Simplify, Perfect, Innovate

# Combinatorial Testing with Design of Experiments 

An Executive Overview

## Introductions

- Name
- Organization
- Job Title/Responsibilities
- Experience in T\&E, Combinatorial Testing, DOE, etc.


## Agenda

- Some Basic Definitions and Terms
- Various Approaches to Testing Multiple Factors
- Design of Experiments (DOE): a Modern Approach to Combinatorial Testing
- Examples and Demonstration of a DOE
- Using DOE to Achieve Design Optimization
- Testing a Very Large Number of Factors
- Test Designs for Mixed Factors (Qualitative and Quantitative) and Mixed Levels


## Definition of a Process



## Web-Based Application Process



## Combinatorial Test Terminology

Y: Output, response variable, dependent variable
X: Input, factor, independent variable (a measurable entity that is purposely changed during an experiment)

Level: A unique value or choice of a factor (X)
Run: An experimental combination of the levels of the $X$ 's
Replication: Doing or repeating an experimental combination

Effect: The difference or impact on $Y$ when changing $X$
Interaction: When the effect of one factor depends on the level of another factor

## Performance Tuning Terminology

| Factors/Inputs <br> (X's) | Levels <br> (Choices) | Performance/Outputs <br> (Y's) |
| :---: | :---: | :---: |
| CPU Type | Itanium, Xeon | \# home page loads/sec |
| CPU Speed | $1 \mathrm{GHz}, 2.5 \mathrm{GHz}$ | Cost |
| RAM Amount | $256 \mathrm{MB}, 1.5 \mathrm{~GB}$ |  |
| HD Size | $50 \mathrm{~GB}, 500 \mathrm{~GB}$ |  |
| VM | J2EE, .NET |  |
| OS | Windows, Linux |  |
|  |  |  |

Which factors are important? Which are not?
Which combination of factor choices will maximize performance?
How do you know for sure? Show me the data.

## Graphical Meaning of $\bar{y}$ and $\sigma$

## $\overline{\mathbf{y}}=$ Average $=$ Mean $=$ Balance Point $\sigma=$ Standard Deviation


$\sigma \approx$ average distance of points from the centerline

## Graphical View of Variation



Typical Areas under the Normal Curve

## Approaches to Testing Multiple Factors

- Traditional Approaches
- One Factor at a Time (OFAT)
- Oracle (Best Guess)
- All possible combinations (full factorial)
- Modern Approach
- Statistically designed experiments (DOE) ... full factorial plus other selected DOE designs, depending on the situation


## OFAT (One Factor at a Time)



2. Hold $X_{1}$ constant at "best setting" and vary $X_{2}$. Find the "best setting" for $X_{2}$.



## The Good and Bad about OFAT

- Good News
- Simple
- Intuitive
- The way we were originally taught
- Bad News
- Will not be able estimate variable interaction effects
- Will not be able to generate prediction models and thus not be able to optimize performance


## Oracle (Best Guess)

$$
\begin{aligned}
& \mathrm{X} 1=\mathrm{W}=\text { Wetting Agent (1=.07 ml; 2=none) } \\
& \mathrm{X} 2=\mathrm{P}=\text { Plasticizer (1=1ml; 2=none) } \\
& \mathrm{X} 3=\mathrm{E}=\text { Environment (1=Ambient Mixing; 2=Semi-Evacuated) } \\
& \mathrm{X} 4=\mathrm{C}=\text { Cement (1=Portland Type III; 2=Calcium Aluminate) } \\
& \mathrm{X} 5=\mathrm{A}=\text { Additive (1=No Reinforcement; 2=Steel) } \\
& \mathrm{Y}=\text { Strength of Lunar Concrete }
\end{aligned}
$$

| Run | W | P | E | C | A | Y |
| ---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 1 | 2 | 1 | 1 | 1 | 5 |
| 2 | 1 | 1 | 1 | 1 | 1 | 6 |
| 3 | 2 | 2 | 1 | 1 | 1 | 5 |
| 4 | 2 | 1 | 1 | 1 | 2 | 6 |
| 5 | 1 | 2 | 2 | 2 | 2 | 7 |
| 6 | 1 | 1 | 2 | 2 | 2 | 8 |
| 7 | 2 | 2 | 2 | 2 | 2 | 10 |
| 8 | 2 | 1 | 2 | 2 | 1 | 11 |

Does factor $C$ shift the average of $Y$ ?

## Evaluating the Effects of Variables on Y

What we have is:


What we need is a design to provide independent estimates of effects:


How do we obtain this independence of variables?


## Design of Experiments (DOE)

- An optimal data collection methodology
- "Interrogates" the process
- Used to identify important relationships between input and output factors
- Identifies important interactions between process variables
- Can be used to optimize a process
- Changes "I think" to "I know"


## Important Contributions From:

|  |  |  | BLENDED |  |
| :--- | :---: | :---: | :---: | :---: |
| Loss Function | TAGUCHI | SHAININ | CLASSICAL | APPROACH |
| Emphasis on Variance | $*$ |  |  | $*$ |
| Reduction | $*$ |  |  | $*$ |
| Robust Designs | $*$ |  |  | $*$ |
| KISS | $*$ | $*$ |  | $*$ |
| Simple Significance |  | $*$ |  | $*$ |
| Tests |  | $*$ |  | $*$ |
| Component Swapping |  | $*$ |  | $*$ |
| Multivariate Charts |  |  | $*$ | $*$ |
| Modeling |  |  | $*$ | $*$ |
| Sample Size |  |  | $*$ | $*$ |
| Efficient Designs <br> Optimization <br> Confirmation <br> Response Surface <br> Methods |  |  |  |  |



Which bag would a world class golfer prefer?

## Statistically Designed Experiments (DOE): Orthogonal or Nearly Orthogonal Designs

- FULL FACTORIALS (for small numbers of factors)
- FRACTIONAL FACTORIALS
- PLACKETT-BURMAN
- LATIN SQUARES

Taguchi Designs

- HADAMARD MATRICES
- BOX - BEHNKEN DESIGNS
- CENTRAL COMPOSITE DESIGNS
- NEARLY ORTHOGONAL LATIN HYPERCUBE DESIGNS

SIMPLE DEFINITION OF TWO-LEVEL ORTHOGONAL DESIGNS


|  |  |  | la |  | atio |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | Fu | oria | gn | 3 Fa | rs, Each | 2 L |  |
|  | Run | A | B | C | AB | AC | BC | ABC |
|  | 1 | - | - | - | + | + | + | - |
|  | 2 | - | - | + | + | - | - | + |
|  | 3 | - | + | - | - | + | - | + |
|  | 4 | - | + | + | - | - | + | - |
|  | 5 | + | - | - | - | - | + | + |
|  | 6 | + | - | + | - | + | - | - |
| AIR ${ }^{2}$ ACADEMY ASSOCIATES Simplify, Perfect, Innovate | 7 | + | + | - | + | - | - | - |
|  | 8 | + | + | + | + | + | + | + |
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## Full Factorial vs. Fractional Factorial

 (3 factors at 2 levels)

## Screening Design

| Taguchi $\mathrm{L}_{12}$ Design |  |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Run | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
| 1 | - | - | - | - | - | - | - | - | - | - | - |
| 2 | - | - | - | - | - | + | + | + | + | + | + |
| 3 | - | - | + | + | + | - | - | - | + | + | + |
| 4 | - | + | - | + | + | - | + | + | - | - | + |
| 5 | - | + | + | - | + | + | - | + | - | + | - |
| 6 | - | + | + | + | . | + | + | - | + | - | - |
| 7 | + | - | + | + | - | - | + | + | - | + | - |
| 8 | + | - | + | . | + | + | + | - | - | . | + |
| 9 | + | - | - | + | + | + | - | + | + | - | - |
| 10 | + | + | + | - | - | - | - | + | + | - | + |
| 11 | + | + | - | + | - | + | - | - | - | + | + |
| 12 | + | + | - | - | + | . | + | . | + | + | - |

## The Purpose of a Designed Experiment

Purposeful changes of the inputs (factors) in order to observe corresponding changes in the output (response).


## DOE Helps Determine How Inputs Affect Outputs

i) Factor A affects the average of y

ii) Factor B affects the standard deviation of y

iii) Factor $C$ affects the average and the standard deviation of $y$
iv) Factor $D$ has no effect on $y$


## Transfer Functions



Where does the transfer function come from?

- Exact transfer Function
- Approximations
- DOE
- Historical Data Analysis
- Simulation


## Exact Transfer Functions

- Engineering Relationships
- $\quad V=I R$
- $\quad F=m a$


The equation for current (I) through this DC circuit is defined by:

$$
I=\frac{V}{\frac{R_{1} \cdot R_{2}}{R_{1}+R_{2}}}=\frac{V\left(R_{1}+R_{2}\right)}{R_{1} \cdot R_{2}}
$$

The equation for magnetic force at a distance $X$ from the center of a solenoid is:

$$
\mathrm{H}=\frac{\mathrm{NI}}{2 \ell}\left[\frac{.5 \ell+\mathrm{x}}{\sqrt{\mathrm{r}^{2}+(.5 \ell+\mathrm{x})^{2}}}+\frac{.5 \ell-\mathrm{x}}{\sqrt{\mathrm{r}^{2}+(.5 \ell-\mathrm{x})^{2}}}\right]
$$

N : total number of turns of wire in the solenoid
I : current in the wire, in amperes
$r$ : radius of helix (solenoid), in cm
$\ell$ : length of the helix (solenoid), in cm
x : distance from center of helix (solenoid), in cm
H : magnetizing force, in amperes per centimeter

## Hierarchical Transfer Functions

$$
Y=\text { Gross Margin }=\quad \text { Gross Profit }
$$

$$
Y=f\left(y_{1}, y_{2}, y_{3}, y_{4}, y_{5}, y_{6}\right)
$$

$$
=\begin{gathered}
y_{1} \\
=\left(\operatorname{Rev}_{\text {equip }}-\operatorname{cOG}\right) \\
+\left(\operatorname{Rev}_{\text {post sales }}-\operatorname{Cost}_{\text {post sales }}\right)
\end{gathered}+\begin{gathered}
y_{5} \quad y_{6} \\
\left(\operatorname{Rev}_{\text {fin }}-\operatorname{Cost}_{\text {fin }}\right)
\end{gathered}
$$

$$
y_{1}+y_{3}+y_{5}
$$

Cost $_{\text {post sales }}=\mathrm{f}$ (field cost, remote services, suppliers)

$$
\mathrm{x}_{1}=\mathrm{f} \text { (direct labor, freight, parts, depreciation) }
$$

## Catapulting Power into Test and Evaluation



Statapult ${ }^{\circledR}$ Catapult


## The Theoretical Approach (cont.)

$$
\begin{gathered}
I_{0} \ddot{\theta}=r_{F} F(\theta) \sin \theta \cos \varphi-\left(M g r_{G}+m g r_{B}\right) \sin \theta \\
\frac{1}{2} I_{0} \dot{\theta}^{2}=r_{F} \int_{\theta_{0}}^{\theta} F(\theta) \sin \theta \cos \varphi d \theta-\left(M g r_{G}+m g r_{B}\right)\left(\sin \theta-\sin \theta_{0}\right) \\
\frac{1}{2} I_{0} \dot{\theta}_{1}^{2}=r_{F} \operatorname{r} r_{F} \int_{\theta_{0} \sin \theta}^{\theta_{1}} F(\theta) \sin \theta \cos \varphi d \theta-\left(M g r_{G}+m g r_{B}\right)\left(\sin \theta_{1}-\sin \theta_{0}\right) . \\
x=v_{B} \cos \left(\frac{\pi}{2}-\theta_{1}\right) t-\frac{1}{2} r_{B} \cos \theta_{1} \quad y=r_{B} \sin \theta_{1}+v_{B} \sin \left(\frac{\pi}{2}-\theta_{1}\right) t-\frac{1}{2} g t^{2} . \\
r_{B} \sin \theta_{1}+\left(R+r_{B} \cos \theta_{1}\right) \tan \left(\frac{\pi}{2}-\theta_{1}\right)-\frac{g}{2 V_{B}^{2}} \frac{\left(R+r_{B} \cos \theta_{1}\right)^{2}}{\cos \left(\frac{\pi}{2}-\theta_{1}\right)}=0 . \\
\frac{g l_{0}}{4 r_{B}} \frac{\cos ^{2}\left(\frac{\pi}{2}-\theta_{1}\right)\left[r_{B} \sin \theta_{1}+\left(R+r_{B} \cos \theta_{1}\right) \tan \left(\frac{\pi}{2}-\theta_{1}\right)\right]}{\left(R+r_{B} \cos \theta_{1}\right)^{2}} \\
=r_{F} \int_{\theta_{0}}^{\theta_{1}} F(\theta) \sin \theta \cos \phi d \theta-\left(M g r_{G}+m r_{B}\right)\left(\sin \theta_{1}-\sin \theta_{0}\right) .
\end{gathered}
$$



## Value Delivery: Reducing Time to Market for New Technologies

## INPUT



## OUTPUT



- Total \# of Combinations $=3^{5}=243$
- Central Composite Design: $\mathbf{n}=30$

Patent Holder: Dr. Bert Silich

## Aircraft Equations

```
\(C_{L}=\quad .233+.008(P)^{2}+.255(P)+.012(R)-.043(W D 1)-.117(W D 2)+.185(W D 3)+.010(P)(W D 3)-\)
        \(.042(\mathrm{R})(\mathrm{WD} 1)+.035(\mathrm{R})(\mathrm{WD} 2)+.016(\mathrm{R})(\mathrm{WD} 3)+.010(\mathrm{P})(\mathrm{R})-.003(\mathrm{WD} 1)(\mathrm{WD} 2)-\)
        .006(WD1)(WD3)
\(C_{D}=\quad .058+.016(P)^{2}+.028(P)-.004(W D 1)-.013(W D 2)+.013(W D 3)+.002(P)(R)-.004(P)(W D 1)\)
        \(-.009(\mathrm{P})(\mathrm{WD} 2)+.016(\mathrm{P})(\mathrm{WD} 3)-.004(\mathrm{R})(\mathrm{WD} 1)+.003(\mathrm{R})(\mathrm{WD} 2)+.020(\mathrm{WD} 1)^{2}+.017(\mathrm{WD} 2)^{2}\)
        \(+.021(\text { WD3 })^{2}\)
\(C_{Y}=\quad-.006(P)-.006(R)+.169(W D 1)-.121(W D 2)-.063(W D 3)-.004(P)(R)+.008(P)(W D 1)-\)
        .006(P)(WD2) - .008(P)(WD3) - .012(R)(WD1) - .029(R)(WD2) + .048(R)(WD3) - .008(WD1) \({ }^{2}\)
\(\mathrm{C}_{\mathrm{M}}=\quad .023-.008(\mathrm{P})^{2}+.004(\mathrm{P})-.007(\mathrm{R})+.024(\mathrm{WD} 1)+.066(\mathrm{WD} 2)-.099(\mathrm{WD} 3)-.006(\mathrm{P})(\mathrm{R})+\)
        \(.002(P)(W D 2)-.005(P)(W D 3)+.023(R)(W D 1)-.019(R)(W D 2)-.007(R)(W D 3)+.007(W D 1)^{2}\)
        \(-.008(W D 2)^{2}+.002(W D 1)(W D 2)+.002(W D 1)(W D 3)\)
\(C_{Y M}=.001(P)+.001(R)-.050(W D 1)+.029(W D 2)+.012(W D 3)+.001(P)(R)-.005(P)(W D 1)-\)
        \(.004(\mathrm{P})(\mathrm{WD} 2)-.004(\mathrm{P})(\mathrm{WD} 3)+.003(\mathrm{R})(\mathrm{WD} 1)+.008(\mathrm{R})(\mathrm{WD} 2)-.013(\mathrm{R})(\mathrm{WD} 3)+.004(W D 1)^{2}\)
        \(+.003(\text { WD2 })^{2}-.005(\text { WD3 })^{2}\)
\(C_{e}=\quad .003(P)+.035(W D 1)+.048(W D 2)+.051(W D 3)-.003(R)(W D 3)+.003(P)(R)-.005(P)(W D 1)\)
    + .005(P)(WD2) + .006(P)(WD3) + .002(R)(WD1)
```


## Fusing Titanium and Cobalt-Chrome

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## DOE "Market Research" Example

Suppose that, in the auto industry, we would like to investigate the following automobile attributes (i.e., factors), along with accompanying levels of those attributes:

| A: Brand of Auto: | $-1=$ foreign |  | $+1=$ domestic |
| :--- | :--- | :--- | :--- |
| B: Auto Color: | $-1=$ light | $0=$ bright | $+1=$ dark |
| C: Body Style: | $-1=2$-door | $0=4$-door | $+1=$ sliding door/hatchback |
| D: Drive Mechanism: | $-1=$ rear wheel | $0=$ front wheel | $+1=4$-wheel |
| E: Engine Size: | $-1=4$-cylinder | $0=6$-cylinder | $+1=8$-cylinder |
| F: Interior Size: | $-1 \leq 2$ people | $0=3-5$ people | $+1 \geq 6$ people |
| G: Gas Mileage: | $-1 \leq 20 \mathrm{mpg}$ | $0=20-30 \mathrm{mpg}$ | $+1 \geq 30 \mathrm{mpg}$ |
| H: Price: | $-1 \leq \$ 20 \mathrm{~K}$ | $0=\$ 20-\$ 40 \mathrm{~K}$ | $+1 \geq \$ 40 \mathrm{~K}$ |

In addition, suppose the respondents chosen to provide their preferences to product profiles are taken based on the following demographic:
J: Age:
K: Income:
$-1 \leq 25$ years old
$+1 \geq 35$ years old
L: Education:
$-1 \leq \$ 30 \mathrm{~K}$
$+1 \geq \$ 40 K$
$-1<B S$
$+1 \geq$ BS

## DOE "Market Research" Example (cont.)

Question: Choose the best design for evaluating this scenario
Answer: $\quad L_{18}$ design with attributes $\mathrm{A}-\mathrm{H}$ in the inner array and factors $J, K$, and $L$ in the outer array, resembling an $\mathrm{L}_{18}$ robust design, as shown below:


## Modeling The Drivers of Turnover



## Google on DOE (quotes* from Daryl Pregibon, Google Engineer)

"From a user's perspective, a query was submitted and results appear. From Google's perspective, the user has provided an opportunity to test something. What can we test? Well, there is so much to test that we have an Experiment Council that vets experiment proposals and quickly approves those that pass muster."
"We evangelize experimentation to the extent that we provide a mechanism for advertisers to run their own experiments.
. . . allows an advertiser to run a (full) factorial experiment on its web page. Advertisers can explore layout and content alternatives while Google randomly directs queries to the resulting treatment combinations. Simple analysis of click and conversion rates allows advertisers to explore a range of alternatives and their effect on user awareness and interest."

* Taken From: Statistics @ Google in Amstat News, May 2011


## DOE Enables Critical Parameter Management (CPM)

CPM is a systems engineering best practice that is extremely useful in managing, analyzing, and reporting technical product performance.
"The System Can...."


## Critical Parameter Management and COIs

- A Critical Operational Issue (COI) is linked to operational effectiveness and suitability.
- It is typically phrased as a question, e.g.,

Will the system detect the threat in a combat environment at adequate range to allow for successful engagement?


## DOE: the bridge to Design Optimization and Systematic Innovation

- Expected Value Analysis
- Parameter (Robust) Design


## Expected Value Analysis (EVA)

EVA is the technique used to determine the characteristics of the output distribution (mean, standard deviation, and shape) when we have knowledge of (1) the input variable distributions and (2) the transfer functions.


## Expected Value Analysis Example



What is the mean or expected value of the $y$ distribution?
What is the shape of the $y$ distribution?

## Parameter Design (Robust Design)



Process of finding the optimal mean settings of the input variables to minimize the resulting dpm.


## Parameter Design (Robust Design)




Changing the mean of an input may possibly reduce the output variation!

## Robust (Parameter) Design Simulation* Example



## Prior to Robust Design



## After Robust Design



## Growth Rate of Factorial Designs

For 2-level designs and k factors: $2^{\mathrm{k}}$ combinations

- for $k=2$ factors: $2^{2}=4$ combinations
- for $k=3$ factors: $2^{3}=8$ combinations
- for $k=10$ factors: $2^{10}=1,024$ combinations

For 3-level designs and k factors: $3^{\mathrm{k}}$ combinations

- for $k=2$ factors: $3^{2}=9$ combinations
- for $k=3$ factors: $3^{3}=27$ combinations
- for $k=10$ factors: $3^{10}=59,049$ combinations

What if the \# of factors and/or the number of levels gets large?

## Representative Sampling <br> (Space Filling Designs)

- Method to populate the design space when many variables are involved (e.g., deterministic simulators) or when there are a fixed/limited number of tests specified.
- Design space has $k$ variables (or dimensions).

Ex: Assume k = 2


- Suppose a sample of size n is to be taken; stratify the design space into $\mathrm{n}^{\mathrm{k}}$ cells.
Ex: Assume $\mathrm{n}=5 ; \mathrm{n}^{\mathrm{k}}=5^{2}=25$.
- Note: there are $\mathrm{n}=5$ strata for each of the $\mathrm{k}=2$
 dimensions.
- Each of the n points is sampled such that each marginal strata is represented only once in the sample.
- Note: each sample point has its own unique row and
 column.


## Nearly Orthogonal Latin Hypercube Designs (NOLHD)

- Method to populate a large or high-dimension design space with small samples for the purpose of estimating
 Ex: Assume k=2.

- Total number of sampled data points is $\mathrm{n}=\mathrm{km}$ or, for this example, $n=(2)(5)=10$.
- Each of the n points is selected in such a manner that the resulting design for estimating the desired effects is as orthogonal as possible. This is sometimes called orthogonal space filling, and it will be extremely useful
 to screen many, many factors.


## Applying DOE to Automotive Vehicle Design



## Nearly Orthogonal Latin Hypercube Design

 (20 variables each at 20 levels projected onto x1 vs x2)

Note the balance in the design.


## Using DOE to "Optimize the Simulator"



## Environments Where DOE is Beneficial in Simulation and Modeling

- A high number of design variables
- A substantial number of design subsystems and engineering disciplines
- Interdependency and interaction between the subsystems and variables
- Multiple response variables
- Need to characterize the system at a higher level of abstraction
- Time and/or space must be compressed


## Test Designs for Mixed Factors and Mixed Levels a.k.a. High Throughput Testing (HTT) or Combinatorial Testing

- A recently developed technique based on combinatorics
- Used to test myriad combinations of many factors (quantitative or qualitative) where the factors could have many levels
- Uses a minimum number of runs or combinations to do this
- Software is needed to select the minimal subset of all possible combinations to be tested so that all 2-way combinations are tested, i.e., all pairs testing
- HTT is not a DOE technique, although the terminology is similar
- A run or row in an HTT matrix is, like DOE, a combination of different factor levels which, after being tested, will result in a successful or failed run
- HTT has its origins in the pharmaceutical business where in drug discovery many chemical compounds are combined together (combinatorial chemistry) at many different strengths to try to produce a reaction.
- Other industries are now using HTT, e.g., software testing, materials discovery, integration, and verification testing (see example on next page).


## All Pairs Testing Example (Performance Verification and Validation)

- We would like to perform verification testing with 4 input factors described below.
- All possible combinations would involve how many test combinations?
- If we were interested in testing all pairs only, how many runs would be in the test matrix and what would those combinations be? To answer this question, we used ProTest software. See next page.

| Sensor <br> Type | Weapon Type | External Data <br> Link | Target Type |
| :---: | :---: | :---: | :---: |
| S1 | W1 | Yes | T1 |
| S2 | w2 | No | T2 |
| S3 | w3 |  | T3 |
| S4 |  |  | T4 |
|  |  |  | T5 |



## Submarine Threat Detection Test Example

- Suppose we want to perform a verification test with the following 7 input factors (with their respective settings):
- Submarine Type (S1, S2, S3)
- Ocean Depth (Shallow, Deep, Very Deep)
- Sonar Type (Active, Passive)
- Target Depth (Surface, Shallow, Deep, Very Deep)
- Sea Bottom (Rock, Sand, Mud)
- Control Mode (Autonomous, Manual)

Ocean Current (Strong, Moderate, Minimal)

- All possible combinations would involve how many runs in the test?
- If we were interested in testing all pairs only, how many runs would be in the test? Pro Test generated the following test matrix.

|  | Factor_A | Factor_B | Factor_C | Factor_D | Factor_E | Factor_F | Factor_G |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Factor Name | Submarine Type | Ocean Depth | Sonar Type | Target Depth | Sea Bottom | Control Mode | Ocean Current |
| Case 1 | 53 | Deep | Passive | Very Deep | Mud | Manual | Minimal |
| Case 2 | S1 | Very Deep | Passive | Surface | Rock | Autonomous | Strong |
| Case 3 | S2 | Shallow | Active | Shallow | Rock | Manual | Moderate |
| Case 4 | S2 | Deep | Passive | Deep | Sand | Autonomous | Moderate |
| Case 5 | S1 | Shallow | Active | Surface | Sand | Manual | Minimal |
| Case 6 | S1 | Very Deep | Passive | Shallow | Mud | Autonomous | Minimal |
| Case 7 | 53 | Very Deep | Active | Deep | Mud | Manual | Strong |
| Case 8 | S2 | Very Deep | Active | Very Deep | Sand | Autonomous | Strong |
| Case 9 | S3 | Shallow | Passive | Shallow | Mud | Autonomous | Strong |
| Case 10 | S3 | Deep | Active | Surface | Rock | Manual | Moderate |
| Case 11 | S1 | Shallow | Active | Deep | Rock | Autonomous | Minimal |
| Case 12 | S1 | Deep | Passive | Very Deep | Rock | Manual | Moderate |
| Case 13 | S2 | Very Deep | Active | Sufface | Mud | Autonomous | Moderate |
| Case 14 | 53 | Deep | Active | Shallow | Sand | Manual | Strong |
| Case 15 | S2 | Shallow | Active | Very Deep | Rock | Manual | Minimal |

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## Command \& Control Test Example

(15 factors each at various levels)
Total Combinations: 20,155,392

## Variable or Factor

## Mission Snapshots

Network Size
Network Loading
Movement Posture
SATCOM Band
SATCOM Look Angle
Link Degradation
Node Degradation
EW
Interoperability
IA
Security
Message Type
Message Size
Distance Between Nodes

LevelsEntry, Operations, Consolidation(3)
10 Nodes, 50 Nodes, 100 Nodes ..... (3)
Nominal, 2X, 4X(3)
ATH, OTM1, OTM2 ..... (3)
Ku, Ka, Combo ..... (3)
0, 45, 75 ..... (3)
0\%, 5\%, 10\%, 20\% ..... (4)
0\%, 5\%, 10\%, 20\% ..... (4)
None, Terrestrial, GPS ..... (3)
Joint Services, NATO ..... (2)
None, Spoofing, Hacking, Flooding ..... (4)
NIPR, SIPIR ..... (2)
Data, Voice, Video ..... (3)
Small, Medium, Large, Mega ..... (4)Short, Average, Long(3)

## Command \& Control Test Example

(All Pairs Testing from ProTest generates 26 test cases)

|  | Factor_A | or_ | acto | actor | Factor_E | Factor_F | Factor_G | Factor_H | Factor_I | Factor_J | Factor | actor | Factor_M | Factor_N | Factor_0 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Factor Name | Mission | Network <br> Size | Network <br> Load | Movement | SATCOM <br> Band | SATCOM Angle | Link Degradation | Node Degradation | EW | Interoperability | 的, | Security | Message Type | Size of Message | Node Distance |
| Case 1 | Entry | 100 nodes |  | OTM2 | Combo | 0 | 0\% | 0\% | None | NATO | None | SIPIR | Voice | Medium | Short |
| Case 2 | Consolidation | 10 nodes | Normal | ATH | Ka | 45 | 5\% | 5\% | GPS | NATO | Spoofing | NIPR | Video | Large | Normal |
| Case 3 | Operation | 50 nodes | $2 \times$ | OTM1 | Ku | 75 | 20\% | 20\% | Terrestrial | Joint Sery | Hacking | NIPR | Voice | Small | Long |
| Case 4 | Entry | 50 nodes | $2 \times$ | ATH | Ku | 45 | 10\% | 10\% | None | NATO | Flooding | NIPR | Data | Mega | Short |
| Case 5 | Operation | 100 nodes | Normal | OTM1 | Combo | 75 | 10\% | 10\% | GPS | NATO | Spoofing | SIPIR | Data | Small | Normal |
| Case 6 | Operation | 10 nodes | $4 \times$ | OTM2 | Combo | 45 | 0\% | 5\% | Terrestrial | 1 Joint Serv | None | NIPR | Video | Mega | Long |
| Case 7 | Consolidation | 100 nodes |  | ATH | Ka | 75 | 20\% | 10\% | Terrestrial | NATO | Hacking | SIPIR | Video | Medium | Long |
| Case 8 | Operation | 10 nodes | Normal | ATH | Ka | 0 | 20\% | 0\% | Terrestrial | Joint Serv | Flooding | NIPR | Data | Large | Short |
| Case 9 | Consolidation | 10 nodes | $2 \times$ | OTM2 | Ku | 45 | 5\% | 20\% | None | Joint Serv | Flooding | SIPIR | Voice | Medium | Normal |
| Case 10 | Consolidation | 50 nodes | $2 \times$ | OTM1 | Combo | 0 | 0\% | 20\% | GPS | NATO | None | NIPR | Data | Mega | Normal |
| Case 11 | Entry | 50 nodes | Normal | OTM2 | Ka | 75 | 10\% | 5\% | GPS | Joint Serv | Hacking | SIPIR | Voice | Large | Long |
| Case 12 | Entry | 50 nodes | 4X | OTM1 | Ku | 0 | 5\% | 0\% | None | Joint Serv | Spoofing | SIPIR | Video | Small | Long |
| Case 13 | Consolidation | 100 nodes | 4X | OTM2 | Ku | 45 | 20\% | 5\% | GPS | Joint Serv | Flooding | NIPR | Data | Small | Short |
| Case 14 | Entry | 10 nodes |  | OTM1 | Ka | 75 | 5\% | 0\% | None | Joint Serv | Hacking | SIPIR | Data | Mega | Normal |
| Case 15 | Entry | 50 nodes | $2 \times$ | ATH | Ka | 75 | 0\% | 20\% | Terrestrial | NATO | Spoofing | NIPR | Video | Large | Short |
| Case 16 | Consolidation | 10 nodes | $4 \times$ | ATH | Ku | 0 | 10\% | 20\% | Terrestrial | NATO | None | NIPR | Video | Small | Normal |
| Case 17 | Operation | 50 nodes | Normal | OTM1 | Ku | 75 | 0\% | 5\% | None | Joint Serv | Flooding | NIPR | Data | Medium | Short |
| Case 18 | Operation | 10 nodes | Normal | OTM1 | Ka | 75 | 20\% | 10\% | None | Joint Serv | None | SIPIR | Video | Large | Normal |
| Case 19 | Operation | 100 nodes |  | OTM2 | Combo | 0 | 5\% | 10\% | Terrestrial | NATO | Hacking | SIPIR | Data | Large | Short |
| Case 20 | Consolidation | 100 nodes | Normal | ATH | Combo | 0 | 20\% | 20\% | Terrestrial | JJoint Serv | Spoofing | NIPR | Voice | Mega | Short |
| Case 21 | Consolidation | 50 nodes | $2 \times$ | OTM1 | Ka | 45 | 10\% | 0\% | GPS | Joint Serv | Spoofing | SIPIR | Data | Medium | Normal |
| Case 22 | Entry | 100 nodes | Normal | OTM1 | Combo | 0 | 20\% | 5\% | GPS | NATO | Flooding | NIPR | Video | Medium | Long |
| Case 23 | Operation | 10 nodes | Normal | ATH | Ka | 45 | 0\% | 10\% | None | NATO | Hacking | SIPIR | Voice | Small | Normal |
| Case 24 | Entry | 50 nodes | $4 \times$ | ATH | Ku | 45 | 5\% | 20\% | None | NATO | None | NIPR | Video | Large | Long |
| Case 25 | Consolidation | 10 nodes | $2 \times$ | ATH | Ku | 75 | 10\% | 5\% | None | Joint Serv | Spoofing | NIPR | Data | Large | Long |
| Case 26 | Consolidation | 100 nodes | Normal | OTM2 | Combo | 45 | 5\% | 20\% | GPS | Joint Sery | Spoofing | NIPR | Voice | Mega | Normal |

## The Efficiency of All Pairs Testing

- Suppose we had 75 Factors to test.
- Suppose we wanted to test each of these at 2 levels.
- How many total combinations are there?
$2^{75}=37,778,931,862,957,161,709,568$
i.e., 37 Sextillion, 778 Quintillion, 931 Quadrillion, 862 Trillion, 957 Billion, 161 Million, 709 Thousand, 568
- What is the minimum number of these combinations that will have to be tested in order to test every 2-way combination?
- To answer this question, we used our Pro-Test software. The answer is 14 runs or experimental combinations.
- For $k$ factors each having the same number of levels tested, say $\mathbf{v}$, then the minimum number of tests $\approx v^{\mathbf{2}}(\ln k)$


## Useful Applications of HTT

- Reducing the cost and time of testing while maintaining adequate test coverage
- Integration, functionality, and verification testing
- Creating a test plan to stress a product and discover problems
- Identifying the critical factors affecting performance in an operational test environment
- Prescreening before a large DOE to ensure all 2-way combinations are feasible before discovering, midway through an experiment, that certain combinations are not feasible
- Developing an "outer array" of noise combinations to use in a robust design DOE when the number of noise factors and settings is large


## The 12-Step Approach to DOE

Steps for Experimental Design
I. Statement of the Problem:

II. Objective of the Experiment:

IV. Select Quality Characteristics (also known as responses, outputs, or Y's).

| Response | Type <br> (attribute or <br> continuous) | Anticipated <br> Range | How will you measure the <br> response? Is the measruement <br> method accurate and precise? |
| :---: | :---: | :---: | :---: |
|  |  |  |  |

## The 12-Step Approach to DOE (cont.)

V. Complete a literature review, process flow diagram, and cause/effect diagram. Select factors which are anticipated to have an effect on the response. Write SOPs for all variables that are to be held constant.
$\left.\begin{array}{|l|c|c|c|c|c|}\hline \text { Factor } & \begin{array}{c}\text { Type } \\ \text { (attribute or } \\ \text { continuous) }\end{array} & \begin{array}{c}\text { Controllable } \\ \text { or Noise }\end{array} & \text { Range of Interest } & \text { Levels } & \begin{array}{c}\text { Anticipated } \\ \text { Interactions } \\ \text { With }\end{array}\end{array} \begin{array}{c}\text { How } \\ \text { Measured? }\end{array}\right]$
VI. Determine the number of resources to be used in the experiment.
$\square$
VII. Which design types and analysis strategies are appropriate?
$\square$
VIII. Select the best design type and analysis strategy to suit your needs.


## The 12-Step Approach to DOE (cont.)

IX. Can all the runs be randomized? Which factors are most difficult to randomize?

X. Conduct the experiment and record the data.

XI. Analyze the data, draw conclusions, make predictions, and do confirmatory tests.

XII. Assess results, make decisions, and document your results.
$\square$

## Key Take-Aways

- Various approaches to combinatorial test, to include OFAT and Oracle (Best Guess).
- DOE brings orthogonal or nearly orthogonal designs into play.
- Orthogonality (both vertical and horizontal balance in a design) is key to being able to evaluate the effects of factors and their interactions independently from one another.
- Factorial designs are great, but in a world of large test design spaces, we need something else.
- Latin Hypercube Sampling and Descriptive Sampling are useful design strategies when we want good test coverage for many variables with a minimum or specified number of tests. However, these designs are typically not orthogonal.
- Nearly Orthogonal Latin Hypercube Designs provide a sampling strategy to test a large number of factors with a much smaller number of runs than what a factorial design requires, while still retaining adequate orthogonality. These are particularly useful when designing experiments for computer simulations.
- All Pairs Testing, a type of HTT, is a way to get great test coverage (i.e., all pairwise combinations) with a minimal number of runs for a test scenario involving mixed factors (quantitative or qualitative) with a mixed number of levels. This would be a candidate design for OT\&E when we are trying to verify and validate performance in an operational envelope. These designs can be orthogonal or nearly orthogonal.



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