23

COMPUTER AIDED EXPERIMENTS: TWO CASE STUDIES

by

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Abstract: Experimental Designs are aimed at scanning the entire design space with a small number of experiments which will give statistically valid results. In Engineering Design, optimisation means the selection of the values for the Design Parameters, which represent the design, and minimises or maximises an engineering property of the product which is being designed. In traditional design practice the engineer has limited opportunity to perform optimisation. Computer Aided Experiments is a method to use the Experimental Designs employing a computer based model and software to estimate the objective function. This leads to the identification of the sensitive parameters which the designer can use for optimisation. The paper describes a four stepped method for Computer Experiments and two case studies illustrating its use.

1.0 Introduction

Optimisation can be defined as the process of finding the conditions that give the maximum or minimum value of a function [E.P.Box,et.al,1978]. In Engineering Design this means the selection of the values for the Design Parameters which represent the design, and minimises or maximises an engineering property of the product which is being designed. Any engineering system or component is described by a set of quantities of which some are viewed as variables during the design process. In general certain quantities are initially fixed at the outset and these are called the pre-assigned parameters. All other variables are called the design variables. All design variables are collectively represented as a design vector $[x_1 \ x_2 \ --- x_n]$. If an n dimensional Cartesian space with each co-ordinate axis representing a design variable $x_i (i = 1 --- n)$ is considered, the space is called the design variable space. Each point in the n dimensional space can be represented by the vector $[x_1 \ x_2 \ --- x_n]$ and is called a design point. It represents either a possible or impossible solution to the design problem. Optimisation **is the identification of the best possible solution, i.e. design point, which meets the constraints.** The conventional design procedures aim at finding an acceptable or adequate design, which merely satisfies the functional and other requirements of the problem. In general there will be more than one acceptable designs and the purpose of optimisation is to choose the best one out of the many acceptable designs available. Thus a criterion has to be chosen to compare the different alternate acceptable designs and to select the best one. The criterion with respect to which the design is optimised, when expressed as a function of the design variables, is known as the objective function. When the design space and the objective function are known the optimisation problem can be easily set up. However in many engineering situations these objective functions are complex or not easy to set up. In these situations the engineers use Computer Software using numerical techniques called analysis to give values of the objective function under given conditions. The design engineer with his expertise selects the worst case situations for analysis and ensures that the objective function lies within the required limits for all possible conditions. This identification of the critical parameters and their ranges are left to the expert choice of the design engineer. However with the rapid availability of cheap computing power, engineers can now conduct several analyses with limited cost. Computer Experiments is aimed at scanning the **Design Space in a systematic way to perform the analyses and to identify the sensitive parameters.** This methodology follows the work done by Fisher [N. Logothetis and H.P. Wynn; 1989] in Statistics known as the Design and Analysis of Experiments and its later development by Genichi Taguchi [G. Taguchi; 1988] and others [R A Bates & H P Wynn, 1998; Jerome Sacks,et.al,1989; T W. Simpson, et.al,1997; WJ Welch,et.al,1992]. This paper describes Computer Experiments and its applications in two Case Studies.

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2.0 Experimental Design

The preceding section established that in an n dimensional Cartesian space, where each co-ordinate axis representing a design variable x_i $(i = 1 - - - n)$, called the design variable space, each point represented by the vector $[x_1\ \ x_2\ \ - - - x_n\ ]$ is a design. If the design variables are continuous there can be infinite number of such points. For instance consider a rectangular block with dimensions (l, b, h) has been designed with permissible variations of $\pm l_1, \pm b_1, \pm h_1$. The designs in general can be expressed by a vector (x, y, z) where

x is subjected to the condition $(l-l_1) \leq x \leq (l+l_1)$
y is subjected to the condition $(b-b_1) \leq y \leq (b+b_1)$
z is subjected to the condition $(h-h_1) \leq z \leq (h+h_1)$

This condition is illustrated in Figure 1. All valid designs are represented by points, which lie within the shaded rectangular block. This can be extended to an n dimensional condition, and when extended the shaded rectangular block will be replaced by an n dimensional hypercube.

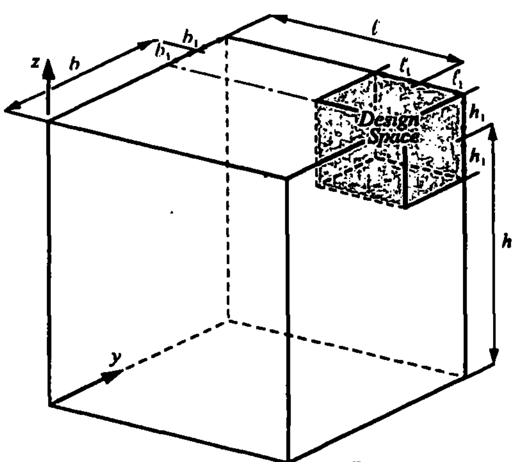


Figure 1 Design Space with three Design Variables

In Engineering Design the designer is faced with the task of finding the most favourable values for (x, y, z). There can be several performance characteristics or objective functions for which the design has to be optimised. In order to do this he often embarks on analyses where he picks random points from the design space and measures or computes the objective functions. From the insights provided by these analyses he then chooses the best values for the design variables (the best design point). Experimental design is the process of selecting candidate design points to represent the entire design space. This is a mathematical technique developed by Fisher [N. Logothetis and H.P. Wynn; 1989;].

2.1 Factorial Experiments and their Designs

An experiment involving the study of more than one factor is called a factorial experiment. Such an experiment is called "Full Factorial" experiment, if all possible factor level combinations are being experimented upon. Otherwise it is called a "Fractional Factorial" experiment. An experiment is discussed below to give an over view of how the fractional factorial experiments are efficient than the full factorial experiment.

As an example consider a blower which sucks the dust laden air from a duct and pumps it to another duct as shown in Figure 2. A factorial experiment can be used to study effects of design parameters in power consumption. Design parameters are defined as dust load, temperature of the flow, upstream pressure, downstream pressure, position of damper1, position of damper2 and speed of the blower. The levels for the designed parameters are assigned as follows. The dust load in the air can take two values say 'high' or 'low'. In a similar way the temperature in the duct can take two values, and so can the upstream or downstream pressures and the speed of the blower. Each duct has a damper which could be set at two different positions. The response or objective function (F) under investigation is power consumption. This can be expressed as $F= \phi\ (P_1, P_2, P_3, P_4, P_5, P_6, P_7)$ where ϕ denotes a function of the values of parameters $P_1, P_2, P_3, P_4, P_5, P_6, P_7$. This is a situation where there are seven factors or parameters each of which have two levels as shown below:

Parameter	Notation	Value1	Value 2	Factor	Level1	Level2
Dust Load	P1	Low	High	A	1	2
Temperature	P2	T1	T2	B	1	2
Upstream pressure	P3	UP1	UP2	C	1	2
Downstream pressure	P4	DP1	DP2	D	1	2
Position of damper 1	P5	One1	One2	E	1	2
Position of damper 2	P6	Two1	Two2	F	1	2
Speed of the blower	P7	S1	S2	G	1	2

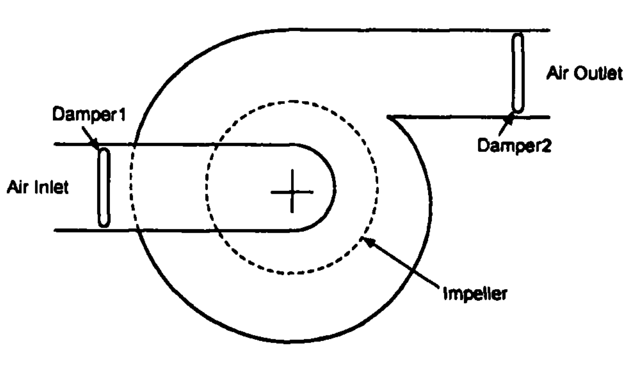


Figure 2: Blower

A full factorial experiment here, would have 128 trials and a half-factorial experiment, would have 64 trials. The "Full Factorial" design can be expressed as a 128x7 matrix where each column represents a factor and each row represents an experimental trial as shown below:

$$\begin{bmatrix} A & B & C & D & E & F & G \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 2 & 2 & 2 & 2 \\ 1 & 2 & 2 & 1 & 1 & 2 & 2 \\ 1 & 2 & 2 & 2 & 2 & 1 & 1 \\ - & - & - & - & - & - & - \\ - & - & - & - & - & - & - \\ - & - & - & - & - & - & - \\ - & - & - & - & - & - & - \\ 2 & 2 & 2 & 2 & 2 & 2 & 2 \end{bmatrix}$$

A 'Fractional Factorial Design' is made up of some of the rows from this full factorial design. Often they can be formulated from 'Orthogonal Arrays'. Fractional Factorial Designs are very economical to scan the design space in experimentation in the absence of many interactions. In this context 'the main effect of a certain factor, in a factorial experiment, is the effect by the factor on the response, taken over the various levels of other factors'. An interaction effect is a measure of the extent to which the level of one factor depends on the level or levels of one or more levels of the other factors. **This paper illustrates the use of Fractional Factorial Experiments designed from Orthogonal Arrays to scan the design space for computer experiments.** Experimental Design methodology using orthogonal arrays can be found in [E.P.Box,et.al,1978; Glen Stuart Peace, 1993; N. Logothetis and H.P. Wynn; 1989; G. Taguchi; 1988, T W. Simpson, et.al,1997].

2.2 Computer Experiments

Computer Experiments are conducted using a computer model and computer based methods to obtain values for the objective function as opposed to physical model based experiments. These maybe Finite Element Analysis software, Computational Fluid Dynamics software, Mechanism Analysis software, Mould Flow Analysis software and other similar ones. They are aimed at reducing the run time of the software to scan the entire design space. However the accuracy of the results largely depend on the validity of the computer models and therefore **it is very important to ensure the validity of the computer model before starting the experimentation.**

One fundamental characteristic of computer experiments is that there are no experimental or random errors in computer experiments. Absence of experimental error ensures a clear understanding of the underlying technical process. However mistakes on the computer model may lead to incorrect conclusions and hence carefully designed computer experiments are essential for effective and reliable results. In the case studies presented here Finite Element Analysis software Pro/MECHANICA and MSC/Nastran are used to perform the experiments. Section 2.3 outlines the procedure.

2.3 Procedure for computer experiments

Computer Experimentation can be carried out in the sequence consisting of four stages: (a) Planning, (b) Designing, (c) Conducting and (d) Analysing [Glen Stuart Peace, 1993]. The flow chart given in Figure 3 explains this process.

(a) *Planning:* In the Planning stage, the problem is studied carefully by identifying the design variables, limitations of the system and the boundary conditions with the consideration of possible working conditions. Then the performance criteria or objectives of the experiment are defined. The pre-assigned variables and design parameters are selected. Possible interactions within the identified design parameters are then identified. According to the 'working condition', suitable ranges (maximum and minimum values) for the design parameters are identified to establish the 'Design Space'. For each design parameter in the Design Space the number of levels are chosen. In short this defines the performance criteria and the requirements to establish a 'Full Factorial' experiment and the interactions that need to be investigated.

(b) *Designing:* In the Designing stage, a suitable experimental plan is formed, using a chosen orthogonal array from the library, based on the identified number of factors and the identified number of levels. When the factor values are chosen, checks need to be made to ensure (geometric) consistency of the computer model.

(c) *Conducting:* In the Conducting stage, computer models are built using the chosen dimensions (from the experimental design array) and the analysis is performed using the computer software. Values of the performance criteria or objective under study are recorded.

(d) *Analysing:* In the Analysing stage the results are analysed to find out factors which affect the performance characteristic or the objective significantly. When there is a large number of insignificant factors, it is advisable to carryout another experimental design with the sensitive factors. This is because the insignificant factors can create a large pooled-error which may discredit the analysis. From the analysis it is possible to identify the sensitive parameters and the values for the design parameters which provide the optimal conditions with reference to a single performance characteristic or objective.

sign variable together with their values at these levels are then decided. The experiments were then designed to vary the design variables in these levels and to computationally estimate the objective function. In order to estimate the values for the objective functions, a solid model of the object was constructed, with the design variables as parametric variables of the solid model. These models were then regenerated, using the appropriate values stipulated for the experimental run by the experimental design. Once the solid

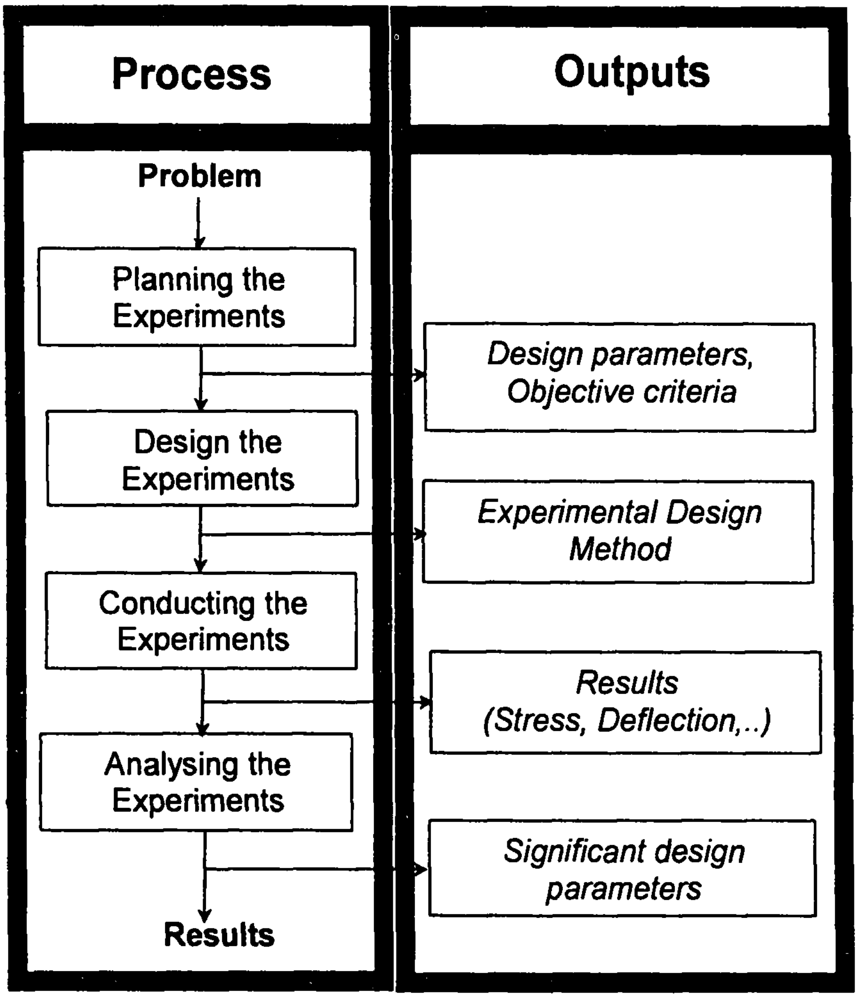


Figure 3: Methodology for identifying sensitive Parameters

2.4 Strategy for Case Studies.

The case studies reported here use the stress/deflection analysis of the Finite Element Method. As the first step the objectives and design parameters were identified. Some of the identified design parameters were then assigned with values. The remaining were called the design variables. The design variables (*n* in number) were allowed to vary within specified values and hence formed the design space as an n dimensional hyper-cube. The number of levels for each de-

model for the experimental run was established, it was meshed and submitted for analysis. The results were processed and the values for the objective function were obtained. The values for each of the experimental run and their variable settings were then subjected to analysis to obtain "Factor Plots" and "ANOVA" tables from which significant or sensitive design variables were identified. The identified sensitive variables were then assigned with suitable values to get an optimal design.

3.0 Case study1: Deflection analysis of the Superstructure for a Niftylift Hydraulic Access Platform.

An access platform provides the ability for a worker to reach heights. It has a boom structure mounted on a base at one end with a cage for the workman at the other end. For the machine to be safe and comfortable to the operator, the cage must have minimum deflections. The superstructure connects the boom to the base. A typical machine is shown in Figure 4.

This study is aimed at minimising the **Deflections on the Superstructure** of a Niftylift HR14 mobile work platform. This machine is used to access up to fourteen-meter height and the boom lengths are approximately six meters. Minimising the deflection at the base is essential to control the deflection at the cage. Thus deflection at the base becomes the objective function of the design problem.

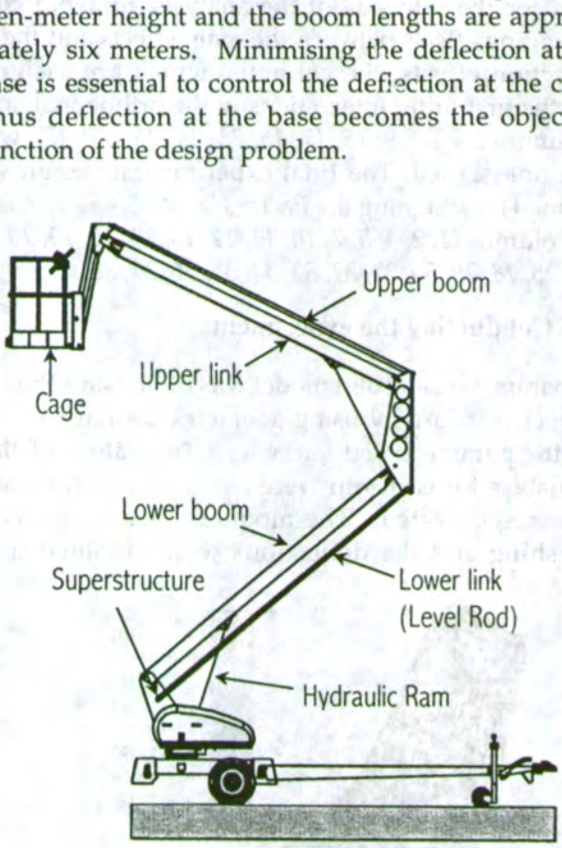


Figure 4 A typical Access Platform

3.1 Planning the experiment

The objective of this study is to identify the sensitive parameters which contribute towards the deflection of the superstructure. This will then allow the designer to select the right values to minimise the deflection. The parameters under consideration are of two-types (a) the geometric parameters and (b) dynamic loads or reaction parameters, which will vary due to the position of the cage.

Geometric parameters of the superstructure are shown in the figure 5 and Table 1.

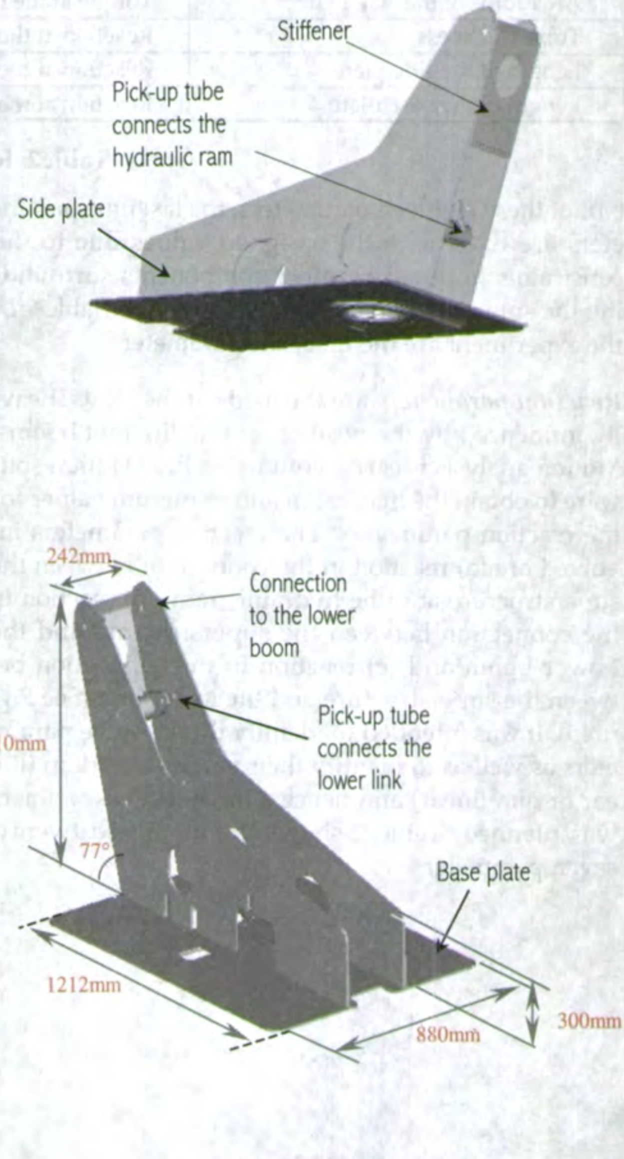


Figure 5: Superstructure

PARAMETERS	PARAMETERS
1. Diameter of the stiffener hole	10. Length between side plates
2. Thickness of the stiffener	11. Thickness of the side plates
3. Length (vertical)of the stiffener	12. Width of the base plate
4. Length (angle) of the stiffener	13. Thickness of the base plate
5. Height of the side plate	14. Slots of the base plate
6. Arc radius of the side plate	15. Slots in the side plate
7. Pick-up tube Thickness	16. Shape of the side plate
8. Length of the side plate	17. Pick-up plates
9. Length of the base plate	18. Position of the pick up tubes.

Table 1: Geometric Parameters

IDENTIFIED FACTORS	IDENTIFIED FACTORS	IDENTIFIED FACTORS
Diameter of the stiffener hole	Reaction at the ram joint in X dir.	Torque at the level joint about X-axis.
Thickness of the stiffener	Reaction at the ram joint in Y dir.	Torque at the level joint about Y-axis.
Length (vertical)of the stiffener	Reaction at the ram joint in Z dir.	Torque at the level joint about Z-axis.
Length (angle) of the stiffener	Torque at the ram joint about X-axis.	Reaction at the boom joint in X dir.
Height of the side plate	Torque at the ram joint about Y-axis.	Reaction at the boom joint in Y dir.
Arc radius of the side plate	Torque at the ram joint about Z-axis.	Reaction at the boom joint in Z dir.
Tube Thickness	Reaction at the level joint in X dir.	Torque at the boom joint about X-axis.
Length of the side plate	Reaction at the level joint in Y dir.	Torque at the boom joint about Y-axis.
Length of the base plate	Reaction at the level joint in Z dir.	Torque at the boom joint about Z-axis.

Table2: Identified factors

Out of these eighteen parameters, the last nine parameters are fixed with the assigned values due to the constraints imposed by other components surrounding the superstructure. Thus, the design variables for the experiment are the first nine parameters.

Reaction parameters are the loads at the joints, heavily influenced by the position of the different booms. Motion analysis is carried out using Pro/Motion software to obtain the maximum and minimum values for the reaction parameters. The reaction parameters involved are (a) reaction in the connection between the superstructure and the hydraulic ram, (b) reaction in the connection between the superstructure and the Lower boom and (c) reaction in the connection between the superstructure and the lower link (See Figure5). It was intended to identify the sensitive parameters as well as to identify their variation pattern (linear or non-linear) and hence a three-level experiment was planned. Table 2 shows the identified twenty-seven parameters.

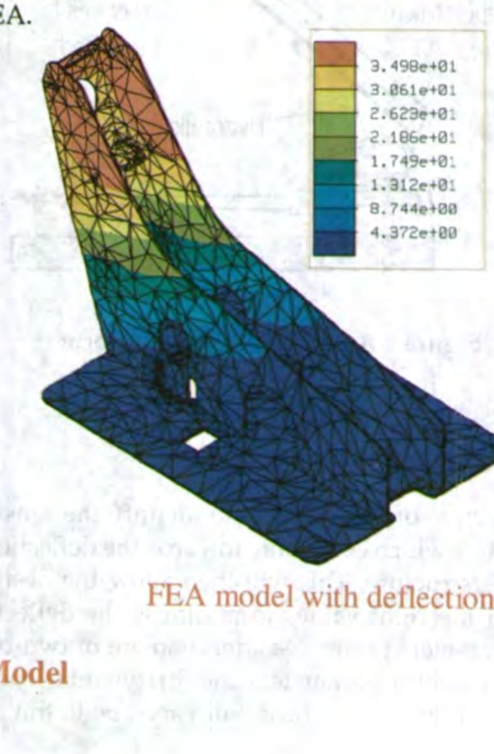
3.2 Design of the experiments

Taguchi's $L_{81}3^{40}$ [N. Logothetis and H.P. Wynn; 1989] orthogonal array was used to design the experiment. It has been decided to ignore the interactions. However for the safe side of the analysis, to avoid compounding effects between the main effects and the interaction effects, the columns, which are assigned for the first order interactions in the orthogonal array (columns *3, 6, 8, 9, 15, 17, 18, 23, 24, 26* and *27*), were left unassigned. The final experimental design was formed by assigning the Factors *[A, B, C, - - - Y, Z, AA]* to columns *[1, 2, 4, 5, 7, 10, 11, 12, 13, 14, 16, 19, 20, 21, 22, 25, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38]*.

3.3 Conducting the experiments

A parameterised solid model was built using Pro/Engineer software by using geometric design variables as the parameterised variables. The values of these variables for each run were assigned and the model was re-generated. The model is then subjected to meshing and the deflections were obtained using FEA.

FEA Mesh model



FEA model with deflection

Figure 6: FEA Model

A typical output of the run is given in figure 7. The maximum deflections were obtained from these outputs. Table 3 shows the average deflections in millimetres. Due to confidential restrictions fictional names are given to the design variables.

FACTORS	LEVEL 1	LEVEL 2	LEVEL 3	FACTORS	LEVEL 1	LEVEL 2	LEVEL 3
A	50.87	49.09	52.23	O	48.60	51.51	52.08
B	49.68	47.75	54.76	P	50.29	49.25	52.64
C	60.89	37.71	53.59	Q	50.18	52.21	49.80
D	54.54	51.87	45.77	R	11.56	46.56	94.06
E	50.62	48.08	53.48	S	50.03	52.22	49.94
F	52.95	43.73	55.50	T	51.18	50.08	50.93
G	51.09	51.69	49.40	U	49.98	50.88	51.32
H	56.76	46.56	48.86	V	50.20	50.27	51.72
I	55.92	52.43	43.83	W	48.62	50.78	51.48
J	50.60	51.24	50.34	X	50.66	49.66	51.86
K	49.20	49.54	53.44	Y	48.05	50.49	53.64
L	49.86	49.29	53.44	Z	51.12	49.67	51.39
M	48.74	53.45	49.99	AA	49.93	52.48	49.77
N	52.14	50.73	49.32				

TABLE 3: Average Deflections

3.4 Analysing the results

A factor plot was constructed using the results in Table 3. This factor plot is shown in Fig 7. As seen from the factor plot, Design variable R has been identified as the most sensitive factor. Other six factors which are identified to be sensitive are, B, C, D, F, H, and I. Individual factor plots for these are shown in Figure 8. It shows that the variation of factor R is about linear.

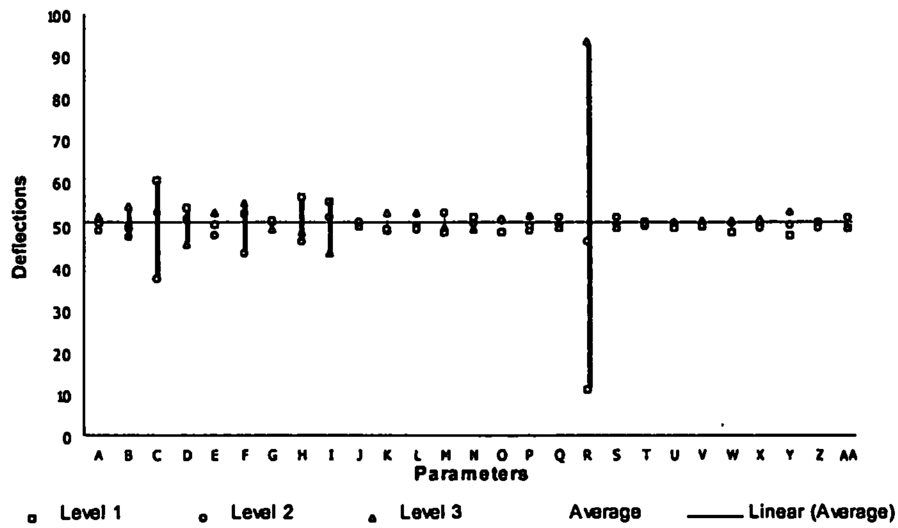


Figure 7: Factor plot

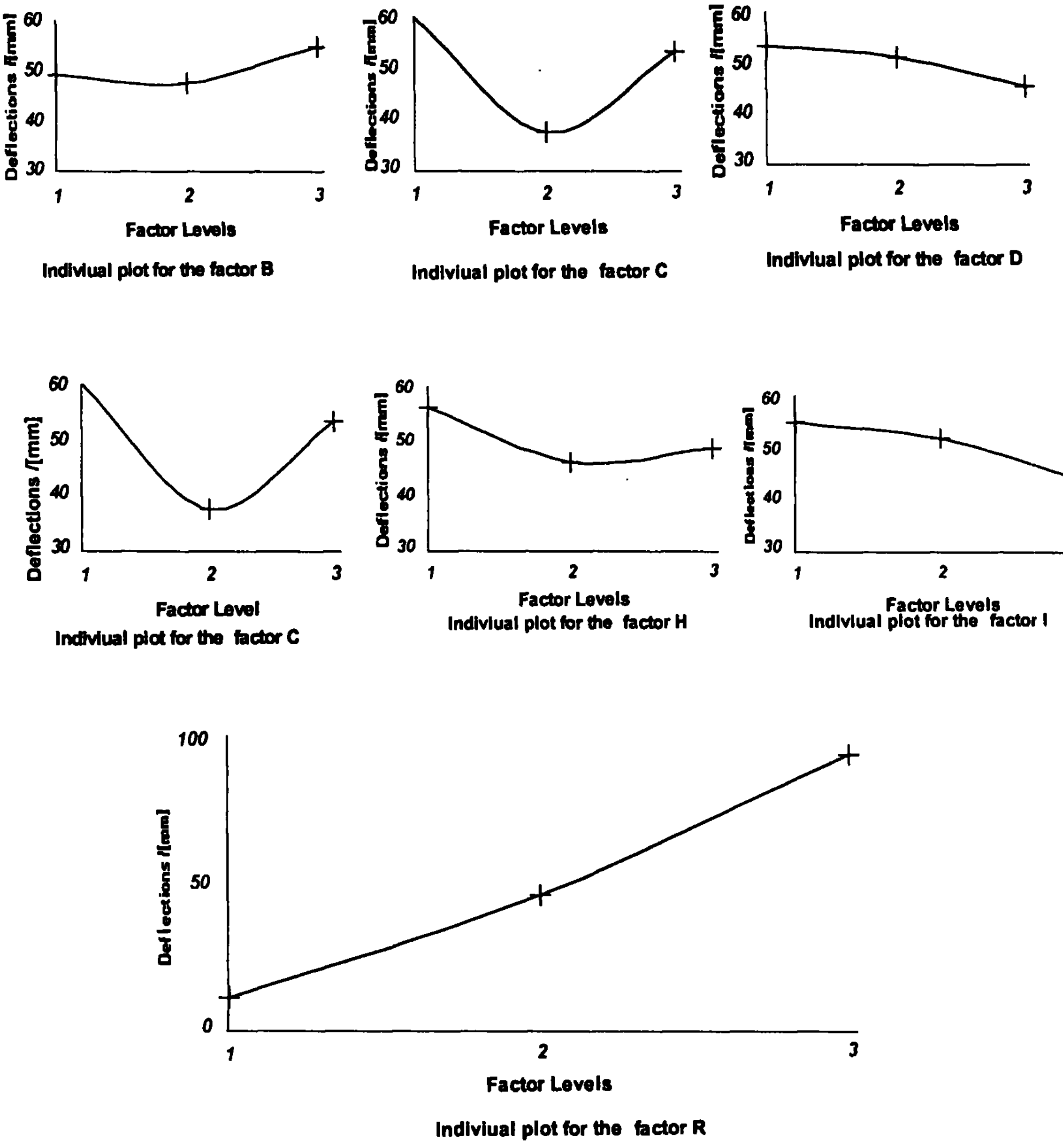


Figure 8: Individual Plot for the sensitive parameters

From this experiment it is safe to conclude that variables B, C, D, E, F, H, I and R have significant effect on deflection of the superstructure. The most significant factor R has a linear variation.

These results, were then passed down to design, manufacture and testing with the prototype. Deflection, the objective function of the study, was found to vary significantly with variations in the identified sensitive parameters. Once the results and the design have been proven to work in accordance it became easier to find the optimal solution.

4.0 Case study 2: Stress analysis of Radiator tank (Jaguar XK8)

Radiator tanks are located at the top of a radiator core in an automobile, to contain the high pressure cooling water, which circulates through the cooling tubes in the core. The radiator tanks undergo high stress distribution at elevated temperatures. These mechanical and thermal loads cayse some tanks start developing leaks while in service. This experiment is aimed at **minimising the stress distribution** at the radiator tank of the Jaguar XK8. The objective function therefore is the stress distribution at the tank. Minimising the stress distribution is essential to minimise the failure rate and to provide a better performance and long life for the radiator unit.[Jayesh S.Ravat; 1997]

4.1 Planning the experiments

The objective of the study is to identify the sensitive parameters which have significant effects on the stress distribution of the radiator tank (Figure 8). Parameters were chosen due to their known effect on stress distribution (with knowledge of past experiences) and with the careful consideration of whole process the cooling water undergoes, in the radiator tank. The parameters identified are shown in Table 4.

PARAMETERS
System Pressure
Shell thickness
Rib thickness
Number of ribs
Young's Modulus

Table 4

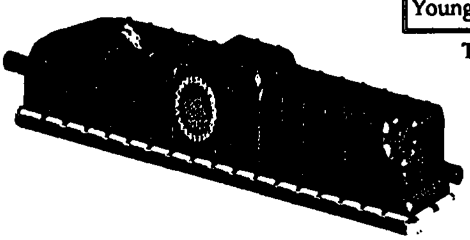


Figure8: Radiator tank

4.2 Design of the experiments

Experiments were planned and implemented using Taguchi's $L_{27}(3^{13})$ orthogonal array[N. Logothetis and H.P. Wynn; 1989]. Some interaction effects were considered with an assumption that the interaction effects between the other parameters can be negligible. The interactions intended for investigation were AB, BE and CD. The columns assigned for factors [A, B, C, D, E] are [1, 2, 4, 5, 6].

4.3 Conducting the experiments

The initial Solid Model of the tank was created using the MSC/Aries software and the resulting CSG tree was extracted [Tamer M.M Shahin, 1996]. A macro was then written to parameterise the geometric variables. The constraints were also included in the macro. The macro was then used to generate the solid model with each parameter combination identified by the experimental design. The models thus built were then subjected to meshing and the stress distributions were obtained using the FEA software MSC/NASTRAN.

4.4 Analysing the experiments

The first trial was carried out with the nominal working condition and the trial shows that a greater stress is present at the ribs and in particular towards the middle of the tank, where it is most flexible. In addition, the stress at the rear of the tank is greater than front where outlet tube is located. This is due to the structure of the outlet tubing and its position mid-way between the end of the tank. The FE stress distribution shows high stress at the ribs, which proves that the form and position of the ribs has a major impact on the stress distribution.

Analysis of Variance (ANOVA) was carried out for the stress distribution. The resulting table is given in Table 5. Due to confidential restrictions fictional names are given to the design variables.

In this experiment, experimental errors are not present, for the purpose of the analysis the sums of square less than 4% the total sums of square are pooled together [N. Logothetis and H.P. Wynn; 1989]. Mean sum of square of the design parameter is compared with the mean sum of square of the pooled error using F-test, which provides a decision at some confidence level as to whether these variances are significantly different.

	SUM OF SQUARE	DEGREES OF FREEDOM	MEAN SUMS OF SQUARE	F-RATIO	SIGNIFICANCE (1%-18)	CONTRIBUTION FACTOR (%)
A	4.1755	2	2.0877	35.6772	1	9.17
B	28.8288	2	14.414	246.3228	1	63.34
AB	2.9755	2	1.4877	25.4240	1	6.54
C	2.7466	2	1.3733	23.4683	1	6.03
D	6.6155	2	3.3077	56.5253	1	14.53
E	0.0026(p)	2	0.0133	0.2278	0.06	
BE	0.1177(p)	2	0.0588	1.0063	0.26	
CD	0.0311(p)	2	0.0155	0.2658	0.07	
Pooled error	0.1755	6(3)	0.0292			
Total	45.5177					

Table 5: ANOVA table

F-value can be defined as,

$$F = \frac{\text{Mean sum of square of a parameter}}{\text{Pooled error sum of square}}$$

To determine whether an F ratio of two sample variances is statistically large enough, three pieces of information are considered. They are

(a) The confidence level necessary.

(b) Degrees of freedom associated with the sample variance in the numerator.

(c) Degrees of freedom associated with the sample variance in the denominator. According to the selected degrees of freedom and confidence level, F-value from the table is compared with the calculated F-value. If the calculated value is less than the value read from the table it is assumed that the contribution by that factor to any variation is insignificant and otherwise it is significant.

ANOVA table 5 shows that the effect of the factors A, B and the interaction effect between A&B, C and D have significant effect on a 99% confidence on the stress distribution. Factor E has almost no effect on the stress distribution (maybe due to the small range of variation of the parameter considered in the analysis). The table also shows Taguchi's controversial Contribution Ratios. The contribution ratios are used by Taguchi as a measure of the magnitude of variance contribution by that factor. This usage is controversial because of its lack of statistical explanation. Using Taguchi's contribution ratio, it is possible to say that the effect of factor A on the overall variance is 9.17% and that of factor B is 63.34% in the design, whereas the ANOVA only says that the factors A and B are significant at 99% of confidence level.

It can be seen from the table that factor B has a greater contribution on stress distribution. This is followed by factor D. There is only a small contribution from the factors A and C. From this experiment it is safe to conclude that the factors A, B, C, and D have significant effect on the stress distribution of the radiator unit and there is a significant interaction between factors A and B.

5. Conclusion

A method for screening sensitive factors based on computer experiments, has been described and demonstrated for problems with single objective function or criteria. This allows the identification of the 'Design Space' together with details on the assigned parameters. Identifying the contributing or sensitive parameters is the fundamental step towards the optimisation process. The values of the design parameters describing a design point in the design space and the value of the objective function at these points form the basis of optimisation. They tell whether the relationship between the objective function and the design variable is linear or otherwise (seen from the factor plot). The values can then be used to fit a model which can then be subjected to classical methods of optimisation. In the HR14 case study, seven such parameters were identified and used in the manual optimisation process, which until then was left to the engineer's ingenuity.

A four stepped method is developed for this process. This is discussed in section 2.3, it provides the starting point and finishing point of the optimisation process.

The case studies show how sensitive parameters are identified using this model. In particular they provide two methods, the first one, the Factor Plot method, giving a qualitative measure of the sensitive parameters. This identification gives a better insight into the problem thus facilitating optimisation. In the ANOVA method a rough measure of the contribution by each factor to variances is also given.

The Case Studies illustrated the enormous power of Computer Experiments on the identification of significant factors amidst a lot of other factors, and in analysing the results and making robust designs.

6. References

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