ISEA WEBINAR A CASE STUDY OF A MIXED-LEVEL OMARS DESIGN

Maria Lanzerath W. L. Gore & Associates

September 20, 2023

Together, improving life



What is the talk about?

From the perspective of a statistical consultant

The company that allows me to do such a valued and enjoyable body of work

The journey of applying a(n OMARS) design

- Insight into the application behind
- My way to, and success factors of, experimental planning
- What is an OMARS design, also relative to other designs?
- Results from the DOE and how they were analyzed in a new software prototype (EFFEX)











1 0.013 -0.0319 5.593k 12.033 0.00013 201.267 193.786 202.82

Agenda

- 1. W. L. Gore & Associates
- 2. Product and process
- 3. Experimental design
- 4. Statistical analysis
- 5. Summary

Advanced Materials Capabilities

Our solutions are based on sound science and fundamental understanding.



One of the **200** largest

privately-held U.S. companies

Global



Gore has manufacturing facilities in the United States, Germany, United Kingdom, the Netherlands, Japan and China, and sales offices around the world.







Globally recognized as a great place to work.

 $\ensuremath{\mathbb{C}}$ 2023 W. L. Gore & Associates

Gore innovates across 15+ diverse industries



INNOVATION

Gore innovates with purpose to deliver meaningful solutions that solve the challenges of our customers and communities.

The case study

WHAT

- Chemical product
- Functionalized fine powder copolymer
- Used for liquid filtration applications within the semiconductor industry
- Strong surface properties of the filtration element improve filtration efficiency



The case study

WHY

- Supplier shutdown
- Move production from external to internal

CHALLENGE

- "Copy that product as similarly as possible"
- Improvements welcome
- Timelines short
- Materials extremely expensive





Chemical view

 Two different monomers result in one co-polymer

Polymerization → Coagulation → Drying
Finishing

- Polymer is made in first step
- The following two steps are for extracting and drying of the product



HOMOPOLYMERS



The production process

Properties and constraints

- Batch process
 - -In one batch, all factor settings remain the same
 - -Batch = production unit = experimental unit
 - -No blocking, no split-plot structure
 - -Full randomization
 - -Material can be tested after each step
- One batch takes 30 hours of making on a full-scale production line
- Raw material cost
- DOE size limited due to the cost
- Execution of the DOE took several months

EXPERIMENTAL DESIGN

Experimental design

BUDGET

Maximum 24 runs

GOALS

- Validate from development stage to commercial production
- Meet all customer specifications reliably
- Identify key process factors screening
- Predict future process capability optimization/ response-surface modeling
- Combine screening phase and optimization into ONE single experiment

Process and Factors (X)

Polymerization



Finishing

- 1. Setting T
- 2. Setting P
- 3. Chemical S (2 levels)
- 4. Chemical E

- 5. Acid amount
- 6. Composition ratio
- 7. Polishing time (2 levels)
- 8. Drying temperature

Two-factor interactions evaluation

Factor names standardized

	Pol	y factors (process ste	Finishing factors (process step 2)				
Factor	s1_x1	s1_x2 s1_x3		s1_x4	s2_x5	s2_x6	s2_x7	s2_x8
s1_x1		high	medium	high	0	high	?	0
s1_x2			medium	?	0	high	0	0
s1_x3				high	0	medium	medium	0
s1_x4					0	high	0	0
s2_x5						0	?	high
s2_x6							?	high
s2_x7								0
s2_x8								

- Helps combine statistical properties with subject matter expertise
- Brings knowledge, assumptions, and uncertainties to the table

Statistical model

FACTORS

- All factors continuous
- 6 on three levels each
- 2 on two levels each

MINIMUM VIABLE MODEL

- 8 main effects
- 6 quadratic effects
- 8 key two-factor interactions selected by applying subject matter expertise

Statistical model

Full response surface model

- 1 constant term (intercept)
- 8 main effects
- 6 quadratic effects
- 3 main effects of covariates
- 28 two-factor interactions
- 46 model degrees of freedom \rightarrow 2⁴⁶ = 70,368,744,177,664 potential models !

Covariates on top...

- Several covariates were recorded and considered influential
- Not part of the design or model setup
- 3 of them were included in the analysis later on



Design choice

REQUIREMENTS

- As many as 8 factors → typically use a screening design
- Optimization & prediction \rightarrow typically use a response surface design
- → Minimum 3 levels per factor required
- → How to handle that many model effects?

CHOICE

What designs with 3 levels per factor exist that can cover both, screening and optimization, in one step instead of two and hence save a full DOE?

Design choice

An OMARS design was considered the best choice

OMARS designs?

Courtesy of Peter Goos, KU Leuven

- Experimental designs for quantitative factors
- Every factor is studied at three levels
- → Therefore, they are called response surface designs
- All main effects are orthogonal to each other
- → Therefore, they are called orthogonal designs
- All main effects are orthogonal to
 - -all two-factor interactions
 - -all quadratic effects
- → Therefore, they are called minimally aliased

Orthogonal Minimally Aliased Response Surface

Designs

OMARS designs that you might know already

Courtesy of Peter Goos, KU Leuven

Traditional response surface designs

- Central composite designs (axials on face)
- Box-Behnken designs

They are "strong" OMARS designs

- Interaction effects are orthogonal to each other
- Interaction effects are orthogonal to quadratic effects



Definitive screening designs (DSD)

- 3 levels per factor
- Much smaller than traditional RS designs
- Still screening designs but with the potential to do response surface modeling, IF effect sparsity applies
- Substantial aliasing among interactions
- Substantial aliasing between interactions and quadratics





Catalog of original OMARS designs

Courtesy of Peter Goos, KU Leuven

- Bridge the gap between small DSDs and large traditional RS designs
- Screening and response surface experiment in one, guaranteed
- Good projection properties
- Less aliasing
- Better power for quadratic effects

Catalog of OMARS designs

What's in there today?

- Three level designs for quantitative factors
- Mixed-levels: Quantitative factors can have 2 or 3 levels
 - Categorical factors with 2 levels possible
- Orthogonally blocked designs
- Orthogonality and minimal aliasing property are kept

→ Mixed-level OMARS design

Properties of the chosen design

- Uniform precision
- Good powers just weaker for quadratics
 price to pay for a small design size
- Prediction variances below 0.5



Effect	Relative estimate error
intercept	0.204
X1	0.223
X2	0.223
X3	0.223
X4	0.223
X5	0.223
X6	0.223
C7	0.204
C8	0.204

© 2023 W. L. Gore & Associates

Powers for alpha=0.05

model	effects	SNR=1	SNR=1.5
Intercept	main	0.989	0.999
ME	main	0.986	0.999
ME	interaction	0.96	0.995
ME	quadratic	0.403	0.556

Color map on correlations

Main effects orthogonal to

- Other main effects
- Two-factor interactions
- Quadratic effects

Please note: Factors on 3 levels are labeled X (X1 – X6), factors on 2 levels are labeled C (C7, C8)



© 2023 W. L. Gore & Associates

0

Color map on correlations

- Correlations between any pair of 2-factor interactions are <= 0.5
- Correlations between 2-factor interactions and quadratic effects are <= 0.54



		Polymeria	zation factor	S		Finishing factors					
	Process	Process	Chemical S	Chemical E	Acid	Composition	Polishing	Drying			
EU	Setting T	Setting P	amount	amount	amount	ratio	time	temperature			
	s1_x1	s1_x2	s1_x3	s1_x4	s2_x5	s2_x6	s2_x7	s2_x8			
1	-1	1	-1	1	1	1	-1	0			
2	-1	-1	-1	0	1	-1	1	-1			
3	1	0	1	-1	1	1	-1	-1			
4	1	0	-1	-1	-1	1	1	1			
5	0	-1		-1	1	1	1	-1			
6	-1	1		1	0	1	-1	1			
7	1	1	_		1	0	-1	1			
8	1	-1	Fre			0	-1	-1			
9	1	-1)Ari.			1	-1			
10	0		-	~'Im	lan,		1	1			
11	1				CIT	7/	_1	1			
12	1					רי DIA	-1	-1			
13	1		T				1	1			
14	-1	-1					1	1			
15	0	1	-1				1	-1			
16	-1	0	-1	1			1	1			
17	1	1	1	-1	-1		1	0			
18	-1	-1	1	-1	-1	U	1	-1			
19	-1	0	1	1	1	-1	-1	-1			
20	1	1	1	1	1	1	1	0			
21	0	1	1	1	-1	-1	-1	1			
22	-1	1	1	-1	1	0	1	1			
23	-1	1	1	0	-1	1	-1	-1			
24	-1	-1	-1	-1	-1	-1	-1	0			

		Polymeri	zation facto	rs		Finishin	g factors			Covariates		
	Process	Process	Chemical S	Chemical E	Acid	Composition	Polishing	Drying	Drying	Particle	TGA after	
EU	Setting T	Setting P	amount	amount	amount	ratio	time	temperature	oven	size	Poly	
	s1_x1	s1_x2	s1_x3	s1_x4	s2_x5	s2_x6	s2_x7	s2_x8	s2_z5	s2_z6	s2_z7	
1	-1	1	-1	1	1	1	-1	0	1	197	6,50	
2	-1	-1	-1	0	1	-1	1	-1	2	234	4,13	
3	1	0	1	-1	1	1	-1	-1	1	128	6,21	
4	1	0	-1	-1	-1	1	1	1	2	133	6,26	
5	0	-1		-1	1	1	1	-1	1	171	6,20	
6	-1	1			0	1	-1	1	2	247	5,06	
7	1	1				0	-1	1	1	170	5,99	
8	1	-1				0	-1	-1	2	153	6,56	(O) O
9	1	-1	<u>۲</u>	Xna.			1	-1	1	170	6,80	
10	0	-1		"PCI	Im_			1	2	238	5,76	
11	1	-1		Dhin		ntar		1	1	153	6,02	J Faka
12	1	1	4	rus	Co.	ral r)/~.	-1	2	299	5,41	
13	1	-1			UV	Ari~	'an	1	1	182	7,44	Campers
14	-1	-1		-		'''dta		1	2	265	6,73	
15	0	1	-1				3	-1	1	256	6,29	
16	-1	0	-1	1			1	1	2	154	4,99	
17	1	1	1	-1	-1		1	0	1	287	5,67	
18	-1	-1	1	-1	-1	0	1	-1	2	222	5,76	
19	-1	0	1	1	1	-1	-1	-1	1	124	5,33	
20	1	1	1	1	1	1	1	0	2	195	7,28	
21	0	1	1	1	-1	-1	-1	1	1	194	5,53	
22	-1	1	1	-1	1	0	1	1	2	128	5,03	
23	-1	1	1	0	-1	1	-1	-1	1	119	5,78	
24	-1	-1	-1	-1	-1	-1	-1	0	2	165	5,06	

Where do you get OMARS designs?



- Spin-off company for OMARS designs
- 500,000 OMARS Pareto-optimal designs are available in the web-based EFFEX[™] software
 - Three-level OMARS designs
 - Mixed-level OMARS designs
 - Orthogonally blocked OMARS designs
- Multi-criteria design selection
- José Nuñez Ares and Peter Goos



WANNA TAKE A BREATH? I DO!

STATISTICAL ANALYSIS

Model selection for a single response (particle size) after process step 1 (polymerization)

Plots with courtesy of José Nunez Ares

- Effects in the generated raster plot show how often and how strong each effect appears in the many models adjusted (166 and 155, resp.)
- Frequency approach for model selection
- Model candidates also available with standard transformations
- Here: clearer picture with no transformation



51 23 51 10 51 42 51 22 SIT

© 2023 W. L. Gore & Associates

Transformation

original	× 🔺
original	
sqrt	
log	
square	
inverse	

Model selection for a single response (particle size) after process step 1 (polymerization)

Plots with courtesy of José Nunez Ares

Model quality parallel coordinates plot

- Nine model performance criteria for filtering
- All in one graph







Model selection for a single response (particle size) after process step 1 (polymerization)

Plots with courtesy of José Nunez Ares

- Now: down-select one final model candidate from the many
- Two model selection criteria applied



f_pvalue aicc adjr2 press rmse 12 0.8217 0.7018 17.644k 22.383 0.59594 238.075 219,219 221,575 220 16k 0.5 10 0.4 0.2

1 0.013 -0.0319 5.593k 12.033 0.00013 201.267 193.786 202.825

Model selection for a single response (TGA after finishing) after process step 2 (finishing)

Plots with courtesy of José Nunez Ares

Same procedure after process step 2 – just with even more model effects





Model selection for a single response (TGA after finishing) after process step 2 (finishing)

Plots with courtesy of José Nunez Ares



residual vs predicted plot



Optimization for multiple responses

Plots with courtesy of José Nunez Ares

Chose the interval type for Probability of Success calculation										
O Confidence intervals	\odot Tolerance intervals									
Specification limits for the responses										
s2 v12	e2 v13	2.18	2 v11							
→	400 440 480 532.781	0	•••••							
⊖minimize ⊖maximize	\bigcirc minimize \bigcirc maximize \bigcirc on interval	\bigcirc minimize \bigcirc maximize \bigcirc on interval	\bigcirc minimize \bigcirc maximize \bigcirc on interval							

Optimization for multiple responses

Plots with courtesy of José Nunez Ares

POS = probability of success to meet all customer specifications



Optimization for multiple responses

Plots with courtesy of José Nunez Ares

Factor level settings for the five process stetting conditions with the highest POS (best)

s1_x1	s1_x2	s1_x3	s1_x4	s2_x5	s2_x6	s2_x7	s2_x8	s2_z5	s2_z7	s2_y8	s2_y12	s2_y13	PoS
-1	-1	1	-1	-1	-1	1	-1	-1	-1				0.87
-1	1	1	-1	-1	1	1	-1	-1	-1	roc	nonco	data	0.87
1	-1	-1	-1	1	1	-1	-1	1	-1	162	punse		0.86
-1	-1	-1	-1	-1	-1	1	-1	-1	-1		blinde	ea	0.86
1	-1	-1	1	1	1	-1	-1	-1	-1				0.85

Summary

- In a challenging case of product development, we found an efficient and powerful OMARS DOE that allowed us to combine screening and optimization steps into ONE, with a guarantee to get a clear analysis of the effects.
- In the analysis, we could study much more effects than in a more traditional DOE.
- The engineers could even learn about the effect of covariates that were not part of the design.

Acknowledgements to

My colleagues

- Philipp Meier, PE
- Kathrin Weger, PE
- Mihir Khadilkar, data scientist

Partners in finding and analyzing OMARS designs

- José Nunez Ares, EFFEX
- Peter Goos, KU Leuven

THANK YOU

Together, improving life

