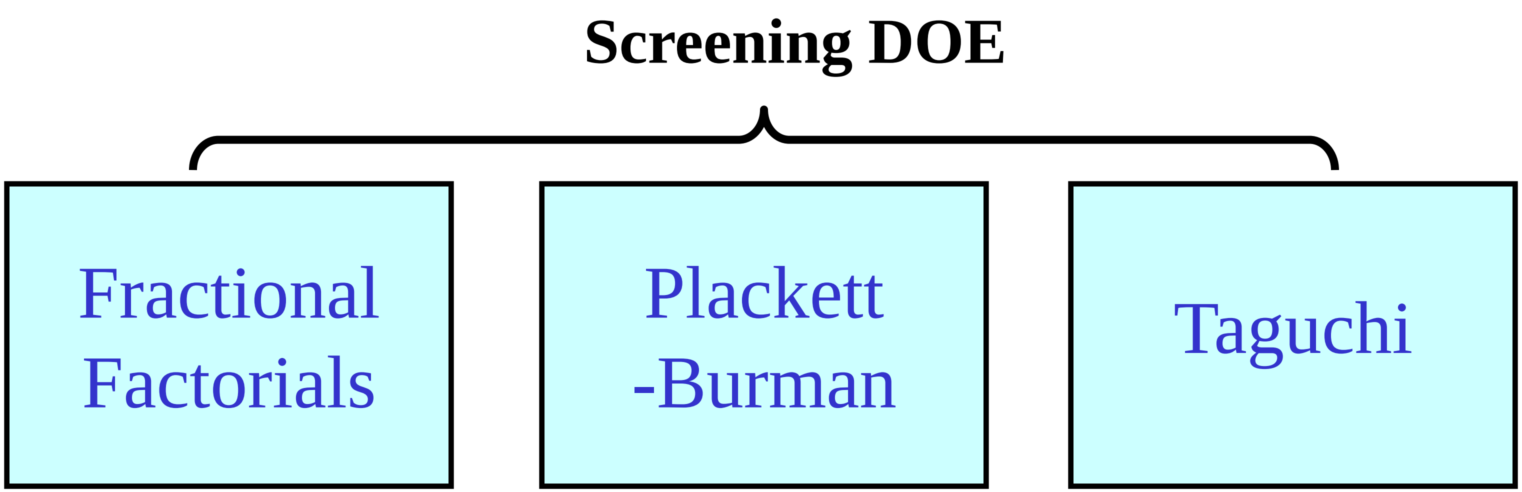
Screening Designs:

- An experimental design which allows us to evaluate the effects of a large number of potential factors on the response in the fewest possible runs.
- Helps to screen out the trivial many factors and identify the significant few affecting the response.
- Used when there is a low level of knowledge about the X's that are critical to optimizing the Y's.
- Screening designs reduce the number of trials and hence the cost of an experiment. They tend to be highly fractionated.

- Design of Experiment

We Use Screening Designs When:

- When process knowledge is low.
- We have too many factors.
- It is difficult to run the experiments.
- It is expensive to run the experiments.



- Design of Experiment

Taguchi Methods:

- A special variant of Design of Experiments (DOE).
- It's based on the principle that processes can be made insensitive (robust) to random variation from uncontrollable (noise) factors by including these factors in the experimental design.