

# Screening Designs

BIOE 498/598 PJ

Spring 2022

# Why do we use screening designs?

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- ▶ Too many factors waste resources
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- ▶ Optimization is expensive—many runs/factor at  $> 2$  levels
- ▶ Too many factors waste resources
- ▶ Too few factors lead to suboptimal results
- ▶ **Solution:** A *screening design* tests a large number of factors
- ▶ Only active factors are carried forward for optimization

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- ▶ We don't worry about estimates of TWIs. We're selecting factors, not interactions.

# Types of screening designs

- ▶ Resolution III Fractional Factorial Design
  - ▶ Pro: Mirror image can clear main effects
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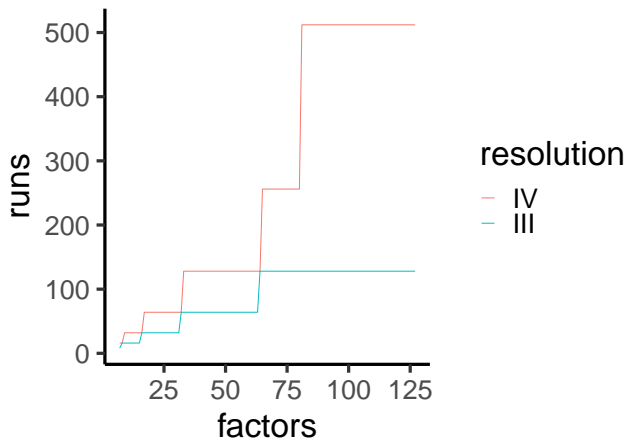
- ▶ Resolution III Fractional Factorial Design
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- ▶ PB Design
  - ▶ Pro: Run size in multiples of 4
  - ▶ Con: Complex aliasing



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  - ▶ Con: Complex aliasing
- ▶ Definitive Screening Designs
  - ▶ Hybrid screening/optimization design. We'll discuss later!

## Don't rule out Fractional Factorial Designs.



number of runs

	8	16	32	64	128	256	512	1024	2048	4096
						<i>only the MA design</i>				
3	full									
4	IV	full								
5	III	V	full							
6	III	IV	VI	full						
7	III	IV	IV	VII	full					
8		IV	IV	V	VIII	full				
9		III	IV	IV	VI	IX	full			
10		III	IV	IV	V	VI	X	full		
11		III	IV	IV	V	VI	VII	XI	full	
12		III	IV	IV	IV	VI	VI	VIII	XII	full
13		III	IV	IV	IV	V	VI	VII	VIII	XIII
14		III	IV	IV	IV	V	VI	VII	VIII	IX
15		III	IV	IV	IV	V	VI	VII	VIII	VIII
16			IV	IV	IV	V	VI	VI	VIII	VIII
17			III	IV	IV	V	VI	VI	VII	VIII
18			III	IV	IV	IV	VI	VI	VII	VIII
19			III	IV	IV	IV	V	VI	VII	VIII
20			III	IV	IV	IV	V	VI	VII	VIII
21			III	IV	IV	IV	V	VI	VII	VIII
22			III	IV	IV	IV	V	VI	VII	VIII
23			III	IV	IV	IV	V	VI	VII	VIII
24			III	IV	IV	IV	IV	VI	VI	VIII

Resolution III up to 31 63 127 factors.

Resolution IV up to 32 64 80 160 factors.

Resolution V up to number of factors: 33 47 65

Resolution VI up to number of factors: 24 34 48

First design is MA up to number of factors:

31 63 127 36 29 28 32 26

Gromping, 2014  
J. Stat. Software

## Workflow for Resolution III screens

1. Run the design
2. Fit the model with main effects. If you have DoF left over, add any TWIs that are **not** confounded with main effects.
3. If the overall model fit is bad, or if you expected certain effects to be significant that were not, consider a second batch of runs with a mirror image design.
4. Drop any factors that are not **important** (practically or statistically).

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# Plackett-Burman Designs

- ▶ Discovered in 1946 while working in the British Ministry of Supply
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- ▶ Run sizes in **multiples of 4**
- ▶ Both PB designs and FF designs are *Orthogonal Arrays*
  - ▶ PB = FF when  $N = 2^k$
- ▶ PB designs have *complex aliasing*. Every ME is partially confounded with all TWIs.

## Creating a PB design (up to 23 factors)

1. Start with the first run from the following table.

Runs	Factor Levels
12	+ + - + + + - - - + -
20	+ + - - + + + + - + - + - - - - + + -
24	+ + + + + - + - + + - - + + - - + - + - - - -

2. Cycle the factor levels by one to get run #2. Repeat for 11, 19, or 23 runs.
3. Set the final run to all low (-).
4. If the number of factors  $k$  is less than the number of runs, select the first  $k$  columns.



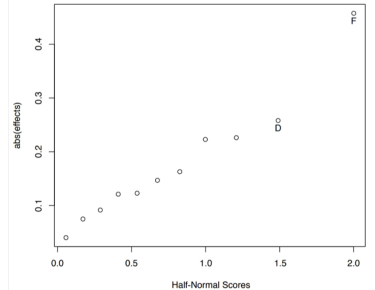
## Workflow for PB designs

1. Run the design.
2. Fit a model with main effects plus an effect for any unused column in the design.
3. Optional: Perform subset regression to identify factors that appear frequently in smaller models with good predictive power.
4. Drop any factors that are not **important** (practically or statistically).
5. If only a small number of factors remain, try refitting the small model.

# Example PB design: Cast fatigue

Table 6.11 *Design Matrix and Lifetime Data for Cast Fatigue Experiment*

Run	A	B	C	D	E	F	G	c8	c9	c10	c11	
1	+	-	+	+	+	-	-	-	+	-	+	4.733
2	-	+	+	+	-	-	-	+	-	+	+	4.625
3	+	+	+	-	-	-	+	-	+	+	-	5.899
4	+	+	-	-	-	+	-	+	+	-	+	7.000
5	+	-	-	-	+	-	+	+	-	+	+	5.752
6	-	-	-	+	-	+	+	-	+	+	+	5.682
7	-	-	+	-	+	+	-	+	+	+	-	6.607
8	-	+	-	+	+	-	+	+	+	-	-	5.818
9	+	-	+	+	-	+	+	+	-	-	-	5.917
10	-	+	+	-	+	+	+	-	-	-	+	5.863
11	+	+	-	+	+	+	-	+	-	+	-	6.058
12	-	-	-	-	-	-	-	-	-	-	-	4.809



This design includes 7 factors; however, effects are estimated for all columns. The last 4 “factors” are interactions with complex aliasing.

## To replicate or not to replicate?

- ▶ Many screening designs are *saturated* — there are no DoF to estimate confidence intervals for the parameters.
- ▶ The number of estimable factors is bounded by the rank of the model matrix. Replicates do not change the rank.
- ▶ If you don't replicate the design, you can select factors based on the magnitude of the effects alone (half-normal plot).
  - ▶ Remember that half-normal plots work better as the number of factors grows.

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  - ▶ Remember that half-normal plots work better as the number of factors grows.
- ▶ Replicating a Resolution III Design
  - ▶ Consider a mirror-image instead. This will give clear main effects.
  - ▶ Check if you can afford a Resolution IV instead. This gives clear main effects and a confounding structure.
- ▶ Replicating a PB Design
  - ▶ Replicating the design will help you estimate the “pure error”.
  - ▶ You can “move up” to a larger PB design to get extra runs. This won't estimate pure error, but you can add more confounded effects to the model to improve the estimates.