

KOREA 2021

DISCOVERY SUMMIT

EXPLORING DATA
INSPIRING INNOVATION



최적화 방법의 새로운 접근

- Rubber Track 내구성 향상을 위한 Rubber Compound 개발 사례

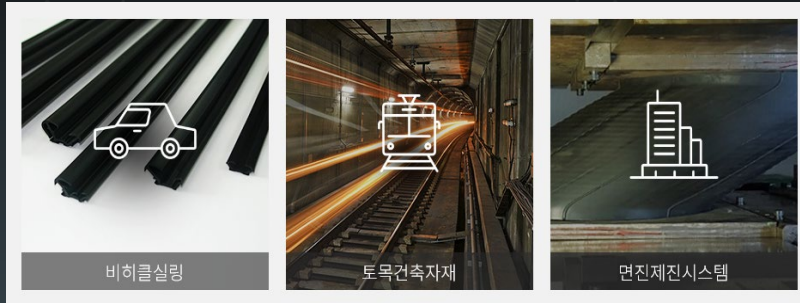


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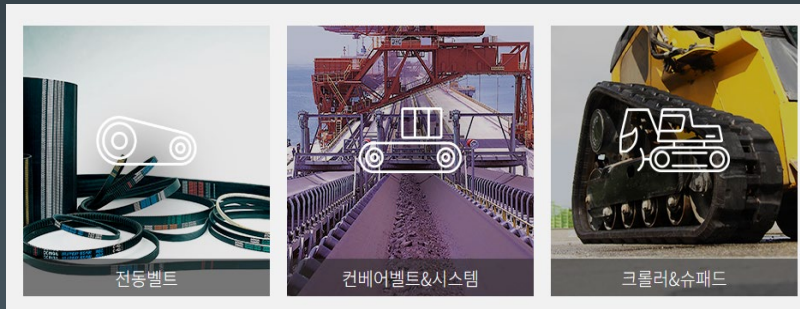
- Introduction
- Rubber track Tread Process
- DOE Concept
- 1st DOE and Result
- 2nd DOE and Result
- Summary of 1st, 2nd DOE
- 3rd DOE(Custom Design) and Result
- Conclusion

Introduction

- 주식회사 DRB동일



- 동일고무벨트 주식회사



Introduction



Introduction



CRS : 사용시간 25% 향상

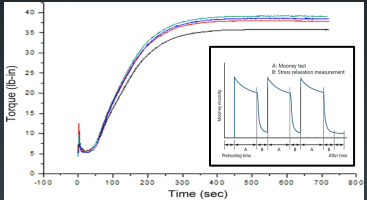
Rubber track Tread Process

Ingredients(x1~x6)



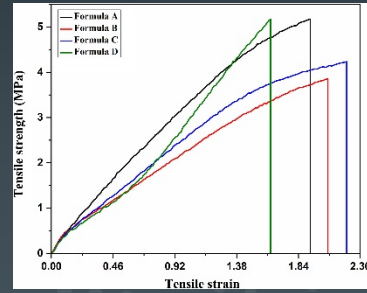
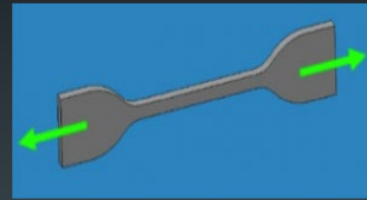
Weighing

Output : y4~y7



Mixing

Output : y1,y2,y3



Physical property test

Final Out put : Durability



Using time(hrs)

DOE Concept

Factor	Level	Response
X1	4	Y1
X2	3	Y2
X3	2	Y3
X4	2	Y4
X5	2	Y5
X6	2	Y6
		Y7



Full factorial Design → n = 192

Factor	Level	Factor	Level
X1	4	X1	Fixed
X2	3	X2	
X3	Fixed	X3	2
X4		X4	2
X5		X5	2
X6		X6	2

Full factorial Design
1st DOE → n = 12 Full factorial Design
2nd DOE → n = 54

Factor	Level
X1	4
X2	3
X3	2
X4	2
X5	2
X6	2

Custom Design
3rd DOE → n = 48

1st DOE Design

Factor

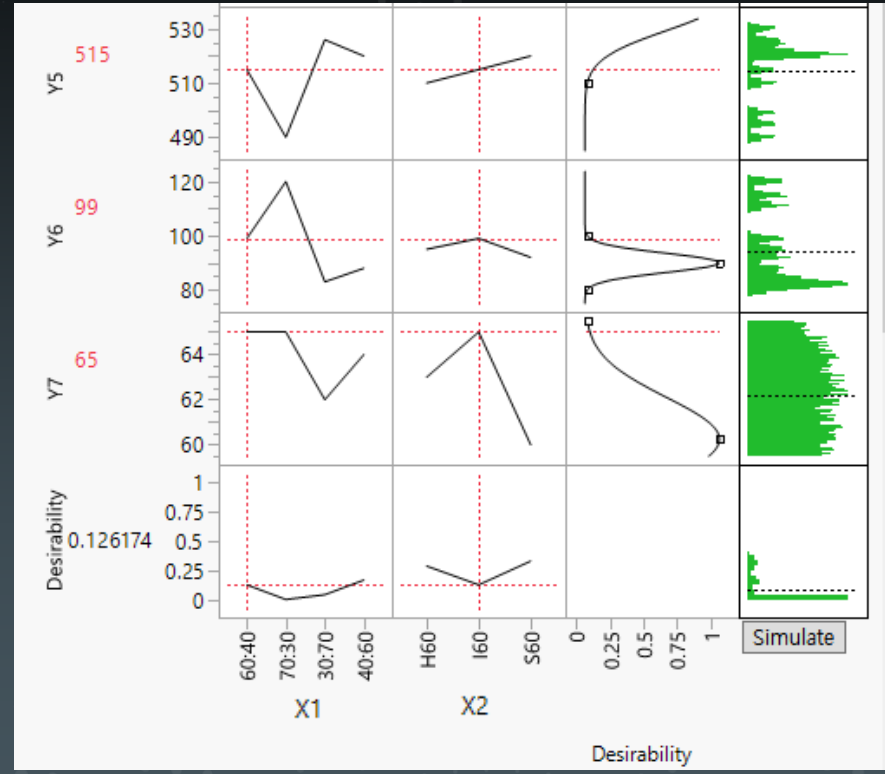
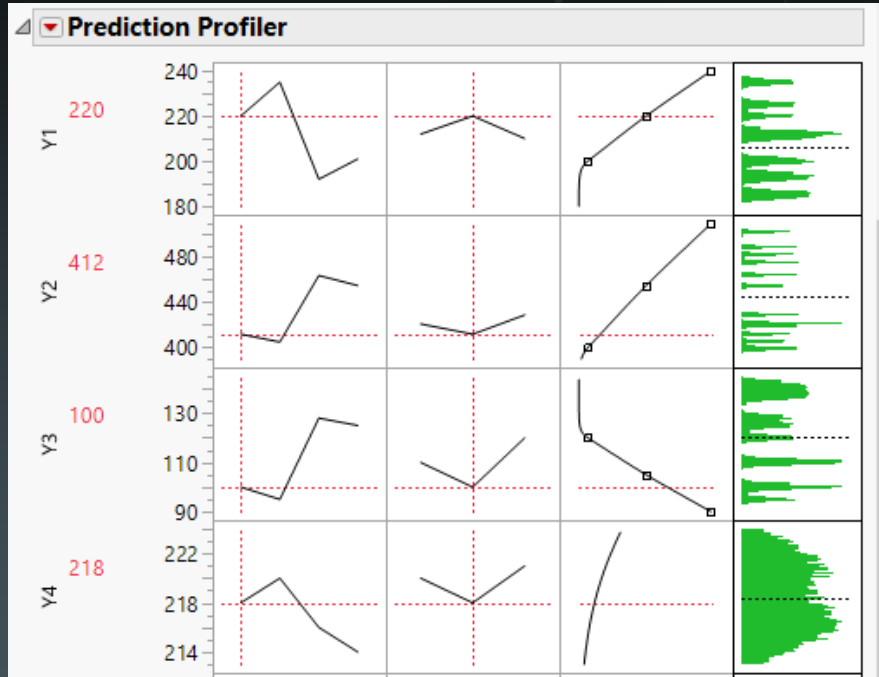
	X1	X2
1	60:40	H60
2	70:30	I60
3	30:70	S60
4	40:60	

Response

	Response Name	Lower Limit	Upper Limit	Response Goal	Importance
1	Y1	200		• Maximize	3
2	Y2	400		• Maximize	3
3	Y3		• 120	Minimize	5
4	Y4	210	270	Match Target	1
5	Y5	510	570	Match Target	1
6	Y6	80	100	Match Target	10
7	Y7	55		• Match Target	0.5

Design		
Run	X1	X2
1	30:70	I60
2	60:40	S60
3	70:30	S60
4	70:30	H60
5	40:60	S60
6	30:70	H60
7	60:40	I60
8	40:60	I60
9	30:70	S60
10	60:40	H60
11	40:60	H60
12	70:30	I60

1st DOE Results



2nd DOE Design

Model Specification

Select Columns

▼ 12 Columns

- Pattern
- X1
- X2
- X3
- X4
- Y1
- Y2
- Y3
- Y4
- Y5
- Y6
- Y7

Pick Role Variables

Y

- Y1
- Y2
- Y3
- Y4

Weight

Freq

By

Personality: Standard Least Squares

Emphasis: Effect Screening

Fit Separately

Help Run

Recall Keep dialog open

Remove

Construct Model Effects

Add X1

Cross X2

Nest X3

Macros X4

Degree X1*X2

Attributes X1*X3

Transform X2*X3

No Intercept X1*X4

X2*X4

X3*X4

2nd DOE Design

Screening Design

Responses

Add Response ▼ Remove Number of Responses...

Response Name	Goal	Lower Limit	Upper Limit	Importance
Y1	Maximize	200	.	3
Y2	Maximize	400	.	3
Y3	Minimize	.	120	5
Y4	Match Target	210	270	3
Y5	Match Target	510	570	1
Y6	Match Target	80	100	5
Y7(ML)	Match Target	55	65	1

Factors

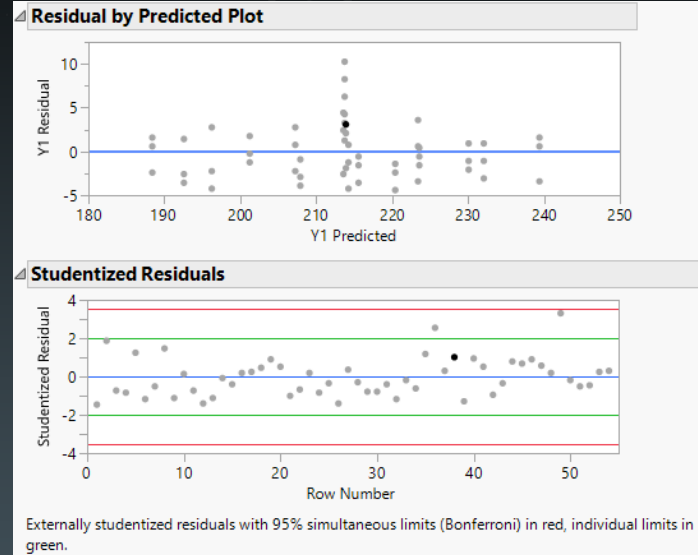
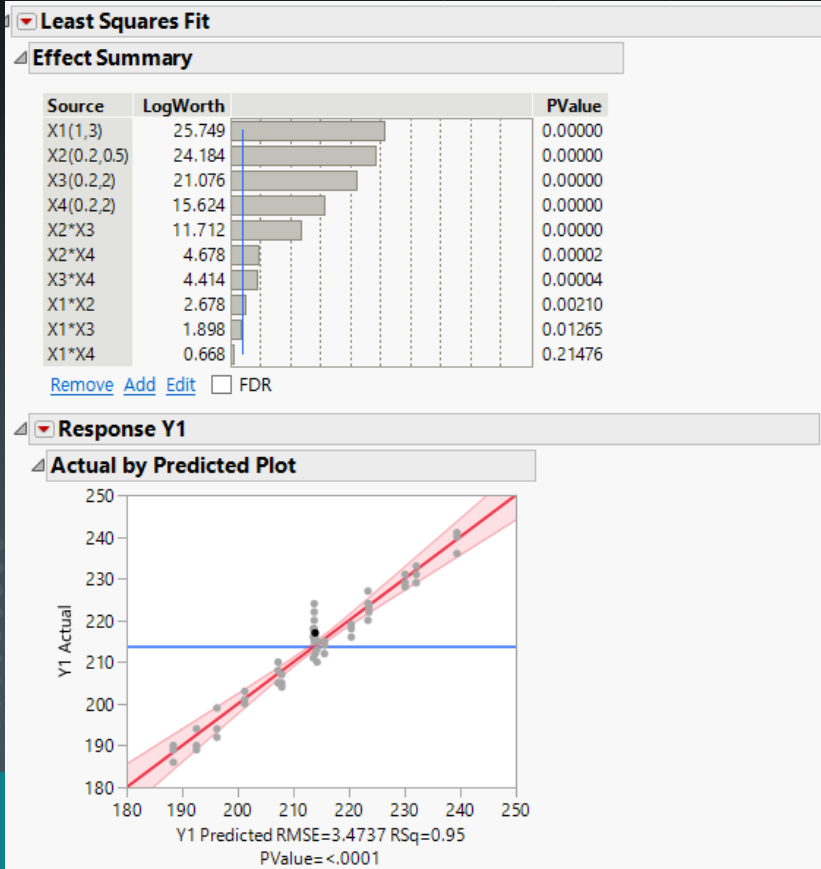
Continuous Discrete Numeric ▼ Categorical ▼ Remove Add N Factors 1

Name	Role	Values
X1	Continuous	1 3
X2	Continuous	0.2 0.5
X3	Continuous	0.2 2
X4	Continuous	0.2 2

Design

Run	X1	X2	X3	X4
1	3	0.2	2	2
2	2	0.35	1.1	1.1
3	1	0.5	0.2	0.2
4	3	0.2	2	0.2
5	2	0.35	1.1	1.1
6	1	0.5	0.2	2
7	3	0.5	0.2	0.2
8	3	0.2	2	0.2
9	3	0.5	2	2
10	3	0.5	0.2	0.2
11	1	0.2	0.2	2
12	1	0.2	0.2	2
13	1	0.5	2	2
14	1	0.2	2	2
15	1	0.5	2	2
16	1	0.2	2	2
17	1	0.5	2	2
18	1	0.2	2	2
19	1	0.5	2	2
20	1	0.2	2	2
21	1	0.5	2	2
22	1	0.2	2	2
23	1	0.5	2	2
24	1	0.2	2	2
25	1	0.5	2	2
26	1	0.2	2	2
27	1	0.5	2	2
28	1	0.2	2	2
29	1	0.5	2	2
30	1	0.2	2	2
31	1	0.5	2	2
32	1	0.2	2	2
33	1	0.5	2	2
34	1	0.2	2	2
35	1	0.5	2	2
36	1	0.2	2	2
37	1	0.5	2	2
38	1	0.2	2	2
39	1	0.5	2	2
40	1	0.2	2	2
41	1	0.5	2	2
42	1	0.2	2	2
43	1	0.5	2	2
44	1	0.2	2	2
45	1	0.5	2	2
46	1	0.2	2	2
47	1	0.2	2	2
48	1	0.5	2	2
49	2	0.35	1.1	1.1
50	1	0.5	0.2	2
51	1	0.5	0.2	2
52	3	0.2	2	2
53	1	0.5	2	0.2
54	3	0.5	0.2	2

2nd DOE Result



2nd DOE Result

	X1	X2	X3	X4	Desirability
	Random	Random	Random	Random	
	Normal	Normal	Normal	Normal	
Mean	2.07381	0.5	2	2	
SD	0.2	0.06	0.2	0.2	

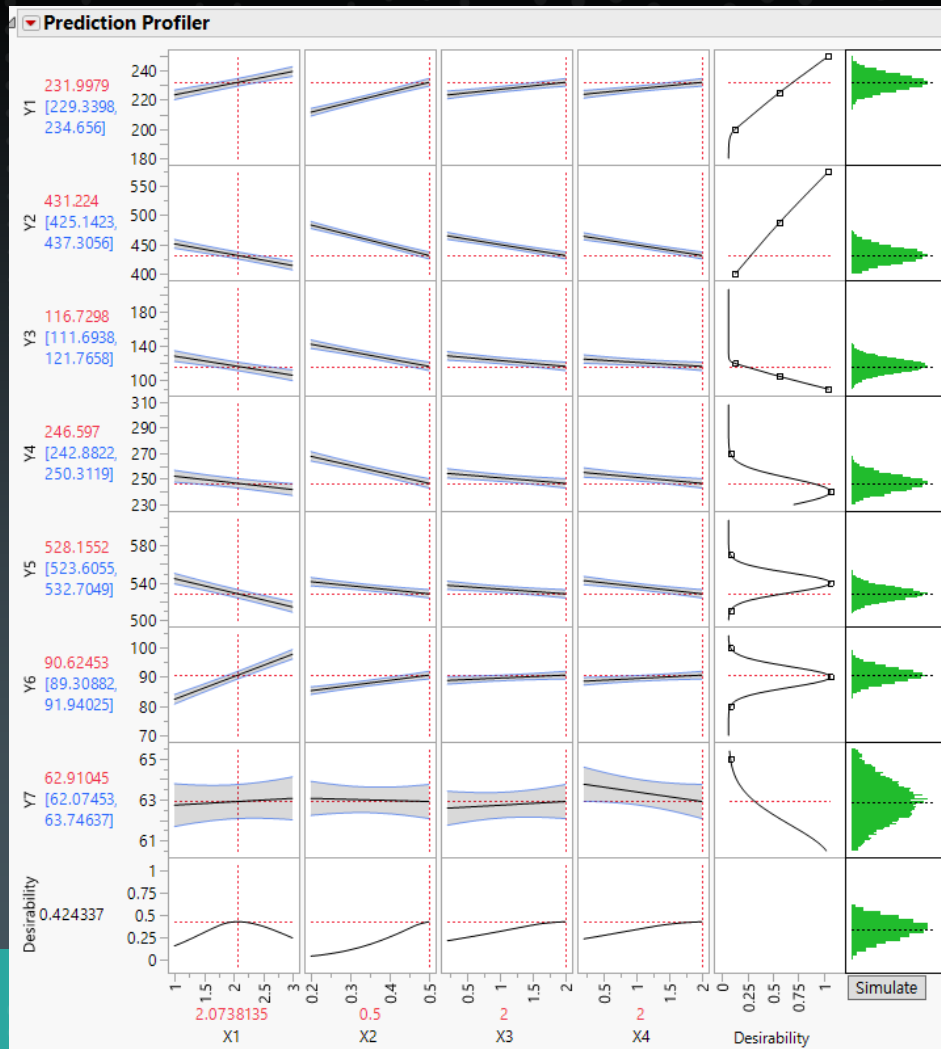
Simulator

Responses

Y1	Add Multivariate Noise	Std Dev:	3.4737232
Y2	Add Multivariate Noise	Std Dev:	7.9477392
Y3	Add Multivariate Noise	Std Dev:	6.5812274
Y4	Add Multivariate Noise	Std Dev:	4.8547263
Y5	Add Multivariate Noise	Std Dev:	5.9457333
Y6	Add Multivariate Noise	Std Dev:	1.7194172
Y7	Add Multivariate Noise	Std Dev:	1.0924137

N Runs: 10000

2nd DOE Result



Summary of 1st, 2nd DOE

Factor	Level	Factor	Level
X1	4	X1	Fixed
X2	3	X2	
X3	Fixed	X3	2
X4		X4	2
X5		X5	2
X6		X6	2



Factor	Level	Response	
X1	60:40	Y1	231
X2	160	Y2	431
X3	2.07	Y3	116
X4	0.5	Y4	246
X5	2	Y5	528
X6	2	Y6	91
		Y7	63

3rd DOE by Custom Design

Factor

Factor	X1	X2	X3	X4	X5	X6
1	70:30	H60	1	0.2	0.2	0.2
2	60:40	I60	3	0.5	2	2
3	40:60	S60	•	•	•	•
4	30:70		•	•	•	•

Response

Response	Response Name	Lower Limit	Upper Limit	Response Goal	Importance
1	Y1	200	•	Maximize	3
2	Y2	400	•	Maximize	3
3	Y3	•	120	Minimize	5
4	Y4	210	270	Match Target	3
5	Y5	510	570	Match Target	1
6	Y6	80	100	Match Target	5
7	Y7	55	65	Match Target	1

Factor	X1	X2	X3	X4	X5	X6
1	30:70	H60	3	0.2	0.2	2
2	70:30	H60	1	0.5	2	0.2
3	70:30	I60	1	0.5	0.2	0.2
4	30:70	H60	1	0.5	2	2
5	40:60	S60	1	0.5	0.2	0.2
6	40:60	S60	3	0.2	0.2	0.2
7	60:40	H60	3	0.2	0.2	0.2

38	40:60	I60	3	0.5	0.2	2
39	70:30	I60	3	0.5	2	2
40	30:70	I60	3	0.2	2	2
41	30:70	I60	1	0.5	0.2	2
42	70:30	H60	1	0.2	0.2	0.2
43	30:70	S60	3	0.2	2	0.2
44	60:40	S60	3	0.5	2	0.2
45	60:40	S60	3	0.2	0.2	2
46	30:70	S60	3	0.5	0.2	2
47	40:60	H60	1	0.2	2	0.2
48	70:30	I60	3	0.2	0.2	2

3rd DOE by Custom Design

Model Specification

Select Columns: 13 Columns
X1, X2, X3, X4, X5, X6, Y1, Y2, Y3, Y4, Y5, Y6, Y7

Pick Role Variables:
Y: Y1, Y2, Y3, Y4, Y5, Y6, Y7

Weight: optional numeric
Freq: optional numeric
By: optional

Personality: Standard Least Squares
Emphasis: Effect Screening

Fit Separately

Buttons: Help, Run, Recall, Remove

Keep dialog open

Construct Model Effects: Add X1

Construct Model Effects

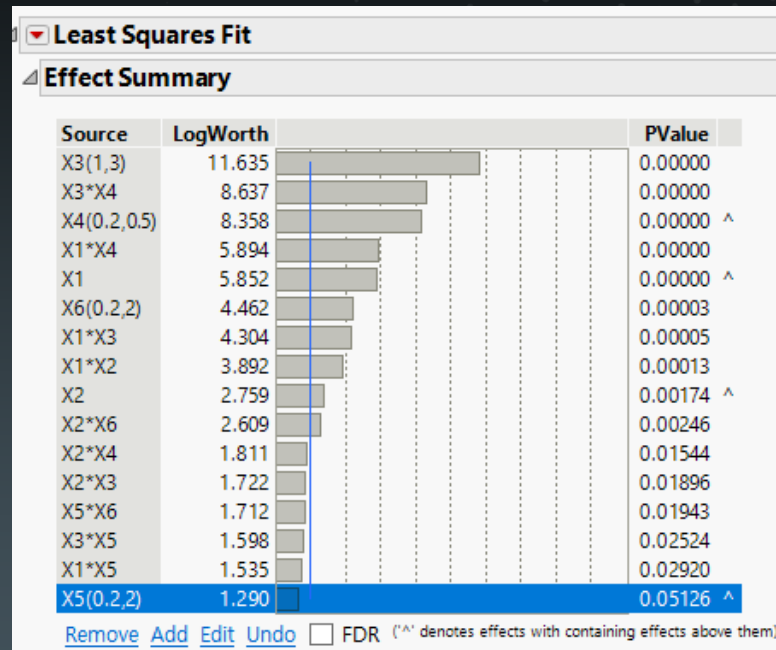
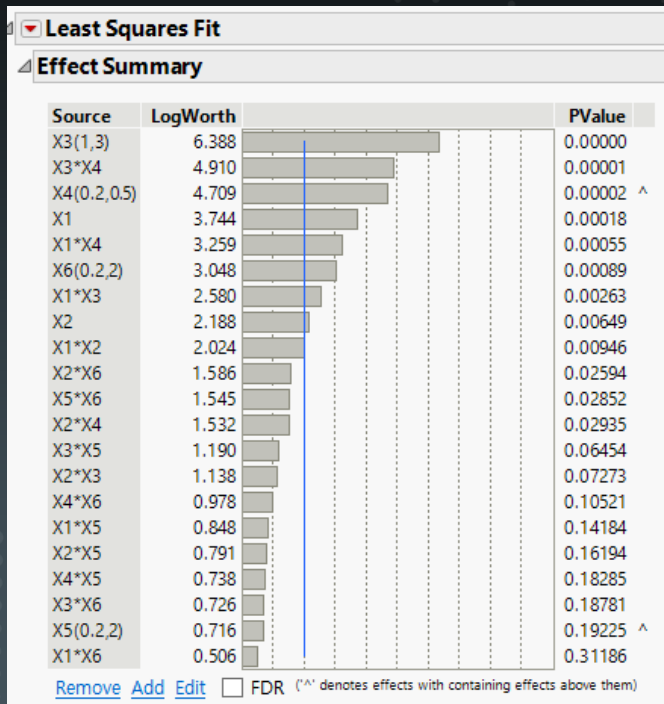
Buttons: Add, Cross, Nest, Macros

Degree: 2
Attributes: [dropdown]
Transform: [dropdown]

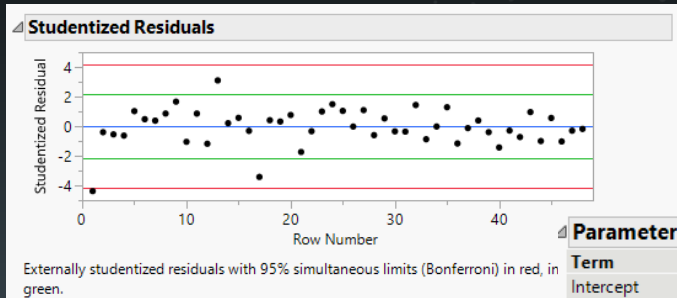
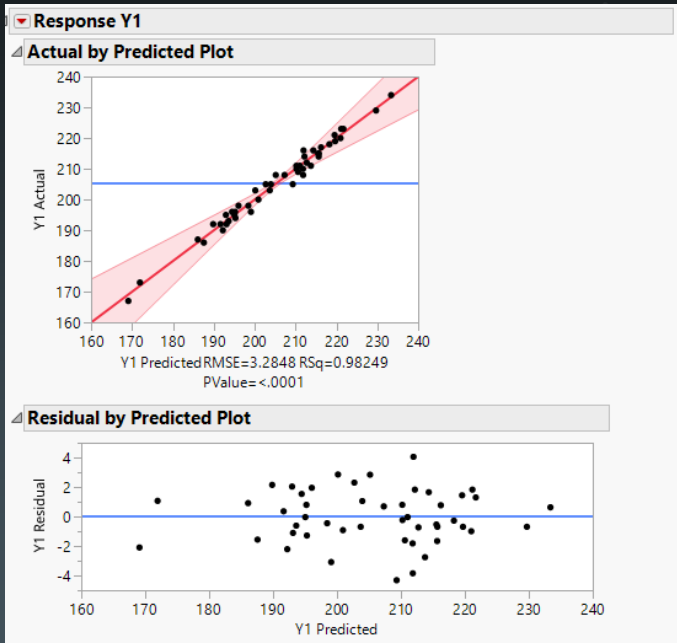
No Intercept

- X1
- X3
- X4
- X5
- X6
- X1*X3
- X1*X4
- X1*X5
- X1*X6
- X3*X4
- X3*X5
- X3*X6
- X4*X5
- X4*X6
- X5*X6

3rd Custom Design Result



3rd Custom Design Result



Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	205.27083	0.474127	432.94	<.0001*
X3(1,3)	7.3708333	0.492727	14.96	<.0001*
X4(0.2,0.5)	6.8369069	0.537201	12.73	<.0001*
X1[40:60]*X3	-5.526369	0.896633	-6.16	<.0001*
X1[40:60]*X2[I60]	-5.932906	1.302152	-4.56	0.0004*
X1[40:60]*X4	4.364188	1.004907	4.34	0.0007*
X2[I60]	2.9416667	0.70004	4.20	0.0009*
X1[60:40]*X2[I60]	4.952255	1.269941	3.90	0.0016*
X3*X4	-1.931548	0.498881	-3.87	0.0017*
X1[70:30]	3.060371	0.856423	3.57	0.0031*
X6(0.2,2)	1.8799603	0.533445	3.52	0.0034*
X1[70:30]*X2[I60]	4.4144117	1.269941	3.48	0.0037*
X1[70:30]*X5	-3.054897	0.928197	-3.29	0.0054*
X2[H60]*X6	-2.341704	0.819566	-2.86	0.0127*
X2[I60]*X3	-1.908333	0.673861	-2.83	0.0133*
X1[60:40]*X3	2.3940476	0.860549	2.78	0.0147*
X3*X5	1.1875	0.474127	2.50	0.0252*
X5(0.2,2)	1.0416667	0.488719	2.13	0.0513

3rd Custom Design Result

X1: Fixed (60:40) | X2: Random | X3: Random | X4: Random | X5: Random | X6: Random | Desirability

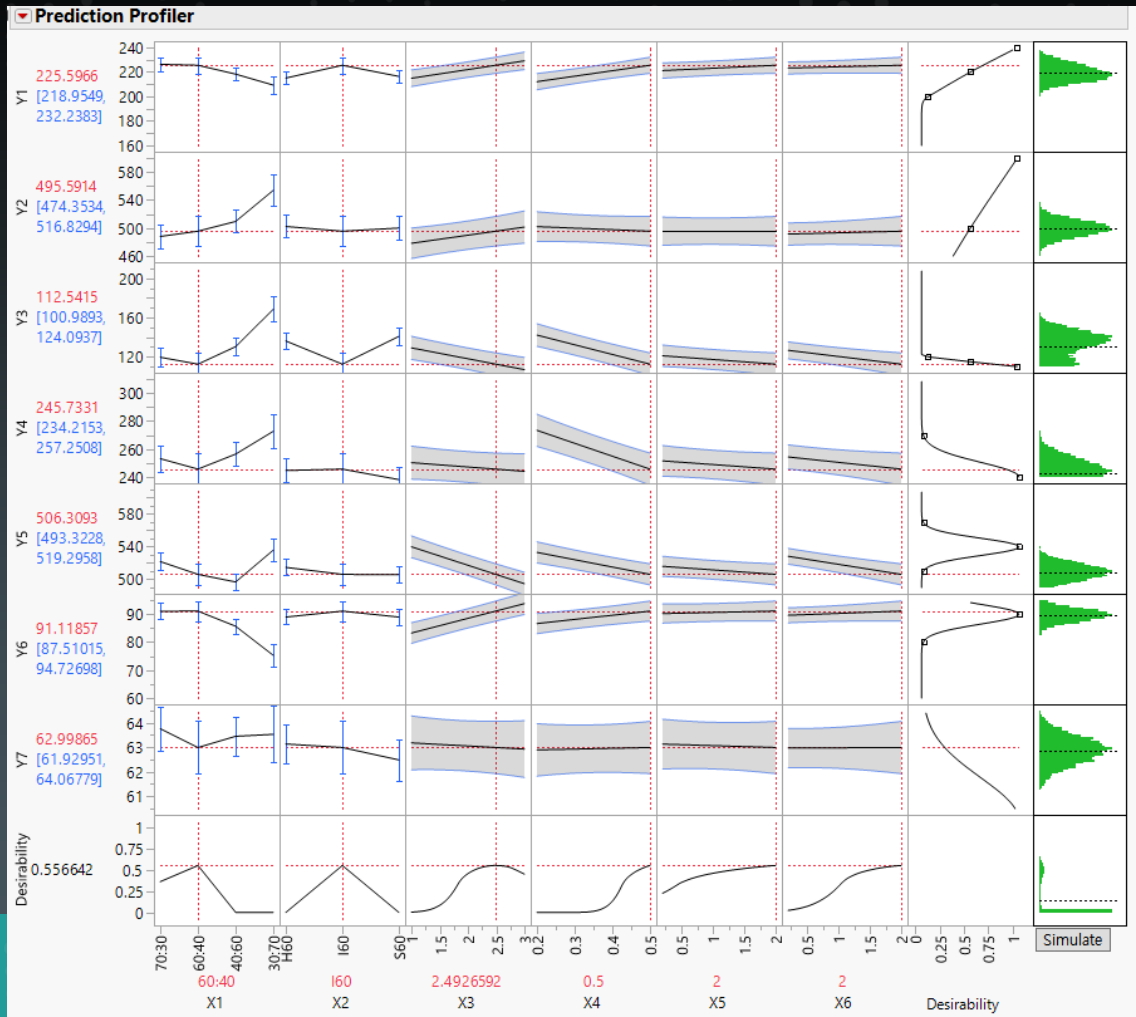
Levels	Prob	Normal	Normal	Normal	Normal
H60	0.33333	Mean 2.49266	Mean 0.5	Mean 2	Mean 2
I60	0.33333	SD 0.2	SD 0.06	SD 0.2	SD 0.2
S60	0.33333				

Interaction Profiles
Simulator
Responses

- Y1: Add Multivariate Noise (Std Dev: 3.6401616)
- Y2: Add Multivariate Noise (Std Dev: 10.698208)
- Y3: Add Multivariate Noise (Std Dev: 5.4998854)
- Y4: Add Multivariate Noise (Std Dev: 7.0586772)
- Y5: Add Multivariate Noise (Std Dev: 6.4592245)
- Y6: Add Multivariate Noise (Std Dev: 1.5071467)
- Y7: Add Multivariate Noise (Std Dev: 0.4870643)

N Runs: 10000

3rd Custom



3rd Custom Design Result

Local Data Filter

Clear Favorites

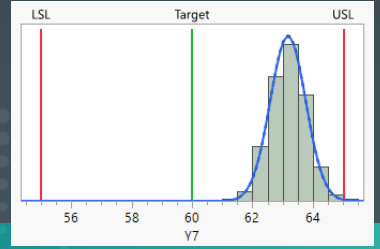
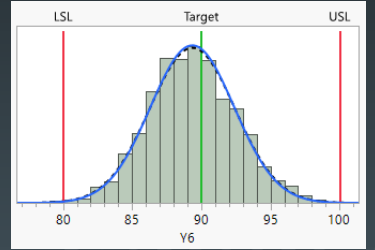
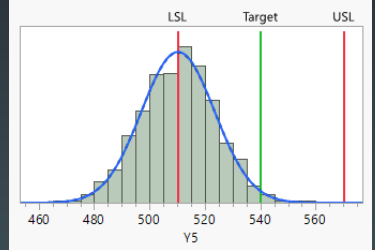
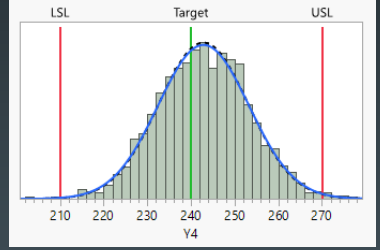
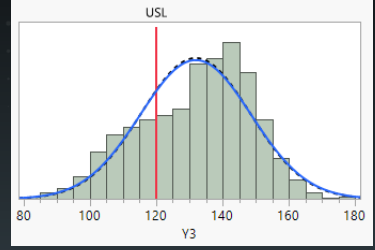
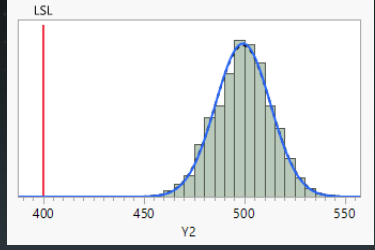
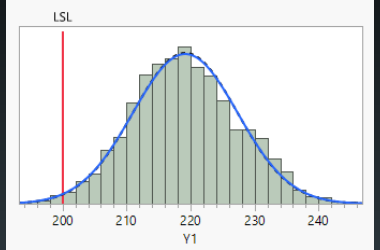
Show Include
2416 matching rows

Inverse

X1 (4)

30:70	2589
40:60	2489
60:40	2416
70:30	2506

AND OR



3rd Custom

Local Data Filter

Clear Favorites

Show Include
5095 matching rows

Inverse

X1 (4)

30:70	2589
40:60	2489
60:40	2416
70:30	2506

X2 (3)

H60 I60 S60

X3

0.7128937087 4.0260163714

X4

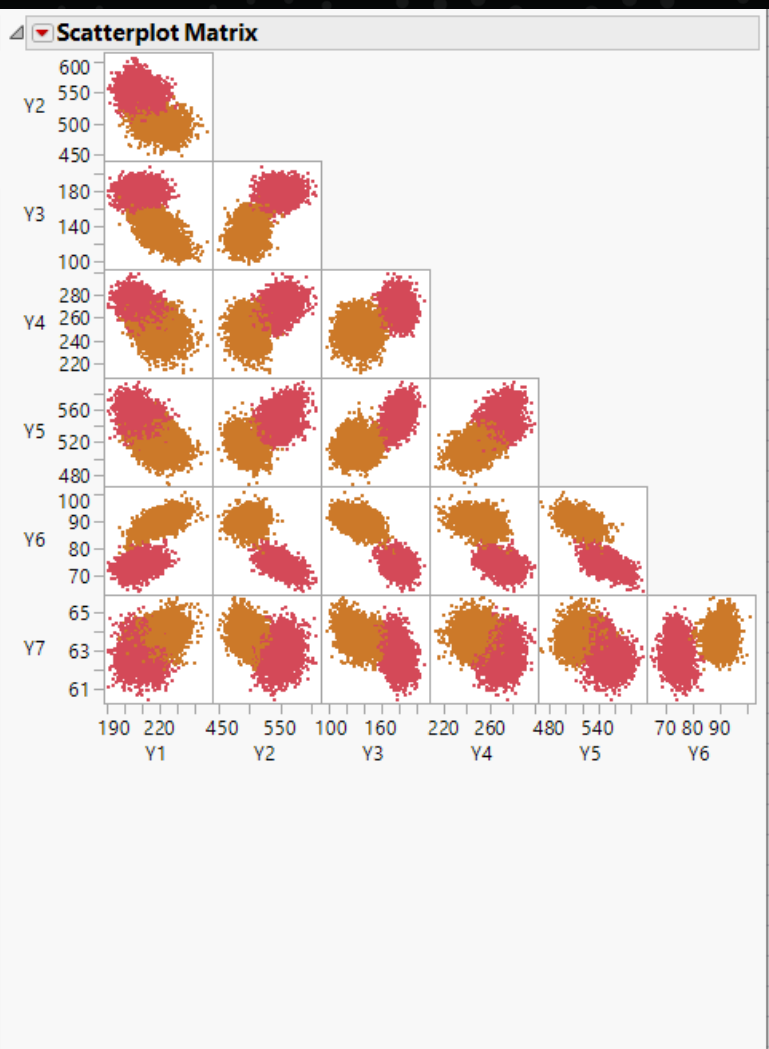
0.2675884636 0.7644498688

X5

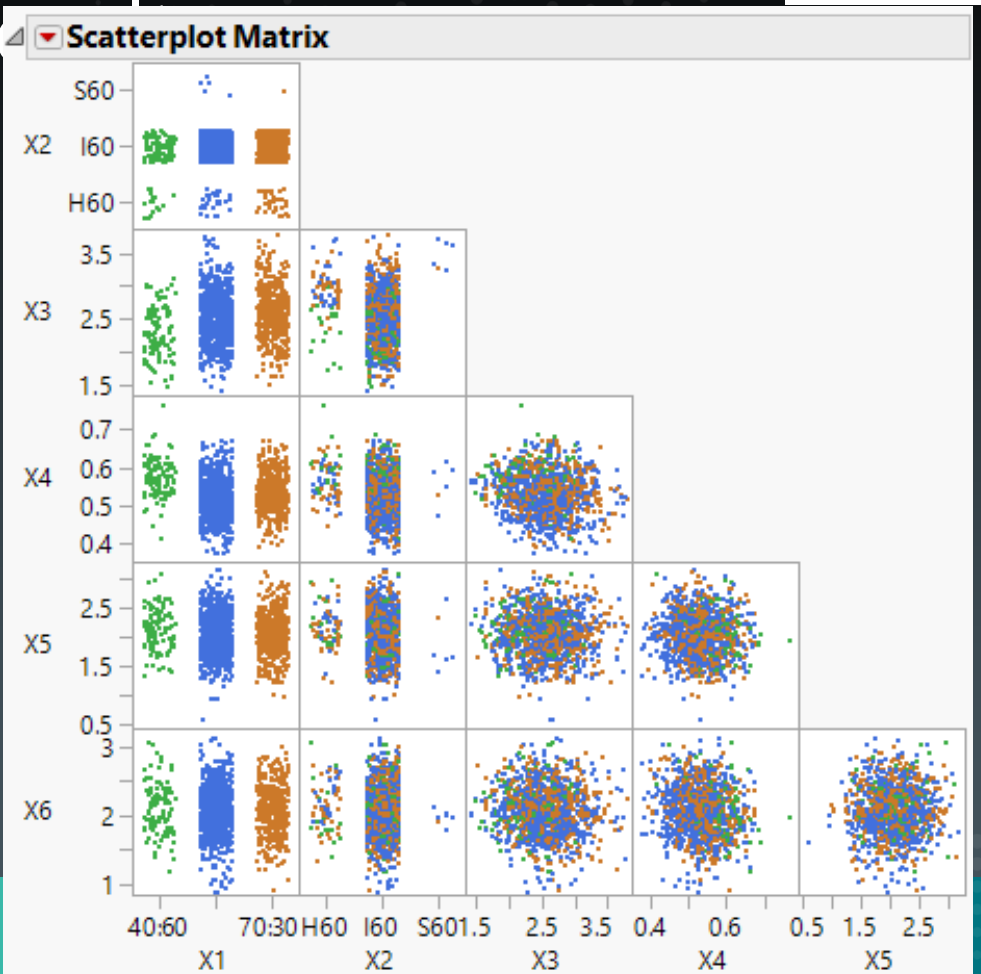
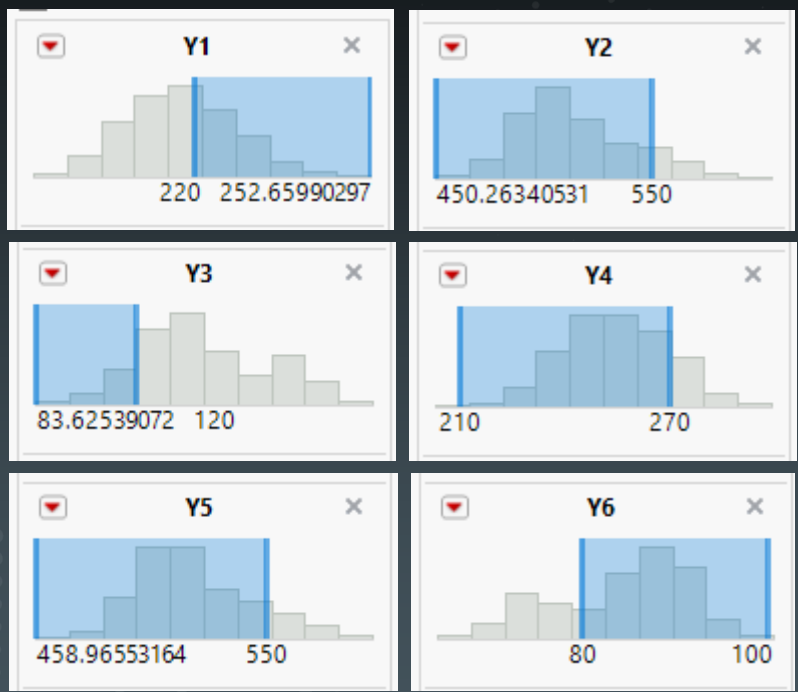
0.5977169983 3.3860556858

X6

0.7607451868 3.3868835849



3rd Custom Design Report



Conclusion

- 이전의 통계프로그램으로도 배합개발의 목적을 달성할 수 있었습니다. 하지만 JMP의 Custom Design을 통해 더 적은 실험횟수로도 같은 목적을 달성할 수 있었음
- 적은 횟수의 실험결과로 모델링하였을 때, 이전에 발견하지 못한 다양한 조건에서도 배합개발 목적을 달성할 수 있는 방법이 있음을 확인할 수 있었음
- JMP의 Custom Design을 통해 적은 시간과 비용의 결과로 Simulation / Distribution 기능을 통해 대량 생산시 불량율을 예측 할 수 있었음

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