


Streamlined Models for Combined Mixture-Process Designs

KCV Models (Kowalski, Cornell and Vining)

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KCV Model

Combining Mixture and Process Variables




- KCV models for combining mixture and process variables.
 - Example ($3M+2P$)
 - Exercise (*cordogs*)

1. Scott Kowalski, John A. Cornell & G. Geoffrey Vining (2000) A new model and class of designs for mixture experiments with process variables, *Communications in Statistics - Theory and Methods*, 29:9-10, 2255-2280.
2. Mark Anderson, Pat Whitcomb and Martin Bezener (2018), *Formulation Simplified*, Productivity Press, appendix 9A, chapter 9.

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Agenda




- **KCV models for combining mixture and process variables.**
 - Example (3M+2P)
 - Exercise (corndogs)

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Crossed Model
Combining Mixture and Process



The big reason to combine mixture components and process factors in a single DOE is to model the dependence of one on the other. The crossed model is the ultimate realization of this.

Mixture quadratic: $\eta(x) = \sum_{i=1}^q \beta_i x_i + \sum_{i < j} \beta_{ij} x_i x_j$

Process quadratic: $\eta(z) = \alpha_0 + \sum_{k=1}^n \alpha_k z_k + \sum_{k < l} \alpha_{kl} z_k z_l + \sum_{k=1}^n \alpha_{kk} z_k^2$

Crossed quadratic by quadratic model:

$$\eta(x, z) = \sum_{i=1}^q \beta_i x_i + \sum_{i < j} \beta_{ij} x_i x_j + \sum_{i=1}^q \sum_{k=1}^n \gamma_{ik} x_i z_k + \sum_{i < j} \sum_{k=1}^n \gamma_{ijk} x_i x_j z_k + \sum_{i=1}^q \sum_{k < l} \sum_{l=1}^n \gamma_{ikl} x_i z_k z_l$$

$$+ \sum_{i < j} \sum_{k < l} \sum_{l=1}^n \gamma_{ijkl} x_i x_j z_k z_l + \sum_{i=1}^q \sum_{k=1}^n \gamma_{ikk} x_i z_k^2 + \sum_{i < j} \sum_{k=1}^n \gamma_{ijkk} x_i x_j z_k^2$$

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Additive Model

Combining Mixture and Process



The advantage of an additive model is fewer coefficients, therefore fewer runs are required. However, the ability to model the dependence of mixture components and process factors on one another is lost.

$$\text{Mixture quadratic: } \eta(x) = \sum_{i=1}^q \beta_i x_i + \sum_{i < j} \sum_{j}^q \beta_{ij} x_i x_j$$

$$\text{Process quadratic: } \eta(z) = \alpha_0 + \sum_{k=1}^n \alpha_k z_k + \sum_{k < l} \sum_{l}^n \alpha_{kl} z_k z_l + \sum_{k=1}^n \alpha_{kk} z_k^2$$

Additive quadratic and quadratic model:

$$\eta(x, z) = \sum_{i=1}^q \beta_i x_i + \sum_{i < j} \sum_{j}^q \beta_{ij} x_i x_j + \sum_{k=1}^n \alpha_k z_k + \sum_{k < l} \sum_{l}^n \alpha_{kl} z_k z_l + \sum_{k=1}^n \alpha_{kk} z_k^2$$

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Crossed vs Additive

Combining Mixture and Process



The crossed model:

- Completely links the mixture components and process factors. *I.e. all model terms are crossed.*
- This requires lots of coefficients (therefore lots of runs).

The additive model:

- Has a smaller model (requires fewer runs).
- Does not link the mixture and process factors. It does not contain any cross product terms.
- Might as well do separate designs on the mixture components and process factors.


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KCV Model

Compromise Model



A compromise model was proposed by Kowalski, Cornell and Vining¹. In their approach the linear models are crossed and higher order terms are additive.

Cross linear models:

$$\left(\eta(x) = \sum_{i=1}^q \beta_i x_i \times \eta(z) = \beta_0 + \sum_{k=1}^n \beta_k z_k \right) \rightarrow \eta(x, z) = \sum_{i=1}^q \beta_i x_i + \sum_{i=1}^q \sum_{k=1}^n \gamma_{ik} x_i z_k$$

Add second order terms:

Mix: $\sum_{i < j} \beta_{ij} x_i x_j$ Process: $\sum_{k < l} \alpha_{kl} z_k z_l + \sum_{k=1}^n \alpha_{kk} z_k^2$

KVC combined model:

$$\eta(x, z) = \sum_{i=1}^q \beta_i x_i + \sum_{i < j} \beta_{ij} x_i x_j + \sum_{i=1}^q \sum_{k=1}^n \gamma_{ik} x_i z_k + \sum_{k < l} \alpha_{kl} z_k z_l + \sum_{k=1}^n \alpha_{kk} z_k^2$$


Red terms from crossed linear models, **Blue** terms are additive.

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KCV Model

Compromise Model (3-Mix + 2-Process)



E.g.: If we had three mixture components and two process factors, the quadratic by quadratic KCV model is:

$$\eta(x) = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{23} x_2 x_3$$

$$\eta(z) = \beta_0 + \beta_1 z_4 + \beta_1 z_5 + \beta_{45} z_4 z_5 + \beta_{44} z_4^2 + \beta_{55} z_5^2$$

$$\eta(x, z) = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3$$

$+ \beta_{14} x_1 z_4 + \beta_{24} x_2 z_4 + \beta_{34} x_3 z_4$
 $+ \beta_{15} x_1 z_5 + \beta_{25} x_2 z_5 + \beta_{35} x_3 z_5$

}

Red crossed linear models

$+ \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{23} x_2 x_3$
 $+ \beta_{45} z_4 z_5 + \beta_{44} z_4^2 + \beta_{55} z_5^2$

}


Blue terms are additive

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KCV versus Additive Model

Compromise Model (3-Mix + 2-Process)




KCV Model 15 terms	Additive Model 11 terms
$\eta(x, z) = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3$	$\eta(x, z) = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3$
$+ \beta_{14} x_1 z_4 + \beta_{24} x_2 z_4 + \beta_{34} x_3 z_4$	$+ \beta_{12} x_1 x_2 + \beta_{12} x_1 x_3 + \beta_{23} x_2 x_3$
$+ \beta_{15} x_1 z_5 + \beta_{25} x_2 z_5 + \beta_{35} x_3 z_5$	$+ \alpha_1 z_1 + \alpha_2 z_2$
$+ \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{23} x_2 x_3$	$+ \alpha_{12} z_1 z_2 + \alpha_{11} z_1^2 + \alpha_{22} z_2^2$
$+ \beta_{45} z_4 z_5 + \beta_{44} z_4^2 + \beta_{55} z_5^2$	

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KCV versus Crossed Model

Compromise Model (3-Mix + 2-Process)




KCV Model 15 terms	Crossed Model 36 terms
$\eta(x, z) = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3$	$\eta(x, z) = \sum_{i=1}^q \beta_i x_i + \sum_{i < j} \sum_{j=1}^q \beta_{ij} x_i x_j$
$+ \beta_{14} x_1 z_4 + \beta_{24} x_2 z_4 + \beta_{34} x_3 z_4$	$+ \sum_{i=1}^q \sum_{k=1}^n \gamma_{ik} x_i z_k + \sum_{i < j} \sum_{k=1}^n \sum_{l=1}^n \gamma_{ijk} x_i x_j z_k$
$+ \beta_{15} x_1 z_5 + \beta_{25} x_2 z_5 + \beta_{35} x_3 z_5$	$+ \sum_{i=1}^q \sum_{k < l} \sum_{l=1}^n \gamma_{ikl} x_i z_k z_l + \sum_{i < j} \sum_{k < l} \sum_{l=1}^n \gamma_{ijkl} x_i x_j z_k z_l$
$+ \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{23} x_2 x_3$	$+ \sum_{i=1}^q \sum_{k=1}^n \gamma_{ikk} x_i z_k^2 + \sum_{i < j} \sum_{k=1}^n \sum_{l=1}^n \gamma_{ijkk} x_i x_j z_k^2$
$+ \beta_{45} z_4 z_5 + \beta_{44} z_4^2 + \beta_{55} z_5^2$	

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Kowalski, Cornell and Vining

KCV Combined Models




Mixture Components	Process Factors	Crossed Q by Q	Q by Q max cubic	KCV Q by Q	Additive Q plus Q
2	2	18	15	10	8
3	2	36	27	15	11
4	2	60	42	21	15
3	3	60	42	21	15
4	3	100	64	28	19
5	3	150	90	36	24
4	4	150	90	36	24
5	4	225	125	45	29
6	4	315	165	55	35

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KCV Model

Alternative to Ratios



KCV Model

$$\eta(x,z) = \beta_1x_1 + \beta_2x_2 + \beta_3x_3$$

$$+ \beta_{14}x_1z_4 + \beta_{24}x_2z_4 + \beta_{34}x_3z_4$$

$$+ \beta_{15}x_1z_5 + \beta_{25}x_2z_5 + \beta_{35}x_3z_5$$

$$+ \beta_{12}x_1x_2 + \beta_{13}x_1x_3 + \beta_{23}x_2x_3$$

$$+ \beta_{45}z_4z_5 + \beta_{44}z_4^2 + \beta_{55}z_5^2$$

Ratio Model

$$\eta(R,z) = \beta_0 + \beta_1R_1 + \beta_2R_2 + \beta_3z_3 + \beta_4z_4$$

$$+ \beta_{13}R_1z_3 + \beta_{14}R_1z_4$$

$$+ \beta_{23}R_2z_3 + \beta_{24}R_2z_4$$


$$+ \beta_{12}R_1R_2 + \beta_{11}R_1^2 + \beta_{22}R_2^2$$

$$+ \beta_{34}z_3z_4 + \beta_{33}z_3^2 + \beta_{44}z_4^2$$

Models have the same number of coefficients and similar **linear by linear links** between the components and factors.

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Agenda 

- **KCV models for combining mixture and process variables.**
 - **Example (3M+2P)**
 - Exercise (*corndogs*)

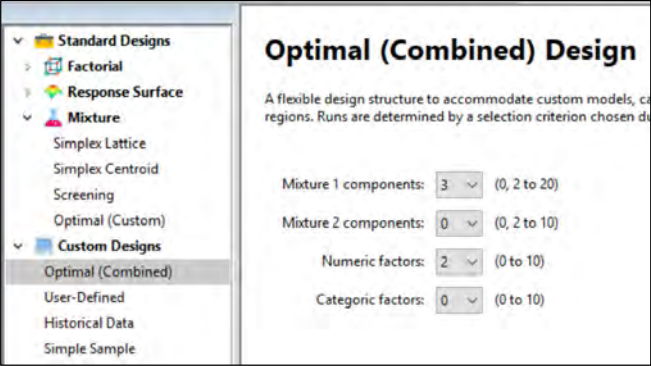
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3 Mixture + 2 Process Variables 
 KCV Model - Build *(page 1 of 4)*

Build a three component mixture with two process using a KCV model:

1. Three mixture components and two process factors:




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3 Mixture + 2 Process Variables

KCV Model - Build *(page 2 of 4)*



2. Enter the mixture components:

Mixture 1 components: 3

Total: Horizontal Vertical

Units:

	Name	Change	Low	High
A [Mixture]	A	Easy	0.25	0.6
B [Mixture]	B	Easy	0.1	0.4
C [Mixture]	C	Easy	0.2	0.6


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3 Mixture + 2 Process Variables

KCV Model - Build *(page 3 of 4)*



3. Enter the process factors:

Numeric factors: 2 Horizontal Vertical

Categoric factors: 0 Vertical

	Name	Units	Change	Type	Levels	L[1]	L[2]
D [Numeric]	D		Easy	Continuous	N/A	-1	1
D [Numeric]	E		Easy	Continuous	N/A	-1	1

KCV models

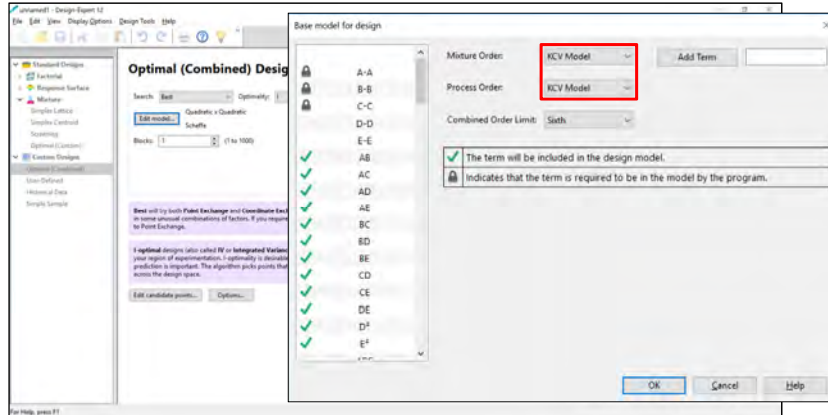
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3 Mixture + 2 Process Variables KCV Model - Build (page 4 of 4)



4. Change the model, “Edit model...”, to “KCV Model” by “KCV Model”:



OK Next >> Finish

KCV models

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3 Mixture + 2 Process Variables KCV Model – Simulate and Analyze



1. Right click on the response (R1) column header then “Simulate...” to “Load an existing simulation” and open “KCV MP combined.simx”.
2. Analyze and model octane.
3. Find the composition and the process factor settings that maximize R1.

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3 Mixture + 2 Process Variables KCV Model – Design



Run	Component 1 A:A	Component 2 B:B	Component 3 C:C	Factor 4 D:D	Factor 5 E:E	Response 1 R1
1	0.548053	0.251947	0.2	-0.04	-0.9	82.05
2	0.404171	0.213959	0.381869	0	1	75.65
3	0.25	0.4	0.35	1	-1	99.54
4	0.25	0.15	0.6	-0.05	-0.03	68.87
5	0.4	0.4	0.2	-1	-1	71.53
6	0.404763	0.212816	0.382421	1	0	98.35
7	0.6	0.2	0.2	-1	1	31.51
8	0.25	0.4	0.35	-1	1	55.67
9	0.404763	0.212816	0.382421	1	0	87.98
10	0.487379	0.1	0.412621	-1	0.06	64.48
11	0.264633	0.4	0.335367	-0.44	-0.35	84.1
12	0.6	0.1685	0.2315	0.1	0.1	81.39
13	0.404171	0.213959	0.381869	0	1	83.63
14	0.6	0.1	0.3	-1	-1	60.04
15	0.404171	0.213959	0.381869	0	1	75.26
16	0.3	0.1	0.6	1	-1	84.21
17	0.6	0.2	0.2	1	-1	102
18	0.25	0.15	0.6	1	1	81.36
19	0.3	0.1	0.6	-1	1	61.97
20	0.6	0.1	0.3	1	1	95.39
21	0.6	0.1685	0.2315	0.1	0.1	89.53
22	0.328236	0.109588	0.562176	0.01	-1	84.23
23	0.4	0.4	0.2	1	1	62.41
24	0.404763	0.212816	0.382421	1	0	95.14
25	0.25	0.20625	0.54375	-1	-1	79.71

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3 Mixture + 2 Process Variables KCV Model – Fit Summary



Mixture Order	Process Order	Mixture p-value	Process p-value	Lack of Fit p-value	Adjusted R ²	Predicted R ²	
M	M						
M	L	< 0.0001	0.0470	0.6012	0.5072		
M	2P	0.5198	0.0427	0.5868	0.4238		
M	Q	0.2890	0.0489	0.5962	0.4193		
M	C	0.8398	0.0279	0.5357	0.1354		
L	M	0.0737		0.0047	-0.0885	-0.2288	
L	L	0.0355	< 0.0001	0.1088	0.7435	0.4168	Suggested
L	2P	0.0734	0.5161	0.0874	0.7335	-1.4142	
L	Q	0.0740	0.1724	0.1134	0.8249	-12.9687	
L	C	0.0279	0.1124		0.8974		Aliased
Q	M	0.5507		0.0040	-0.1318	-0.6052	
Q	L	0.1860	0.0024	0.1336	0.8360	-9.1454	
Q	2P	0.0874	0.1356		0.8974		Aliased
Q	C	0.1134			0.8974		Aliased
Q	C				0.8974		Aliased
SC	M	0.4723		0.0036	-0.1569	-0.6371	
SC	L	0.1336	0.0036		0.8974		Aliased
SC	2P				0.8974		Aliased
SC	Q				0.8974		Aliased
SC	C				0.8974		Aliased
C	M	0.9915	0.0021	-0.3843	-1.9252		
C	L		0.0021		0.8974		Aliased
C	2P				0.8974		Aliased
C	Q				0.8974		Aliased
C	C				0.8974		Aliased

Model	Lack of Fit p-value	Adjusted R ²	Predicted R ²	Recommended	
Design Model	0.0001	0.3425	0.8735	0.1565	Recommended

Suggested Models

Order Abbreviations in Fit Summary Table:

Mean Linear Quadratic Special Cubic Cubic

M L Q SC C

Design Model Order: KCV

Design Model is recommended over Suggested Models

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3 Mixture + 2 Process Variables KCV Model – Model Reduction



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3 Mixture + 2 Process Variables KCV Model – ANOVA



Source	Sum of Squares	df	Mean Square	F-value	p-value
Model	3879.04	9	431.00	24.83	< 0.0001 significant
Linear Mixture	34.00	2	17.00	0.2664	0.7697
AC	273.93	1	273.93	16.40	0.0017
AD	2566.51	1	2566.51	148.40	< 0.0001
AE	138.17	1	138.17	5.26	0.0287
BC	194.78	1	194.78	7.41	0.0157
BE	972.98	1	972.98	37.01	< 0.0001
CD	248.83	1	248.83	9.39	0.0079
D ²	152.18	1	152.18	5.79	0.0285
Residual	394.29	15	26.29		
Lack of Fit	260.17	10	26.02	0.9698	0.5501 not significant
Pure Error	134.12	5	26.82		
Cor Total	6272.24	24			

Std. Dev.	R ²
5.13	0.9371
Mean	Adjusted R ²
79.24	0.8994
C.V. %	Predicted R ²
6.53	0.7949
	Ades Precision
	21.0500

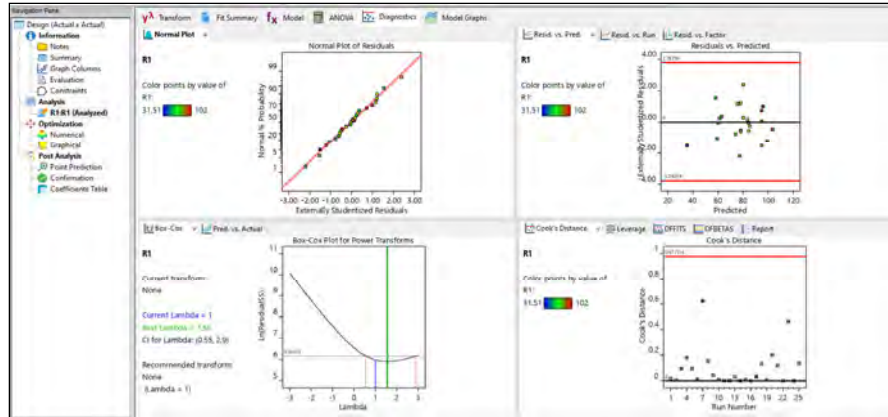
Component	Coefficient Estimate	Standard Error	95% CI Low	95% CI High	VF
A-A	76.41	3.88	68.14	84.68	3.05
B-B	68.96	6.26	55.61	82.30	4.39
C-C	72.08	3.78	64.01	80.15	3.27
AC	56.15	17.41	19.04	93.26	3.26
AD	29.99	3.02	23.54	36.43	1.15
AE	-7.23	3.15	-13.56	-0.5085	1.29
BC	58.04	21.32	12.59	103.49	4.39
BE	-23.32	8.83	-31.49	-15.15	1.28
CD	8.41	2.74	3.56	14.26	1.15

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3 Mixture + 2 Process Variables KCV Model – Diagnostics

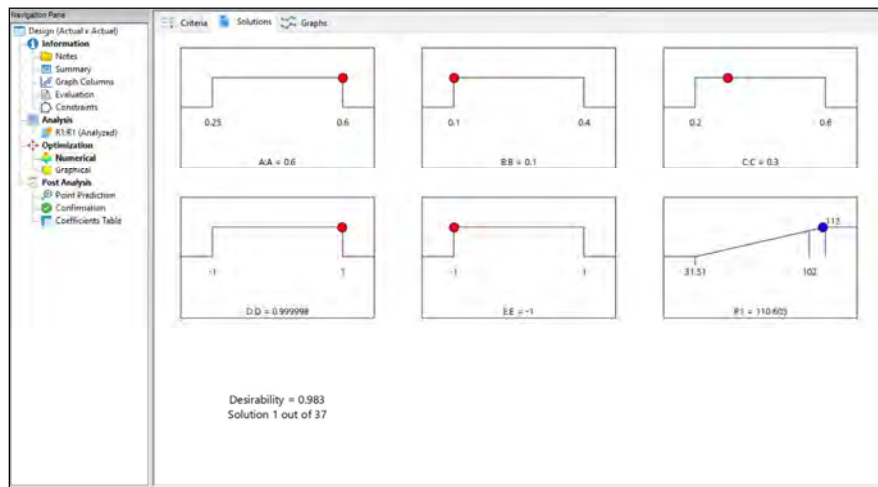


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3 Mixture + 2 Process Variables KCV Model – Numerical Optimization



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3 Mixture + 2 Process Variables Designing for KCV Model



- The additive quadratic model has 11 coefficients.
NO linkage between mixture components and process factors.
- The KCV quadratic model has 15 coefficients.
The linkage between mixture components and process factors is the component by factor interactions.
- The quadratic crossed model has 36 coefficients.
The linkage between mixture components and process factors is complete; i.e. all terms are crossed.
- The quadratic crossed model limited to cubic terms to has 27 terms.
The linkage between mixture components and process factors is intermediate between KCV and crossed.

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Agenda



- **KCV models for combining mixture and process variables.**
 - **Example (3M+2P)**
 - **Exercise (corndogs)**


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Corn Dogs

Combined Mixture Process Design





Vary four of the ingredients:

Components	Varied	Ingredients	Fixed
Flour	7 to 9 oz.	Baking powder	1½ teaspoons
Cornmeal	4 to 7 oz.	Salt	1 teaspoon
Sugar	1.5 to 2.5 oz.	Egg (beaten)	1
Buttermilk	9 to 11 oz.	Baking soda	½ teaspoon

Vary three process factors:


Process factors	Range
Temperature (<i>oven</i>)	175 to 195 degrees C
Time (<i>oven</i>)	3 to 5 minutes
Deep fry	45 to 75 seconds


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Corn Dogs

Combined Mixture Process Design





Model Choices

Mixture	Process	Type	Coefficients
Quadratic	Quadratic	Crossed	100
Quadratic	Quadratic	Crossed (max cubic)	64
Quadratic	2FI	Crossed	70
Quadratic	Linear	Crossed	40
Quadratic	Quadratic	KCV	28
Quadratic	Quadratic	Additive	20 (10+10)


Choose KCV model


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Building a Design (KCV model)

Corn Dogs (page 1 of 5)





1. Set up an Optimal combined design with 4 mixture components and 3 numeric factors:

- Standard Designs
- Factorial
- Response Surface
- Mixture
 - Simplex Lattice
 - Simplex Centroid
 - Screening
 - Optimal (Custom)
- Custom Designs
 - Optimal (Combined)**
 - User-Defined
 - Historical Data
 - Simple Sample

Optimal (Combined) Design

A flexible design structure to accommodate custom models, constraints, and regions. Runs are determined by a selection criterion chosen by the user.

Mixture 1 components: (0, 2 to 20)

Mixture 2 components: (0, 2 to 10)

Numeric factors: (0 to 10)

Categoric factors: (0 to 10)


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Building a Design (KCV model)

Corn Dogs (page 2 of 5)





2. Enter the mixture components:

Optimal (Combined) Design

Mixture 1 components: 4

Total: Horizontal

Units: Vertical

	Name		Low	High
A [Mixture]	Flour	Easy	7	9
B [Mixture]	Cornmeal	Easy	4	7
C [Mixture]	Sugar	Easy	1.5	2.5
D [Mixture]	Buttermilk	Easy	9	11

[Edit constraints...](#)


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Building a Design (KCV model)

Corn Dogs (page 3 of 5)





3. Enter the numeric factors

Optimal (Combined) Design

Numeric factors: 3 Horizontal

Categoric factors: 0 Vertical


	Name	Units	Change	Type	Levels	L[1]	L[2]
E [Numeric]	Temperature	deg C	Easy	Continuous	N/A	175	195
F [Numeric]	Time	minutes	Easy	Continuous	N/A	3	5
G [Numeric]	Deep fry	Seconds	Easy	Continuous	N/A	45	75


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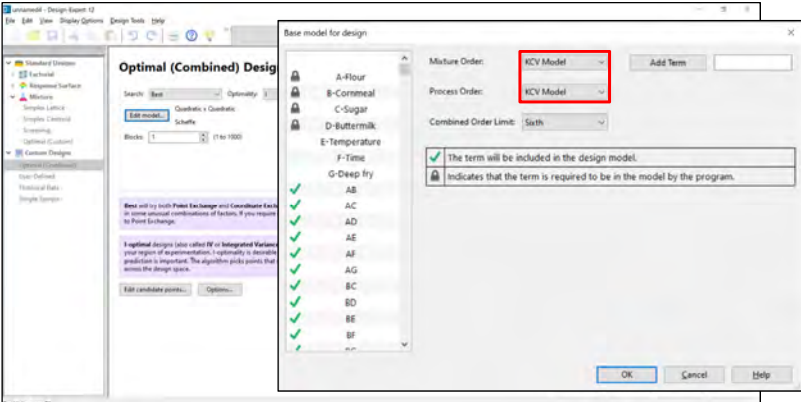
Building a Design (KCV model)

Corn Dogs (page 4 of 5)





4. Change the model, "Edit model...", to "KCV Model" by "KCV Model":




and then


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Building a Design *(KCV model)*

Corn Dogs *(page 5 of 5)*





8. Enter the responses:

Responses: (1 to 999)

	Name	Units
	Taste	1 - 5
	Texture	1 - 5


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Corn Dogs

Analyze and Optimize





1. Right click on the column header of the response and **“Simulate...”** to **“Load an existing simulation”** and open **“corn dog KCV.simx”**.
2. Analyze – *Hint: Use “AICc” with “Backward” selection.*
3. Optimize:
 - Maximize Taste: lower limit = 3, upper limit = 5
 - Maximize Texture : lower limit = 3, upper limit = 5

Scale for responses (compared to competitor's corn dog):

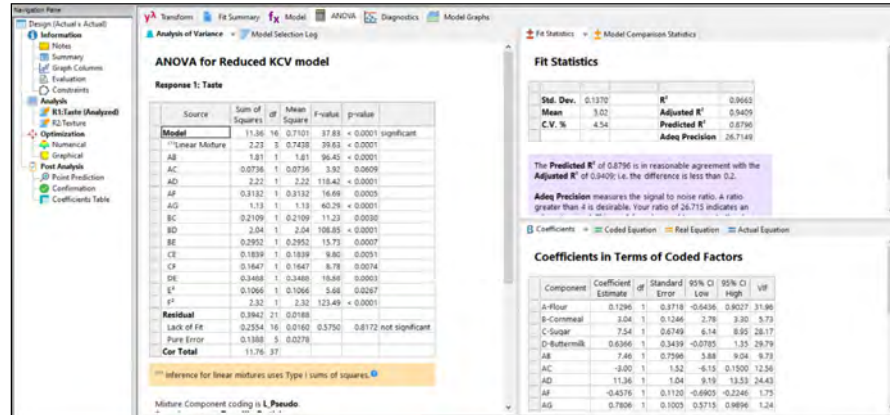
 1. worse
 2. somewhat worse
 3. same as competition
 4. somewhat better
 5. better

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Corn Dogs Reduced KCV Model – Taste

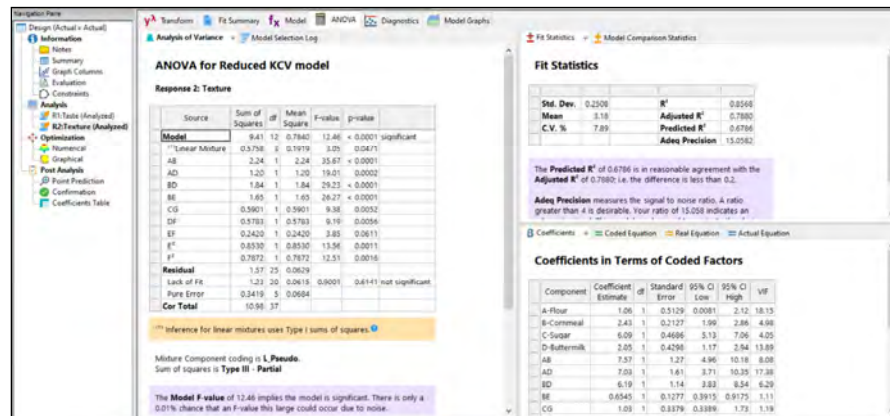


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Corn Dogs Reduced KCV Model – Texture




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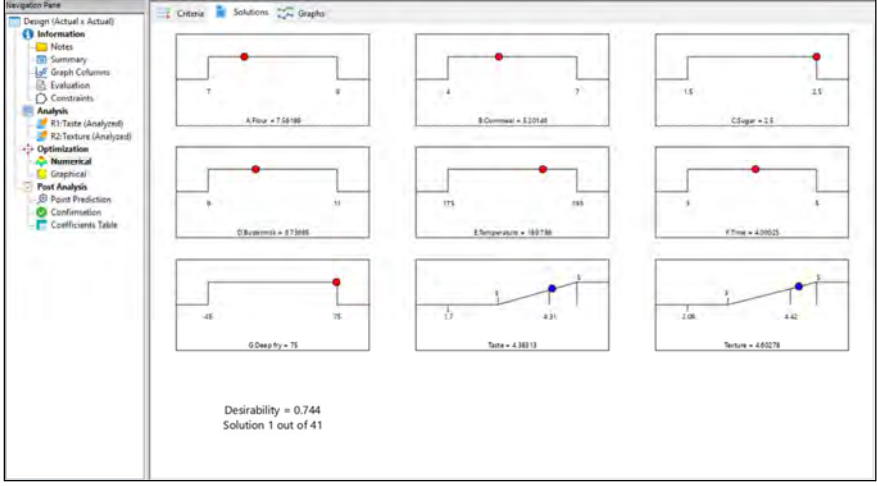
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Corn Dogs

KCV Model – Numerical Optimization









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Corn Dogs

KCV Model – Summary





- The additive quadratic model has 20 coefficients.
NO linkage between mixture components and process factors.
- The KCV quadratic model has 28 coefficients.
The linkage between mixture components and process factors is the component by factor interactions.
- The quadratic crossed model has 100 coefficients.
The linkage between mixture components and process factors is complete; i.e. all terms are crossed.
- The quadratic crossed model limited to cubic terms to has 64 terms.
The linkage between mixture components and process factors is intermediate between KCV and crossed.

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What's Next?



- ✓ Next Up: Webinar on “Multiple Response Optimization” in May 2020
- ✓ Watch previously recorded webinars from our website
(*see next slide for some of my favorite topics*)
- ✓ Attend a public workshop, or bring us on-site!

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Recorded Webinars

Existing DX features



- Sizing for precision.
Webinars: *Sizing Mixture (RSM) Designs for Adequate Precision via Fraction of Design Space (FDS)* and *Unleashing Evaluation: Giving Perspective to Power, Precision, and Problems*.
- Multilinear constraints (MLCs) and non-linear constraints.
Webinar: *Advanced Tools for Building Designs for Irregularly Shaped DOE Spaces*.
- Propagation of error (POE).
Webinar: *Overview of Robust Design, Propagation of Error, and Tolerance Analysis*.
- Optimization using Cpk and Ppk.
Webinar: *Practical DOE – “Tricks of the Trade”*.
- Using intervals to frame your operating space.
Webinar: *Quality by Design (QbD) Space for Pharmaceuticals and Beyond*.

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Thank You for Attending!

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