

LEAN

Design of Experiments (DoE)

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Lecture Summary – Intro to QFD

“All of my experiments are designed experiments; it is just that some are designed poorly”

1. Understand the issues and principles of Design of Experiments (DOE),
2. Understand experimentation is a process,
3. List the guidelines for designing experiments
4. recognize the key historical figures in DOE.

Do you Remember the Scientific Method?

- **Decide what phenomenon you wish to investigate.** Specify how you can **manipulate the factor** and **hold all other conditions fixed**, to ensure that these extraneous conditions aren't influencing the response you plan to measure.
- Then **measure your chosen response variable at several (at least two) settings of the factor under study.** If changing the factor causes the phenomenon to change, then you conclude that **there is indeed a cause-and-effect relationship at work.**
- How many factors are involved when you do an experiment?
 - Some say two – perhaps this is a comparative experiment?
 - Perhaps there is a treatment group and a control group? If you have a treatment group and a control group then, in this case, you probably only have one factor with two levels.

Design of Experiments

- The term experiment is defined as the **systematic procedure carried out under controlled conditions** to discover an unknown effect, test or establish a hypothesis, or illustrate a known effect.
- When analysing a process, experiments are often used to evaluate **which process inputs significantly impact the process output**, and what the target level of those inputs should be to achieve a desired result (output).
- Experiments can be designed in many ways to collect this information. Design of Experiments (DOE) is also referred to as Designed Experiments or Experimental Design (**same meaning**)

Design of Experiments - background

- If we had infinite time, resource and budget there probably wouldn't be a big fuss made over designing experiments.
- In production and quality control we want to control the error/problem and learn as much as we can about the process (or underlying theory) with the (often limited!) resources at hand.
- Thus, a more effective technique (than the classic scientific method) is necessitated.

Design of Experiments - background

From an engineering perspective, we're trying to use experimentation for the following purposes:

1. Reduce **time** to design/develop new products & processes
2. Improve **performance** of existing processes
3. Improve **reliability** and performance of products
4. Achieve product & process **robustness**
5. Perform **evaluation** of materials, design alternatives, **setting** component & system tolerances, etc.

Cake Baking Example – DoE

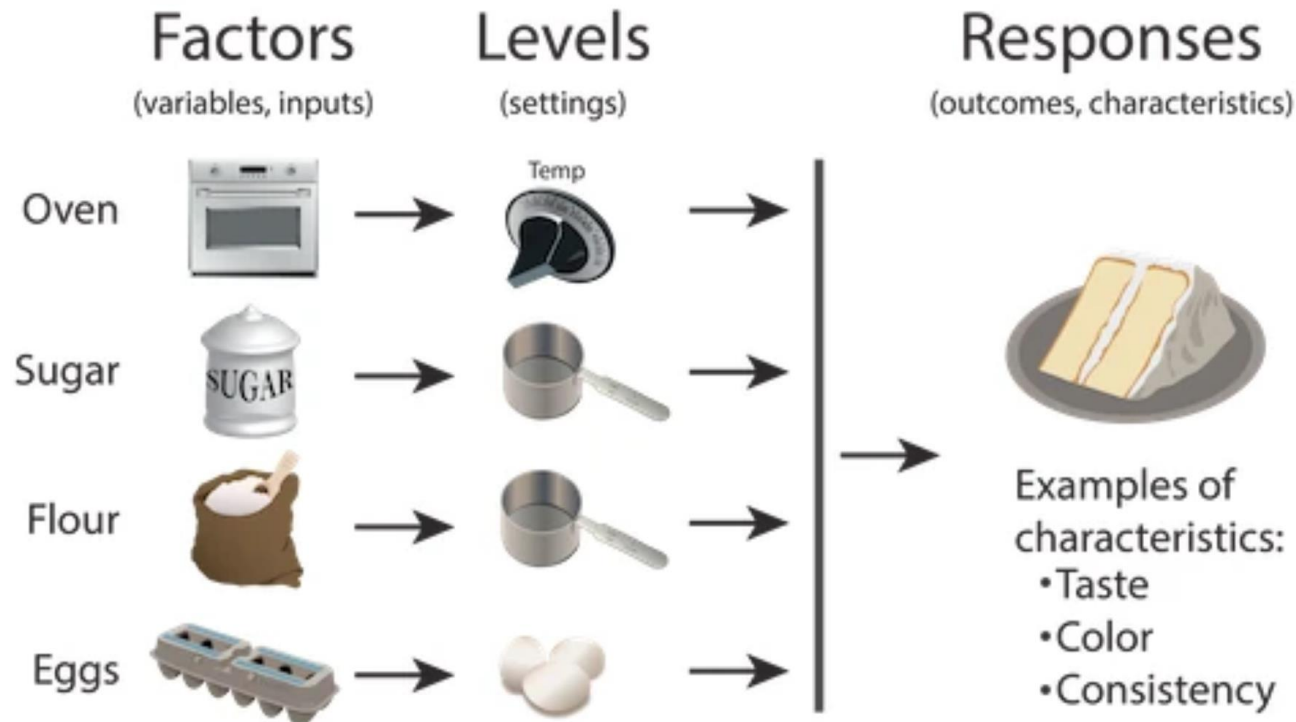
What are the factors involved to ensure a successful cake?

- Factors might include preheating the oven, baking time, ingredients, amount of moisture, baking temperature, etc.- what else?
- You would probably follow a recipe so there are many additional factors that control the ingredients - i.e., a mixture. In other words, someone did the experiment in advance!

What parts of the recipe did they vary to make the recipe a success?

Probably many factors, temperature and moisture, various ratios of ingredients, and the presence or absence of many additives.

Design of Experiments – Baking Example

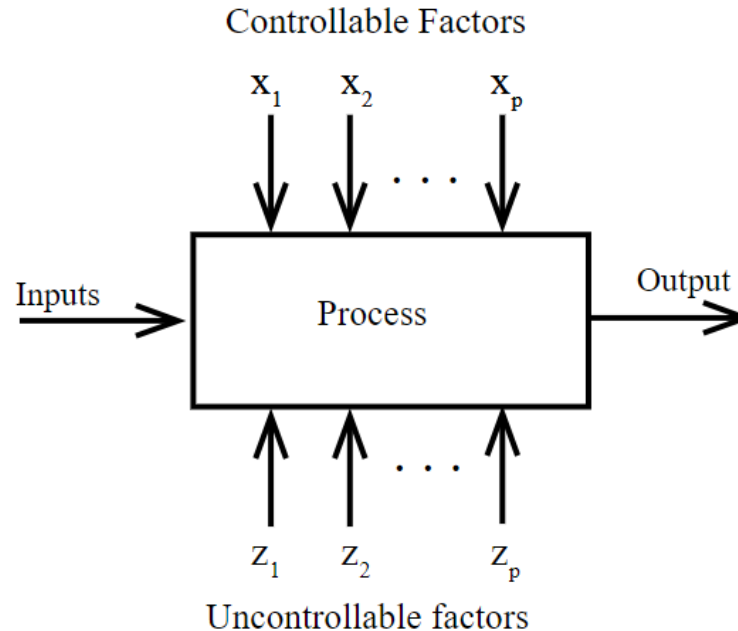


- Consider the following diagram of a cake-baking process.
- There are three aspects of the process that are analysed by a designed experiment:

Controllable / Uncontrollable factors

(Time of baking, temperature, geometry of the cake pan, etc.)

- Flour
- Sugar
- Milk
- Eggs



- Texture
- Flavour
- Height
- Size

Regardless of the quality of these ingredients we still want our cake to come out successfully.

DoE – Understanding Factors

- We usually talk about "treatment" factors, which are the factors of primary interest to the experimenter.
- In addition to treatment factors, there are nuisance factors which are not your primary focus, but you must deal with them.
- Sometimes these are called blocking factors, mainly because we will try to block these factors to prevent them from influencing the results.

DoE -Experimental vs. Classification Factors

There are other terms we can use to categorise factors:

- **Experimental Factors**

These are factors that you can specify (and set the levels) and then assign at random as the treatment to the experimental units. **Consider a medical test, examples would be dosage of drug given, potency of a drug, duration treated etc.**

- **Classification Factors**

These can't be changed or assigned, these come as labels on the experimental units. **The age and sex of the participants in the above study would be classification factors which can't be changed or randomly assigned.** But remember, you can select individuals from these groups randomly.

DoE – Understanding Levels/Response

- **Levels** (or settings) of each factor in the experiment. i.e. oven temperature setting, quantities of sugar, flour, and eggs that were chosen for evaluation.
- **Response** (or outputs) in this example the taste, consistency, and appearance of the cake are measurable outcomes potentially influenced by the factors and their respective levels.

Typically, we need to avoid optimising the process for one response at the expense of another. For this reason, important outcomes are measured and analysed to determine the factors and their settings that will provide the best overall outcome for the critical-to-quality characteristics.

DoE- Understanding Randomisation

- This is an essential component of any experiment that is going to have validity.
- If you are doing a comparative experiment where you have two treatments, a treatment and a control, you need to include in your experimental process the assignment of those treatments by some random process.
- You need to have a deliberate process to eliminate potential biases from the conclusions, and random assignment is a critical step.

Basic DoE Principles – Replication

- Replication is (in some sense) the heart of all of statistics.
- Replication is the basic issue behind every method we will use to get a handle on how precise our conclusions are at the end.
- We always want to estimate or control the uncertainty in our results. We achieve this estimate through replication.
- Another way is to reduce the size, **or the length of the confidence interval**, is to reduce the error variance - which brings us to blocking.

Basic DoE Principles – Blocking

- Blocking is a technique used to include other factors in our experiment which contribute to undesirable variation and Involves organising a test into groups or batches to reduce variability.
- **Imagine you're testing a new fertiliser on plants. Instead of randomly applying it to all plants, you might group plants by similar characteristics (like size or species) and then apply the fertiliser to each group (block) separately. This helps you see the true effects of the fertiliser without other factors getting in the way.**
- By using these as blocking factors, you can avoid biases that might occur due to differences between the allocation of subjects making your experiment more precise by managing these differences that could skew your results.

Basic DoE Principles – Confounding

- Confounding is something we typically want to avoid!
- Refers to the combining influences of two or more factor effects and their interaction effects independently. Effects which are confounded are called aliases
- When building complex experiments, we sometimes can use confounding to our advantage. We will confound things we are not interested to have more efficient experiments for the things we are interested in. We may be interested in main effects but not interactions.
- Confounding the interactions can be used to reduce the sample size, and thus the cost of the experiment, but still have good information on the main effects.

Basic DoE Principles - Multi-factor Designs

- The intent of multi-factor designs is contrary to the scientific method (where everything is held constant except one factor).
- The “one factor at a time” method is a very inefficient way of making scientific observations. It is much better to design an experiment that simultaneously includes combinations of multiple factors that may affect the outcome.
- As a result, you learn not only about the primary factors of interest but also about these other factors. These may be blocking factors which deal with nuisance parameters, or they may just help you understand the interactions or the relationships between the factors that influence the response.

Design of Experiments – Why bother?

- **Comparing Alternatives** In the case of our cake-baking example, we might want to compare the results from two different types of flour. If it turned out that the flour from different vendors was not significant, we could select the lowest-cost vendor. If flour were significant, then we would select the best flour. The experiment(s) should allow us to make an informed decision that evaluates both quality and cost.
- **Identifying the Significant Inputs** (Factors) Affecting an Output (Response) - separating the vital few from the trivial many. We might ask a question: "What are the significant factors beyond flour, eggs, sugar and baking?"
- **Achieving an Optimal Process Output (Response).** "What are the necessary factors, and what are the levels of those factors, to achieve the exact taste and consistency of the aforementioned perfect cake?"

DoE – Practical Workflow

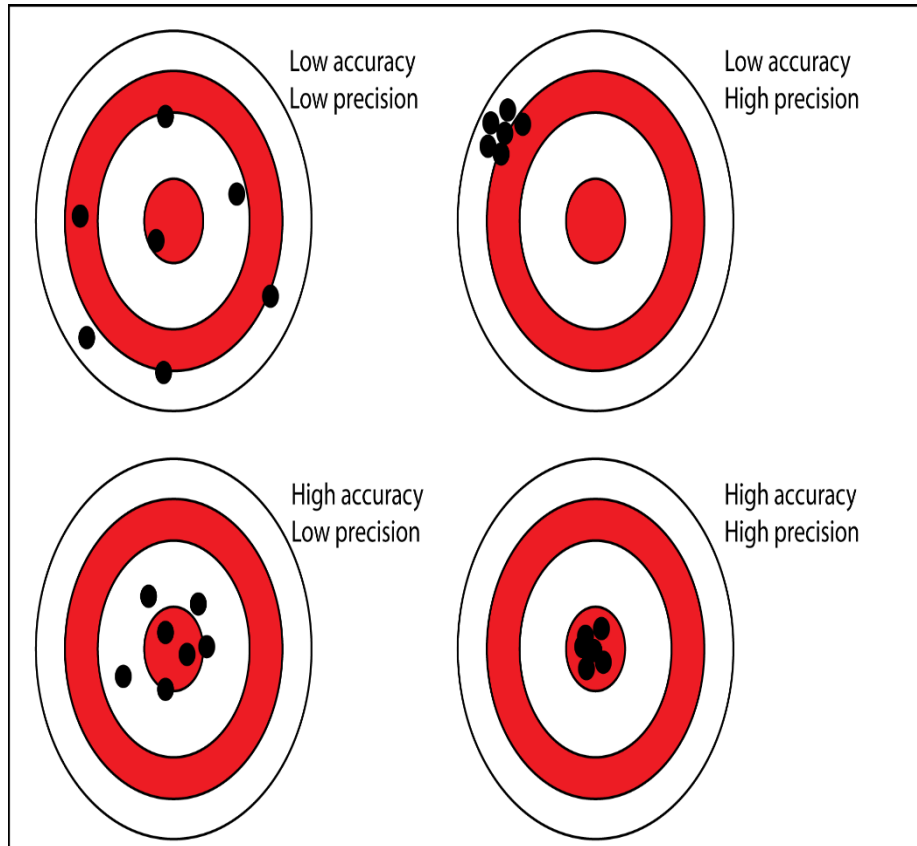
The practical steps needed for planning and conducting an experiment include Choice of factors, levels, and ranges

1. Selection of the response variable(s)
2. Choice of design
3. Conducting the experiment
4. Statistical analysis
5. Drawing conclusions, and making recommendations

DoE - Measurement Systems

- Quality feature/Characteristics will have to be measured either by direct or indirect methods.
- These measurement methods produce variation in the response.
- Every measurement process is subject to inherent variation.
- Identifying, stratifying and eliminating sources of measurement variation leads to improvements to the actual measured values.

Measurement System

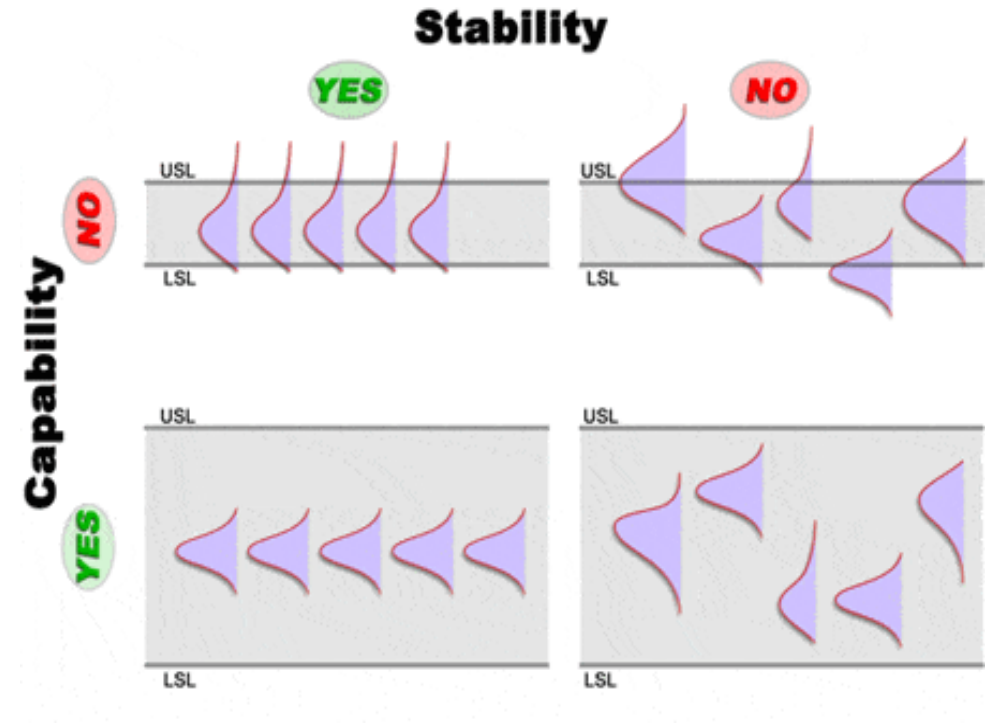


- The following characteristics need to be considered for a measurement system:
- **Accuracy**: - Refers to the degree of closeness between the measured value and the true value or reference value
 - **Precision**: - It is a measure of the scatter of results of several observations and is not related to the true value. It is a comparative measure of the observations and is only a measure of the random errors

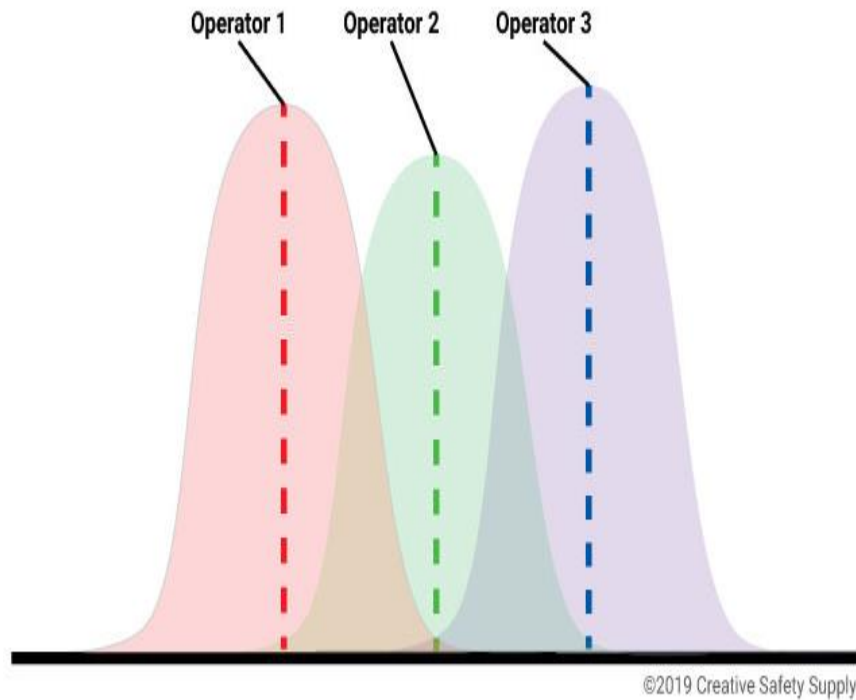
Measurement System

- **Stability**: - A measurement is said to be stable if the measurements do not change overtime.
- **Capability**: - A measurement system is capable if the measurements are free from bias (accurate) and sensitive

A capable measurement system requires sensitivity, but the variation around the average should be small compared to the specification limits (process variance and accuracy)



Measurement System Capability



- The goal of measurement system capability study is to understand and quantify the sources of variability present in the measurement system.
- Repeatability and reproducibility (R&R) studies analyse the variation of measurements of a gage and the variation of measurements by operators, respectively.

Measurement System Capability

Table 1: Gage R&R Results

Operator	Part	Result 1	Result 2
A	1	257	252
A	2	300	303
A	3	277	273
A	4	279	286
A	5	246	237
B	1	245	247
B	2	296	289
B	3	272	269
B	4	274	268
B	5	233	232
C	1	242	245
C	2	296	293
C	3	270	271
C	4	270	272
C	5	236	244

- **Repeatability** - refers to the variation in measurements obtained when **an operator** uses the same gage several times for measuring the identical characteristics on the same part.
- **Reproducibility** - refers to the variation in measurements when **several operators** use the same gauge for measuring the identical characteristic on the same part.

Measurement system capability – P/T ratio

AIAG guidelines for what acceptable and unacceptable P/T values are:

- Under 0.10: generally considered to be an acceptable measurement system.
- 0.10 – 0.30: may be acceptable for some applications.
- Over 0.30: considered to be unacceptable.

A measurement system is generally considered to be capable if it satisfies the following criterion:

$$\frac{P}{T} \leq 10\%$$

Where P/T (Precision-to-Tolerance ratio) is given by:

$$\frac{P}{T} = \frac{6\sigma_e}{USL - LSL}$$

From data above:

$$P/T = \frac{6\sigma_e}{USL - LSL} = \frac{6(5.654)}{305 - 225} = 0.4241 = 42.4\%$$

Measurement system capability

Moreover,

- There are risks associated when relying too much on the P/T ratio
- For example, the P/T ratio may be made arbitrary small by increasing the width of the specification of tolerance band.
- The gage must be able to have sufficient capability to detect meaningful variation in product.

Measurement System Capability - GRR value

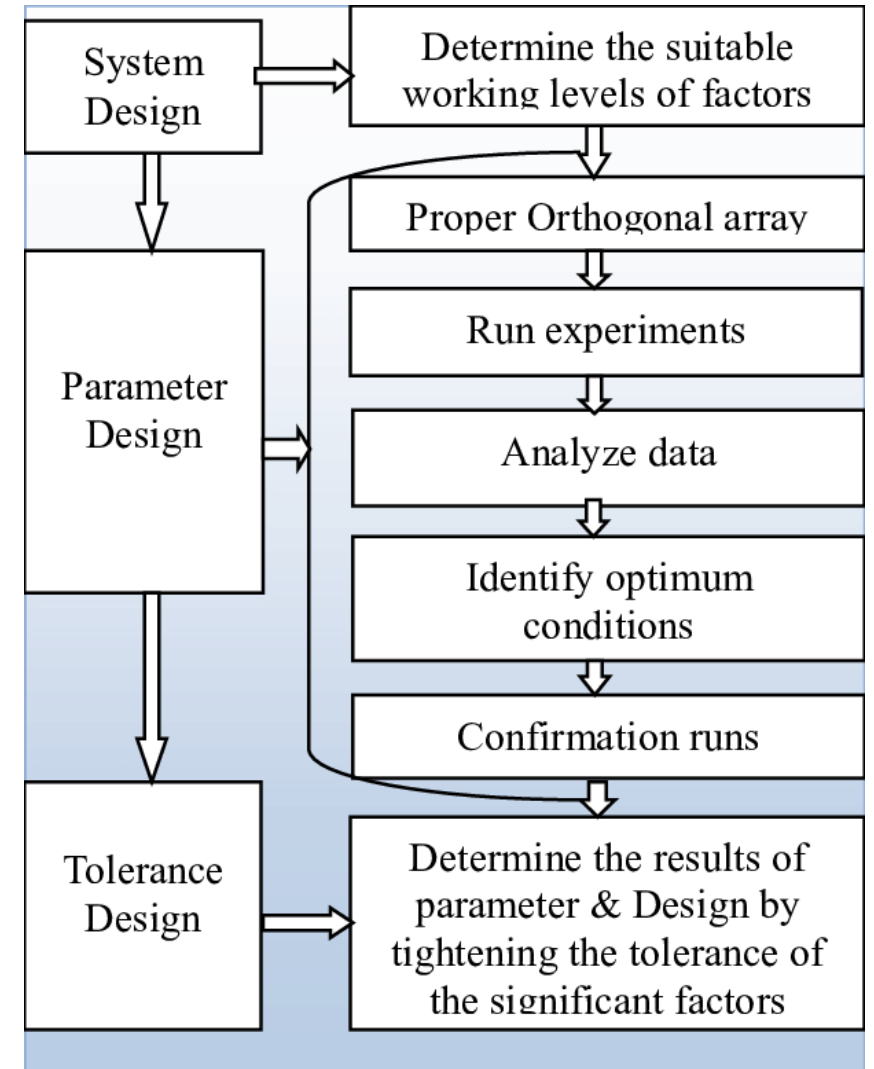
- The contribution of the gage variability offers a more useful criterion for deterring the measurement system capability.
- The following equation can be used to determine whether the given measurement system is capable or not.

$$\text{GRR value} = \frac{\sigma_{error}}{\sigma_{total}} \leq 10\%$$

σ error is the variance component due to measurement error (σ *Reprod.* + σ *repeat.*).

σ total is the total variance, which includes both the variance due to measurement error and the variance due to part-to-part variation.

Stages in the Taguchi Approach for Experimental Design



The significance of Parameter Design

- In parameter design, the most important job of the engineer is to select an effective characteristic to measure as data...
- We should measure data that relate to the function itself and **not the symptom of variability**...
- You should aim to measure continuous parameters such as: force, acceleration, distance, pressure, velocity & time etc.

The significance of Parameter Design

Avoid using indirect measures, such as:

- Yield
- Number of defects
- Faults
- Reliability
- Appearance
- Pass/fail ratios
- Fractions defective
- % Non-Conforming

These are performance indicators, but they are symptoms of the underlying physical problems.

DoE - Orthogonal Arrays

- Experimental design technique that are commonly used in industrial and manufacturing settings to optimise product and process designs.
- Used to systematically vary the levels of input factors to identify the most significant factors and levels that affect the output or response variable.
- Designed to minimise the number of experiments required to identify the key factors and levels, while still providing statistically valid results.

DoE - Orthogonal Arrays

Experiment Number	Column										
	1	2	3	4	5	6	7	8	9	10	11
1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	2	2	2	2	2	2
3	1	1	2	2	2	1	1	1	2	2	2
4	1	2	1	2	2	1	2	2	1	1	2
5	1	2	2	1	2	2	1	2	1	2	1
6	1	2	2	2	1	2	2	1	2	1	1
7	2	1	2	2	1	1	2	2	1	2	1
8	2	1	2	1	2	2	2	1	1	1	2
9	2	1	1	2	2	2	1	2	2	1	1
10	2	2	2	1	1	1	1	2	2	1	2
11	2	2	1	2	1	2	1	1	1	2	2
12	2	2	1	1	2	1	2	1	2	2	1

The experimental design is based on a set of orthogonal arrays

OAs are matrices that are carefully constructed to ensure that all possible combinations of factor levels are included in the experiments, while minimizing the number of runs required.

Taguchi Arrays – Why Bother?

Consider the following (full factorial) example:

If we were tasked with analysing a simple process with 8 variables, each with 3 states (levels), how many experiments would we need to test all combinations of variables and states?

We would require 6561 (3^8) separate experiments!

However, using Taguchi's orthogonal arrays, only 18 experiments are necessary, or less than .3% of the original number of experiments.

Taguchi (Orthogonal) Array

Factors / parameters



Number of
Experiments



Experiment Number	Column										
	1	2	3	4	5	6	7	8	9	10	11
1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	2	2	2	2	2	2
3	1	1	2	2	2	1	1	1	2	2	2
4	1	2	1	2	2	1	2	2	1	1	2
5	1	2	2	1	2	2	1	2	1	2	1
6	1	2	2	2	1	2	2	1	2	1	1
7	2	1	2	2	1	1	2	2	1	2	1
8	2	1	2	1	2	2	2	1	1	1	2
9	2	1	1	2	2	2	1	2	2	1	1
10	2	2	2	1	1	1	1	2	2	1	2
11	2	2	1	2	1	2	1	1	1	2	2
12	2	2	1	1	2	1	2	1	2	2	1

Levels /
Settings



Selecting the Correct Array

- Knowing the number of parameters and the number of levels, the proper orthogonal array can be selected.
- Using the array selector table shown below, the name of the appropriate array can be found by looking at the column and row corresponding to the number of parameters and number of levels. Once the name has been determined (the subscript represents the number of experiments that must be completed), the predefined array can be looked up.

		Number of Parameters (P)																														
		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	
Number of Levels	2	L4	L4	L8	L8	L8	L8	L12	L12	L12	L12	L16	L16	L16	L16	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	
	3	L9	L9	L9	L18	L18	L18	L18	L27	L27	L27	L27	L27	L36	L36	L36	L36	L36	L36	L36	L36	L36	L36									
	4	L'16	L'16	L'16	L'16	L'32	L'32	L'32	L'32	L'32																						
	5	L25	L25	L25	L25	L25	L50	L50	L50	L50	L50	L50																				

What type
(L?) of array
is shown
here?

Number of
Experiments

Factors / parameters

Experiment Number	Column										
	1	2	3	4	5	6	7	8	9	10	11
1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	2	2	2	2	2	2
3	1	1	2	2	2	1	1	1	2	2	2
4	1	2	1	2	2	1	2	2	1	1	2
5	1	2	2	1	2	2	1	2	1	2	1
6	1	2	2	2	1	2	2	1	2	1	1
7	2	1	2	2	1	1	2	2	1	2	1
8	2	1	2	1	2	2	2	1	1	1	2
9	2	1	1	2	2	2	1	2	2	1	1
10	2	2	2	1	1	1	1	2	2	1	2
11	2	2	1	2	1	2	1	1	1	2	2
12	2	2	1	1	2	1	2	1	2	2	1

Levels /
Settings

		Number of Parameters (P)																														
		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	
Number of Levels	2	L4	L4	L8	L8	L8	L8	L12	L12	L12	L12	L16	L16	L16	L16	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	
	3	L9	L9	L9	L18	L18	L18	L18	L27	L27	L27	L27	L27	L36	L36	L36	L36	L36	L36	L36	L36	L36	L36									
	4	L'16	L'16	L'16	L'16	L'32	L'32	L'32	L'32	L'32																						
	5	L25	L25	L25	L25	L25	L50	L50	L50	L50	L50	L50																				

Important Notes - Selection of Orthogonal Arrays

The array selector assumes that each parameter has the same number of levels. Sometimes this is not the case. Generally, the highest value will be taken, or the difference will be split.

Example 1:

Parameter: A, B, C, D = 4 - levels: 3, 3, 3, 2 = ~3 **array = L9**

Example 2:

Parameter: A, B, C, D, E, F = 6 - levels: 4, 5, 3, 2, 2, 2 = ~3 **array = L18**

Using Orthogonal Arrays – Example

A reactor's behaviour is dependent upon impeller model, mixer speed, the control algorithm employed, and the cooling water valve type. The possible values for each are as follows:

1. Impeller model: A, B, or C
2. Mixer speed: 300, 350, or 400 RPM
3. Control algorithm: PID, PI, or P
4. Valve type: butterfly or globe

There are 4 parameters, and each one has 3 levels except for valve type. The highest number of levels is 3, so we will use a value of 3 when choosing our orthogonal array.

		Number of Parameters (P)																														
		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	
Number of Levels	2	L4	L4	L8	L8	L8	L8	L12	L12	L12	L12	L16	L16	L16	L16	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	
	3	L9	L9	L9	L18	L18	L18	L18	L27	L27	L27	L27	L27	L36	L36	L36	L36	L36	L36	L36	L36	L36	L36									
	4	L'16	L'16	L'16	L'16	L'32	L'32	L'32	L'32	L'32																						
	5	L25	L25	L25	L25	L25	L50	L50	L50	L50	L50	L50																				

Using the array selector, we find that the appropriate orthogonal array is L9:

Experiment	A	B	C	D
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1



Experiment	Impeller	Motor Speed	Control	Valve
1	A	300	PID	BF
2	A	350	PI	G
3	A	400	P	G
4	B	300	PI	BF
5	B	350	P	BF
6	B	400	PID	G
7	C	300	P	G
8	C	350	PID	BF
9	C	400	PI	BF

Using Orthogonal Arrays – Note

- If the array selected based on the number of parameters and levels includes more parameters than are used in the experimental design, ignore the additional parameter columns.
- For example, if a process has 8 parameters with 2 levels each, the L12 array should be selected according to the array selector. As can be seen below, the L12 Array has columns for 11 parameters (P1-P11). The right 3 columns should be ignored.

Experiment	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11
1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	2	2	2	2	2	2
3	1	1	2	2	2	1	1	1	2	2	2
4	1	2	1	2	2	1	2	2	1	1	2
5	1	2	2	1	2	2	1	2	1	2	1
6	1	2	2	1	2	2	1	2	1	1	1
7	1	2	2	2	1	2	2	1	2	1	1
8	2	1	2	1	2	2	2	1	1	1	2
9	2	1	1	2	2	2	1	2	2	1	1
10	2	2	2	1	1	1	1	2	2	1	2
11	2	2	1	2	1	2	1	1	1	2	2
12	2	2	1	1	2	1	2	1	2	2	1

Features of Orthogonal Arrays

- Efficient
- Systematic-balanced
- Small number of tests
- Large amount of information gained
- Simple analysis
- Produces representative and reproducible results
- High level of confidence

Design of Experiments - Example

Factors	Levels		
	1	2	3
A. Temperature	100°C	150°C	200°C
B. Pressure	2 psi	5 psi	8 psi
C. Doping amount	4%	6%	8%
D. Deposition Rate	0.1 mg/s	0.2 mg/s	0.3 mg/s

- A microprocessor company is having difficulty with its current yields.
- Silicon processors are made on a large die, cut into pieces, and each one is tested to match specifications.
- The factors that affect processor yields are temperature, pressure, doping amount, and deposition rate.

		Number of Parameters (P)																														
		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	
Number of Levels	2	L4	L4	L8	L8	L8	L8	L12	L12	L12	L12	L16	L16	L16	L16	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32
	3	L9	L9	L9	L18	L18	L18	L18	L27	L27	L27	L27	L27	L36	L36	L36	L36	L36	L36	L36	L36	L36	L36									
	4	L'16	L'16	L'16	L'16	L'32	L'32	L'32	L'32	L'32																						
	5	L25	L25	L25	L25	L25	L50	L50	L50	L50	L50	L50																				

Experiment	A	B	C	D
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1



Experiment	Temp	pressure	Doping	Deposition
1	100	2	4	0.1
2	100	5	6	0.2
3	100	8	8	0.3
4	150	2	6	0.3
5	150	5	8	0.1
6	150	8	4	0.2
7	200	2	8	0.2
8	200	5	4	0.3
9	200	8	6	0.1

Experiment	Temp	Pressure	Doping	Deposition	Results (Yield)
1	100	2	4	0.1	80.1
2	100	5	6	0.2	69.6
3	100	8	8	0.3	52.1
4	150	2	6	0.3	73.4
5	150	5	8	0.1	69.3
6	150	8	4	0.2	86.5
7	200	2	8	0.2	60.9
8	200	5	4	0.3	93.2
9	200	8	6	0.1	71

Perform
Experiments &
Collect Results

Design of Experiment Example

$$\sum total = 656.1$$

$$\bar{T} = 656.1 / 9 = 72.9$$

$$Temp_1 = (80.1 + 69.6 + 52.1)/3 = 67.27$$

$$Temp_2 = (73.4 + 69.3 + 86.5)/3 = 76.4$$

$$Temp_3 = (60.9 + 93.2 + 71)/3 = 75.03$$

Now calculate the values for pressure, doping and deposition rate to complete the response table

Response Table

Levels	Temp	Pressure	Doping	Deposition
1	67.27	71.46	86.6	73.46
2	76.4	77.36	71.33	72.33
3	75.03	69.86	60.76	72.9
Range	9.13	7.5	25.84	1.13
Rank	2	3	1	4

Experiment	Temp	Pressure	Doping	Deposition	Results (Yield)
1	100	2	4	0.1	80.1
2	100	5	6	0.2	69.6
3	100	8	8	0.3	52.1
4	150	2	6	0.3	73.4
5	150	5	8	0.1	69.3
6	150	8	4	0.2	86.5
7	200	2	8	0.2	60.9
8	200	5	4	0.3	93.2
9	200	8	6	0.1	71

Which factor has the largest effect on the processor yield?

What is the best combination of factors?

Signal to noise ratio

The signal-to-noise ratio measures how the response varies relative to the nominal or target value under different noise conditions. You can choose from different signal-to-noise ratios, depending on the goal of your experiment.

Objective	S/N ratio
Nominal-the-best	$S/N = -10 \log \bar{y}_i^2 / s^2$
Smaller-the-better	$S/N = -10 \log \left(\frac{1}{n} \sum_{i=1}^n y_i^2 \right)$
Larger-the-better	$S/N = -10 \log \left(\frac{1}{n} \sum_{i=1}^n 1/y_i^2 \right)$

y_i denotes the results of the i -th turn of a set of n simulated trials.

Think of "signal" as the desired outcome or target value you want to achieve, like the mean or ideal result.

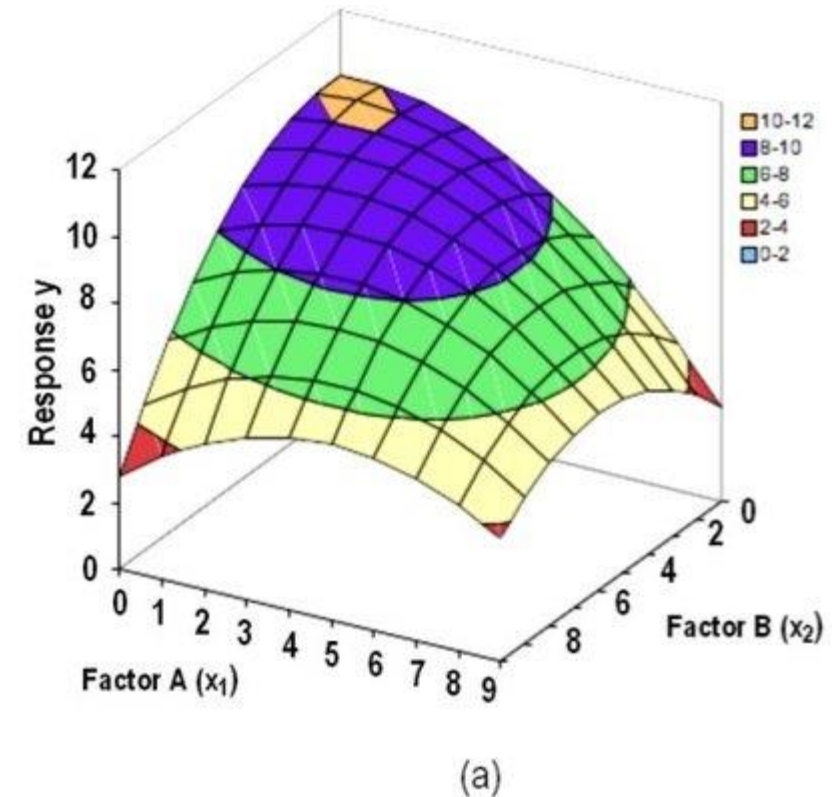
"Noise" represents the variability or deviation from that desired outcome, like errors or fluctuations.

So, in simple terms, the SNR tells us how much the desired outcome (signal) stands out compared to the undesirable variations (noise). Higher SNR means less variation or interference compared to the desired result, indicating better quality.



Design of Experiment Types

- One Factorial
- Full Factorials
- Fractional Factorials
- Screening Experiments
 - Plackett-Burman Designs
 - Taguchis Orthogonal Arrays
- Response Surface Analysis (such as Box-Behnken)



DOE Software

Possible software to use for DOE work:

Design Expert 11 or 13 by Statease

<https://www.statease.com/software/design-expert/>

Minitab also has DOE functionality

<https://www.minitab.com/en-us/>

**Both are available with free trials, Design Expert is only 14 days,
Minitab is 30 days.**

DO NOT sign up until you are ready to use it!