Tab 6:

Planning an Experiment

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Purpose:

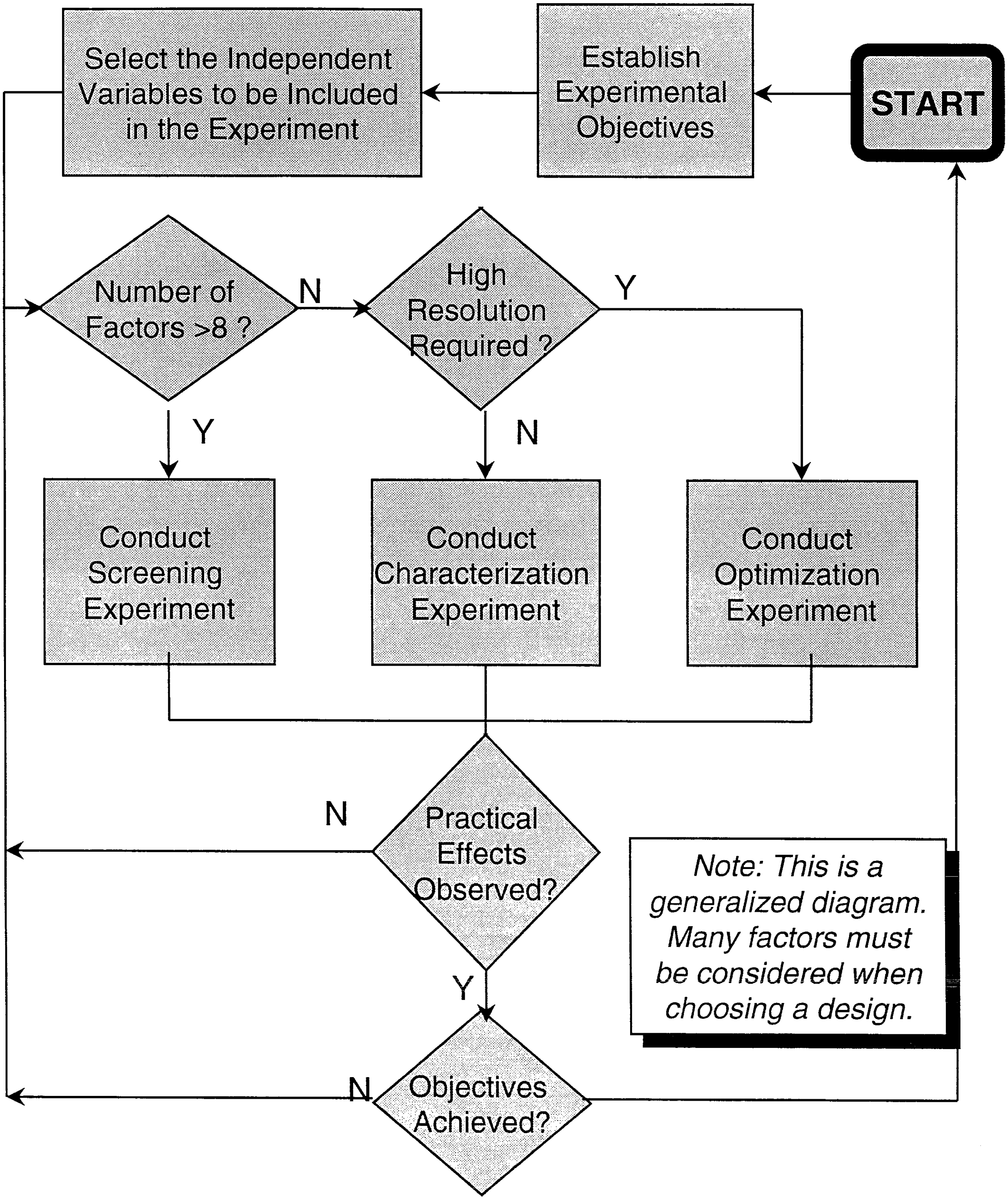
The purpose of this section is to give some practical guidelines in planning experiments. This section is intended to be a "checklist" of items to review before running an experiment.

Objectives:

1) Define steps in planning an experiment

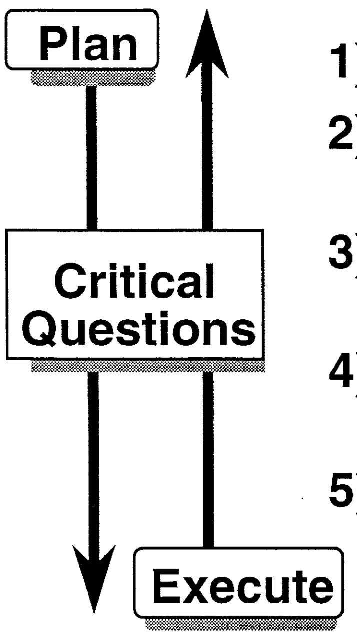
2) Recognize potential barriers to effective designs

Selecting an Approach



Note: This is a generalized diagram. Many factors must be considered when choosing a design.

The Planning Questions



1) What do you want to know?

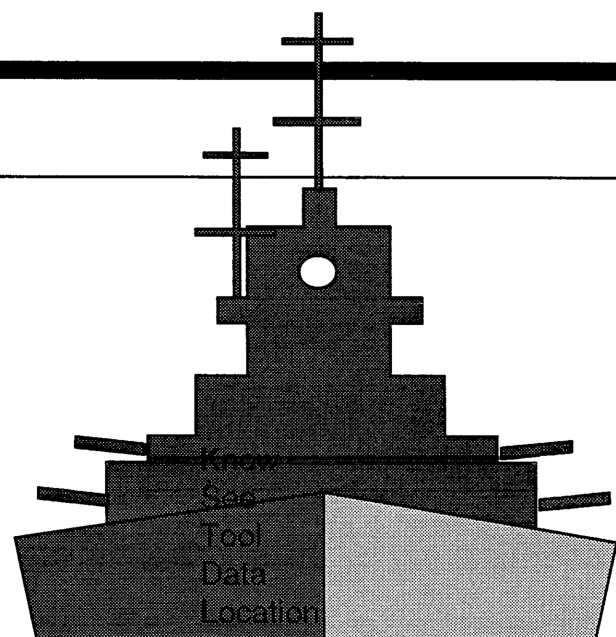
2) How do you want to look at what you need to know?

3) What type of tool will generate what you need to see?

4) What type of data is required of the selected tool ?

5) Where can you get the required type of data?

The Principle of Reverse Loading



What do you need at the Improve Phase dock?

Measure Phase Deliverables:

- Advocacy Team
- Problem Statement, including Y response
- Process map of process
- Baseline of Y response
- 4-block for area of focus

Analyze Phase Deliverables:

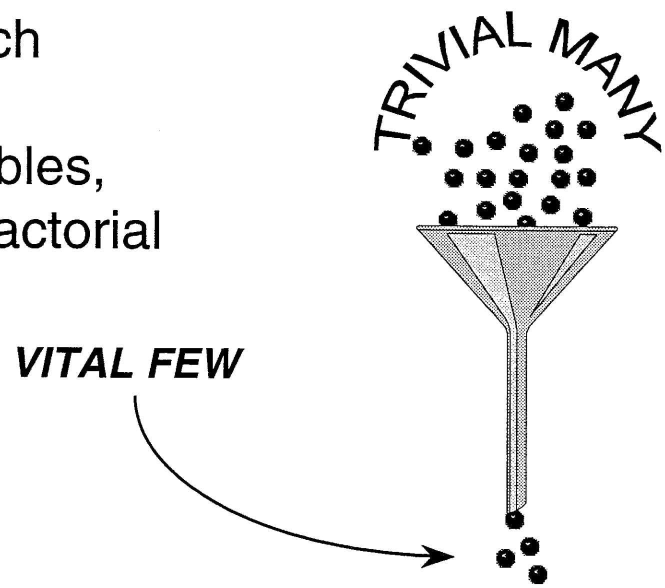
- Analysis of baseline data
  - Graphs
  - F, t and Chi^2 Tests
  - ANOVA
- Suspected Vital X's

Management Team Buy-in:

- Time
- Cost
- Support of DOE Strategy
- Resources

Types of Experiments

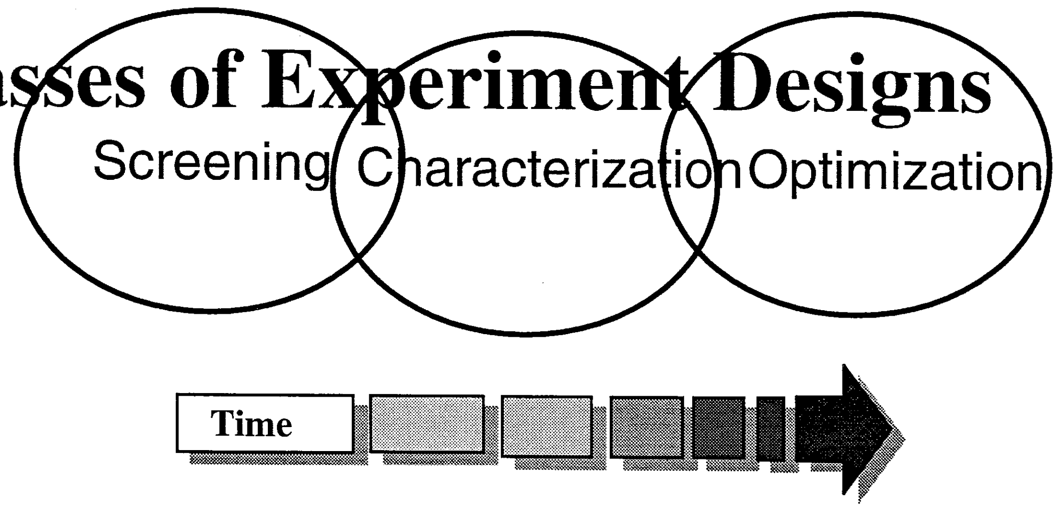
1. **Screening experiments** -- used to determine which variables are the most important (many variables, few levels - fractional factorial designs).



2. **Detailed study of a few variables** -- Use more levels of the independent variables (full factorial designs, response surface designs) to fit a more complex model via regression analysis.

3. **Confirming experiments** -- used to demonstrate that promising results can be repeated.

Classes of Experiment Designs



Screening Designs: Resolution III designs. Used to isolate the "vital few" variables from the "trivial many;" i.e., those instances involving a very large number of factors. Such designs are most often limited to two levels and are principally used to for the study of main effects.

Characterization Designs: Resolution IV and V designs. Generally used to study relatively uncomplicated effects and interactions resulting from a relatively small number of factors. Generally speaking, such designs are based on the full factorial model using two or three levels. Sometimes, fractional factorials are employed for this purpose when there is a moderate number of factors to be studied and the confounding of certain interactions does not pose a problem.

Optimization Designs: Resolution V and higher designs. Most often used to study highly complicated effects and relationships involving two or three variables. In general, such designs are employed to yield a reasonably precise mathematical model of the phenomenon under investigation.

Note: The class descriptions are very general by nature. Such descriptions are intended for instructional purposes only and should not be used as as the sole benchmark when designing an experiment.

Iterative Nature of the Experimental Process:

- **Preliminary Experiments:**

  It is sometimes better to run a series of small or screening experiments first, rather than relying on one large experiment. In the early experiments you can learn:

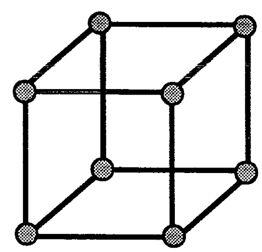
  1. What variables are important. This may give insight into mechanisms that might control the process, and suggest variables to use in later experiments.

  2. How to conduct the experiments. This can be used to improve your experimentation technique in later experiments.

- **Sequential Experiments:**

  Run an initial design and analyze results. Decide if more experimentation is warranted to test additional regions/variables, or to explore the current region/variable in more detail.

  Example: Start with a 2^2 design (4 runs). If results show that you are not quite in the desired region, chose levels in the desired direction and run another small experiment.



Steps in Planning an Experiment

1) Define the Objective
2) Select the 'Y'-Response (Dependent) Variables
3) Select the 'X' (Independent) Variables
4) Choose the 'X' Variable Levels
5) Select the Experimental Design
6) Run the Experiment & Collect the Data
7) Analyze the Data
8) Draw Conclusions
9) Perform Confirmation Run

The purpose of an experiment is to better understand the real world, not to understand the experimental data

William Diamond
IBM - Retired Statistician

1. Define the Objective

State the objective of an experiment in the form:

- Estimate the effects of: [list of <u>independent</u> variables]
- On the responses of: [list of <u>dependent</u> variables]

<u>Examples:</u>

1) Estimate effects of time, temperature and cleaner concentration on the response of residue.

2) Estimate the effects of region and % floor loading on sales volume.

While planning an experiment, it is useful to ask the following questions:

1) What decisions are to be made with the data?
2) How will the data be analyzed after it is collected?
3) Will the data and analyses allow the required decisions to be made?

If the answer to # 3 is no, then re-design the experiment.

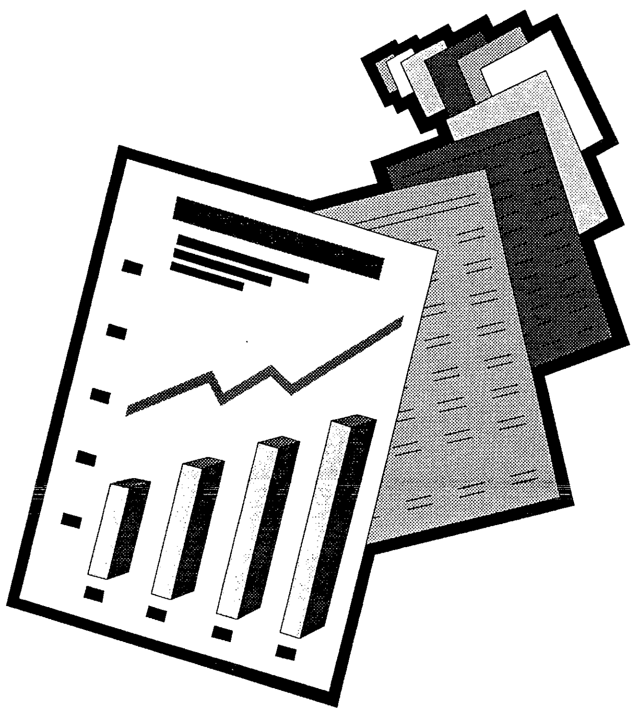
2. Select the ‘Y’ Response (Dependent) Variables

It is possible to measure *several* dependent (response) variables and model each of these as a functions of the independent variables at the same time.

Variable vs. Attribute data

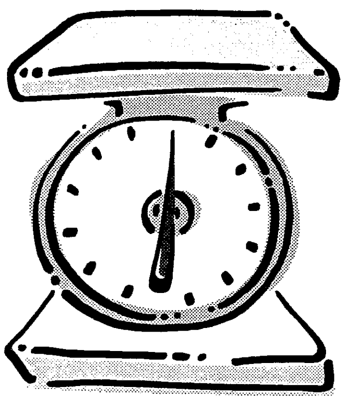
Attribute data (pass/fail) is less than 63% as efficient as variable data (continuous measurements). This means that much more data is required to draw statistically valid conclusions.

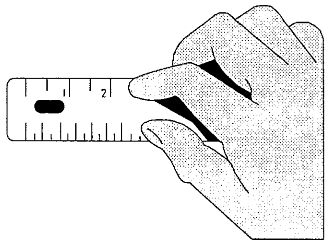
However, sometimes it is difficult to get quantitative measurements of the response of interest. It is often possible to use *rankings* or *comparisons to standards.*

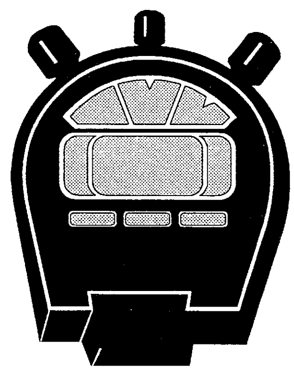


Don't forget Gauge R&R...

Regardless of the type of data you have you must validate your <u>measurement system</u> *before* running your experiment. If it is unacceptable, it <u>must</u> be improved (reduced) to <20%.







Remember - Gauge R&R is important for both Y's <u>and</u> X's!

3. Select 'X' (Independent) Variables

There are many types of 'X' variables:

- Design variables, intentionally varied in the experiment
- Blocking variables
- Variables that are held constant
- Variables that are monitored, but not intentionally changed
- Noise variables
- Lurking variables

Select the 'X' variables to study through:

- Expert opinion
- Brainstorming
- Flow charts
- Baseline data
- Cause & Effect diagrams
- Competitive analysis
- Supplier input
- "Walk the Process"
- Rolled Throughput Yield

3. Select 'X' (Independent) Variables (cont'd)

Rationale for studying **many variables at once...**

- There are often many candidate variables.
- Experiments give team members a chance to input and test their variables of interest.
- You can follow-up later with a confirming experiment or a more detailed experiment with fewer variables.

Selecting the Right 'X' Variables:

- Experience shows that **only 2 to 6** variables will end up being the 'Vital Few'

- The challenge is to find the most influential "X"s and the *test range* that makes them visible.

- Test the *most likely* candidates **first**

- Keep the design *simple* unless little is known about the process. In that case, test many variables to narrow in on the 'Vital Few' (screening experiment)

- Remember, experimentation is a *judgement call* made by you and your advocacy team --- **Sometimes you could be wrong!**

4. Choose Levels for the 'X' Variables

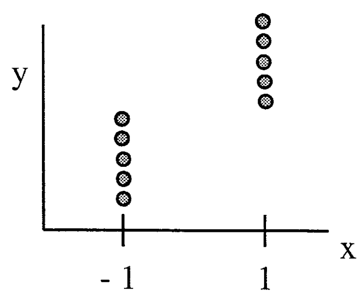
The number of levels you choose depends on the **objective** of the experiment and the **graph** of the response.

- If you are searching for the important variables with a screening experiment, typically two levels are used.

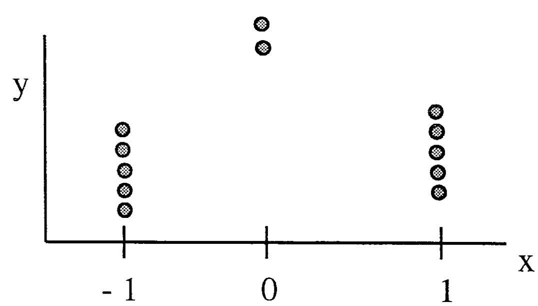
- If you can't fit a line through the data (a potentially non-linear response), don't model with a line.

- If you know the variable is Vital and want to study its effect in detail, typically more than two levels are used.

TWO-LEVEL EXPERIMENT:



THREE-LEVEL EXPERIMENT:



When choosing the Variable Levels...

- The range must be wide enough to show a difference, IF there is a difference.

  Example: Changing temperature by one degree will likely have little effect on the outcome, and you might *incorrectly* conclude that temperature is not an important variable.

- Understand that levels must not be beyond the range of feasibility (but they may be beyond current process range!).

- Realize that some combinations in the test will produce unacceptable responses, and that these results are expected and desirable.

5. Select the Experimental Design

When designing the experiment, consider 10 Key Elements...

a) Orthogonality
b) Randomization
c) Replication
d) Repetition
e) Controls
f) Lurking Variables
g) Noise Variables
h) Blocking
i) Sample Size
j) Confounding

10 Key Elements of Experimental Designs

a) Orthogonal arrangements (factorial and fractional factorial test plans) are used to separate the effects of the variables.

b) Randomization to reduce the effects of extraneous variables, and ensure that the statistical tests of significance are valid.

Randomize:
- Run order
- Assignment of experimental units
- Measurement order

c) Replication (completely re-setting the experiment and obtaining additional results at the same levels)
- Reduces the variability of an estimate (shorter confidence intervals)
- Gives an estimate of variation and confidence in the results.

10 Key Elements of Experimental Designs (cont'd)

d) Repetition (measure multiple samples from each experimental run)

- Not as beneficial as Replication, but does allow you to estimate variation.

e) Controls and reference distributions. Most experiments are comparative. Including a control or baseline can be extremely useful.

f) Lurking Variables are variables that can affect the results but are unknown, uncontrolled, uncontrollable or un-measurable.

The influence of lurking variables can often be reduced by blocking and randomization.

10 Key Elements of Experimental Designs (cont'd)

g) Noise Variables are known (or thought) to affect the results, but we either cannot or choose not to control them. Examples: humidity, day of the week, competitor incentives.

To reduce the effect of noise variables, select test variables that can be monitored across all levels in the experiment.

Example:
We want a washer design that works well for all fabrics and all loads because we cannot predict or control this in our consumer's homes. 'Time' and 'Gallons' are test variables. 'Load Size' (6 or 10 lbs) and 'Fabric Type' (Cotton or Blend) are *noise variables.*

We could set up the experiment like this:

(Test Variables)		*(Noise Variables)*				
		Cotton	Cotton	Blend	Blend	Fabric Type
Time	Gallons	6	10	6	10	Load Size
10	4	X	X	X	X	
10	8	X	X	X	X	
10	4	X	X	X	X	
10	8	X	X	X	X	

10 Key Elements of Experimental Designs

h) Blocking (cont'd)

A 'block' is group of homogeneous units.
Compare independent variables within blocks, not between blocks.

Benefits of blocking:

- Gives all independent variables an equal chance (a fair test)
- Gives some protection against confounding and lurking variables
- Reduces variation and gives higher precision of the estimates

(It is often good to block on time or run order)

Blocking example 1: Test 4 types of coatings (A, B, C, D) on 4 samples of steel.

Steel sample 1	A	B	C	D
Steel sample 2	B	C	D	A
Steel sample 3	C	D	A	B
Steel sample 4	D	A	B	C

A blocking variable is generally a variable that "gets in the way." You could consider it just another independent variable . . . .

Blocking example 2: Block on time or run order

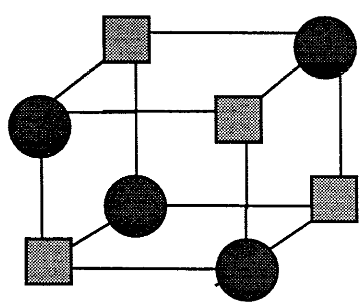
Scenario: Take samples on Monday and Wednesday at a call-taking center, in order to capture the effects of day of the week.

2^3 experiment, 8 runs, 2 blocks (days) with 4 runs per block

X_1	X_2	X_3	$X_1{*}X_2{*}X_3$	Block
-1	-1	-1	-1	1 - Mon
-1	-1	1	1	2 - Wed
-1	1	-1	1	2 - Wed
-1	1	1	-1	1 - Mon
1	-1	-1	1	2 - Wed
1	-1	1	-1	1 - Mon
1	1	-1	-1	1 - Mon
1	1	1	1	2 - Wed

Runs with $X_1{*}X_2{*}X_3 = -1$ become block 1, and are run on day 1
Runs with $X_1{*}X_2{*}X_3 = 1$ become block 2, and are run on day 2

Each block is a 2^{3-1} fractional factorial experiment.



10 Key Elements of Experimental Designs (cont'd)

i) Determining Sample Size

There is usually a **trade-off** between cost and precision when deciding how many samples to take

You must consider:
- Variability
- The size of difference that is important
- The level of confidence to determine the appropriate sample size

(See the Bill Wunderlin paper on "Determining Sample Size", in the Appendix of this tab)

Example: You have a distribution with $\sigma = 1$ and want to see a shift of $\delta = 0.8$. From the sample size table ($\alpha = .05$, $\beta = .10$) we see that n = 33. Since we have set up a 2^3 design (8 Runs), we will need to measure 8 samples at each level combination as shown below:

A	B	C	n / Cell	
-	-	-	8	32 samples
+	-	-	8	
-	+	-	8	
+	+	-	8	
-	-	+	8	32 samples
+	-	+	8	
-	+	+	8	
+	+	+	8	

A Basic Sample Size Table

Applies to continuous data only

α → (column groups); β → (sub-columns)

	α = 20%				α = 10%				α = 5%				α = 1%			
δ/σ	20%	10%	5%	1%	20%	10%	5%	1%	20%	10%	5%	1%	20%	10%	5%	1%
0.2	225	328	428	651	309	428	541	789	392	525	650	919	584	744	891	1202
0.3	100	146	190	289	137	190	241	350	174	234	289	408	260	331	396	534
0.4	56	82	107	163	77	107	135	197	98	131	162	230	146	186	223	300
0.5	36	53	69	104	49	69	87	126	63	84	104	147	93	119	143	192
0.6	25	36	48	72	34	48	60	88	44	58	72	102	65	83	99	134
0.7	18	27	35	53	25	35	44	64	32	43	53	75	48	61	73	98
0.8	14	21	27	41	19	27	34	49	25	33	41	57	36	46	56	75
0.9	11	16	21	32	15	21	27	39	19	26	32	45	29	37	44	59
1.0	9	13	17	26	12	17	22	32	16	21	26	37	23	30	[illegible]	[illegible]
1.1	7	11	14	22	10	14	18	26	13	17	21	30	19	25	[illegible]	[illegible]
1.2	6	9	12	18	9	12	15	22	11	15	18	26	16	21	[illegible]	[illegible]
1.3	5	8	10	15	7	10	13	19	9	12	15	22	14	18	[illegible]	[illegible]
1.4	5	7	9	13	6	9	11	16	8	11	13	19	12	15	18	25
1.5	4	6	8	12	5	8	10	14	7	9	12	16	10	13	16	21
1.6	4	5	7	10	5	7	8	12	6	8	10	14	9	12	14	19
1.7	3	5	6	9	4	6	7	11	5	7	9	13	8	10	12	17
1.8	3	4	5	8	4	5	7	10	5	6	8	11	7	9	11	15
1.9	2	4	5	7	3	5	6	9	4	6	7	10	6	8	10	13
2.0	2	3	4	7	3	4	5	8	4	5	6	9	6	7	9	12
2.1	2	3	4	6	3	4	5	7	4	5	6	8	5	7	8	11
2.2	2	3	4	5	3	4	4	7	3	4	5	8	5	6	7	10
2.3	2	2	3	5	2	3	4	6	3	4	5	7	4	6	7	9
2.4	2	2	3	5	2	3	4	5	3	4	5	6	4	5	6	8
2.5	1	2	3	4	2	3	3	5	3	3	4	6	4	5	6	8
2.6	1	2	3	4	2	3	3	5	2	3	4	5	3	4	5	7
2.7	1	2	2	4	2	2	3	4	2	3	4	5	3	4	5	7
2.8	1	2	2	3	2	2	3	4	2	3	3	5	3	4	5	6
2.9	1	2	2	3	1	2	3	4	2	2	3	4	3	4	4	6
3.0	1	1	2	3	1	2	2	4	2	2	3	4	3	3	4	5
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3.4	1	1	1	2	1	1	2	3	1	2	2	3	2	3	3	4
3.5	1	1	1	2	1	1	2	3	1	2	2	3	2	2	3	4
3.6	1	1	1	2	1	1	2	2	1	2	2	3	2	2	3	4
3.7	1	1	1	2	1	1	2	2	1	2	2	3	2	2	3	4
3.8	1	1	1	2	1	1	1	2	1	1	2	3	2	2	2	3
3.9	1	1	1	2	1	1	1	2	1	1	2	2	2	2	2	3
4.0	1	1	1	2	1	1	1	2	1	1	2	2	1	2	2	3

Example

10 Key Elements of Experimental Designs (cont'd)

j) Confounding is the inability to separate effects of variables from one another, or from interactions. Remember that all fractional factorials have some degree of confounding.

Example 1: Changing 2 variables together.

Run	X_1	X_2
1	low	low
2	high	high

Did X_1 or X_2 cause the effect??

Example 2: A main effect confounded with an interaction.

Run	X_1	X_2	(X_3) $X_1 * X_2$
1	-1	-1	1
2	-1	1	-1
3	1	-1	1
4	1	1	1

An apparent X_3 effect could also be due to an $X_1 * X_2$ interaction.

Interactions can be important, and must be investigated; however, Main Effects are usually more important than interactions.

Choose a Fractional Factorial Design that minimizes confounding so that Main Effects and important Interactions can be separated

Use of a Design Center Point

- A “center point” is often included in a DOE. Typically the center point is the *normal* operating condition.
- Inclusion of one or more center points in a 2 level factorial design allows the estimation of curvature.
- Use of a center point allows the “interior space” (of the cube) to be investigated.
- The center point may be replicated without destroying the balance of the design.
- The number of center points will not affect the estimation of main effects or interactions.
- The number of center points will not affect the precision of effect estimates.

The Notion of Design Resolution

Resolution III:

No main effect is aliased with any other main effect

Main effects are aliased with second order interactions

Second order interactions are aliased with other second order interactions

Resolution IV:

No main effect is aliased with any other main effect

No main effects are aliased with any second order interactions

Second order interactions are aliased with other second order interactions

Resolution V:

No main effect is aliased with any other main effect

No main effect is aliased with any second order interactions

No second order interaction is aliased with any other second order interaction

Second order interactions are aliased with third order interactions

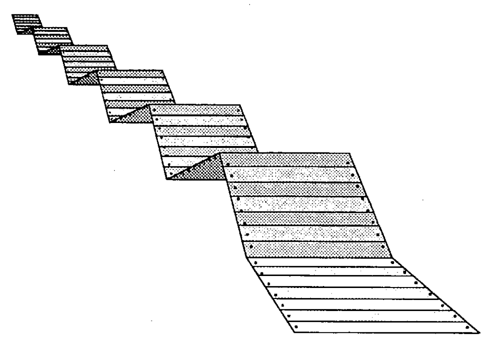
When selecting an experimental design, remember...

Your results must apply beyond:

- one batch of raw materials
- one telephone operator
- one product line
- a lab or pilot plant (but not production)

Example: Sample 4 parts per day for 10 days, rather than 40 consecutive parts on one day.

Deming: To demonstrate success, you need repeated tests over time, with no failures

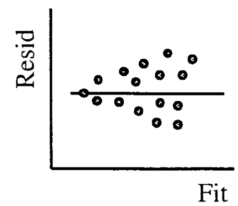


If you want your results to be generic and to apply over a wide range of conditions, then **test** over a wide range of conditions

6) Run the Experiment & Collect Data

- Be sure to set up your data sheet before running experiment to be sure all values are recorded in the desired form.
- Be sure to <u>be</u> there during the experiment - you never know what may happen!
- It is often useful to <u>retain</u> samples, which can be measured again later if there are questions about a particular measurement.

7) Analyze the Data



A) graph GRAPH **GRAPH** **<u>GRAPH</u>**

- Histograms
- Scatter plots
- Cube plots
- Main effects plots - for both mean and standard deviation
- Interaction plots - for both mean and standard deviation
- Contour plots - for Response Surface designs

B) **Confidence Intervals** - valuable because they give a range of plausible values.

C) **ANOVA tables** (Session window) - look for low p-values that indicate significant factors.

8) Draw Conclusions

<u>Questions to be answered:</u>

- Are the results statistically significant?
- Is there evidence of change?
- Are the results <u>practically</u> significant?
- Does the experiment direct you towards how to fix the problem?
- Should we run additional experiments?

9) Perform Confirmation Run

- The Confirmation Run is necessary to verify that you have truly made improvements. Confirmation Runs should be set up in rational subgroups, similar to process baselining. In effect, you are 're-baselining' your process at the new settings.

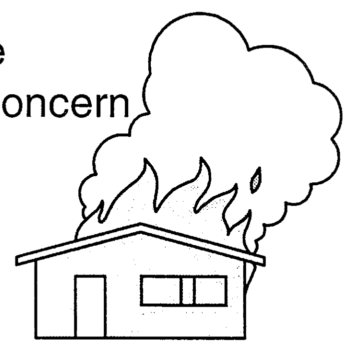
- Be sure to allow the Vital Few X's to naturally vary within the levels set during your confirmation run...but again, do not '<u>tweak</u>' the process. You want to be sure to capture the natural variation of the process to verify that you made an improvement.

WORDS OF WISDOM FROM PEOPLE IN PREVIOUS CLASSES

- **Be present** during the test run

- Make sure that the levels of the independent variables are accurate

- Be sure the changes do not destroy the equipment, or create a safety concern



- You cannot detect the effect of a 2 degree change if you can control only within +/- 1 degree

WHY EXPERIMENTS FAIL

by Bill Wunderlin

- Incorrect assumption about the "acceleration factor" in an accelerated life test (Ex: rotary compressor).
- Test that does not match usage conditions (Ex: Burcliff defrost heater - the heater continues to degrade when it is off).
- No controls, no way to determine if something else changed -- a "lurking" variable (Ex: compressor noise changed with humidity; AP2 calrod - failures were due to high voltage on test stands).
- Tested over too narrow a range: favorable test results do not repeat. If you want your results to be generic and to apply over a wide range of conditions, then *test* over a wide range of conditions.
- Did not include important independent variables -- a "shot in the dark" experiment (Ex: washer brake - a series of changes were made, success was assumed).
- High measurement variation -- cannot detect a change (Ex: washer 'turnover' - the CU test is variable and must be repeated many times).

Key Concepts: Planning an Experiment

- There are 9 steps to planning an experiment:

1) Define the Objective
2) Select the 'Y'-Response (Dependent) Variables
3) Select the 'X' (Independent) Variables
4) Choose the 'X' Variable Levels
5) Select the Experimental Design
6) Run the Experiment & Collect the Data
7) Analyze the Data
8) Draw Conclusions
9) Perform Confirmation Run

- There are 10 key elements to consider when designing an experiment:

- Orthogonality	- Lurking Variables
- Randomization	- Noise Variables
- Replication	- Blocking
- Repetition	- Sample Size
- Control	- Confounding

Trial Advice

- **Preplan the trials**
  - Anticipate potential problems with trial and adjust test plan to minimize the effects.
- **Prepare run sequence considering the following:**
  - Random or "Constrained Random"
  - Consider these factors:
    - Difficulty of setup change
    - Effect of time trends
    - Changes of test equipment
    - Changes of ambient conditions
  - Prepare logical, clear data sheets to match run sequence.
  - Be present during the trial; document conditions or unplanned events.

The Missile

BM (Ballistic Missile) Range Optimization
Design of Experiments Exercise

PHASE 2

1. Multiple teams, with approximately 7 people per team
2. Objective: optimize the firing range of ballistic missiles ('BMs').

NOTE: Two different BMs are available for launch:

A) Yellow missiles (known in military parlance as "soft & cushy, urgent delivery", or 'SCUDs') . COST: $1,000,000 per launch

B) Green missiles ("sleek & pointy, urgent delivery", or 'SPUDs') COST: $1,000,000 per launch

3. Situation: GE has recently bid on a contract with a top secret military installation somewhere in the vicinity of Area 51, somewhere in the southwestern desert of the United States. A lucrative government contract is dependent upon our ability to optimize the travel distance of the BMs, from launch point to initial impact. This distance is measured by a complex, retractible metallic measurement instrument, known in layman's terms as a "tape measure". Your team's mission, should you decide to accept it, (which would be a REALLY good plan, in this case) is to find the ~~combination of variables that will shoot the BM the required distance,~~ which is 48 inches (measured from the leading edge of the catapult base), ~~with a tolerance~~ of +/- 6 inches.

10' ± 6"

4. Methodology:

A. Brainstorm potential variables that could influence the launch distance - agree as a team to the top 5 (or fewer) on which to run the experiment. NOTE: you have worked with this missile launching system in the past, but you may want to baseline this process a second time. Since the baseline is the foundation of our understanding of the process, the government has agreed to pay for the baselining - regardless of sample size (translation: you don't have to count baselining missile shots). Remember: "Baselining" means characterizing your process as it stands today, WITHOUT changing the process settings!

Every shot you make (after baselining) must be accounted for in order for GE to be reimbursed by the government for the cost of the preliminary testing. One of the reasons we are being considered for this contract is the level of respect for our integrity policy . . . keeping track of all shots made is YOUR responsibility (your conscience). Shots using psuedo-missiles (rolled-up tape or other creative designs) WILL count towards your total dollars expended!

B. Choose levels to test for the independent variables.

C. You have a total of 16 experimental runs that you are allowed to make. Design your 2-level experiment(s) so that the maximum total number of runs is 16. You may decide to perform multiple experiments (fractional and/or full factorial designs), as long as the total number of runs in all experiments combined is 16.

D. Determine if blocking variables should be included.

E. Choose one or more individuals on each team to fill the following roles:

1. Catapult operator
2. Distance Judge #1
3. Distance Judge #2 (take the median of the 3)
4. Distance Judge #3
5. Data recorder

F. Describe the confounding pattern. Determine if it will be possible to estimate and interpret interactions.

G. Randomize the order of the runs.

H. Create a standard "data recording sheet" before running the experiment.

I. The data analysis and presentations should include plenty of graphs. Have all graphs available at the presentation, so you will be able to answer questions.

J. Once the optimized launcher setting/missile configuration has been determined, each team must perform 30 confirmation runs with all team members present and calculate a Z.lt value for the process. Each team will present their findings to the class in a formal 10-minute presentation, using charts and whatever backup data is deemed appropriate by the team. A second confirmation run (consisting of 10 launches) will be done in front in the class, and will be part of the overall team rating (a 'Z.lt' value will be calculated from these 10 shots). The winning team will be determined their performance during the second confirmation run. A standard rating form will be used.

<u>Be sure to show the following information in your presentation:</u>

1. The objective of the test. This should include the business (military) objective and the objective of this experiment. Indicate the independent and dependent variables.
2. A listing of the test runs.
3. The one or two graphs of the results that are most enlightening (label the graphs well!).
4. Recommended running conditions (levels of the independent variables).
5. The results of the confirming experiment.

Have back-up charts available with more detail, so you will be able to answer questions.

In creating the optimized settings, you may NOT under any circumstances use multiple bands on the same launcher, or twist the bands in any way other than their original design! If you do, you will destroy the missile launching station, and its cost will be deducted from your paycheck.

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Appendix

DOE Planning Worksheet

1. Objective

2. Background information

3. Experimental variables:
   A. Response Variables — Measurement technique

   B. Factors under study — Levels

   C. Background noise variables — Method of control

4. Number of Replications:

5. Design matrices: (attach copy)

6. Data collection forms: (attach copy)

7. Planned method of statistical analysis:

8. Estimated cost, schedule and other resource considerations:

DOE Planning Pointers

- Attention to detail
- Design choice - screening, characterization, optimization
- 10 Step planning tool
- Variables and variable levels
- Sample size table
- Repetition and replication
- Blocking

Designed experiments planned and executed well are a powerful to tool to drive improvement yet done incorrectly are time consuming and expensive!