# Section V

**Improve**

# Agenda

- ✓ Pre-Improve Considerations
- ✓ Design of Experiments – Theory
- ✓ Design of Experiments – Practical
- ✓ Brainstorming for Solutions, Solutions Prioritization, and Cost Benefit Analysis
- ✓ Piloting, Validating, and FMEA

# Section V, Lesson 1

## Pre-Improve Considerations

# Agenda

- ✓ Pre-Improve Considerations
- ✓ Model Adequacy Checking
- ✓ Multi-Vari Charts
- ✓ 7M Tools
- ✓ Activity Network Diagram
- ✓ Point and Interval Estimation
- ✓ Porter's Five Forces
- ✓ Pugh Analysis
- ✓ Lean 5S

# Pre-Improve Considerations

- ✓One of the key understandings from the Analyze phase is that the output variable variation is because of the input variable variation.
- ✓Input variable was identified using a variety of tools like CE diagram, CE matrix, and validated correlation with the help of regression.
- ✓Ran a series of confidence intervals and hypothesis tests to confirm if they were special or common causes of variation.
- ✓Multi-vari chart is an important tool that the Six Sigma practitioners, especially the Black Belts use.

# Model Adequacy Checking

- ✓ Is used during regression analysis to check if the model found by regression analysis is adequate.
- ✓ Adequacy checks are done by multiple methods.
  - Check if all the points fit the regression line. Look for linearity.
  - Check the r-square or r-square adjusted value. Look for r-square value greater than 80%. If it is – model is adequate.
  - Check for non-linearity of residuals. Non-linearity shows that model is not adequate.
  - Check if 95% of scaled individuals are within the range of -1 and 1.

# Model Adequacy Checking (Contd.)

**Checking adequacy of model using lack of fit test:**

✓ A perfect regression model, with all points fitting the regression line, has 0 $SS_E$. $SS_E$ stands for sum squares of errors.

✓ On replicating the readings or observations in identical conditions, error observed is sum squares due to pure error ($SS_{PE}$).

✓ In case of an imperfect regression model, when repeated observations are used, sum squares of errors will have two components:

- Sum squares due to pure error ($SS_{PE}$)
- Sum squares due to lack of fit ($SS_{LOF}$)

# Model Adequacy Checking (Contd.)

- $SS_E = SS_{PE} + SS_{LOF}$
- $SS_{LOF} = SS_E - SS_{PE}$
- On finding lack of fit sum of squares, it is important that the black belt checks for goodness of fit for the data. If goodness of fit value is less than 0.05, reject the fit of the model.
- If goodness of fit value is greater than 0.05, accept the fit of the data.

# Multi Vari Charts

- ✓Multi-vari charts help understand within piece, piece-piece, and time-time variation.
- ✓These variations are also known as positional variation, cyclical variation, and temporal variation.
- ✓With the help of multi-vari charts, the major source of variation in the process can be identified.
- ✓This variation has its roots in common and special causes of variation, so Black Belts need not worry dealing with a new type of variation.
- ✓Use the tool MVA, provided in the toolkit to conduct a multi-vari analysis.
- ✓Multi-vari analysis helps in identifying the dominant source of variation, i.e., within piece, piece-piece, or lot-lot.

# 7M Tools

1. Affinity diagrams: This tool helps us organize ideas into meaningful categories by recognizing the underlying similarity.
2. Tree diagrams: This helps to break down ideas in progressively greater detail in systematic way.
3. Process decision program charts (PDPC): This tool helps in preparing contingency plans.
4. Matrix diagrams: The matrix diagram is constructed to analyze the correlations between two groups of data.
5. Interrelationship digraph (ID):This helps in organizing disparate ideas by arranging related ideas into groups.
6. Prioritization matrices:This is used to help decision makers determine the order of importance of the activities being considered.
7. Activity network diagram: This is used for scheduling and monitoring tasks within a project or process that has several dependent tasks and resources.

# Activity Network Diagram

- ✓It is also called as arrow diagram, network diagram, activity chart, node diagram, CPM (critical path method) chart, or PERT (program evaluation and review technique) chart.

- ✓It is used for scheduling and monitoring tasks within a project or process that has several dependent tasks and resources.

- ✓The project or process steps are organized in sequence with details around the time that each step takes.

- ✓Steps:
  - List all the necessary tasks in the project or process;
  - Determine the correct sequence of the tasks;
  - Between two tasks, draw circles for ‘events; and
  - Walk the tasks and see if there are any challenges and update the sequence, accordingly.

# Point and Interval Estimation

✓ For point estimation, a random variable is used to estimate a characteristic or relationship in the population. The formula is specified before gathering the sample, and the actual numerical value obtained is called an estimate.

✓ Example: For estimating the mean of the population, use:

- Sample mean: $\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i$

Or

- An average of the largest and the smallest values observed: $\frac{\max\{X_i\} + \min\{X_i\}}{2}$

✓ Example: For estimating the variance of the population, use:

- Sample variance: $\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i$

Or

- Alternative : $S_n^2 = \frac{1}{n}\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2$

# Porter's Five Forces

- ✓Porter's five forces analysis is a framework for industry analysis and business strategy development.
- ✓It draws upon the industrial organization economics to derive five forces that determine the competitive intensity and therefore attractiveness of a market.
- ✓An unattractive industry is one in which the combination of these five forces acts to drive down overall profitability.
- ✓In a very unattractive industry approaching 'pure competition', the available profits for all firms are driven to normal profit.

# Porter's Five Forces (Contd.)

1. Threat of new entrants
2. Threat of substitute products or services
3. Bargaining power of the customers
4. Bargaining power of the suppliers
5. Intensity of competitive rivalry

# Pugh Analysis

- ✓Pugh analysis charts are used for evaluating multiple options against each other, in relation to a baseline option.
- ✓Pugh analysis charts are similar to pros vs. cons lists.
- ✓There is a systematic way of selecting between alternatives:
  - Identify relevant user requirements, develop engineering specifications for those requirements;
  - Develop weights for each of the requirements,
  - Generate several viable design concepts;
  - Rank the concepts using Pugh analysis;
  - Synthesize the best elements of each initial concept into a final optimal concept; and
  - Iterate until a clearly superior concept emerges.

# Lean 5S

- ✓ 5S is the Japanese word for a workplace organization method that uses a list of five Japanese words:
  - Seiri (Sort);
  - Seiton (Set in Order);
  - Seiso (Sweep);
  - Seiketsu (Standardize); and
  - Shitsuke (Sustain).
- ✓ 5S simplifies the workplace environments and assists with the reduction of wastage and other forms of non-value adding activities whilst improving quality, effectiveness, process efficiencies, and employee safety.

# Summary

In this lesson we have learned:

- ✓Pre-improve considerations
- ✓Model adequacy checking
- ✓Multi-vari charts
- ✓Different 7M tools
- ✓Constructing an activity network diagram
- ✓The concept of point and interval estimation
- ✓Porter's five forces
- ✓Use of Pugh analysis
- ✓Lean 5S

# Section V, Lesson 2

## Design of Experiments – Theory

# Agenda

- ✓Introduction to DOE
- ✓Types of Designed Experiments
- ✓Main and Interaction Effects
- ✓Replication
- ✓Randomization
- ✓Blocking
- ✓Confounding
- ✓Coding and other DOE Terms
- ✓Sum Squares Analysis

# Introduction to DOE

- ✓ Design of experiments is a series of scientific experiments planned to measure the optimal response of the output variable Y (response) by varying input variables X (factors) at various levels.
- ✓ Objectives of conducting designed experiments:
  - Determine which variable influence Y the most.
  - Determine the optimal levels for X so Y is always at the optimal output.
  - Determine optimal levels for X so that variability for Y is small.
  - Determine the optimal levels for X so that effects of uncontrolled variables are minimized at all times.

# Introduction to DOE (Contd.)

Let us understand the objective behind conducting DOE with a simple example.

✓ A golf player wishes to optimize his golf score by hitting birdies all the time.

To do this, he understands that a lot of factors would impact the end result.

The end factors are:

- Type of driver used;
- Type of ball used;
- Walk through the golf course;
- Time of the day;
- Type of golf shoe worn; and
- Strength of the ball.

# Introduction to DOE (Contd.)

- ✓There are many factors (of input or process) that could impact the output.
- ✓Factors could be qualitative as well as quantitative.
- ✓Experimenters prefer quantitative factors, as these can be measured and set at appropriate levels.
- ✓Qualitative factors can only be rated. In other words, qualitative factors form the basic principles of attribute data.
- ✓For example, playing golf in the mornings or afternoons is often considered attribute, as the levels are set with a yes or a no.
- ✓Strength of the ball is continuous data as that can be measured.

**Approaches for experimenting**

1. Best guess approach

✓ The experimenter rules out certain factors and tests for an arbitrary combination of factors until optimal results are achieved.

✓ Advantage

- Works well when the experimenter has a good knowledge of the process and his technical knowledge on the dynamics of the process is also good.
- Example: A golfer would know best how much energy to be used, based on the strength and type of the golf ball, to get the best shot.

✓ Disadvantage

- Initial best guesses may not always produce the best results. The best guess approach can continue for a long time without producing the desired result.
- Example: A golfer might be using certain level of energy for a type of golf ball for a long time without exploring other options to see if the results improve.

**Approaches for experimenting**

2. One factor at a time

✓ All the factors are chosen. One factor is varied in the range keeping all other factors constant and the response is measured.

✓ Advantages

- Gives the impact each factor has on the response, individually.

✓ Disadvantages

- Misses out on interactions. For example, if the golf score is studied only on the type of golf ball used, the experimenter may miss out on a possible interaction between type of golf ball and whether he played golf in the mornings and afternoons.

**Approaches for experimenting**

3. Factorial Experiments

- ✓In factorial experiments, multiple factors are varied simultaneously and the corresponding output is noted against each combination.
- ✓This allows the experimenter to test interactions between factors which could have made an impact on the response.
- ✓Factorial experiments are the most commonly used experiments in designed experiments.
- ✓Example: For a particular process, there are multiple factors (temperature, duration and pressure). To do a factorial experiment, all the combinations of these variables should be checked by varying each of the factors and note the output.
- ✓Advantage: Provides a list of outputs for all possible inputs, to decide the most appropriate one.
- ✓Disadvantage: Number of tests to be done might be too many if there are multiple factors.

# Types of Designed Experiments

- ✓ $2^2$ Full factorial – 2 factors are tested at 2 levels completely
- ✓ $2^3$ Full factorial – 3 factors are tested at 2 levels completely
- ✓ $3^2$ Full factorial – 2 factors are tested at 3 levels completely
- ✓ $3^3$ Full factorial – 3 factors are tested at 3 levels completely
- ✓ $2^4$ Fractional factorial – 4 factors are tested at 2 levels at 3 combinations
- ✓ $2^5$ Fractional factorial – 5 factors are tested at 2 levels at 4 and 3 combinations
- ✓ Taguchi's designs
- ✓ Plackett Burman's designs
- ✓ Response surface designs

The practical working of most of these experimental settings would be discussed in DOE – practical

# Main and Interaction Effects

- Main effect is the effect of an individual factor on the response variable.

- **Example:** A golf player decides to use an over-sized driver and a regular sized driver on four tries. He maps the scores thus:

| Oversized Driver | Regular Driver |
|---|---|
| 92 | 88 |
| 94 | 91 |
| 93 | 88 |
| 91 | 90 |

# Main and Interaction Effects (Contd.)

**Main effect**

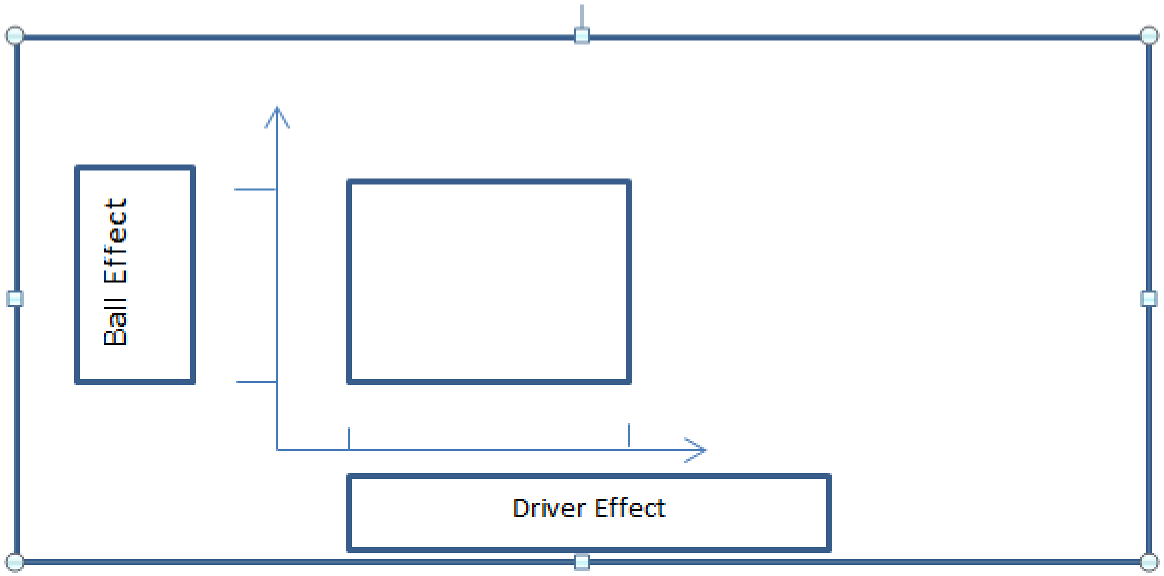
- ✓Driver effect = (92 + 94 + 93 + 91)/4 – (88 + 91 + 88 + 90)/4 = 3.25
- ✓Using the oversized driver, the golfer is able to increase his scores to 3.25 per round.
- ✓Similarly, for types of balls used, i.e., light ball and a heavy ball, the scores are:

| Heavy Ball | Light Ball |
|---|---|
| 88 | 88 |
| 91 | 90 |
| 92 | 93 |
| 94 | 91 |

## Main effect

✓ Ball effect = (88 + 91 + 92 + 94)/4 – (88 + 90 + 93 + 91)/4 = 0.75

✓ **Interpretation:** In terms of individual factor effects, the type of driver used in hitting the golf ball has a greater impact (3.25) than the ball used (0.75).



# Main and Interaction Effects (Contd.)

**Interaction effect**

✓Interaction effects are observed when two or more factors interact and result in a change in the response. For example, the type of ball and the type of driver interact to result in responses are measured below:

- Hard ball-oversized driver – 92, 88
- Soft ball-oversized driver – 94, 91
- Hard ball-regular driver – 90, 93
- Soft ball-regular driver – 88, 91

✓The interaction effect = (92 + 94 + 90 + 88)/4 – (88 + 91 + 93 + 91)/4 = 0.25

✓**Interpretation:** The interaction effect is negligible.

# Replication

- ✓Replication means the experimenter has repeated the set of experiments.
- ✓This is often done to get an estimate of the experimental error.
- ✓For example, the golf player could have just done four strokes to understand the significance of the type of ball and the type of golf driver used. Instead, he repeats the same settings twice in order to know if there are any experimental errors at all.
- ✓Replication helps the experimenter understand variations between separate ***runs*** within the same ***runs.***
- ✓An experiment in a designed experiments setting is known as run.

# Randomization

- ✓Randomization means running the experiments in a random order and not in a set order.
- ✓The allocation of experimental inputs, and the order in which the trials/experiments/runs has to be conducted, are completely random.
- ✓Randomization is done to aid the statistical concept that the observations or errors need to be independently distributed random variables.
- ✓By randomizing, effects of extraneous factors are averaged out.
- ✓For example, if we conduct continuous trials of golf scores with an over-sized driver and a slightly heavier ball, results could be **biased**.
- ✓This bias is eliminated by randomizing the conduct of golf trials.

# Blocking

- It is a design technique that helps in improving the **precision** of an experiment.
- Blocking is done to reduce or eliminate variability due to **nuisance factors**.
- A nuisance factor is one that is not considered as a **factor of interest** by the experimenter, i.e., this factor could be a factor but is ignored in the designed experiments setting.
- For example, if the golf driver A used by the golfer comes from supplier X and golf driver B comes from supplier Y, there could be differences in the golf scores.
- These differences could be because of supplier variability. Assuming that the experimenter is not interested in studying supplier variability, this could be a nuisance factor.

# Confounding

- ✓Confounding means high order interaction effects are indistinguishable from or getting mixed with the blocks. In other words, blocks overshadow the high order interaction effects.
- ✓Happens when the block size is smaller than number of treatment combinations in one replicate.
- ✓Confounding can happen in any experimental setting, but occurs more often in fractional factorial settings.

# Coding and other DOE Terms

- ✓Coding refers to transforming the scale of measurement so that the high value of level becomes + and low value becomes -. This is also represented as +1 and -1.
- ✓Error is unexplained variation in a collection of observations. The error includes pure error as well as lack of fit error.
- ✓Fixed effect is an effect associated with the input that has a limited number of levels, or an effect in which only a certain number of levels are of interest to the experimenter.
- ✓Lack of fit error occurs when the analysis excludes one or more important factors from the model. By using **replication**, the error can be partitioned into lack of fit and pure error.
- ✓Random error is an error that occurs due to natural variation in the process. Random error normally has a normal distribution with mean = 0 and a constant variance.

# Sum of Squares Analysis

- ✓The sum of squares is an excellent method to analyze fixed effects model.
- ✓Sum of squares is popularly used in the technique, analysis of variance (ANOVA).
- ✓The sum of squares table is constructed as below:

| Source of Variation | Sum of Squares | Degree of Freedom | Mean Squares | Fo |
|---|---|---|---|---|
| Between treatments | $SS_{treatments}$ | A-1 | $Ss_{treatments}/(a-1)$ | $MS_{treatments}/MS_E$ |
| Error (Within) | $SS_E$ | N-a | $MS_E$ | |
| Total | Sum of Squares | N-1 | | |

# Sum of Squares Analysis (Contd.)

- ✓**Example:** An experimenter has varied percentage of polyester in a cloth 5 times and for each reading, 5 replicates have been taken. We will do the sum of squares analysis to see if the tensile strength in each of the 5 reading groups is indeed the same.
- ✓Data table presented below:

| % Polyster | Observed Tensile Strength | | | | |
|---|---|---|---|---|---|
| 15 | 7 | 7 | 15 | 11 | 9 |
| 20 | 12 | 17 | 12 | 18 | 18 |
| 25 | 14 | 18 | 18 | 19 | 19 |
| 30 | 19 | 25 | 22 | 19 | 23 |
| 35 | 7 | 10 | 11 | 15 | 11 |

# Sum of Squares Analysis (Contd.)

- ✓**Step 1:** Calculate the totals of the readings by adding the observations and averages by taking an average of the readings.
- ✓**Step 2:** Calculate the grand total of all the sums and average of averages. Data sheet is shown below:

| % Polyster | Observed Tensile Strength | | | | | Totals ($y_i$) | Average ($y_i$bar) | |
|---|---|---|---|---|---|---|---|---|
| 15 | 7 | 7 | 15 | 11 | 9 | 49 | 9.8 | |
| 20 | 12 | 17 | 12 | 18 | 18 | 77 | 15.4 | |
| 25 | 14 | 18 | 18 | 19 | 19 | 88 | 17.6 | |
| 30 | 19 | 25 | 22 | 19 | 23 | 108 | 21.6 | |
| 35 | 7 | 10 | 11 | 15 | 11 | 54 | 10.8 | |
| | | | | | | | | |
| | | | | | Total | 376 | 15.04 | Average |

# Sum of Squares Analysis (Contd.)

✓ **Step 3:** Calculate the squares table and find out the sum of squares. The sum of squares is 6292. Next, square the totals under yi, and divide it by 25 (the total number of observations).

| The Squares Table | | | | | |
|---|---|---|---|---|---|
| | | | | | |
| | 49 | 49 | 225 | 121 | 81 |
| | 144 | 289 | 144 | 324 | 324 |
| | 196 | 324 | 324 | 361 | 361 |
| | 361 | 625 | 484 | 361 | 529 |
| | 49 | 100 | 121 | 225 | 121 |

# Sum of Squares Analysis (Contd.)

✓ **Step 4:** Find the difference of both the sum of squares. This is the total sum of squares.

- $SS_{total}$ = 6292 – 5655.04 = 636.96

✓ **Step 5:** Find the sum of squares of treatments.

✓ $SS_{treatments} = 1/n \sum y_i^2 - y^2/N$ (where, $y_i$ stands for sum of values with a treatment and y stands for sum of values across all the treatment.)

$$= 1/5\,(49^2 + 77^2 + 88^2 + 108^2 + 54^2) - (376^2/25)$$

$$= 6130.8 - 5655.04 = 475.56$$

✓ **Step 6:** Find the sum of squares of errors, $SS_E$.

- $SS_E = SS_{total} - SS_{treatments}$ = 636.96 – 475.56 = 161.20

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# Sum of Squares Analysis (Contd.)

✓**Step 7:** Calculate mean squares

- Mean squares $_{treatments}$ = Sum of squares $_{treatments}$/ (5-1) = 475.56/4 = 118.94
- Mean squares $_{errors}$ = Sum of squares $_{errors}$/(n-a) = 161.2/(25-5) = 8.06

✓**Step 8:** Calculate f-statistic

- F-Statistic = Mean squares $_{treatments}$ / Mean squares $_{errors}$
- **F-Statistic = 14.76**

✓Use FINV function in Excel with degree of freedom between treatments 4 and 20. Critical value of f-statistic = 2.86. f-Statistic is greater than critical value, i.e., treatment means are different.

# Sum of Squares Analysis (Contd.)

| | |
|---|---|
| Sum of Sum of Squares | 6292 |
| Average of Squared totals | 5655.04 |
| Total Sum of Squares | 636.96 |
| | |
| Sum of Total Squares | 30654 |
| Division factor | 0.2 |
| Average of Squared totals | 5655.04 |
| Sum of Squares for treatments | 475.76 |
| | |
| Sum of Squares for Error | 161.2 |

**Use the tool sheet sum of squares analysis and sum of squares table in Simplilearn toolkit to do the calculations and summary table.**

| Source of Variation | Sum of Squares | Degrees of Freedom | Mean Squares | Fo | Fcrit | Status |
|---|---|---|---|---|---|---|
| Polyster Weight % | 475.56 | 4 | 118.89 | 14.75062 | 2.866081 | Reject Null |
| Error | 161.2 | 20 | 8.06 | | | |
| Total | 636.76 | | | | | |

# Summary

In this lesson we have learned:

- ✓ Design of experiments along with their approaches
- ✓ Types of designed experiments
- ✓ Interaction effects between factors in an experiment
- ✓ Replication and randomization in an experiment
- ✓ Using blocking techniques to improve precision
- ✓ Understood the confounding effect
- ✓ Coding and other DOE terms
- ✓ Sum squares analysis

# Section V, Lesson 3

**Design of Experiments – Practice**

# Agenda

- ✓ Introduction to the 2 Factor Factorial Design
- ✓ $2^2$ Design
- ✓ General $2^k$ Design
- ✓ Single Replicate of $2^k$ Design
- ✓ Half Fractional $2^{k-1}$ Design
- ✓ Quarter Fractional $2^{k-2}$ Design
- ✓ The $3^k$ Design
- ✓ Analysis of 2nd Order Response Surface
- ✓ Nested Design
- ✓ Split Plot Design
- ✓ Taguchi's L4 and L6 Design
- ✓ Plackett Burman's Design

**Concepts**

- ✓Experiments that involve the study of two or more factors at two levels are known as the 2 level factorial design. When the experiment tests two factors at two levels, the experiment is known as 2 level 2 factor factorial design.
- ✓A 2 factor factorial design will have two factors A and B, a levels of factor A and b levels of factor B.
- ✓Every replicate in the experiment will contain ab level of treatments, i.e., the number of treatments or runs in the experiment would be ab.

# Introduction to 2 Factor Factorial Design (Contd.)

✓ **Example:** An engineer designing a battery for use understands that the temperature could be a major impact factor in the battery life. He also understands that the battery type, i.e., raw materials used for making the battery often influences its temperature volatility resistance. Temperature, as a parameter, determined by the experimenter, can be controlled in a laboratory setting. By conducting the experiment, the engineer wishes to answer two questions:

1. What are the effects of material type and temperature on the battery life?
2. Do we have a type of material that resists temperature regardless of the extremes?

# Introduction to 2 Factor Factorial Design (Contd.)

✓ By conducting a factorial design, the main effects and interaction effects are studied and analyzed.

✓ The sum of squares analysis method is used to study the main effects and interaction effects in the factorial method setting.

✓ The analysis of the experimental setting could be done by:

- Effects model – The most popular analytic technique;
- Means model; and
- Regression model.

# $2^2$ Design

- ✓The tool used for designs of experiments from here on is an excel file, DOE, which is provided as an excel worksheet.
- ✓Can also use Design Expert ™, a free downloadable software, which allows to design experiments.
- ✓The $2^2$ design is considered a very simple and powerful experiment to be run at 2 levels for 2 factors.
- ✓Without any replicate, the $2^2$ design will have 4 runs. With two replicates, the $2^2$ design will have 8 runs; and with 3 replicates, it will have 12 runs.

# $2^2$ Design (Contd.)

- **Example:** An investigation is done on the effect of concentration of reactant and the amount of chemical catalyst used on the yield of the chemical process. Thus, yield is the response we wish to study. Conduct a $2^2$ study with 3 replicates.
- **Tool to use:** Design Expert Free Trial

✓**Step 1:** Choose the type of experiment.

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 4 | $2^2$ | $2^{3-1}_{III}$ | | | | | | |
| 8 | | $2^3$ | $2^{4-1}_{IV}$ | $2^{5-2}_{III}$ | $2^{6-3}_{III}$ | $2^{7-4}_{III}$ | | |
| 16 | | | $2^4$ | $2^{5-1}_{V}$ | $2^{6-2}_{IV}$ | $2^{7-3}_{IV}$ | $2^{8-4}_{IV}$ | $2^{9-5}_{III}$ |
| 32 | | | | $2^5$ | $2^{6-1}_{VI}$ | $2^{7-2}_{IV}$ | $2^{8-3}_{IV}$ | $2^{9-4}_{IV}$ |
| 64 | | | | | $2^6$ | $2^{7-1}_{VII}$ | $2^{8-2}_{V}$ | $2^{9-3}_{IV}$ |
| 128 | | | | | | $2^7$ | $2^{8-1}_{VIII}$ | $2^{9-2}_{VI}$ |
| 256 | | | | | | | $2^8$ | $2^{9-1}_{IX}$ |
| 512 | | | | | | | | $2^9$ |

Replicates: 3 Blocks: 1 Center points per block: 0 Show Generators

✓**Step 2:** Name the factors and set the type of data.

## 2-Level Factorial Design

Factors

- (selected) Horizontal
- Vertical

| | Name | Units | Type | Low | High |
|---|---|---|---|---|---|
| A [Numeric] | Reactant Conc | %age | Numeric | -1 | 1 |
| B [Numeric] | Catalyst Weigl | Pounds | Numeric | -1 | 1 |

- ✓ **Step 3:** Set the number of responses to measure per run. For example, in this experiment, we wish to test 3 responses per run to get an adequate number of observations and give enough room for a variability check.

| Name | Units | Diff. to detect Delta("Signal") | Est. Std. Dev. Sigma("Noise") | Delta/Sigma (Signal/Noise Ratio) |
|---|---|---|---|---|
| R1 | Percent | | | |
| R2 | Percent | | | |
| R3 | Percent | | | |

# $2^2$ Design (Contd.)

✓**Step 4:** Enter the responses under R1, R2, and R3. Before doing so, check if the **run order is randomized.**

Randomized run order

| Select | Std | Run | Factor 1 A:Reactant ... %age | Factor 2 B:Catalyst W... Pounds | Response 1 R1 Percent | Response 2 R2 Percent | Response 3 R3 Percent |
|---|---|---|---|---|---|---|---|
| | 8 | 1 | -1.00 | 1.00 | 28 | 27 | 31 |
| | 12 | 2 | 1.00 | 1.00 | 26 | 25 | 26 |
| | 6 | 3 | 1.00 | -1.00 | 32 | 31 | 30 |
| | 3 | 4 | -1.00 | -1.00 | 29 | 31 | 36 |
| | 1 | 5 | -1.00 | -1.00 | 40 | 31 | 36 |
| | 10 | 6 | 1.00 | 1.00 | 38 | 37 | 46 |
| | 5 | 7 | 1.00 | -1.00 | 36 | 35 | 36 |
| | 11 | 8 | 1.00 | 1.00 | 37 | 37 | 37 |
| | 7 | 9 | -1.00 | 1.00 | 35 | 34 | 31 |
| | 4 | 10 | 1.00 | -1.00 | 32 | 31 | 29 |
| | 2 | 11 | -1.00 | -1.00 | 28 | 27 | 26 |
| | 9 | 12 | -1.00 | 1.00 | 30 | 31 | 32 |

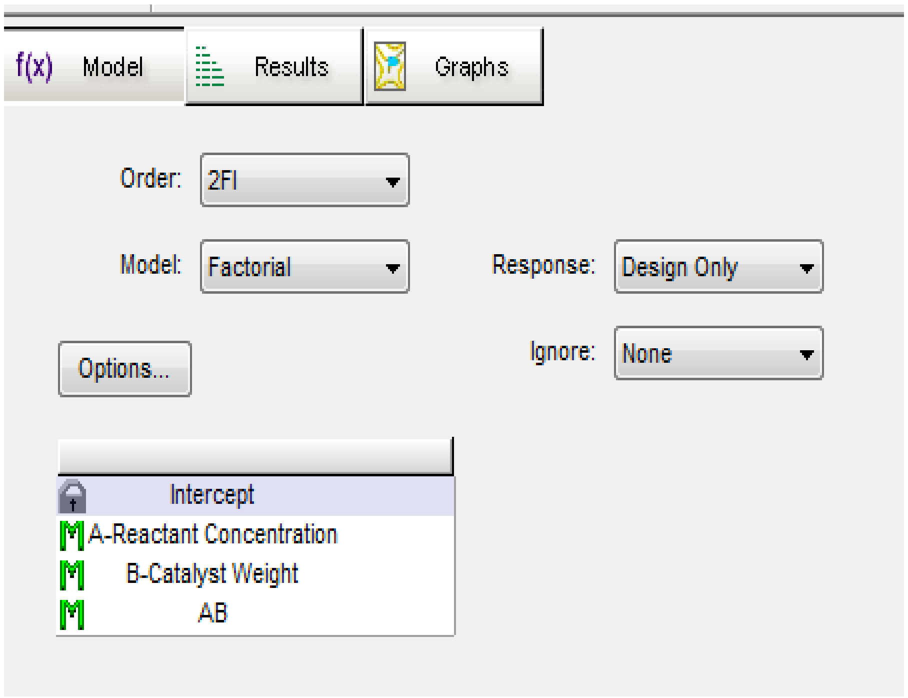
# $2^2$ Design (Contd.)

- **Step 5:** Once the design is made, analyze the design model. Design expert allows to choose default options; and present a wide range of plots, graphs, and results to be interpreted.
- 5a) Check the Design Summary (Design → Summary)

| Response | Name | Units | Obs | Analysis | Minimum | Maximum | Mean | Std. Dev. | Ratio |
|---|---|---|---|---|---|---|---|---|---|
| Y1 | R1 | Percent | 12 | Factorial | 26 | 40 | 32.5833 | 4.54189 | 1.53846 |
| Y2 | R2 | Percent | 12 | Factorial | 25 | 37 | 31.4167 | 3.84846 | 1.48 |
| Y3 | R3 | Percent | 12 | Factorial | 26 | 46 | 33 | 5.5922 | 1.76923 |

✓5b) Click on Design → Evaluation → f(x) Model

- Let the order be 2FI, model be factorial, and response be design only. By selecting this, the graphs will be presented for the design as well as response.



# $2^2$ Design (Contd.)

5c) Click on Design → Evaluation → Results

A recommendation is a minimum of 3 lack of fit df and 4 df for pure error.

This ensures a valid lack of fit test.

Fewer df will lead to a test that may not detect lack of fit.

| | | | | Power at 5 % alpha level to detect signal/noise | | |
|---|---|---|---|---|---|---|
| Term | StdErr** | VIF | Ri-Squared | 0.5 Std. Dev. | 1 Std. Dev. | 2 Std. Dev. |
| A | 0.29 | 1.00 | 0.0000 | 11.9 % | 33.3 % | 85.7 % |
| B | 0.29 | 1.00 | 0.0000 | 11.9 % | 33.3 % | 85.7 % |
| AB | 0.29 | 1.00 | 0.0000 | 11.9 % | 33.3 % | 85.7 % |

**Basis Std. Dev. = 1.0

Standard errors should be similar within type of coefficient. Smaller is better.

Ideal VIF is 1.0. VIFs above 10 are cause for alarm,

indicating coefficients are poorly estimated due to multicollinearity.

Ideal Ri-squared is 0.0. High Ri-squared means terms are correlated with each other,

possibly leading to poor models.

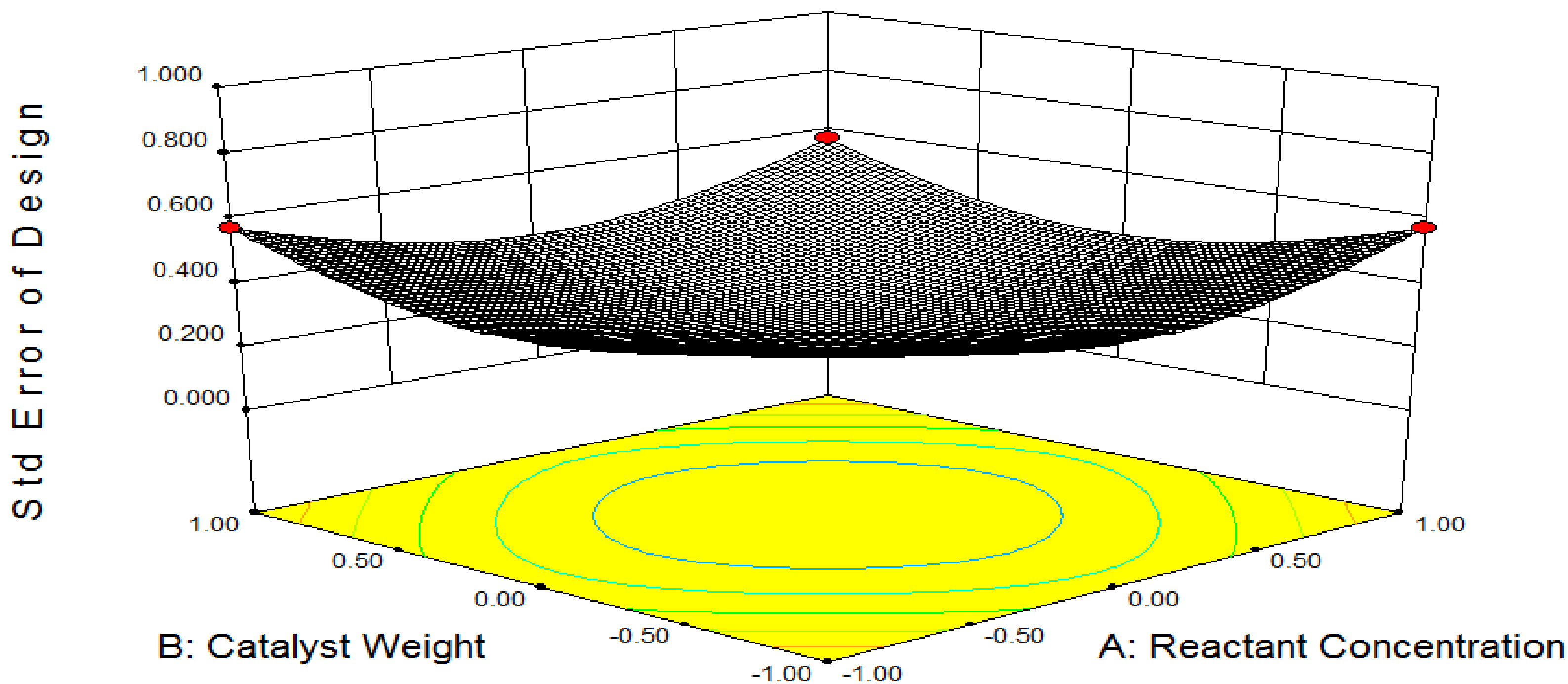
# $2^2$ Design (Contd.)

A Black Belt should know how to use his DOE knowledge to interpret results for the business.

✓Main findings from the results page:

1. VIF is 1. It is acceptable.
2. The model passes the lack of fit test. Any error is thus pure error and there are no lack of fit issues.
3. Low Ri-square value, indicating that the terms are not correlated to each other.

✓ **Step 6:** Finally, select a 3D surface plot for the design and get a design plot like the one shown below:



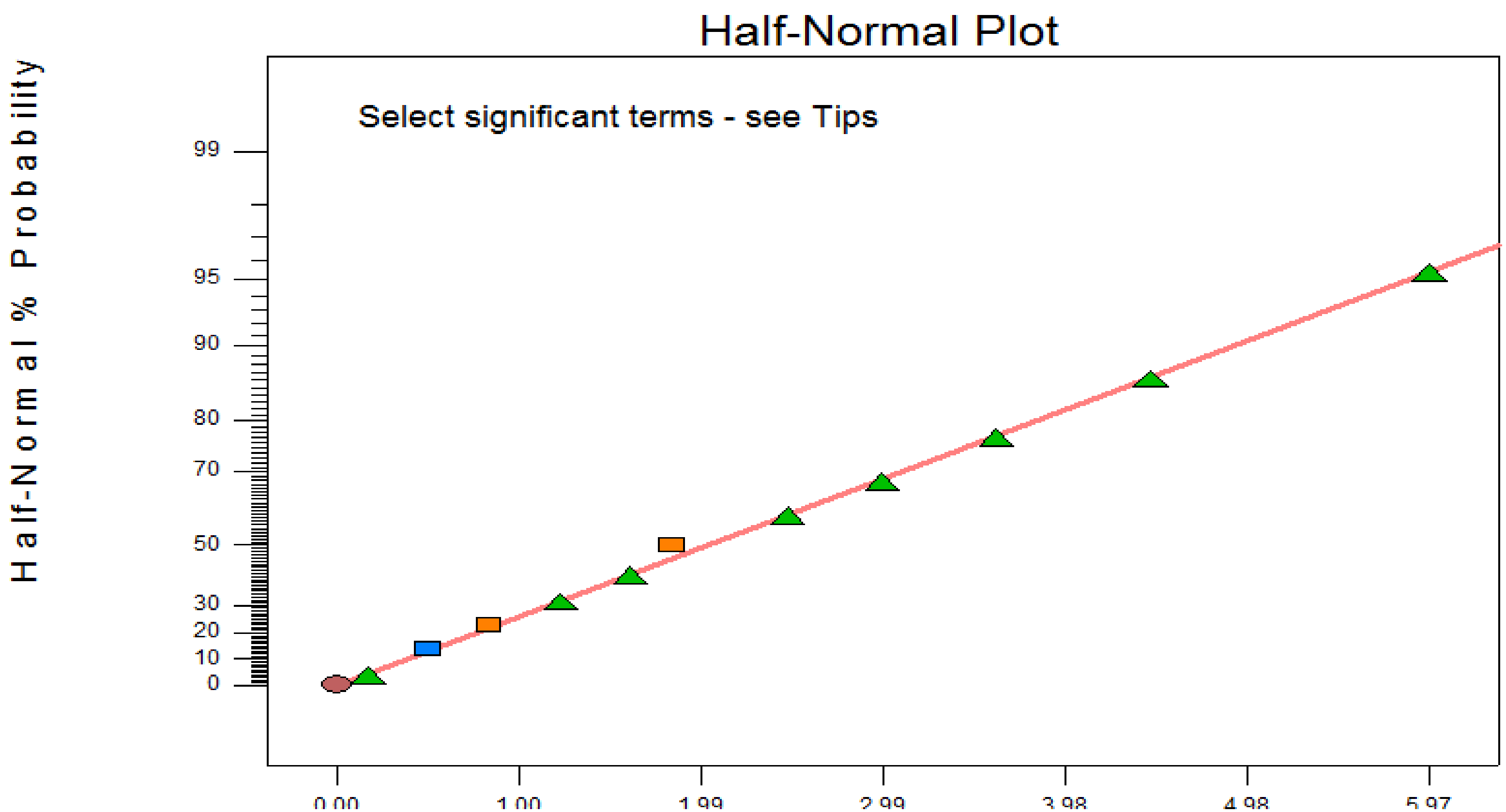
# $2^2$ Design (Contd.)

✓ **Step 7:** Click on Analysis. The analysis option will give the analysis for each of the responses influenced by the two factors. Click on Effects after selecting R1. This means we are now interested in studying the response R1.

**As seen from the table, variability in response 1 is due to pure error, which happens almost always by chance.**

| Term | Stdized Effects | Sum of Squares | % Contribution |
|---|---|---|---|
| Intercept | | | |
| A-Reactant Concentration | 1.83 | 10.08 | 4.44 |
| B-Catalyst Weight | -0.50 | 0.75 | 0.33 |
| AB | 0.83 | 2.08 | 0.92 |
| Lack Of Fit | | 0.000 | 0.000 |
| Pure Error | | 214.00 | 94.31 |
| Lenth's ME | 6.44 | | |
| Lenth's SME | 8.32 | | |

✓**Step 8:** Check the half normal plots. From the graph seen below, they seem okay.



✓**Step 9:** Click on Effects list on the effects tool on the toolbar and change the order to design model. Click on ANOVA. The table seen in the next slide is one of the most important slides in making inferences about the model itself.

Use your mouse to right click on individual cells for definitions.

Response 1 R1

ANOVA for selected factorial model

Analysis of variance table [Partial sum of squares - Type III]

| Source | Sum of Squares | df | Mean Square | F Value | p-value Prob > F | |
|---|---|---|---|---|---|---|
| Model | 12.92 | 3 | 4.31 | 0.16 | 0.9196 | not significant |
| *A-Reactant C* | *10.08* | *1* | *10.08* | *0.38* | *0.5563* | |
| *B-Catalyst W* | *0.75* | *1* | *0.75* | *0.028* | *0.8712* | |
| *AB* | *2.08* | *1* | *2.08* | *0.078* | *0.7873* | |
| Pure Error | 214.00 | 8 | 26.75 | | | |
| Cor Total | 226.92 | 11 | | | | |

The "Model F-value" of 0.16 implies the model is not significant relative to the noise. There is a 91.96 % chance that a "Model F-value" this large could occur due to noise.

Values of "Prob > F" less than 0.0500 indicate model terms are significant.

In this case there are no significant model terms.

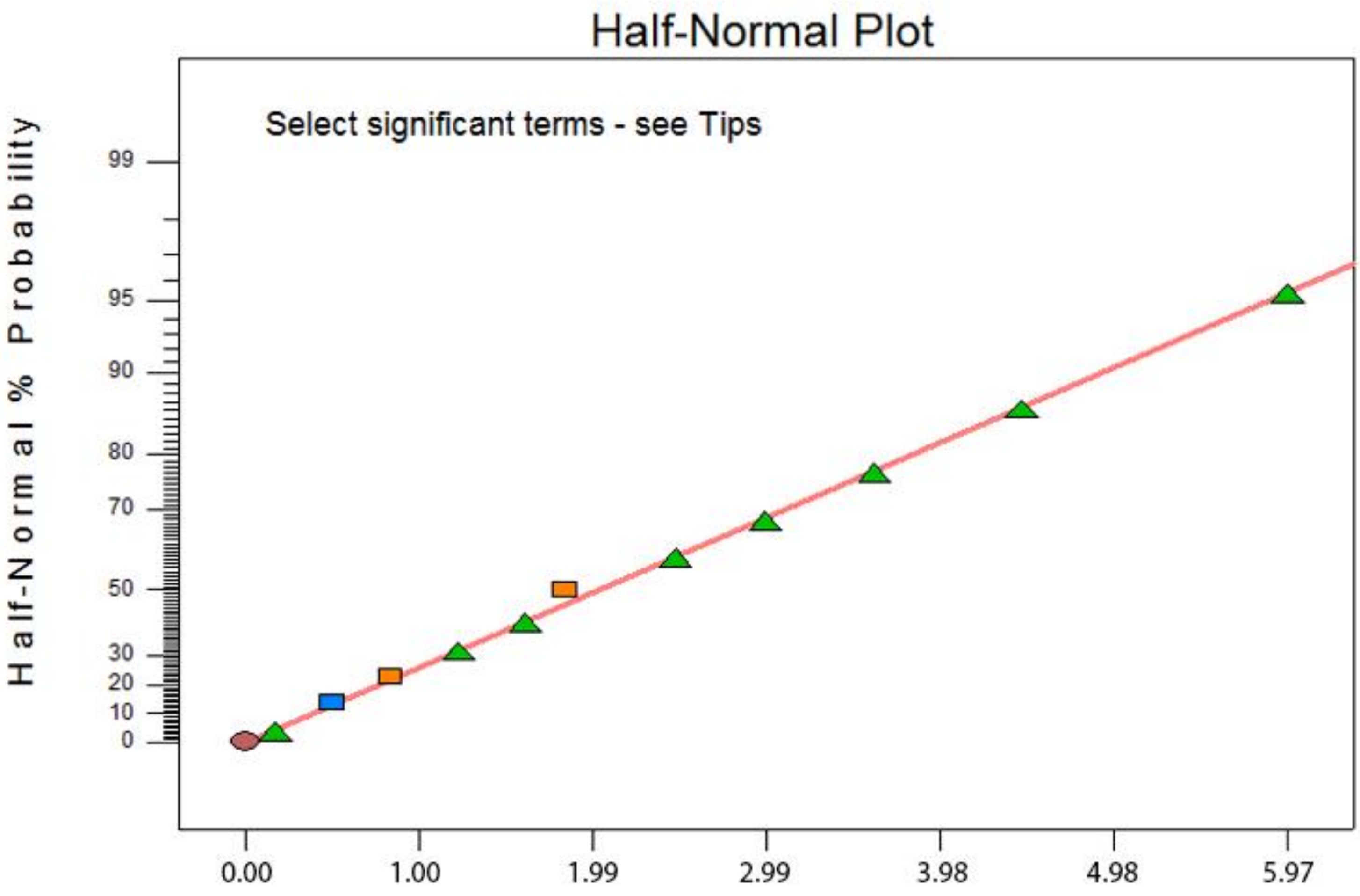
# $2^2$ Design (Contd.)

✓**Step 10 :** The model also gives the best possible equation. We may not be able to use this equation, as a high degree of the variance here is by chance; and we still have not been able to determine the real reason for variability.

| Factor | Coefficient Estimate | df | Standard Error | 95% CI Low | 95% CI High | VIF |
|---|---|---|---|---|---|---|
| Intercept | 32.58 | 1 | 1.49 | 29.14 | 36.03 | |
| A-Reactant Co | 0.92 | 1 | 1.49 | -2.53 | 4.36 | 1.00 |
| B-Catalyst We | -0.25 | 1 | 1.49 | -3.69 | 3.19 | 1.00 |
| AB | 0.42 | 1 | 1.49 | -3.03 | 3.86 | 1.00 |

**Final Equation in Terms of Coded Factors:**

R1 =
+32.58
+0.92 * A
-0.25 * B
+0.42 * A * B


Half-Normal Plot
Select significant terms - see Tips
Half-Normal % Probability
99
95
90
80
70
50
30
20
10
0
0.00
1.00
1.99
2.99
3.98
4.98
5.97

# $2^2$ Design Summary

Using the Design Expert software, we were able to:

✓Set up a $2^2$ designed experiment setting with 3 replicates.

✓Enter the response and find out what is causing the impact on the response.

✓Analyze graphs and understand the variability in the experiment.

**We can use the optimization tool of Design Expert to help improve our process.**

# General $2^k$ Design

- ✓In a $2^2$ design, the experiment tests 2 factors at 2 levels. The example we tested was reactant concentration and catalyst weight.
- ✓Let us introduce a 3rd factor in the setting. This is "process time".
- ✓Now, 3 factors need to be tested at 2 levels, resulting in $2^3$ runs in one replicate. This is known as $2^3$ design.
- ✓All these designs discussed so far follow a generalized norm of $2^k$.
- ✓Thus, they are referred to as $2^k$ designs, i.e., k factors are tested at 2 levels.
- ✓We can use Design Expert to make the designs. Here, we will use Microsoft Excel to understand the designs. Choose the excel file DOE provided in the toolkit and the worksheet, full factorial. Snapshot of this worksheet is in the next slide for easy reference.

# General $2^k$ Design (Contd.)

| | | | |
|---|---|---|---|
| | 6 | 12 | Three Factor Experiment |
| X c | | | |
| | | | Four Factor Experiment |
| X d<br>X d<br>X d<br>X c X d | | | |

rs

| B | AB | C | AC | BC | ABC | D | AD | BD | A |
|---|---|---|---|---|---|---|---|---|---|
| - | + | - | + | + | - | - | + | + | |
| - | - | - | - | + | + | - | - | + | |
| + | - | - | + | - | + | - | + | - | |
| + | + | - | - | - | - | - | - | - | |
| - | + | + | - | - | + | - | + | + | |
| - | - | + | + | - | - | - | - | + | |
| + | - | + | - | + | - | - | + | - | |
| + | + | + | + | + | + | - | - | - | |
| - | + | - | + | + | - | + | - | - | |
| - | - | - | - | + | + | + | + | - | |
| + | - | - | + | - | + | + | - | + | |
| + | + | - | - | - | - | + | + | + | |
| - | + | + | - | - | + | + | - | - | |
| - | - | + | + | - | - | + | + | - | |

L4 Taguchi | L8 Taguchi | L16 Taguchi | Instructions | **Full Factorial** | Frac

✓Step 1: Define the factors in cells D2, D3, and D5. Write the factor levels in G2, G3, and G5; and I2, I3, and I5.

The table shown is a snapshot from the DOE tool, summarizes all possible main and interaction effects.

| | Factor | Factor Name | | | Level 1 | Low(-) | Level 2 | High(+) |
|---|---|---|---|---|---|---|---|---|
| $2^2$ | A | a | Reactant Concentration | | | 15 | 35 | |
| | B | b | Catalyst Weight | | | 2 | 5 | |
| | AB | a X b | | | | | | |
| $2^3$ | C | c | Process Time | | | 6 | 12 | |
| | AC | a X c | | | | | | |
| | BC | b X c | | | | | | |
| | ABC | a X b X c | | | | | | |
| $2^4$ | D | d | | | | | | |
| | AD | a X d | | | | | | |
| | BD | b X d | | | | | | |
| | CD | c X d | | | | | | |
| | ABD | a X b X d | | | | | | |
| | ACD | a X c X d | | | | | | |
| | BCD | b X c X d | | | | | | |
| | ABCD | a X b X c X d | | | | | | |

# General $2^k$ Design (Contd.)

✓Step 2: The run sequence of interest is presented as a snapshot below. The same is provided in the form of shaded boxes in the excel file.

In the first run thus, we keep a low setting of reactant concentration, catalyst weight, and process time.

In the second run, we keep a high setting of reactant concentration while the other two factors are kept at low.

| | Design | Factors | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Trial | A | B | AB | C | AC | BC | ABC |
| $2^2$ | 1 | - | - | + | - | + | + | - |
| | 2 | + | - | - | - | - | + | + |
| | 3 | - | + | - | - | + | - | + |
| | 4 | + | + | + | - | - | - | - |
| $2^3$ | 5 | - | - | + | + | - | - | + |
| | 6 | + | - | - | + | + | - | - |
| | 7 | - | + | - | + | - | + | - |
| | 8 | + | + | + | + | + | + | + |

- Step 3: We try to measure 5 responses for the model. The responses indicated in the sheet cells, R20: V27.

| 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|
| 10 | 11 | 10 | 10 | 10 |
| 11 | 11 | 11 | 11 | 11 |
| 12 | 12 | 12 | 15 | 14 |
| 13 | 13 | 13 | 13 | 13 |
| 14 | 14 | 14 | 14 | 14 |
| 18 | 18 | 18 | 18 | 18 |
| 16 | 16 | 16 | 16 | 16 |
| 17 | 17 | 17 | 17 | 17 |

# General $2^k$ Design (Contd.)

✓ Step 4 : Review the experimental setting.

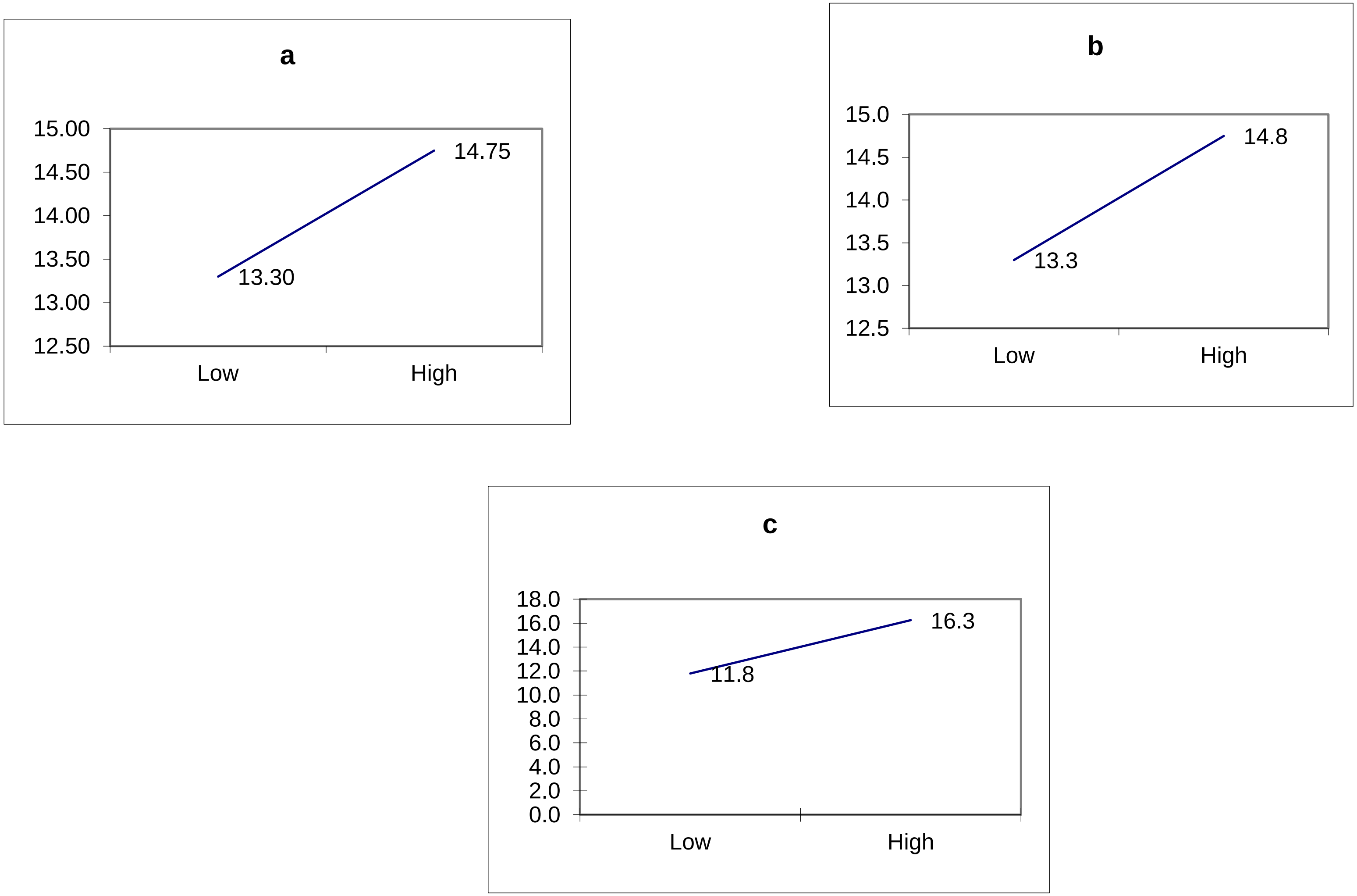
| Design | Factors | | | | | | | | Responses | | | Enter Your | Data Here |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Trial | A | B | AB | C | AC | BC | ABC | 1 | 2 | 3 | 4 | 5 | Average |
| 1 | - | - | + | - | + | + | - | 10 | 11 | 10 | 10 | 10 | 10.20 |
| 2 | + | - | - | - | - | + | + | 11 | 11 | 11 | 11 | 11 | 11.00 |
| 3 | - | + | - | - | + | - | + | 12 | 12 | 12 | 15 | 14 | 13.00 |
| 4 | + | + | + | - | - | - | - | 13 | 13 | 13 | 13 | 13 | 13.00 |
| 5 | - | - | + | + | - | - | + | 14 | 14 | 14 | 14 | 14 | 14.00 |
| 6 | + | - | - | + | + | - | - | 18 | 18 | 18 | 18 | 18 | 18.00 |
| 7 | - | + | - | + | - | + | - | 16 | 16 | 16 | 16 | 16 | 16.00 |
| 8 | + | + | + | + | + | + | + | 17 | 17 | 17 | 17 | 17 | 17.00 |

# General $2^k$ Design (Contd.)

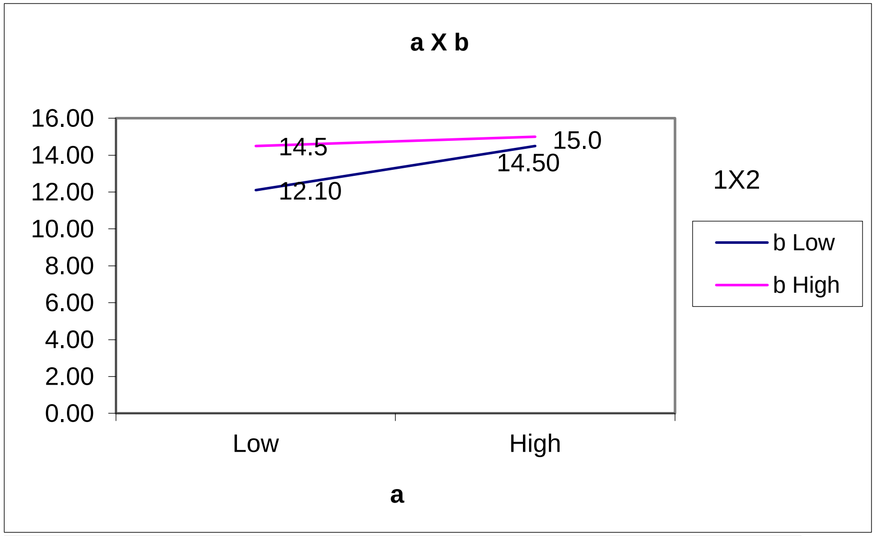
- Step 5: Move to the results table, which is displayed starting from cell B44 to L51 in the excel worksheet. The results below I51 are not significant as we are doing a $2^3$ design.

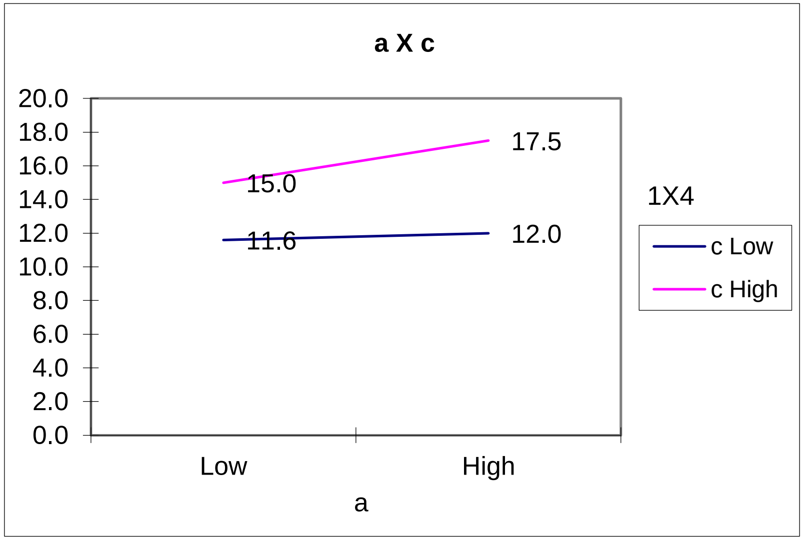
| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Anova | Factor | | | df | SS | MS | F | Effect | Contrast | p |
| Source | a | | | 1 | 21.0 | 21.0 | 76.455 | 1.45 | 29.00 | 0.00 |
| | b | | | 1 | 21.0 | 21.0 | 76.455 | 1.45 | 29.00 | 0.00 |
| | a X b | | | 1 | 9.0 | 9.0 | 32.818 | -0.95 | -19.00 | 0.00 |
| | c | | | 1 | 198.0 | 198.0 | 720.09 | 4.45 | 89.00 | 0.00 |
| | a X c | | | 1 | 11.0 | 11.0 | 40.091 | 1.05 | 21.00 | 0.00 |
| | b X c | | | 1 | 9.0 | 9.0 | 32.818 | -0.95 | -19.00 | 0.00 |
| | a X b X c | | | 1 | 3.0 | 3.0 | 11 | -0.55 | -11.00 | 0.00 |

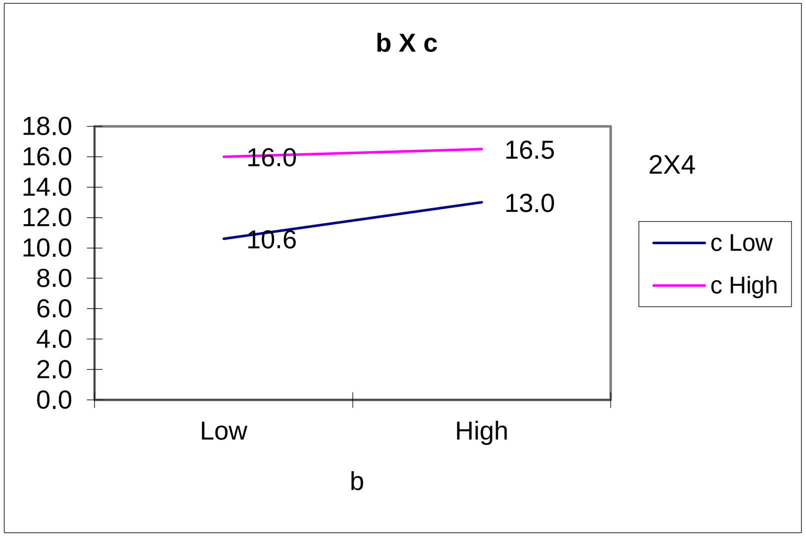
## Effects plot



## Interaction effects plot



# General $2^k$ Design (Contd.)

✓**Step 6: Analysis of the model**

1. All the p-values are significant.
2. Both the main and the interaction effect are to be considered for developing the model with these terms.
3. The effects column is interesting. It shows that factor c (process time) has the highest possible effect on the average response. Factors a, b, and c, have a positive effect on the response, while the interactions predominantly have a negative effect.
4. The contribution of error, 'sum of squares' is marginal as compared to the total sum of squares. Thus, this model can be regressed.

# Single Replicate of $2^k$ Design

- ✓ For up to 3 factors in a design, running a $2^k$ design on multiple replicates make sense. For example on 3 factors, a $2^k$ design with 2 replicates will have 16 runs.

- ✓ A 5 factor design with one replicate will have 32 runs. Adding another replicate means 32 + 32 = 64 runs. The experimenter may not have time to experiment with so many runs.

- ✓ Thus, each test combination is tested only **at one run,** which may expose the experiment or the model to noise.

- ✓ Single replicate designs are used in screening designs, where a lot of factors are to be considered and the most unimportant ones are screened out.

- ✓ Linearity in factor effects is an assumption in conducting $2^k$ experiments with a single design.

- ✓ Adding interaction terms to the main effects of the model could result in curvature, resulting in the linearity assumption not holding good anymore.

# Half Fractional $2^{k-1}$ Design

- ✓Often, conducting a full factorial experiment on all factors at all runs is considered most beneficial because not many interactions are missed.
- ✓Running a lot of experiments though may take the experimenter a lot of time, as a result of which, the experimenter may want a run combination with lesser number of runs where all the factors would be tested.
- ✓The choice thus is half fractional factorial experiment. For a 5 factor 2 level, a full factorial experiment will need 32 experiments on one replicate, while a half factor factorial will only need 16 experiments.
- ✓Typically, in fractional factorial experiments, high order interactions get aliased with either the main effects or the 2nd order interactions.

- ✓Using Design Expert software, let us create a fractional factorial experiment for 3 factors. New terms are observed in this design. Aliased terms are ABC, BC, and AB. Thus, in the final model we can expect not to see these terms appearing.

**Factorial Effects Aliases**

**st. Terms] Aliased Terms**

[Intercept] = Intercept + ABC

[A] = A + BC

[B] = B + AC

[C] = C + AB

**Factor Generator**

C = AB

**Factorial Effects Defining Contrast**

I = ABC

Please note:
Alias is used for demonstration purpose.
Factors like temperature, pressure, size, weight, etc., can also be used to see interaction effects.

- ✓ The effects table clearly tells us the effects that are contributing to the model. In this 3 factor fractional factorial experiment, all the effects are contributed due to the main effects, and that too the main effects of B and C.
- ✓ Look at the percentage contribution in the extreme right column. The main effect of A is hardly contributing to the response. Main effects, B and C contribute, with B contributing almost two thirds of the variability in the response.

**All interactions are aliased**

✓Defining A:A as an error term, let us move to the ANOVA analysis section.

**Response 1 R1**

**ANOVA for selected factorial model**

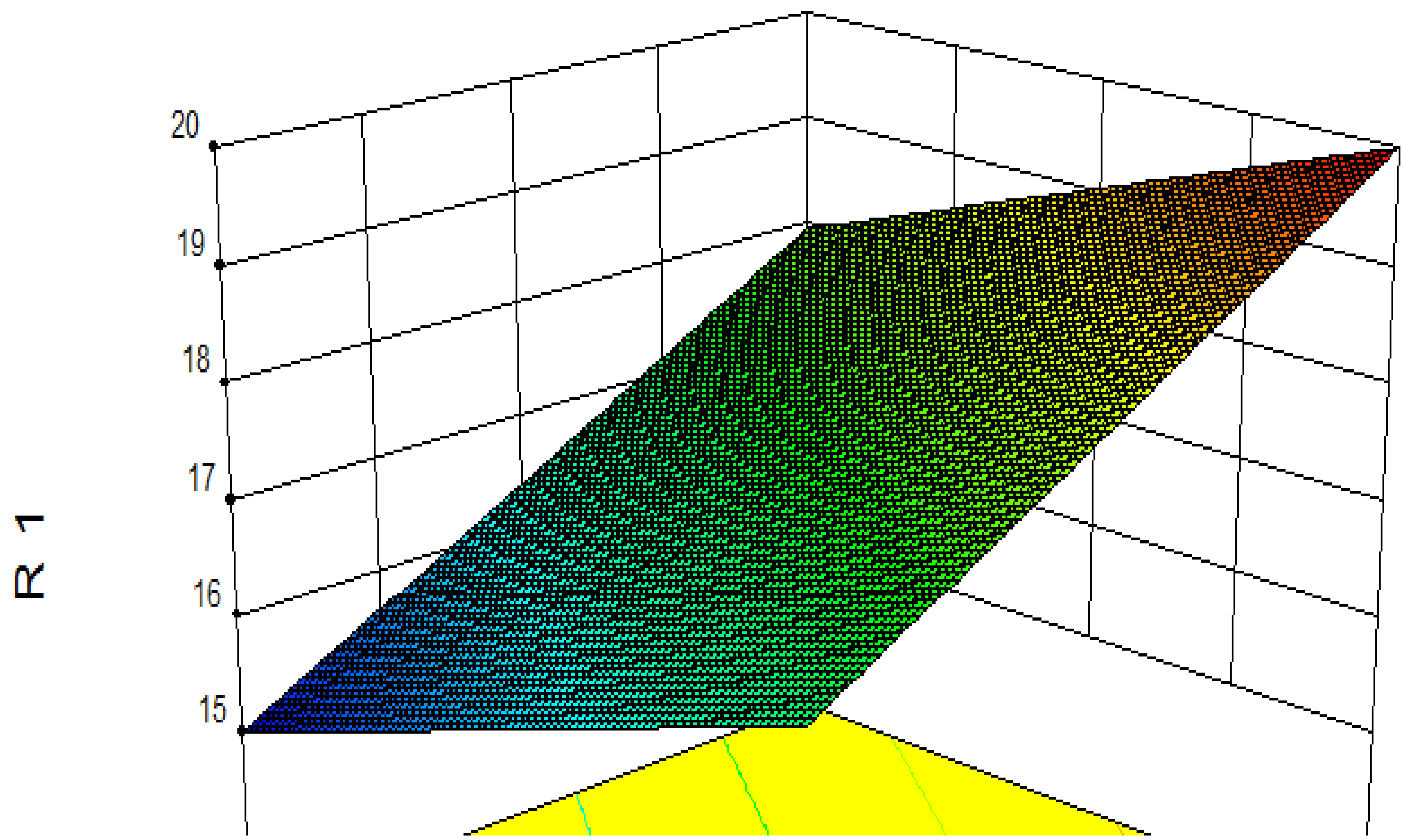
**Analysis of variance table [Partial sum of squares - Type III]**

| Source | Sum of Squares | df | Mean Square | F Value | p-value Prob > F | |
|---|---|---|---|---|---|---|
| Model | 13.00 | 2 | 6.50 | 6.366E+007 | < 0.0001 | significant |
| *B-B* | *9.00* | *1* | *9.00* | *6.366E+007* | *< 0.0001* | |
| *C-C* | *4.00* | *1* | *4.00* | *6.366E+007* | *< 0.0001* | |
| Residual | 0.000 | 1 | 0.000 | | | |
| Cor Total | 13.00 | 3 | | | | |

The Model F-value of 63660000.00 implies the model is significant. There is only a 0.01% chance that a "Model F-Value" this large could occur due to noise.

Values of "Prob > F" less than 0.0500 indicate model terms are significant.
In this case B, C are significant model terms.
Values greater than 0.1000 indicate the model terms are not significant.

**3D surface plot**



# Half Fractional $2^{k-1}$ Design (Contd.)

- ✓Using Design Expert software, let us create a fractional factorial experiment for 4 factors. New terms are observed in this design. Aliased terms are BC, BD, CD, ABC, ABD, ACD, BCD, and ABCD.
- ✓Thus, for a fractional factorial experiment for four factors, the $4^{th}$ order and $3^{rd}$ order interactions are all aliased. Some $2^{nd}$ order interactions are also aliased.
- ✓Table shown gives the alias list:

| Term | Aliases |
|---|---|
| Intercept | |
| A-A | BCD |
| B-B | ACD |
| C-C | ABD |
| D-D | ABC |
| AB | CD |
| AC | BD |
| AD | BC |
| BC | |
| BD | |
| CD | |
| ABC | |
| ABD | |
| ACD | |
| BCD | |
| ABCD | |

## Effects list

| | Term | Stdized Effects | Sum of Squares | % Contribution |
|---|---|---|---|---|
| | Intercept | | | |
| M | A-A | -1.50 | 4.50 | 7.50 |
| M | B-B | -1.00 | 2.00 | 3.33 |
| M | C-C | -2.50 | 12.50 | 20.83 |
| M | D-D | -1.00 | 2.00 | 3.33 |
| M | AB | -2.50 | 12.50 | 20.83 |
| M | AC | 1.00 | 2.00 | 3.33 |
| M | AD | 3.50 | 24.50 | 40.83 |
| ~ | BC | | Aliased | |
| ~ | BD | | Aliased | |
| ~ | CD | | Aliased | |
| ~ | ABC | | Aliased | |
| ~ | ABD | | Aliased | |
| ~ | ACD | | Aliased | |

## ANOVA Analysis

Diagnostic graphs cannot be created because the model is over-specified.

All degrees of freedom are in the model and none are assigned to the residual (error).

Notice also that the ANOVA had no calculated p-values because without residual error there is nothing to test against.

To fix the problem, return to the Effects or Model button and assign at least one term to error.

# Quarter Fractional $2^{k-2}$ Design

✓ Quarter fractional $2^{k-2}$ designs are available from 5 factors onwards. The basis of this experiment is to test k factors at 2 levels in $2^{k-2}$ runs. For 5 factors and 2 levels on one replicate, the experimental settings are as given below:

- Full factorial = 32
- Half fractional factorial = 16
- Quarter fractional factorial = 8

✓ A sample 5 factors quarter fractional factorial experiment with 2 replicates, i.e., 16 runs has been setup using Design Expert.

# Quarter Fractional $2^{k-2}$ Design (Contd.)

## Effects list

| | | | | |
|---|---|---|---|---|
| | Intercept | | | |
| M | A-A | 0.000 | -1.421E-014 | -1.247E-014 |
| M | B-B | 1.00 | 4.00 | 3.51 |
| M | C-C | -0.75 | 2.25 | 1.97 |
| M | D-D | 1.50 | 9.00 | 7.89 |
| M | E-E | 3.25 | 42.25 | 37.06 |
| ~ | AB | | Aliased | |
| ~ | AC | | Aliased | |
| ~ | AD | | Aliased | |
| ~ | AE | | Aliased | |
| M | BC | 2.25 | 20.25 | 17.76 |
| ~ | BD | | Aliased | |
| M | BE | 1.75 | 12.25 | 10.75 |
| ~ | CD | | Aliased | |
| ~ | CE | | Aliased | |
| ~ | DE | | Aliased | |
| ~ | ABC | | Aliased | |
| ~ | ABD | | Aliased | |
| ~ | ABE | | Aliased | |
| ~ | ACD | | Aliased | |
| ~ | ACE | | Aliased | |
| ~ | ADE | | Aliased | |
| ~ | BCD | | Aliased | |
| ~ | BCE | | Aliased | |
| ~ | BDE | | Aliased | |
| ~ | CDE | | Aliased | |
| ~ | ABCD | | Aliased | |
| ~ | ABCE | | Aliased | |
| ~ | ABDE | | Aliased | |
| ~ | ACDE | | Aliased | |
| ~ | BCDE | | Aliased | |
| ~ | ABCDE | | Aliased | |
| e | Lack Of Fit | | 0.000 | 0.000 |

# ANOVA analysis

Response 1 R1

ANOVA for selected factorial model

Analysis of variance table [Partial sum of squares - Type III]

| Source | Sum of Squares | df | Mean Square | F Value | p-value Prob > F | |
|---|---|---|---|---|---|---|
| Model | 90.00 | 7 | 12.86 | 4.29 | 0.0292 | significant |
| *A-A* | *-1.421E-014* | *1* | *-1.421E-014* | *-4.737E-015* | *1.0000* | |
| *B-B* | *4.00* | *1* | *4.00* | *1.33* | *0.2815* | |
| *C-C* | *2.25* | *1* | *2.25* | *0.75* | *0.4117* | |
| *D-D* | *9.00* | *1* | *9.00* | *3.00* | *0.1215* | |
| *E-E* | *42.25* | *1* | *42.25* | *14.08* | *0.0056* | |
| *BC* | *20.25* | *1* | *20.25* | *6.75* | *0.0317* | |
| *BE* | *12.25* | *1* | *12.25* | *4.08* | *0.0780* | |
| Pure Error | 24.00 | 8 | 3.00 | | | |
| Cor Total | 114.00 | 15 | | | | |

The Model F-value of 4.29 implies the model is significant. There is only
a 2.92% chance that a "Model F-Value" this large could occur due to noise.

Values of "Prob > F" less than 0.0500 indicate model terms are significant.
In this case E, BC are significant model terms.
Values greater than 0.1000 indicate the model terms are not significant.
If there are many insignificant model terms (not counting those required to support hierarchy),

simplilearn your pace, your place

## Model analysis

| | | | |
|---|---|---|---|
| Std. Dev. | 1.73 | R-Squared | 0.7895 |
| Mean | 24.00 | Adj R-Squared | 0.6053 |
| C.V. % | 7.22 | Pred R-Square | 0.1579 |
| PRESS | 96.00 | Adeq Precisior | 5.307 |

The "Pred R-Squared" of 0.1579 is not as close to the "Adj R-Squared" of 0.6053 as one might normally expect. This may indicate a large block effect or a possible problem with your model and/or data. Things to consider are model reduction, response transformation, outliers, etc.

"Adeq Precision" measures the signal to noise ratio. A ratio greater than 4 is desirable. Your ratio of 5.307 indicates an adequate signal. This model can be used to navigate the design space.

# $3^k$ Factorial Design

- ✓The $2^k$ fractional factorial designs are most preferred in industrial applications and research. A variant of this design is the $3^k$ factorial design: full factorial and fractional factorial.
- ✓While notations in the $2^k$ designs were ±1 as it facilitates the geometric view of the design, in the $3^k$ designs the notations used will be -1, 0, and 1.
- ✓The $3^k$ design is often used by experimenters for curvature estimation. Considering estimation of curvature, the $2^k$ designs augmented with center points are often considered an excellent alternative.
- ✓Another alternative to estimate curvature in a design is response surface design.

# $3^k$ Factorial Design (Contd.)

- ✓The simplest form of $3^k$ factorial design is the $3^2$ factorial design. In one replicate, this experiment has 9 runs. The 2 factors are tested at three levels, i.e., 0, -1 and 1; or 0, 1, and 2.
- ✓The sum of squares for 2nd order interactions and higher are often partitioned into single degree of freedom components and multiple degree of freedom components.
- ✓The sums of squares can be determined by two methods:
  - The method used for determining the sum of squares for the $2^k$ designs; and
  - The Latin square method.

# Response Surface Designs

- ✓The $2^k$ and the $3^k$ factorial designs will help estimate curvature effects of a model by addition of a center point.
- ✓Despite this, the $2^k$ models are not considered robust models to study quadratic effects.
- ✓To study quadratic effects, use response surface designs.
- ✓Response surface designs help in:
  - Finding improved or optimal designs;
  - Troubleshoot process issues; and
  - Make a product or process robust against external influences.

# Response Surface Designs (Contd.)

- ✓Choose from two types of response surface designs – Central composite and box behnken designs. The central composite designs will be studied for 3 factors.
- ✓Each factor is varied at 5 levels. This makes an RS design robust.
- ✓The 5 levels are ±1, ±α (where α is an axial point), and 0 as center point.
- ✓Use Design Expert to draw a response surface design experiment.
- ✓Add two blocks to see how blocking helps a response surface design.

# Response Surface Designs (Contd.)

✓Step 1: Check the experiment setup screen.

| Select | Std | Run | Block | Factor 1 A:A Reactant Co... | Factor 2 B:B Catalyst Wei... | Factor 3 C:C Process Time | Response 1 R1 |
|---|---|---|---|---|---|---|---|
| | 3 | 1 | Block 1 | -1.00 | 1.00 | -1.00 | |
| | 7 | 2 | Block 1 | -1.00 | 1.00 | 1.00 | |
| | 6 | 3 | Block 1 | 1.00 | -1.00 | 1.00 | |
| | 11 | 4 | Block 1 | 0.00 | 0.00 | 0.00 | |
| | 1 | 5 | Block 1 | -1.00 | -1.00 | -1.00 | |
| | 9 | 6 | Block 1 | 0.00 | 0.00 | 0.00 | |
| | 12 | 7 | Block 1 | 0.00 | 0.00 | 0.00 | |
| | 8 | 8 | Block 1 | 1.00 | 1.00 | 1.00 | |
| | 10 | 9 | Block 1 | 0.00 | 0.00 | 0.00 | |
| | 5 | 10 | Block 1 | -1.00 | -1.00 | 1.00 | |
| | 4 | 11 | Block 1 | 1.00 | 1.00 | -1.00 | |
| | 2 | 12 | Block 1 | 1.00 | -1.00 | -1.00 | |
| | 16 | 13 | Block 2 | 0.00 | 1.68 | 0.00 | |
| | 20 | 14 | Block 2 | 0.00 | 0.00 | 0.00 | |
| | 14 | 15 | Block 2 | 1.68 | 0.00 | 0.00 | |
| | 18 | 16 | Block 2 | 0.00 | 0.00 | 1.68 | |
| | 17 | 17 | Block 2 | 0.00 | 0.00 | -1.68 | |
| | 13 | 18 | Block 2 | -1.68 | 0.00 | 0.00 | |
| | 15 | 19 | Block 2 | 0.00 | -1.68 | 0.00 | |
| | 19 | 20 | Block 2 | 0.00 | 0.00 | 0.00 | |

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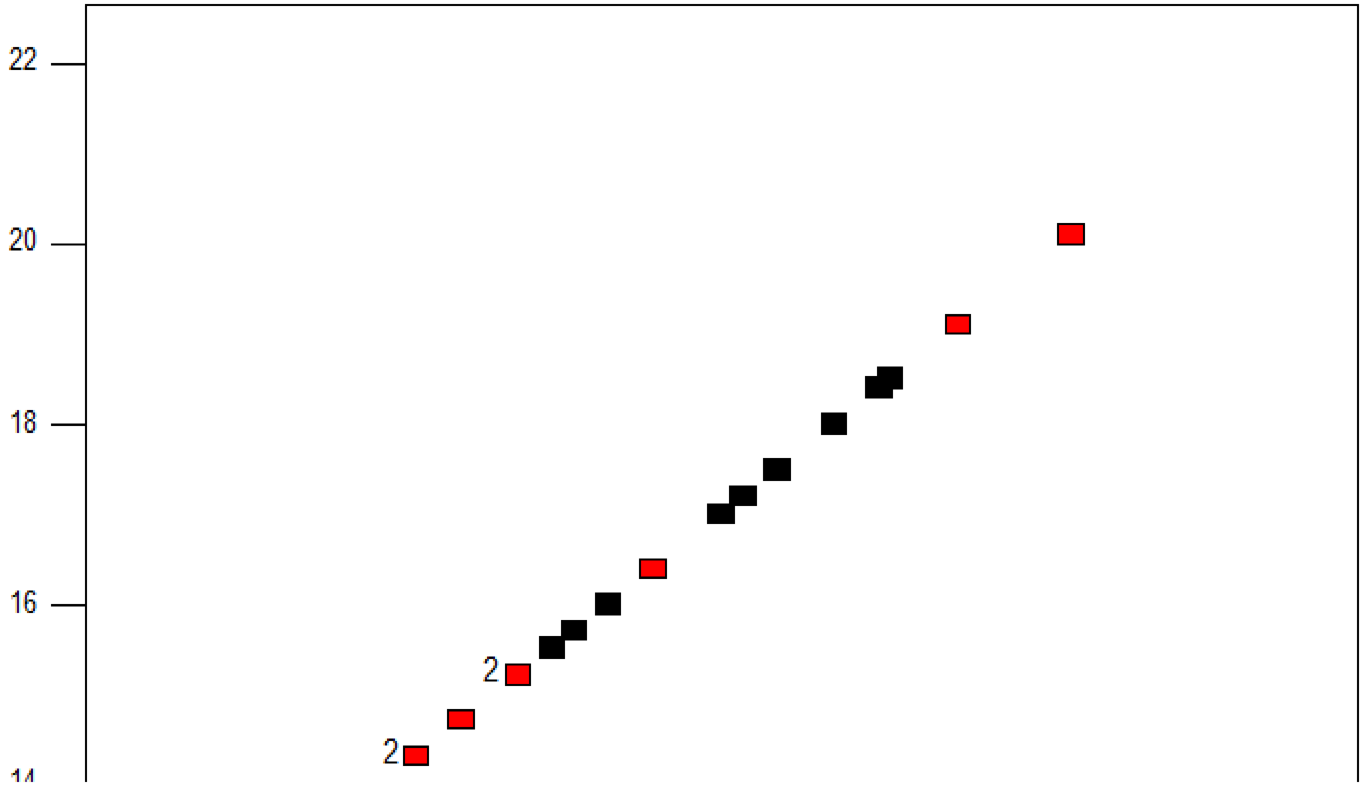
✓Step 2: Enter the responses for the level settings as shown in the snapshot.

| Std | Run | Block | Factor 1 A:A Reactant Co... | Factor 2 B:B Catalyst Wei... | Factor 3 C:C Process Time | Response 1 R1 |
|---|---|---|---|---|---|---|
| 3 | 1 | Block 1 | -1.00 | 1.00 | -1.00 | 16 |
| 7 | 2 | Block 1 | -1.00 | 1.00 | 1.00 | 17 |
| 6 | 3 | Block 1 | 1.00 | -1.00 | 1.00 | 17.5 |
| 11 | 4 | Block 1 | 0.00 | 0.00 | 0.00 | 18.5 |
| 1 | 5 | Block 1 | -1.00 | -1.00 | -1.00 | 15.5 |
| 9 | 6 | Block 1 | 0.00 | 0.00 | 0.00 | 15.7 |
| 12 | 7 | Block 1 | 0.00 | 0.00 | 0.00 | 18 |
| 8 | 8 | Block 1 | 1.00 | 1.00 | 1.00 | 18.4 |
| 10 | 9 | Block 1 | 0.00 | 0.00 | 0.00 | 13.4 |
| 5 | 10 | Block 1 | -1.00 | -1.00 | 1.00 | 15.2 |
| 4 | 11 | Block 1 | 1.00 | 1.00 | -1.00 | 14.3 |
| 2 | 12 | Block 1 | 1.00 | -1.00 | -1.00 | 17.2 |
| 16 | 13 | Block 2 | 0.00 | 1.68 | 0.00 | 19.1 |

# Response Surface Designs (Contd.)

- ✓ Step 3: Check the block – block variability. The black boxes indicate data for block 1 and red blocks indicate block 2 data.



# Response Surface Designs (Contd.)

✓Step 4: Check the design evaluation report. Observe the lack of fit degree of freedom most importantly.

Aliases are calculated based on your response selection,

taking into account missing datapoints, if necessary.

Watch for aliases among terms you need to estimate.

Degrees of Freedom for Evaluation

| | |
|---|---|
| Blocks | 1 |
| Model | 9 |
| Residuals | 9 |
| *Lack Of Fit* | 5 |
| *Pure Error* | 4 |
| Corr Total | 19 |

| | | | | Power at 5 % alpha level to detect signal/noise ratic | | |
|---|---|---|---|---|---|---|
| Term | StdErr** | VIF | Ri-Squared | 0.5 Std. Dev. | 1 Std. Dev. | 2 Std. Dev. |
| Block 1 | 0.23 | | | | | |
| Block 2 | | | | | | |
| A | 0.27 | 1.00 | 0.0000 | 13.2 % | 37.9 % | 90.7 % |
| B | 0.27 | 1.00 | 0.0000 | 13.2 % | 37.9 % | 90.7 % |
| C | 0.27 | 1.00 | 0.0000 | 13.2 % | 37.9 % | 90.7 % |
| AB | 0.35 | 1.00 | 0.0000 | 9.7 % | 24.5 % | 71.2 % |
| AC | 0.35 | 1.00 | 0.0000 | 9.7 % | 24.5 % | 71.2 % |
| BC | 0.35 | 1.00 | 0.0000 | 9.7 % | 24.5 % | 71.2 % |
| $A^2$ | 0.26 | 1.02 | 0.0187 | 39.6 % | 92.0 % | 99.9 % |
| $B^2$ | 0.26 | 1.02 | 0.0187 | 39.6 % | 92.0 % | 99.9 % |

✓Results analysis

Summary (detailed tables shown below)

| Source | Sequential p-value | Lack of Fit p-value | Adjusted R-Squared | Predicted R-Squared | |
|---|---|---|---|---|---|
| Mean | < 0.0001 | | | | Suggested |
| Linear | 0.6442 | 0.9433 | -0.0775 | -0.4824 | |
| 2FI | 0.7181 | 0.9123 | -0.2091 | -0.7217 | |
| Quadratic | 0.5086 | 0.9224 | -0.2616 | -1.2082 | |
| Cubic | 0.8661 | 0.6696 | -0.8304 | -20.0528 | Aliased |

| Source | Sum of Squares | df | Mean Square | F Value | p-value Prob > F | |
|---|---|---|---|---|---|---|
| Mean vs Total | 5200.31 | 1 | 5200.31 | | | Suggested |
| Block vs Mean | 2.13 | 1 | 2.13 | | | |
| Linear vs Block | 8.08 | 3 | 2.69 | 0.57 | 0.6442 | |
| 2FI vs Linear | 7.27 | 3 | 2.42 | 0.46 | 0.7181 | |
| Quadratic vs 2 | 13.87 | 3 | 4.62 | 0.83 | 0.5086 | |
| Cubic vs Quad | 9.69 | 4 | 2.42 | 0.30 | 0.8661 | Aliased |
| Residual | 40.26 | 5 | 8.05 | | | |
| Total | 5281.63 | 20 | 264.08 | | | |

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Response 1 R1

ANOVA for Response Surface Mean Model

Analysis of variance table [Partial sum of squares - Type III]

| Source | Sum of Squares | df | Mean Square | F Value | p-value Prob > F |
|---|---|---|---|---|---|
| Block | 2.13 | 1 | 2.13 | | |
| Model | 0.000 | 0 | | | |
| Residual | 79.18 | 18 | 4.40 | | |
| *Lack of Fit* | *40.94* | *14* | *2.92* | *0.31* | *0.9567 not significant* |
| *Pure Error* | *38.24* | *4* | *9.56* | | |
| Cor Total | 81.32 | 19 | | | |

# Response Surface Designs (Contd.)

Values of "Prob > F" less than 0.0500 indicate model terms are significant.

In this case there are no significant model terms.

Values greater than 0.1000 indicate the model terms are not significant.

If there are many insignificant model terms (not counting those required to support hierarchy), model reduction may improve your model.

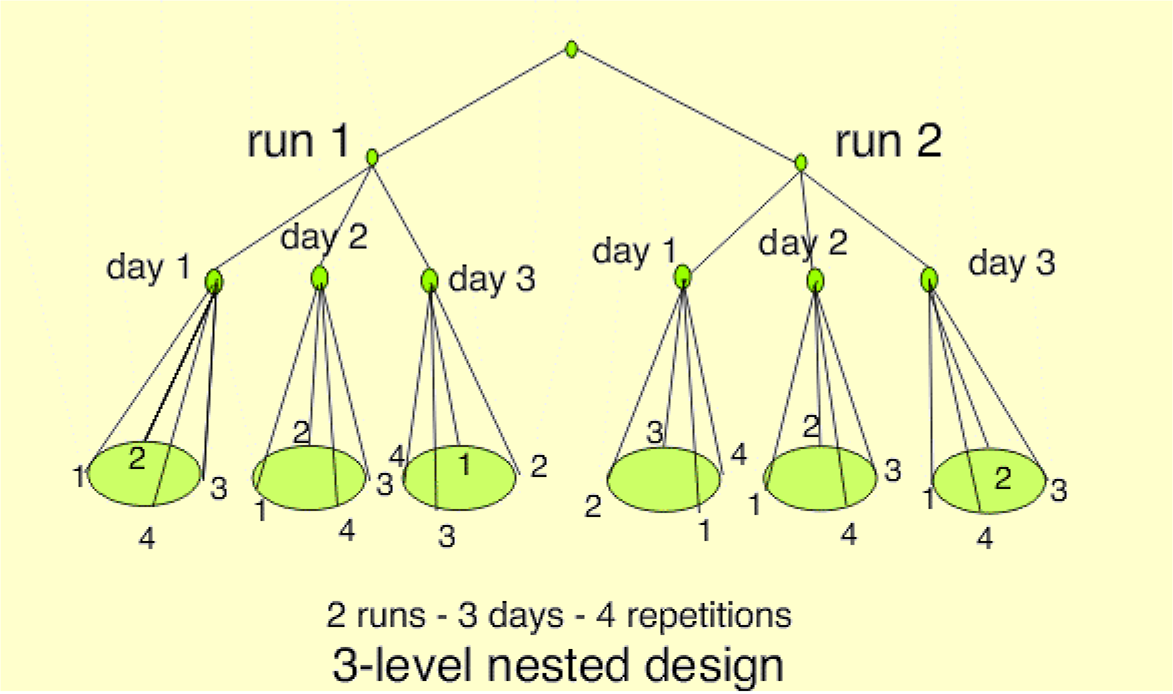
The "Lack of Fit F-value" of 0.31 implies the Lack of Fit is not significant relative to the pure error. There is a 95.67% chance that a "Lack of Fit F-value" this large could occur due to noise. Non-significant lack of fit is good -- we want the model to fit.

| | | | |
|---|---|---|---|
| Std. Dev. | 2.10 | R-Squared | 0.0000 |
| Mean | 16.13 | Adj R-Squared | 0.0000 |
| C.V. % | 13.01 | Pred R-Square | -0.2629 |
| PRESS | 100.00 | Adeq Precisior | 1.005 |

A negative "Pred R-Squared" implies that the overall mean is a better predictor of your response than the current model.

# Nested Designs

- ✓A nested design is recommended for studying the effect of sources of variability that repeat themselves over time.
- ✓Data collection and analysis for nested designs are straightforward. Interactions are not significant any more, to be studied for time-dependent errors.



# Split Plot Designs – Introduction

- ✓ Split plot designs are blocked designs, where blocks serve as experimental units for subset of factors.
- ✓ For a typical 2 level factorial experiment, the 2 levels and factors are setup in two blocks. These blocks are known as whole plots.
- ✓ The experimental units setup within these blocks is known as split plots or block plots.
- ✓ The entire design is randomized twice – 1) To determine block level treatment to whole plots and 2) To determine split plot experimental unit treatments within each block.
- ✓ Differs from a completely randomized design because of random errors' presence in split plots as well as whole plots.
- ✓ Randomization ensures that split plot errors are independently distributed and mutually independent within the whole plot.

# Taguchi's Designs

- ✓Conceived and developed by Dr. Genichi Taguchi.
- ✓Focuses on the robustness of the product. Focuses on designing a product in such a way that it is insensitive to common cause of variation existing in the process.
- ✓Quantifies the effects of deviation in a process to financial loss with the function, $L(y) = k(y-m)^2$; where y = value of quality characteristic, m = target for quality characteristic, and k = the constant that signifies financial importance of quality characteristic.

# Taguchi's Designs (Contd.)

✓ The nominal signal to noise ratio (S-N Ratio) is given by the formula:

$$S/N_{\text{Nominal}} = 10 \log (Ybar^2)/s^2$$

✓ Available Taguchi's designs:

- L4 – Geometric design – Up to 3 factors
- L8 – Geometric design – Up to 7 factors
- L12 – Non-geometric design – Up to 11 factors
- L16 – Geometric design – Up to 15 factors
- L20 – Non-Geometric design – Up to 19 factors
- L24 – Non-Geometric design – Up to 23 factors

# Taguchi's L4 Design

- The Taguchi's L4 design can be constructed using the tool, DOE, provided as a Microsoft Excel spreadsheet in the toolkit. From the excel worksheet it can be seen that all the three factors have significant p-values.

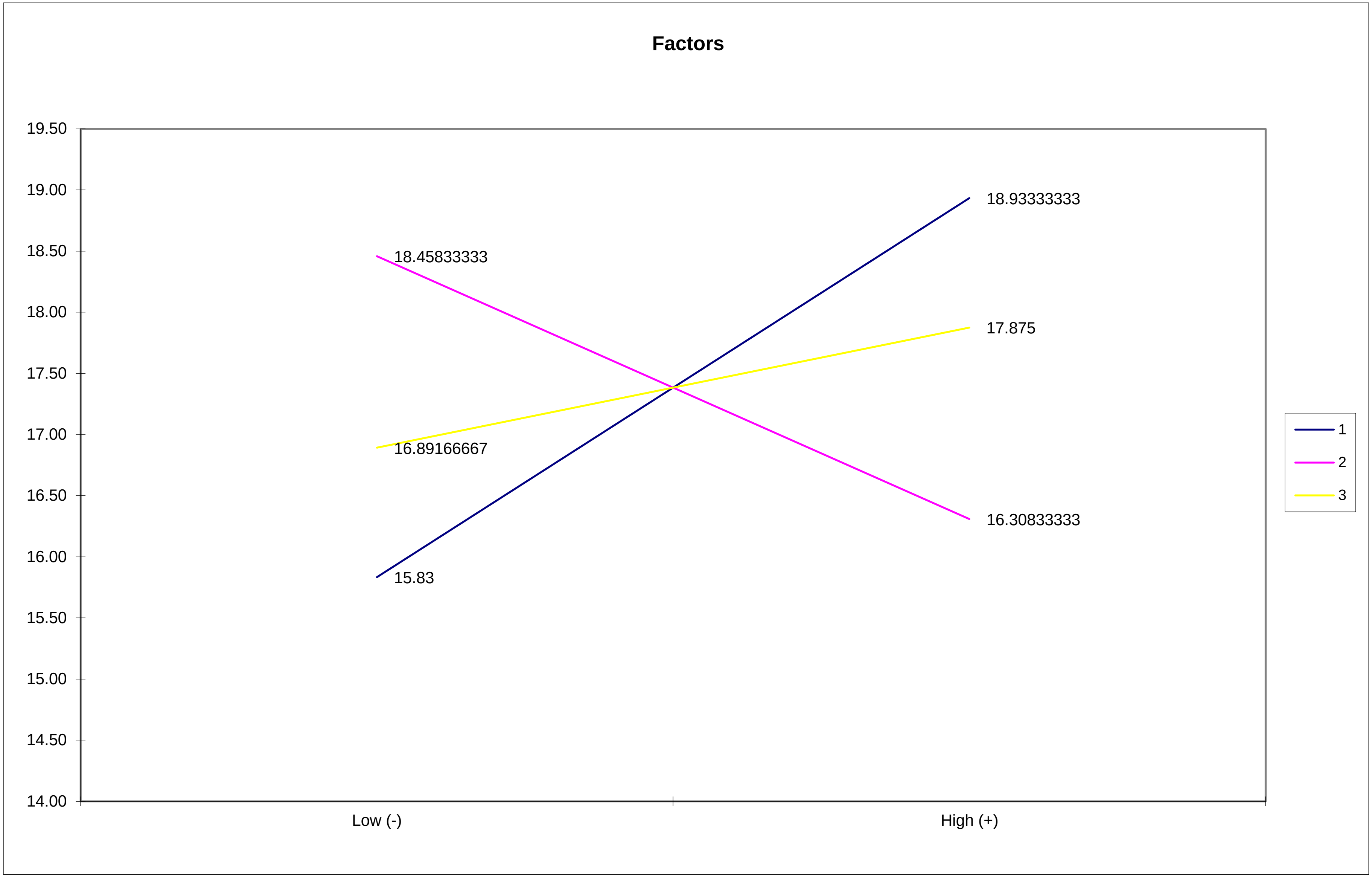
| Design of Experiments | | L4 | | | | Two-Way Interactions Appear Below | | |
|---|---|---|---|---|---|---|---|---|
| Factor | Factor Name | Level | Low(-) | Level 2 | High(+) | 2 | 3 | |
| 1 | 1 Reactant | | 15 | | 35 | | 1X3 | Create Input Table |
| 2 | 2 Catalyst | | 10 | | 14 | 2X3 | | |
| 3 | 3 Process time | | 6 | | 12 | | | |

| Design | Factors | | | | Responses | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Trial | 1 | 2 | 3 | verage | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| 1 | - | - | - | 16.42 | 16 | 16.5 | 16.75 | | | | | | | |
| 2 | - | + | + | 15.25 | 15 | 15.25 | 15.5 | | | | | | | |
| 3 | + | - | + | 20.50 | 20 | 21 | 20.5 | | | | | | | |
| 4 | + | + | - | 17.37 | 17 | 17.5 | 17.6 | | | | | | | |
| | | -A | verage | 17.38 | 17.00 | 17.56 | 17.59 | | | | | | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | 3 | 2 | | | | | | |
| Interactions | | (2) | 1 | | | | | | |
| | | | (3) | 1X2 | | 1X3 | | 2X3 | |
| | 1 | 2 | 3 | 2 Low | 2 High | 3 Low | 3 High | 3 Low | 3 High |
| Low (-) | 15.83 | 18.46 | 16.89 | 16.42 | 15.25 | 16.42 | 15.25 | 16.42 | 20.50 |
| High (+ | 18.9333 | 16.31 | 17.88 | 20.50 | 17.37 | 17.37 | 20.50 | 17.37 | 15.25 |

| Anova | Factor | df | SS | MS | F | Effect | Contras | *p* |
|---|---|---|---|---|---|---|---|---|
| Source | 1 | 1 | 28.83 | 28.83 | 205.3 | 3.1 | 18.60 | 0.00 |
| | 2 | 1 | 13.87 | 13.868 | 98.76 | -2.2 | -12.90 | 0.00 |
| | 3 | 1 | 2.90 | 2.9008 | 20.66 | 1.0 | 5.90 | 0.00 |
| | Error | 8 | 1.12 | 0.140 | | | | |
| | Total | 11 | 46.72 | | | | | |

# Taguchi's L4 Design Graphs



✓ The Taguchi's L8 design can be constructed using the tool, DOE, provided as a Microsoft Excel spreadsheet in the toolkit. From the excel worksheet, it can be seen that all the three factors have significant p-values.

| Design of Experiments | | L8 | | Two-Way Interactions Appear Below | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Facto | Factor Name | Level 1 Low(-) | Level 2 High(+) | 2 | 3 | 4 | 5 | 6 | 7 |
| 1 | 1 RC | 15 | 35 | | 1X3 | 1X4 | | 1X6 | |
| 2 | 2 CW | 10 | 14 | | 2X3 | 2X4 | | | 2X7 |
| 3 | 3 PT | 6 | 12 | | | 3X4 | | 3X6 | |
| 4 | 4 LT | 5 | 7 | | | | | 4X6 | |
| 5 | 5 Chemical | 100 | 150 | | | | | | 5X7 |
| 6 | 6 Solution | 120 | 165 | | | | | | |
| 7 | 7 Boiling temp | 100 | 200 | | | | | | |

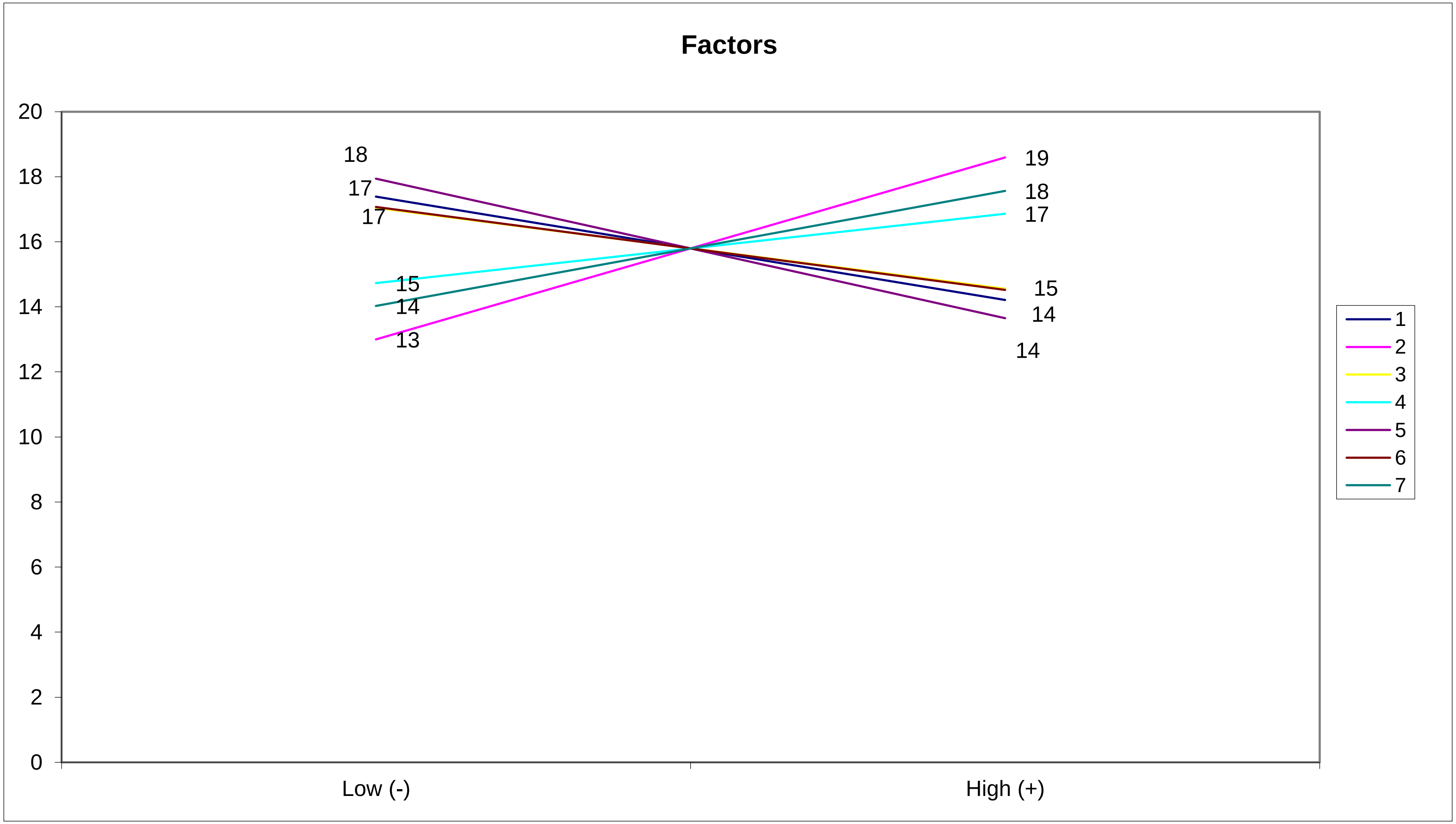
Create Input Table

| Design Factors | | | | | | | | Responses | | | Enter Your Data Here! | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Trial | 1 | 2 | 3 | 4 | 5 | 6 | 7 | verage | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| 1 | - | - | - | - | - | - | - | 16 | 16 | 16.5 | 16.75 | | | | | | | |
| 2 | - | - | - | + | + | + | + | 15 | 15 | 15.25 | 15.5 | | | | | | | |
| 3 | - | + | + | - | - | + | + | 21 | 20 | 21 | 20.5 | | | | | | | |
| 4 | - | + | + | + | + | - | - | 17 | 17 | 17.5 | 17.6 | | | | | | | |
| 5 | + | - | + | - | + | - | + | 10 | 10 | 10 | 10 | | | | | | | |
| 6 | + | - | + | + | - | + | - | 10 | 11 | 10 | 10 | | | | | | | |
| 7 | + | + | - | - | + | + | - | 12 | 12 | 12 | 12 | | | | | | | |
| 8 | + | + | - | + | - | - | + | 25 | 24 | 25 | 24.5 | | | | | | | |
| | C | B | -BC | A | -AC | -AB | ABC | 16 | 16 | 16 | 15.86 | | | | | | | |

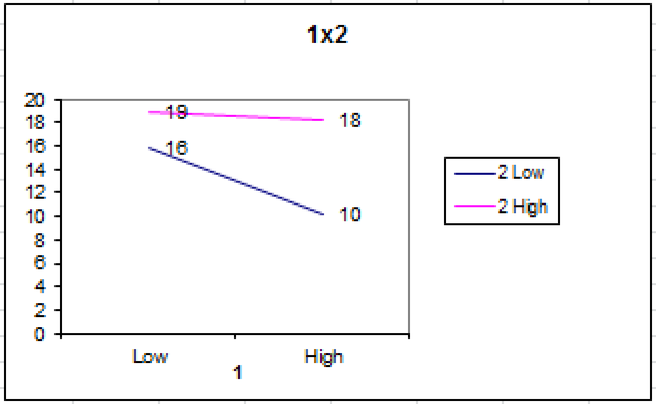
## Results table

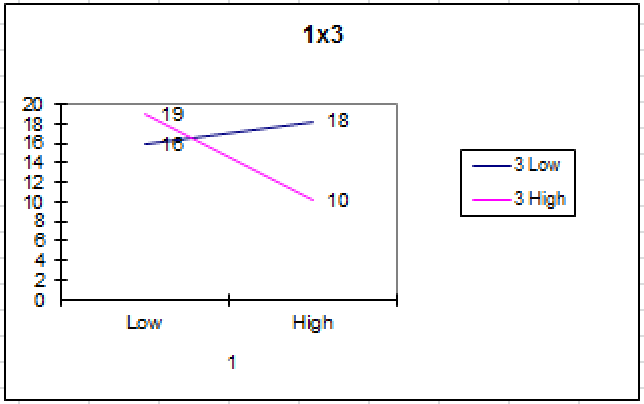
| Anova | Factor | df | SS | MS | F | Effect | Contrast | *p* |
|---|---|---|---|---|---|---|---|---|
| Source | 1 | 1 | 60 | 60.484 | 422.594 | -3.175 | -38.1 | 0.00 |
| | 2 | 1 | 188 | 187.600 | 1310.745 | 5.592 | 67.1 | 0.00 |
| | 3 | 1 | 37 | 37.250 | 260.265 | -2.492 | -29.9 | 0.00 |
| | 4 | 1 | 27 | 27.307 | 190.789 | 2.133 | 25.6 | 0.00 |
| | 5 | 1 | 110 | 110.082 | 769.130 | -4.283 | -51.4 | 0.00 |
| | 6 | 1 | 39 | 39.015 | 272.594 | -2.550 | -30.6 | 0.00 |
| | 7 | 1 | 75 | 74.907 | 523.365 | 3.533 | 42.4 | 0.00 |
| | Error | 16 | 2 | 0 | | | | |
| | Total | 23 | 539 | | | | | |

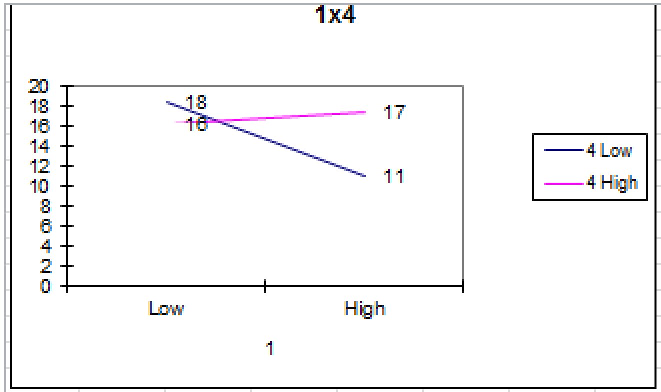
## Graphs

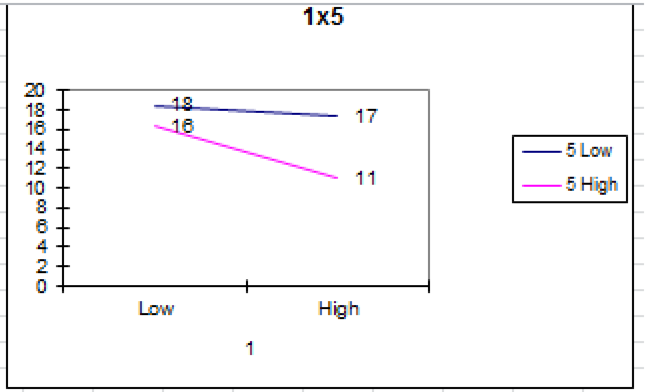

Factors
20
18
16
14
12
10
8
6
4
2
0
18
17
17
15
14
13
19
18
17
15
14
14
Low (-)
High (+)
1
2
3
4
5
6
7

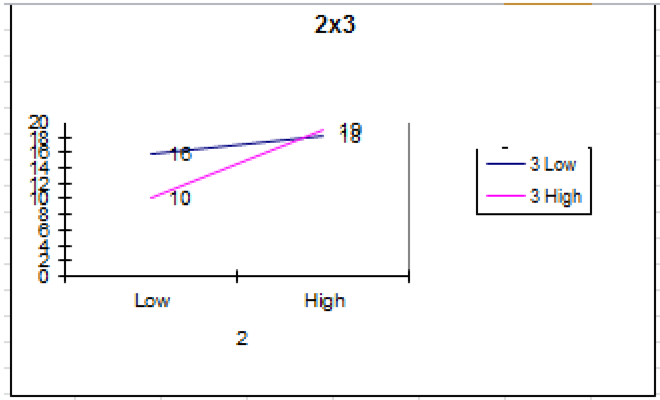
# Taguchi's L8 Design (Contd.)

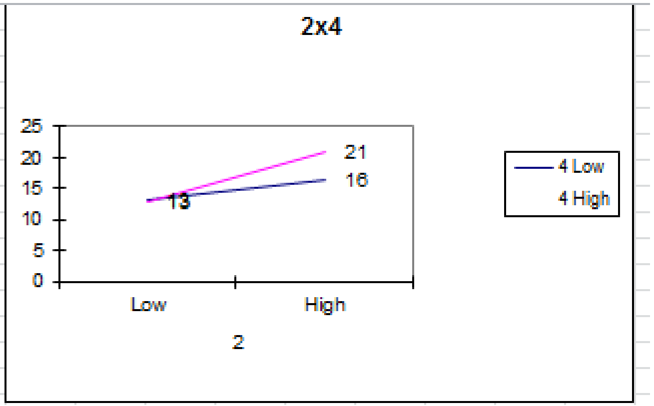


# Plackett Burman's Design

- Resolution designs can be used to investigate k main effects using k+1 runs. Highly fractional $2^{k-p}$ designs miss a lot of interaction effects due to aliasing.
- Plackett Burman's design allows investigation of k main effects using k+1 runs with the valid runs being multiples of 4. Valid runs for Plackett Burman's designs are 4,8,12, 16, 20, 24, and so on.
- Table below summarizes designs used:

| Design | Runs | Type | Effects Investigated |
|---|---|---|---|
| $2_{III}^{3-1}$ | 4 | Two level Fractional Factorial | Up to 3 main effects |
| $2_{III}^{7-4}$ | 8 | Two level Fractional Factorial | Up to 7 main effects |
| 12-run P-B | 12 | Plackett-Burman | Up to 11 main effects |
| $2_{III}^{15-11}$ | 16 | Two level Fractional Factorial | Up to 15 main effects |
| 20-run P-B | 20 | Plackett-Burman | Up to 19 main effects |
| 24-run P-B | 24 | Plackett-Burman | Up to 23 main effects |
| 28-run P-B | 28 | Plackett-Burman | Up to 27 main effects |
| $2_{III}^{31-26}$ | 32 | Two level Fractional Factorial | Up to 31 main effects |

# Plackett Burman's Designs (Contd.)

| | | | | |
|---|---|---|---|---|
| 1 | A | RC | 15 | 35 |
| 2 | B | CW | 10 | 14 |
| 3 | C | PT | 6 | 12 |
| 4 | D | LT | 5 | 7 |
| 5 | E | Chemical | 100 | 150 |
| 6 | F | Solution | 120 | 165 |
| 7 | G | Boiling temp | 100 | 200 |

| 8-Run | MEAN | A | B | C | D | E | F | G | Average | Range | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | + | + | + | + | - | + | - | - | 16.42 | 0.750 | 16 | 16.5 | 16.75 | |
| 2 | + | - | + | + | + | - | + | - | 15.25 | 0.500 | 15 | 15.25 | 15.5 | |
| 3 | + | - | - | + | + | + | - | + | 20.50 | 1.000 | 20 | 21 | 20.5 | |
| 4 | + | + | - | - | + | + | + | - | 17.37 | 0.600 | 17 | 17.5 | 17.6 | |
| 5 | + | - | + | - | - | + | + | + | 10.00 | 0.000 | 10 | 10 | 10 | |
| 6 | + | + | - | + | - | - | + | + | 10.33 | 1.000 | 11 | 10 | 10 | |
| 7 | + | + | + | - | + | - | - | + | 12.00 | 0.000 | 12 | 12 | 12 | |
| 8 | + | - | - | - | - | - | - | - | 24.50 | 1.000 | 24 | 25 | 24.5 | |
| Effects | 15.796 | -3.533 | -4.758 | -0.342 | 0.96667 | 0.55 | -5.1167 | -5.175 | 15.80 | 0.61 | 16 | 16 | 15.86 | |
| | Significant | Significan | Significan | Significant | Significant | Significant | Significant | Significant | $S_{ee}$ | 0.358 | d2 | 1.128 | 1.693 | 2.( |
| Low | | 17.6 | 18.2 | 16.0 | 15.3 | 15.5 | 18.4 | 18.4 | $S_{eff}$ | 0.146 | | | | |
| High | 15.80 | 14.0 | 13.4 | 15.6 | 16.3 | 16.1 | 13.2 | 13.2 | df | 16 | Q | 0.256 | | |

# Quality Function Deployment (House of Quality)

✓Quality function deployment (QFD) is a method to:

- Transform user demands into design quality;
- To deploy the functions forming quality; and
- To deploy methods for achieving the design quality in subsystems and component parts, and finally to specific elements of the manufacturing process.

✓QFD is designed to help planners focus on the characteristics of a new, or existing product or service from the viewpoints of market segments, company, or technology-development needs.

✓QFD helps transform customer needs into engineering characteristics for a product or service prioritizing each product or service characteristic, while setting development targets for product or service.

# Summary

In this lesson, we have learned how to do and interpret:

- ✓ $2^2$ Design
- ✓ General $2^k$ design
- ✓ Single Replicate of $2^k$ design
- ✓ Half fractional $2^{k-1}$ design
- ✓ Quarter fraction $2^{k-2}$ design
- ✓ The $3^k$ design
- ✓ Response Surface designs

In addition, we have also been introduced to:

- ✓ Nested design
- ✓ Split Plot design
- ✓ Taguchi's L4 and L6 design
- ✓ Plackett Burman's design

# Section V, Lesson 4

**Brainstorming, Solutions Prioritization and Cost Benefit Analysis**

# Agenda

- ✓ Brainstorming
- ✓ Multi-Voting
- ✓ Brainstorming, Prioritization, and Cost Benefit Analysis
- ✓ Poka Yoke

# Brainstorming

- ✓The analyze phase gave us inputs on why the input variable was varying. This statement was validated by conducting additional DOE tests to see if the variability was due to noise or any special cause.
- ✓The KPOV was delivery hours and the KPIV identified was training time, packaging weight, and hold time (for illustration purpose), which was impacting the delivery hours.
- ✓The Six Sigma team should brainstorm for possible solutions that could attack the root cause of the issue.
- ✓Brainstorming is an open ended activity, which helps the team generate multiple solutions for the root cause of the problem.
- ✓Assume that the root cause of the problem, hold time, was "employees didn't have enough on-hand assistance ever."

# Multi-Voting

- ✓Multi-voting is a voting/brainstorming technique that prioritizes ideas. Its primary goal is to reduce the range of options available, and thereby preventing an information overload.

- ✓Also known as N/3 voting in multi-voting, where N refers to the total number of ideas. Every team member is then given N/3 votes and instructed to vote for the most important ideas.

- ✓The team member can only assign one vote per idea. Since there are less votes than the number of ideas, the less important idea will naturally be 'weeded out', thus reducing the number of ideas the team must deal with.

- The tool the Six Sigma team will use is countermeasures sheet provided with the excel file, improve toolkit. The improve toolkit contains all the tools that can be used in the improve phase.
- Snapshot of the countermeasures sheet is attached below:

| Problem Statement: | During (time), major contributor accounted for 40% of problem which was 2X higher than desired. | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Root Cause | Countermeasure/Proposed Solutions | Feasibility | Specific Actions | Effectiveness | Overall | Action (Who?) | Value ($/period) |
| | | 3 | | 5 | 15 | | |
| | | 2 | | 2 | 4 | | |
| | | | | | | | |
| | | | | | | | |
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# Brainstorming, Prioritization, and Cost Benefit Analysis (Contd.)

| Problem Statement: | During (time), major contributor acounteted for ian cthan | | | | | | |
|---|---|---|---|---|---|---|---|
| Root Cause | Countermeasure/Proposed Solutions | Feasibility | Specific Actions | Effectiveness | Overall | Action (Who?) | Value ($/period) |
| Lack of hands on assistance | Website to be updated with all issues and solutions | 4 | Project Manager to ensure the website to be setup with all necessary documentation | 4 | 16 | PM | $2000 |
| Lack of hands on assistance | Special team to be setup which will handle escalated or difficult situations | 3 | Operations Manager to identify key employees to be a part of L2 team | 5 | 15 | OM | $3000 |

- ✓ From the countermeasures sheet, it can be seen that solution 2 that is aimed at attacking the same root cause is probably more effective than solution 1, though solution 1 is more feasible.
- ✓ Note that the ratings should be provided as a team. The graph presented in the countermeasures sheet will tell the priority of the solutions to be implemented.
- ✓ This tool can be used by the team to update preventive actions if any.

- ✓ The Six Sigma team should also update the tool, action plan provided with the improve toolkit. The action plan document is a documentary of the change that is proposed and how the change would be carried out. Snapshot of the tool is attached here.

**Action Plan**

| Type | What | How | Who | When | Where | Why |
|---|---|---|---|---|---|---|
| Strategy | | | | | | |
| People Organization | | | | | | |
| Process | | | | | | |
| Technology | | | | | | |

# Brainstorming, Prioritization, and Cost Benefit Analysis (Contd.)

- ✓ Cost benefit analysis is an important analysis the Six Sigma team needs to do, as every solution to be implemented is judged on two main things – Cost needed to implement the solution; and the benefits the company would get out of implementing the solution.
- ✓ Cost benefit analysis is often expressed by three main metrics:
  - B-C ratio (Benefit to Cost Ratio);
  - Net present value (also called as NPV); and
  - Internal rate of return (also called as IRR).

# Brainstorming, Prioritization, and Cost Benefit Analysis (Contd.)

✓**Example:** 3 solutions have been thought of by the Six Sigma improvement team. The associated costs and benefits for a six month review range is presented below. The B-C ratio is also presented for review.

| Solution | Costs (In $) | Benefits projected ($) | B-C Ratio |
|---|---|---|---|
| A | $10,000 | $20,000 | 2 |
| B | $25,000 | $75,000 | 3 |
| C | $5,000 | $30,000 | 6 |

**Which one of these solutions would the Sponsor prefer?**

# Brainstorming, Prioritization, and Cost Benefit Analysis (Contd.)

✓ **Net Present Value**

- Cost = $20,000
- Rate of discount = 10%
- Benefits year 1 = $5,000
- Benefits year 2 = $5,000
- Benefits year 3 = $11,000

✓ To calculate NPV, use the excel formula =NPV(). Add a negative sign to the costs to calculate NPV.

✓ The benefit value after using the NPV formula is $16,932. Subtract $20,000 from $16,932.

✓ Net present value = -$3,068.

✓ Profitability index = -$3068/$20000 = -0.15.

**Internal rate of return**

- ✓The company benchmarks its cost of capital on 16%. To calculate internal rate of return, use the formula =IRR(). Include the costs and benefits in the formula.
- ✓Using the formula on the costs and benefits mentioned, the IRR is 2%.
- ✓The IRR is less than the cost of capital. The solution that has IRR value less than cost of capital **will not be chosen** due to benefit constraints.
- ✓The profitability index from NPV calculations had a negative result. The solution definitely cannot be chosen for over the next 3 years; **this solution will not yield financial benefits.**

# Poka Yoke

- ✓Poka yoke is a Japanese term that means “mistake proofing”.
- ✓Poka yoke is any mechanism in a lean manufacturing process that helps an equipment operator avoid mistakes.
- ✓Its purpose is to eliminate product defects by preventing, correcting, or drawing attention to human errors as they are occurring.
- ✓Poka yoke forces the user to do a task only one way.
- ✓Poka yoke creates less waste and increases productivity.
- ✓By implementing a fail-safe environment, less focus is placed on those tasks, workloads on the employees are decreased, and outputs are increased.

# Summary

In this lesson, we have learned:

✓Brainstorming

✓Multi-voting techniques

✓Solutions prioritization

✓Cost benefit analysis

✓Poka yoke

# Section V, Lesson 5

## Piloting, Validating, and FMEA

# Agenda

- ✓Pilot Solutions
- ✓Piloting Tools
- ✓Paired t Test
- ✓Improve – Next Steps
- ✓Failure Mode Effects Analysis

# Pilot Solutions

- ✓Lean Six Sigma Black Belts are trained to implement and work on enterprise wide deployments.
- ✓Deploying a solution in the improve stage on the entire enterprise may be fraught with risk.
- ✓The solution is theoretical and has only been tested from a cost/benefit angle. Evidence needs to be gathered on the on-ground success of the solution.
- ✓On-ground success or failure of the solution can be determined by piloting, i.e., deploying the change effort in small teams.
- ✓The ratio to be followed is 10-40-50, i.e. ,deploy the solution on 10% of the entire scope span of control, then 40%, and finally 50%. This allows the Six Sigma team to delimit the possible risks of the solution.

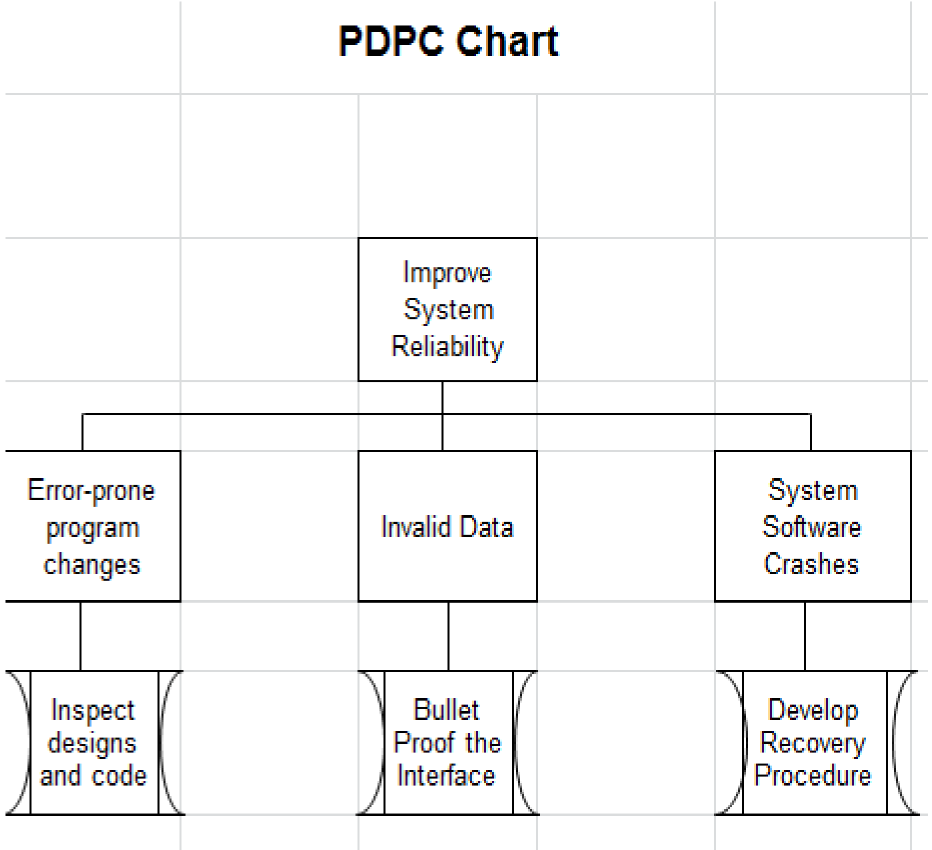
✓Risk assessment matrix – To be updated first in phase 1 pilot and then in subsequent phases.

RISK ASSESSMENT MATRIX

| Risk Description | Business Impact (1, 3, 5) | Probability of Occurance (1, 3, 5) | Priority |
|---|---|---|---|
| | | | 0 |
| | | | 0 |
| | | | 0 |
| | | | 0 |
| | | | 0 |
| | | | 0 |
| | | | 0 |

# Piloting Tools (Contd.)

- ✓PDPC – To be used as a contingency planning tool. Pre-empts possible reasons why a change effort could fail.



# Paired t Test

- The piloting phase must last at least one week, during which the Six Sigma team must understand possible risks.
- In the next week, the Six Sigma team must collect post improvement data. Any improvement made must be statistically validated. The paired t test is an excellent tool for statistical validation of the data collected.
- Data collected for hold time before and after improvement given on a pilot run is as shown here:

| Before Hold Time (in seconds) | After Hold Time (in seconds) |
|---:|---:|
| 27 | 15 |
| 28 | 17 |
| 52 | 28 |
| 30 | 17 |
| 34 | 20 |
| 62 | 31 |
| 71 | 55 |
| 65 | 26 |

## Paired t test results

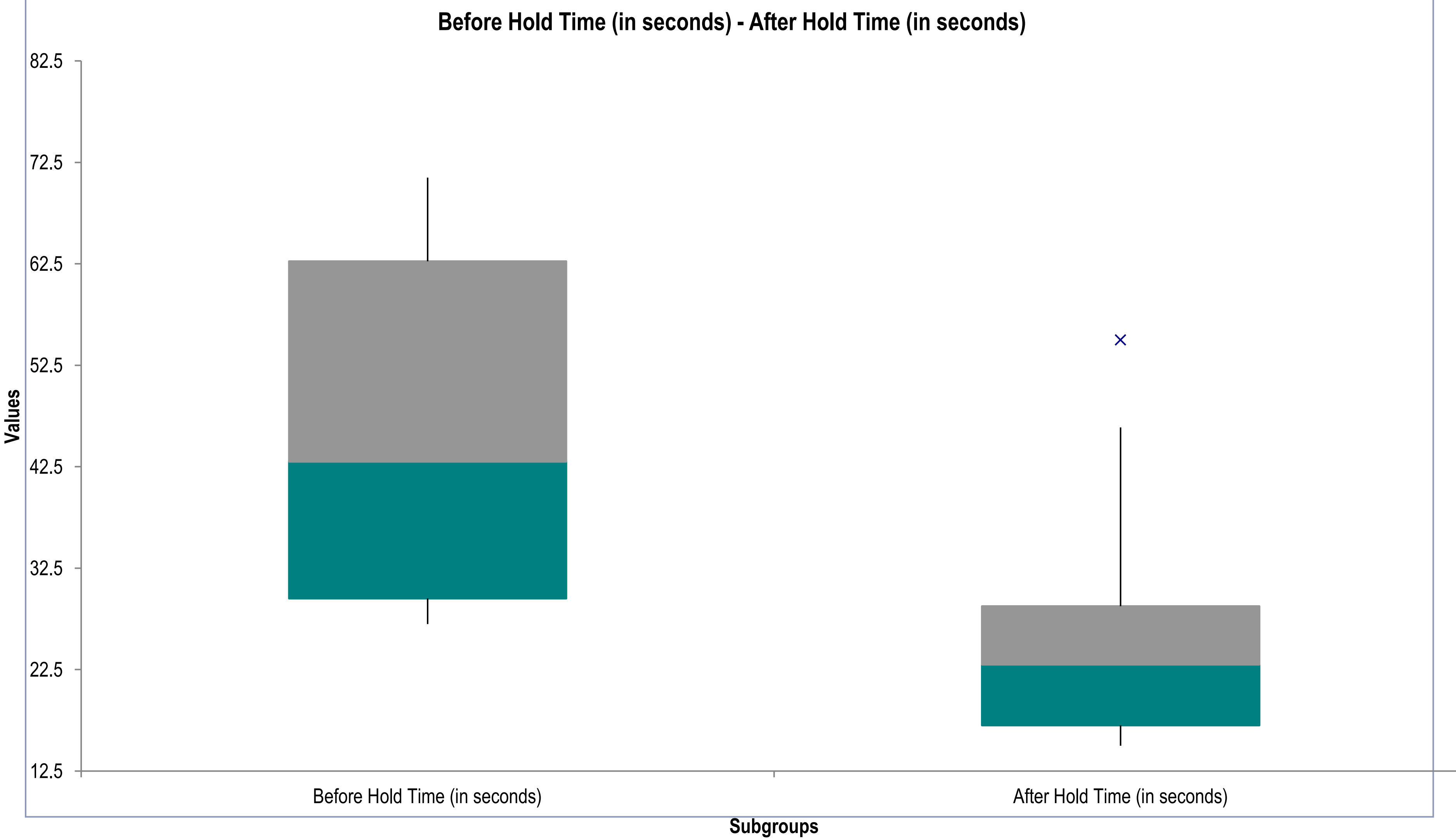
| | | |
|---|---|---|
| t-Test: Paired Two Sample for Means | α | 0.05 |
| | | |
| | *Before Ho* | *After Hold Time (in seconds)* |
| Mean | 46.125 | 26.125 |
| Variance | 337.5536 | 169.8393 |
| Observations | 8 | 8 |
| Pearson Correlation | 0.837606 | |
| Hypothesized Mean Difference | 0 | |
| df | 7 | |
| t Stat | 5.487 | |
| P(T<=t) one-tail | 0.000 | Reject Null Hypothesis because p < 0.05 (Means are Different) |
| T Critical one-tail | 1.895 | |
| P(T<=t) two-tail | 0.001 | Reject Null Hypothesis because p < 0.05 (Means are Different) |
| T Critical Two-tail | 2.365 | |

# Paired t Test Interpretations

- ✓The null should be rejected due to a significant p-value.
- ✓That means, the before group mean and the after group mean are different. Whether the after group mean is less than the before group mean, it can be tested by looking at the box plot.
- ✓If the box plot shows that after hold time is less than before hold time, it means that the improvement measure has worked. The solution, if all risks have been identified, can be deployed across the enterprise.

# Paired t Test (Contd.)

## Graphical analysis



# Paired t Test (Contd.)

- ✓ The paired t test has been done on the KPIV (hold time), as our improvement measure was directed at improving the KPIV.
- ✓ Do a paired t test on the KPOV performance and see if improvement in KPOV is validated or not. If the test passes, i.e., the null for the KPOV groups could be rejected, the improvement measure has been able to work on the KPOV as well.

**Important : Please note the following conditions for a paired t test:**

1) Data must come from a normal distribution.
2) Data must come from related groups and not independent groups.
3) Sample size must be less than 30.

# Improve – Next Steps

- ✓ If the pilot run has been successful, i.e., if we have managed to statistically validate the change, following steps would be to run the solution through phase 2, and phase 3 of implementations.
- ✓ The pilot run for each phase should be 1-2 weeks.
- ✓ To ensure repeatability and reproducibility, do not change the operators and the measurement system.
- ✓ Statistically validate all solution deployments with the help of a paired t test.
- ✓ Test with simple linear or multiple linear regression, and half normal plots if all relationship conditions are met by the model.
- ✓ If all deployments across phases are statistically validated, conduct an enterprise wide deployment study for one month. Re-validate the data using a paired t test.

# Failure Mode Effects Analysis

- ✓ Failure mode effects analysis (FMEA) is commonly referred to as a pre-emptive tool, i.e., with the risk assessment matrix, this tool can be used to assess possible risks to the process. The FMEA sheet is provided in the improve toolkit.
- ✓ FMEA is also used as a business measure to show improvement.
- ✓ The key metric to be noted in an FMEA matrix is RPN or risk priority number.
- ✓ Risk priority number = Severity * Occurrence * Detection, where,
  - Severity = How severe the failure mode is;
  - Occurrence = How probable the failure mode is to occur; and
  - Detection = How easy would it be for the process team to detect the failure mode.

- ✓The first document that needs to be updated is the FMEA checklist.
- ✓The FMEA document should only be updated once the checklist questions are answered. Snapshot of the FMEA checklist is attached below:

| | Question | Yes | No | N/A | Comment / Action Required | Person Responsible | Due Date |
|---|---|---|---|---|---|---|---|
| 1 | Was the Process FMEA prepared by a cross functional team? Has the team taken into account all customer specific requirements, including FMEA methodologies as shown in the current edition of FMEA? | | | | | | |
| 2 | Have all operations including subcontracted or 2 outsourced processes and services been considered? | | | | | | |
| 3 | Have all operations affecting customer requirements including fit, function, durability, governmental regulations and safety been identified and listed sequentially? | | | | | | |
| 4 | Were similar part/process FMEAs considered? | | | | | | |
| 5 | Have historical campaign and warranty data been reviewed and used in the analysis? | | | | | | |
| | Have you applied the appropriate controls to address all of the identified failure modes? — | | | | | | |

# Failure Mode Effects Analysis (Contd.)

- ✓The FMEA template is attached in the toolkit.
- ✓Note: A Green Belt will know how to update the template. A Black Belt should ensure that along with the entire Six Sigma team, the process expert is present while the FMEA is being updated.
- ✓The Black Belt needs to be present while documenting the FMEA.

**Potential**
**Failure Mode and Effects Analysis**
**(Process FMEA)**

| | | | | | |
|---|---|---|---|---|---|
| | | | | FMEA Number | Insert FMEA# |
| | | Process | | Page | 1 of 1 |
| Item | Name/number of item | Responsibility: | Name | Prepared by: | who |
| Model Years: | model years/programs | Key Date: | 15-07-2008 | FMEA Date: | 15-07-2008 |
| Core Team: | Team members | | | | |

| Process Step / Requirements | Potential Failure Mode | Potential Effect(s) of Failure | Severity | Class | Potential Cause(s) / Mechanism(s) of Failure | Occurrence | Current Process Controls Prevention | Current Process Controls Detection | Detection | R. P. N. | Recommended Action(s) | Responsibility & Target Completion Date | Action Results: Actions Taken & Completion Date | Severity | Occurrence | Detection | R. P. N. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Name, Part Number, or Class**<br><br>**Function** | **Manner in which part could fail: cracked, loosened, deformed, leaking, oxidized, etc.** | **Consequences on other systems, parts, or people: noise, unstable, inoperative, impaired, etc.** | | | **List every potential cause and/or failure mechanism: incorrect material, improper maintenance, fatigue, wear,** | | **List prevention activities to assure process adequacy and prevent or reduce occurrence** | **List detection activities to assure process adequacy and prevent or reduce occurrence** | | | **Design actions to reduce severity, occurrence and detection ratings. Severity of 9 or 10** | **Name of organization or individual and target completion date** | **Actions and actual completion date** | | | | |

# Failure Mode Effects Analysis (Contd.)

- ✓ A sample part/failure mode is updated in the FMEA template. The failure mode is that the part #103 is found to be deformed (nut bolting process). The deformed part cannot be fitted into car wheels (end customer product). Improper fitting procedure and bolting time has resulted in this failure mode.

- ✓ The severity, occurrence, and detection rating guidelines are presented in the FMEA template. Updating the individual ratings, the existing RPN pre-improvement was 700.

- ✓ The improvement measures taken are documented in the extreme right columns. These measures would have been implemented in the pilot and enterprise wide deployments.

- ✓ The revised RPN is then calculated and presented as a **business measure** to the Sponsor of the Six Sigma team.

# Failure Mode Effects Analysis (Contd.)

| Name, Part Number, or Class<br><br>Function | Manner in which part could fail: cracked, loosened, deformed, leaking, oxidized, etc. | Consequences on other systems, parts, or people: noise, unstable, inoperative, impaired, etc. | | | List every potential cause and/or failure mechanism: incorrect material, improper maintenance, fatigue, wear, etc. | | List prevention activities to assure process adequacy and prevent or reduce occurrence. | List detection activities to assure process adequacy and prevent or reduce occurrence. | | 0 | Design actions to reduce severity, occurrence and detection ratings. Severity of 9 or 10 requires special | Name of organization or individual and target completion date | Actions and actual completion date | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Part #103 | Deformed Part | Part cannot be fit into wheels | 10 | | Improper fitting procedure and screwing time | 7 | No Quality Controls on current fitting process | None as of now | 10 | | Processing line training provided and additional Jidoka check to | Plant Manager | | 10 | 3 | 3 |

# Summary

In this lesson we have learned:

- ✓Piloting
- ✓Validating
- ✓FMEA

By the end of the improve phase, you should have not only validated your improvements, but also measured the revised or new Cp or Cpk value to **show the process has indeed improved.**

# Improve – Activity Summary

1. Test model parameters using designs of experiments.
2. Understand improvement model using DOE with regression.
3. Brainstorm for solutions.
4. Do a cost benefit analysis using NPV/IRR.
5. Pilot the solutions.
6. Validate using paired t.
7. Phase 2 deployment.
8. Validate using paired t.
9. Phase 3 deployment.
10. Validate using paired t.
11. If no improvements made, re-engineer using DFSS.

11a. If improvements made, update FMEA and calculate new Cp and Cpk.

# Quiz

1. Which of these is true about designed experiments?

a) Misses out on interactions

b) Tests one factor at a time

c) Will be able to show the lack of fit for model

d) Depends on the skill of the Black Belt

2. For a full factorial $2^3$ design with 1 replicate, how many runs could you expect?

a) 8

b) 16

c) 4

d) 32

# Quiz

3. For a 2 level, 5 factor experiment, if the number of runs on 2 replicates is 16, which of the following experiment is the Black Belt looking at?

a) Full factorial

b) Half fractional factorial

c) Quarter fractional factorial

d) None of the above

4. Which of the below techniques allows you to eliminate errors due to nuisance factors?

a) Blocking

b) Coding

c) Transformation

d) Replication

5. In a four factor factorial experiment (fractional), the design results show I = ABCD? What does ABCD here stand for?

a) Coded interactions

b) Aliased interactions

c) Combination of main effects

d) Design Generator

# Answers

1. c) Note the other options, they are not even close to qualify to being characteristics of designed experiments, so answer c) is the only logical option.
2. a) Generally, 1 replicate means 1 additional replicate, which is not the case. Designed experiments run by default on one replicate, so 8 runs is the right answer.
3. b) 2 Factors and 5 levels on one replicate = 32 runs, meaning it is a full factorial. For half factorial designs, the fractionating factor is f-1, thus, the correct answer is half fractional factorial with 16 runs.
4. a) Blocking is the correct answer.
5. d) In a four factor experiment, the notation of I = ABCD means ABCD is a design generator.

# Thank You