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“Deploying ‘Design of Experiment’ by leveraging ‘CAE’ for Plastic Component”

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Abstract - The Design of Experiments (DoE) is an important step in system identification.. The DoE quality establishes an upper constraint on the correctness of the identified models, regardless of the model structure and identification technique selected.

***Key Words*:** DOE, DFSS, Design Of Experiment, Factors, Level settings

1.INTRODUCTION

The design of experiments (DOE or DOX), sometimes referred to as experiment design or experimental design, is the planning of any task with the goal of describing and explaining the variance of information under circumstances that are thought to reflect the variation. However, it can also refer to the design of quasi-experiments, in which natural conditions that have an impact on the variation are chosen for observation. The phrase is typically used in conjunction with experiments in which the design introduces conditions that directly affect the variation.

2. Body of Paper

The goal of an experiment is to predict the result in its most basic form by altering the preconditions, which are represented by one or more independent variables, often known as "input variables" or "predictor variables." The basic assumption is that changing one or more independent variables will alter one or more dependent variables, often known as "output variables" or "response variables." In order to avoid outside influences from influencing the results, the experimental design may additionally specify control variables that must be maintained constant. In addition to choosing appropriate independent, dependent, and control variables, the experimental design also entails scheduling the experiment's execution under statistically ideal circumstances while taking into account resource limitations.

Table -1: DOE Table (3 Factors & 2 levels)

Run	Treatment	Factors		
		A	B	C
1	I	-1	-1	-1
2	a	+1	-1	-1
3	b	-1	+1	-1
4	ab	+1	+1	-1
5	c	-1	-1	+1
6	ac	+1	-1	+1
7	bc	-1	+1	+1
8	abc	+1	+1	+1

Consider the two-level, full factorial design for three factors, namely the 2^3 design. This implies eight runs (not counting replications or center point runs). Graphically, we can represent the 2^3 design by the cube shown in Figure 1. The arrows show the direction of increase of the factors. The numbers `1' through `8' at the corners of the design box reference the `Standard Order' of runs.

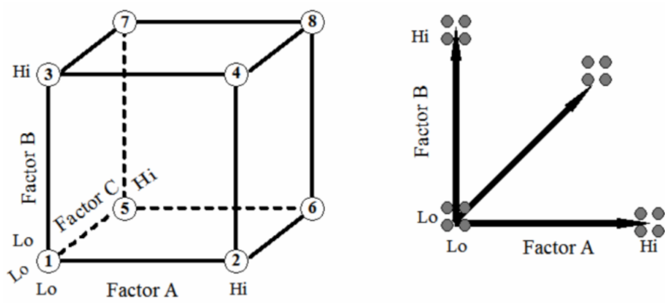

Fig -1: Plastic Part Design

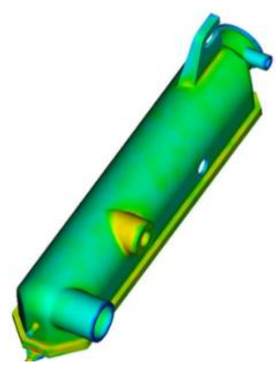

Fig -2: CAE - Plastic Part Design

Table -2: DOE Table, 3 Factors & 2 levels

Sequence	Factor	-1	1
A	A	-1	+1
B	B	-1	+1
C	C	-1	+1

DOE analysis could be followed by 3 steps

1. Practical Analysis
   -has the target value been achieved
   -was enough variation created on either side of target value
2. Graphical Analysis
   -can be done by using main effect and interaction plot, normal plot and paratro Plot
3. Quantitative Analysis
   -can be done using and ANOVA, p-value

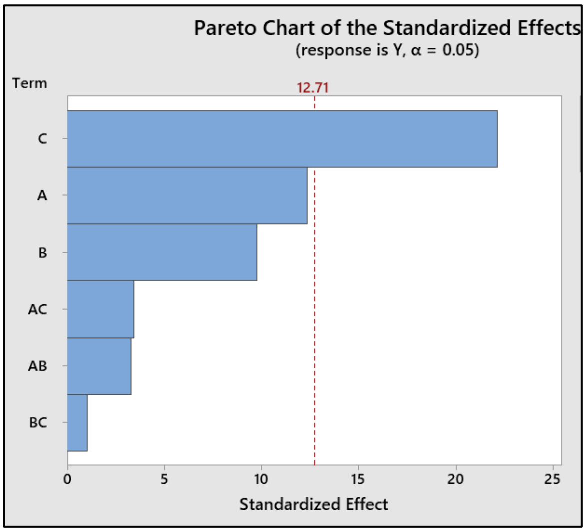

Fig 3 Parato Analysis

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
2.98399	99.87%	99.08%	91.59%

From model summary R square and R square adjusted values are close to each other which is ~99% so we have very less chance to have noise level in between that and it good model to consider with
R square prediction is above 90% so which is a good model to consider.

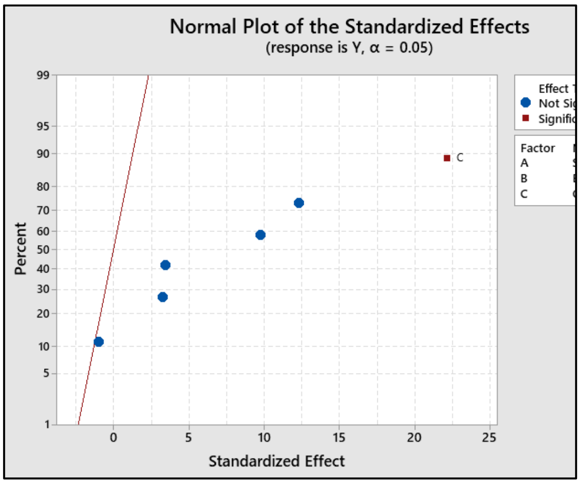

Fig 4 Normal Plot

Looking at the normal plot factor C has a significant impact on the result which we are expecting.

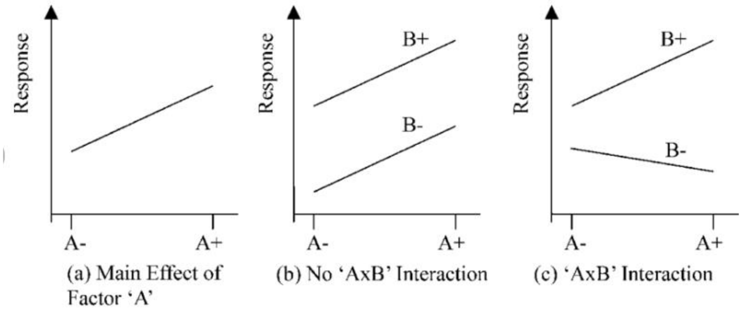

Fig 5 Interaction Plot

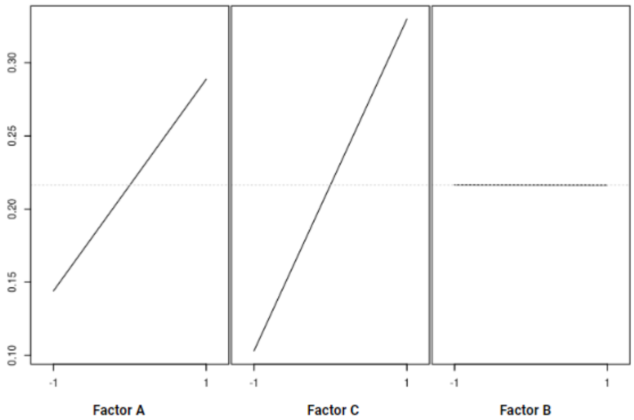

Fig 6 Main Effect Plot

Looking at the main effect and interaction plot factor C has a significant impact on the result which we are expecting.

3. CONCLUSIONS

Methodology of DOE paneling with the FEA simulation process is useful to reduce the expensive tool trails and save Design to manufacturing cycle time. This is achieved by simulating multiple possibilities in a virtual environment at an early stage of design and narrowing down the experimental trails.

The calculation from analytical calculation through DOE strategy yields good results which is confirmed in FEA simulation and experimental trial as well. FEA simulation predicts which results helps Design and tooling and production team to experiment with digital prototype and arrive at decision much faster with agility.Performing FEA simulation before going for actual tool helps to strategies the complete tool design and experimental trial with soft tool.

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REFERENCES

1. CanaleM. et al.
Nsm constrained approximation of Lipschitz functions from data Systems Control Lett (2010)

2. DeflorianM. et al.
Online dynamic black box modelling and adaptive experiment design in combustion engine calibration IFAC Proc Vol (2010)

3. DeflorianM. et al.
Design of experiments for nonlinear dynamic system identification IFAC Proc Vol (2011)

4. ForssellU. et al.
Some results on optimal experiment design Automatica (2000)

5. MilaneseM. et al.
Optimal algorithms estimation theory for dynamic systems with set membership uncertainty: an overview Automaticam (1991)