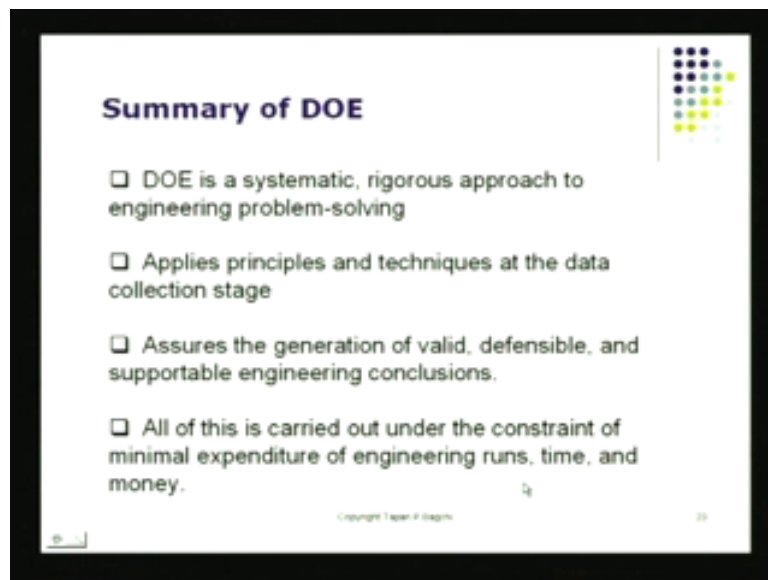


**Six Sigma**  
**Prof. Dr. T. P. Bagchi**  
**Department of Management**  
**Indian Institute of Technology, Kharagpur**

**Lecture No. # 27**  
**Planning for DOE**

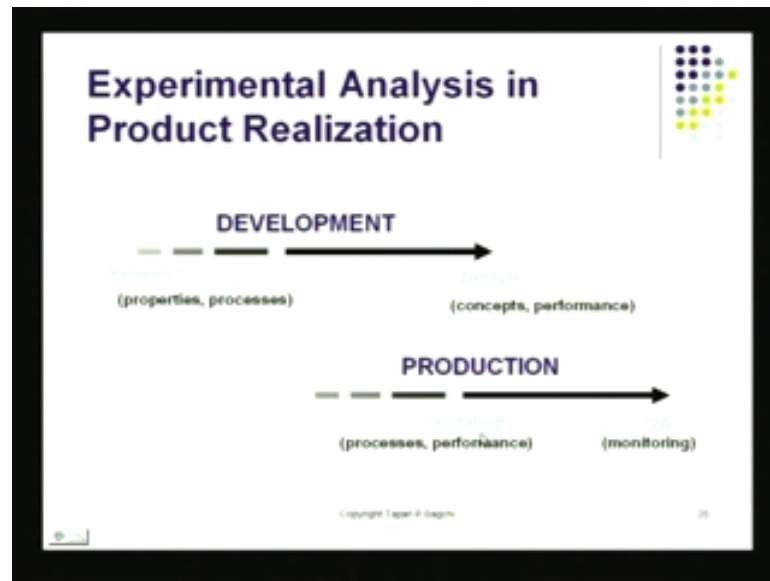
Hello, good afternoon; we resume our lecture on six sigma; and the session that we are starting right now is called planning for DOE. And what we will be doing is be continuing from what have been doing till now; and I will begin with the slide which is there, which is a summary of the of what we done so far.

(Refer Slide Time 00:37)



DOE is a systematic procedure, design experiment; it is a systematic and a rigorous approach to engineering problem solving that is, DOE. It applies principles sounds, statistical principles and techniques at the data collection stage; there is something that DOE does. It assure the generation of valid, defensible and supportable engineering conclusion. This is something that results if we conduct experiments under the DOE framework. And all the system carried out and there your constraints of minimum expenditure of engineering runs time and money, because you know the whole planning is quite efficient.

(Refer Slide Time 01:26)



Let us see how you go about planning for it. In fact, it turns out at the motivation for doing experiments. It can come from many different places; one of the key ones is of course, development product development for example, or even process development, we start with design; we start with research and we move toward design; and in going from the left, from this left end of the arrow there moving to the right, would need to do a lot of experiments; that is like something that is one place, we do a lot of it, a lot of work which is like this. Then of course, we got to validate the process, and that validation you know whether you got the right design done with the process conditions of right and so on so forth. Then again, we can use an experimental work; and then throughout the end when we do monitoring thus, when quality assurance is done you got to make sure you monitor the right quantities.

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The slide is titled "Experimentation in Development— A way to gather critical knowledge". It features a central image of an elephant with several lines pointing to different parts of its body, each with a small text label. To the right of the elephant is a bulleted list of factors that influence what we learn. In the top right corner, there is a decorative graphic of a grid of colored dots. At the bottom, there is a small copyright notice and a page number.

### Experimentation in Development— A way to gather critical knowledge

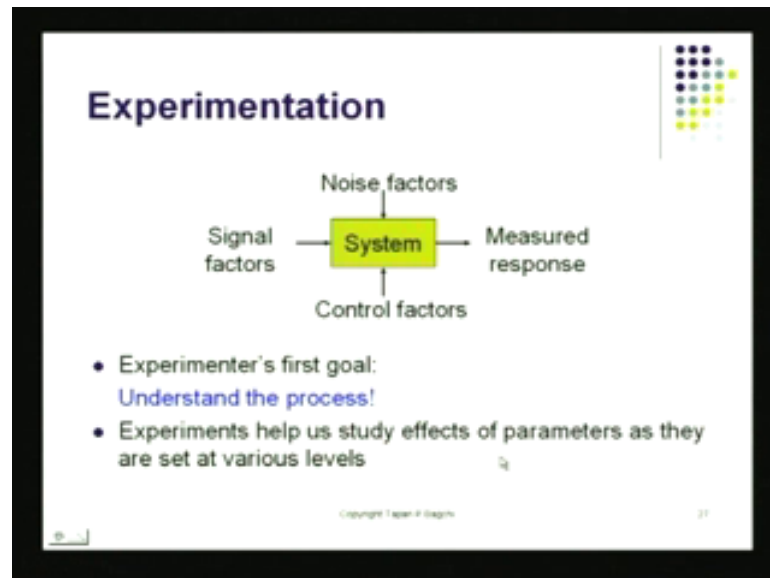
What we learn depends on

- where we look,
- how we look, and
- the scope of our view
- Resources (people, equipment, etc.)
- Time
- Material (unprocessed or unusable product)

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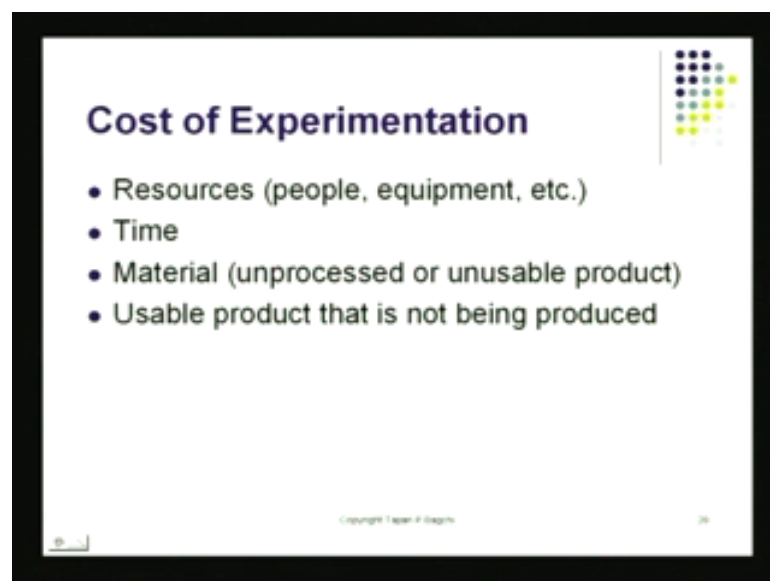
This is like one large area, where many times the technique actually is experimental. So, that is like something that is there, whenever you are trying to release a new product, in particular. It is a way to gather data; doing experiments is the way to gather data, but the problem is that what we learnt depends very much on what we look. So, if it touching the elephant depending on which would what part of the elephant you are touching, you will end up learning just that kind of you know, information, is like also how do we look? Do you have a blind fold on top of (( )) or can we see things? Can we trust things? Can we feel things? Those spoke of or drew what can be seen and what if I what we are not able to see resources utilised, time of variable and material available; you know, all these things; basically they control how much we learned; how we learned?

(Refer Slide Time 03:04)



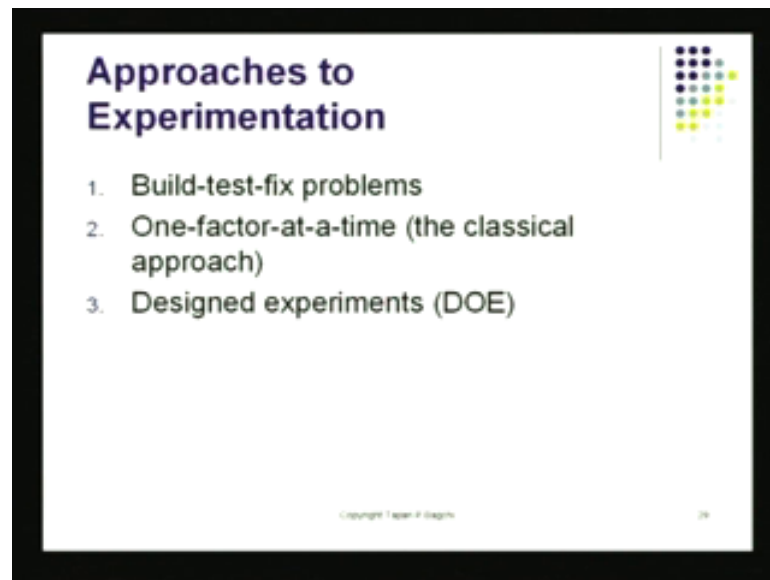
When we do experiments we are basically looking at a situation a system, which has got signal factors some control factors and of course, noise factors, and we are trying to measure the response there. Our goal really is one and single, we are trying to understand the process. This is primarily the goal of R and D; the goal of R and D is basically is to try to sort of understand; how does this process work; that is what we are trying to do there. We will see specifically will try to see the effect of the various parameters as just set at different levels, which are like called treatment levels.

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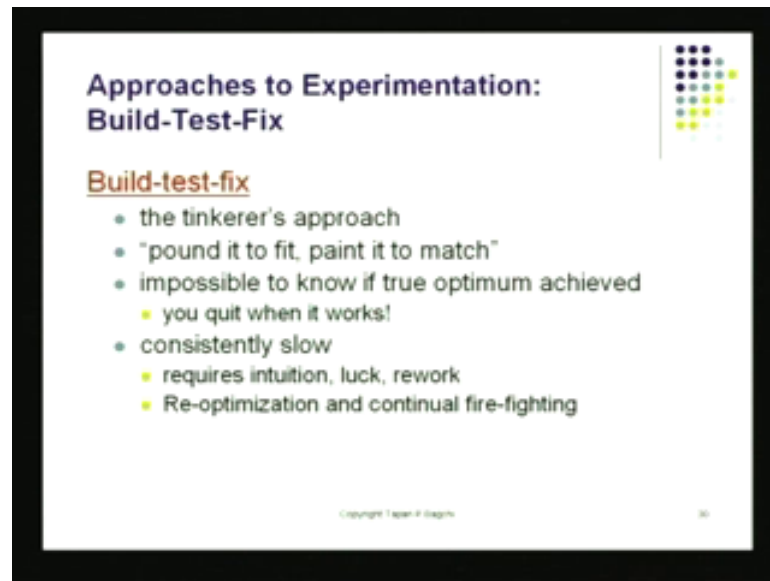
In fact if you see the cost of experimentation, where does money go, when I try do experiments in to resources, people equipments so on so forth, time, material and usable product that is not produce, that is not being produced. These are the places, where we spend our money and therefore, what we have to do is, we have to be most efficient.

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What are the different approaches by which experiments are done? Well one way would be to build test and fix; basically build something you test you to be does not work, you fix and you come back and build it again that (( )) this is like one way. The other way would be to change one factor, you have the full system in front of you give twisting one factor at a time you see the response. If we did this you would not be able to study interactions, the best way of course, to generating empirical work; empirical knowledge is to apply the DOE framework.

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**Approaches to Experimentation:  
Build-Test-Fix**

**Build-test-fix**

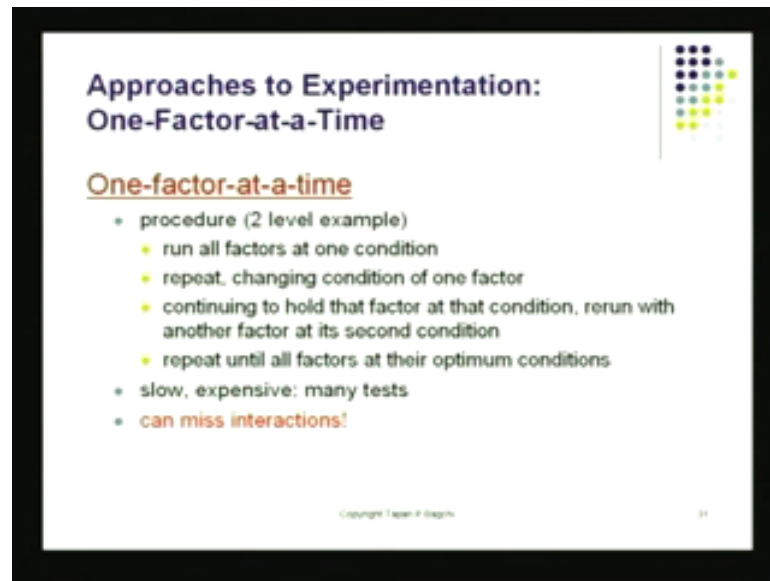
- the tinkerer's approach
- "pound it to fit, paint it to match"
- impossible to know if true optimum achieved
  - you quit when it works!
- consistently slow
  - requires intuition, luck, rework
  - Re-optimization and continual fire-fighting

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If we did that, you would be the long as **the** you would be the ahead. What happens if we try to build test and fix? This is really the tinkerer's approach **was they**; what does it tinkerer do? Tinkerer does not have any standard framework guiding him; you basically manipulate the refund factor, which are there. So if you, you know, give it somebody, please see how this pen can be that some done something with. You would start tinkering with it you probably manipulate the clip manipulate this, manipulate that, we probably take the back end off you probably, you know take the tip off and so on so forth this do basically manipulation.

If I wanted to ask him set the condition such way that are rights perfectly. A tinkerer will start playing with the different factors without any kind of system, systematic approach apply to it. In fact that is your approach sometimes while receive we **we** force things to fit, then we paint it to match that is the tinkerer's approach. Build test if it works fine otherwise fix it again and build it again, rebuild it. It is impossible really to know, whether you are performance is optimum that is like something that is not possible to **to** figure out, when I just building, testing and fixing. Also its consistently slow its **its** actually in variably this is the slow approach particularly, when you see some of the advance design of experiments approaches you would actually come to realise that we probably should not be spending even one rupee was the material or time or resources by doing it this way, which is like build test and fix.

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**Approaches to Experimentation:  
One-Factor-at-a-Time**

One-factor-at-a-time

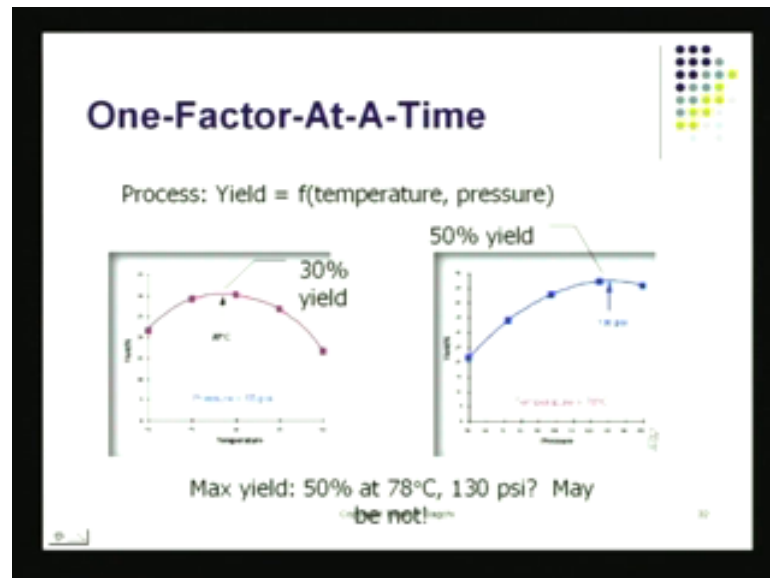
- procedure (2 level example)
  - run all factors at one condition
  - repeat, changing condition of one factor
  - continuing to hold that factor at that condition, rerun with another factor at its second condition
  - repeat until all factors at their optimum conditions
- slow, expensive: many tests
- **can miss interactions!**

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What about one factor at a time? That seems like quite scientific, lot of people in chemistry, and many physics also, they run one factor at a time experiments. And we will see, what are the benefits? If indeed are there, are there **are there** any benefits from this?

The big problem in this which have put in red here that if we do one factor at a time trials, you can miss interactions; interactions are not there, because a manipulating one factor at a time. The moment if I manipulate one factor at a time, you have no idea what **what** were happen if two factors were change together or if three factors would change together, what would happen? You would not know that if you doing one factor at a time trials.

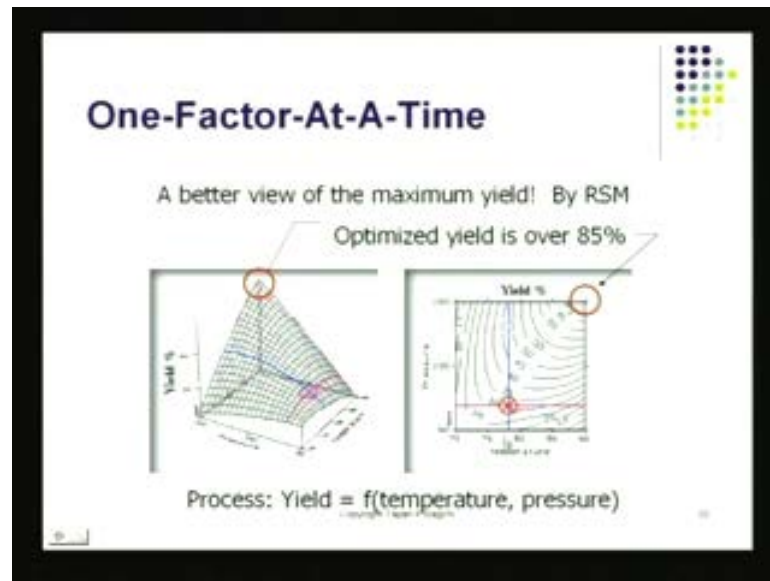
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What do you say? As the result of a one factor at a time like for example, I have got couple of situations here. I have really in the process is supposed to be affected by two variables temperature and pressure. When I am doing one factor at a trial, one factor at a time experiment, I fix one of the **one of the** factor, so here in this case I fix pressure at 65 psi. And I manipulated temperature, and looked at yield, so that was like response being observed, when one only one factor was changed, the other was fixed at **at** the six. What I do see from this, I see when pressure is fixed at 65 psi, somewhere in between around 78 degree celsius yield becomes maximum. Then I move to the next round of trials in that case I will fix temperature as 78 **78** turn out to be the best point by this **less** the experiment done to the left. And then I find when I vary pressure at 130 psi I get maximum.



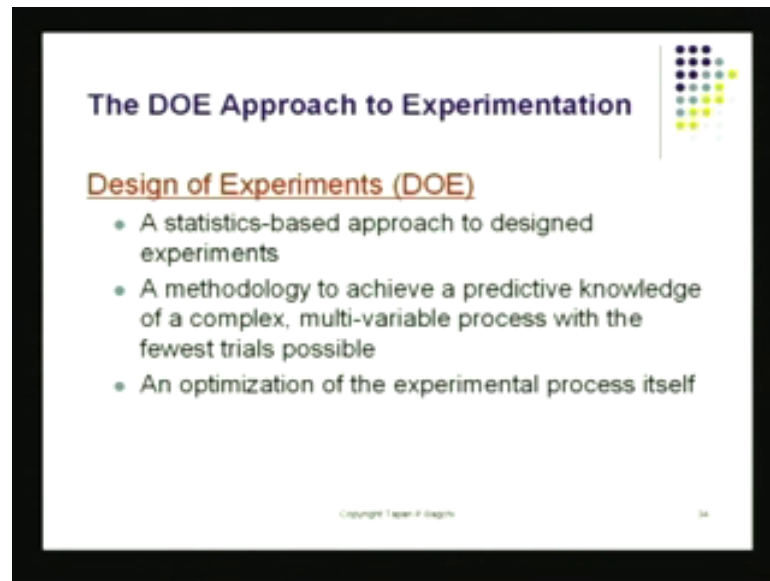
(Refer Slide Time 08:06)



So now I am hoping, I am praying and hoping that I have hit the optimum. The optimum is basically the peak here found, use that in the next round of trials, and I found another peak there and hopefully this is the best peak possible. Is that really the peak? And in fact have I really missed out something that is optimum; just take a look at the full process. Will the pull full process has a responsive is like this, when I look at the full range of change of pressure possibilities, and full range of temperature change possibilities.

Our initial experiment the one factor at a time experiment it was struck right there, in front is struck right and there is like way out yield can be much more I never really got to that range there, because I was struck here by manipulating one factor at run trail; I struck right there. So this is something I would not be able to figure out if I continue to do one factor at a time experiment. I have no idea what the full response, because I have not manipulated two factors together to see what that response is like.

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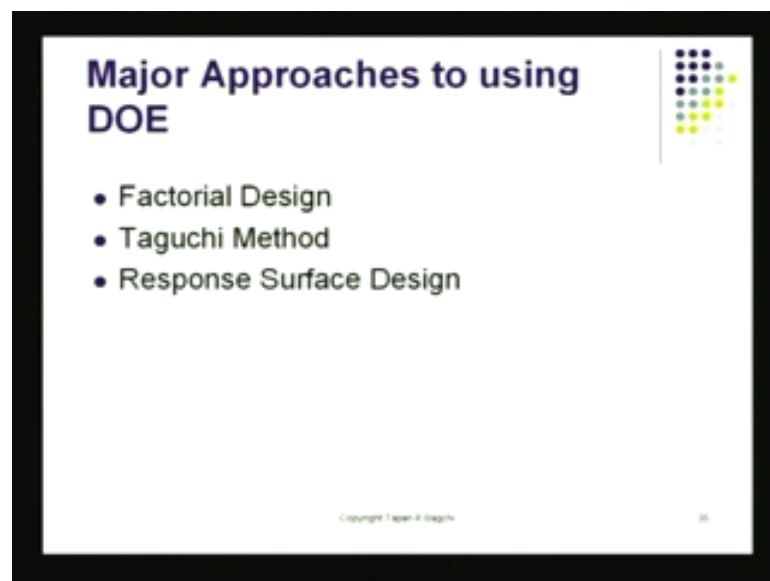
**The DOE Approach to Experimentation**

**Design of Experiments (DOE)**

- A statistics-based approach to designed experiments
- A methodology to achieve a predictive knowledge of a complex, multi-variable process with the fewest trials possible
- An optimization of the experimental process itself

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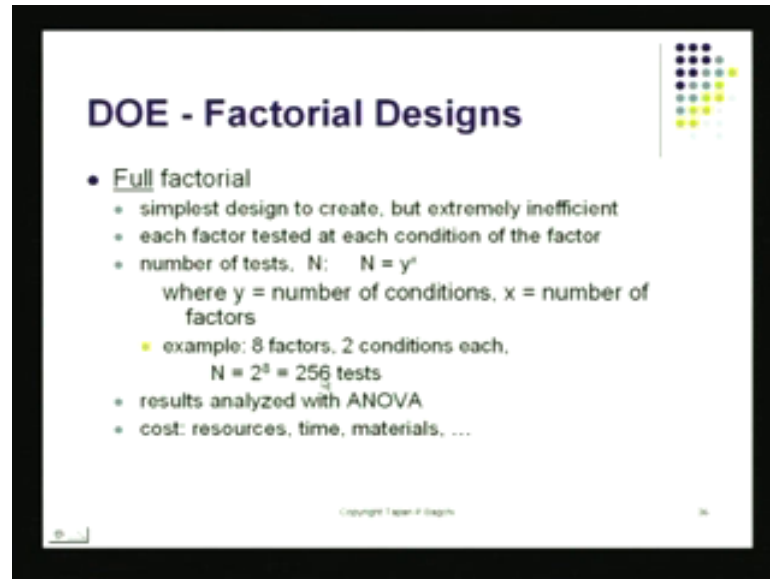
**Major Approaches to using DOE**

- Factorial Design
- Taguchi Method
- Response Surface Design

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You change that to DOE and what is the DOE approach? It is just a statistical approach is it systematic approach, and choose some special approaches, it uses factorial design and in some cases, it uses Taguchi design, and in some cases it uses what we call response surface design. These are schemes these are experimental schemes that we use we could use the full factorial design or we could use the Taguchi design or we could use what we call the **the** response surface design. And these three approaches, they will give you different results, but these are all scientifically derived, these are all going to be scientifically derived.

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## DOE - Factorial Designs

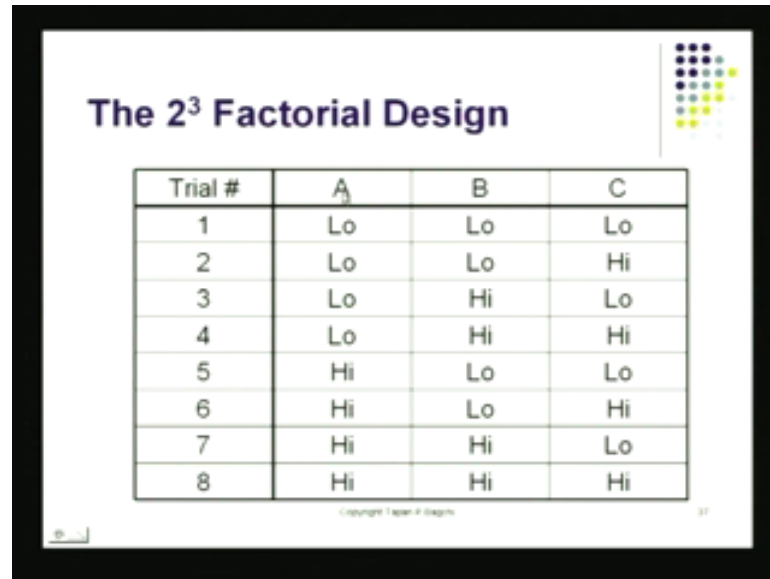
- Full factorial
  - simplest design to create, but extremely inefficient
  - each factor tested at each condition of the factor
  - number of tests,  $N$ :  $N = y^x$   
where  $y$  = number of conditions,  $x$  = number of factors
    - example: 8 factors, 2 conditions each,  
 $N = 2^8 = 256$  tests
  - results analyzed with ANOVA
  - cost: resources, time, materials, ...

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Let us take a look at the full factorial design. Right now we are basically trying to plan a trial plan an experiment, what does the full factorial design do? Full factorial experimental design do for us, It is a simplest design to create, but extremely inefficient because it ends up with sometimes a large number of trials for example, if I had eight factors, and if I had manipulated the eight factors at two sets in each; if I did that, I had end up running 256 test, thus way too many test and while we have manipulating these different eight factors is possible that other factors also perhaps change, and the conditions would differ from the first few experiments to the last two experiments those conditions they are different.

Then of course, your whole experiment is found up that is one of the problems will full factorial experiments because really speaking many times the full factorial design requires you to run many experiments. Thus like on the short terminal, but it is pretty power full method, it can let you find all the main effects, all the interaction effects, and in some cases it can also lead to that response surface, those things can be done to some degree by using the full factorial design.

(Refer Slide Time: 10:40)



The slide titled "The 2<sup>3</sup> Factorial Design" features a table with 8 rows and 4 columns. The columns are labeled "Trial #", "A", "B", and "C". The rows represent different combinations of factor levels: Trial 1 (Lo, Lo, Lo), Trial 2 (Lo, Lo, Hi), Trial 3 (Lo, Hi, Lo), Trial 4 (Lo, Hi, Hi), Trial 5 (Hi, Lo, Lo), Trial 6 (Hi, Lo, Hi), Trial 7 (Hi, Hi, Lo), and Trial 8 (Hi, Hi, Hi). A decorative graphic of colored dots is in the top right corner.

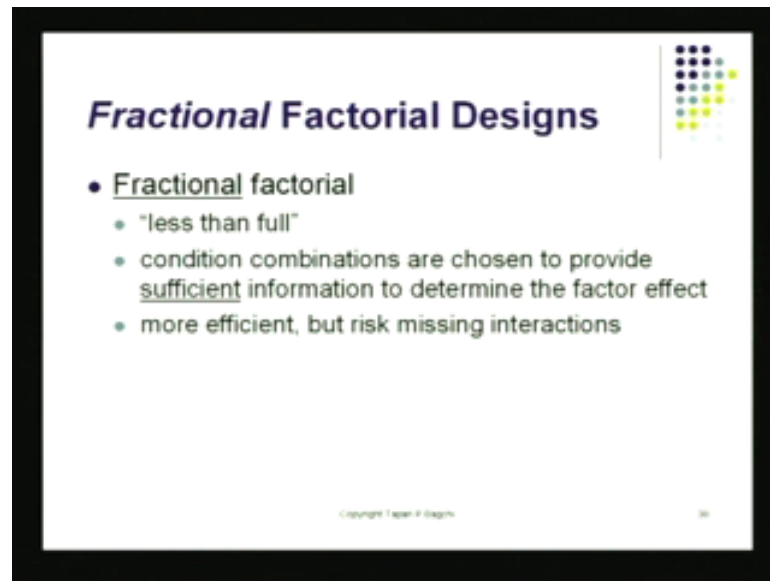
Trial #	A	B	C
1	Lo	Lo	Lo
2	Lo	Lo	Hi
3	Lo	Hi	Lo
4	Lo	Hi	Hi
5	Hi	Lo	Lo
6	Hi	Lo	Hi
7	Hi	Hi	Lo
8	Hi	Hi	Hi

What does it look like? Well if I had three factors if I had factor A, factor B and factor C to manipulate. And if **if** each of those factors could be set at two levels low and high, there is a way of combining the different factor setting. So I have got two levels of A and I am got levels of B, if I am about two levels of C. When I combine the setting to come up with the plan for the scheme for trial number one, I will set A at low level, B at low level, C at low level, then observe the response; run the process, observe the response.

Then I change, I change C from low to high and keep the settings for A at low, and also be at low, they have got low low high, this is my trial number two; then I come to low high low thus trial number three; then I have got low high high that is trial number four. Then of course, I change the setting of A from low to high I have got high low low like the first one; then I have got high low high; then I have got high high low; and high high high. What are these setting? These are the different settings that which I can set factor A, I can set factor B, I can set factor C, and run my trial.

See here in fact I have ended up running eight trials at these different conditions; this is kind of a comminatory situation, I have got, I have combined the different settings possible for A with the different settings possible for B with the different settings possible for C. And each here each of these cases, each factor has two settings, I have got two multiplied by two multiplied by two, which is like eight total trials; that is going to be my experimental plan.

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The slide is titled "Fractional Factorial Designs" in a bold, dark blue font. To the right of the title is a decorative graphic consisting of a grid of colored dots in shades of blue, green, and yellow. Below the title, there is a bulleted list with three main points. The first point is "Fractional factorial", which is underlined. It has three sub-points: "less than full", "condition combinations are chosen to provide sufficient information to determine the factor effect", and "more efficient, but risk missing interactions". At the bottom of the slide, there is a small copyright notice and a page number.

- Fractional factorial
  - "less than full"
  - condition combinations are chosen to provide sufficient information to determine the factor effect
  - more efficient, but risk missing interactions

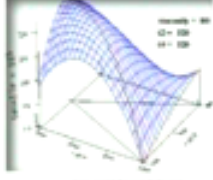
The fraction factorial design chops of part of the full factorial design. So it is not as power full as the full factorial design. What does it give up? Sometimes is give up interaction, sometime I gives up interactions, say some of the interaction effects might not be in fact you may not be able to determine interaction effect, if we running what we call fractional factorial these are part factorial. Here is an example.

I have again eight trials, but here what I have done is, I have got factors A, B, C, D, E, F, G - seven factors. If I had run full factorial experiment with certain factors at two level each, each out of had to run 128 trials. What whatever you chosen to do? I am running on eight trials, and I am running is special schemes; I am running a special scheme of the experiment. And this special scheme in the in run in such a way I can cover two settings of A, two settings of B and two settings of C, two settings of D, two settings of E, two settings of A, F and two setting of G. Having done this or got only eight trials done of course, this scheme is not going to be as powerful is not going to be as powerful as the full factorial experiment. The result is this I will be able to find the main effect, but I will not be able to find any interaction effect that is not something, I will be able to find with my partial factorial design; this is the example of a partial factorial design.

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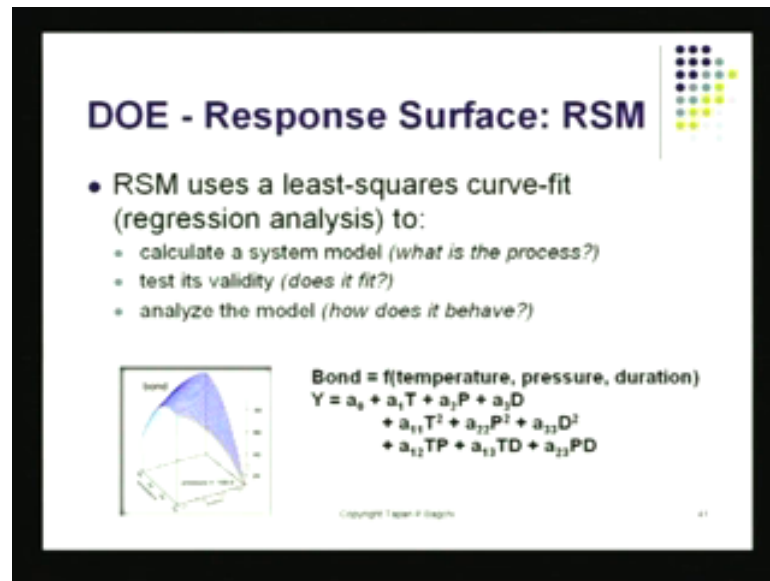
## DOE in Response Surface: RSM

- Goal: develop a model that describes a continuous curve, or surface, that connects the measured data taken at **strategically important places** in the experimental window



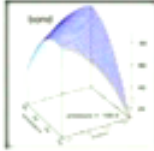
Then of course, I have got the third approach to conduct experiment. And the goal here is to try to generate the response surface. Here I have got two factors; I have got factor one and factor two and I run many, I run the experiment at many different point; and that helps may generate this surface there. This would be found by doing multiple regression, but in trying to produce the data what I have done is, I have set the level of A at multiple points, I have also set the level of B at multiple points; and at each of those points have made an observation; at each of those intersection are made our observation; I have collected the data, then I run my multiple regression model, multiple regression calculation; and I end up generating the surface. You can see the surface right there; this is actually this is actually something that is done, when I am trying to optimise, when I am trying to just response the basically generate the response surface there.

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**DOE - Response Surface: RSM**

- RSM uses a least-squares curve-fit (regression analysis) to:
  - calculate a system model (*what is the process?*)
  - test its validity (*does it fit?*)
  - analyze the model (*how does it behave?*)

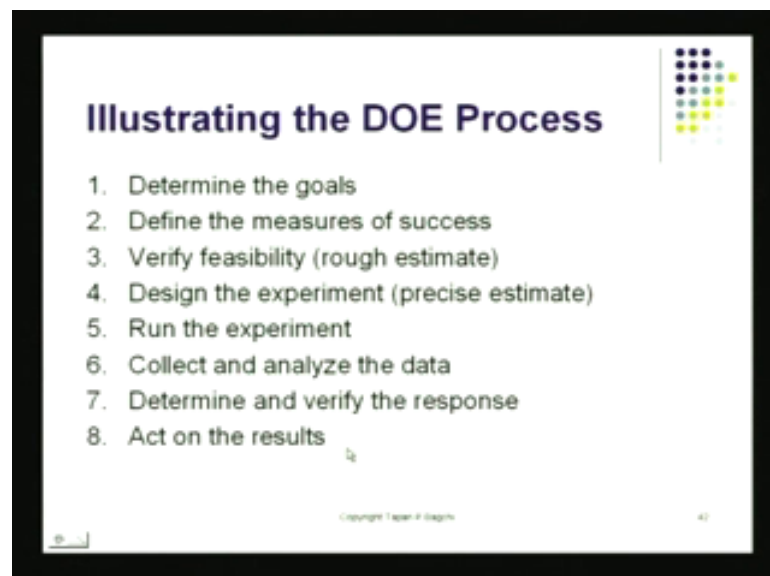


Bond = f(temperature, pressure, duration)  
$$Y = a_0 + a_1T + a_2P + a_3D + a_{11}T^2 + a_{22}P^2 + a_{33}D^2 + a_{12}TP + a_{13}TD + a_{23}PD$$

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In fact here is another example of a response surface and it can manipulate, it can let me manipulate two factors here temperature and pressure and of course, I have got something called duration, which you could be the cooking time for this particular chemical process. Having done that I am able to now generate this **this** model, and this model is actually multiple regression model that I have generated with the help of this response surface design. So this is like the third design.

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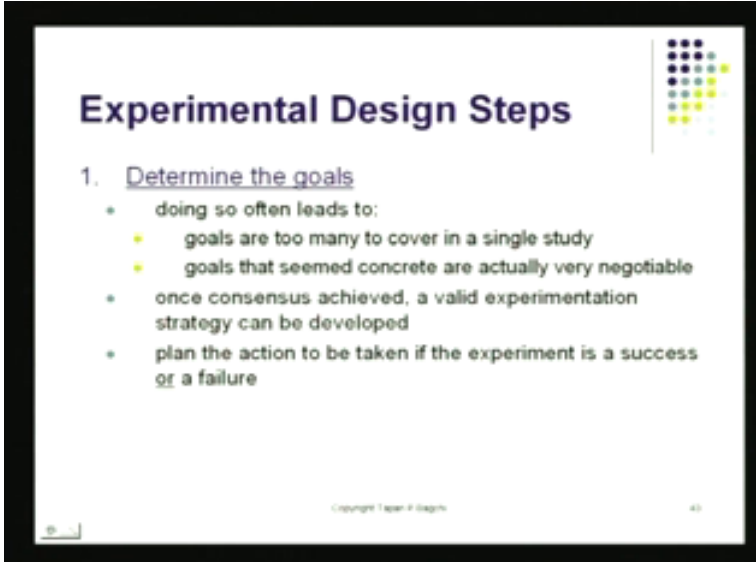
**Illustrating the DOE Process**

1. Determine the goals
2. Define the measures of success
3. Verify feasibility (rough estimate)
4. Design the experiment (precise estimate)
5. Run the experiment
6. Collect and analyze the data
7. Determine and verify the response
8. Act on the results

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So what are all those three designs so far? I have full factorial design, I have a fraction factorial design and I have got a response surface design; these are three different approaches to design my things. How do I go about illustrating design of experiments processes I must of course, the first thing I should do is determine the goals like a set before. Define the measures of successful, when I am going to say that I have succeeded in conducting the experiments. How I am going to check the feasibility of this thing; and then of course, I have got to design the experiment, I have got to run the experiment I am going to collect the data, I got to do my data analysis, and then of course, I am going to act on the results.

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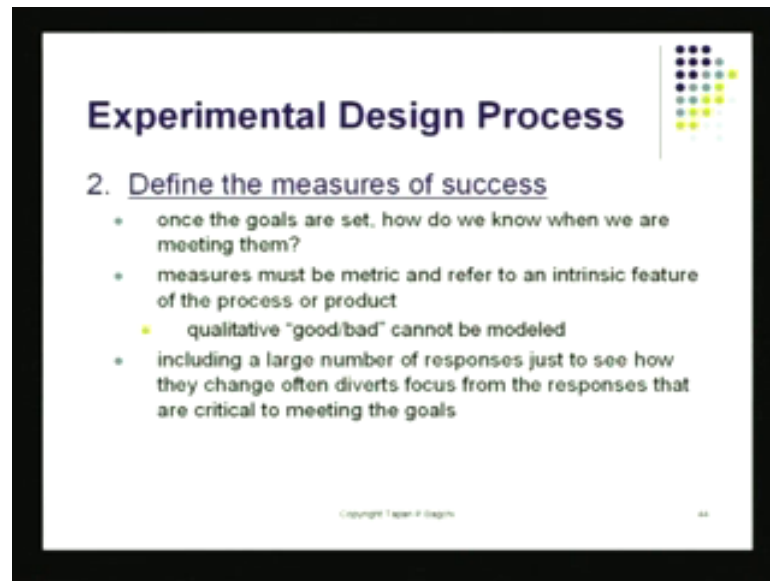


The slide is titled "Experimental Design Steps" in a bold, dark blue font. In the top right corner, there is a decorative graphic consisting of a grid of colored dots in shades of blue, green, and yellow. Below the title, the first step is listed as "1. Determine the goals" in a blue font. Underneath this heading, there are four bullet points, each preceded by a small blue square. The first bullet point is "doing so often leads to:", followed by two sub-bullets: "goals are too many to cover in a single study" and "goals that seemed concrete are actually very negotiable". The second main bullet point is "once consensus achieved, a valid experimentation strategy can be developed". The third main bullet point is "plan the action to be taken if the experiment is a success or a failure". At the bottom of the slide, there is a small copyright notice: "Copyright Taper & Siegel" and the number "40" in the bottom right corner.

Let us see how you end up doing that determining the goal, determining the goals. And goals generally speaking certainly in the six sigma case those are derived based on some business objective; perhaps defectables are high, perhaps evening this low or some like that first perhaps customer services poor, those we use as the response, then **then** we try to see, what are the different factors that make a manipulating trying to make sure we can you do that. So the determining the goal is very important; in starting your planning for conducting an experiment.



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The slide is titled "Experimental Design Process" and is numbered 44. It features a decorative graphic of colored dots in the top right corner. The main content is a list of bullet points under the heading "2. Define the measures of success".

## Experimental Design Process

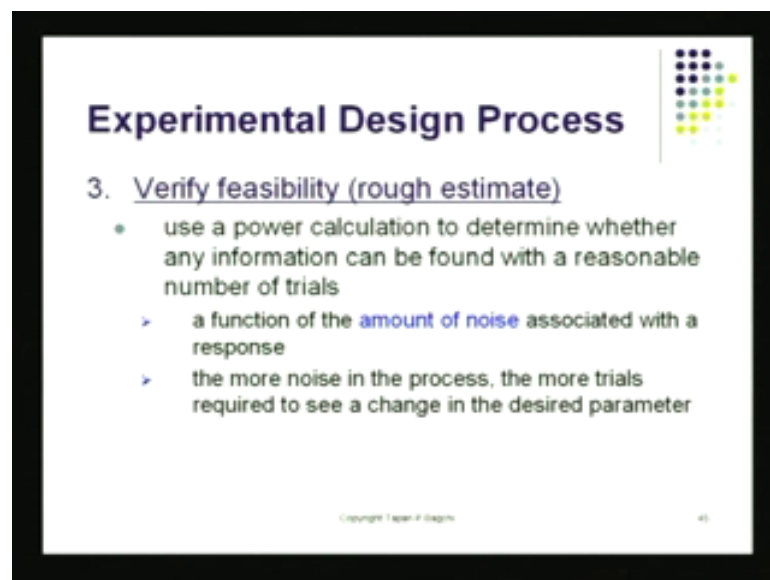
### 2. Define the measures of success

- once the goals are set, how do we know when we are meeting them?
- measures must be metric and refer to an intrinsic feature of the process or product
  - qualitative "good/bad" cannot be modeled
- including a large number of responses just to see how they change often diverts focus from the responses that are critical to meeting the goals

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Then define the measures of success these are of course, going to be how I am going to measure the output; how I am going to judge the output that also will have to be spelled out.

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The slide is titled "Experimental Design Process" and is numbered 45. It features a decorative graphic of colored dots in the top right corner. The main content is a list of bullet points under the heading "3. Verify feasibility (rough estimate)".

## Experimental Design Process

### 3. Verify feasibility (rough estimate)

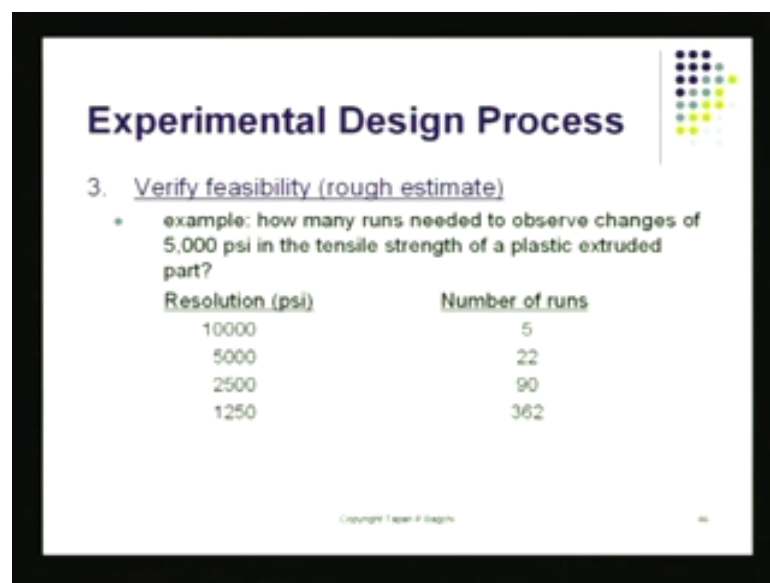
- use a power calculation to determine whether any information can be found with a reasonable number of trials
  - a function of the amount of noise associated with a response
  - the more noise in the process, the more trials required to see a change in the desired parameter

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Then of course, verify feasibility and this actually says, if I conduct when experiment is noisy experiment, in a noisy environment, will I able to hear the signals? If I am not going to **to** be able to do that then of course, I have to make sure the noise is not that high. If noise is not going to be that high, then I want to make sure when I **finally, apply**

the finally, apply the conclusions or the the results that come out of an experiment to a practical situation. I do something to make sure the effect of noise again does not cloud my results; that is something that I will have to be able to do. But in general of course, something that turns out to be significant, stage significant, because something that because statistical significant is always measured with respect to the presence of background noise, and this is done by the anova test. The anova test make sure that what you call significant really is significant, its audible, its visible in the background, in the background of noise that is present there.

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**Experimental Design Process**

3. Verify feasibility (rough estimate)

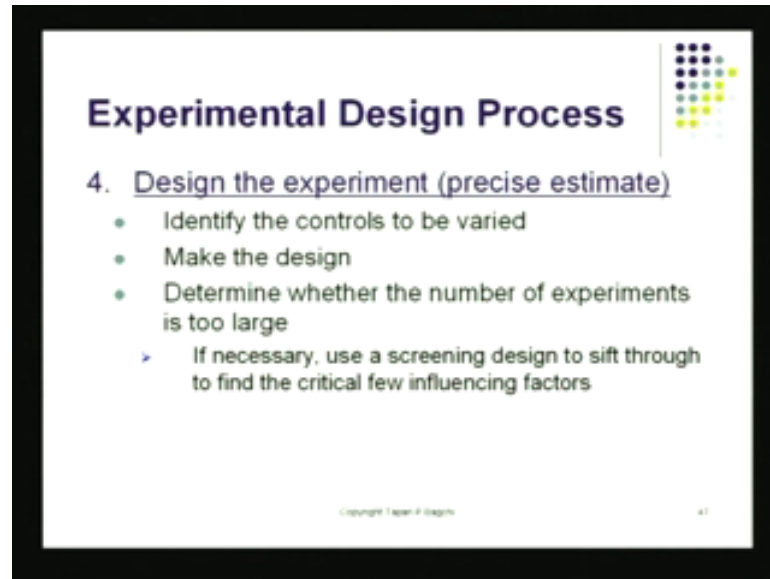
- example: how many runs needed to observe changes of 5,000 psi in the tensile strength of a plastic extruded part?

Resolution (psi)	Number of runs
10000	5
5000	22
2500	90
1250	362

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And something of course, we also have to do is so we have to check out the feasibility of the thing, how many experiments can I run, what sort of precision do I want, and do I have the money to be able to run those trials; that is something that would like to be able to do.

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**Experimental Design Process**

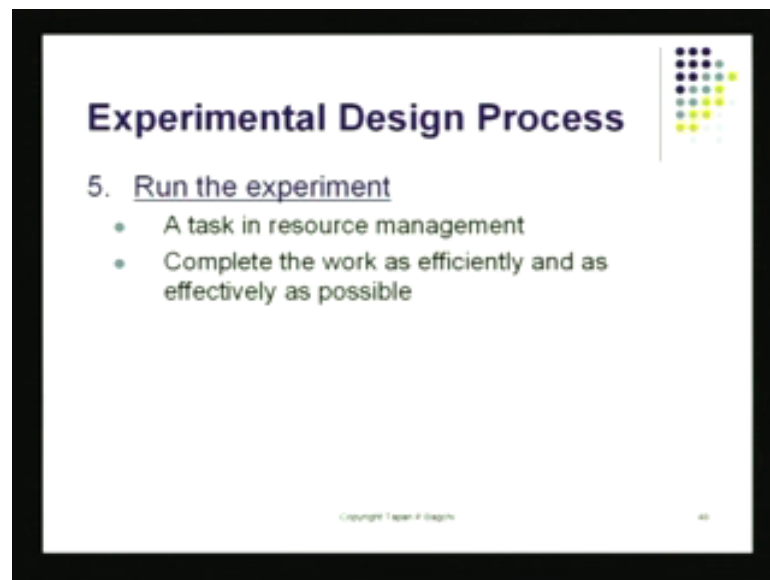
4. Design the experiment (precise estimate)

- Identify the controls to be varied
- Make the design
- Determine whether the number of experiments is too large
  - If necessary, use a screening design to sift through to find the critical few influencing factors

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Then of course, I got to make sure I specify the precision of the experiment; there is something that I have got to do.

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**Experimental Design Process**

5. Run the experiment

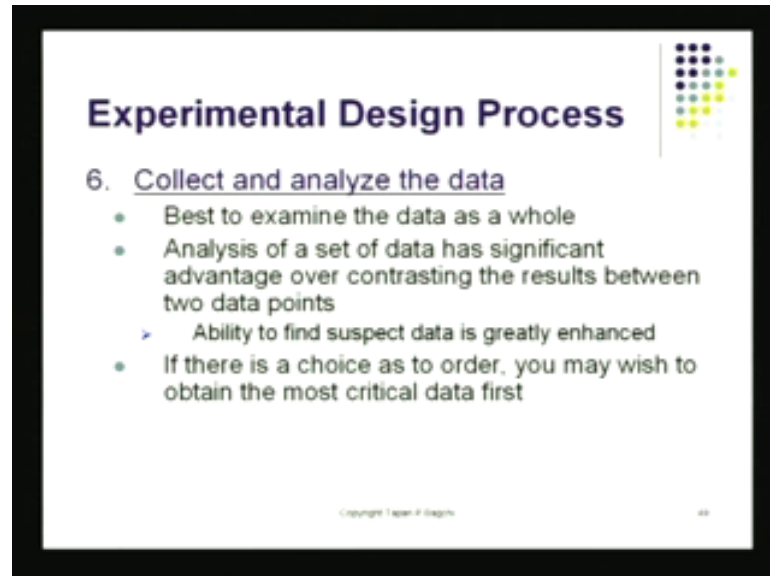
- A task in resource management
- Complete the work as efficiently and as effectively as possible

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I have got to run the experiment; and that is a task that also need to be randomise once in a while, this is something very important; unless you randomise, there may be an factor like sunshine for example. And if you run some of your trials in the morning when temperature is cold cool, then you run it at lunch time when is pretty warm, then you run it again in the evening when temperatures are cool again. These results may not be

comparable, because of the presence of this outside try to which is the environmental factor.

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**Experimental Design Process**

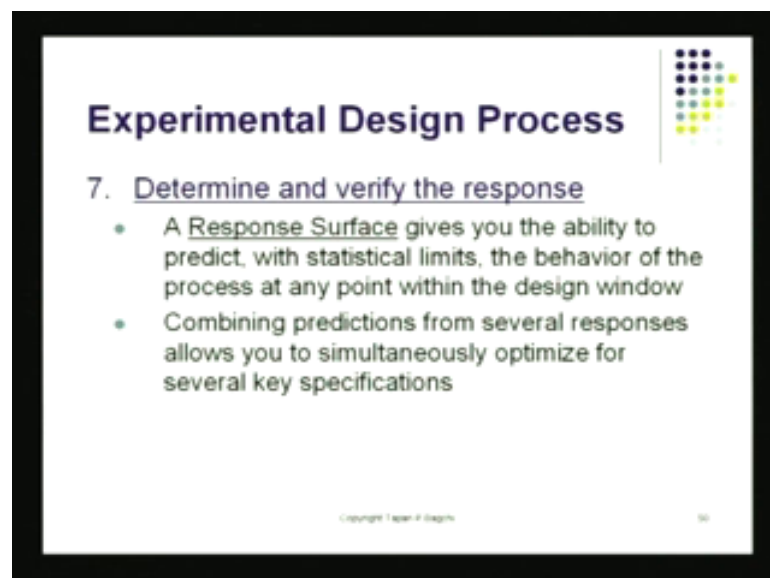
6. Collect and analyze the data

- Best to examine the data as a whole
- Analysis of a set of data has significant advantage over contrasting the results between two data points
  - Ability to find suspect data is greatly enhanced
- If there is a choice as to order, you may wish to obtain the most critical data first

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So this is something you also would be able watch, watch out for, you should be able to watch out for.

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**Experimental Design Process**

7. Determine and verify the response

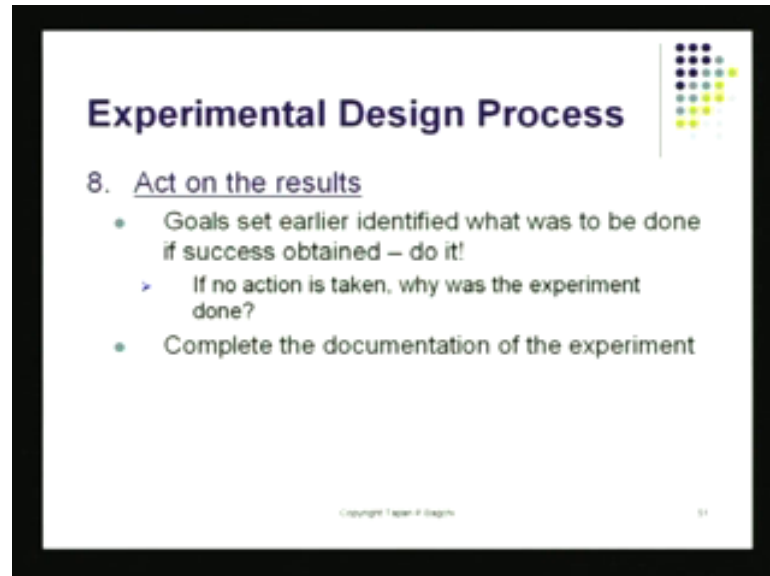
- A Response Surface gives you the ability to predict, with statistical limits, the behavior of the process at any point within the design window
- Combining predictions from several responses allows you to simultaneously optimize for several key specifications

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I collect a analyse data and I always use to statistical methods to may analyze my data, even if I draw **draw** some pictures once in a while I draw some pictures; I really should be able to do this correctly. And of course, in the end when I am conducting my

experiments I should be able to verify the response; this is something I should be able to do.

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**Experimental Design Process**

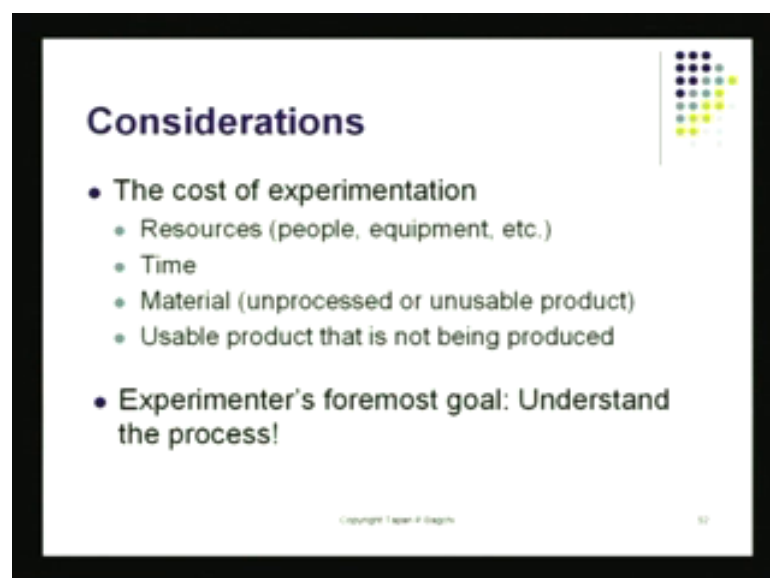
8. Act on the results

- Goals set earlier identified what was to be done if success obtained – do it!
  - If no action is taken, why was the experiment done?
- Complete the documentation of the experiment

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And of course, the end is the **the the** proof is in the putting therefore, once I have derived some inference, drive some conclusion, I got to make sure a run these trial tests, I have got to run these validation or verification test make sure, what I infer from this indeed, turns out to be in the real world; it is something that we really see that.

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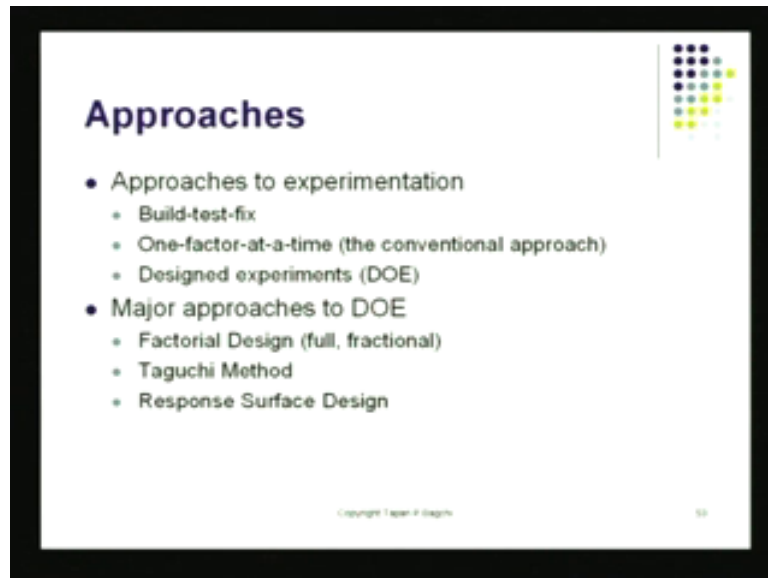
**Considerations**

- The cost of experimentation
  - Resources (people, equipment, etc.)
  - Time
  - Material (unprocessed or unusable product)
  - Usable product that is not being produced
- Experimenter's foremost goal: Understand the process!

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What are the considerations cost of course, in the very big one. Then obtaining the material to be able to do this; **what** why are we trying to do all this, we basically want to understand the process. So when the really process runs, I do not have as many defects as many as many rejections.

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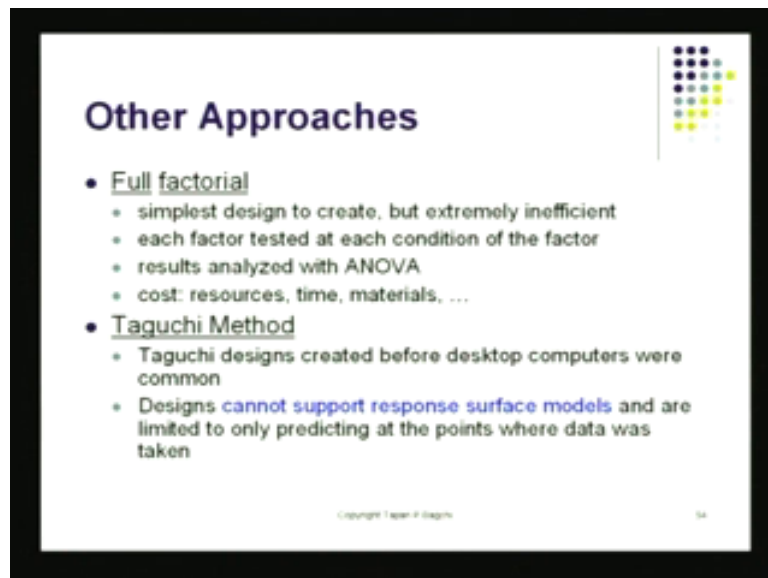


**Approaches**

- Approaches to experimentation
  - Build-test-fix
  - One-factor-at-a-time (the conventional approach)
  - Designed experiments (DOE)
- Major approaches to DOE
  - Factorial Design (full, fractional)
  - Taguchi Method
  - Response Surface Design

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**Other Approaches**

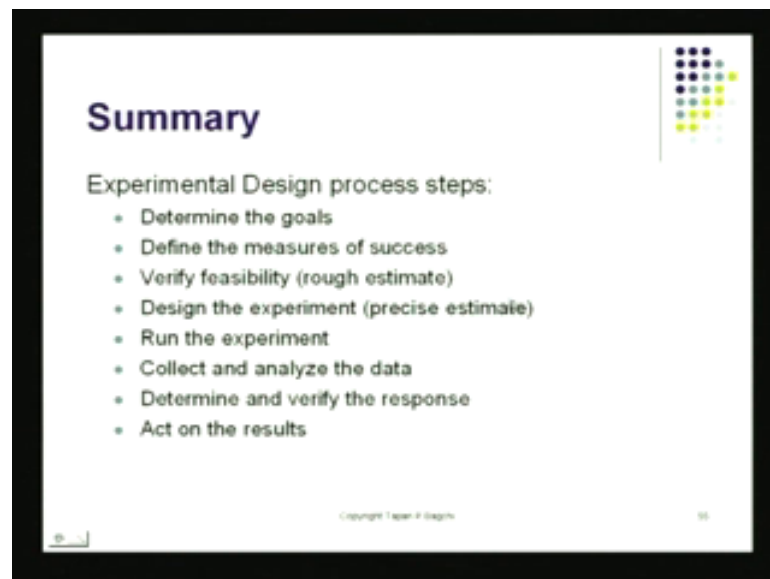
- Full factorial
  - simplest design to create, but extremely inefficient
  - each factor tested at each condition of the factor
  - results analyzed with ANOVA
  - cost: resources, time, materials, ...
- Taguchi Method
  - Taguchi designs created before desktop computers were common
  - Designs cannot support response surface models and are limited to only predicting at the points where data was taken

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What are the different approaches, I already showed you, build to test, build **to build** test and fix; one factor at a time trials and DOE trials. I am going to expand on this a little bit, and also I am going to give you some examples of factorial designs, and the Taguchi

way of designing experiments and the response surface method. Other approaches will also be there for example, the full factorial method is there like I told you earlier. The results have the full factorial trial; those are basically, analyze choosing ANOVA. Taguchi methods on the other hand lead to some very purely simple straight forward calculations, but the Taguchi approach to conducting experiments cannot really figure out many times interaction effects between towards the factors, because most of these are they turn out to be factorial partial factorial designs.

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**Summary**

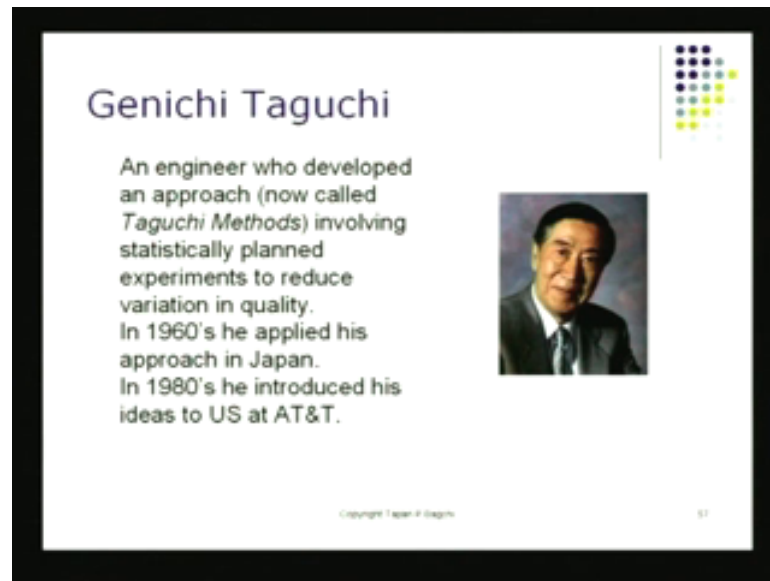
Experimental Design process steps:

- Determine the goals
- Define the measures of success
- Verify feasibility (rough estimate)
- Design the experiment (precise estimate)
- Run the experiment
- Collect and analyze the data
- Determine and verify the response
- Act on the results

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So, what is the summary of all this? I got to design determine the goals, I have go to define measure some success, I have got to verify feasibility, I would like to conduct the experiments, run the experiments design and run the experiment collect the data, look at the response and come back an act on results, in fact on that case, in that situation, we should be able to basically verify what we done. The **the** conclusion that we reach it is a really confirm, if I identify some settings has optimum for a, optimum for b, optimum for c, when I combine the optimums, do I get the best results? That is a validation; that we have to do.

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**Genichi Taguchi**

An engineer who developed an approach (now called *Taguchi Methods*) involving statistically planned experiments to reduce variation in quality. In 1960's he applied his approach in Japan. In 1980's he introduced his ideas to US at AT&T.

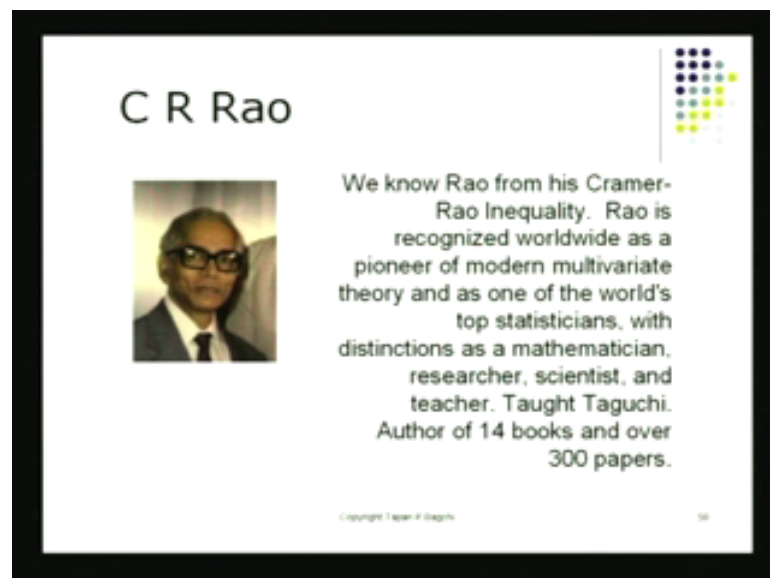


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The slide features a title 'Genichi Taguchi' in a large, dark font. Below the title is a block of text describing his work. To the right of the text is a small, square portrait of Genichi Taguchi, an elderly man with dark hair, wearing a suit and tie. In the top right corner, there is a decorative graphic consisting of a grid of colored dots in shades of blue, green, and yellow. At the bottom of the slide, there is a small copyright notice and the number '57'.

Now let us look at some application. The first application going to talk about is called application of Taguchi methods. This person you see his picture there, he was an engineer; and he was a pretty curious person; and he was very concerned about trying to impact the quality of products that are coming out of the Japanese factories; and he became involved in this game in this sixties; and that was about the time when you also came to India; and he studied under doctor C R Rao.

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**C R Rao**



We know Rao from his Cramer-Rao Inequality. Rao is recognized worldwide as a pioneer of modern multivariate theory and as one of the world's top statisticians, with distinctions as a mathematician, researcher, scientist, and teacher. Taught Taguchi. Author of 14 books and over 300 papers.

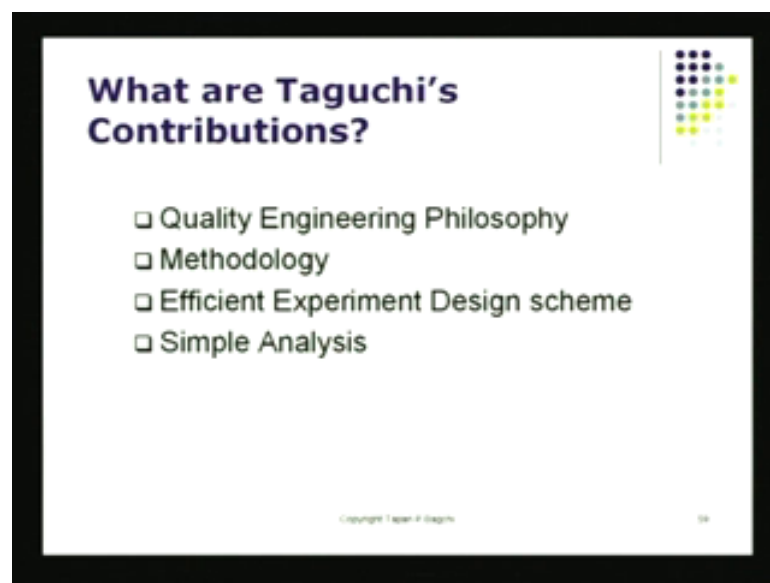
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The slide features a title 'C R Rao' in a large, dark font. To the left of the text is a small, square portrait of C R Rao, an elderly man with glasses, wearing a suit and tie. To the right of the portrait is a block of text describing his work. In the top right corner, there is a decorative graphic consisting of a grid of colored dots in shades of blue, green, and yellow. At the bottom of the slide, there is a small copyright notice and the number '58'.



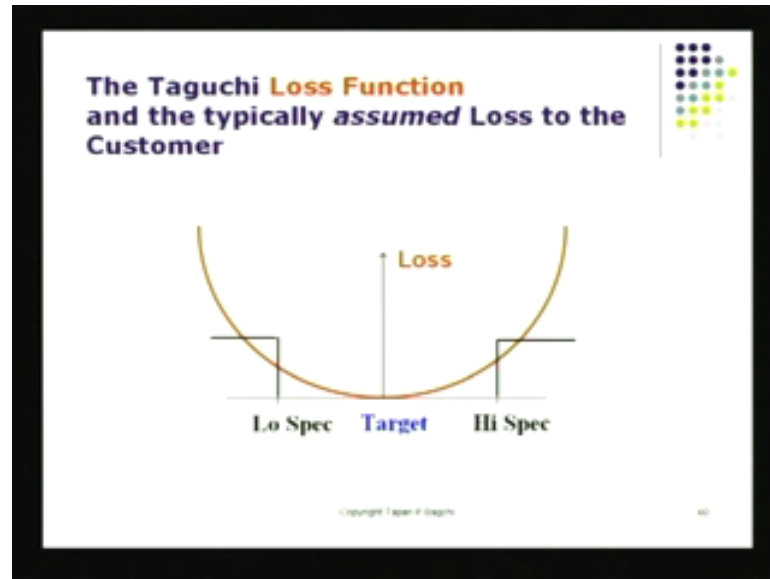
C R Rao was his teacher; and C R Rao was a statistician; **c r** C R Rao right now is in **((** **))**; and his is a professor there. C R Rao when he was in the Indian statistical institute, he was Taguchi's guru; and Taguchi studied **the conduct the** design and conduct **conduct** a different experiments. One of the things that appeal to Taguchi was these simple design of partial factor designs; and these did not require analyse of variance. And what Taguchi was able to see was in many cases, we need not really run the full factorial **will full factorial design**; and would still be able to come up with pretty decent inference; that is something the Taguchi was able to figure out.

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And let us what he ended up doing? He ended up contributing something that truly enormous; he was able to come up with a new philosophy for managing quality; and this we called, this we all call today, the quality engineering philosophy. This is something Taguchi was able to contribute. He gave us a method, which was simpler than the enormous variance technique or the full factorial design.

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So those became fairly efficient design, and the analysis is also was very simpler; these turn out to be pretty major contribution, produced by Taguchi. Taguchi was able to articulate one of the thing that was perhaps known to people, but they did not really put this to put this down or (()). So really it was **it was** not knowledge that could be passed on to other people and so on. People at this feeling, but they never really knew how to exploit this.

What is this issue; this shirt size; this is this shirt is perhaps a little too loose on me. If I had the choice; now this is probably because probably over ageing my neck has probably become slightly a shorter (()). And this shirt is not very old it is about over half two years old and still is fine shirt; nothing is wrong. But the fit is slightly off, if you look at the fit as the shirt is slightly off. As far the customer is concerned, the customer is happiest, when the product that he uses fits in exactly. So there is like a dimension, there is a target dimension of my neck size; at that dimension could be forty centimetres. if I were to choose a shirt today, I had go to a tailor and I ask the tailor please **make my** measure my neck size, and it give me the exact measurement, then I walk up to the self, I perhaps ask to in stitch my shirt that exactly forty point zero centimetre as for as neck size is concerned. Then of course, you do the same thing for sleeve and so on so forth.

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So if a shirt that fits exactly is the one I am going to be happiest one. The same thing goes for no matter, what you do. Even if you look at a pen for example, the **the** thickness of the pen with which at rights you know, we have personal taste, and there are certain tips that we do not know like, certain tips are thick, we do not like them; with this is something that is not like something I have got a requirement, that requirements specifies my targets. My target thickness is this; and if I am going to choice of many different pens, they give me a whole bunch of pen or probably start using them or probably try to see which one comes close to my target, and which one does not. This is something I would like a lot like to figure out, unless I do that, I am not be the happiest person

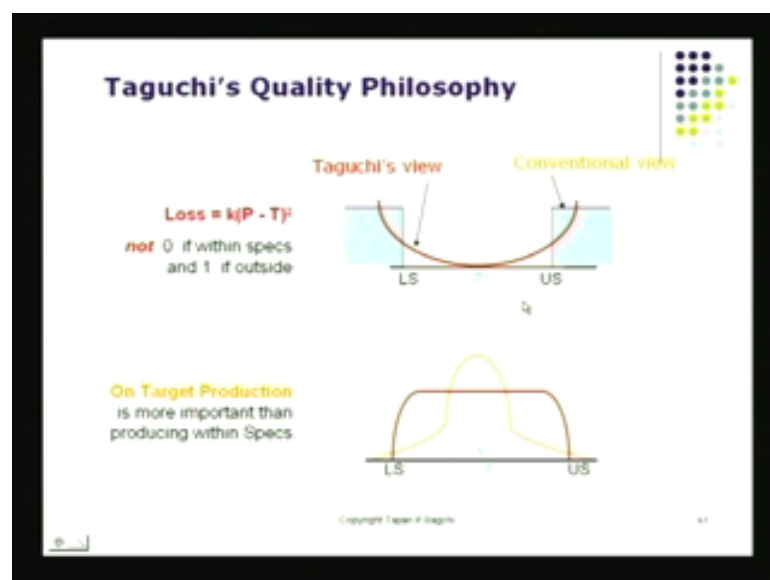
What Taguchi did was he articulated these things by drawing this will picture here. And look at the picture there, the target is the place where the customer is happiest. If you move away, if you often you may product whose dimension is away from the target, whose quality characteristic is away from the target, the customer is going to incurs some that we call a loss.

What is the conversion wisdom? The conversion wisdom is well if a professor Bagchi requires a shirt, his a neck size is forty, but give him plus minus one, who fixes this tolerance, it is probably fix by the tailor or perhaps by the with the guys who merchandise **short** the shirts for example, they are the guys who fix this plus minus one. Now I will not be as happy with a shirt size that is thirty nine or forty one, I just put not

be as happy, I need a shirt size that is exactly 40.0, and that is being **right** at this target there. If I write the target I am happiest. This tolerance, this sort of tolerance that is put down as low specification and high specification limits. This is like the all way to look at quality. What Taguchi said is try to find out what the target is very particular customer; offer him a product that is right exactly on target. Thus when the customers loss is going to be minimal, if this shirt does not fitness, suppose this one a new shirt, suppose somebody gifted me a shirt that is size forty if size forty one or thirty nine. I suddenly would not be able to use it; I will have to take it to **to** tailor, ask him please fit the shirt exact to my size that is an additional cost and perhaps the fit would not be as good.

So, all those problems are there. The moment we start manipulating something there is half, half be a target, would have to spend some extra money for it, and that is a loss to society, because this loss could be avoided all together, nobody gains from it. Therefore basically the idea is a Taguchi said try to find out, what the target is, I keep it there. This was coined as Taguchi's loss function, so you see that red curve there, there actually shows losses go up, the moment you get away from the target either you **given** give it excess or you shrink something there, which end up with causing and lost to get consume customer to the user.

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So, Taguchi's views is stay with the state keep **in keep** your eye on the lost function there and try to deliver things which are right on target. And he even gave us an equation that

equation basically tells us what would **the what would** be the amount of loss if I deviated from the target that is  $P$  performance minus  $T$ , which is the target square that and there is a multiplied that that basically gives you in quantitative terms what that amount of that loss is this kind of a... He say it is a parabola, you can actually see and there is like the way your losses between please if you go went away from the **(( ))** if we went further further away from the target there.

Now this was verified by couple of industrial situations; one of them was the production of TVs - televisions. Now there is a company and this **this** particular case is well documented it came out in a news paper in Japan, the Asahi, the Asahi paper reported on this. You have let me **let me** you about this **this** particular incident you know, there was a time when a lot of this is some years back, some about also about 20 25 years back, when Sony TV produce the best TVs in the world, pretty world and the model was called Trinitron. This Trinitron TV was brought to US and Americans, American consumer suddenly found that these TV they perform must better. The colour quality was good, sharpness was good, everything else was good, it was better than whatever they had on the shelf or in their homes there.

So Sony's TV they started selling very, very well and of course, Japan was a exporting this Sony TVs from Japan into main land USA, it was quite natural for Americans to begin to start of feel that you know, these guys they graving our market, and they not there even robbing people from **from** the jobs, those guys who work in American TV companies they are probably going to be losing jobs, because Sony TVs are basically flooding the market and so on.

So, there was a protest and the result was that a Sony decided that they would set of an assembly plant in San Diego, they would bring the parts, and the assembly would be done in San Diego. So they **they** are of course, American work force was hard, few supervisors came from Japan, they did some training, after that they went away. It was given over given complete into Sony USA, which was in company. And of course, production started and these TVs coming out of can San Diego California, they then got to the shelves of these different, different you know, stores. It turned out after about six months or perhaps year, people started complaining about Sony TV and this was very strange, because Sony had had the reputation of producing the best TV's that you could find anywhere.

Suddenly, there the **the** started complaints; and they are they are pretty smart people what they **what they what they** Japanese trouble shooters try to do was, they try to look at the **the** model, and they looked at the back of it, there was a batch number there, there was a locations such as specified, where that particular TV was assembled, where **the where** did the parts come from and so on. And they form many of these actually came from San Diego, these came from San Diego, and these were actually the once that was causing the maximum out of problems and this was a crazy crazy situation, because what happen here was that the TV's that was otherwise supposed to be good these suddenly started, because the parts were good these started to show problems. And this was a really very crazy situation.

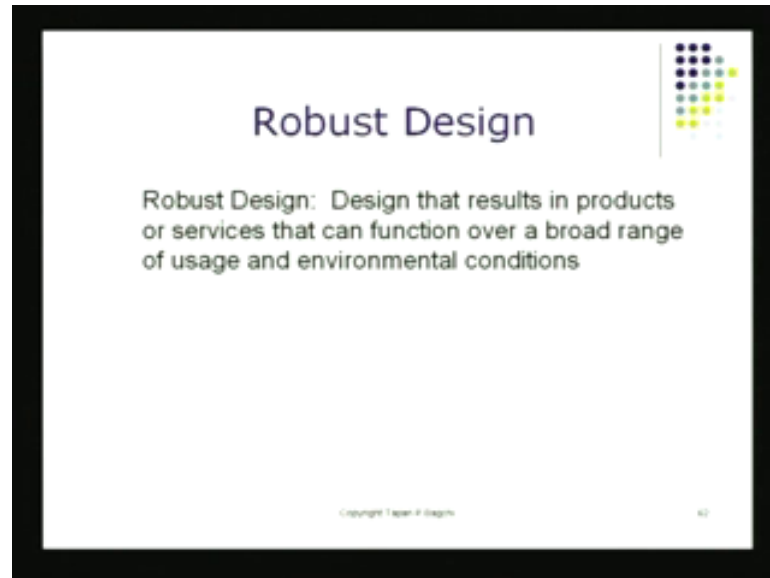
What they did was they looked at the assembly process, what they found was that the assembler, the assembler who is an American US doing this production line he had this spec in front of him and the specification was given just like there is was a lower specification limit and upper specification limit. As long as the parts came together, it was **alright** as long the meet this specification, it was alright, and the parts were put together and the full TV was assemble.

Each of those parts could be anywhere in this specification range, each of those parts could be anywhere in this specification range and of course, that is what the full TV turn out to be, full TV turn out to be an assembly parts that had this sort of slack fitting, and this **this** specifically impacted the colour quality and the sharpness of the TV. Naturally these TV's they were assembled with this philosophy these TV's would not perform as well as those TV's as nicely as those TV's that were made in Japan and assembled all the time to hit exactly the target.

So as far as customer satisfaction was concerned, it turned out customer satisfaction was maximum when TV is basically were assembled with the philosophy of being put together with the target in mind; and customer satisfaction was not as high, when they were basically put together with this philosophy of just meeting specification. This is something, where we got the graphic feedback that it is paste to produce parts and products that meet the target. So do not go to try to produce thing that come within specification. This is something Taguchi said he said do not produce things that just meet specification; try to find the target, and try to hit the target every time. If we do that customer satisfactions go to maximum and your market share is going to grow. This is

one message that came from Taguchi. Taguchi came up with another remarkable insight and that is called robust design. And let me give an idea what this thing is.

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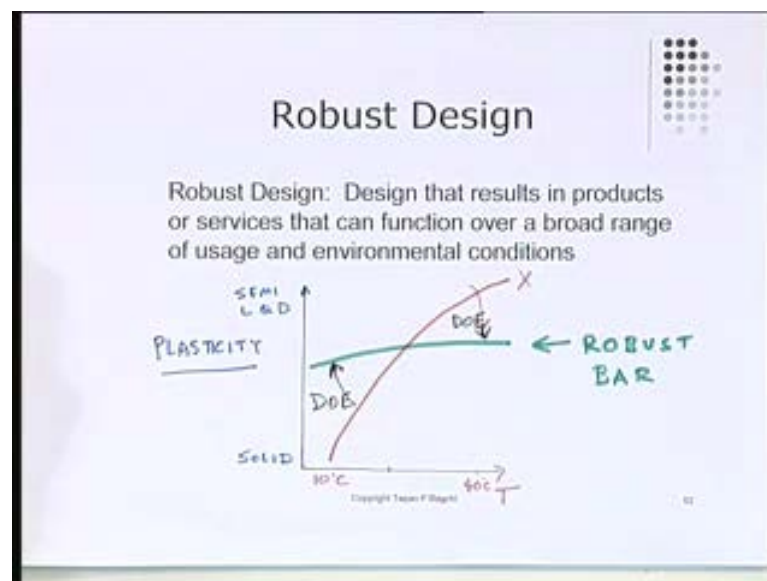
Notice here notice here what we have is we have a product for example, if you look at if you look at chocolate bar for example, the chocolate bar basically is designed a using the best recipe that is there; and he end up with chocolate bar being put together with some nuts, some coco, some milk, some sugar, some butter and so on so forth, and the bar is cost, then **then** bar of course, when it gets a you know stable is packed on so on so forth it is shown.

So now **what a** which chocolate bar you look at; the manufacturing process is exactly the same. Now this obviously are very popular products, this something everybody likes, specially kids they just love, you give them one, they are generally not happy they would like to take another one. But who are the people, who are unhappy with chocolate bars, you can probably guess these are mothers, because what happens when a kid buys a chocolate bar, he will take the first one you probably start munching, if you gets another is going to stick that in his pocket. So the chocolate bar gets in his pocket.

This one by the time the kid ends up eating half with the other, half is already melted because of body temperature. A chocolate bar is something that melt vey easily; if I would store the chocolate bar if I store these chocolate bars in a place where temperature is twenty degree Celsius, there will be no problem at all. But look at the temperature

outside today outside this kharagpur you know, this building if you go outside temperature outside is thirty six degrees then of course, you know I had some fear, when I took this took the out of my drawer and I try to bring them to this studio there, at some fear, the may be the bars are going to melt. So at a rap something around it to make sure still got here and solid piece. Now this is exactly what the complaint is from mothers; mother says that the plasticity of these chocolate bars is too sensitive to ambient temperature.

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And let me show that by drawing a little picture here. I will put down an ambient temperature here, so temperature is going to be, T is here temperature, this is low temperature, so this would be like ten Celsius, this I could protect forty Celsius, and twenty celsius some are a some around here is twenty. This is ambient temperature; now the other condition that is also there, this plasticity that is the response; so I will just put down plasticity. Plasticity there is this that is a ease with ease with which we can melt.

So around here is pretty solid and around here is going to be almost liquid, semi liquid, semi liquid that is the status of plasticity for chocolate. Now what happens to a normal bar; no one that is like this Cadbury dairy milk; if I take this bar if I subject to some **some** experiment, and if I look at the condition of the chocolate bar, gradually is going to melt, gradually is to going to bend and so on. And what is going to be happen is **is** going to go like this plasticity is going to rise that is go to go like this, is going to become

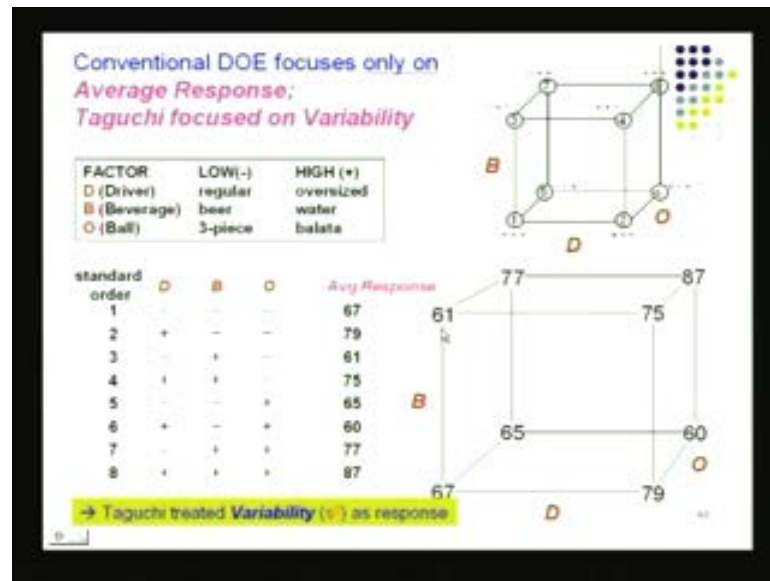


almost fluid at fifty degree celsius is going to be almost solid pretty difficult to bite around ten degree celsius or even below that. That is not something that is going to be very popular mothers, because mother of have to wash mother basically have to clean the shirts and so on, so if I had one of these bars in my pocket, I forgot that the bar was there, by the time I reach my office from the studio, when I reach my office, this is going to be molten blob. So it is not going to be something else something has going to be very popular.

Now suppose there was a company that actually was very perceptive of this problem that is face by **customers** consumers. What about kids well kids like them, when they are semi solid, but kids obviously do not like them when they become all **(( ))**, what would be a good way to go from there will redesign the chocolate bar, redesign this guy, redesign this guy, how would I redesign? We change the recipe, there are multiple factors that I can manipulate; and if I do that using DOE, I can come with the bar that would be like this; that is nearly stable. This is the robust **robust** bar; this is the robust bar and certainly this is not a robust bar. How do I convert, how do I convert design that is here to this one, how do I do that? That will be done using DOE design of experiments; this is done by doing DOE.

If I did DOE, if I did DOE, I will be able to take a **take a** product that is not so good, I will be able to convert it to this or situation. This is something that would like to able to do so would like one great application this is like one really, really good application of robust design and the manipulation of different of the different design variables using the DOE framework. This is the great way to come up with better quality products in fact then of course, the chocolate bars, we have to make sure that the hardness is not to hard, how do I do that I have to find the target, I have to find the target, remember the target with the TVs I have to find the same sort of hardness, the target hardness for kids. For that what I could do is, I could produce chocolate bars and different hardness I could distribute them free of charge in a class I could just see, who is struggling and who is not struggling, and what is the strength that which what is the strength at which most kids same to be manipulating chocolate bars pretty easily. I have got a good design now. I got the target located and also I have got to I made it to robust by applying DOE to the original the original design, which was there that was not going to be such a such a good. This is like a this like a great, great contribution the Taguchi made robust design.

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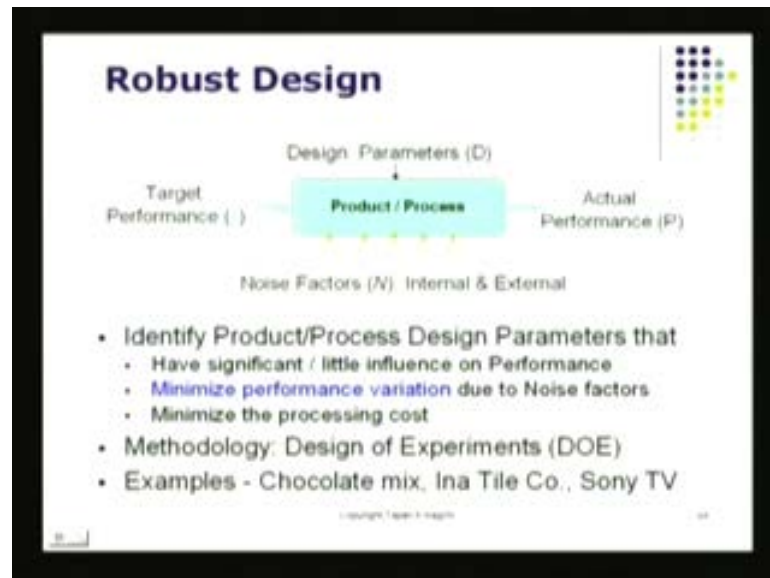
How do he actually, how did Taguchi go about doing this? Let me just give you an example, let me give **give** an example of what it, he have to different kind insight. Now you recognise that this matrix, this matrix here is a lot like what we done before. I have three factors B, D and O, and I have got two settings for of each of those factors, and the result is I have got this two cube, which is like eight trial experiments and these are of course, the response is there are a absorb notice these response is at the average responses these response are the average responsive.

What Taguchi said was of course, the average response would depend on the setting of the factors, but sure so does the variance, the variance of responses. What is the variance cause **cause** by? It is caused by noise factors, because I could have **I could have** for example, I could have here the response is 75, but if we made multiple measurements, if I made replication of this particular setting, I would end up with values that would be probably 75.3 75.2 74.9 74.6 and so on. So the average would be 75, they **they they** would be a variance around it that we variance around this, variance around this and so on.

If there is a lot of variance like this my product, my final product of the final process it is not going to be robust kind of a process. For this, what I have to do is, I have to **I have to** really change the **change my** what I am looking at, change what I am looking at. I have been looking at average response before. What Taguchi telling us is two not just look at

the average response  $\bar{y}$  taking also take  $s^2$  a good look at variability, which is like  $s^2$  square which is right at the bottom of your screen there also take look at that  $s^2$  square, which is the variance that is cause by noise.

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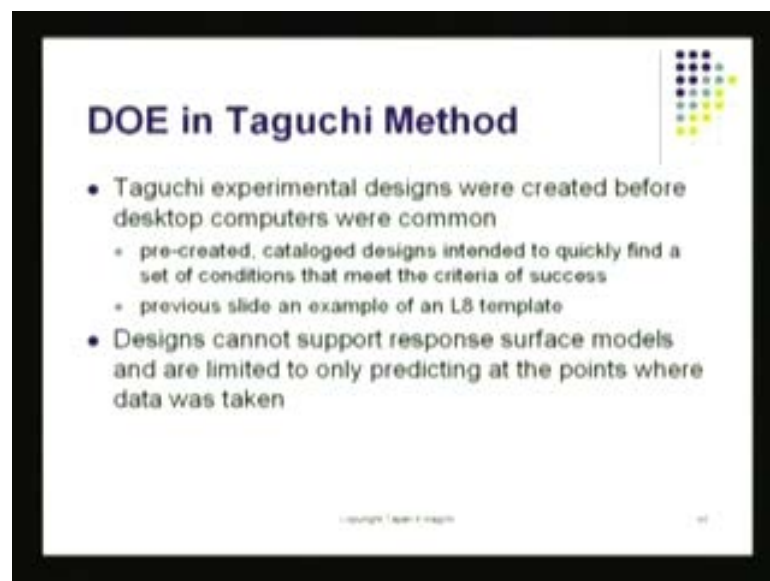
So when I have got this experiment running there take a look at what is the impact of, what is the impact of the different factors settings on  $s^2$  there. So I measure  $s^2$  square all around, so not only I am trying to look at the effect of our variation on look at the effect of the different factors on average response, but also I will be looking at the variance of that response. This is the  $s^2$  idea that was exploited, when Taguchi came up with a scheme to  $s^2$  develop robust design, what he did was for that he included noise factors also in his experiments, in the traditional experiments only control factors for use, what Taguchi did was his as at my goal is going to be something different. I do not just want the  $s^2$  average response to be optimise. I also want to want to make sure that my response is robust; for that I need to bring in temperature, in the case of what we manipulated in the case of our robust design which was using  $s^2$  my remember this picture that I had there, this picture.

Here the design variables would be all the things that going to the chocolate bar; and this is my ambient, this is my ambient factor. So Taguchi said is when I when you trying to produce a robust design do not only manipulate these design factors, but also manipulate this look at the total response look at the total response, which is now the composite, it is

indeed interaction of the design variables, effect of the design variables and that of the ambient condition or the noise condition. This is exactly what he did when you look at my slide there. He brings in **in** the new scheme of things, when you trying to get design, robust design is built he is using noise factors also alongside everything else that his trying to manipulate, which would be the design factors.

The ideas to try to come up with performance that is got smallest variance, when subjected to noise; in the case of chocolate bar, the response first plasticity and I **I** manipulated noise when I was changing my design variables, when I changing the recipe butter, coco, sugar bla bla those things, when I changing them I also change temperature; and I wanted to see what sort of setting of these different design variables would make plasticity, most resistant to change interpreter; that would really results with a **with a** robust chocolate bar basically robust design chocolate bar that is exactly what is done.

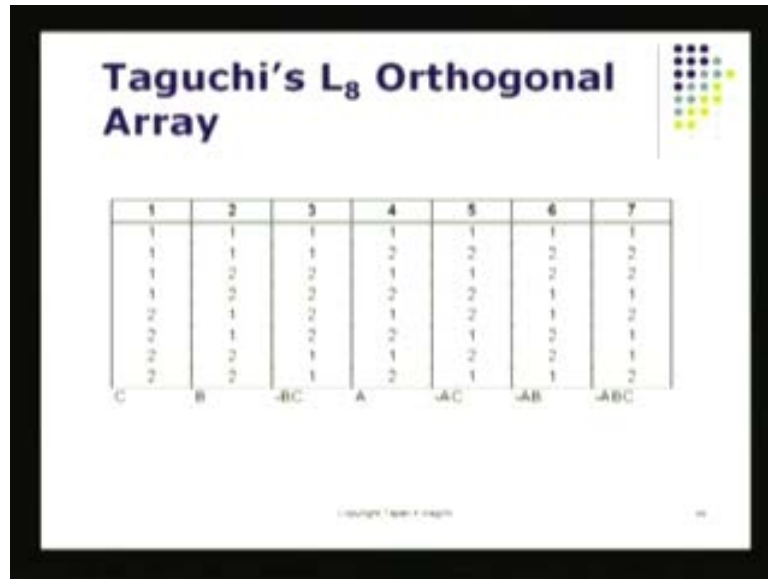
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Of course when you manipulating simultaneously many different variables, the only way to do that is using a DOE set up. And that we can of course, see DOE is a key element in the Taguchi method.

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### Taguchi's $L_8$ Orthogonal Array



The slide displays a Taguchi's  $L_8$  Orthogonal Array. It consists of 8 rows and 7 columns. The columns are labeled C, B, -BC, A, -AC, -AB, and -ABC. The values in each cell are either 1 or 2. The array is as follows:

	1	2	3	4	5	6	7
1	1	1	1	1	1	1	1
1	1	1	1	2	2	2	2
1	2	2	2	1	1	2	2
1	2	2	2	2	2	1	1
2	1	2	2	1	2	1	2
2	1	2	2	2	1	2	1
2	2	2	1	1	2	2	1
2	2	2	1	2	1	1	2

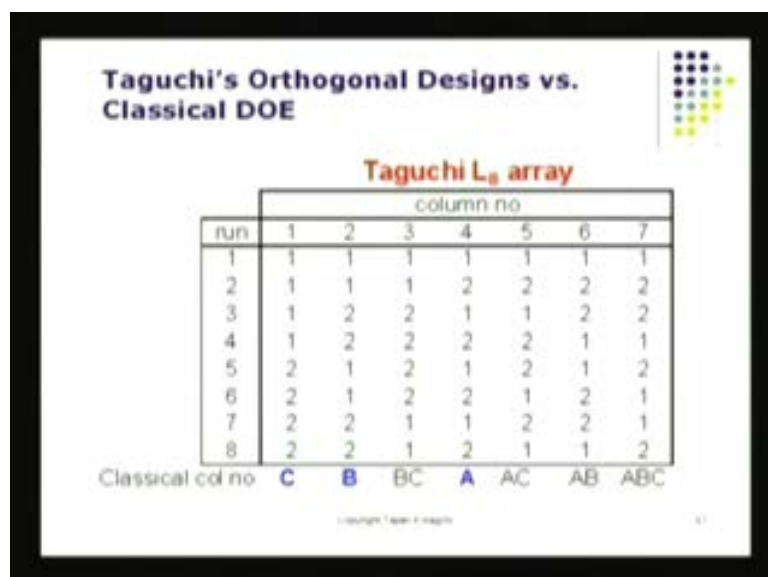
C B -BC A -AC -AB -ABC

And if you look at the **the** plans which are used, Taguchi's plan then look a lot like the a full factorial design, but something I have got remind you of Taguchi is not trying to use a anova, Taguchi does not really try to explicitly monitor the **or** measure interaction between factor effects, Taguchi does not try to do that. He just try to figure out the interaction between noise factors and design factors; that is one thing that he tries to do. And in **in in** that approach, he has state with just partial factorial design, and he calls them orthogonal arrays, this is a special name given by Taguchi to certain classes of these fraction factorial designs.

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### Taguchi's Orthogonal Designs vs. Classical DOE

#### Taguchi $L_8$ array



The slide compares Taguchi's  $L_8$  array with a classical  $2^3$  factorial design. The Taguchi array is shown as a 7-column matrix, while the classical design is shown as an 8-column matrix. The columns are labeled C, B, BC, A, AC, AB, and ABC. The values in each cell are either 1 or 2. The array is as follows:

run	column no						
	1	2	3	4	5	6	7
1	1	1	1	1	1	1	1
2	1	1	1	2	2	2	2
3	1	2	2	1	1	2	2
4	1	2	2	2	2	1	1
5	2	1	2	1	2	1	2
6	2	1	2	2	1	2	1
7	2	2	1	1	2	2	1
8	2	2	1	2	1	1	2

Classical col no C B BC A AC AB ABC

And some examples are there, here there is an example of a Taguchi array these of course, these are become you know common commonly known now as Taguchi array. There were existed before, we **we** had them before, not that these designs are different, not that these designs are new, these have been created by a statisticians, where before Taguchi came along. But Taguchi use thing in a very special way he popularise the thing, so that is why these **these** arrays are these design plans they have become known as Taguchi arrays, Taguchi's L 8 arrays or L 12 arrays or L 16 arrays.

Basically here if I look at columns, I have seven factors that I can manipulate; so certainly for a chocolate bar again if you go back to chocolate bar, there are many factors there probably, seven eight different factors. So if I had to run experiments using a chocolate bar for **for** building chocolate bars of different types allow to minute the manipulate these seven or eight variables together. In trying to manipulate **manipulate** the all the different variables, I cannot really use the full factorial plan B is going to be too large, is going to be an over kill. Instead I use a fractional factor design like the design is shown here, this design can handle up to seven factors and the other; there are other schemes that can handle several mode factors. This is exactly what is used by Taguchi in trying to do this.

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**The Taguchi Experiments**

- Taguchi advocated using *inner and outer array designs* to take into account *noise factors (outer)* and *design factors (inner)*
- Design factors:  $I_1, I_2, I_3$
- Noise factors:  $E_1$  &  $E_2$
- Objective: Maximize response while minimizing its variance

The diagram illustrates an inner-outer array design. It shows a 3x3 grid of points representing design factors  $I_1, I_2, I_3$  and noise factors  $E_1, E_2$ . The design is a fractional factorial design, specifically a  $2^{3-1}$  design, which is a 2-level, 3-factor design. The design is shown as a 3x3 grid of points, with the top row representing the design factors  $I_1, I_2, I_3$  and the bottom row representing the noise factors  $E_1, E_2$ . The design is a fractional factorial design, specifically a  $2^{3-1}$  design, which is a 2-level, 3-factor design. The design is shown as a 3x3 grid of points, with the top row representing the design factors  $I_1, I_2, I_3$  and the bottom row representing the noise factors  $E_1, E_2$ .

Now does Taguchi bring in, how does he bring in noise into all this? Look at the **look at the** matrix inside, this matrix is also now a experimental design plan, it is a DOE plan, so

I have here basically three design variables, these design factors are I 1, I 2 and I 3; I 1, I got I 1, I 2 and I 3. And I manipulate these at two levels each, the result is two times, two times two again, I have got eight possible variations of factors setting or treatments as for as design factors are concerned, there are three design factors and each can be set at two levels, because each can be set at two levels, I can now **I can now** construct a two by two by two or a eight, eight row matrix that is exactly what I show in the inner box.

Look at the corners **look at the corners**, the corners basically is seem to have another matrix imposed on it; these corner matrix is these are constructed by using basically what we call noise factors. In the case of our chocolate design, in the case of a chocolate design, the noise factor was ambient condition that is all that was the only one noise factor that seems to be basically affecting the quality of this chocolate bar. So basically in those cases I basically, I could just manipulate **these** this ambient factor at different settings I could do that I could make this **this** product robust.

When I came to design doing the design using two factors array have got two factors there, these two environmental factors are E 1 and E 2. The way Taguchi combine he said bring in not only your design factors they do a robust design experiment, robust design set of experiments, but you got also bring in these **these** environmental factors or the **or the** these what we call noise factor.

For that, what you also have to do is, you have to select this settings for this noise factors, like for the chocolate bar we used temperature variation, you had a temperature variation of ten, then we went to twenty, then we went to thirty, then we went forty and looked at the trace looked at the effect of it; that we did with different recipe. So we found the recipe that did not really change as much as temperature was change; as temperature was change, we found plasticity is take model as the same that was the recipe that was the robust recipe.

To find that what I have to do in the case of the matrix design is I construct eight call it prototypes, I construct eight prototypes, I have got prototype one, proto type two, proto type three, proto type four, these are four proto types build by changing I 1 and I 2. Then I change I 3 also; I change I 3 also and I produce four more prototypes; In that I have got eight proto types. What is my objective? I want to find that prototype, which is least

affected by the shaking done by noise; that shaking will be done identity to each of these prototypes that is being done by these small matrix.

Look at the small matrix; these are now going to be shaking those prototypes or here this prototype will be shaken over four settings of noise. This one also will be shaken by four settings of noise, just to kind a give you an example, if you look at me, I am you know, I got a few objects on my table here, and I have got this computer screen also on **on** my thing there, and I am also sitting on a chair; now there is a big difference between a chair and a table, when it comes to placing the screen. Obviously we do not want the screen to be placed on a fruit piece of furniture that is bobbling; because that would create a lot of vibration on the screen there and perhaps it will be difficult to see the image that would be there, rather we would like to take a robust a sort of thing.

Now how do I find out, how do I find out which furniture suppose I got some new furniture? I got some Italian tables; I got some cane made furniture and so on so forth. And I had to select a table that is going to be a robust table that is going to be robust table that is going to be table that would not that would be for placing my screen here, my computer screen here. What would I do? I would go to that furniture whatever furniture it was I tried to shake it, I tried to shake the table, I tried to shake the table, I tried to shake the table, and I find the table that is move the least when I try to shake them with my hand. This is exactly what I am doing, when I am shaking these different four different prototypes, I am manipulating these four different prototypes and I am trying to shake them.



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**Case: Robust Design of a Starter Motor**

Outer array: battery voltage, ambient temperature

Run #	Outer array			Repeats →				Starter torque	
	I1	I2	I3	E1	2	3	4	Output MEAN	Output STD.DEV
1	-1	-1	-1	75	86	67	98	81.5	13.5
2	1	-1	-1	87	78	56	91	78.8	15.6
3	-1	1	-1	77	89	78	8	63.8	37.1
4	1	1	-1	95	65	77	95	83.8	14.7
5	-1	-1	1	78	78	59	94	77.3	14.3
6	1	-1	1	56	79	67	94	74.8	16.3
7	-1	1	1	79	80	65	85	77.5	8.1
8	1	1	1	71	80	73	95	79.8	10.9

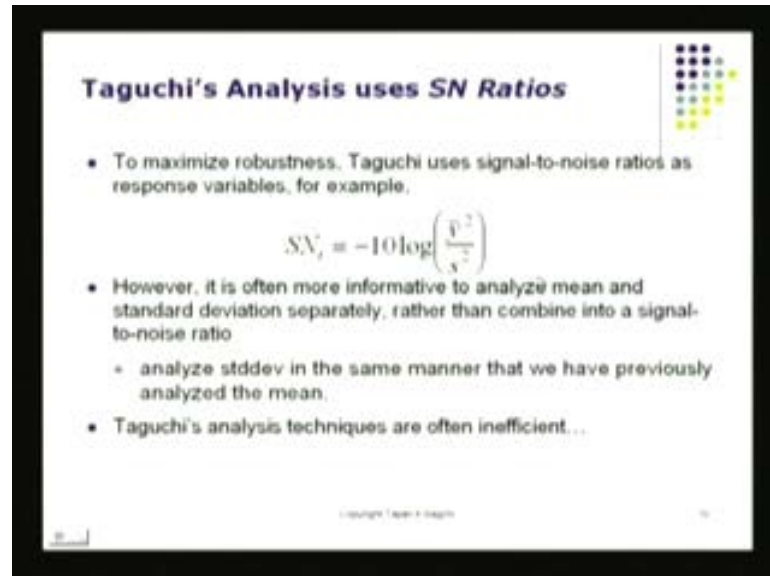
Inner array: armature turns, gage of wire, ferric content of alloy

When I do that? I have tested the four different, the eight different designs here under identical noisy condition. And it will look for the design that is most stable, this is the robust design that was the inside that Taguchi develop, I have given you given you here an example, I have got the same the same design factors I 1, I 2 and I 3 and got a matrix here, which is like the box that we saw there the inner box, and the outer box is this outer box here and for each of those cases I have I have basically run my trials and from this I work out my output mean, which is the average response and also the output standard deviation. This is the measure of that shakiness, this is the measure of that vibration this is the measure of the kind of response that we see for chocolate bar. This is going to be a wide variation, so s square is going to be a large here and s square is going to be quite small here, s square across here is quite small s square across here s square is a sample standard deviation, sample variance sample variance is high here sample variance is low here.

We are seeking, when I am trying to design a robust chocolate bar, I am trying to see that design which is smallest amount of s square. This is exactly what we will be looking for when we look out our matrix here. And we will try to find the variation we will try to find the setting of it, which gives me the smallest variation. So as far as strength is concerned this is the setting 1 1 minus 1, settings for I 1, I 2 and I 3, this going to give me the strongest the strongest signal that is the strongest the high the maximum amount of output is, but as far as robust design concerned, it is going to be this setting there

minus 1 1 1 so this is going to be low high high, if those of the settings used for I 1, I 2 and I 3, you can go back and kind of locate that thing there, I have low high high.

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**Taguchi's Analysis uses SN Ratios**

- To maximize robustness, Taguchi uses signal-to-noise ratios as response variables, for example,

$$SN_r = -10 \log \left( \frac{\bar{y}^2}{s^2} \right)$$

- However, it is often more informative to analyze mean and standard deviation separately, rather than combine into a signal-to-noise ratio
  - analyze stddev in the same manner that we have previously analyzed the mean.
- Taguchi's analysis techniques are often inefficient...

So let us see that low for I 1, high for I 3, and high for this. So it is this point here this is the point that is most robust that is the one that is give me a standard deviation of 8.1. There are other methods also Taguchi also suggested that we use something called signal to noise ratio. Taguchi was actually a electrical engineer, so he played a lot with in a signals and noise and that kind of that thing. So being in electronics and electrical engineering, he kind a thought this would be a good way to check robustness of course, many other people they have felt that probably signal to noise ratio is not the way

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**In seeking a robust design, SN Ratios are Maximized**

- To maximize robustness, when Target performance is the best, Taguchi uses the signal-to-noise ratio

$$SN_r = 10 \log \left( \frac{\mu^2}{\sigma^2} \right)$$

- When response is to be maximized, Taguchi uses

$$SN_r = -10 \log \left( \frac{\sum (y_i - \mu)^2}{\mu^2} \right)$$

- When response is to be minimized, Taguchi uses

$$SN_r = -10 \log \left( \frac{\sum y_i^2}{\mu^2} \right)$$

We can get the best design; there are many other method, many other method that have come along but something you got remember even if these methods are we have the philosophy stays the same. You may not for you own application you may not use signal to noise ratio. But still the idea of robustness is something that you should recapitalize on.

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**Taguchi Analysis of Motor Design Data**

Robustness is maximized with SN ratio is maximized.

Design (inner array) factor *settings* that maximize SN ratio are:

- I1 (turns) = -1
- I2 (gage) = +1
- I3 (ferric %) = -1

Note: This system is not additive! → Results are approximately OK.

This is something as going to give us really, really good performance, and I can do I could do the same plots here are plotted by torch are plotted in some standard deviation

there and also plotted the signal to noise ratio. And Taguchi says to get a robust design maximize try to maximize signal to noise to ratio, this is exactly what we done and we got the optimal setting for this. This is something that we could do.

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Taguchi Orthogonal Array Tables vs. Classical DOE Arrays

**Classical  $2^3$  design**

run	factor			interactions			
	A	B	C	AB	AC	BC	ABC
1	-1	-1	-1	1	1	1	-1
2	1	-1	-1	-1	-1	1	1
3	-1	1	-1	-1	1	-1	1
4	1	1	-1	1	-1	-1	-1
5	-1	-1	1	1	-1	-1	1
6	1	-1	1	-1	1	-1	-1
7	-1	1	1	-1	-1	1	-1
8	1	1	1	1	1	1	1

Taguchi col no: **4** **2** **1** 6 5 3 7

Now, the classical design looks like the same, but Taguchi's columns are somewhat different from the way; our factors are assigned in the classical case. We sometimes actually at the design by a planning many more factors, this is something Taguchi did to try to get make sure that he got. He got large number of factors covered.

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- Taguchi Orthogonal Array Tables**
- 2-level (fractional factorial) arrays
    - =  $L_4(2^3)$ ,  $L_5(2^7)$ ,  $L_{16}(2^{15})$ ,  $L_{32}(2^{31})$ ,  $L_{64}(2^{63})$
  - 2-level array
    - =  $L_{12}(2^{11})$  (Plackett-Burman Design)
  - 3-level arrays
    - =  $L_9(3^4)$ ,  $L_{27}(3^{13})$ ,  $L_{81}(3^{40})$
  - 4-level arrays
    - =  $L_{16}(4^5)$ ,  $L_{64}(4^{21})$
  - 5-level array
    - =  $L_{25}(5^9)$
  - Mixed-level arrays
    - =  $L_{18}(2^1 \times 3^7)$ ,  $L_{32}(2^5 \times 4^9)$ ,  $L_{50}(2^1 \times 5^{11})$
    - =  $L_{36}(2^{11} \times 3^{12})$ ,  $L_{36}(2^3 \times 3^{13})$ ,  $L_{54}(2^1 \times 3^{25})$

In fact, there are many plans the Taguchi has suggested, and those are listed under different types of L; these many lines are there in the matrix is he has got L 4 design or L 8 design or L 16 design and so on so forth. These are different designs that basically have different approaches and they give you this thing. This was one major application of DOE of course, you could use DOE to try to optimize to try to come up with the best settings, but here we are getting robustness this is something that we did not do on your working before. I will continue with another application, which would be the response of method that will done in the next class.

Thank you very much.