Quality Control and Improvement with MINITAB
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Lecture - 37
Blocking in Factorial Design

Hello and welcome to session 37 on our course on Quality Control and Improvement with MINITAB, I am Professor Indrajit Mukherjee from Shailesh J Mehta School of management IIT, Bombay. So, the previous session what we have done is that we have seen 2 to the power 5 design like that. So, 5 factors are 2 levels.

Now, we will move ahead with the number of factors k number of factors, but number of levels is more than 2 there is let us assume that 3 level designs. So, 3 level 3^k and in this case we can assume that simple example let us say 3 square design we which we can consider over here.

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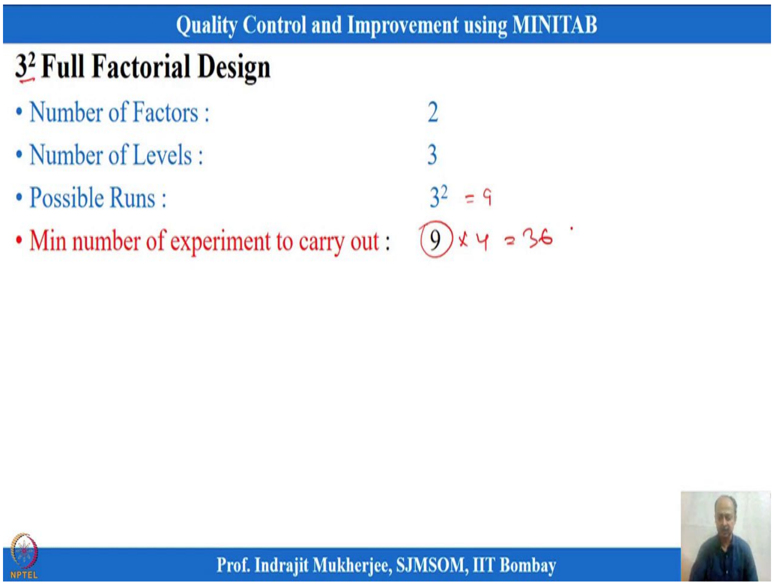

So, one example we have already done into a analysis of variance that we will represent and how it is to be analyzed in MINITAB factorial design and how to create the design that is important to over here ok. So, this is a 3 square design we want to create the design in MINITAB, where 2 factors at 3 levels so minimum number of trial is will be equals to 9 that is written over here and if we want to replicate that one so that will be the multiplication over here. If we replicate it 4 times each of these designs, so then total number of trials will be 36 like that ok.

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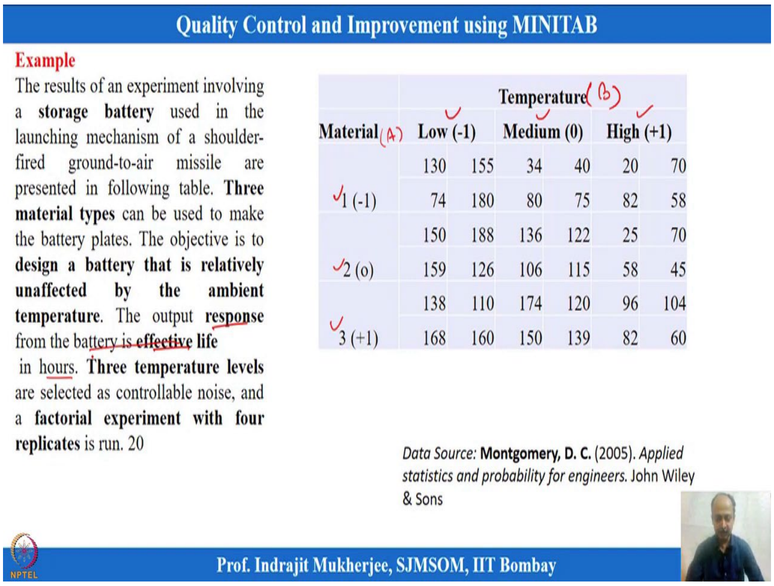

We will take one example that was previously discussed also and here also we will just show you how to create the design in how to create the factorial design when we have 3 k scenarios. When we have 3 k scenarios or k factors are 3 levels like that. So, here a material type is what are the factor let us say this is factor A over here and this is factor B over here and this is having 3 levels material type 1, 2 and 3 and this is having temperature range this is also 1, 2 and 3 like that.

So, 3 level design and 2 factors over here that is considered. One is material type one is temperature and the CTQ that response variable is considered is the effective life battery effective life over here so in hours like that. So, we want to see that how to analyze create the data sheet and how to analyze this data into MINITAB ok. We are interested in to AB and AB interaction.

So, over here so in this case and what should be the final conclusion based on the experimentation that we want to see ok. So, how do we create the design that is important 3 k design how we are creating in MINITAB.

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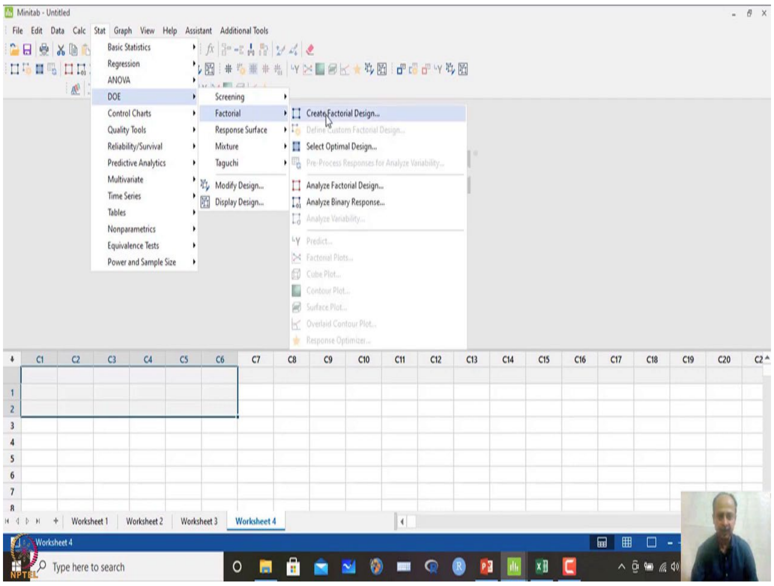

So, I will open a blank excel blank MINITAB sheet over here and we will create the design. So, this is stat over here and design of experiments. So, what we will do is that factorial design create factorial design.

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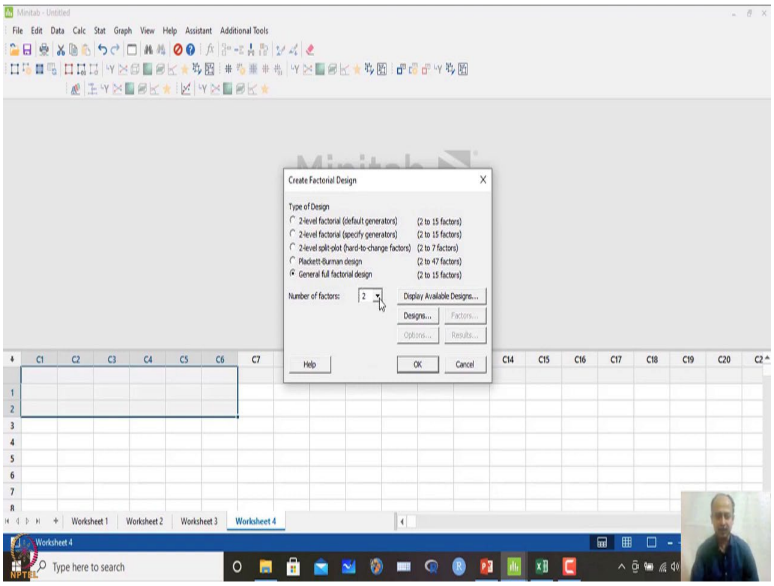

And in this case we cannot select 2 level factors over here, we have to select general full factorial over here number of factor is 2 there is no problem with that.

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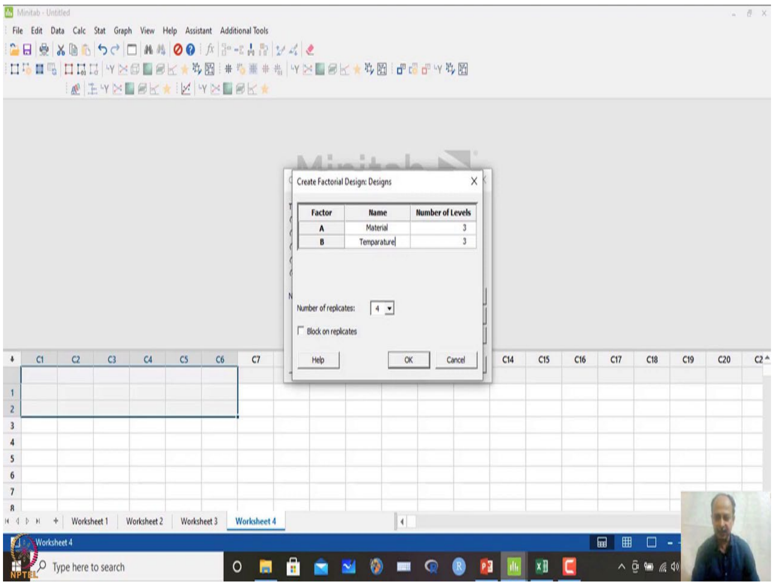

And in design what we have to do is that we have to mention the number of levels over here, so this can be changed I have made it 3 and this is also 3 over here. A, B factors so A can be we can mention this as material and the next one can be considered as temperature over here this is temperature ok.

So, a number of replicates if you see the experimental trial that is done over here. So, here you will find that there are 4 trials that is done for a specific combination. So, this is material type 1 and this is low temperature and I have 4 observations over here. So, this is 4 number of replicates 130, 155 74 and 180.

So, this is a 4 replicate design like that. So, what we can do is that we can just see this one and mentioned that number of replicate is there. We are not consider what blocking over here, so we will just ignore that one at present scenario so this is ok and then factors what we can do material type over here.

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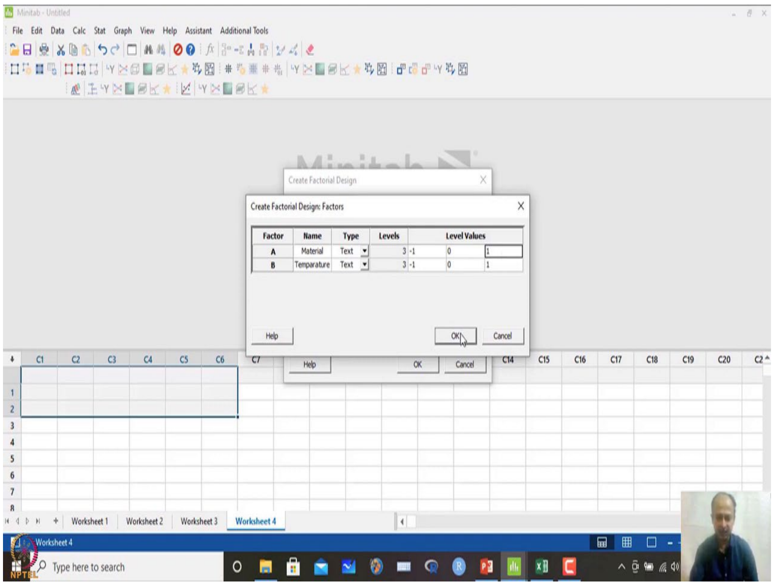

So, either I code this one as minus 1 0 plus 1 that is in coded terminology. If you are; if you are using the arbitrary symbols like minus 1 plus 1 what we have used earlier also and only thing we will mention whether it is take. So, this is categorical variable so we can mention material type and temperature was considered as low, medium and high like that. So, this is also categorical it has 3 levels.

So, either I keep what is the level that is mentioned 1, 2 and 3 and low medium high we can write over here we can also write minus 1 0. So, coded variable we can also mention like that. So, this is 3 levels but in this case this is categorical variable both are considered as categorical variables. So, I click OK and in the factors this is done.

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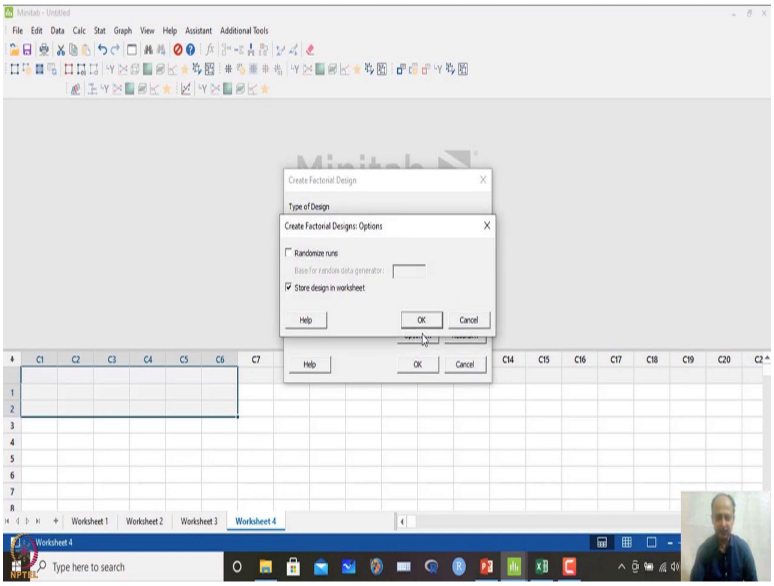

And in options what we will do we will not randomize this one. So, we will not randomize the design. So, this we will click OK, so number of factors so everything is done.

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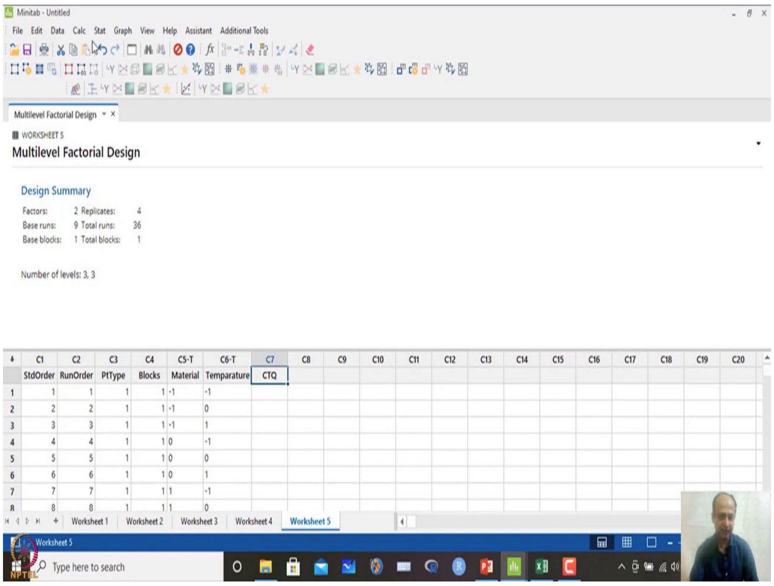

So, design is created over here. So, you see standard order and run order is same because we have not randomized. So, 36 number of trials this is the summary of the design this is created. So, whenever this is created we can just put the CTQ values over here which is the battery life and then we can analyze this one.

So, I have created I have shown you how to create the design, then what we will do is that with this data is already with me. So, unnecessary we are not creating another we will not write down the CTQ values over here.

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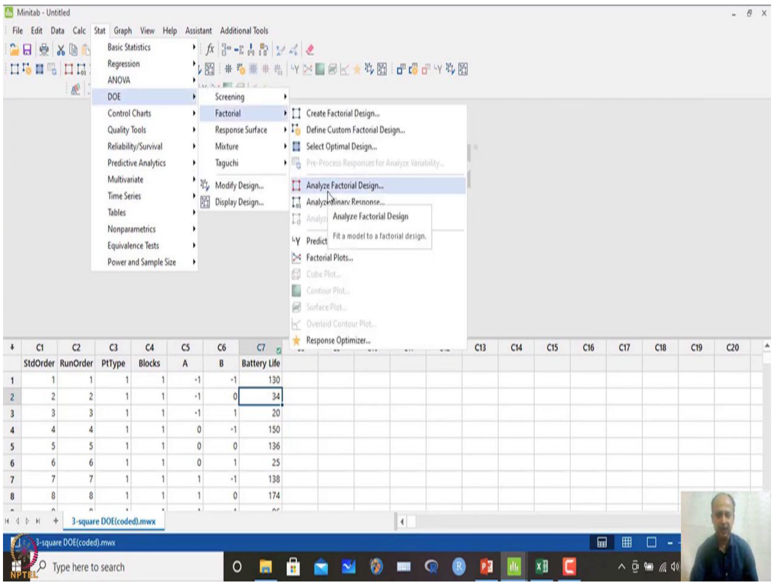

So, we have the data set and this is the data set that we are having and we have entered all the 36 data points over here. So, now we have to only analyze. So, first combination is minus 1 minus 1 that is 130 that is the data set that you have seen is 130. So, this data set is recorded over here. So, this we want to analyze. So now I will go to stat I have created the design.

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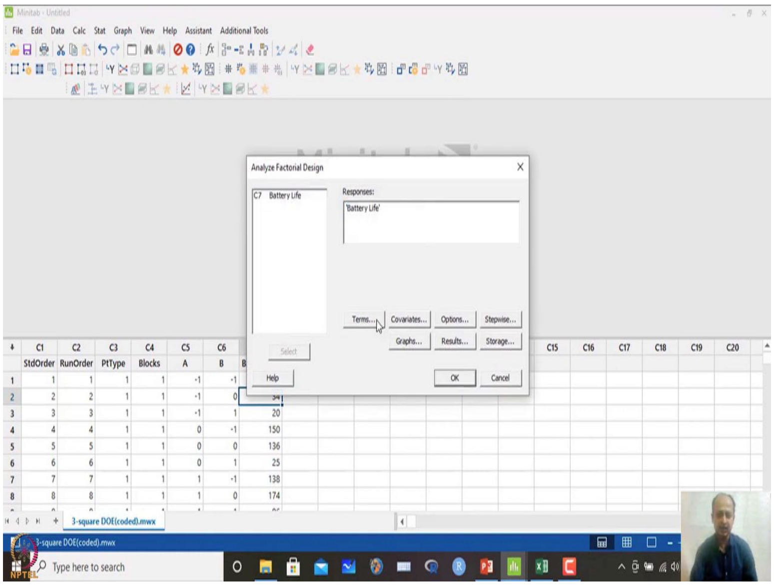

And this I will go to factorial design then go to analyze factorial design over here, then you mentioned which is the response variable this is mentioned over here.

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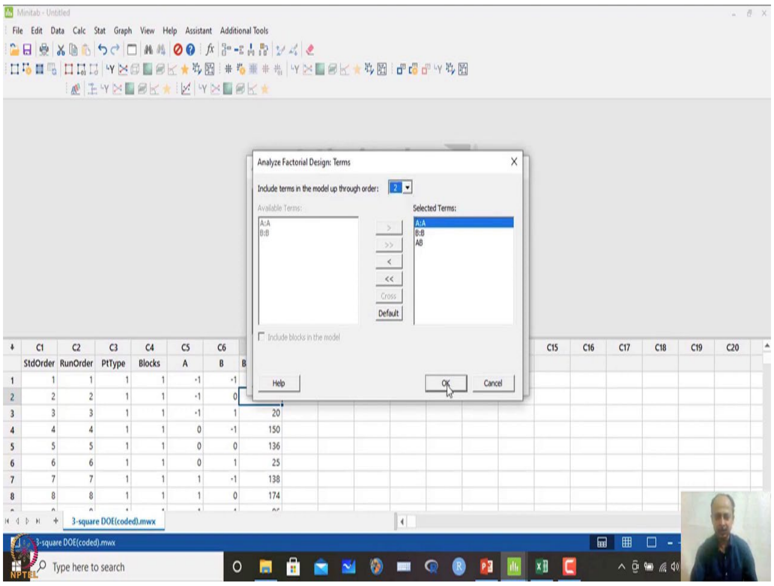

Then in terms I want to see all up to interactions over here. So, I will mention 2 over here in 2 terms and so this will be OK.

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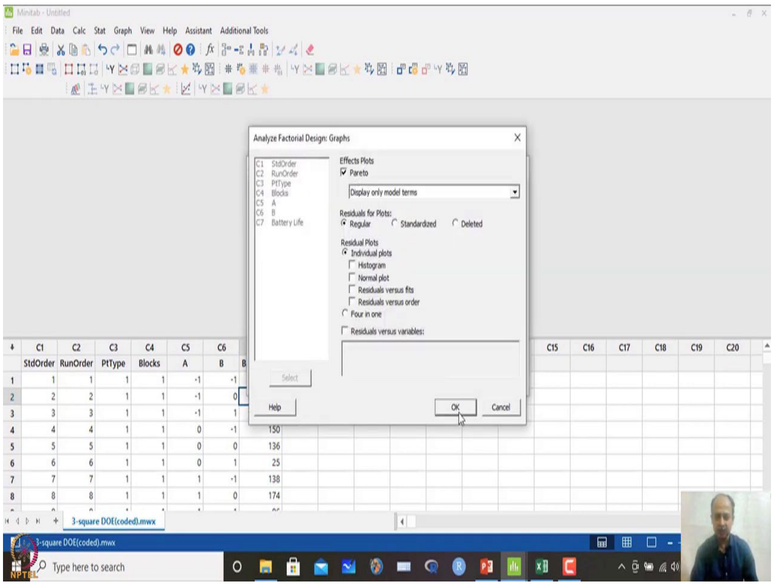

And graph we will have Pareto plots to see this one which is effective which is not effective like that A, B or AB interactions like that. So, other things we will keep as default, so we are not changing anything we are not using stepwise regression; so we will click OK over here.

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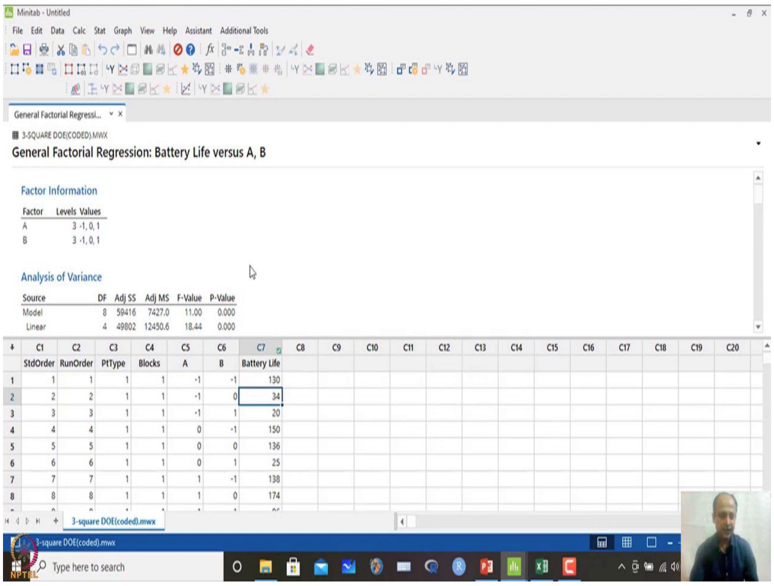

When we do that so A is 3 levels and this is the factor information analysis of variance table.

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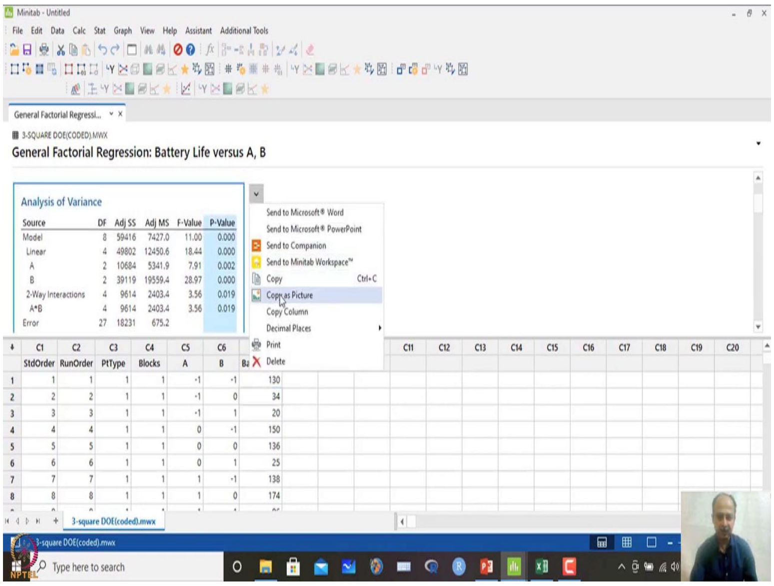

We can see so over here that will tell me that which is significant which is not also Pareto plot is there.

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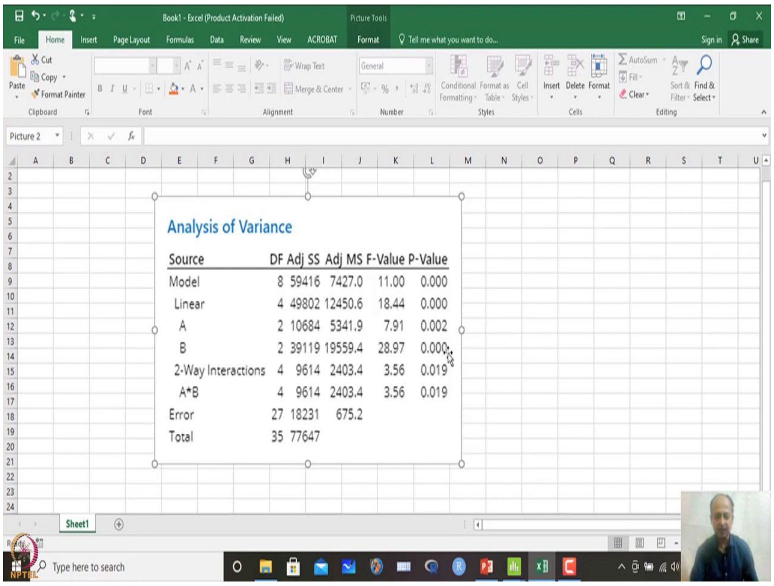

So, in excel we can just paste this one to enhance the image and try to see what is important what is not. So, factor A is having a P-value which is less than 0.05 A is significant B is also significant over here and AB interaction is also significant over here less than 0.05 ok. All the factors and their interaction is significant over here.

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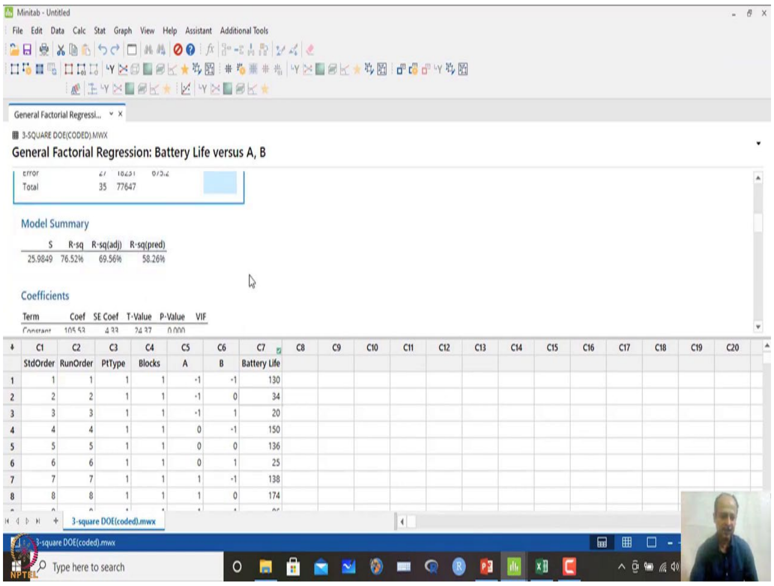

So, in this case what we will do is that we will go down and try to see R square adjusted value is 69 maybe some other factors we are missing over here ok, but that is not of concern to us.

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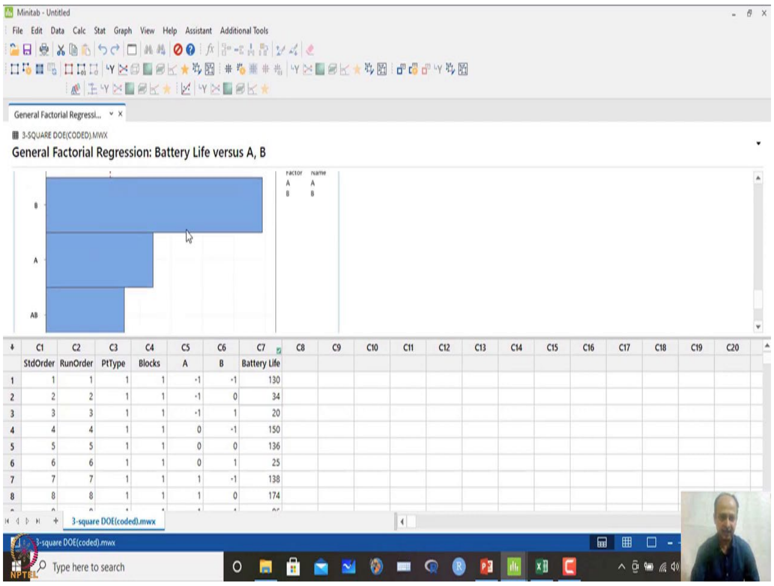

And we at this stage these 2 factors are important or not that is important.

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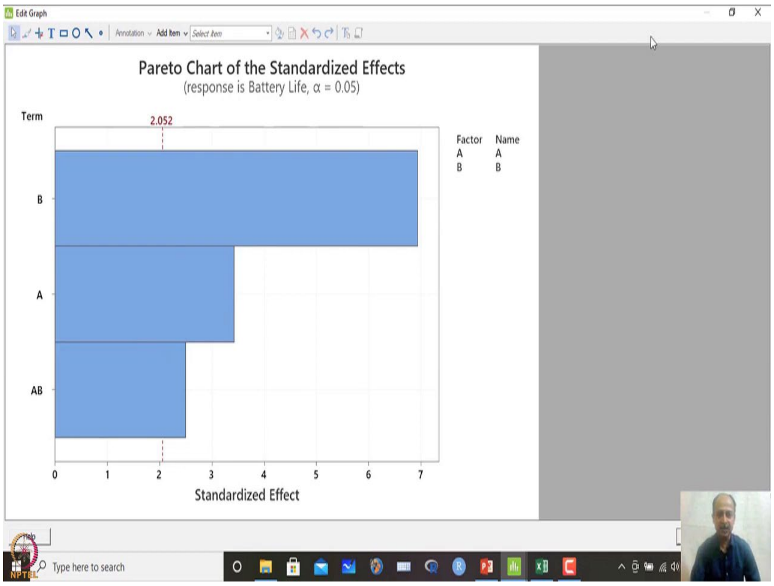

So, in effect analysis Pareto chart what we are seeing is that A, B and AB interaction significant, because this is 2.05 and every standardized effect is more than these values like that. So, all the variables are important A,B and AB interaction. So, first order interaction is important.

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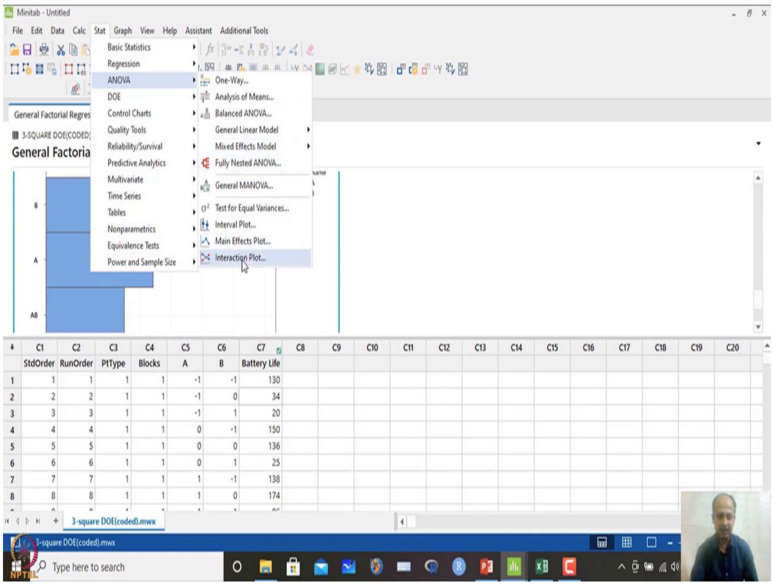

So, then what we can do is that we can just see graphically analyze this one. So, what we can do is that either go by this ANOVA analysis and see the interaction plots like that.

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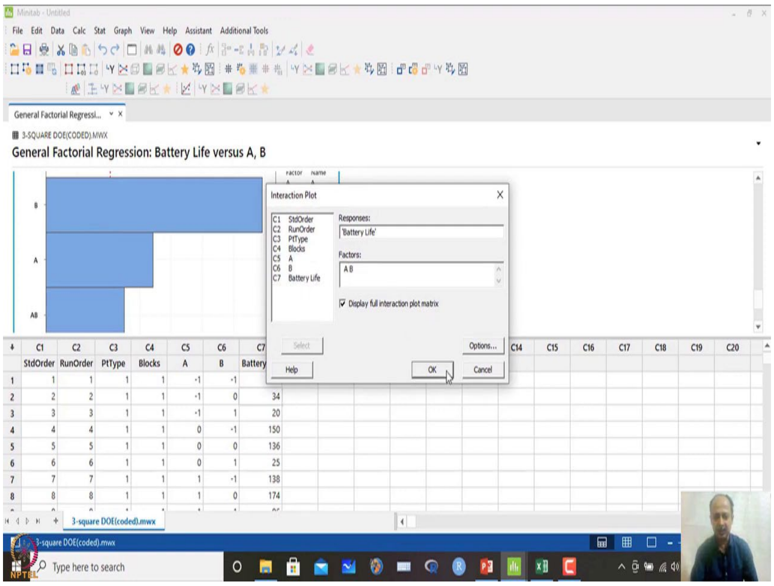

And in that case battery life you have to enter and factors you have to mention and which are the factors A and B factors over here, display full interaction plot and you click OK.

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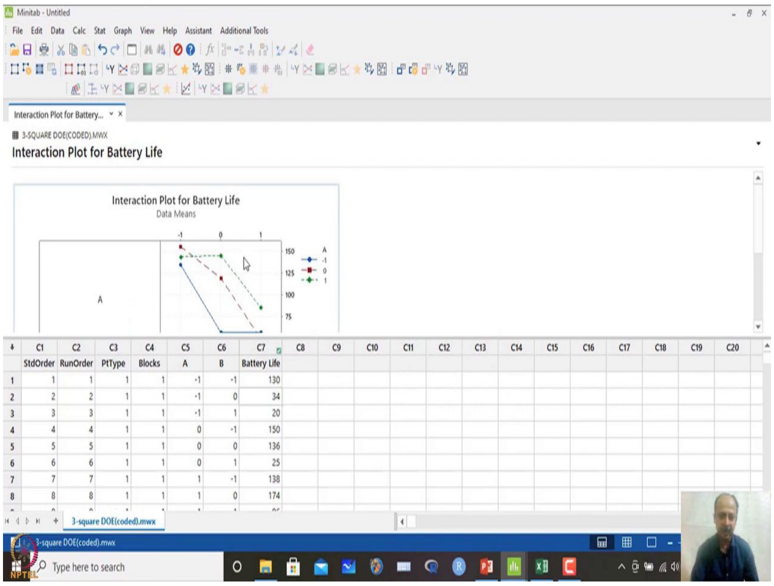

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Then you will get the same graph what we have seen in 2 way analysis of variance over here. So, the same data can be used for interaction plots like that. So, over here what you are observing over here is that and this is the best combinations.

So, minus 1 combination so this is the highest battery life what we are getting. So, minus 1 combination which is basically A at level 0 over here. So, that is material type 2 over here and then what we have is the temperature this minus 1 means this is the low temperature combination.

So, the material type 2 and low temperature is the best combination, but what we mentioned earlier also in our lectures like that and this is more stable what we are seeing over here this is more stable. So, material type 3 is more stable. So, minus this 1 means 3 over here. So, this is green line what you are seeing over here and this is stable throughout the range of this is low-temperature range to medium.

And also high temperature and what we are seeing is the battery life is always higher than any other materials that we considered.

So, we may select material 3 in case we are unable to consider temperature we cannot control the temperature and this is the most robust material we can use which will take protection against this change in temperature like that. So, this is one combination and this graph that you are seeing on the below part of this will also lead to same conclusions over here.

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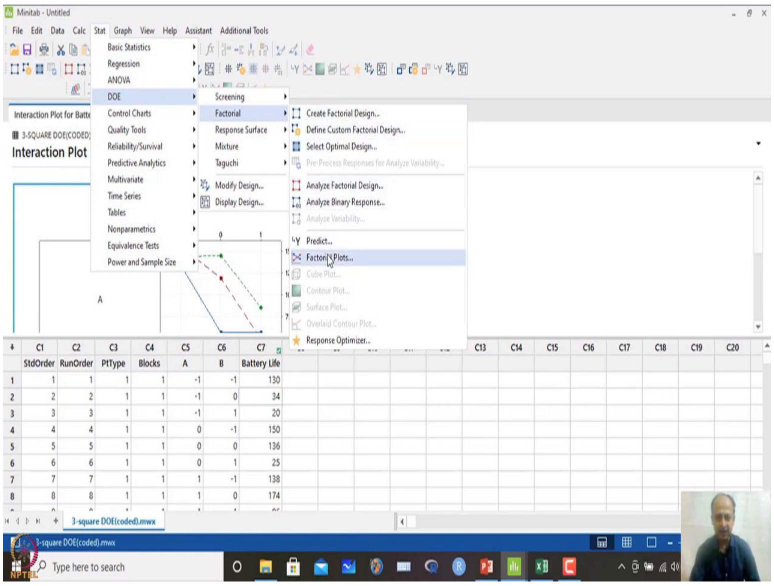

So, this graph also you can see from this way if you go to design of experiment factorial plot.

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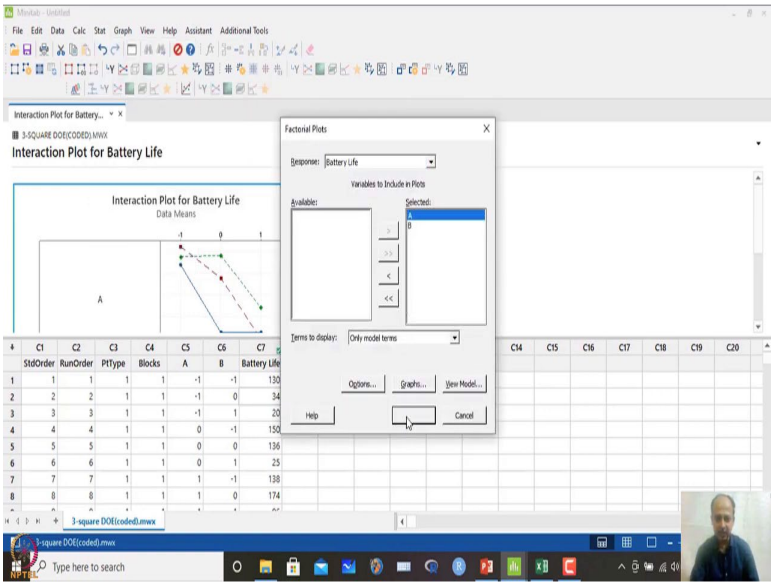

And factorial plot when you do this and you click this one.

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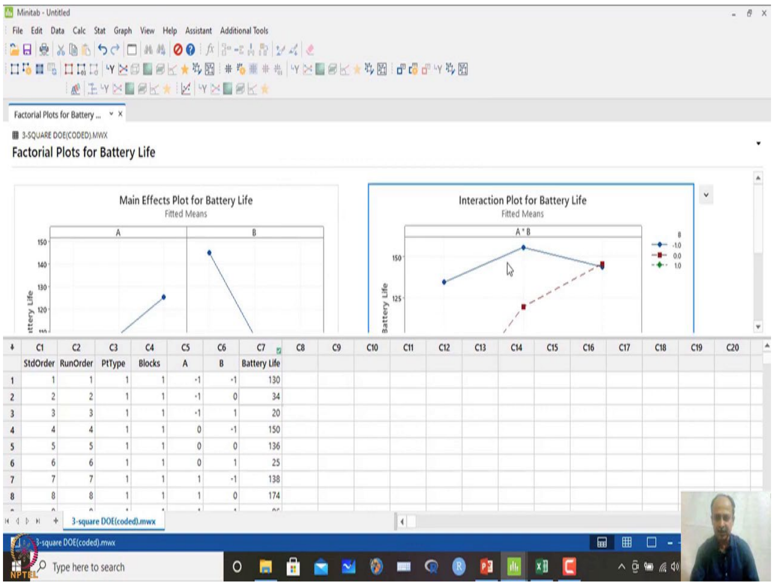

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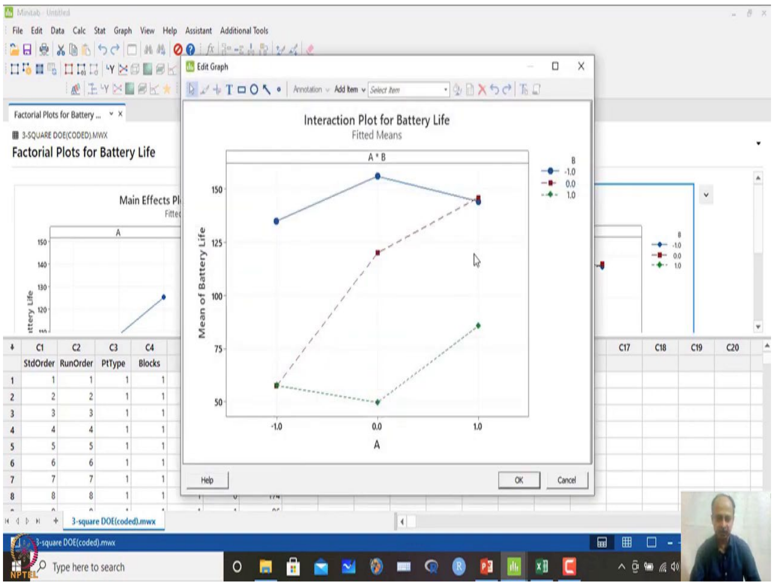

You will get the interaction plots this is given over here what we have seen earlier also. So, this is the same graphical interpretation.

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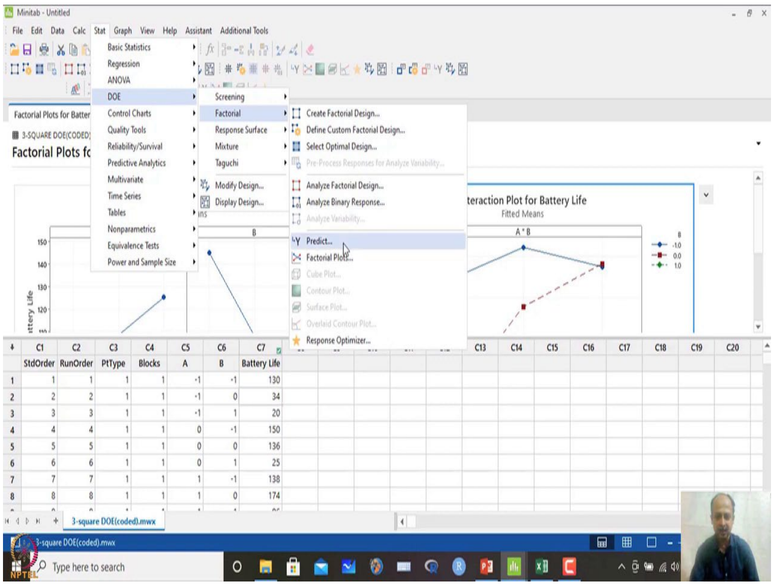

Now you can predict the behaviour what will be the response on this. So, I can predict also over here.

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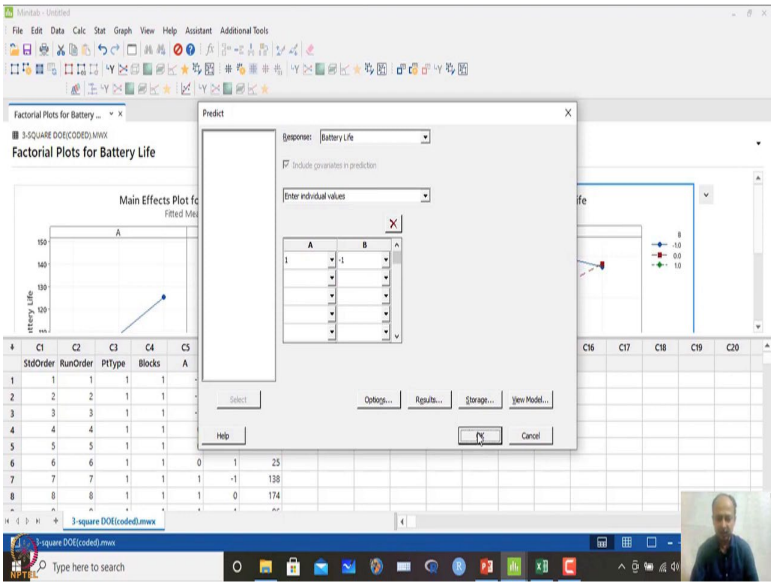

So, if you say which is the level I will choose over here let us say I choose material type 3 over here and I am for the B combination over here I take minus 1 low range that is the combination I want to see and I click OK.

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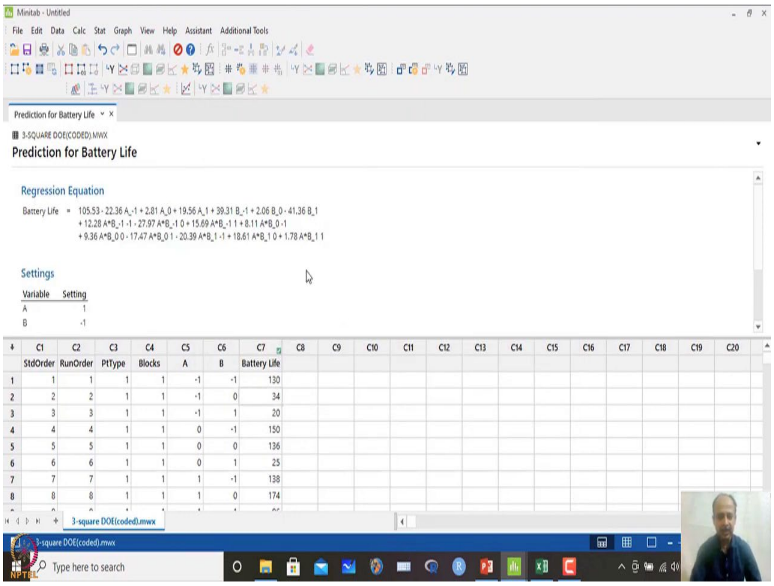

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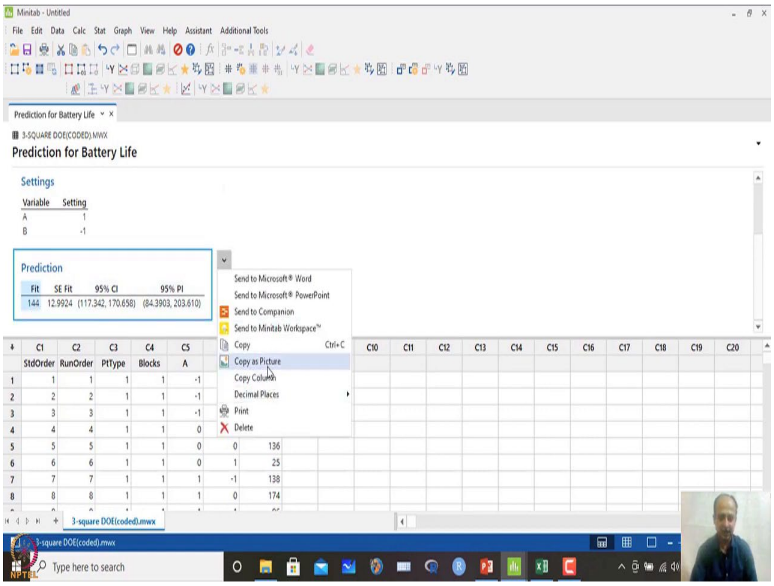

Then I will get the settings and I will get the mean effective live that is generated over here. So, that is the prediction values over here.

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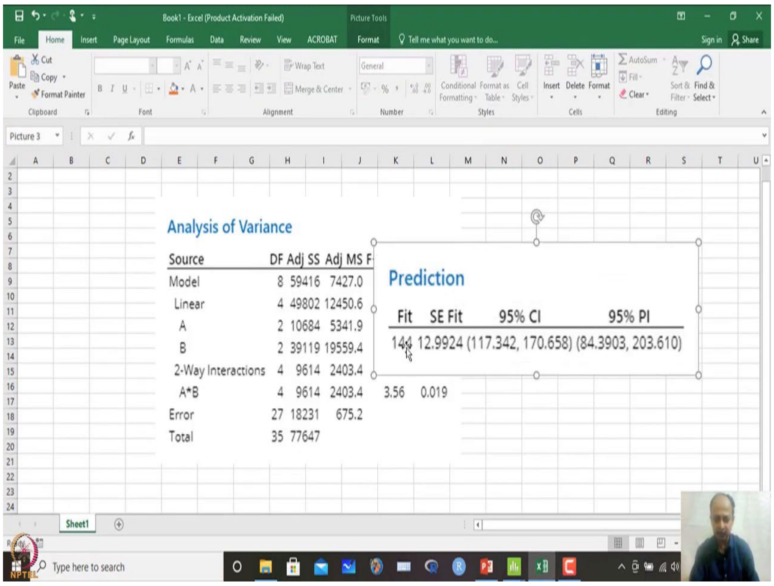

So, the predicted value will be 144. So, predicted value will be and these are the prediction interval confidence interval that can also be seen over here ok. So, this is what we wanted to discuss some of the aspects of 3 square design or 3^k, we can create the design and we can see other examples on this also.

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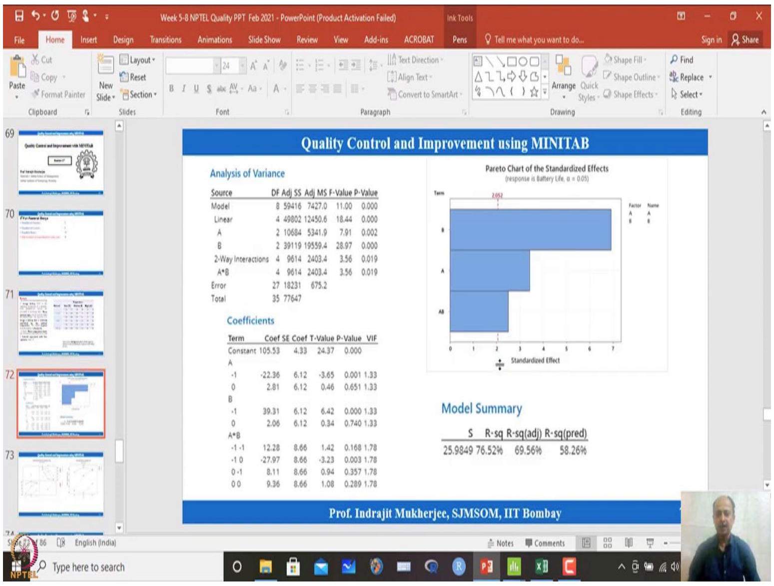

But we will skip this and we will go to a important topic which is known as local control ok.

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So, I mentioned that 3 things are important in design of experiments one is randomization one is replication and the third one is local control which is also known as blocking principle which is also known as blocking principle over here. And that is that deals with noise or nuisance variable you can think of ok and we are not interested in those variables basically. So, sometimes what happens is that while learning design of experiments.

We are not able to learn the complete batch and not a single supplier provides all the materials like that. So, we may have batch wise materials and based on that we have to; we have to do the experimentation in sequence like that ok. So, different batch of material may not be homogeneous.

So, there can be heterogeneity in the batches in that case what happens is that this variation in the raw materials can impact my CTQ values like that. So, in that case we will try to block this variation, we will try to block this variation and then we use a principle of blocking in while we are doing analysis of variance.

So, we can separate this variation and we can see actually the factors that we are the controllable factor which we have considered whether it is affecting CTQ or not. So, until and unless we block this what may happen is that the factor may not be showing significance although it is significant for the CTQ like that. So, that can happen and I will show you the examples ok.

So, sometimes what happens operator to operator variation is there, but we are not interested to study operator to operator variation we are interested in study studying the factor A whether it is significant to the CTQ or not. So, while screening the factors we will try to see that ok, but we are not interested in but this can operator can influence the results like that.

So, we have to block that operator influence or remove the variability that is due to the operator and then we will study whether the factor is important or not. So, ANOVA analysis can be used for that, so blocking principle is used for that to understand the variation for blocks and if we can isolate that one then actual factor whether it is influencing CTQs or not that will be clear ok.

So, here also some examples time of the shift can also create trouble and so we may have to deal with that and block that variations due to shift or due to particular time of the day like that ok. And test samples that is used that can also be also can vary, so that can also be a blocking factor like that. So, that can be these are nuisance variables.

So, you have to understand these are nuisance variable where we are not interested into this, but we will if we do not block this one that will impact the results that is why we are blocking this one ok. So, some more examples like when we are advertising like that, so it is effectiveness and its impact on customer purchase intentions like that. So, if you are type of advertisement, but that will also there will be some variations due to men and female response like that.

So, that is we are not interested into that we are interested into whether the advertisement is affecting the customers purchase intention that is our objective, but men and female men and female can respond differently. So, that variation we have to isolate and then see whether that advertising is effective or not. So, that is also another example where we can apply these blocking principles like that.

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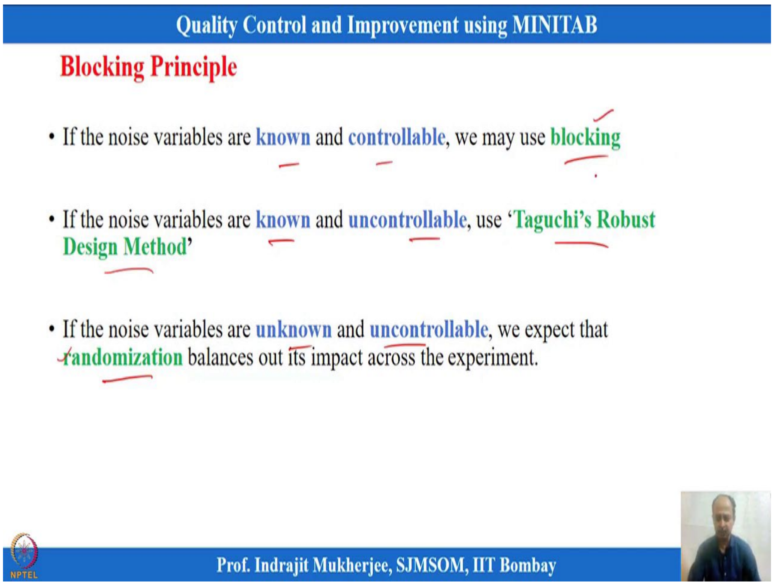

And whether it is manufacturing or service people can use blocking principle while using design of experiments like that ok. So, there are basic things that we try to do when we are using the blocking principle, if the nuisance variable or noise variable is known and controllable we try to block this like what material to material variation or supply to supply variation it is known and we can control that one in real life.

So, in that case we will use blocking principle and sometimes what happens is that it is known and uncontrollable. So, we have no control in the environments or certain other scenarios, but we have to deal with that. So, if it is known if I know about that variation and it is uncontrollable.

Sometimes the concept of Taguchi's robust experimental design is used and we will discuss about Taguchi's experimentation after few sessions over here ok. So, Taguchi's robust design so that can be used when known and uncontrollable, when it is uncontrollable and unknown like that I have no information or clues about these nuisance variable or noise variables like that which impacts the CTQs like that randomization to minimize the effect of that what we do is that randomization.

So, that it is uniformly distributed throughout the experimental results like that. So, we try to balance the impacts like that. So, that is the objective of randomization that we are mentioned earlier also ok. So, here we are dealing with blocking principle where we it is known and controllable that is the scenario.

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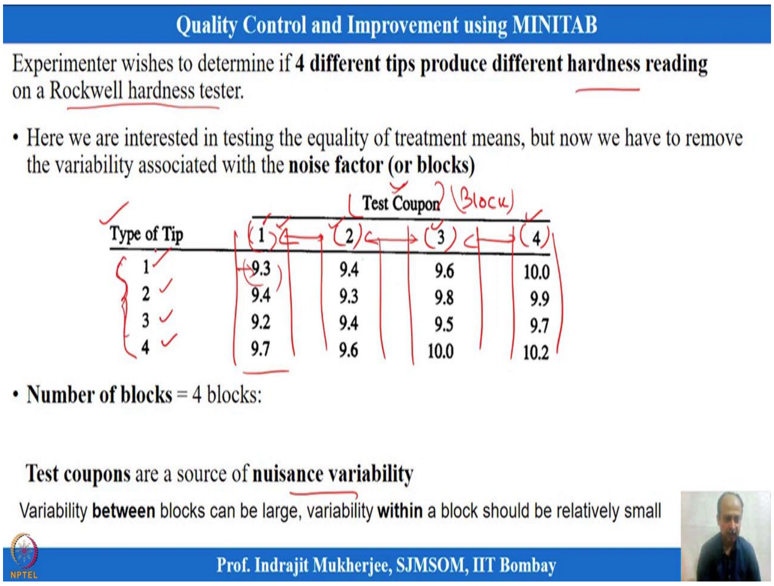

So, I will take one example to illustrate this one example. So, there are 4 different tips 4 different tips, so our objective is to study these 4 different tips which is measuring the hardness of a Rockwell hardness tester of this material like that and there are different test coupons that are used over here.

So, I have a different test coupons 1, 2, 3, 4 like this and each of these test coupons we can measure the hardness by using any of these different types of tips over here and this test coupons can also vary. That means, homogeneity between the test coupons is we are in doubt like that. So, in that case what we will do is that we will try to block this test coupon variations over here.

We will try to block this one and we want to see whether the if I change the types of tips whether the readings are changing basically or a hardness concentration hardness reading is changing or not or Rockwell hardness measurement is changing or not.

So, what we can do is that each of these test coupon we can assume that this is 1 block, this is 2nd block this is 3rd block and this is a 4th block like that each is treated as a block over here. So, blocks this test coupons are blocks over here and there are 4 levels of this block this is 1 level, 2 level, 3 level, it is like 2 factor experimentation basically.

So, block is another factor we can consider over here although this factor we are not so much concerned about that we want to see influence of this factor on the hardness reading, whether it is differing due to different types of tips that is our concern like that. If it is not then any of the tips can be used to measure the hardness like that is the overall objective of experimentation over here.

So, test coupon is a nuisance variation that because of the heterogeneity between the test coupon. So, we have to block this in experimentation we are not interested in the block variables we are interested in the factor which is considered over here which is type of tip like that ok.

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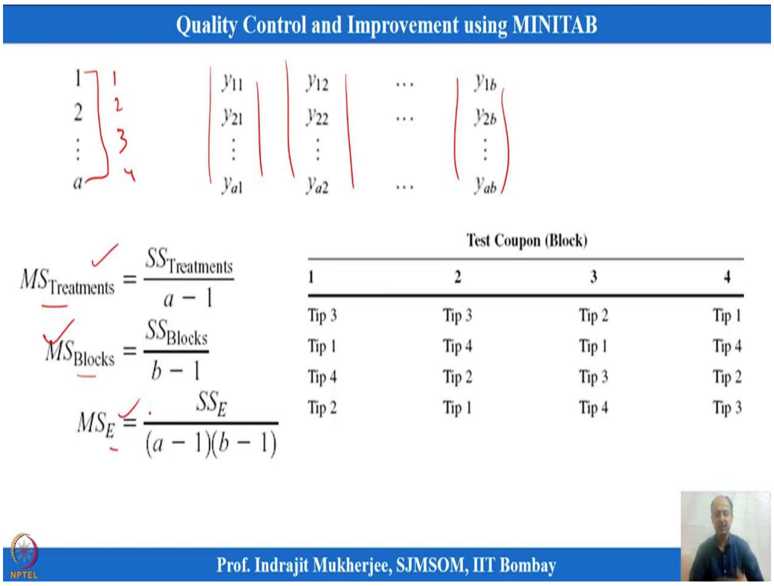

So, how to analyze this one? So in this case what will happen ANOVA analysis will be used like that. So, treatment effects of for this factor over here what we have concerned different types of tips 1, 2, 3, 4 like that and these are the block variables these are the blocks that is considered over here. So, in this case what our theory says is that we can also estimate what is the mean square block effects like that.

So, in that case mean square block effects like that and mean square error can be calculated and these can be isolated. So MS Treatment MS Block, so SS Treatment SS Blocks and SS Error can be calculated like that and MINITAB will do it automatically for you and then it will show whether the factor is important or not.

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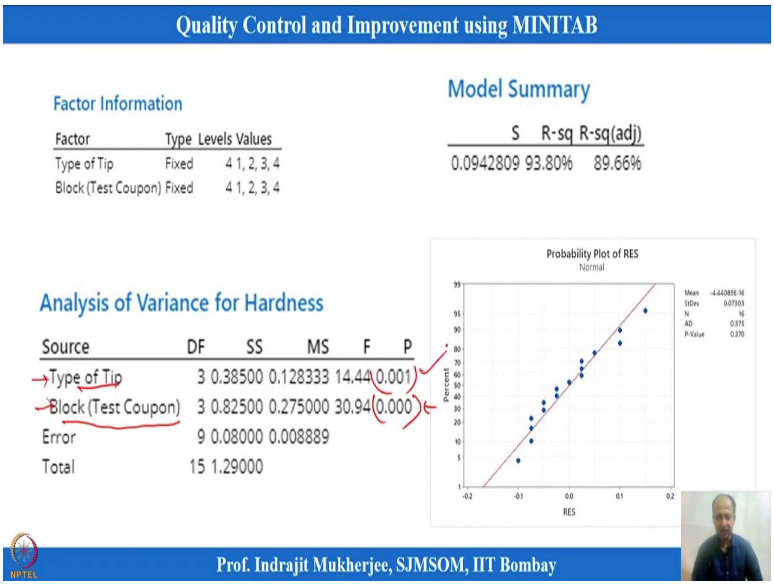

So this is the analysis that was done in MINITAB and then we will see that whether type of tip is significant or not. Yes it is influencing the mean values all the means are not same, if I use the different types of tips and block which we have considered that variation is also I have isolated over here. So, in this case what happens is that when we have isolated this one this is coming out to be significant; that means, test coupon to test coupon there is variation like that.

But we are not interested in the block variable over here and only we are interested into this and that is this is coming out to be significant. Now let us try to see these data set and try to see the analysis how do we do it in MINITAB.

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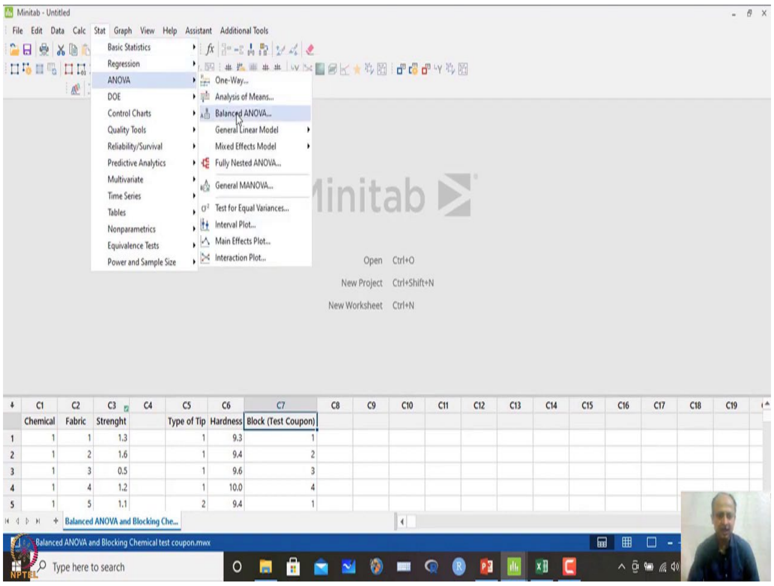

So, in this case what we will do is that we will see that example where we have selected. So, this is the example where we have already created. So, type of tip hardness measurement and this is blocking these are the block factors that is test coupon is considered as block over here, we can analyze this is a balanced design over here. So, in this case what we can do is that we can just analyze this one using analysis of variance and balanced analysis of variance over here.

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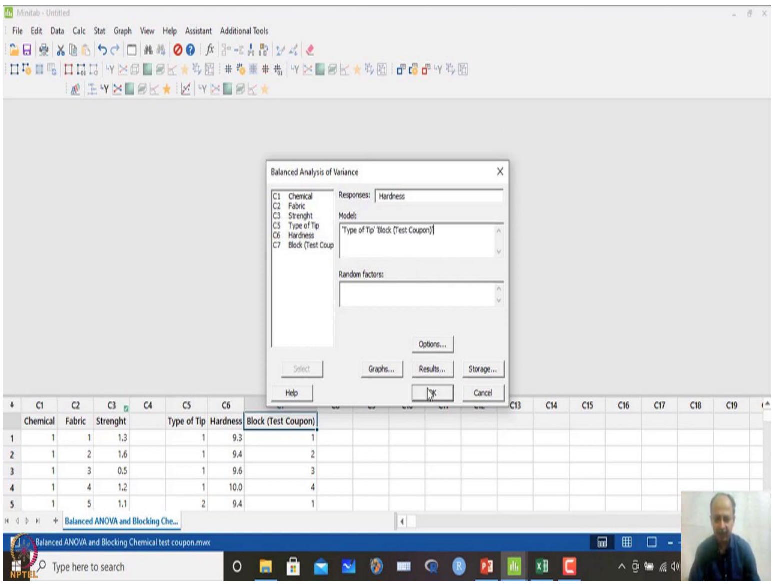

So, we have taken the hardness as the over here and in this case what we have done is that type of tip and this is block which we have considered over here.

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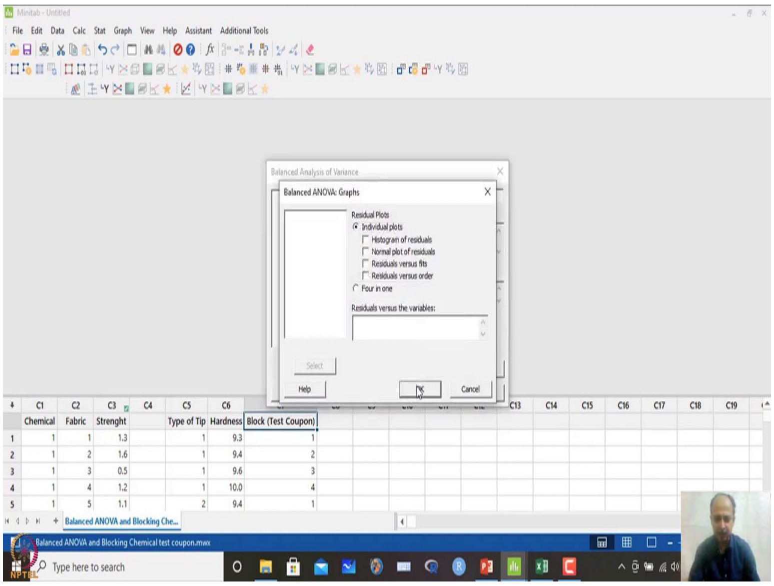

And this graphically we want to see, if we want to see the residual plot that is possible.

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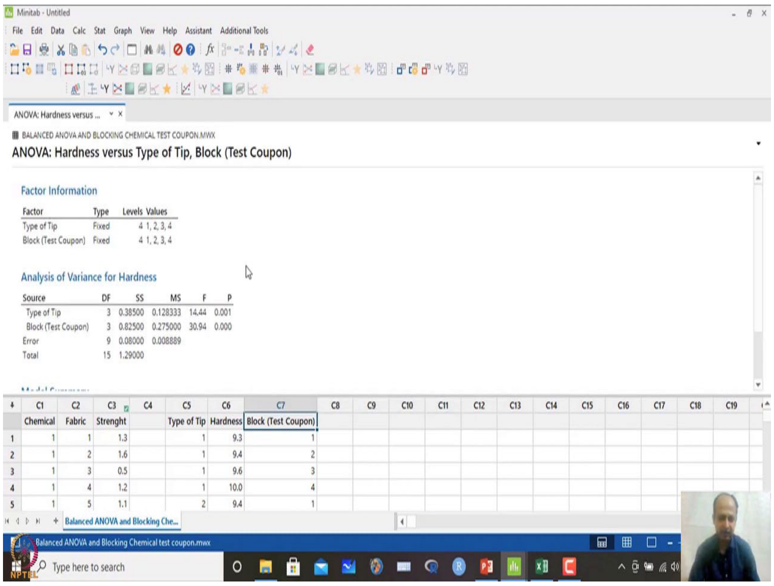

And what we are seeing is the type of tip when block variables are considered. The assumptions over here is that type of tips and block does not interact like that. So, interaction is not significant over here that is the basic assumptions that we are making when we are doing this blocking principle.

When we are implementing the blocking principle we try to minimize the effects of blocks and the interaction between types of tips and blocks over here. So, that is why I have not considered interactions over here. So, in this case what we will do is that this is blocks.

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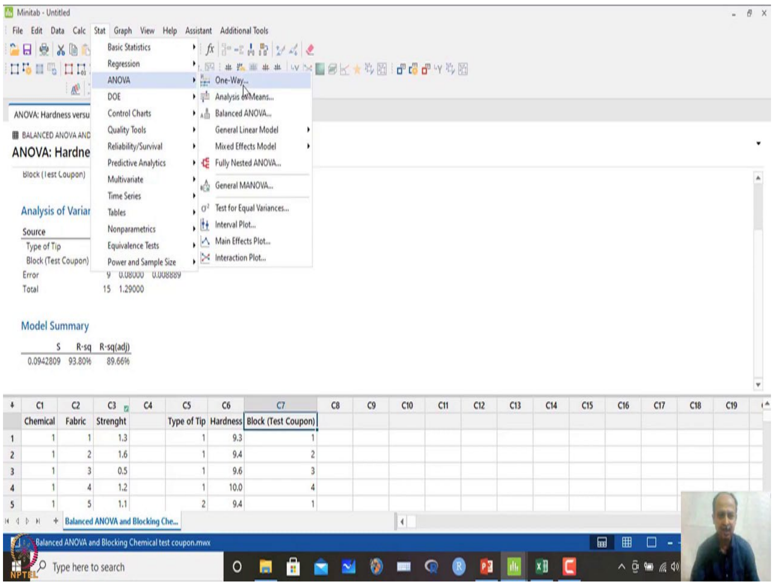

Now, if you do not consider these as blocks and consider randomized experimentation, so here we are not randomizing that is why we are blocking and if I consider random experimentation we will just drop the block variables over here. So, what I will do is that ANOVA analysis 1 way analysis of variance we will go, because there is one factor we are considering.

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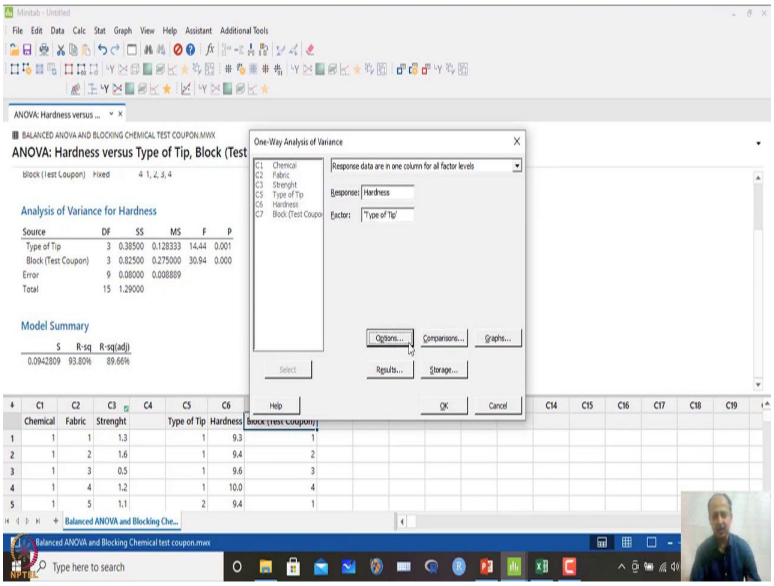

Let us consider this is the hardness one and factor is type of tip.

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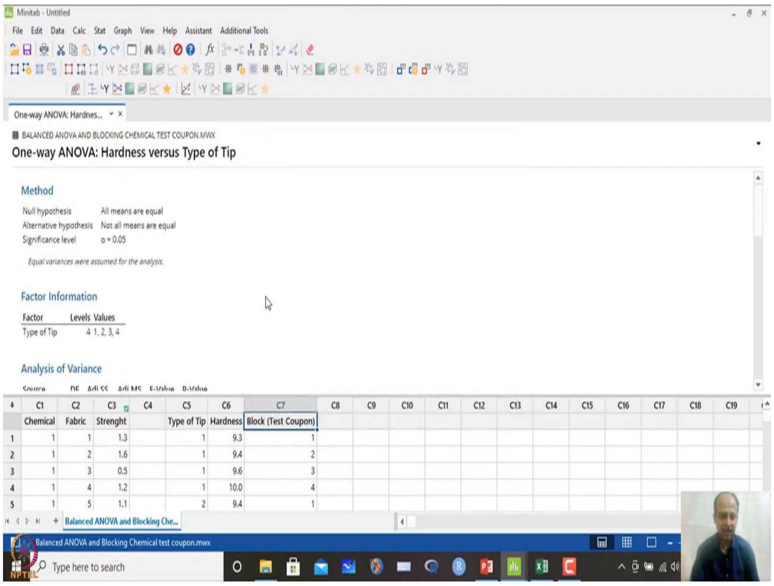

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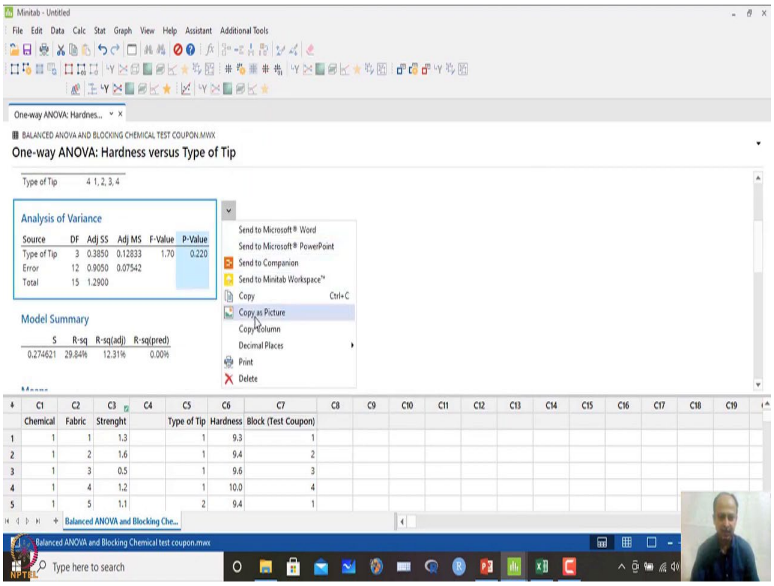

So, let us try to see what comes out of this analysis. So, when we make this analysis over here the ANOVA analysis that you will see copy pictures and we can paste this one. So, this we can eliminate.

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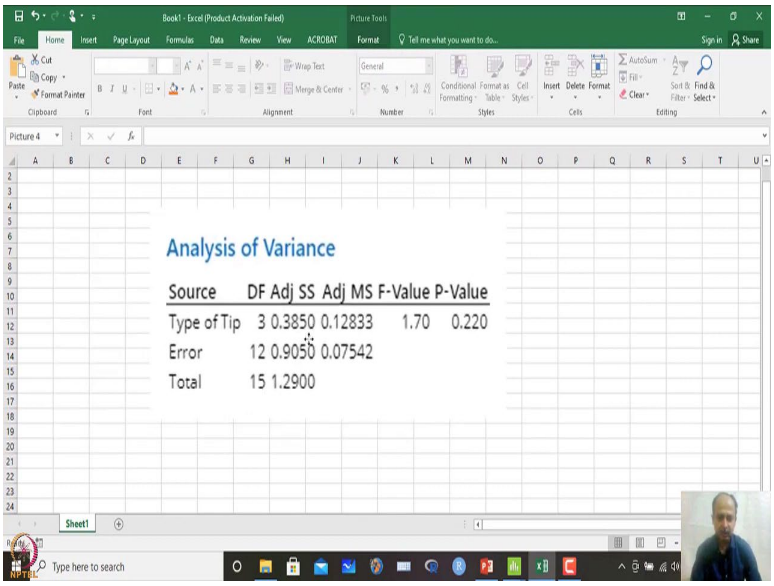

And if we replace this one what happens is that what I am observing over here is that type of tip is not significant you see P-value is more than 0.05. So, if you are treating them in isolation and considering that all test coupons are homogeneous, in that case what is coming out the results that is coming out considering only type of tip. It is not coming out to be significant, but as soon as you consider as soon as you consider that the block variable yes it has influence. So, we should eliminate that variation.

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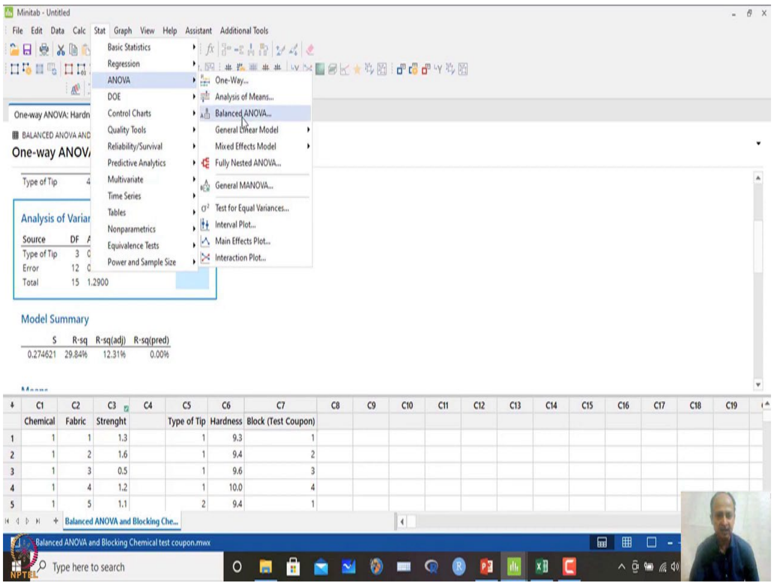

So, in that case what we have done is that we have considered that also.

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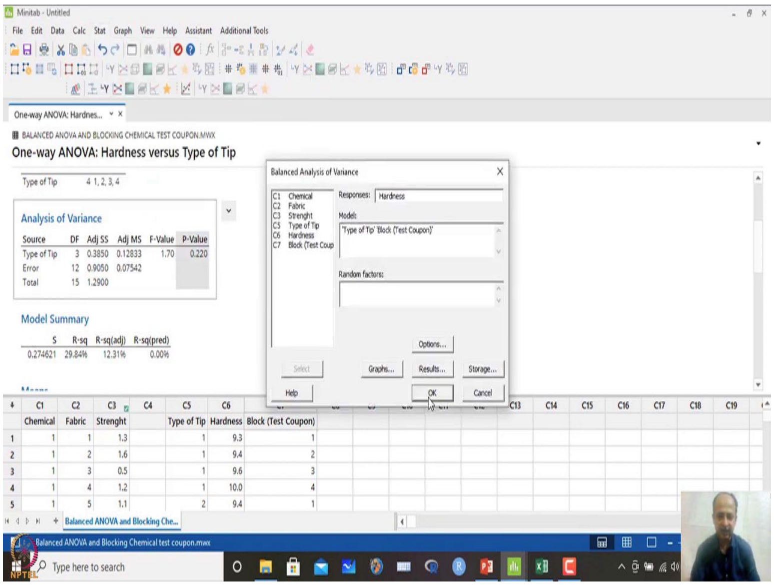

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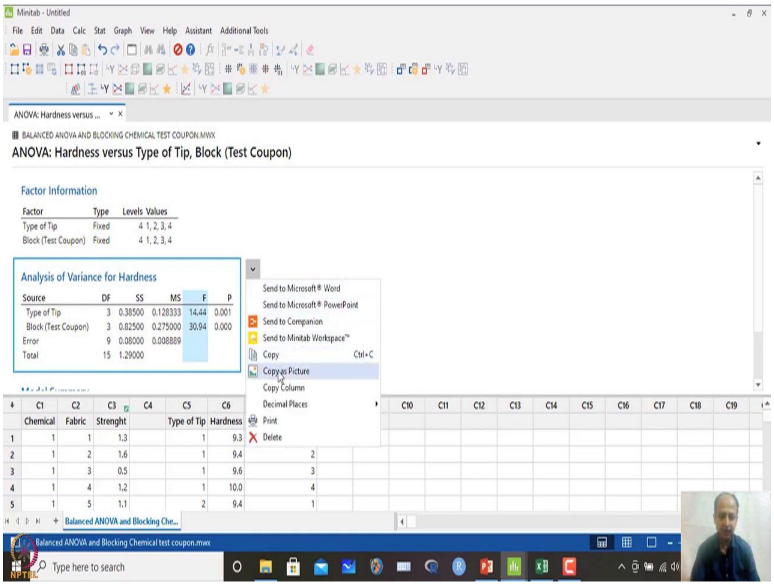

As a factor and we when we analyze that one what we have found is that we have found that this when we consider this one.

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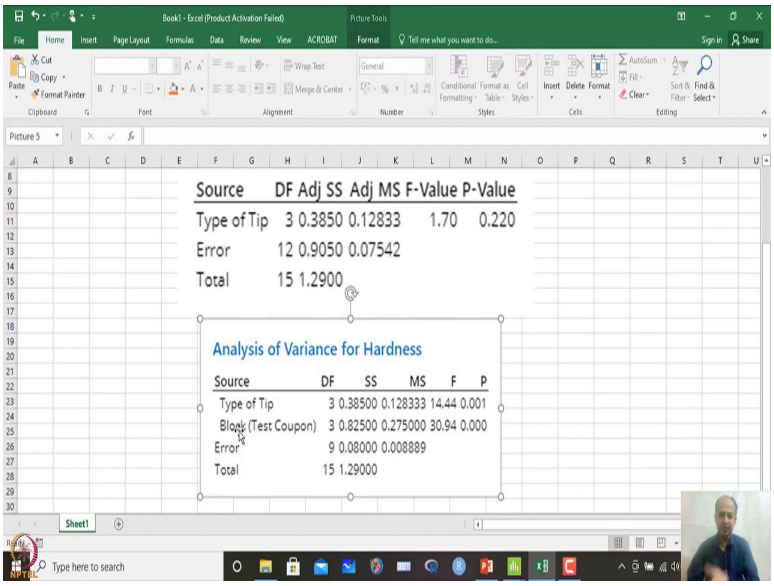

Then it comes out to be results seems to be very different. So, types of tips is now significant and earlier it was 0.22, now it is 0.001 that is significant it is coming out because we have considered this block has another variability that we have tried to isolate over here.

So, we have to apply blocking principle in case we feel that some of the variables are nuisance variables that can impact the results. So, blocking is one of the aspects that is considered in experimentation that is considered in experimentation like that ok. So, this is one example we can take there are other examples also that is given over here.

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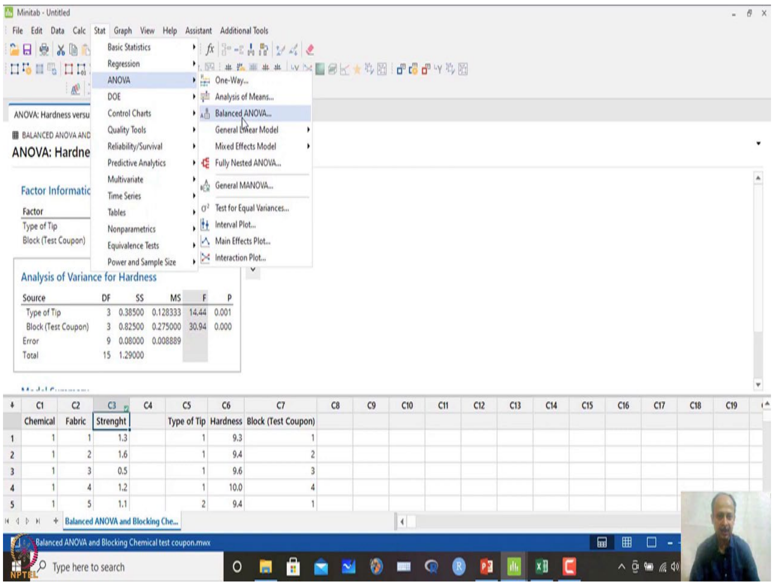

So, in this case we can takes another examples. So, this is chemical and fabric and strength like that, so in this case we can consider this and we can use the balanced ANOVA analysis.

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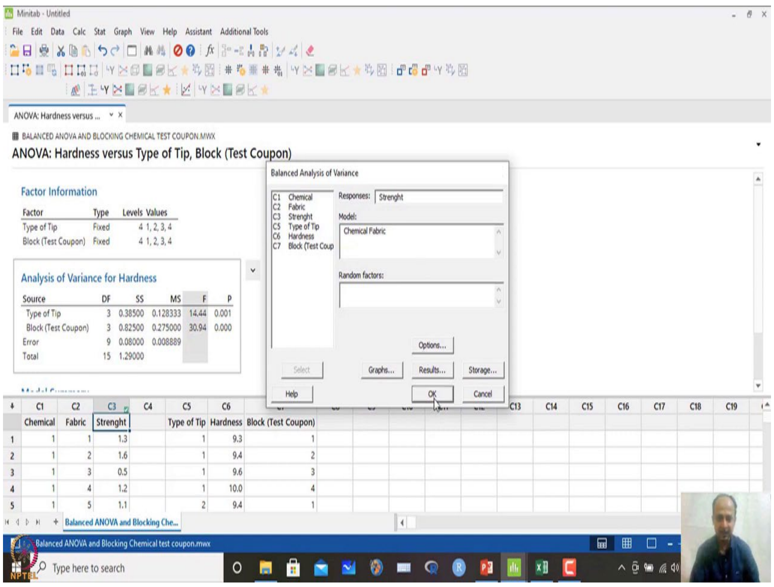

So, strength is the variable let us say this is the y characteristics that we are and chemical and fabric is the block variables that we are using. So, different chemical types and fabric is the block variable that we are using over here. And in this case what we are not considering interaction effects, but we want to see.

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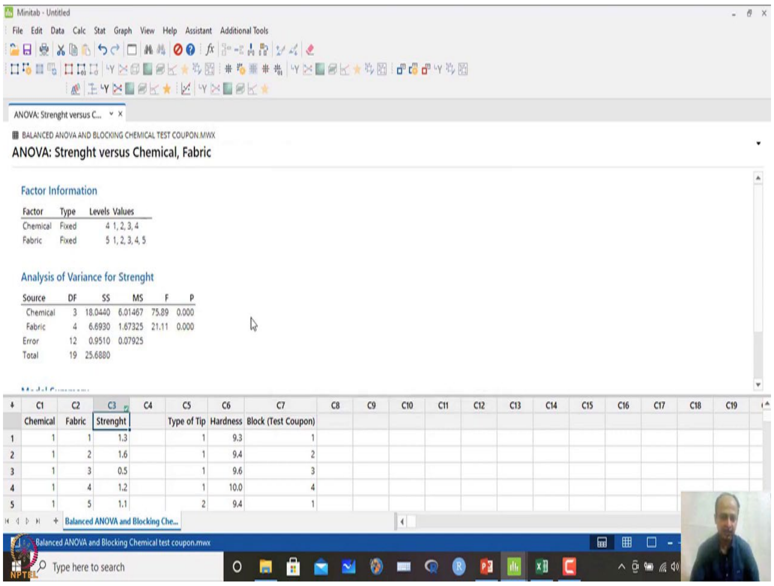

And here what we are seeing is that both chemical and fabric. So, we have blocked the fabric variables like that then only chemical is coming out to be significance like that. So, you can do individual analysis or one way analysis of chemicals over here that may come out to be significant and may not come out to be significant. But when we have blocked the fabric variation due to fabric over here which is blocked over here.

In that case whether I want to see whether chemical is influencing the strength of that is the main relationship I want to see, I am not interested into fabric over here. So, that is the block variable we have considered over here. So, that way we consider the principle of blocking in our experimentation and this is used extensively.

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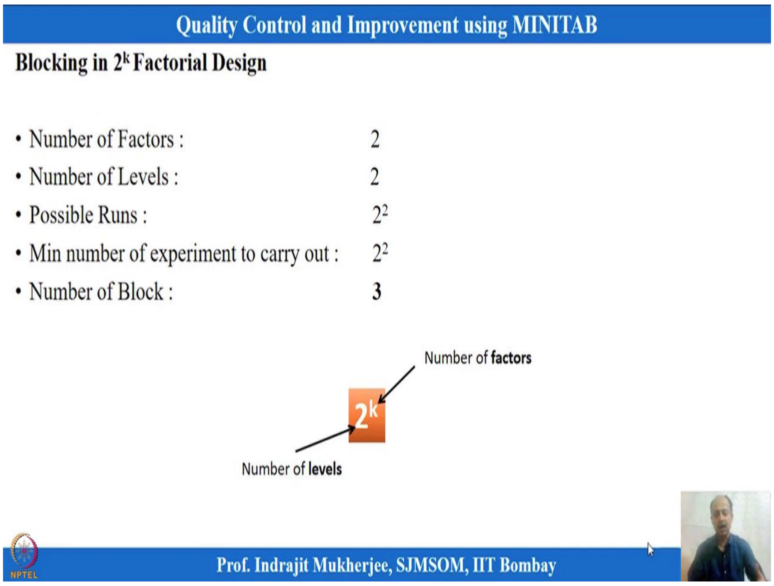

So, now how do we implement blocking in factorial design? How do we create that blocking in factorial design?

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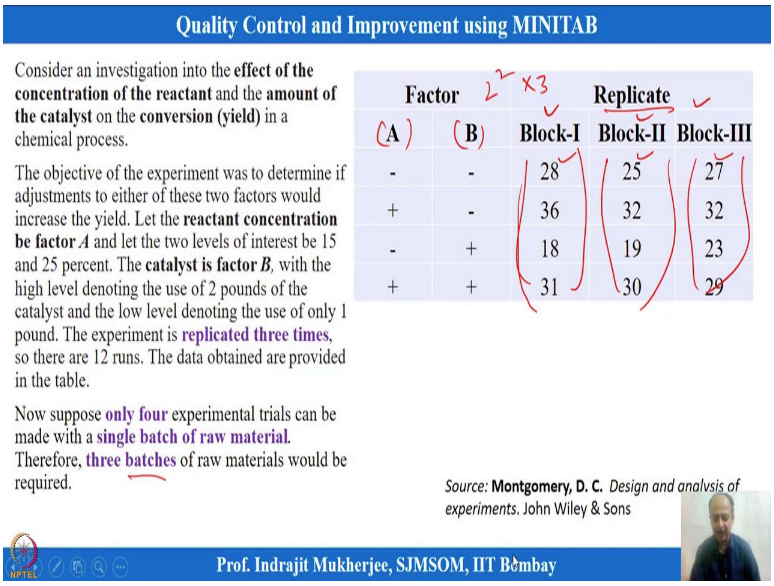

So, I am trying to take an example where the scenario can be we can use this one. So, there are let us consider factorial design you have done. So, factor A and factor B over here and these are the replicates. So, this is one replications that you are seeing this is 1 replicates, 2nd replicates, 3rd replicates.

And, but what we can do is that the condition that is given over here, therefore 3 batches of raw materials are used over here. So, this means only 4 from 1 supplier we have got like that 2nd is coming from 2nd supplier 3rd is coming from 3rd supplier like that. So, supplier to supplier variation is expected over here the material that raw material that comes while we are experimenting with the factors.

So, I am in doubt that the supplier to supplier variation will be there. So, in that case my objective is to basically block this variation, my objective is to block this variation block this variation. So, each of these replicates will be block like that. So, that how to create the design. So, there are 2 factors over here.

So, 2 square design so this is the 2 square design with 3 replicates. So, this will be multiplied by 3, 12 experimentation, but each of this 4 will be created as a block like that then only the analysis becomes meaningful when we are; when we are treating these. Because it is coming from different suppliers like that one batch is coming from different suppliers. So, factor A is reaction concentration factor B is catalysts over here and we want to see what is this influence on the yield like that.

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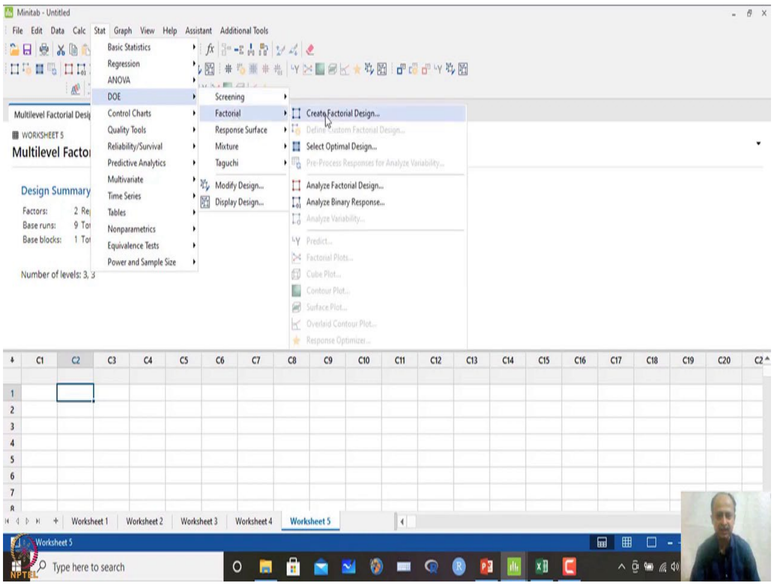

So, let us create the design and then try to see analysis how we can do the analysis ok. So, how do we create blocks in factorial design? So, what we have to do go to stat design of experiments factorial design create factorial design.

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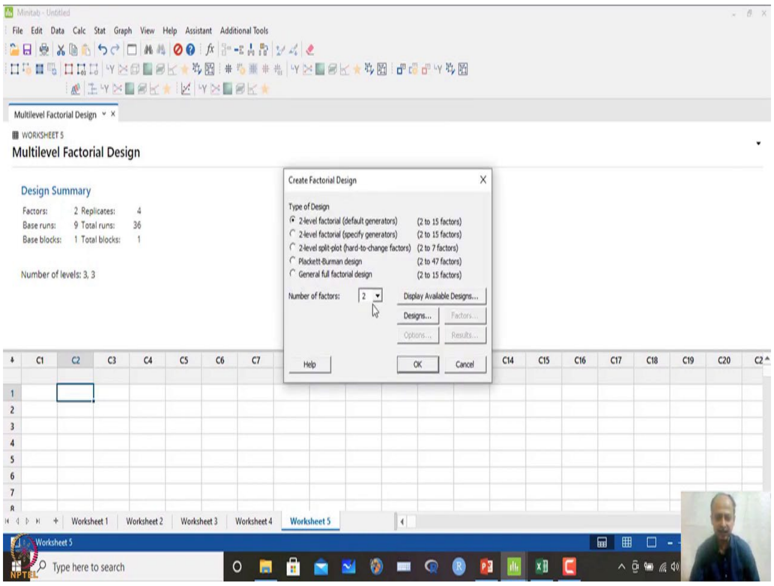

So, let us say this is a 2 square factors like that number of factors over here.

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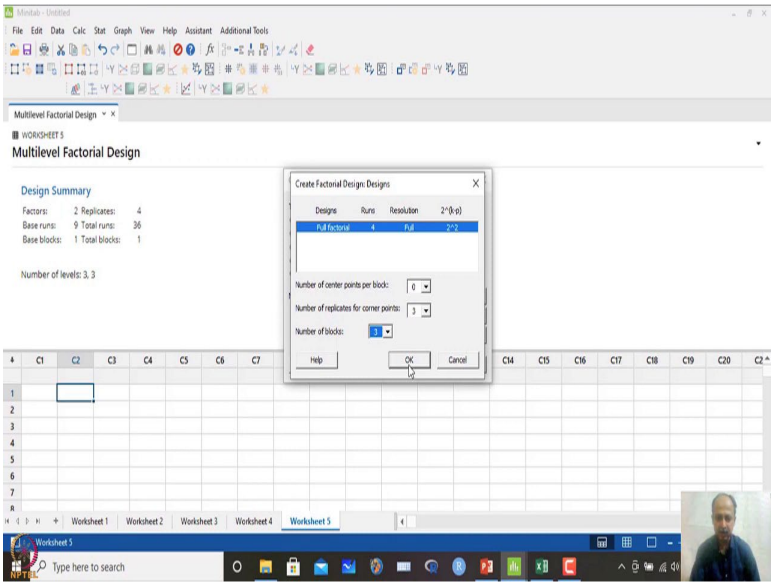

So, then you have to mention over here that how many number of blocks. So, number of replicates over here is 3 and then number of block is over here I am creating is 3. So, when I create and center point we will keep as 0 over here we are not concerned our center point at this time point.

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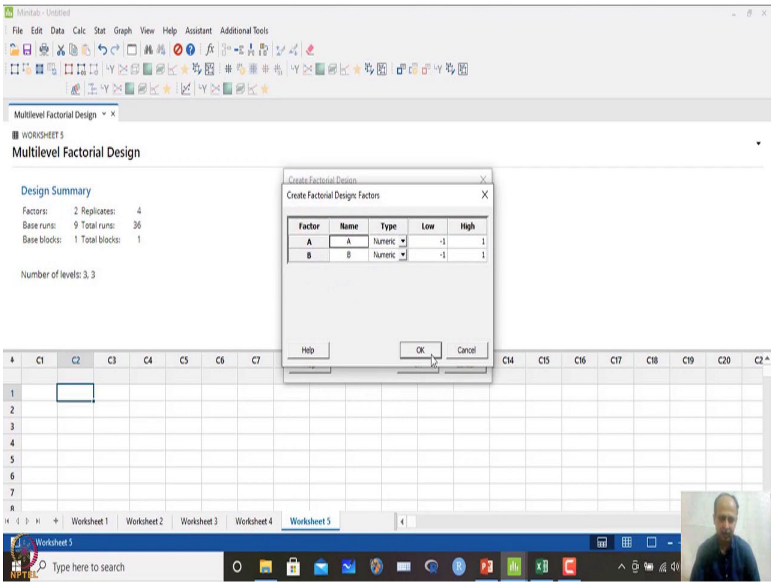

So, then we can write down the factor A and factor B whether it is numeric or text like that, so that you can mention like that.

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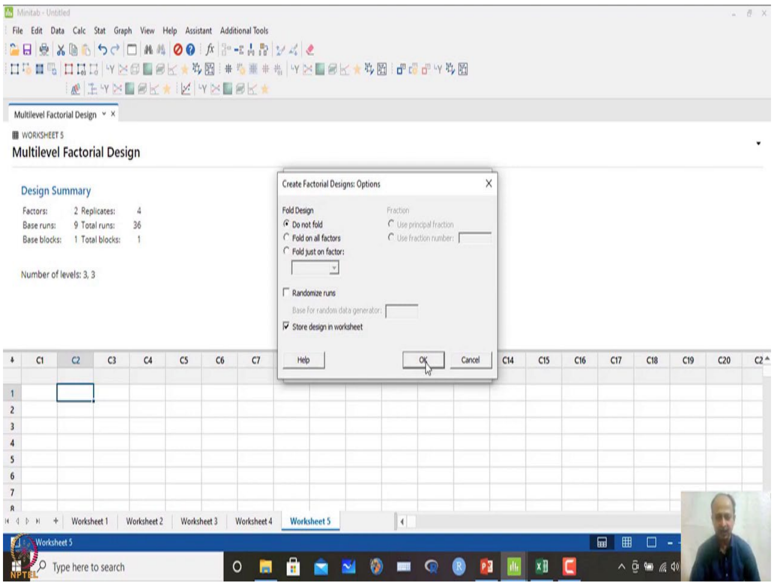

And in options we will not randomize the run and also we will not fold the design like that. So, folding is when we are doing that fraction of factorial that will be used. So, randomize the run we are not randomizing this one. So, standard order and run order will be same.

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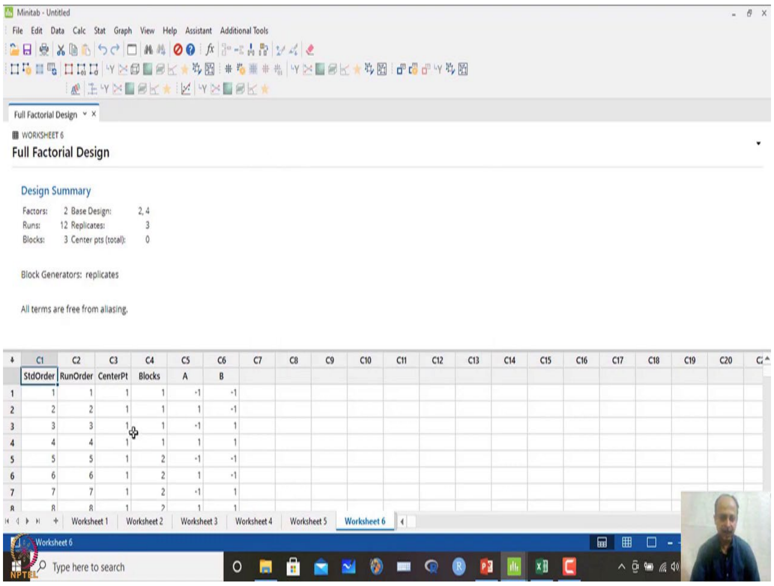

So, in this case when you click OK what will happen is that blocks will be created in the design.

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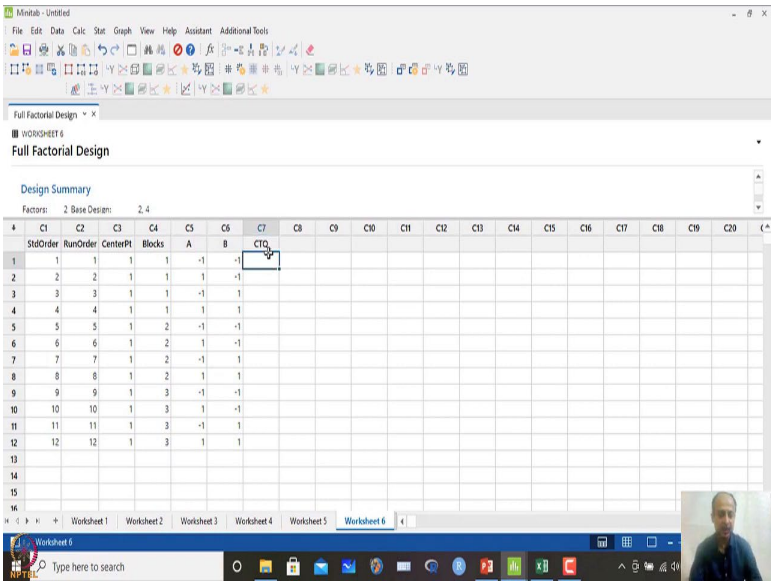

So, blocks will be created. So, you can see that a first experimental trial minus 1 minus 1 1 minus 1 minus 1 plus 1 1 1 this 4 trials what you are seeing is in block 1 like that. So, 1 replica 1 1 set of observation is taken for complete trial is done by a let us say supplier 1 like that is treated as block 1.

Then block 2 and block 3 like this. So, when you have created the design and then mentioned the CTQs values over here. So, when you mentioned the values over here and then we can analyze the data like that. So, I have the data with me. So, we do not need to do this because we have already have these data sets.

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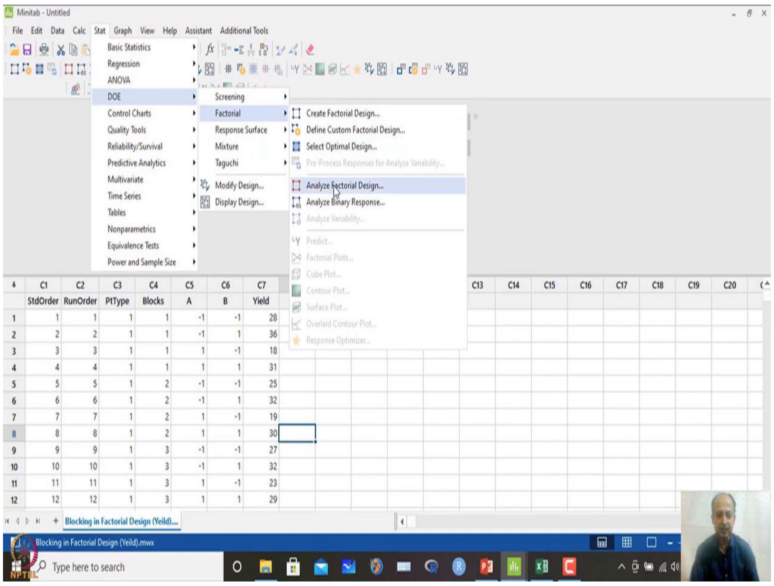

So, let me try to see where it is. So, here it is data set is over here, so here if you can see this trials over here. So, all the data sets are so 12 data points that is collected over here. So, blocks you can see 1st block, 2nd block and 3rd block like that. So, block is already created like that now I have to only analyze the data, what we will do is that stat design of experiment factorial design.

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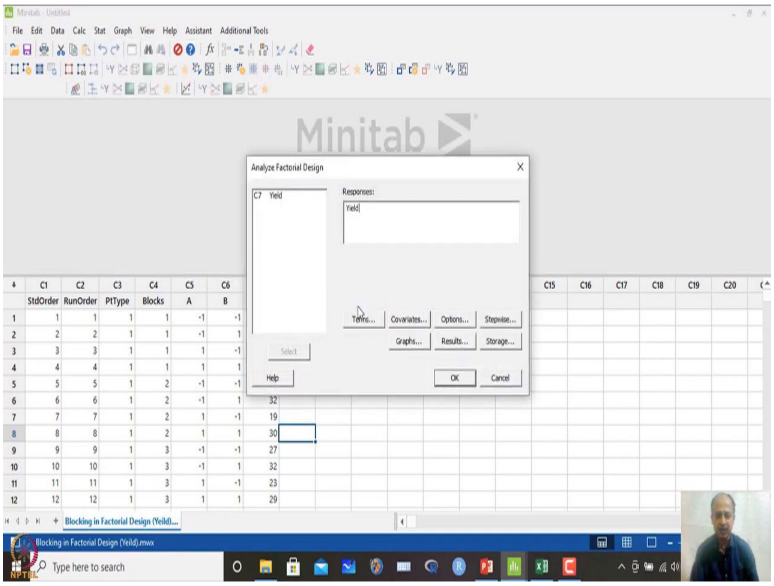

And then we will analyze factorial design response is yield over here.

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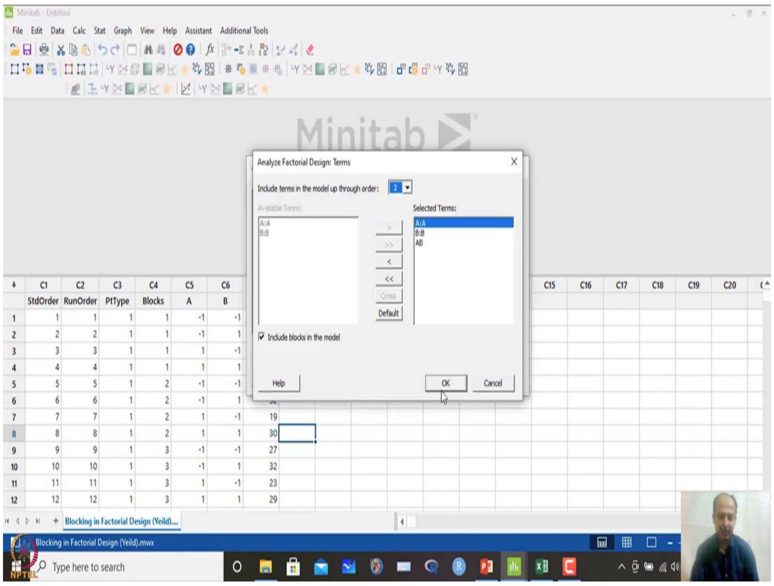

Term we want to consider A, B and AB interactions over here. So, here you will find that include blocks in the model, yes we want to include the blocks in the model that is tip like that.

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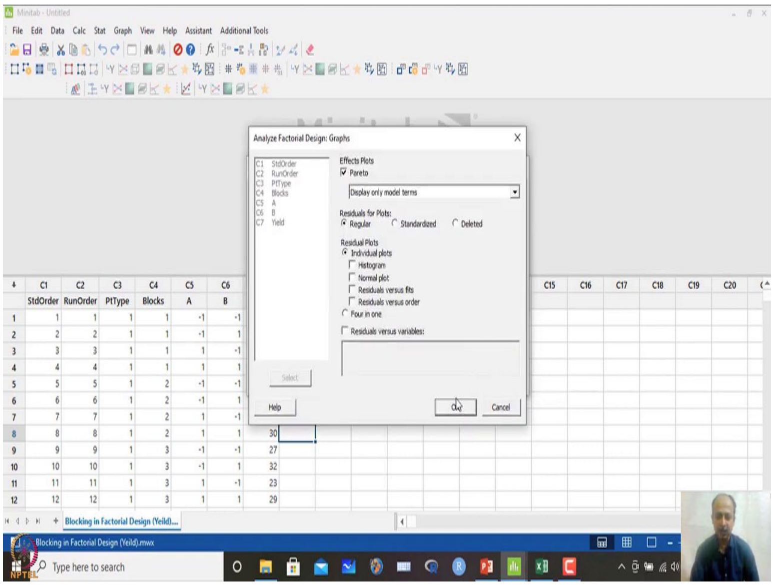

And then Pareto plot all these things are possible and other things are default what we are not changing over here.

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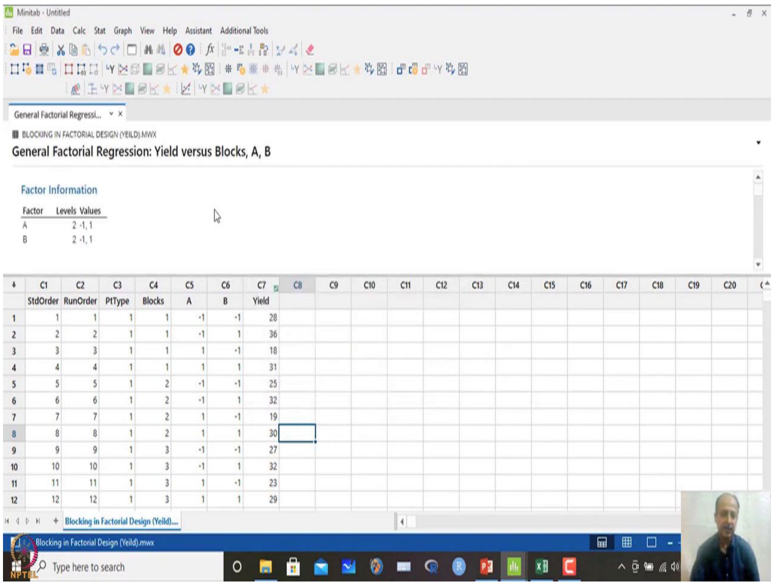

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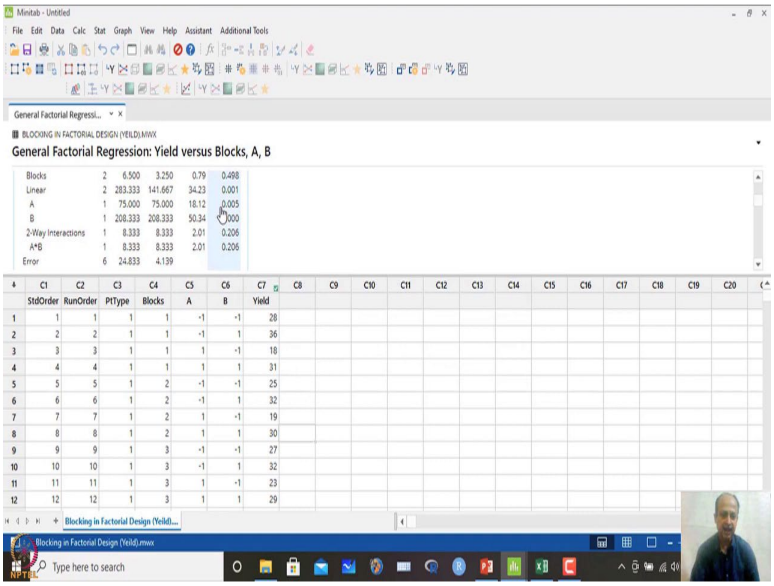

So, when we do that what happens is that I have a ANOVA analysis over here which will indicate that whether blocking has helped or not. So, in this case we can just copy paste this one and delete the earlier information.

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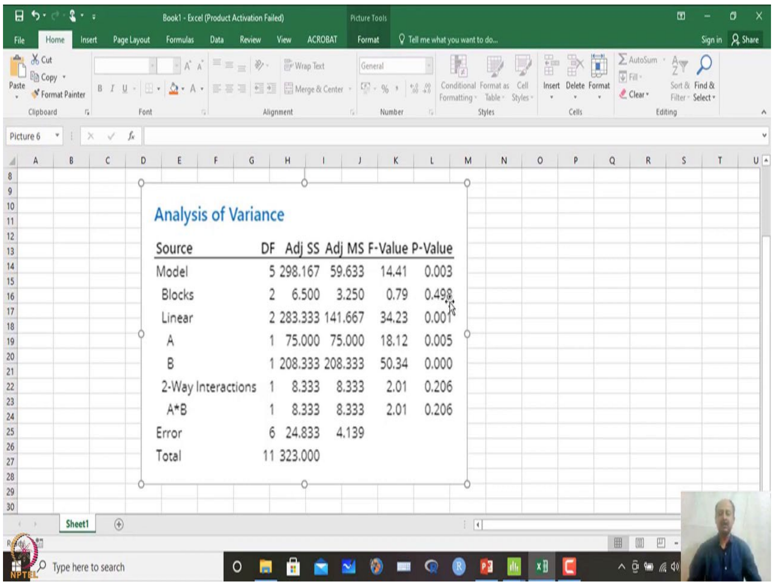

So, we can just copy paste this information and we can just enhance this one. So, model is significant blocking is not significant although the we thought that supplier to supplier variation will be there. But the P-value indicates that the homogeneity in the. So, block to block variation is not so prominent over here and not statistically significant.

But always we prefer to block because whenever there is in doubt you should block ok. So, then what happens is that because we have, so we have taken care of this blocking principle over here. Then whether factor A and factor B is significant yes it is significant interaction is not significant, interaction is not coming out to be significant and that will be also prominent when we study the when we study this Pareto plot when we study this Pareto plot. So, here where is that data points and this is yield and in blocks. So, this you can see.

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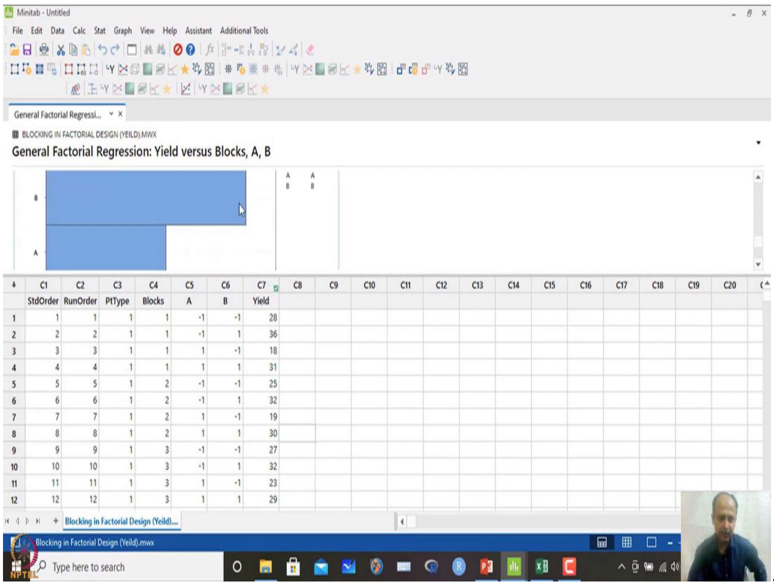

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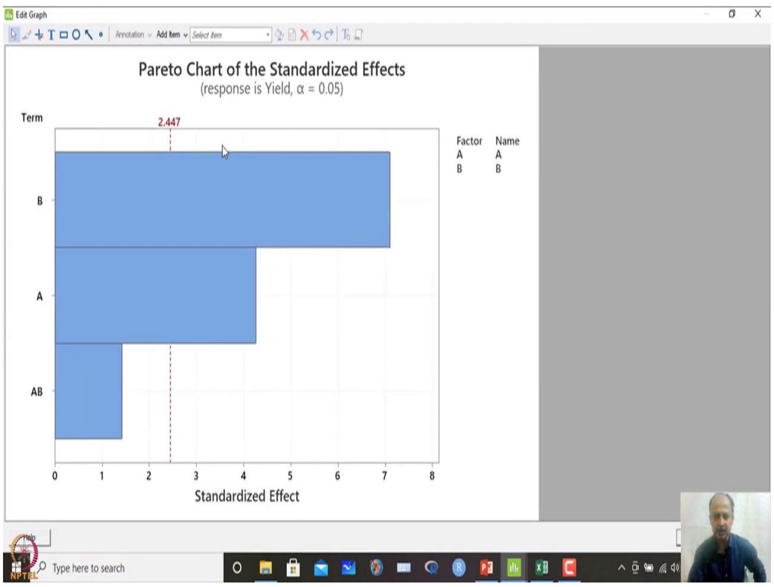

So, this is standard effect plots that we Pareto plot say AB is not coming out to be significant over here.

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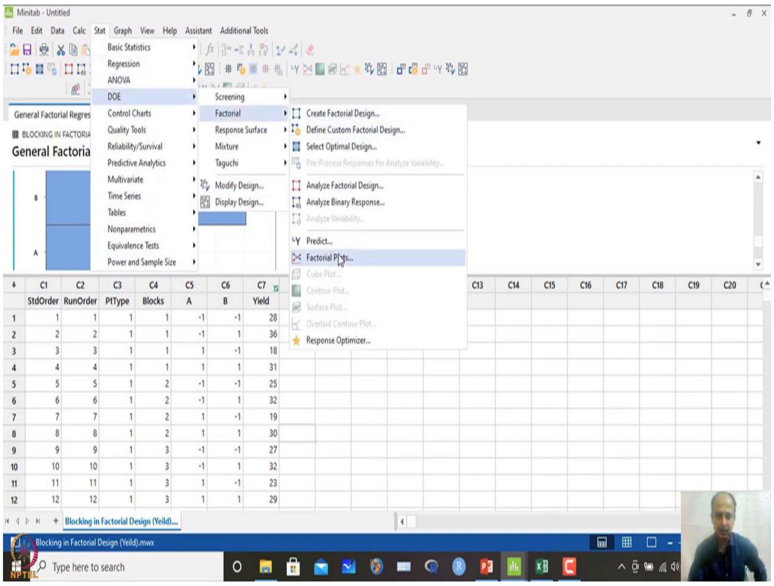

So, what we can do is that settings of this variable what we can do is that only by factor plots like that. So, if we want to set this one.

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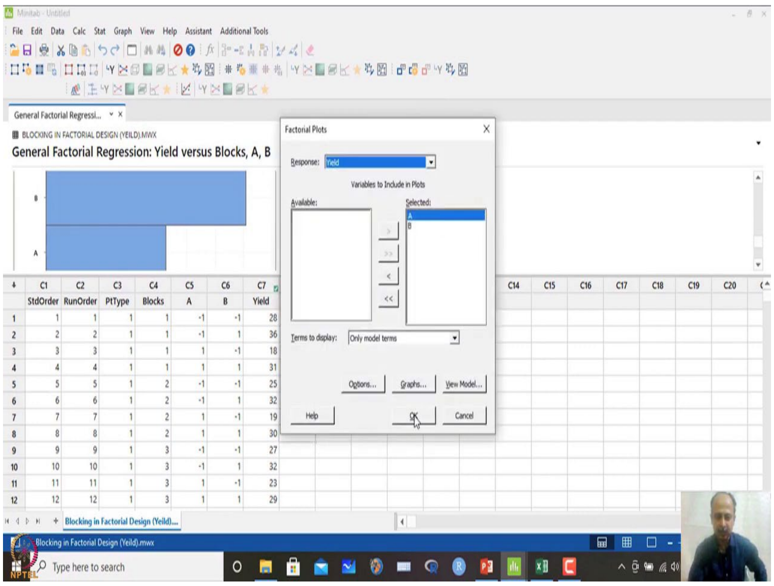

We will go to factor plots and click OK.

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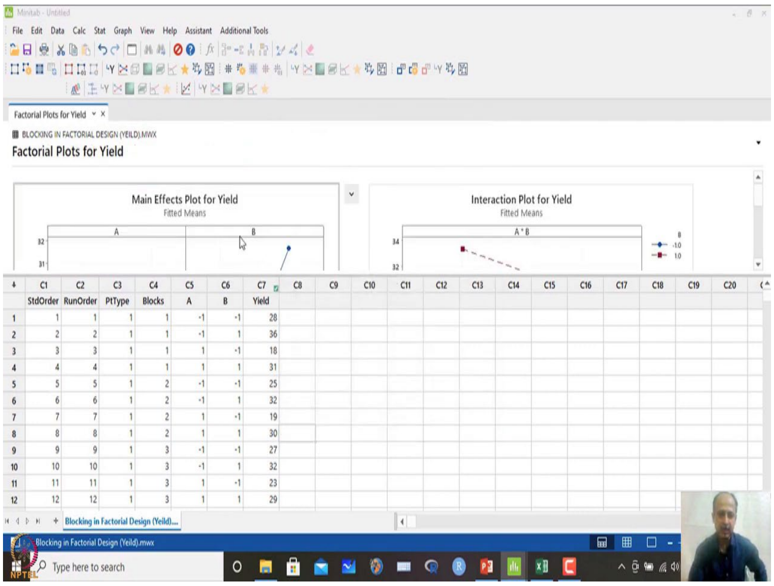

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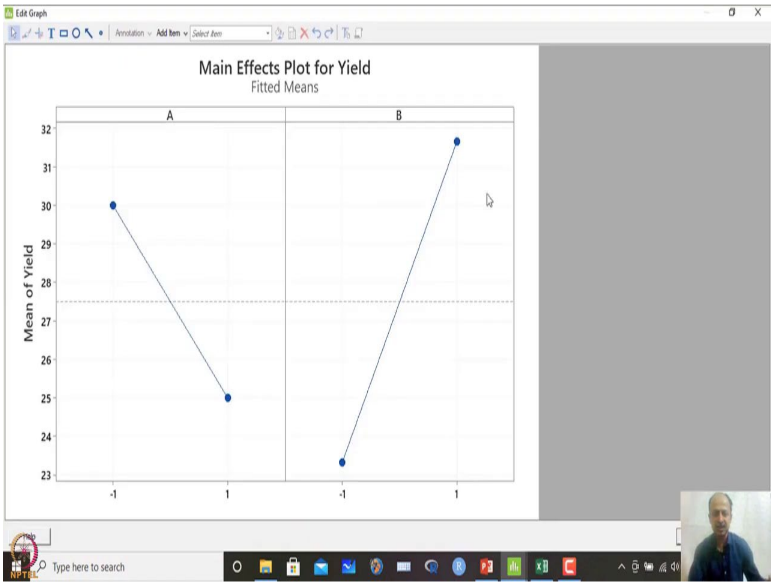

And then only the main effect plots can be used like that interaction is not prominent. So, we want to maximize the yield, so in that case combination will be minus 1 and this will be B will be at plus 1. So, that is a combination that we will use ok. So, that is the way we will analyze. So, in factorial design also we can implement the blocking principle, we can implement the blocking principle over here.

So, that is the one aspects I wanted to mention like that. And there is another aspects that when we are doing design of experiment another one aspects is coming several times there is known as center point that we have not discussed.

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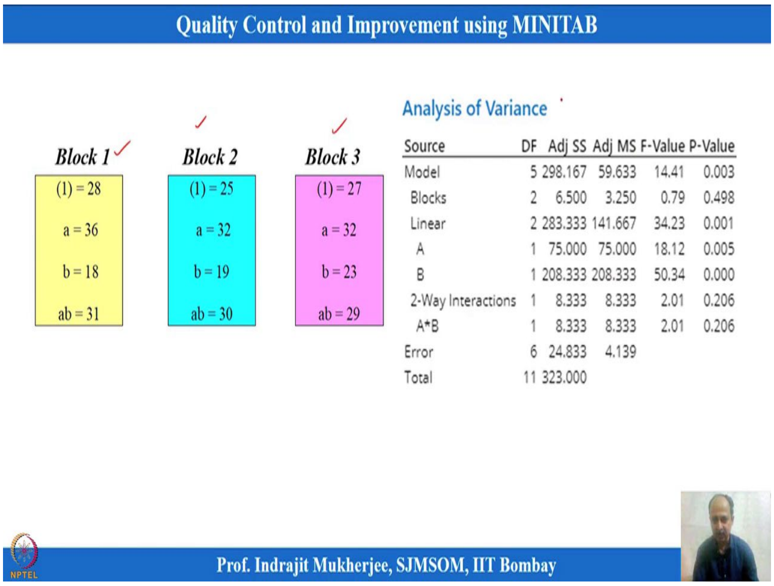

So, this is the block design what you have seen block 1 block, 2 block, 3 like this and this is the analysis that ANOVA analysis that we have shown.

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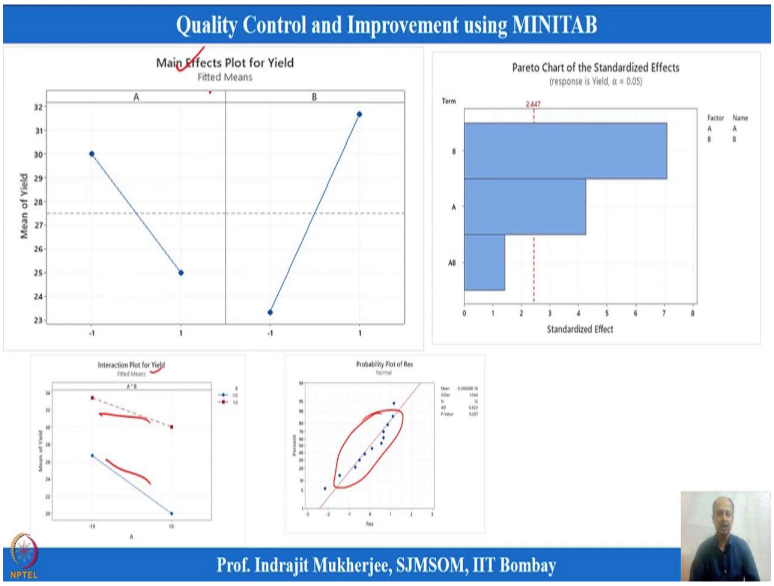

And these are the interaction plots and we can also check the residual plots like that and these comes out to be normal. And because these lines are parallel no interaction this is the interaction plots that you are seeing and because A and B is only prominent. So, we can only see the main effect plot and that will give me the combination that will maximize the yield basically ok.

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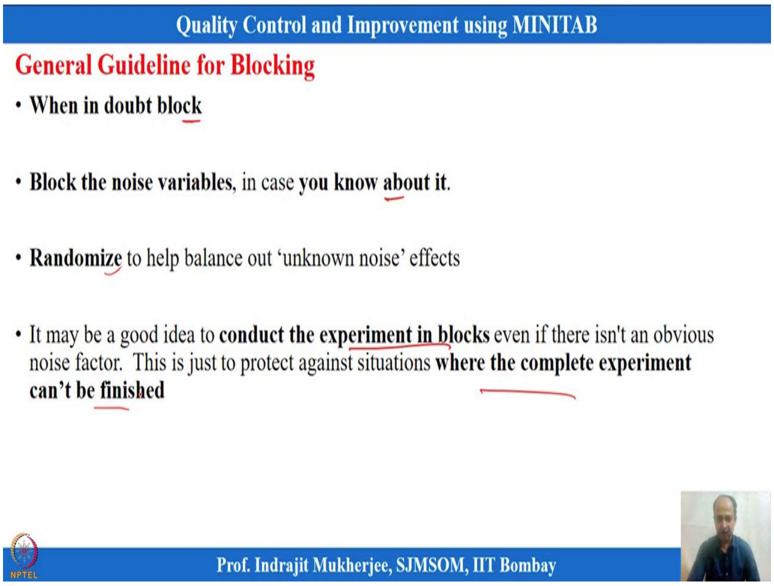

So, general guideline whenever the you are in doubt like you try to block that one and block the noise variable in case you know about it randomize in case it is unknown noise or unknown nuisance variables like that. So, it is good idea to conduct the experiment in blocks, where complete experiment cannot be finished. So, like what we say that it is coming from different suppliers like that, so in that case use the blocking principle like that ok.

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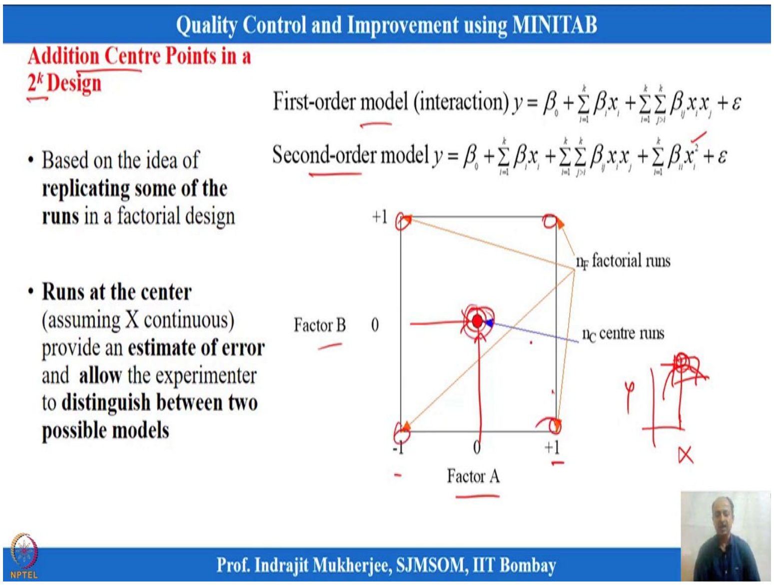

So, blocking is one of the principle that I want to highlight and also one important aspects that is center point we try to add center points in the design of 2 k design let us say. So, how does it help we are moving in design of experiments, let us say sequential experiments from one region to the other region like that and whenever you are the optimal point what happens is that you will find curvature.

So, if this is the y variable and this is the x region like that, so you will find that optimal region maybe over here. So, this is the point which is the optimal over here, because whenever optimal region comes then there will be there will be some curvature in the model like that. So, that is expected let us say this is a function that we are seeing over here.

So, this concave function that we are seeing over here. So, in this case what happens is that we want to see that maximum point is over here. So, if this is the region that I am experimenting over here, so in that case it is expected the second order model will be more effective as compared to the first order model or response surface can be built like that.

So, in that case what is important is that we try to add center points, whenever I am in doubt that whether we are in the region of optimality. So, in that case what happens is that then the model x square terms become prominent like that. So, that can be studied if we are adding center points like that in the design like that ok.

So, what happens is that center points will be added over here. So, this is the experimental zone of factor A and factor B minus 1 plus 1 and for the factor B is minus 1 plus 1. There will be some 0 points over here that will be taken like this 0 points over here and some replications will be done in the center points over here. And in that case average of the corner points will be compared with the center point values over here so average of this.

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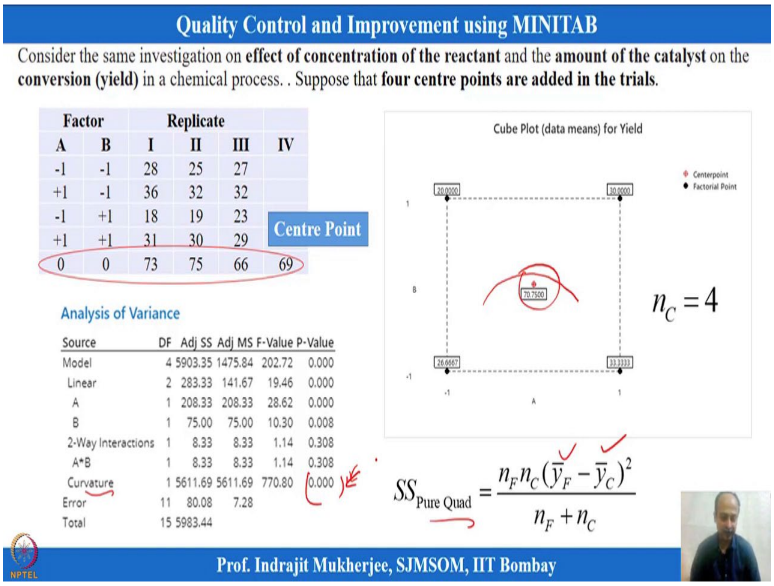

And if there is a difference that will be reflected by this SS pure quadratic term whether it is required or not. So, that means, whenever there is a curvature it will be reflected like this, so whenever there is a curvature the average of this will be different from the average over here.

So, average of corner points will be different from the center points average like that. So, when it is significant when this difference is significant it will the P-value will indicate like that. So, here when I do the ANOVA analysis of curvature what I am getting is that P-value is significant over here and in that case that indicates that the model requires add, we need to add more squared terms on the in the model maybe A square maybe B square over here ok.

So, that is the term we need to add to get a better models like that. So, whenever I add a center point I want to see whether there is a curvature in the model, then we will use certain other designs to get the get the fundamental models of adding the square terms like that ok, so those things we can see.

So, we are adding center points to understand that whether we are in the region of optimality whether we are in the region of optimality or not, that is the main idea. If we are in the region of optimality then we can use central composite design to get the response surface basically at that point. So, that is that comes under the purview of response surface designed.

Because when we are near the optimal point, then we try to use some high end design likes central composites designed to get the response surface equations like that. Which can consist of AB and AB interactions it can also consist of A square and B square terms also we can incorporate that one.

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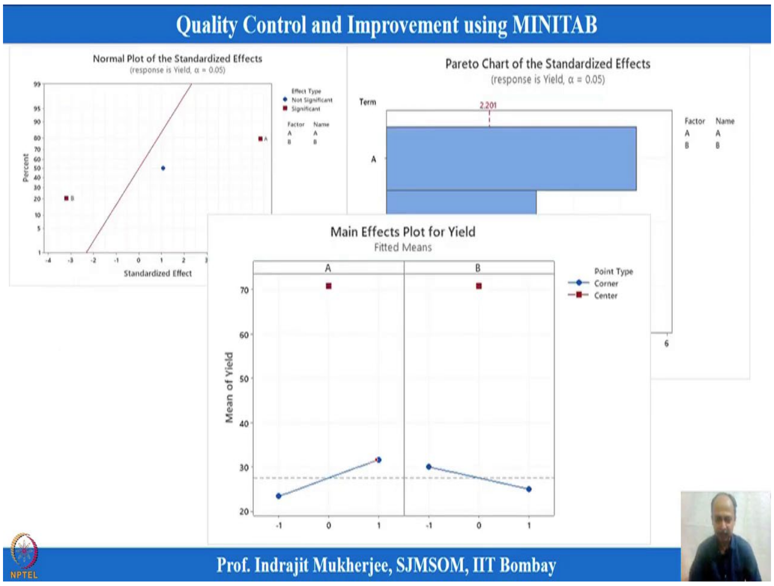

So, this center points we can create like that, so if you go to the center points like that.

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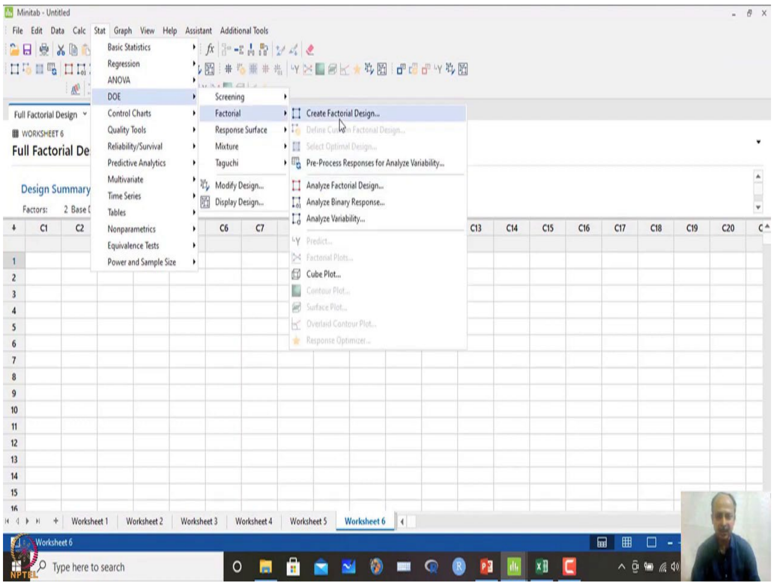

So, if you go to any fundamental design like that. So, in this case what we can do is that we can add center points. So, design of experiment factorial design and we create the factorial design.

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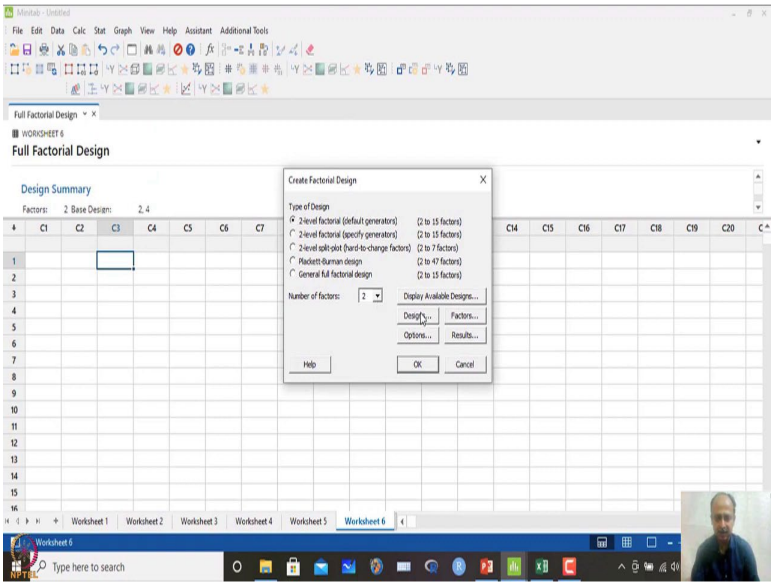

So, when number of factors let us assume this one 2 square design we are assuming over here.

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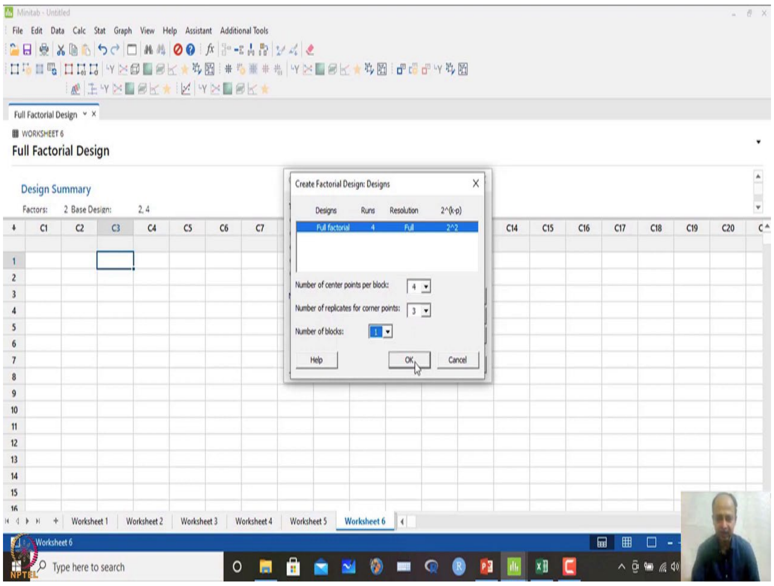

So, in design what we can do is that number of center points. So, if I want to add 4 or 5 center points like that. So, that is and number of replicates over here number of blocks let us say we are not blocking anything.

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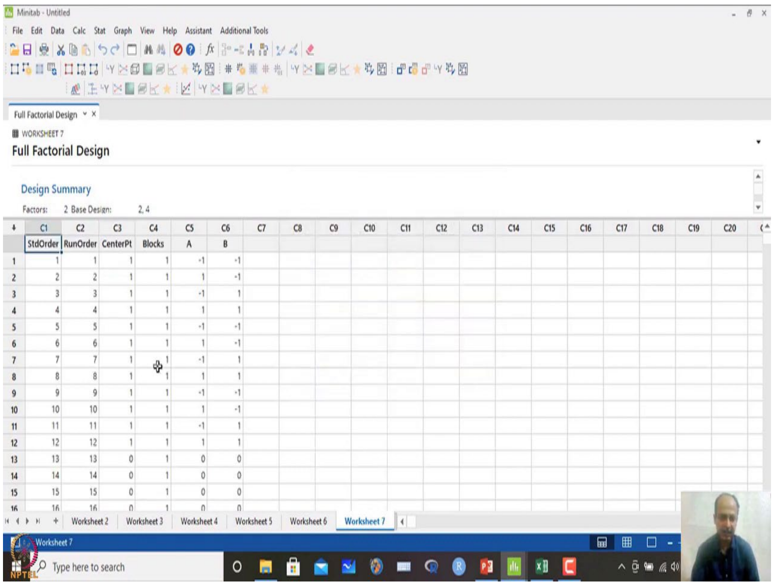

So, if we create like that and we create like that what happens is that there will be some combination 4 points that will be the center points over here. So, AB combination we learn and also that 0 points will also run over here. So, this when I measured the CTQ values at 0 points also we can have an estimate on the center point y values and that will be used to see the corner point average with the this one. So, this value will be calculated.

So, this SS pure quadratic will be calculated at that will tell me whether curvature is present this P-value will indicate whether the curvature is significant or not like that. So, this is also sometimes we try to check when we are near to optimality or not like that whether we have reached optimality.

So, mostly used in response surface methodology, mostly they will try out adding center points and then going to CCD design whenever we are near to optimality is that scenario is mostly we add center points like that ok.

So, we will stop over here we will continue in some other topics from here.

Thank you for listening.