DR. ALVIN'S PUBLICATIONS

DESIGN OF Experiments with Minitab

DR. ALVIN ANG



1 | P A G E

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D. E. 1 2 <i>VII.</i> A. B. C. D. E.	Example: Minimizing the Response (Smaller is Better) a) Minitab Solution (1) Creating the Worksheet (2) Defining the Factors (3) Analyzing the Responses b) Minitab Output c) Predicting Taguchi Results Summary of Taguchi's Example Nominal Response (Nominal is Best) Largest Response (Larger is Better) DOE FAQs What if many / all factors become significant? What if there's missing data? Must we use all factors? What if I can't replicate all runs? Must I randomize all trials?	68 .69 .72 .73 .80 83 .83 .83 .83 .83 .83 .83 .83 .85 .85 .85 .85 .85 .85

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I. INTRODUCTION



There are 4 types of DOEs in Minitab.

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- Factorial (2 Levels)
 - o Full Factorial
 - o Fractional Factorial
- Response Surface Method (RSM) (>2 levels)
 - Central Composite Design (CCD)
 - o Box-Behnken Design
- Mixture
 - o Simplex Centroid
 - o Simplex Lattice
 - o Extreme Vertices
- Taguchi
 - o Larger is Better
 - o Nominal is Best
 - Nominal is Best (Default)
 - Smaller is Better

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II. SIMPLE FULL FACTORIAL EXPERIMENT (2 LEVELS)

Single Cup Catapult



Practice Design of Experiments (DOE)

Go to https://sigmazone.com/catapult-grid/

SigmaZone	There are 5 Facto - Release Angle	Homepage ors affecting the Dista	Products ~ Train nce (Response)	ing ~ Consulting	About U	Js Articles
Grid Interface	- Firing Angle - Cup Elevation - Pin Elevation - Bungee Positior	ng	Run all rows	Number of rows 7		Update
Release Angle	Firing Angle	Cup Elevation	Pin Elevation	Bungee Position		Distance
100	100	300	200		200	
100	100	300	200		200	(Response)
100 100	100 100	300 300	200 200		200 200	(Response)
100 100 100	100 100 100	300 300 300	200 200 200		200 200 200	(Response)
100 100 100 100	100 100 100 100	300 300 300 300	200 200 200 200		200 200 200 200	(Response)
100 100 100 100 100	100 100 100 100 100	300 300 300 300 300 300	200 200 200 200 200		200 200 200 200 200	(Response)

- We will test the following:
 - o Release Angle: 140 / 180
 - Firing Angle: 110 (since this is constant, we will ignore it)
 - o Cup Elevation: 220 / 280
 - o Pin Elevation: 120 / 180
 - o Bungee Position: 120 / 180

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- 4 Factors 2 Levels, this is known as a 2⁴ Factorial Design DOE.
- Total number of runs = $2^4 = 16$ runs
- Now go to Minitab

	Basic Statistics	•••	fx 🗄 📲	2 A d	
	Regression ANOVA	► ►		Minita	k
ing [DOE	•	Screening		
ing [Control Charts		Factorial	🕨 🛄 Create Factorial Design	
Des	Quality Tools		Response Surface	Define Custom Factorial Design	
Desi	Reliability/Survival	•	Mixture	Select Optimal Design	·l+0
Desi	Predictive Analytics	•	Taguchi	Pre-Process Responses for Analyze Variability	
	Multivariate	▶ 啦,	Modify Design	Analyze Factorial Design	(
	Time Series	下	Display Design	Analyze Binary Response	
	Tables			Analyze Variability	
	Nonparametrics	•			
	Equivalence Tests	•			
	Power and Sample Size	•			

A. CREATION OF EXPERIMENT

Create Factorial Design		×
Type of Design		
2-level factorial (default generators)	(2 to 15 fa	actors)
2-level factorial (specify generators)	(2 to 15 f	actors)
2-level split-plot (hard-to-change fact)	tors) (2 to 7 fac	tors)
O Plackett-Burman design	(2 to 47 f	actors)
General full factorial design	(2 to 15 f	actors)
Number of factors:	Display Availa	ble Designs
	Designs	Factors
	Options	Results
Help	ОК	Cancel

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1. DISPLAY AVAILABLE DESIGNS

			Create F	actor	ial De	sign:	Disp	olay A	vailab	le De	esigns	5					×
Create Factorial Design		×				A٧	railabl	e Fact	orial D	esign	s (wit	h Res	olutior	ı)			
Type of Design		C5	Factors														
2-level factorial (default generators)	(2 to 15 factors)	this pops	Run	2	3	4	5	6	7	8	9	10	11	12	13	14	15
© 2-level factorial (specify generators)	(2 to 15 factors)	upwe	4	Full	III	71.7											
C 2-level split-plot (hard-to-change factors)	(2 to 7 factors)	will evolai	8		Full	IV Full		IV	IV	IV	ш	III	ш	III	ш	ш	
C Plackett-Burman design	(2 to 47 factors)		32			run	Full	VI	IV	IV	IV	IV	IV	IV	IV	IV	IV
C General full factorial design	(2 to 15 factors)	later	64					Full	VII	۷	IV	IV	IV	IV	IV	IV	IV
Number of factors: 4	anlay Available Dec	ions	128						Full	VIII	VI	V	V	IV	IV	IV	IV
	splay Available Des	igns				Avai	lable	Resolu	ution II	T Pla	ckett-l	Burma	an Des	ians			
De	signs Fac	tors	Factors	Du	nc	,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,		E	actors		unc	barrine		.g	Eactor	-	Pupe
Op	tions Res	ults	2-7	12	,20,24	,28,	48		20-23	2	4,28,3	32,36,	,48		36-3	9	40,44,48
			8-11	12	,20,24	,28,	.,48		24-27	2	8,32,3	36,40,	44,48		40-4	3	44,48
Help	OK Ca	ancel	12-15	20	,24,28	,36,	,48		28-31	3	2,36,4	10,44,	48		44-4	7	48
			10-19	20,	,24,28	,32,	,48		32-33	5	0,40,4	14,48					
10			He	n	1											(ок 🛛
11				-													
12					_		_			_			_		_		

2. CREATE FACTORIAL DESIGNS

Create Factorial Design	×				Create Factorial Design: Designs	×
Type of Design		C5	C6	С7	Designs Runs Resolut	ion 2^(k-p)
2-level factorial (default generators) (2 to 15 factorial)	rs)	this	pops u	р	1/2 fraction 9 IV Full factorial 16 Ful	20(4.1)
C 2-level factorial (specify generators) (2 to 15 facto C 2-level split-plot (hard-to-change factors) (2 to 7 factors	rs) ;)	we	leave th	е		
C Plackett-Burman design (2 to 47 facto	rs)	defa	ault set	ings.		
C General full factorial design (2 to 15 facto	rs)				Number of center points per block: \int	0 -
Number of factors: 4 Display Available [Designs.	we	will exp	lain	Number of replicates for corner points:	1 💌
Designs	Factors	the	details	later	Number of blocks: 1 💌	
Options	Results			_		
Неір ОК	Cancel				Help	K Cancel

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3. FACTORS

Create Factorial Design	×	1			Open C	trl+0 ial Dosign: Fact	ors	_	×
Time of Dealers		C5	C6	C7	Create ractor	iai Design. ract	013		~
A level factorial (default generators)	(2 to 15 for to m)				Factor	Name	Туре	Low	High
2-level factorial (generators) 2-level factorial (specify generators)	(2 to 15 factors)			_	Α	Release Angle	Numeric 🔻	140	180
 2 level nucconal (specify generators) 2-level split-plot (hard-to-change factors) 	(2 to 7 factors)	ke	v this ir	`	В	Cup Elevation	Numeric 🔹	220	280
C Plackett-Burman design	(2 to 47 factors)	KC	y this h	· 🦯	С	Pin Elevation	Numeric 🔹	120	180
C General full factorial design	(2 to 15 factors)	-			D	Bungee Positi	Numeric 🔹	120	180
Number of factors: 4 Di	splay Available Designs signs Factors tions Results				Help			ОК	Cancel
Help	OK Cancel								
10									

4. OPTIONS

Create Factorial Design X	Fold is out of scope	Create Factorial Designs: Options	×	
Type of Design 2-level factorial (default generators) (2 to 15 factors) C 2-level factorial (specify generators) (2 to 15 factors) C 2-level split-plot (hard-to-change factors) (2 to 7 factors) C Plackett-Burman design (2 to 47 factors) C course [16 factorial target (2 to 47 factors)	^c în this ^{c7 c8} manuscipt	Fold Design Do not fold C Fold on all factors C Fold just on factor: 	Fraction C Use principal fraction C Use fraction number: store design	51
Number of factors: 4 Display Available Designs Designs Factors Options Results	we will explain Randomize later	Randomize runs Base for random data generator: Store design in worksheet Help	OK Cancel	± et

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iew He	lp Assistant	Predictive A	nalytics Mc	odule Addition	nal Tools					Create Factorial De	sign		×
- .	4 0 0	fx ¦≣= =		2/ -4 🧶	Μ	in	ita	b		Type of Design 2-level factorial (2-level factorial (2-level split-plot Plackett-Burman General full factor	default generators) (specify generators) (hard-to-change fact design rial design	(2 to 15 fad (2 to 15 fad ors) (2 to 7 facto (2 to 47 fad (2 to 15 facto	tors) tors) ors) tors)
	we wi	li expl	ain th	ese						Number of factors:	4 -	Display Available	e Designs
	4 colu	imns la	ater				Open Cti	rl+O				Designs	Factors
+	C1	C2	C3	C4	C5	C6	C7	1 61 10	C8			Options	Results
	StdOrder	RunOrder	CenterPt	Blocks Re	elease Angle Cup E	levation	Pin Elevation	Bunge	e Position	Uala		OK	Consul
1	10	1	1	1	180	220	120		180	Help		OK	Cancel
2	5	2	1	1	140	220	180		120				
3	1	3	1	1	140	220	120		120				
4	4	4	1	1	180	280	120		120				
5	2	5	1	1	180	220	120		120	click ok a	and these	4 colum	าทร
7	11	7	1	1	140	280	120		120	will be a	oporated		
8	16	8	1	1	140	280	180		180	will be g	enerateu	•••	
9	6	9	1	1	180	220	180		120				
10	14	10	1	1	180	220	180		180	a total o	f 16 runs	with diff	erent
11	8	11	1	1	180	280	180		120			with an	crent
12	12	12	1	1	180	280	120		180	combina	ittons		
13	15	13	1	1	140	280	180		180				
14	9	14	1	1	140	220	120		180				
15	13	15	1	1	140	220	180		180				
16	3	16	1	1	140	280	120		120				
17	⊲ ⊳ ⊨ +	Worksheet	6					4) }
	_		_				-						
÷		C1		C2	C3		C4		C5	C6	С7	C8	C9
	Releas	e Angle	Cup E	levation	Pin Elevatio	n Bur	ngee Posi	tion					
1		140)	220	12	0		120					
2		180)	220	12	0		120	CO	py and	paste	this	
3		140)	280	12	0		120	Δ	olumn	S		-
4		180)	280	12	0		120			5		
5		140)	220	18	0		120					
6		180)	220	18	0		120	ba	ck into	the		
7		140)	280	18	0		120	h.+-	no. 110	amaz		/
8		180)	280	18	0		120	ntt	.ps://si	gmazo	me.co	лп/
9		140)	220	12	0		180	cat	-tapult	grid/		

| P A G E

website ... to generate

the Distance (response)

B. RUNNING THE EXPERIMENTS & GETTING THE RESULTS (RESPONSE)

• Go to <u>https://sigmazone.com/catapult-grid/</u>

	at 110is not a Factor we consider		when u click on Run all rows, the Response (Distance) an						
Release Angle	Firing Angle	Cup Elevation	Pin Elevation	Bungee Position	Distance				
140	110	220	120	120	90.03				
180	110	220	120	120	175.27				
14C	110	280	120	120	127.44				
180	110	280	120	120	243.28				
14C	110	220	180	120	121.25				
180	110	220	180	120	239.62				
14C	110	280	180	120	169.23				
180	110	280	180	120	338.75				
14C	110	220	120	180	118.35				
180	110	220	120	180	232.99				
14C	110	280	120	180	173.89				
180	110	280	120	180	321.57				
14C	110	220	180	180	159.22				
180	110	220	180	180	320.12				
14C	110	280	180	180	225.81				
180	110	280	180	180	450.74				

	Distance	
20	90.03	сору
20	175.27	paste this
20	127.44	Distance
20	243.28	Column
20	121.25	
20	239.62	
20	169.23	
20	338.75	
80	118.35	
80	232.99	
80	173.89	
80	321.57	
80	159.22	
80	320.12	
80	225.81	
80	450.74	

C5	C6	C7	C8	C9	C10	C11	C12	C13	C1. 4
Release Angle	Cup Elevation	Pin Elevation	Bungee Position	Distance					
140	220	120	120	90.03					
180	220	120	120	175.27					
140	280	120	120	127.44	6	lack	horo		
180	280	120	120	243.28	-	Jack	nere		
140	220	180	120	121.25		nto N	Ainit	ah	
180	220	180	120	239.62			viiiiiu	au	
140	280	180	120	169.23					
180	280	180	120	338.75					
140	220	120	180	118.35					
180	220	120	180	232.99					
140	280	120	180	173.89					
180	280	120	180	321.57					
140	220	180	180	159.22					
180	220	180	180	320.12					
140	280	180	180	225.81					
180	280	180	180	450.74					

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C. ANALYZING THE RESULTS

St	at Graph	View	Help Assi	stant	Predic	tive Analytics I	Modu	ile /	Additional To	ols				
	Basic Sta	tistics			fx a		1	1						
	Regressi	on		•										
	ANOVA			•				Minita						
[DOE			•	Scree	ning	•		C5	C 6	· · · ·	7		
1	Control	Charts			Facto	rial	►	Create Factorial Design						
;	Quality 1	Tools		Response Surface				Define Custom Factorial Design						
	Reliabilit	val	Mixture				Select Optimal Design							
1	Predictiv	tics	Taguchi					Pre-Process	Responses for	Analyze Variab	ility			
	Multivariate			Modify Design			П	Analyze Fact	orial Design					
	Time Ser	ries		<u>۳</u>	. 🔄 Display Design			L.01	Analyze Bina					
	Tables			•	6	1		13	Analyze Vari	Analyze Fact	orial Design			
	Nonpara	ametrics		•	7	1		Lγ	Predict	Fit a model to	a factorial desi	gn.		
	Equivale	nce Test	S		8	1		~	Factorial Plo					
	Power an	nd Sam	ple Size	•	9	1		1	Cube Plot					
		10	10		10	1				t				
		11	11		11	1			Surface Plot					
		12	12		12	1		5		ntour Plot				
		13	13		13	1		*						
		14	14		14	1		1		180	220	180		





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1. PARETO CHART



- We see that the Main Effects are: A, B, C and D.
- Anything that surpasses 36.8 is an important effect.
- We see that all other interaction effects fall below 36.8 (thus unimportant)



2. NORMAL PLOT

• Normal plot shows us the same thing.

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3. FACTORIAL PLOT



Factorial Plots		×
Response: Distant	ce 🗸	
	Variables to Include in Plots	
i	Selected: 'Release Angle' 'Cup Elevation' 'Pin Elevation' 'Bungee Position' <<	
s <u>T</u> erms to display: i	Only model terms	
-	Options <u>G</u> raphs <u>View Model</u>	
Help	<u>O</u> K Cancel	

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If there is a overlap / cross of the lines, there is interaction between the Factors.

However, we see that all 4 Factors have no relationship with each other.



D. PREDICTING RESULTS



Multiple Response Prediction

Variable	Setting
Release Angle	180
Cup Elevation	222.534
Pin Elevation	128.955
Bungee Position	180

we need to set these Factor at these settings should we want to hit 250 as Distance

Response	Fit	SE Fit	95% CI	95% PI
Distance	250.0	*	(*, *)	(*, *)

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III. DEFINITIONS OF DOE

A.	FACTORS	/ LEVELS /	RESPONSES
----	---------	------------	-----------

_	C5	C6	C7	C8	C9 🗾	C10	C11	C12	C1
Rel	ease Angle	Cup Elevation	Pin Elevation	Bungee Position	Distance				
	140	220	120	120	90.03				
	180	220	120	120	175.27				
	140	280	120	120	127.44				
	180	280	120	120	243.28				
	140	220	180	120	121.25				
	180	220	180	120	239.62	RES	PONSE		
	140	280	180	120	169.23	ILU			
	180	280	180	120	338.75				
	140	220	120	180	118.35				
	180	220	120	180	232.99				
	140	280	120	180	173.89				
	180	280	120	180	321.57				
	140	220	180	180	159.22				
	180	220	180	180	320.12				
	140	280	180	180	225.81				
	180	280	180	180	450.74				
	L F	VELS							

- Earlier, we did this test:
 - Release Angle: 140 / 180 \rightarrow LOW / HI
 - Firing Angle: 110 (since this is constant, we will ignore it)
 - Cup Elevation: 220 / 280 \rightarrow LOW / HI
 - Pin Elevation: 120 / 180 \rightarrow LOW / HI
 - Bungee Position: 120 / 180 → LOW / HI
- 4 Factors 2 Levels, this is known as a 2⁴ Factorial Design DOE.
- Total number of runs = $2^4 = 16$ runs

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B. RUN / RANDOMIZATION

+	C1	C2	C3	C4	C5	C6	С7	C8	C
	StdOrder	RunOrder	CenterPt	Blocks					
1	1	1	1	1					
2	2	2	1	1					
3	3	3	1	1					
4	4	4	1	1					
5	5	5	1	1					
6	6	6	1	1	-				
7	7	7	- 1	1	-16	o runs			
8	8	8	1	1					
9	9	9	1	1					
10	10	10	1	1					
11	11	11	1	1					
12	12	12	1	1					
13	13	13	1	1					
14	14	14	1	1					
15	15	15	1	1					
16	16	16	1	1					
17	No	Pandam	ization						
18	NOT	handom	ization						
19									
20									

Respon	se Optir	nization: Di	s ~ ×							 2-level factoria 2-level factoria 2-level split-pl 	al (default generators) al (specify generators) lot (hard-to-change facto	(2 to 15 f (2 to 15 f ors) (2 to 7 fa	actors) actors) ctors)	
a wor Resp	onse	Optim	zation:	Distan	ce					C Plackett-Burman design (2 to 47 factors) C General full factorial design (2 to 15 factors)				
	C1	C2	C3	C4	C5	C6	С7	C8	C9	Number of factors	s: 4 🔻	Display Availa	ble Designs	
Std	Order	RunOrder	CenterPt	Blocks	Release Angle	Cup Elevation	Pin Elevation	Bungee Position				Designs	Eactors	
Г	15	1	1	1	140	280	180	180			-	Ontions	Beculte	
	5	2	1	1	140	220	180	120			-	Options	Result	
	7	3	1	1	140	280	180	120		Help		ОК	Cano	
	12	4	1	1	180	280	120	180					_	
	3	5	1	1	140	280	120	120	Cro	eate Factorial Desig	gns: Options			
	6	6	1	1	180	220	180	120						
	9	7	1	1	140	220	120	180	Fo	Id Design	Fraction			
	13	8	1	1	140	220	180	180	0	Fold on all factors	C Use			
	8	9	1	1	180	280	180	120	0	Fold just on factor:	vou only key	v this in if	vou	
	11	10	1	1	140	280	120	180			your randor	n runs or	dort	
	16	11	1	1	180	280	180	180		Dan domiza runa	your randor		uerti	
	14	12	1	1	180	220	180	180		Randomize runs	nxed everyt	ime		
	10	13	1	1	180	220	120	180	-	Change designs in wear	dia generator.			
	2	14	1	1	180	220	120	120		Store design in wor	e.g. if you p	ut 9 and	l the	
	1	15	1	1	140	220	120	120		Help	random ruñ	s is _{ok}	Cano	
	4	16	1	1	180	280	120	120	-	Trop	15 5 7 13		Curre	
		-									novt timo v		again	
t	he r	uns ar	e now	/ rand	omized		same o	order but ran	dom		next time yo	Ju put 9 a	again	

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- Randomization is important to protect against uncontrolled and/or unknown influences of variables that are not part of the experiment.
- In order to minimize this risk of unknown influence, experimenters randomly assign the order of testing to improve the chances of averaging out this bias or distortion of the responses related to the factor(s) under study.
- If you are unable to randomize due to physical or cost constraints, we will need to do Blocking.

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C. BLOCKING

- If you cannot randomize due to lack of resources, example, not enough raw materials to do so many runs, one may block.
- 1 Block = 1 Batch.
- Possibly, 1 Block = 1 Day. Which means, running an entire experiment in 1 day = 1 block.
- Running the experiment again the next day will be 2 blocks \rightarrow Block 2.
- Blocking minimizes the risk of the nuisance-factor batches creating excessive estimates of the inherent variation.
- For example, you want to test the quality of a new printing press.
- However, press arrangement takes several hours and can only be done four times a day.
- Because the design of the experiment requires at least eight runs, you need at least two days to test the press.
- To distinguish between any block effect (incidental differences between days) and effects because of the experimental factors (temperature, humidity, and press operator), you must include the block (day) in the designed experiment. You should randomize run order within blocks.

21 | P A G E

10	II-la Assis	Land David			Create Factorial Design						
Re	sponse Optin WORKSHEET	mization: D 7 Optim	is × ×	Distanc	Type of Design (2 to 15 factors) © 2-level factorial (default generators) (2 to 15 factors) C 2-level factorial (specify generators) (2 to 15 factors) C 2-level split-plot (hard-to-change factors) (2 to 7 factors) C Plackett-Burman design (2 to 15 factors) C General full factorial design (2 to 15 factors)						
+	C1	C2	C3	C4	Number of factors: 4 Display Available Des	igns					
	StdOrder	RunOrder	CenterPt	Blocks	Release Angle	Cup Elevation	Pin Elevation	Bungee Position		Designs	tors
1	15	1	1	1	140	280	180	180			culto
2	5	2	1	1	140	220	180	120			juits
3	7	3	1	1	140	280	180	120		Help OK Ca	ancel
4	12	4	1	1	180	280	120	180			_
5	3	5	1	1	140	280	120	120		Create Factorial Design: Designs	\times
6	6	6	1	1	180	220	180	120		Desires Dura Desiretar 200(km)	
7	9	7	1	1	140	220	120	180		Designs Runs Resolution 2**(R-p)	
8	13	8	1	1	140	220	180	180		1/2 fraction 8 1V 2^4(4-1) Full factorial 16 Full 2^4	
9	8	9	1	1	180	280	180	120			
10	11	10	1	1	140	280	120	180			
11	16	11	1	1	180	280	180	180		Number of center points per block: 0 -	
12	14	12	1	1	180	220	180	180		Number of replicates for corner points:	
13	10	13	1	1	180	220	120	180			
14	2	14	1	1	180	220	120	120		Number of blocks:	
15	1	15	1	1	140	220	120	120		Help 2 OK Cancel	
16	4	16	1	1	180	280	120	120		8	
17											
18	For th	nis mar	nuscrip	t, we c	only assun	ne I Bloc	k through	nout (take if	t as j	ust 1 Day, or 1 Batch)	
19	Mean	ing, w	e run t	he ent	ire experi	ment in 1	. day, not	more.			
20		0,			1.						

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D. REPLICATE VS REPEAT

Create Factorial Design	~~	× C9	Create Factorial Design: Designs X
Type of Design 2-level factorial (default generators) 2-level factorial (specify generators) 2-level split-plot (hard-to-change factor Plackett-Burman design General full factorial design Number of factors: 4	(2 to 15 factors) (2 to 15 factors) (2 to 7 factors) (2 to 47 factors) (2 to 15 factors) Display Available Designs. Designs		Designs Runs Resolution 2^(k-p) 1/2 fraction 8 IV 2^(4-1) Full factorial 16 Full 2^4 We will discuss center points later Number of center points rer block: 0 • Number of replicates for corner points 1 • Number of blocks: •
Help 220	OK Cancel	180	Help 6 7 V
180 220	120	180	
180 220 180 220 140 220	120	120 120	one corner point = 1 run we will show what does Corner Point
180 280	120	120	mean later

- Replication = Performing more than one trial of each run
- (Completely NEW SETUP each trial).
- A Replicate is an Independent and Random application of the run, including the setup.
- Repeat = a Repetition of a run WITHOUT going through a NEW SETUP.

E. WHAT IF MANY OF THE EFFECTS ARE SIGNIFICANT?

- Check \rightarrow Was the setup for each trial really randomly replicated?
- If not, the responses are repeats, not replicates.
- Replication assumes that each trial is an independent and random performance of the process, specifically including any process setup.
- If not, the experimenter has repeats that may be neither independent nor random.
- The estimate of s (standard deviation), using repeats will be much smaller than the actual inherent variation of the process.
- This will make most effects appear significant, when in reality they have not been randomly replicated to properly estimate the inherent variation.

F. CORNER POINT / CENTER POINT



• There are 4 Corner Points:

○ $(-1, -1) / (-1, 1) / (1, -1) / (1, 1) \rightarrow$ Each is 1 Run

- The Centre Point is (0,0).
- Currently, we don't use it.
- We will explore Centre Point in the next section on Response Surface Design (RSM): Central Composite Design (CCD).

25 | PAGE

G. FULL VS FRACTIONAL FACTORIALS



64

128

Factors

2-7

8-11

12-15

16-19

Help

100

180

180

180

Runs

12,20,24,28,...,48

12,20,24,28,...,48

20,24,28,36,...,48

20,24,28,32,...,48

v IV IV IV IV

Available Resolution III Plackett-Burman Designs

Factors

20-23 24-27

28-31

32-35

Runs

24,28,32,36,...,48

28,32,36,40,44,48

32,36,40,44,48

36,40,44,48

IV IV

τv

Runs

44,48

ОК

40,44,48

IV

Factors

36-39

40-43

44-47 48

IV

Full Factorial means All Runs •

4 🔻

11

12

13

14

Number of factors:

Help

н

12

13

14

10

14

10

2

For example, $2^3 \rightarrow 2$ Levels 3 Factors = Total 8 Runs

Display Available Designs..

1

1

1

Factors..

Results.

Cancel

Designs...

Options..

ОК

т

1

1

1

- But if you lack resources, are you able to do it in just 4 Runs? •
- Yes, but its labelled as Resolution III Design (see picture above, in Red \rightarrow 4 Run, 3 Factors). •

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Num	ber of Fac	Runs ctoric	in Two Level Full I Design	Numb	er of I Fa	Runs iı ctoria	n Three Level Full l Design
Factors 2 3 4	Levels 2 2 2	Runs 4 8 16	Full Factorial design increase with by Geometric progression with ratio of number of levels for each factor.	Factors 2 3 4	Levels 3 3 3	Runs 9 27 81	The number of runs exacerbate with more levels.
5 6 7 8 9 10	2 2 2 2 2 2 2	32 64 128 256 512 1024		5 6 7 8 9 10	3 3 3 3 3 3 3 3	243 729 2187 6561 19683 59049	surpassing 5 Factors will require crazy number of runs!

- You can see that the number of Runs increase dramatically as number of Factors increase!
- Thus we need Fractional Factorial to cut down the number of Runs (we can do Screening to Screen out the unimportant Runs as shown later).

Create Factorial Design	\times	Create Factorial Design: Designs	(10	C11	C12	C13	C14	
Type of Design 2-level factorial (default generators) (2 to 15 factors) 2-level factorial (specify generators) (2 to 15 factors) 2-level split-plot (hard-to-change factors) (2 to 7 factors) Plackett-Burman design (2 to 47 factors) General full factorial design (2 to 15 factors) Number of factors: 4 Display Available besign Designs Factor Options Result	5	Designs Runs Resolution 2^(k-p) 1/2 fraction 8 IV 2^(4-1) Full 10 Full 2^4 Number of center points per block: 0 Image: Control of the second se		we 1/2 Ful	have 2 Fract Il Fact	a chc tion o orial	vice of r		
Help OK Cance		Help OK Cancel							

• Similarly, in the previous experiment (Create Factorial Designs) we did a 2⁴ (2 Levels 4 Factors) which we have the option of running the Full Experiment (=16 runs... in which we did...), or we could just do 8 runs.

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Factors														
Run	2	3	4	5	6	7	8	9	10	11	12	13	14	15
4	Full	III												
8	F	Full	IV	III	III	III								
16			Full	V	IV	IV	IV	III	III	III	III	III	III	III
32				Full	VI	IV	IV	IV	IV	IV	IV	IV	IV	IV
64					Full	VII	V	IV	IV	IV	IV	IV	IV	IV
128						Full	VIII	VI	V	V	IV	IV	IV	IV
actors 2-7	Run	s 20.24	Avai 4 28	lable	Resolı F	ution 1 actors	III Pla	ckett-l uns 4 28 ?	Burma	in Des 48	igns	Factor	s	Runs
actors 2-7 8-11	Run 12,2 12.2	s 20,24 20,24	Avai 4,28,. 4,28	lable ,48 48	Resolı F	ution 1 actors 20-23 24-27	III Pla R B 2 Z 2	ckett-l uns 4,28,3 8.32,3	Burma 32,36, 36,40,	in Des ,48 44,48	igns	Factor 36-3 40-4	s 9 3	Runs 40,44, 44,48
actors 2-7 8-11 12-15	Run 12,2 12,2 20,2	s 20,24 20,24 20,24	Avai 4,28,. 4,28,. 3,36,.	lable ,48 ,48 ,48	Resolı F	ution 1 actors 20-23 24-27 28-31	III Pla R 2 2 2 3	ckett-l uns 4,28,3 8,32,3 2,36,4	Burma 32,36, 36,40, 40,44,	in Des ,48 44,48 48	igns	Factor 36-3 40-4 44-4	s 9 3 7	Runs 40,44, 44,48 48

• If we had chosen 8 Runs, this would be a resolution IV (see picture above, in Yellow)

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H. RESOLUTION AND CONFOUNDING

• So long as you do not Run Full Factorials (which means, Run all possible combinations i.e. perform ALL experiments), you will experience Confounding.



• Presume we have the above: 8 runs cut down to 4 runs....

A	в	с	AB	BC	AC	ABC
-1	-1	-1	1	1	1	-1
1	-1	-1	-1	1	-1	1
-1	1	-1	-1	-1	1	1
1	1	-1		-1	-1	-1
-1	-1	1	1	-1	-1	1
1	-1	1	-1	-1	1	-1
-1	1	1	-1	1	-1	-1
1	1	1	1	1	1	1

• Notice that C and AB have the same effects! They are Confounded!

9				<u>_</u>				P
	A	в	С	AB	BC	AC	ABC	
	-1	-1	-1	1	1	1	-1	
	1	-1	-1	-1	1	-1	1	
	-1	1	-1	-1	-1	1	1	
9	1	1	-1	1	-1	-1	-1	Ρ
	-1	-1	1	1	-1	-1	1	
	1	-1	1	-1	-1	1	-1	
	-1	1	1	-1	1	-1	-1	
	1	1	1	1	1	1	1	Ι
9								Ь

• Notice that B and AC have the same effects! They are Confounded!

А	в	с	AB	BC	AC	ABC
-1	-1	-1	1	1	1	-1
1	-1	-1	-1	1	-1	1
-1	1	-1	-1	-1	1	1
1	1	-1	1	-1	-1	-1
-1	-1	1	1	-1	-1	1
1	-1	1	-1	-1	1	-1
-1	1	1	-1	1	-1	-1
1	1	1	1	1	1	1

• Notice that A and BC have the same effects! They are Confounded!

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- Since they have the same effects, Confounding means that you cannot tell whether the Response is due to
 - o A or BC?
 - B or AC?
 - o C or AB?

1. RESOLUTION III



2. RESOLUTION IV



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3. RESOLUTION V



• Confounding should be Avoided because we cannot differentiate which Factor is affecting the Response.

Resolution V

• However, due to limitations of Resources, we need to Screen out the unimportant Runs.

AD + BCE

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I. SCREENING (PLACKETT BURMAN DESIGN)

- We already know (from Section: Full vs Fractional Factorials) that the number of Runs increase dramatically as number of Factors increase (>5 Factors)!
- Thus we need Fractional Factorial to cut down the number of Runs
- Screening helps to Screen out unimportant Runs and cut it down to a Fractional Factorial.
- In this manuscript, we consider 2 ways of Screening:
 - o Using Assistant
 - Screening while Creating the Factorial Design
- Note that in this Manuscript we only consider Plackett Burman Screening Design.
- And if we use Assistant option in Minitab, we are actually doing Plackett Burman Screening.
- Plackett Burman designs are only Resolution III experiments AND 6 or more factors.
- It only identifies Main effects and ignore Interaction effects
- In other words, Minitab only performs Screening when we have >6 Factors.
- Else, Minitab will auto-generate the Fractional Factorial Options for us to choose from (while we create the Factorial Design).

1. USING ASSISTANT

Note that Assistant Screening = Plackett Burman Screening

lp	Assistan	Predictive Analytics Module	Additional 1	Tools			
44	Meas	urement Systems Analysis (M	SA)				
nse	Сара	bility Analysis					
RKS	Grap	hical Analysis					
pc	Нурс	othesis Tests					
-	Regre	ession				1	
C	DOE		•	Pla	n and Create		
dO	Befor	e/After Capability Analysis		Ana	alyze and Interp	ret	1C
	Defe	a /After Centrel Charts		140	280	18	8(
	Belor	e/Arter Control Charts		140	220	18	8(
	Cont	rol Charts		140	280) 18	8(

Plan and Create Experiments



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Create Screening Design	X
Response and factors Enter the name of your response variable: Response	
Number of factors:	let's say you have 6 Factors which requires 2^6 Runs (ALOT!) you may cut it down to 12
Number of runs Adding runs allows you to detect smaller effect sizes Iotal number of runs in your design: 12	options here are 12 or 24

Create Screening Design

			<u> </u>														
+	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	
	StdOrder	RunOrder	PtType	Blocks	А	В	С	D	E	F	Response						
1	4	1	1	1	1	0	1	1	0	1							
2	7	2	1	1	0	1	1	1	0	1	Min	itab aut	omatic	ally gen	erates		
3	10	3	1	1	1	0	0	0	1	1	a Re	cine for	vouto	Run			
4	3	4	1	1	0	1	1	0	1	0	une	cipe ioi	,00.00	nan			
5	12	5	1	1	0	0	0	0	0	0							
6	2	6	1	1	1	1	0	1	0	0	6 Fa	ctors w	ith 2 Le	vels			
7	9	7	1	1	0	0	0	1	1	1	usin	g only 1	.2 Runs				
8	8	8	1	1	0	0	1	1	1	0							
9	1	9	1	1	1	0	1	0	0	0	Just	follow	the Rec	ipe and	input to	get	
10	5	10	1	1	1	1	0	1	1	0	the	Respon	6			0	
11	6	11	1	1	1	1	1	0	1	1	the	пезроп	30				
12	11	12	1	1	0	1	0	0	0	1							
13																	

- C3 (CenterPt or PtType) stores the point type.
- If you create a 2-level design, Minitab names this column CenterPt.
- If you create a Plackett-Burman or general full factorial design, Minitab names this column PtType.
- The codes are: 0 is a Center Point run and 1 is a Corner Point. (we will explain Centre Point and Corner Point later in RSM CCD, next section).

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2. SCREENING WHILE CREATING FACTORIAL DESIGN

			$J^{*} = -i + i = 0$	0 0	i <
	Regression	•			
	ANOVA	•			Minital
gl	DOE	•	Screening	•	IIIIICAI
g (Control Charts	→ [Factorial	→□	Create Factorial Design
es	Quality Tools	•	Response Surface	- F 🔓	Define Custom Factorial Design
oci	Reliability/Survival	•	Mixture) 🖿 🛄	Select Optimal Design 1+
251	Predictive Analytics	•	Taguchi	•	Pre-Process Responses for Analyze Variability
	Multivariate	• 町,	Modify Design		Analyze Factorial Design
	Time Series	▶ 晒	Display Design	-01	Analyze Binary Response
	Tables			13	Analyze Variability
	Nonparametrics	•		4V	Prodict
	Equivalence Tests	•			

Create Factorial Design X	whi	le we	are ci	reatin	g	Creat	e Factorial De	esign: Desig	jns		×
Type of Design					•		Designs	Runs	Resolution	2^(k-n	
 2-level factorial (default generators) (2 to 15 factors) 	our	Facto	rial D	esign	s, 🗌		Designs	Runo	Resolution	2 (10)	<u> </u>
C 2-level factorial (specify generators) (2 to 15 factors)				Ŭ	· 1		1/16 fraction	16	IV	2^(8-4)	
C 2-level split-plot (hard-to-change factors) (2 to 7 factors)							1/4 fraction	64	v	2^(8-2)	j l
C Plackett-Burman design (2 to 47 factors)					_		1/2 fraction	128	VIII	2^(8-1))
C General full factorial design (2 to 15 factors)	Mir	iitab a	utoe	enera	ates	s' 🛏					
			- 0			Num	ber of center p	oints per blo	ck: 0	•	
Display Available Designs	the	list of	optic	bn							
Designs Factors						Num	per of replicate	s for corner	points: 1	•	
Options Results	whi	ch we	can d	choos	e fo	Num	ber of blocks:	1	•		
Heln OK Cancel	Frac	tiona	Fact	orial			Help		ОК	Can	cel
			_								l
	(a to	orm o	t scre	ening)						

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IV. RESPONSE SURFACE METHODS (>2 LEVELS)

- There are two types of Response Surface Methods (RSM)
 - o Central Composite Design (CCD)
 - o Box-Behnken
 - A. CENTRAL COMPOSITE DESIGN (CCD)





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1. CREATING THE EXPERIMENT



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Create Response Surface Design	×	Create Respo	onse Surface	Design: Facto	ors
Fype of Design Central composite (2 to 10 continuous factor Box-Behnken (3,4,5,6,7,9, or 10 contini	s) uous factors)	Levels Define	ts ke	y in th	e
		Factor	Name	Low	Γ
Number of continuous factors:	Display Available Designs	A	Pressure	220	
	Display Available Designs	В	Temp	32	!
	Options Factors				
Help	OK Cancel	Help		ОК	

lit	Create Response Surface Design		×
:0	Type of Design Central composite Box-Behnken (3,4,5,6,7,9, or 10 continuous)	us factors)	4
	Number of continuous factors: 2	Display Availa	ble Designs
	Number of categorical factors: 0	Designs	Factors
		Options	Results
	Help	ОК	Cancel
	Create Response Surface Design: Options		×
	Randomize runs		
	Store design in worksheet		-
	Help	ОК	Cancel

As you can see frrom the above, we have many CCDs....

- Full / Half / Quarter / Eighth....
- We will not go through them
- More explanation here: <u>https://support.minitab.com/en-us/minitab/21/help-and-how-to/statistical-modeling/doe/supporting-topics/response-surface-designs/summary-of-central-composite-designs/</u>

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2. EXPLAINING THE PT TYPE

	+	C1	C2	C3	C4	C5	C6	С7	C8	C9
		StdOrder	RunOrder	PtType	Blocks	Pressire	Temp	Retention Time		
4 corner	1	1	1	1	1	220.000	32.0000	72		
noints	2	2	2	1	1	732.000	32.0000	79		
points	3	3	3	1	1	220.000	68.0000	60	key	
	4	4	4	1	1	732.000	68.0000	68	tho	
	5	5	5	-1	1	113.961	50.0000	55	the	
4 axial	6	6	6	-1	1	838.039	50.0000	85	resp	onses
in a linta	7	7	7	-1	1	476.000	24.5442	104	in	
points	8	8	8	-1	1	476.000	75.4558	135		
	9	9	9	0	1	476.000	50.0000	118		
5 center	10	10	10	0	1	476.000	50.0000	119		
noints	11	11	11	0	1	476.000	50.0000	123		
points	12	12	12	0	1	476.000	50.0000	123		
	13	13	13	0	1	476.000	50.0000	127		
	14		13 runs	produce	ed.					
	15		10 runs	product						

How did we manage to achieve 13 runs?



• 5 Centre Points + 4 Axial Points + 4 Corner Points = 13 Runs in total

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a) Blocking within CCD

- Previously, we saw that 5 Centre Points + 4 Axial Points + 4 Corner Points = 13 Runs in total
- But they were all run in 1 Block. (unblocked)

13 runs				Co	ontin	uous	Facto	ors		
Design		2	3	4	5	6	7	8	9	10
Control composite full	unblocked	13	20	31	52	90	152			
Central composite full	blocked	14	20	30	54	90	160			
Control composite half	unblocked				32	53	88	154		
Central composite nair	blocked				33	54	90	160		
Control compatible constant	unblocked							90	156	
Central composite quarter	blocked							90	160	
	unblocked									15
Central composite eighth	blocked									16
	unblocked		15	27	46	54	62		130	17
Box-Bennken	blocked			27	46	54	62		130	17

• Presume now there was Blocking (we wanted to Run the experiment in 2 days or 2 blocks).

	A	vailable Respo	nse Surf	ace D	esign	s					
	Design				Co	ontin	uous	Facto	ors		
	Design		2	3	4	5	6	7	8	9	10
		unblocked	13	20	31	52	90	152			
	Central composite full	blocked	14	20	30	54	90	160			
		unblocked				32	53	88	154		
	Central composite nail	blocked	Т			33	54	90	160		
		unblocked			1.4		2		90	156	
•	Lentral composite quarter	blocked	w	י אי	14 r	un	s r		90	160	
	6	unblocked									15
	Central composite eighth	blocked									160
	Deve Debeleen	unblocked		15	27	46	54	62		130	17
	Box-Bennken	blocked			27	46	54	62		130	17

• Why do we need 14 runs?

Pattern	Block	<i>X</i> ₁	<i>X</i> ₂	Comment
	1	-1	-1	Full Factorial
-+	1	-1	+1	Full Factorial
+-	1	+1	-1	Full Factorial
++	1	+1	+1	Full Factorial
00	1	0	0	Center-Full Factorial
00	1	0	0	Center-Full Factorial
00	1	0	0	Center-Full Factorial
-0	2	-1.414214	0	Axial
+0	2	+1.414214	0	Axial
0-	2	0	-1.414214	Axial
0+	2	0	+1.414214	Axial
00	2	0	0	Center-Axial
00	2	0	0	Center-Axial
00	2	0	0	Center-Axial

(this picture shows 14 runs = 7 Corner (Factorial) Runs and 7 Axial Runs)

- 14 Runs is because, when two blocks are required there should be a
 - Factorial Block (Block 1 = 7 Factorial Runs) and
 - An Axial Block (Block 2 = 7 Axial Runs).





3. ANALYZING THE CCD EXPERIMENT

a) Factorial Plot

q	Stat Graph View Help A	ssistant Predictive Analytics N	Iodule Additional Tools
1	Basic Statistics	🕨 : fx 📴 📲 👫 🔛	2 L &
	Regression		
	ANOVA	Regressi V X	
D	DOE	► Screening	•
eg	Control Charts	Factorial	Retention Time versus Pressire, Temp
et	Quality Tools	Response Surface	+ Create Response Surface Design
	Reliability/Survival	Mixture	b b Define Custom Response Surface Design
.eí	Predictive Analytics	Taguchi	# Select Optimal Design
	Multivariate	Modify Design	# Analyze Response Surface Design
	Time Series	Display Design	#11 Analyze Binary Response
	Tables	7.18 5.91	Ly Predict
	Nonparametrics	2.61 5.91	Sectorial Plate
	Equivalence Tests	re -32.25 6.34	
	Power and Sample Size	-7.50 6.34	Contou Factorial Plots
	(reduire		Overlaic Overlaic Overlaic
	Model	Summary	Respon interact.

si	Factorial Plots ×
	Retention Time
	Variables to Include in Plots
_	Available: Selected: Pressire Temp >> < < <
	Terms to display: Only model terms
q	Options <u>G</u> raphs <u>V</u> iew Model
(le	Help <u>OK</u> Cancel

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- Notice the difference between the chart above vs the one in Section: Factorial Plot (ctrl click the link).
- The Factorial Plot of a CCD is curved because Minitab generated many points to test per Factor. E.g. Pressure = 220 / 732 / 114 / 838 / 476...
- If you compare this to a Factorial Plot of a Simple 2 points experiment (shown below).... You see that its impossible to generate a curve with just 2 points....(high and low)
- Thus, CCD (RSM) is better than a Simple Factorial Experiment because it can detect curvature (Non-Linear)



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We note that there is a maximum Retention Time when the Pressure is around 500 and the Temperature around 50.

Stat Graph View Help Assistant Predictive Analytics Module Additional Tools : fx 🗄 🖃 👫 👫 🤧 🍂 🧶 **Basic Statistics** ۱ 🖌 Regression Regressi... ~ X ANOVA DOE Di Screening Control Charts Factorial **•** :: Retention Time versus Pressire, Temp вç Response Surface ▶ # Create Response Surface Design... Quality Tools et Reliability/Survival Define Custom Response Surface Design... Mixture Predictive Analytics Select Optimal Design... Taguchi Multivariate 🖏 Modify Design... # Analyze Response Surface Design... **Time Series** 书。Analyze Binary Respor Analyze Response Surface Design 🕅 Display Design... Tables 7.18 5.91 LY Predict... Fit a model to a response surface design. b Nonparametrics 2.61 5.91 ➢ Factorial Plots... -32.25 6.34 Equivalence Tests re Contour Plot... 6.34 -7.50 ▶ Power and Sample Size 0.25 8.35 Surface Plot... Overlaid Contour Plot... 📩 Response Optimizer...

b) Pareto Chart and Model Equation

Model Summary



Regression Equation in Uncoded Units

Retention Time = -66.7 + 0.494 Pressire + 2.43 Temp - 0.000492 Pressire*Pressire - 0.0231 Temp*Temp + 0.00005 Pressire*Temp An equation to model the relationship is created.... Note that its non-linear...

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Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value	
Model	5	7778.75	1555.75	5.57	0.022	
Linear	2	466.52	233.26	0.84	0.473	we ignore the linear model since surveture is significant
Pressire	1	412.22	412.22	1.48	0.264	we ignore the intear model since curvature is significant
Temp	1	54.29	54.29	0.19	0.673	
Square	2	7311.98	3655.99	13.09	0.004	
Pressire*Pressire	1	7235.22	7235.22	25.91	0.001	0.001 < 0.05 means that Pressure is significant
Temp*Temp	1	391.30	391.30	1.40	0.275	0.275 > 0.05 means that Temperature is insignificant
2-Way Interaction	1	0.25	0.25	0.00	0.977	
Pressire*Temp	1	0.25	0.25	0.00	0.977	the interatction between Press and Temp is insignificant
Error	7	1954.48	279.21			
Lack-of-Fit	3	1902.48	634.16	48.78	0.001	0.001 < 0.05 means that the curvature is significant
Pure Error	4	52.00	13.00			0.001 < 0.05 means that the curvature is significant
Total	12	9733.23				

Total



- We note that Pressure is the Key Factor affecting Response Time. •
- Temperature is insignificant. •

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c) Surface Plot





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B. BOX-BEHNKEN DESIGN





Create Response Surface Design	×	Create Response Surface Desigr	n: Display Availa	able D	Desig	ns						\times
Type of Design			vailable Respons	e Surf	ace D	esign	s					
C Central composite (2 to 10 continuous factors)	i i i i i i i i i i i i i i i i i i i					Со	ntinu	ous F	acto	rs		
Box-Behnken (3,4,5,6,7,9, or 10 continuous factors))	Design		2	3	4	5	6	7	8	9	10
		Control composito full	unblocked	13	20	31	52	90	152			
		Central composite full	blocked	14	20	30	54	90	160			
Number of continuous factors: 3	Available Designs	Contral composito half	unblocked				32	53	88	154		
		Central composite hair	blocked				33	54	90	160		
Number of categorical factors: 0 Design	s Factors	Central composite quarter	unblocked							90	156	
	c Poculte	Central composite quarter	blocked							90	160	
IVIIN BB Design is 3 Factors	5 Kesuits	Central composite eighth	unblocked									158
		entral composite eighti	blocked									160
Youp can't go lower than or	Cancel	Boy-Behnken	unblocked		15	27	46	54	62		130	170
		Dox Dellikeli	blocked			27	46	54	62		130	170
3 factors ⁹ ² ¹	0 -1											
10 10 2 1	0 1	Help									OK	
11 11 2 1	0 1										OK	
11 11 2 1	0 -1											

- Note that a 3 Factor 2 Level BB Design minimum is 15 Runs
 - Note that BB Design are ALL Centre Point Runs!!!
- In other words, BB is a special subset of the CCD (you can imagine it to be a Fractional Factorial of a Full Factorial Design).

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1. CREATING THE BB EXPERIMENT



• We shall not carry on with further experiments.

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- We shall stop here at only creating the BB experimental design.
- This is because the rest of the steps are similar and can be repeated as above (see section: CCD: Creating the Experiment (ctrl click the link))

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Sta	at Graph View Help Ass	istant	Predictive Analytics M	1odule	Additional To	ols				
	Basic Statistics	•	fx 🗄 🖃 📲 👫	Lost 1	4 🧶					
	Regression ANOVA	De	esign × ×							
۵	DOE	•	Screening							
E	Control Charts		Factorial	•						
s	Quality Tools		Response Surface	•	C5	C6	C7	C8	C9	C10
ci	Reliability/Survival		Mixture	- ► ⊿	Create Mixt	ure Design				
51	Predictive Analytics	•	Taguchi	• 4	👔 Define Cust	ा Create N	/lixture Des	ign		
:	Multivariate	▶頃	Modify Design	1	Select Optin	na Create a	simplex cent	roid, simplex	lattice, or ex	treme
is	Time Series	• F	Display Design	A	Simplex De	vertices r	nixture desig	n.		
tic	Tables			>	 Factorial Plc 	ts				
tic	Nonparametrics			4	– Analyze Mix	ture Design	l			
tic	Equivalence Tests			N.	- Response Tr	aco Plot				
tic	Power and Sample Size	•			Contour/Su	rface Plots				

Create Mixture Design		×	Create Mixture [Desigr	n: Disj	play A	vailal	ble D	esign	s						\times
Type of Design			-	Avail	able M	lixture	Desig	ins (w	rith Nu	ımber	of Ru	ıns)				
Simplex centroid (2 to 10 compone)	nts)		(Con	npon	ents		^
 Simplex lattice (2 to 20 compone 	nts)		Design	2	3	4	5	6	7	8	9	10	11	12	13	
C Extreme vertices (2 to 10 compone	nts)		Centroid	3	7	15	31	63	127	255	511	1023				
			Lattice 1	2	3	4	5	6	7	8	9	10	11	12	13	
			Lattice 2	3	6	10	15	21	28	36	45	55	66	78	91	
Number of components: 3	Display Avail	able Designs	Lattice 3	4	10	20	35	56	84	120	165	220	286	364	455	
		1	Lattice 4	5	15	35	70	126	210	330	495	715	1001			
	Desi	gns	Lattice 5	6	21	56	126	252	462	792						
		Decement View	Lattice 6	7	28	84	210	462	924							
	omponents	Process vars	Lattice 7	8	36	120	330	792								~
	Options	Results	<												>	
Help	ОК	Cancel	Help												OK	

There are 3 types of Mixture Designs:

- Simplex Centroid
- Simplex Lattice
- Extreme Vertices

V. MIXTURE DESIGNS

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A. WHAT IS A MIXTURE DESIGN



Extreme vertices designs

In extreme vertices designs, MINITAB employs an algorithm that generates extreme vertices and their blends up to the specified degree. These designs must be used when your chosen design space is not an L-simplex. The presence of both lower and upper bound constraints on the components often create this condition. The goal of an extreme vertices design is to choose design points that adequately cover the design space. The illustration below shows the extreme vertices for two three-component designs with both upper and lower constraints:

dwell further into this....

Very Complex

We will not

The light gray lines represent the lower and upper bound constraints on the components. The dark gray area represents the design space. The points are placed at the extreme vertices of design space.

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- Picture above shows a Simplex Centroid (Unaugmented) with 7 Points (7 Runs)
- There are 3 Components / Factors (X1 / X2 / X3)
- X1 + X2 + X3 Must == 100% \rightarrow They are ingredients (mixture) which make up a total percentage of 100%.

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B. MIXTURE EXPERIMENT EXAMPLE

• Go <u>https://cusum.mx/en/simuladores/</u>

Mixture and Gage R&R Destructive Simulator 2022



Femperatura Extrusión / 8	30-150	80
Femperatura Enfriamiente	o /10-60	10
/elocidad del Tornillo / 60	0-100	60
Presión de Aire / 0.5-5.0		0.5
/elocidad de Puller / 2-8		2
Parámetros Ma % de Polietileno / 10-99%	steria P \$0.25	99
% de Aditivos / 0-5%	\$0.82	0
% de Colorantes / 1-4%	\$0.15	1
% de Remolido / 0-75%	\$0.02	0

Parámetros de Máquina ------

Costo de Mezcla: \$ 24.90

When optimizing raw materials Engineers commonly use mixtures. This type of DOE is different from the previous ones and this simulator teaches students how to approach and optimize a mixture process. It also teaches them how to validate a destructive type Gage R&R.

--> Download Excel Grid for Faster Analysis

click this to download the .xls for faster results...

[Machine Parameter	15			Raw Materia	Parameters	
	Extrusion Temperature	Cooling Temperature	Screw Speed	Air Pressure	Puller Speed	%Polyethylene	%Additives	%Colorants	%Regrind
Minimum	80	10	60	0.5	2	10%	0%	1%	0%
Maximum	150	60	100	5	8	99%	5%	4%	75%
Run No.	_								
1	80.00	10.00	60.00	0.50	2.00				
2									
3	-leave +	hin in		habing		the	se are	our	
4	кеу і			achine			50 0	. 001	
5									
6	Darar	notor				- VII)	cture	ngred	ients I
7	raiai	neter	Þ						
8									
9	Not t	hat th	000 21	CO EIVI	-n	- wn	icn we	e will u	ise i
10	NULL	Πάιτι	iese a	CIN	-U				
11					,	<u>м л:.</u>		0.000	arata
12	anda	are NIC)T our	Facto	rc /		IIIad I	o gen	erate
13				Tucto	137			<u> </u>	
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15	- Mixt i	ire ing	redie	nts		·····V		ι τομλ	
10			PICAIC						
19						nac	to ho	o lato	r l
19						- pas			1
20									
21									
neal Simu	ulator Ur	ania Quadrat	ic Simulator	Chatillon	Simulator	+		: 📢	

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The Machine Parameters (Fixed Constants) are:

- Extrusion: 80
- Cooling: 10
- Screw: 60
- Air: 0.5
- Puller: 2

The Raw Material Parameters (Mixture Ingredients) are:

- Polyethylene: $10 \sim 99\%$
- Additives: $0 \sim 5\%$
- Colorants: $1 \sim 4\%$
- Regrind: 0~75%

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1. CREATING THE MIXTURE EXPERIMENT

Create Mixture Design		×	Create Mixture Design: Extreme Vertices Design X C13 C14 C15 C16
Type of Design C Simplex centroid (2 to 10 comp Simplex lattice (2 to 20 comp Extreme vertices (2 to 10 comp Number of components: 4	onents) onents) onents) Disolay Availa	ble Desians	Degree of design: We shall explain what is meant We shall explain what is meant by Augment with Center and Augment with Center and Axial Point Number of replicates for the whole design: 1 •
Help	Components Options	Process Vars Results Cancel	Point Type Description Number 1 vertex 1 2 double blend 1 3 triple blend 1 0 center point 1 -1 axial point 1
we simply choc Vertices becaus	ose Extre se its the	me best one	Help OK Cancel



An Augmented Simplex Centroid has 10 Points (see above picture).. thus it will produce a table of 10

runs...

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Create Mixture Design X	C8 C9 C10 C	C Create Mixture Design: Components	×
Type of Design C Simplex centroid (2 to 10 components) C Simplex lattice (2 to 20 components) • Extreme vertices (2 to 10 components)	Mixture should add up to 100%	Total Mixture Amount Single total: 1.0 Multiple totals (up to 5): Component Bounds Specified in Amount Generate Bounds Generate Bounds Generate Bounds Generate Bounds Generate Bounds Generate Bounds	
Number of components: Image: Test State Stat	Key in the 4 component name	Component Name Lower Upper A Polyethylene 0.1 0.99 B Additives 0 0.05	
Components Process Vars	as well as the	C Colorants 0.01 0.04 D Regrind 0 0.75	
Help OK Cancel	Lower and Upper constrained percentages	Linear Constraints.	

Create Mixture Design	× C8 C9 C10	Create Mixture Design: Options X
Type of Design C Simplex centroid (2 to 10 components)	deselect	Randomize runs Base for random data generator:
C Simplex lattice (2 to 20 components) Extreme vertices (2 to 10 components)	randomize	✓ Store design in worksheet
Number of components: 4 Display Available Designs Designs	runs	Help OK Cancel
Components Process Var Options Results.	and leave the	e other options as defaults
Help OK Cancel	then click OK	

Extreme Vertices Design this new table has been created....

÷	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	
	StdOrder	RunOrder	PtType	Blocks	Polyethylene	Additives	Colorants	Regrind						
1	1	1	1	1	0.9900	0.0000	0.0100	0.0000	сору	and p	aste t	nese		
2	2	2	1	1	0.2400	0.0000	0.0100	0.7500	4 col	umns	back i	nto th	е	
3	3	3	1	1	0.2100	0.0000	0.0400	0.7500	Гисс					
4	4	4	1	1	0.1900	0.0500	0.0100	0.7500	Exce	sprea	adsnee	et		
5	5	5	1	1	0.1600	0.0500	0.0400	0.7500						
6	6	6	1	1	0.9600	0.0000	0.0400	0.0000	+	norat				
7	7	7	1	1	0.9400	0.0500	0.0100	0.0000	to ge	enerat	e			
8	8	8	1	1	0.9100	0.0500	0.0400	0.0000	- Res	ults				
9	9	9	0	1	0.5750	0.0250	0.0250	0.3750	Cas	to				
10	10	10	-1	1	0.7825	0.0125	0.0175	0.1875	- COS	us				
11	11	11	-1	1	0.4075	0.0125	0.0175	0.5625						
12	12	12	-1	1	0.3925	0.0125	0.0325	0.5625	ac th	o Poci	onco			
13	13	13	-1	1	0.3825	0.0375	0.0175	0.5625	as th	e nes	Jonse	•••		
14	14	14	-1	1	0.3675	0.0375	0.0325	0.5625						
15	15	15	-1	1	0.7675	0.0125	0.0325	0.1875						
16	16	16	-1	1	0.7575	0.0375	0.0175	0.1875						
17	17	17	-1	1	0.7425	0.0375	0.0325	0.1875						

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- Recall: PtType stores the point type.
- The codes are:
 - o 0 is a Centre Point run and
 - o 1 is a Corner Point.
 - 0 I think -1 is an Axial Point

		P	Aachine Parameter	'S			Raw Materia	I Parameters			Results		
	Extrusion Temperature	Cooling Temperature	Screw Speed	Air Pressure	Puller Speed	%Polyethylene	%Additives	%Colorants	%Regrind	Multiplier	Mixture Cost	Tension Results Lbs/f	
Minimun	80	10	60	0.5	2	10%	0%	1%	0%	N/A	N/A	10	1
Maximun	150	60	100	5	8	99%	5%	4%	75%	N/A	N/A	12	1
Run No.													
1	80.00	10.00	60.00	0.50	2.00	0.99	0	0.01	0	0.993	\$ 24.90	7.411	
2	80.00	10.00	60.00	0.50	2.00	0.24	0	0.01	0.75	0.183	\$ 7.65	1.354	
3	80.00	10.00	60.00	0.50	2.00	0.21	0	0.04	0.75	0.162	\$ 7.35	1.201	1
4	80.00	10.00	60.00	0.50	2.00	0.19	0.05	0.01	0.75	0.633	\$ 10.50	4.648	1
5	80.00	10.00	60.00	0.50	2.00	0.16	0.05	0.04	0.75	0.612	\$ 10.20	4.449	
6	80.00	10.00	60.00	0.50	2.00	0.96	0	0.04	0	0.972	\$ 24.60	7.294	
7	80.00	10.00	60.00	0.50	2.00	0.94	0.05	0.01	0	1.443	\$ 27.75	10.670	
8	80.00	10.00	60.00	0.50	2.00	0.91	0.05	0.04	0	1.422	\$ 27.45	10.591	1
9	80.00	10.00	60.00	0.50	2.00	0.575	0.025	0.025	0.375	0.8025	\$ 17.55	5.992	
10	80.00	10.00	60.00	0.50	2.00	0.7825	0.0125	0.0175	0.1875	0.89775	\$ 21.23	6.695	
11	80.00	10.00	60.00	0.50	2.00	0.4075	0.0125	0.0175	0.5625	0.49275	\$ 12.60	3.588	
12	80.00	10.00	60.00	0.50	2.00	0.3925	0.0125	0.0325	0.5625	0.48225	\$ 12.45	3.618	
13	80.00	10.00	60.00	0.50	2.00	0.3825	0.0375	0.0175	0.5625	0.71775	\$ 14.03	5.267	
14	80.00	10.00	60.00	0.50	2.00	0.3675	0.0375	0.0325	0.5625	0.70725	\$ 13.88	5.155	
15	80.00	10.00	60.00	0.50	2.00	0.7675	0.0125	0.0325	0.1875	0.88725	\$ 21.08	6.626	
16	80.00	10.00	60.00	0.50	2.00	0.7575	0.0375	0.0175	0.1875	1.12275	\$ 22.65	8.326	
17	80.00	10.00	60.00	0.50	2.00	0.7425	0.0375	0.0325	0.1875	1.11225	\$ 22.50	8.085	
18											¢		
19	those a	ro tho m	hchino n	ramotor	c	those	aro my N	Aivturo Ir	gradiant	c	\$		
20	these a	re the m	actime pr	arameter	0	these	are my n	inxture ii	greuent	3	s the	se are r	nv 2
21	that are	loft con	ctant			which	should a	dd up to	100%		\$ -		
22	that are		stant			which	Should a	iuu up to	100%		\$ roci	ancoc	which
23						ner ro	\A/				\$ 165	JOURSES	which
24						perio	••••••				\$		
25											\$ W	I CODV	paste
26											\$ -	1.4	
27						which	i conied	nasted f	rrom		s into	Minita	h
28							reopied	publica			s niệc		D
29						Minita	b				\$ -		
30	1										\$ -		
neal Sim	ulator U	rania Quadrat	ic Simulator	Chatillon	Simulator			: •					

2. PREDICTING THE MIXTURE EXPERIMENT

Basic S	Statistics	,	Jx 📑	-2 00 00	2 2	2											
Regree	ssion)	hat was C														
ANOV	Α)	ixtures: C	* ^													
DOE)	Screenin	ng	•												•
Contro	ol Charts	•	Factoria	I	⇒6Т,	TENSION	ther	n clic	k her	e							
Qualit	y Tools	,	Respons	se Surface	•			1									
Reliab	ility/Survival	,	Mixture		► A	Create Mixture	Design		C8	60	C10	C11	C12	C13	C14	C15	C16 4
Predic	tive Analytics	.)	Taguchi		🕨 🗛	Define Custom	Mixture Desi	gn	Regrind	COST	TENSION	en	CIL	0.5	0.4	cis	0.0
Multiv	ariate)	🖏 Modify	Design	Δ	Select Optimal	Design		0.0000	\$ 24.90	7,411						
Time S	Series	,	Display	Design	A	Simplex Design	Plot		0.7500	\$ 7.65	1.354	cor	v nas	te th	ese 2		
Tables		,	3	1	\geq				0.7500	\$ 7.35	1.201	cop	y pus	ne in	CSC 2		
Nonpa	arametrics)	4	1		Analyze Mixture	Design		0.7500	\$ 10.50	4.648	col	umns	in fr	om th	ie 👘	
Equiva	alence Tests)	5	1	⊯	Response Trace	Plot		0.7500	\$ 10.20	4.449	_					
Power	and Sample	Size)	6	1		Contour/Surfac	e Plots		0.0000	\$ 24.60	7.294	Exc	el spr	reads	heet.	as	
	7	7	7	1		Overlaid Conto	ur Plat		0.0000	\$ 27.75	10.670	Dec	none	~~			
	8	8	8	1	*	Response Optir	nizer		0.0000	\$ 27.45	10.591	Res	pons	es			
	9	9	9	0	1	0.575					992						
	10	10	10	-1	1	0.782	Response O	pumizer			695						
	11	11	11	-1	1	0.407	optimize one	or more fitt	of predictor ed response	settings that	Jointly 588						
	12	12	12	-1	1	0.3925	0.0125	0.0325	0.5625	\$ 12.45	3.618						
	13	13	13	-1	1	0.3825	0.0375	0.0175	0.5625	\$ 14.02	5.267						
	14	14	14	-1	1	0.3675	0.0375	0.0325	0.5625	\$ 13.88	5.155						
	15	15	15	-1	1	0.7675	0.0125	0.0325	0.1875	\$ 21.07	6.626						
	16	16	16	-1	1	0.7575	0.0375	0.0175	0.1875	\$ 22.65	8.326						
	17	17	17	-1	1	0.7425	0.0375	0.0325	0.1875	\$ 22.50	8.085						



Response Optimization



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VI. TAGUCHI METHOD



- By right, a Full Factorial for a 3 factor 2 level $(2^3) = 8$ runs required.
- Taguchi can reduce the number of runs to only 4.
- This is possible because Taguchi assumes the 3rd column (3rd factor) to be the interaction effect of factors 1 and 2, thus it can be ignored.

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- Taguchi regards Factor Interaction Effects as Noise (thus they are insignificant and ignored).
- Taguchi only regards Main Factor Effects.

B. TAGUCHI'S OPTIMIZATION



- Precision relates to the Standard Deviation (SD)
 - Target Value relates to the Mean



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C. MEANING OF SIGNAL TO NOISE RATIO (S/N)



- S/N ratio combines the effect of the Mean and Standard Deviation **into one value** used to gage the process output.¹
- In other words, the larger the S/N ratio, the more robust the process is to Noise.
- As mentioned above,
 - Precision relates to the Standard Deviation (Step 1 for Optimization). We use the S/N ratio to identify those Control Factors that reduce variability.

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¹ <u>https://www.amazon.com/Practical-Design-Experiments-DOE-Optimizing/dp/0873899245</u>

- Accuracy relates to the Target Value (Mean) (Step 2 for Optimization). We identify Control Factors that move the mean to target and have no effect on the S/N ratio.
- There are 4 types of S/N ratio in Minitab: (note that for all types, our objective is to Maximize the S/N ratio → increase Signal, lower Noise)

Analyze Ta	aguchi Design: Optio	ons 🙁
Signal to Noise Ratio:	Formula	
C Larger is better	-10×Log10(sum(1/Y^2)/n)	
O Nominal is best	-10×Log10(s^2)	
Nominal is best	10×Log10(Ybar^2/s^2)	Default
O Smaller is better	-10×Log10(sum(Y^2)/n)	Most
Use adjusted formula	for nominal is best	commonly
Use In(s) for all standa	ard deviation output	chosen
Help	<u>0</u> K	Cancel

- 1. LARGER IS BETTER
- Objective is to Maximize the Response.
- Example: Identify the Factors that Increase the hardness of the steel alloy.

2. NOMINAL IS BEST

• Objective is to try to hit the Target Response using S/N ratio based on Standard Deviations.

3. NOMINAL IS BEST (DEFAULT)

- Objective is to try to hit the Target Response using S/N ratio based on Means and Standard Deviations.
- Example: Identify the Factors that allow the manufacture to find the nominal specification.

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4. SMALLER IS BETTER

- Objective is to Minimize the Response.
- Example: Identify the Factors that Reduce the force necessary to open the sealed packaging.

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Time	Temp	Pressure	With Noise 1	With Noise 2	With Noise 3
1.25	250	80	2.9	3	2.8
1.25	260	90	2.4	2.2	2.3
2.5	250	90	3.5	3.6	3.7
2.5	260	80	2.6	2.5	2.7

D. EXAMPLE: MINIMIZING THE RESPONSE (SMALLER IS BETTER)

- This example is taken from (Durivage, 2016)
- A sealing process requires large force to open the packaging.
- 3 Factors, 2 Levels
 - Time: 1.25 and 2.5 seconds
 - o Temperature: 250 and 260 Degree Celsius
 - o Pressure: 80 and 90 PSI
- By right, a 2³ will take total 8 runs, but we will do a L4 (only 4 runs)
- Responses (Three outputs collected under three different noise conditions)
 - With Noise 1
 - With Noise 2
 - With Noise 3
- Objective:
 - What are the Factors that help to reduce the Force required to open the package?
 - o Noise is irremovable, we can only try to Maximize the S/N ratio

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a) Minitab Solution



(1) Creating the Worksheet





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	Taguchi	Design	8		т	aguchi I	Design:	Design	6	3	
Type of Design				₽	uns	2 ^ Colum	ns				
<u>2</u> -Level Desig	n (2 to 31 fac	ctors)			L4	2^3					
C 3-Level Desig	n (2 to 13 fac	ctors)			L8 112	2 ^ 3					
C 4-Level Desig	n (2 to 5 fact	ors)			L16	2 ^ 3					
C <u>5</u> -Level Desig	n (2 to 6 ract Design (2 to 26 fac	ors) (tors)			L32	2^3					
	(2 to 20 to										
Number of facto	rs: 3 💌	Display A	vailable Designs								
		Designs	<u>Factors</u>		Add a signa	al factor for o	ivnamic char	acteristics			
		Options			ridd d <u>S</u> igna						
1					Help		(ок	Cancel	11	
Help		<u>O</u> K	Cancel				-			- 1	
			Taguc	hi Desig	n	8					
		Type of D	ecian								
		• <u>2</u> -Leve	el Design (2 to 31	factors)							
		O 3-Leve	el Design (2 to 13	factors)							
		C <u>4</u> -Leve	el Design (2 to 5 f	actors)							
		O Mixed	Level Design (2 to 26	factors)							
				Dist	lav Available D	esions					
		Number o	f factors: 3	Deci		actors					
				020	ons	1					
		Help	,	9	<u>o</u> k	Cancel					
				_							
	Taguchi Desig	gn: Factors	8								
Assign Factors	array as specified bel	ow			we do	not s	elect				
C To allow estimation	on of selected interacti	ions Interactio	ль 		thic ou	ation	hoca	100			
Facto Name	Level Val	ues	Column Level			JUOII	Deca	ise			
A Time	1.25 2.5		1 💌 2		we are	e not	keen	to stu	idy th	е	
B Temp	250 260		2 2 2		Intora	ction	Effor	to i	~ ^ A D	110	
					intera	CHOIT	Ellec	LS I.	e. AD	/ AC .	
ke	v this in		ł	C14	C15	C16	C17	C18	C19	C20	C21
	y chi s hi.			011	015	010		010	015	020	
]			[
-	r				Taguc	hi fee	ls tha	t Inte	ractic	on Effe	ects
Help	l	<u>0</u> K	Cancel			مانمنه	lo and		choul	d only	,
		_				giigin	ie and	u we :	snoui	u oniy	
					study	Main	Effec	ts i.	e. A /	B/C	

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	Taguchi D)esign	8
Type of Design 2-Level Design 3-Level Design 4-Level Design 5-Level Design Mixed Level Design	(2 to 31 facto (2 to 13 facto (2 to 5 factor (2 to 6 factor (2 to 26 facto	prs) prs) s) s) prs)	
Number of factors: 3	•	Display Availat Designs Options	Eactors 3
Help		ОК	Cancel

🗰 Worksheet 4 ***												
÷	C1	C2	C3	C4	C5	C6	C7	C8				
	Time	Temp	Pressure									
1	1.25	250	80	ALC: N	.							
2	1.25	260	90	this	table	e pop	s up					
3	2.50	250	90									
4	2.50	260	80	and	has	been	crea	ted				
5												
6												
7												
0						1						

Worksheet 4 ***											
÷	C1	C2	С3	C4	C5	C6		C7			
	Time	Temp	Pressure	With Noise 1	With Noise 2	With Noise 3					
1	1.25	250	8	2.9	3.0	2.8					
2	1.25	260	9	2.4	2.2	2.3					
3	2.50	250	9	3.5	3.6	3.7					
4	2.50	260	8	2.6	2.5	2.7					
5											
6	key the three responses in										
7											
8											
9											
10											

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(2) Defining the Factors

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(3) Analyzing the Responses

(a) Defining the Responses



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Analyze Taguchi Design								
C4 With Noise 1 C5 With Noise 2 C6 With Noise 3	Response data are in: 'With Noise 1'-'With Noise 3'							
Select Help	Graphs Analysis Analysis Graphs Options QK	<u>T</u> erms Storage Cancel						

Analyze Taguchi Design: Graphs						
C1 Time C2 Temp C3 Pressure	 Generate plots of main effects and interactions in the model Signal to Noise ratios Meansi Standard deviations Interaction plots Display interaction plot matrix Use all factors that interact as rows and columns of the matrix or Specify factors for rows: 					
Select	Specify factors for <u>c</u> olumns: O Display each interaction on a separate graph					
Help	<u>OK</u> Cance	2				

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(c) Analyses

Ana	alyze Taguchi Design	8
C4 With Noise 1 C5 With Noise 2 C6 With Noise 3	Response data are in: 'With Noise 1'-'With Noise 3'	
Select	Graphs Analysis Analysis Graphs Options Options Options	<u>T</u> erms Storage Cancel

ULINUISE T TESPONS	
Analyze Taguchi I	Design: Analy 🛛 🖉
Display response tables for	Fit linear model for
<u>Means</u> Standard deviations	Means Standard deviations
Help	OK Cancel

(d) Terms

Analyze Taguchi Design 🛛 😣							
C4 With Noise 1 C5 With Noise 2 C6 With Noise 3	Response data are in: 'With Noise 1'-'With Noise 3'						
Select Help	Graphs Analysis Agalysis Graphs, Options QK	<u>T</u> erms Storage Cancel					



(e) Options

		Ana	alyze Taguchi Design 🛛 🛛
	C4 C5 C6	With Noise 1 With Noise 2 With Noise 3	Response data are in: 'With Noise 1'-'With Noise 3'
		Select	Graphs Analysis Terms Analysis Graphs Options Storage QK Cancel
Analy	/ze Ta	guchi Design: Optic	ns 🛛
Signal to Noise Ra	itio:	Formula	remember earlier we choose
C Larger is bette C Nominal is bes	r t	-10×Log10(sum(1/Y^2)/n) -10×Log10(s^2)	smaller is better because we
Nominal is bes Smaller is better	t er	10×Log10(Ybar≏2/s 2) -10×Log10(sum(Y^2)/n)	want to minimize the force used
Use In(s) for a	ll standar	d deviation output	cito open the packagecia. Cig C20 C
Help			Cancel

	(f) Storage
Ana	alyze Taguchi Design 🛛 🛛 😣
C4 With Noise 1 C5 With Noise 2 C6 With Noise 3	Response data are in: 'With Noise 1'-'With Noise 3'
Select Help	Graphs Analysis Terms Agalysis Graphs Options Storage QK Cancel



b) Minitab Output

Session	✓ Main Effects Plot for SN ratios	
123 Taguchi Analysis: With Noise 1, With Noise 2, With Noise 3 versus Time, Temp, Pressure	Main Effects Plot for SN ratios	
Response Table for Signal to Noise Ratios Smaller is better Level Time Temp Pressure 1 -8.246 -10.190 -8.778 2 -9.716 -7.772 -9.184 Petta 1.470 -2.418 0.407 Rank 2 1 3 Main Effects Plot for SN ratios Main Effects Plot for SN ratios	-8.0 - -8.0 - -8.5 - -10.0 - Time Temp Pressure 7 Temp - Pressure	
Image: Worksheet 4 *** Image: Vorksheet 4 **** Image: Vorksheet	-10.5 1.25 2.50 250 260 80 90 Signal-to-noise: Smaller is better	
1 1.25 250 60 2.3 -3.2314 2 1.25 260 90 2.4 2.2 2.3 -7.2400 3 2.50 250 90 3.5 3.6 3.7 -11.1283 4 2.50 260 80 2.6 2.5 2.7 -8.3037 5	specific SN ratio for each run.	
11 because it requires the smallest force to open the seal 12 13 • •		

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Stat Graph Editor Tools Window <u>H</u>elp Assistant Basic Statistics 🔽 🗄 🖫 🔂 🖸 💭 🗍 🛣 🖾 🖾 🕞 🥀 , $\otimes \bigcirc$ Regression $\times | \mathbb{Q} [\mathbb{I}] \mathbb{Q}]$ • ANOVA . DOE Þ **Factorial** ۲ Control Charts ۲ Response Surface ۲ Quality Tools Mixture ٠ • Reliability/Survival Þ ₽ <u>T</u>aguchi Create Taguchi Design... 80 Multivariate Define Custom Taguchi Design... 丏, Modify Design... Time Series ٠ Display Design... æ Analyze Taguchi Design... Tables . źω, ₩Ŷ Predict Taguchi Results... Nonparametrics • Equivalence Tests • Power and Sample Size ۲



c) Predicting Taguchi Results

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	Predict	Taguchi Results: Levels 🛛 🛽 🕄	7	-10.5	1 25	2.50	250	200		0		
R 9. 7. 1. 8.	C1 Time C2 Temp C3 Pressure C4 With Noise 1 C5 With Noise 2 C6 With Noise 3 C7 SNRA1	Method of specifying new factor levels		signal-to-noi	e trv	better	o pre	dict t	he R	espo	nse	
		Factor Levels Time 1.25 V Temp 260 V		(Mea and T	n) by emp	setti ~ 26	ng th 0(ne Tir ignoi	ne ~ ring f	1.25 Press	ure)	
	Select	<u>O</u> K Cancel										

Taguchi Analysis: With Noise 1, With Noise 2, With Noise 3 versus Time, Temp, Pressure
Predicted values
We see that the predicted response
is 2.25 when

Time ~ 1.25 Temp ~ 260

Factor levels for predictions

Time Temp 1.25 260

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E. SUMMARY OF TAGUCHI'S EXAMPLE

With reference to Example: Minimizing the Response (Smaller is Better), we can repeat this example for:

	Temp	Time	Pressure	Polymer
Level 1 – 1 Lo	125	80	2	0.5
Level 2 –2Mid	150	85	4	1
Level 3 – 3 Hi	200	90	6	1.5

1. NOMINAL RESPONSE (NOMINAL IS BEST)

- We want to nominalize the product specifications
- Choose a L9 (4 Factor 3 Levels) Taguchi Experiment

Run	1 Temp	2 Time	3 Pressure	4 Polymer	Y 1	Y ₂	Y ₃	S/N
1	1	1	1	1	88.2	82.4	70.3	18.88
2	1	2	2	2	74.7	69.2	64.1	22.33
3	1	3	3	3	56.4	53.7	44.9	18.69
4	2	1	2	3	80.2	78.9	63.2	17.88
5	2	2	3	1	77.4	76.2	53.9	14.37
6	2	3	1	2	88.9	88.1	82.9	28.48
7	3	1	3	2	64.3	61.9	56.1	23.17
8	3	2	1	3	98.6	92.6	88.8	25.53
9	3	3	2	1	75.9	73.4	62.8	20.11

• Produce the table above (where Y1, Y2 and Y3 are the Responses with Noise).

2. LARGEST RESPONSE (LARGER IS BETTER)

	Preheat	Equalize	Austenize	Temper	Quench
Level 1 – Low	1250	1350	1725	750	150
Level 2 – Hi	1450	1450	1775	950	200

- We want to increase the hardness of steel alloy.
- o Choose a L8 (5 Factor 2 Levels) Taguchi Experiment

Run	1 Preheat	2 Equalize	3 Austenize	4 Temper	5 Quench	Y 1	Y ₂	Y ₃	S/N
1	1	1	1	1	1	38.0	36.3	38.3	31.48
2	1	1	1	2	2	39.9	56.2	35.1	32.32
3	1	2	2	1	1	45.1	65.7	32.1	32.48
4	1	2	2	2	2	41.5	46.8	29.7	31.40
5	2	1	2	1	2	62.1	53.9	61.3	35.38
6	2	1	2	2	1	23.4	19.8	42.9	27.85
7	2	2	1	1	2	33.7	43.0	61.8	32.51
8	2	2	1	2	1	31.4	47.7	31.2	30.82

- Produce the following table above (where Y1, Y2 and Y3 are the Responses with Noise).
- The S/N ration should be the same as above.

VII. DOE FAQS

A. WHAT IF MANY / ALL FACTORS BECOME SIGNIFICANT?

- There could be outliers or special causes that distort each run.
- Check if there are any unusual values.
- Outliers should be removed or replaced.

B. WHAT IF THERE'S MISSING DATA?

• Replace missing data with average.

C. MUST WE USE ALL FACTORS?

- Yes, try to. it is to your advantage.
- If you don't use them, the unused factors will be called "dummy" factors.

D. WHAT IF I CAN'T REPLICATE ALL RUNS?

• Randomly select runs to be replicated

E. MUST I RANDOMIZE ALL TRIALS?

- No, but it would be best.
- Sometimes it's not possible to re-setup e.g., setting up a furnace temperature is only done once.
- You can't randomize and must carry things out in certain order at one go.
- This may lead to confounding the temperature with another unknown factor. (Due to no randomization).

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VIII. SUCCESSFUL STEPS TO IMPLEMENT DOE

- 1. Define objectives
- 2. Assemble a small knowledge team
- 3. Review all pertinent relevant data
- 4. Brainstorm to generate potential factors.
 - a. Be creative and do not accept existing theories without data.
- 5. Segregate (from the list) those factors that can be controlled vs uncontrollable.
- 6. Separate the expensive factors vs cheap factors.
 - a. Always include factors that are cheap, quick and easy to study.
- 7. For every factor, set levels boldly but NOT carelessly.
 - a. You need levels to be as wide as possible to force effects out of them.
 - b. But you must avoid dangerous or unfeasible conditions.
- 8. Design your study.
 - a. Narrow down the factors + review the total cost + complexity and control of the experiment + need for replications.
- 9. Randomize but if you can't, be aware of drawing false conclusions due to unknown external influence affecting the DOE.
- 10. Run the DOE + ensure correct levels + ensure materials are correct and keep good records.
- 11. Use Graphs to communicate findings.
 - a. Report conclusions in simple language for the audience, not statistical terminologies.

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IX. OBSTACLES TO DOE

A. RESISTANCE INERTIA

- "We have always used OFAT and no time to learn new approach!"
- Answer: You will always get what you have always gotten if you keep doing what you keep doing!

B. EXPENSIVE COST

- Nothing is free.
- DOE is an investment with a payback.
- Normally, the main cost is not Material Cost nor Processing Cost.
- Its the cost of using People's time.
- Use it carefully.

C. LACK OF MANAGEMENT SUPPORT

- Management must be involved.
- They must be educated and understanding what the objectives are, what the costs will be, what is expected, and believe the power of DOE.

D. LACK OF TRAINING

• You need educated people who knows DOE techniques to carry it out.

E. WRONG THINKING THAT DOE IS ONLY USED FOR MANUFACTURING

- DOE can be used for any area that can define factors for study.
- Including strategy and sales.

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APPENDIX

A. SELECTED FACTORIAL DESIGNS

1. 2^2 FULL FACTORIAL

2 Γι	un Factoriai									
	A	в								
1	-	-								
2	+	-								
3	-	+								
4	+	+								

2² Full Eactorial

All terms are free from aliasing. Full Resolution

2. 2³ FULL FACTORIAL

2 ³ Full Factorial									
	A B								
1	-1	-1	_						
2	1	-1	_						
3	-1	1	-						
4	1	1	_						
5	-1	-1	+						
6	1	-1	+						
7	-1	1	+						
8	1	1	+						

All terms are free from aliasing.

Full Resolution

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3. 2^3 HALF FRACTIONAL FACTORIAL

2 ³ Half Fractional Factorial										
	Α	в	С							
1	-	-	+							
2	+	-	-							
3	-	+	-							
4	+	+	+							

I + ABC A + BC B + AC C + AB Resolution III

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F. SELECTED PLACKET BURMAN DESIGNS

	Α	В	С	D	Е	F	G
1	+	_	_	+	_	+	+
2	+	+	-	-	+	-	+
3	+	+	+	_	_	+	_
4	-	+	+	+	_	_	+
5	+	_	+	+	+	_	_
6	-	+	_	+	+	+	_
7	_	_	+	_	+	+	+
8	_	_	_	_	_	_	_

Eight-Run 2⁷ Plackett-Burman

12-Run 2 ¹¹ Pla	ckett-Burman
----------------------------	--------------

	Α	В	С	D	E	F	G	н	I	J	к
1	+	-	+	_	_	-	+	+	+	_	+
2	+	+	-	+	_	-	-	+	+	+	-
3	_	+	+	_	+	_	-	_	+	+	+
4	+	-	+	+	_	+	-	_	_	+	+
5	+	+	_	+	+	-	+	_	_	_	+
6	+	+	+	_	+	+	-	+	_	_	_
7	_	+	+	+	_	+	+	_	+	_	_
8	_	_	+	+	+	_	+	+	_	+	_
9	_	_	_	+	+	+	-	+	+	_	+
10	+	_	_	_	+	+	+	_	+	+	_
11	_	+	_	_	_	+	+	+	_	+	+
12	_	_	_	_	_	_	_	_	_	_	_

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	Α	В	С	D	Е	F	G	н	Т	J	к	L	М	N	0
1	+	-	-	-	+	-	-	+	+	-	+	-	+	+	+
2	+	+	-	-	-	+	-	-	+	+	-	+	-	+	+
3	+	+	+	-	-	-	+	-	-	+	+	-	+	-	+
4	+	+	+	+	-	-	-	+	-	-	+	+	-	+	-
5	-	+	+	+	+	-	-	-	+	-	-	+	+	-	+
6	+	-	+	+	+	+	-	-	-	+	-	-	+	+	-
7	-	+	-	+	+	+	+	-	-	-	+	-	-	+	+
8	+	-	+	-	+	+	+	+	-	-	-	+	-	-	+
9	+	+	-	+	-	+	+	+	+	-	-	-	+	-	-
10	-	+	+	-	+	-	+	+	+	+	-	-	-	+	-
11	-	-	+	+	-	+	-	+	+	+	+	-	-	-	+
12	+	-	-	+	+	-	+	-	+	+	+	+	-	-	-
13	-	+	-	-	+	+	-	+	-	+	+	+	+	-	-
14	-	-	+	-	-	+	+	-	+	-	+	+	+	+	-

16-Run 2¹⁵ Plackett-Burman

Taguchi L4 (2 ³)								
	1	2	3					
1	1	1	1					
2	1	2	2					
3	2	1	2					
4	2	2	1					

	1	2	3
1		3	2
2			1

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	Taguchi L8 (2')										
	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				
	1	2	3	4	5	6	7				
1		3	2	5	4	7	6				
2			1	6	7	4	5				
3				7	6	5	4				
4					1	2	3				
5						3	2				
~											

Taguchi L8 (1 ⁴ with up to 2 ⁴)										
	1	2	3	4	5					
1	1	1	1	1	1					
2	1	2	2	2	2					
3	2	1	1	2	2					
4	2	2	2	1	1					
5	3	1	2	1	2					
6	3	2	1	2	1					
7	4	1	2	2	1					
8	4	2	1	1	2					

The L8 (1^4 with up to 2^4) array does not have an interaction table.

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Taguchi L9 (3 ⁴)						
	1	2	3	4		
1	1	1	1	1		
2	1	2	2	2		
3	1	3	3	3		
4	2	1	2	3		
5	2	2	3	1		
6	2	3	1	2		
7	3	1	3	2		
8	3	2	1	3		
9	3	3	2	1		

The L9 (3⁴) array does not have an interaction table.

H. SELECTED MIXTURE DESIGNS



Three-Factor Simplex Centroid Design

Run	Α	В	С
1	1	0	0
2	0	1	0
3	0	0	1
4	0.5	0.5	0
5	0.5	0	0.5
6	0	0.5	0.5
7	0.333	0.333	0.333

Three-Factor Simplex Lattice Design

Run	Α	В	С
1	1	0	0
2	0	1	0
3	0	0	1
4	0.333	0.333	0.333
5	0.667	0.167	0.167
6	0.167	0.667	0.167
7	0.167	0.167	0.667

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ABOUT DR. ALVIN ANG



Dr. Alvin Ang earned his Ph.D., Masters and Bachelor degrees from NTU, Singapore. He is a scientist, entrepreneur, as well as a personal/business advisor. More about him at <u>www.AlvinAng.sg</u>.

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