5 DESIGN OF EXPERIMENTS

Description

Design of Experiments (DOE) is used to provide a structured, statistical approach to test planning and execution. The technique uses a systematic variation of parameters to determine the effect of those parameters on the result.

Purpose

The purpose of DOE is to study the effect of process and design variables on the performance and reliability of products.

By means of a comparative analysis, we attempt to determine the effects of single / multiple parametric variations on the output, which is linked to product performance or reliability.

- Characterization determines the effect of a range of parameters on the output.
- Modeling uses functions of the input variables to predict output behavior.
- Optimizing determines the levels of control parameters to generate the best output.

DOE can be used to explore, confirm, or optimize relationships between influential variables and product performance and reliability.

Benefits

DOE is generally used to enhance the robustness of product performance and reliability by understanding and controlling the variables that most influence those two features. In some cases, products can be made insensitive to uncontrolled variables.

In many cases there are interactions between variables that influence product performance and reliability. DOE is used to understand that interaction.

DOE is used to simultaneously study the effect of influencing parameters. This is a very efficient manner of testing.

Implementation

DOE is most effectively used by trained and knowledgeable personnel when cause and effect relationships are to be determined. Rigorous attention to proper selection of design to be used and of input variables and their level settings is critical to the success of the technique. Knowledgeable objective setting, i.e., selecting the information on the variable relationships to be defined and their interaction, is critical to the success of a DOE exercise. DOE generally is an efficient approach to testing, but an ineffective selection of variables, factor levels, and design can nullify the benefits.

For large-scale "screening of input variables," Neural Network Analysis should be consulted. The benefit here is the ability to gather data without impacting manufacturing process throughput.

There are many DOE types available, each with its particular situational use. Existing types are the following:

- 2**(K-p) standard designs (Box,Hunter & Hunter)
- 2-level screening designs (Plackett-Burman)
- 2**(K-p) maximum unconfounded or minimum aberration designs
- 3**(K-p) and Box-Behnken designs
- Mixed 2- and 3-level designs
- Central composite, non-factorial surface designs
- Latin squares, Greco-Latin squares
- Taguchi robust design experiments (orthogonal arrays)
- Mixture designs and triangular surface designs
- Designs for constrained surfaces and mixtures
- D- and A-(T-) optimal algorithmic designs.

Process Flow

1. Define the experimental goal.
2. Determine the output variable to be measured.
3. Determine the input variables to be controlled and their level settings.
4. Determine the uncontrolled variables that may influence the output variable (to be measured).
5. Determine the input variables that will be held constant.
6. Select the test approach that will be used.
7. Determine and justify the resources.
8. Design the test.
9. Conduct the test.
10. Analyze the results.
11. Confirm the results.
12. Formulate the resulting conclusions and implement the appropriate actions.

Example

A DOE was conducted on synchronizer material wear for heavy transmissions.

1. This DOE was designed to determine what effects lot number, oil type, and oil level have on the axial wear of synchronizer friction material.
2. The output variable to be measured is axial wear of the friction material.
3. The controlled input variables are lot number (26 & 27), oil type (Supplier 1 and 2), and oil level (+15% & -15%).
4. The uncontrolled variable that can influence the outcome of the test is the production process of the friction material.
5. The constant input variables are sump temperature, pressure, actuation time, and differential speed across the synchronizer.
6. The test approach used was a three-factor, two-level, full factorial DOE. (Table 1)
7. Eight samples per lot are available and entail replications. Replications are used in an attempt to reduce the amount of “pure error” (or Total SS residual error) potential in the results of a designed experiment analysis of variance (ANOVA).
8. When setting up your DOE matrix, be sure to randomize the testing / run order. Randomization is the best way to reduce biased results.
9. The test was performed and the axial wear was measured.

Standard	Design: 2**(3-0) design (DOE Spreadsheet)				
Run	Replicat	Oil Level	OilType	Lot#	Results
6	1	15.0000	1.000000	27.00000	0.0080
8	1	15.0000	2.000000	27.00000	0.0135
9	2	-15.0000	1.000000	26.00000	0.0140
14	2	15.0000	1.000000	27.00000	0.0090
12	2	-15.0000	2.000000	27.00000	0.0140
16	2	15.0000	2.000000	27.00000	0.0133
15	2	15.0000	2.000000	26.00000	0.0130
4	1	-15.0000	2.000000	27.00000	0.0145
10	2	-15.0000	1.000000	27.00000	0.0090
7	1	15.0000	2.000000	26.00000	0.0125
3	1	-15.0000	2.000000	26.00000	0.0180
13	2	15.0000	1.000000	26.00000	0.0150
1	1	-15.0000	1.000000	26.00000	0.0135
2	1	-15.0000	1.000000	27.00000	0.0080
11	2	-15.0000	2.000000	26.00000	0.0175
5	1	15.0000	1.000000	26.00000	0.0155

Table 5.1. DOE Test Design

Factor	Alias Matrix (Design: 2**(3-0) design 2**(3-0) design Oil Level	OilType	Lot#	1*2	1*3	2*3
Oil Level	1.00	0.00	0.00	0.00	0.00	0.00
OilType	0.00	1.00	0.00	0.00	0.00	0.00
Lot#	0.00	0.00	1.00	0.00	0.00	0.00
1*2	0.00	0.00	0.00	1.00	0.00	0.00
1*3	0.00	0.00	0.00	0.00	1.00	0.00
2*3	0.00	0.00	0.00	0.00	0.00	1.00

Table 5.2. Assessment of Experimental Design Suitability: "The Alias Matrix"

All one- and two-way interactions are potentially "free and clear." This means we can assess the effects free of confounding. The experimental design is deemed suitable. NOTE: This may not be true if three- way interactions impede the results or the effect of setting the factor levels (so that the differences in a particular factor level are small) impede the analysis discrimination.

Factor	ANOVA; Var.:Results; R-sqr=.98846; Adj:.97837 2**(3-0) design; MS Residual=.0000002 DV: Results SS	df	MS	F	p
(1)Oil Level	0.000005	1	0.000005	23.0061	0.001362
(2)OilType	0.000037	1	0.000037	179.4802	0.000001
(3)Lot#	0.000055	1	0.000055	268.1125	0.000000
1 by 2	0.000014	1	0.000014	65.6809	0.000040
1 by 3	0.000002	1	0.000002	8.5380	0.019233
2 by 3	0.000021	1	0.000021	101.7903	0.000008
1*2*3	0.000008	1	0.000008	38.8116	0.000251
Error	0.000002	8	0.000000		
Total SS	0.000143	15			

Table 5.3. Results

A graphical means of viewing the results uses the Pareto chart of Effects. All factors and interactions are deemed significant (highlighted) at the alpha = .05 level.

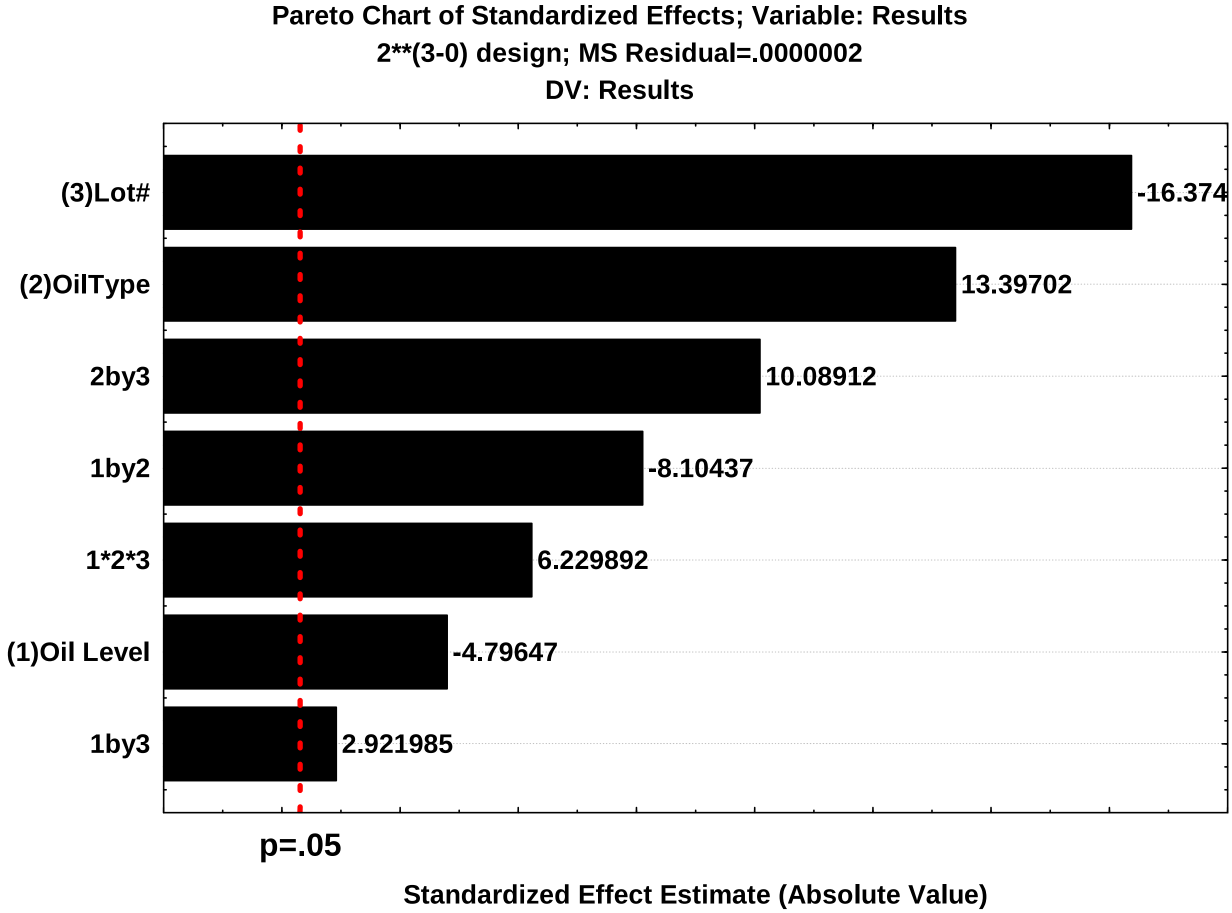

Figure 5.1. Pareto of Effects

We now look to optimize and find the values of those critical settings that will do this. If the goal is to reduce the axial wear (***the <u>smaller, the better</u>***), then the following is noted:

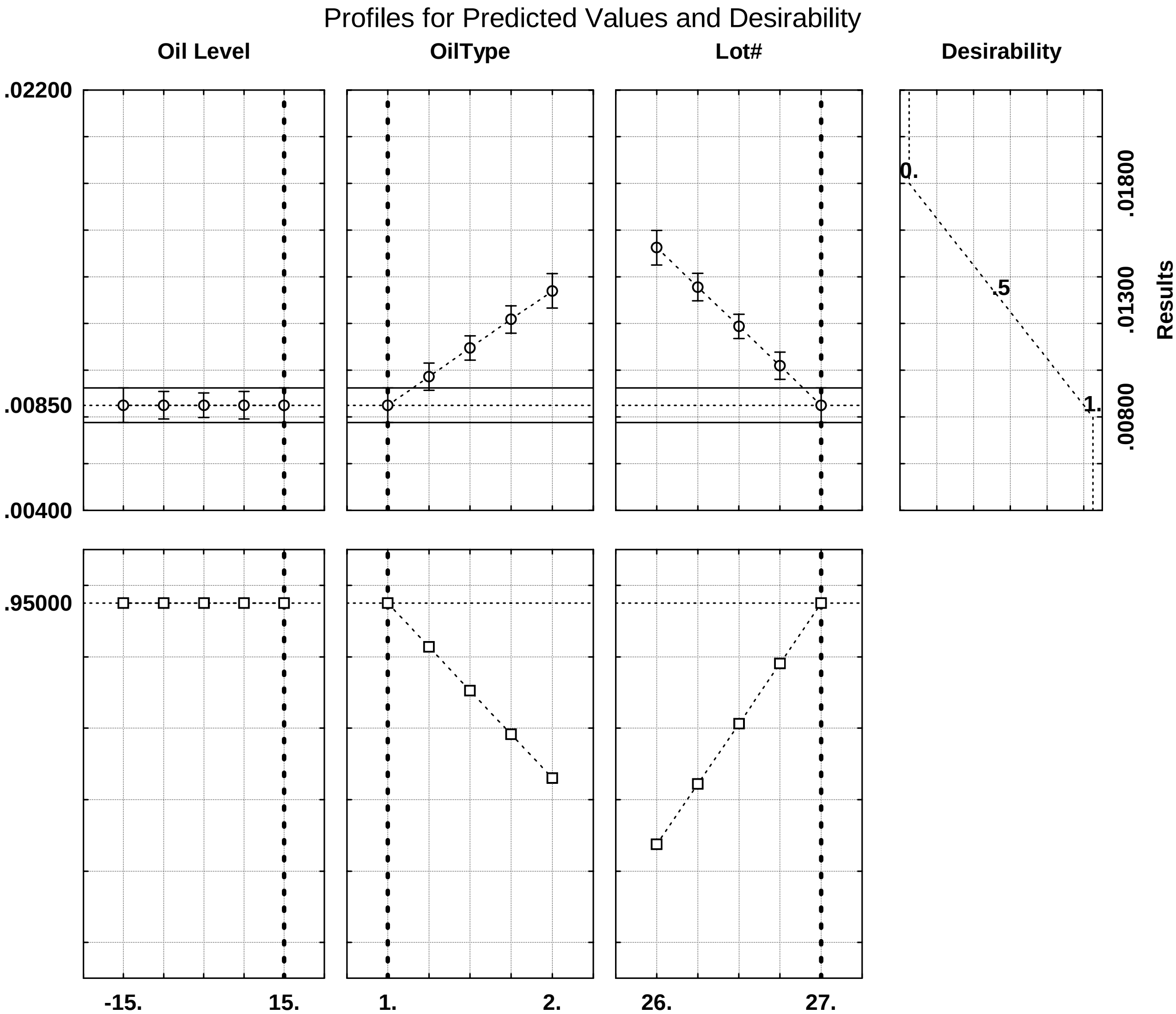

Figure 5.2. Parametric Sensitivity

Interpretation

Oil level should be set at +15%.
Oil type should be supplier 1.
Whatever was distinguishing about lot 27 should be standardized.

Recommendation

Set the factors at the derived optimum levels and run a confirmation experiment.

General Comments

This process is integral to the Phases 2 and 3--Product and Process Design and Development activities. Its success is tightly linked to using the QFD, Product Performance Specification, and FMEAs to drive the selection of important variables.

Process Capability Analysis can benefit from this technique. This tool can also help determine the causes of variation in Phase 5.

References

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