

Design of Experiments (DOE) with Attribute Response

July 20, 2026

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FIRMWARE UPDATE BOOT SUCCESS STUDY

Goal: Determine the combination of software design choices that maximizes the probability of a successful boot after a firmware update.

LAB RULES

- ✓ ESD Protection
- ✓ Check Connections
- ✓ Verify Power
- ✓ Log Results
- ✓ Repeatable Tests

FACTORS (2 LEVELS EACH)



A. Memory Allocation Strategy

- Low (-1): Legacy Allocator
- High (+1): Optimized Allocator



B. Thread Scheduling

- Low (-1): Round Robin
- High (+1): Priority-Based



C. Flash Write Method

- Low (-1): Standard Driver
- High (+1): DMA Driver

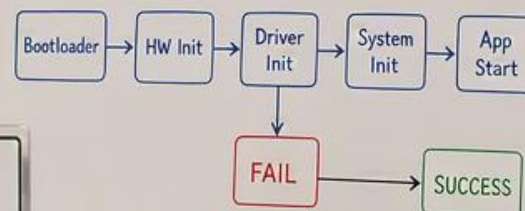
TEST DEVICE

Firmware Update
in Progress...



Do not power off.

FIRMWARE BOOT SEQUENCE



WHY THESE FACTORS?

- ✓ Affect memory usage patterns
- ✓ Impact timing and resource access
- ✓ Influence flash write reliability

TEST DASHBOARD

Total Tests: 160
Pass Rate: 88.1%

Pass: 141
Fail: 19
In Progress: 0

BOOT SUCCESS RATE (%)



CI / CD BUILD STATUS

Build 44821	✓ SUCCESS	10:42 AM
Unit Tests	✓ PASS	10:44 AM
Integration Tests	✓ PASS	10:46 AM
Hardware Tests	✓ PASS	10:50 AM
Deploy to Lab	✓ PASS	10:52 AM

DEVICE CONSOLE LOG

```
Erasing flash... OK
Writing firmware... OK
Verifying... OK
Starting system...
Initializing drivers... OK
Launching application...
```

BOOT SUCCESSFUL ✓

EXPERIMENTAL STUDY PLAN

Run	Memory Allocator	Thread Scheduling	Flash Write Method	Replications	Response
1	Legacy Allocator	Round Robin	Standard Driver	20	Pass / Fail
2	Optimized Allocator	Round Robin	Standard Driver	20	Pass / Fail

SUCCESS CRITERIA

Full Factorial 2³ Design
8 Treatment Combinations
20 Replications Each

Case Study: Firmware Deployment Reliability

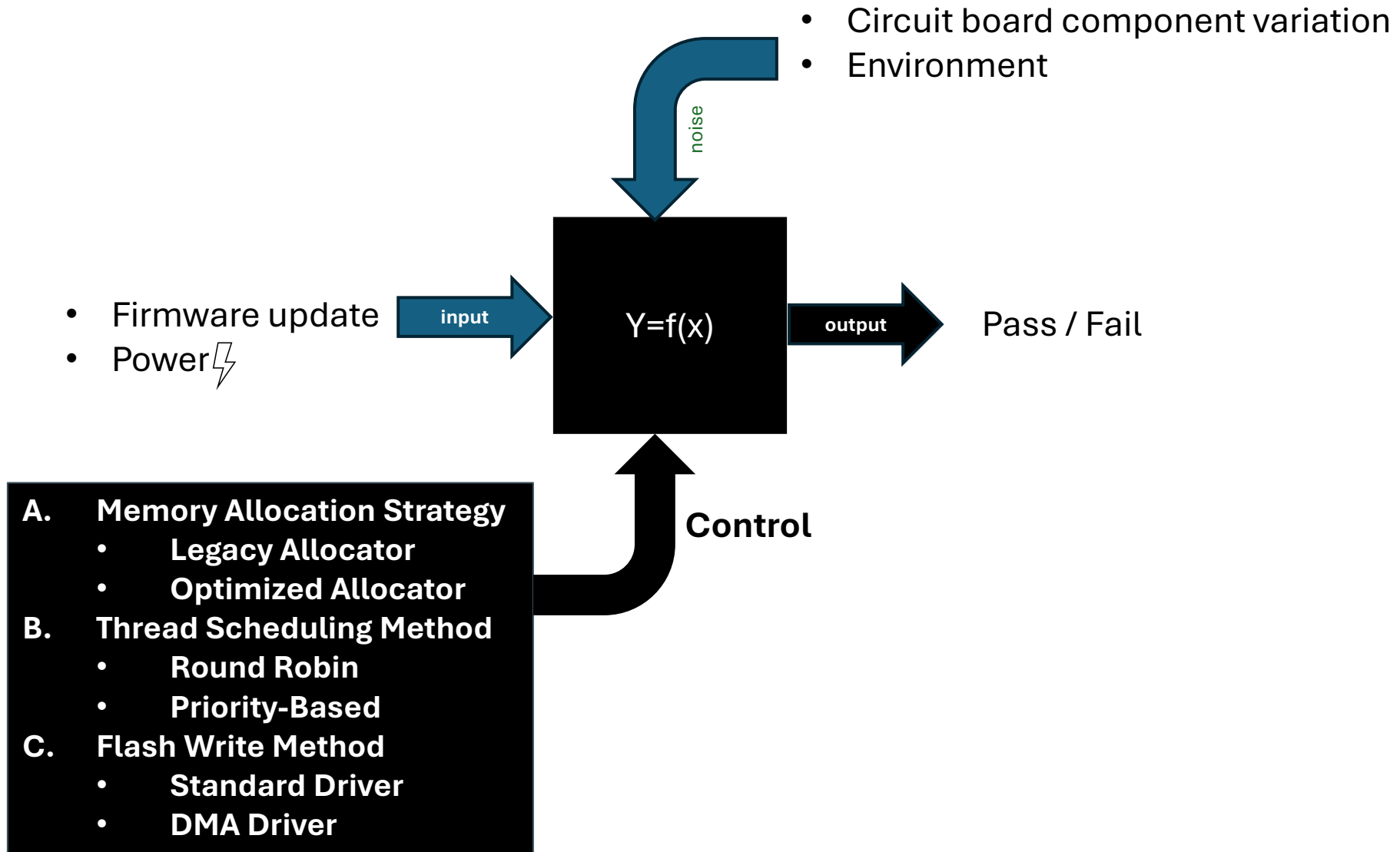
Firmware engineering would like to predict the probability of a successful firmware deployment based on key software architecture decisions. The objective is to determine how different implementation strategies affect the likelihood that an embedded device successfully boots and passes verification after a firmware update.

Response Variable: Pass (1) = successful deployment and boot; Fail (0) = deployment or boot failure.

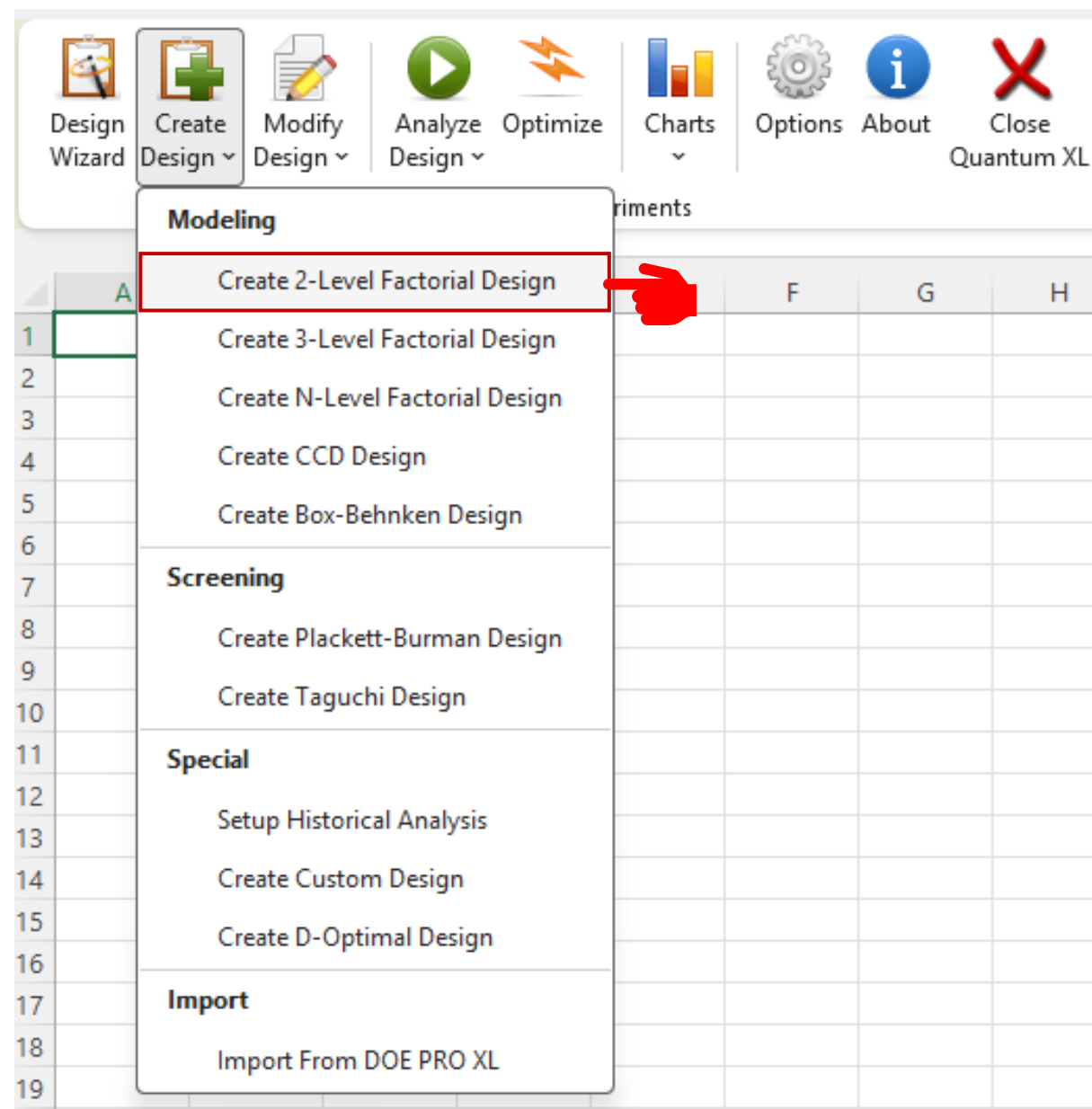
Experimental Factors

- A. Memory Allocation Strategy (Legacy Allocator vs Optimized Allocator)
- B. Thread Scheduling Method (Round Robin vs Priority-Based)
- C. Flash Write Method (Standard Driver vs DMA Driver)

Parameter Diagram



QXL DOE >Create Design >Create 2-Level Factorial Design



Select 3 factors with 8 number of runs

Factorial Design

Select 2-level factorial design.

	Factors														
	2	3	4	5	6	7	8	9	10	11	12	13	14	15	
4	Full	III													
8		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	

Number of runs

Full Factorial Design, 3 Factors in 8 Runs.
Resolution: Full. There is no aliasing.

Help Cancel Next > Finish

Enter factor names and high and low settings for each factor

The screenshot shows a software window titled 'Factorial Design' with a close button (X) in the top right corner. The main heading is 'Enter Factor Names and Coding'. Below this, there are two instructions: 'For Quantitative Inputs enter the low and high values (e.g. low=10 high=20)' and 'For Categorical Inputs enter the name of each level (e.g. Red,Blue)'. A table with four columns is present: 'Name', 'Low (or Name)', 'High (or Name)', and 'Categorical'. The table contains three rows of data: 'A' with low -1 and high 1, 'B' with low -1 and high 1, and 'C' with low -1 and high 1. Each row has an unchecked checkbox in the 'Categorical' column. Below the table is a large empty text area. At the bottom of the window are five buttons: 'Help', 'Cancel', '< Back', 'Next >', and 'Finish'.

Factorial Design

Enter Factor Names and Coding

For Quantitative Inputs enter the low and high values (e.g. low=10 high=20)
For Categorical Inputs enter the name of each level (e.g. Red,Blue)

Name	Low (or Name)	High (or Name)	Categorical
A	-1	1	☐
B	-1	1	☐
C	-1	1	☐

Help Cancel < Back Next > Finish

Enter factor names and high and low settings for each factor

Factorial Design

Enter Factor Names and Coding

For Quantitative Inputs enter the low and high values (e.g. low=10 high=20)
For Categorical Inputs enter the name of each level (e.g. Red,Blue)

Name	Low (or Name)	High (or Name)	Categorical
Memory_Allocator	Legacy Allocator	Optimized Allocator	☒
Thread_Scheduling	Round Robin	Priority-Based	☒
Flash_Write_Method	Standard Driver	DMA Driver	☒

Help Cancel < Back Next > Finish

Choose binary for output type.

Factorial Design

Define outputs (responses)

Select number of outputs: 1

Weights and sample size columns are only available with stacked replicates

Name: Output 1 Type: Quantitative

Quantitative
Binary
Nominal

Has weights column

Design format

Table
Stacked

Help Cancel < Back Next > Finish

Complete the dialog box as shown before clicking Next.

Factorial Design

Define outputs (responses)

Select number of outputs: 1

Name: Pass Type: Binary ☐ Events / Sample size

Design format

☐ Table

☒ Stacked

Help Cancel < Back Next > Finish

Select 20 for number of replicates.

Modify Design

Enter number of replicates and number of blocks

Replicates

Select number of replicates: 20

Help Me Choose Power/Sample Size Quantitative Outputs

Select number of blocks:

Fold design:

Blocking

Help Cancel Finish

Why so many replications?

Treatment	Combination	Pass	Fail	Replications	Pass Rate
1	Legacy, RR, Standard	1	9	10	10%
2	Optimized, RR, Standard	3	7	10	30%
3	Legacy, Priority, Standard	3	7	10	30%
4	Optimized, Priority, Standard	9	1	10	90%
5	Legacy, RR, DMA	2	8	10	20%
6	Optimized, RR, DMA	8	2	10	80%
7	Legacy, Priority, DMA	8	2	10	80%
8	Optimized, Priority, DMA	10	0	10	100%

- Binary logistic regression requires both response outcomes (Pass and Fail) to be represented in the data. If a treatment combination produces all successes or all failures, the model may experience complete separation and fail to converge.
- In the original experiment with 10 replications per treatment combination, Treatment 8 produced zero failures. Because one response category was absent, the logistic regression algorithm could not reliably estimate the logit function and transfer function.
- To address this issue, additional replications were collected. Increasing the sample size improves the likelihood of observing both Pass and Fail outcomes within each treatment combination.

Why so many replications?

Treatment	Combination	Pass	Fail	Replications	Pass Rate
1	Legacy, RR, Standard	2	18	20	10%
2	Optimized, RR, Standard	6	14	20	30%
3	Legacy, Priority, Standard	6	14	20	30%
4	Optimized, Priority, Standard	18	2	20	90%
5	Legacy, RR, DMA	4	16	20	20%
6	Optimized, RR, DMA	16	4	20	80%
7	Legacy, Priority, DMA	16	4	20	80%
8	Optimized, Priority, DMA	19	1	20	95%

- After increasing to 20 replications per treatment combination, Treatment 8 produced at least one failure. This eliminated the zero-count condition and allowed the logistic regression model to converge successfully.
- Because every treatment combination now contains both Pass and Fail observations, the binary logistic regression model can estimate the coefficients and generate a valid transfer function for predicting the probability of successful firmware deployment.
- As a practical guideline, logistic regression models generally require an adequate number of observations for each model term. For a full factorial experiment with three factors and all interaction terms, a target of 20 observations per treatment combination provides a more stable and reliable model. In this example, a 2^3 full factorial design with 20 replications per treatment yields 160 total observations, which is a reasonable sample size for estimating main effects and interactions.

Full Factorial Design

Number of replicates: 20

[edit response](#)

<-- reference level

```
<-- enter factor names
```

Replicate #19

Pass

> Event:

1

Data

Quantum XL

Full Factorial Design

3 Factors in 8 Runs

Number of replicates: 20

	A	B	C
Run	Memory_Allocator	Thread_Scheduling	Flash_Write_Method
145	Legacy Allocator	Round Robin	Standard Driver
146	Legacy Allocator	Round Robin	DMA Driver
147	Legacy Allocator	Priority-Based	Standard Driver
148	Legacy Allocator	Priority-Based	DMA Driver
149	Optimized Allocator	Round Robin	Standard Driver
150	Optimized Allocator	Round Robin	DMA Driver
151	Optimized Allocator	Priority-Based	Standard Driver
152	Optimized Allocator	Priority-Based	DMA Driver
153	Legacy Allocator	Round Robin	Standard Driver
154	Legacy Allocator	Round Robin	DMA Driver
155	Legacy Allocator	Priority-Based	Standard Driver
156	Legacy Allocator	Priority-Based	DMA Driver
157	Optimized Allocator	Round Robin	Standard Driver
158	Optimized Allocator	Round Robin	DMA Driver
159	Optimized Allocator	Priority-Based	Standard Driver
160	Optimized Allocator	Priority-Based	DMA Driver

Pass	
Event:	1
Data	
0	
1	
1	
0	
1	
1	
0	
1	
0	
1	
1	
0	
1	
1	
0	

run experiments
and record results


DOE Data in Excel
[Open Embedded File](#)

QXL DOE > Analyze Design > Run Regression



The transfer function will take this form:

$$\text{logit}(p) = \ln \left(\frac{p}{1-p} \right) = \beta_0 + \beta_A A + \beta_B B + \beta_C C + \beta_{AB} AB + \beta_{AC} AC + \beta_{BC} BC$$

Degrees of freedom (DF) should not be zero. There are too many terms in the model. The P-value for the Goodness of Fit Tests cannot be calculated.

Goodness of Fit Test

	Chi-Sq	DF	P
Pearson	0.0	0	NA
Deviance	0.0	0	NA

Association

	Number	Percent
Concordant	4,804	75.06%
Discordant	724	11.31%
Ties	872	13.63%
Total	6,400	100.00%

Summary Measures

	Value
Somers' D	0.6375
Goodman-Kruskal Gamma	0.7381
Kendall's Tau	0.3208

Remove the 3-way interaction ABC. Run regression model again.

There are no warnings for this model. Click here to see DOE Advisor.

Pass

Binary Logistic Output - Converged in 7 iterations.

Name	Factor	Coeff	SE	Z	P	Odds Ratio	95% CI Lower	95% CI Upper	In Model
	Const	-2.1972	0.7454	-2.9479	0.003	0.1111	0.0258	0.4789	
Memory	Memory_Allocator (A)	1.3499	0.8909	1.5153	0.130	3.8571	0.6729	22.109	☒
Thread	Thread_Scheduling (B)	1.3499	0.8909	1.5153	0.130	3.8571	0.6729	22.109	☒
Flash_Write	Flash_Write_Method (C)	0.8109	0.9317	0.8704	0.384	2.25	0.3623	13.971	☒
Memory	AB	0.8837	1.1594	0.7622	0.446	2.4198	0.2494	23.478	☒
Memory	AC	0.8837	1.1594	0.7622	0.446	2.4198	0.2494	23.478	☒
Thread	BC	0.8837	1.1594	0.7622	0.446	2.4198	0.2494	23.478	☒
Memory	ABC	-1.7673	1.6397	-1.0779	0.281	0.1708	0.0069	4.2	☐

Remove 2-way Interactions because of the high P-values. Run regression a third time.

There are no warnings for this model. Click here to see DOE Advisor.

Pass

Binary Logistic Output - Converged in 9 iterations.

Name	Factor	Coeff	SE	Z	P	Odds Ratio	95% CI Lower	95% CI Upper	In Model
	Const	-2.6062	0.7613	-3.4234	0.001	0.0738	0.0166	0.3282	
Memory_Allocator (ref='Legacy Allocator')	Memory_Allocator (A)	1.9037	0.8197	2.3223	0.020	6.7107	1.3459	33.46	☒
Thread_Scheduling (ref='Round Robin')	Thread_Scheduling (B)	1.9037	0.8197	2.3223	0.020	6.7107	1.3459	33.46	☒
Flash_Write_Method (ref='Standard Driver')	Flash_Write_Method (C)	1.405	0.8304	1.692	0.091	4.0755	0.8005	20.75	☒
Memory_Allocator*Thread_Scheduling	AB	0.0	0.87	0.0	1.000	1.0	0.1817	5.5021	☐
Memory_Allocator*Flash_Write_Method	AC	0.0	0.87	0.0	1.000	1.0	0.1817	5.5021	☐
Thread_Scheduling*Flash_Write_Method	BC	0.0	0.87	0.0	1.000	1.0	0.1817	5.5021	☐

Introduction to Odds Ratio

$$\log\left(\frac{p}{1-p}\right) = \log(odds)$$

- The odds ratio (OR) is often the most useful output from a logistic regression because it translates statistical coefficients into something engineers and managers can understand: “How much does changing a factor increase or decrease the odds of success?”
- Odds ratio > 1 indicates the odds of the event are increased by the variable. Odds ratio < 1 indicates the odds of the event are decreased by the variable.
- For example, changing the flash write method from the low setting of standard driver to the high setting of DMA drive increases successful deployment odds by approximately 4x.

Name	Factor	P	Odds Ratio	95% CI Lower	95% CI Upper	In Model
	Const	0.000	0.0738	0.0291	0.1872	
Memory_Allocator (ref='Legacy Allocator')	Memory_Allocator (A)	0.000	6.7107	3.001	15.006	☑
Thread_Scheduling (ref='Round Robin')	Thread_Scheduling (B)	0.000	6.7107	3.001	15.006	☑
Flash_Write_Method (ref='Standard Driver')	Flash_Write_Method (C)	0.000	4.0755	1.8681	8.891	☑

What does the **G P-value** tell us?

- It tells us whether the factors in our experiment collectively help predict firmware deployment success. A small **G P-value** means the software architecture choices have a real effect on reliability; a large **G P-value** means the model performs no better than random guessing based on the overall average success rate.
- If the **G P-value** < 0.05 , we are at least 95% confident that the slopes are not at all equal to zero (the model is significant for prediction).
- Think of the **G P-value** as the logistic-regression equivalent of the overall ANOVA Model P-value.

G P-Value tells us the transfer function is significant.

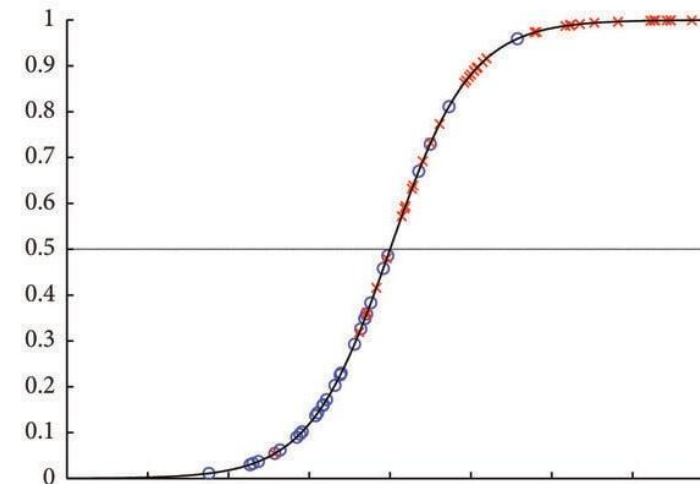
There are no warnings for this model. Click here to see DOE Advisor.

Pass

Binary Logistic Output - Converged in 6 iterations.

Name	Factor	Coeff	SE	Z	P	Odds Ratio	95% CI Lower	95% CI Upper	In Model
	Const	-2.6062	0.4749	-5.4879	0.000	0.0738	0.0291	0.1872	
Memory_Allocator (ref='Legacy Allocator')	Memory_Allocator (A)	1.9037	0.4106	4.6365	0.000	6.7107	3.001	15.006	☒
Thread_Scheduling (ref='Round Robin')	Thread_Scheduling (B)	1.9037	0.4106	4.6365	0.000	6.7107	3.001	15.006	☒
Flash_Write_Method (ref='Standard Driver')	Flash_Write_Method (C)	1.405	0.398	3.5302	0.000	4.0755	1.8681	8.891	☒

LogLikelihood	-82.452
RSquaredU	0.2565
AIC	172.904
BIC	185.204
RMSE	0.4105
G Stat	56.903
G df	3
G P-Value	0.000



For Illustrative Purpose Only

Goodness of Fit (GOF) Test for Binary Logistic Regression

GOF Test	Question Answered and Description
Pearson	Are observed counts close to predicted counts? It compares the predicted pass rate to the actual pass rate. $X^2 = \sum \frac{(\text{Observed} - \text{Expected})^2}{\text{Expected}}$
Deviance	How close is the model to a perfect model? This test is based on likelihoods. A perfect model would exactly predict every observed proportion. $D = 2 \times (\text{Log Likelihood of Perfect Model} - \text{Log Likelihood of Current Model})$

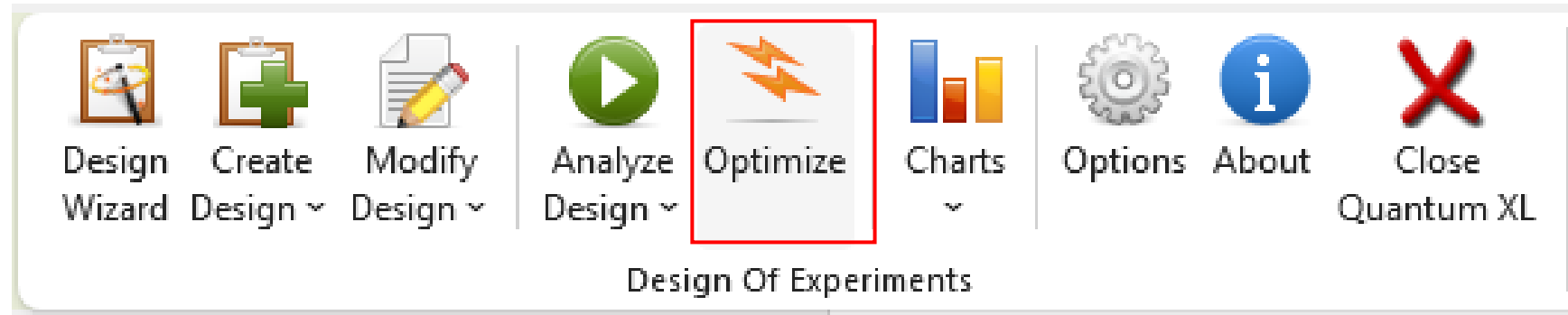
- If both P-values > 0.05, it means the model is both statistically significant and practically representative of the data.
- The Deviance GOF is preferred over the Pearson because it is directly tied to the likelihood function used to estimate logistic regression coefficients. Many statisticians consider the Deviance the primary GOF metric.

The P-values for Pearson and Deviance Good of Fit Test indicate the model is both statistically significant and practically representative of the data.

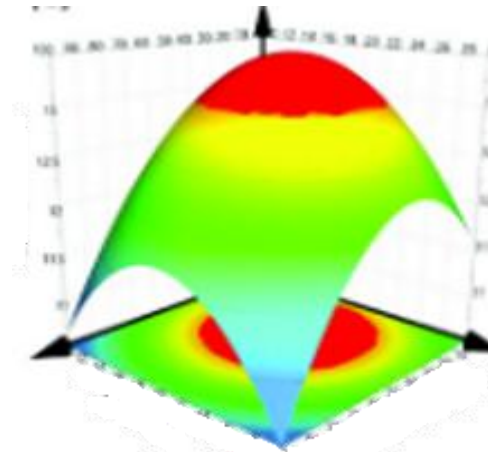
LogLikelihood	▼	-82.452
RSquaredU	▼	0.2565
AIC	▼	172.904
BIC	▼	185.204
RMSE	▼	0.4105
G Stat	▼	56.903
G df	▼	3
G P-Value	▼	0.000

Goodness of Fit Test				
	Chi-Sq	DF	P	
Pearson	▼	1.1833	4	0.881
Deviance	▼	1.1266	4	0.890

QXL DOE > Optimize



Find the set points that will yield the highest success rate.



For Illustrative Purpose Only

Optimizer

Enter low and high values for factors

Memory_Allocator	Select input levels	els. (Optimized Allocator, Legacy Allocator) ▾
Thread_Scheduling	Select input levels	All levels. (Priority-Based, Round Robin) ▾
Flash_Write_Metho	Select input levels	All levels. (DMA Driver, Standard Driver) ▾

Help Cancel Next > 

Optimizer

Optimization goal and constraints

Set the optimization goal

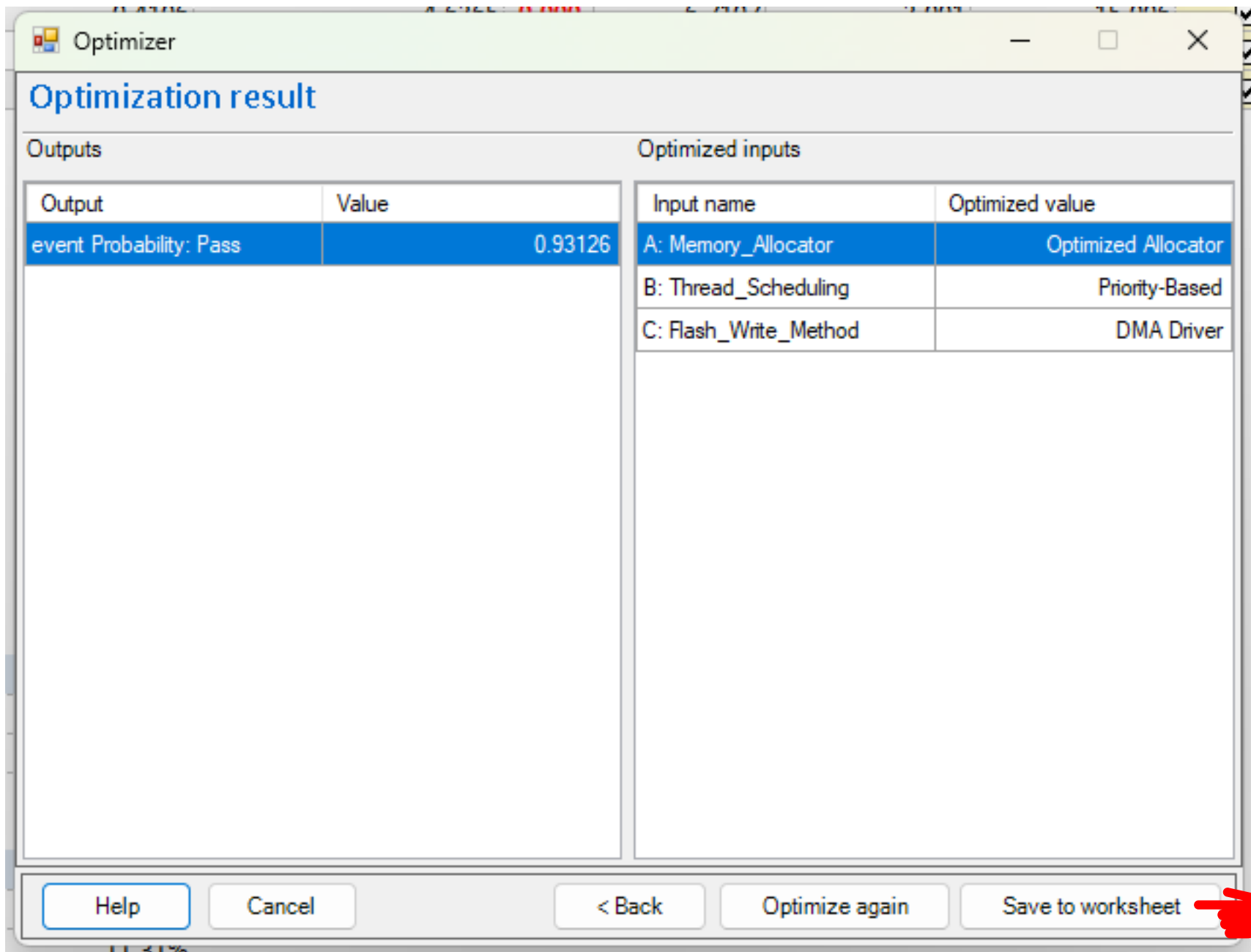
Maximize the Pass - event Probability
Min=0.06874; Max=0.93126

Set the optimization constraints (optional)

Add constraint

Help Cancel < Back Optimize





Below are the settings for the highest probability of success (93%).

Quantum XL Regression Analysis

Design sheet: DOE Design

Regression in coded units

Factors				
Name	Factor	Range		Set point
		Low	High	
Memory_Allocator	A	Legacy Allocator	Optimized Allocator	Optimized Allocator
Thread_Scheduling	B	Round Robin	Priority-Based	Priority-Based
Flash_Write_Method	C	Standard Driver	DMA Driver	DMA Driver

Prediction	
Pass	
Probability	
0	7%
1 (Event)	93%

Key Takeaways

1) Binary Logistic Regression Requirements

- Use a minimum of **20 observations per model term** to obtain stable coefficient estimates and reliable prediction performance.
- Ensure that every treatment combination contains at least one success and one failure to avoid complete separation and convergence issues.

2) Goodness-of-Fit Evaluation

- The **Pearson** and **Deviance Goodness-of-Fit Tests** assess whether the logistic regression model adequately represents the observed data.
- Because the null hypothesis assumes the model fits the data, larger P-values (> 0.05) indicate no evidence of lack of fit and are therefore desirable.

3) Transfer Function Development. The fitted binary logistic regression model generates a transfer function that predicts the probability of a successful firmware deployment as a function of the software architecture factors and their interactions.