OPTIMIZATION OF SHEAROGRAPHY TESTING USING STATISTICAL DESIGN OF EXPERIMENTS

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Abstract: Shearography finds more and more use in the industry. Setting up a shearography test you find that there are a number of parameters that have to be set which will affect the testing result. To date, very little is found generally available on how to do this for various testing conditions. The lack of previous references and standardised procedures makes every testing set up very time consuming.

In this study a statistical method has been used to get a better understanding of how different shearography parameters affect the testing result with a final goal to be able to optimise testing set-ups. Statistical design of experiments (DoE) is a method to maximise the amount of information from an experiment while minimising the number of experiments. The principles of how to use DoE as a practical tool will be described using a specific shearography test situation as example.

The experiments in this study have been performed on samples made of carbon fibre with an aluminium honeycomb structure taken from the Saab Gripen aircraft. The samples contain both real and artificial defects.

The use of DoE has shown what parameters are important to optimise and what parameters are of little influence to the final testing result. In all, this study has shown that DoE can be an efficient tool when setting up shearography tests.

Introduction: Shearography is an ndt method where very little is known, i.e. written, concerning the various inspection parameters and how they affect the inspection. When entering the world of shearography you find that you need to do a large amount of experimenting yourself, complemented by contacts with colleagues who have already left the beginners stage.

In general, experimenting is expensive. Traditionally, experiments are performed in such way that you study one parameter at a time. This is very time consuming, thus costly, and can also lead to sub-optimizations. Especially if you are investigating a complex process with a large amount of parameters that may influence the outcome of it, one parameter at a time experiments can be detrimental. A better approach is needed.

Statistical design of experiments, DoE, is one method that will reduce experimenting costs while providing a maximized amount of information about the investigated process.

In this work, DoE has been applied to shearography.

Purpose: The purpose of this work was to investigate if statistical design of experiments, referred to as DoE, can be a useful tool setting up shearography tests. It will generally serve as an example on how DoE could be used in non destructive testing in general. A better understanding of what factors affect shearography are also sought.

What is Statistical Design of Experiments (DoE)? DoE is a method to organize and perform experiments in order to minimize experimental costs while maximizing the experimental outcome. According to [1] designed experiments are very common in Japan during product- and process development phases. Estimations say that 1 million designed experiments each year are performed there. This has reduced the times spent during product development significantly. It has also shown to be a valuable tool to avoid changes in later stages of development, which are very costly.

The best way to give an introduction to DoE is with an example from [2]:

Production of springs is the process that is studied in this example. A manufacturer has a problem with occurrence of cracks in his springs. It is decided to investigate what factors in production might affect this. Three factors are chosen to study:

Steel temperature before hardening (S)
Temperature of the oil bath during hardening (O)
Carbon content (C).

For each factor two experimental levels have to be defined. During the experiment each factor is kept at either of these two levels. They are symbolized with "-" and "+". Combining the levels for all factors give 8 different sets of conditions. This represents the complete experiment. The experiment matrix for this example is shown in table 1.

Experiment no	Factor		
	S	O	C
1	-	-	-
2	+	-	-
3	-	+	-
4	+	+	-
5	-	-	+
6	+	-	+
7	-	+	+
8	+	+	+

Table 1. Experiment matrix for the shown example.

For completeness, the levels for each factor are shown in table 2.

	S [°C]	O [°C]	C %
-	830	70	0,50
+	910	120	0,70

Table 2. Experiment conditions for the shown example.

A set of springs was produced for each of the 8 experimental conditions. The springs were subject to an accelerated life-cycle test. After this the number of springs without cracks was registered. The results are shown in the extended experiment matrix in table 3.

Experiment no	S	O	C	result
1	-	-	-	67
2	+	-	-	79
3	-	+	-	59
4	+	+	-	90
5	-	-	+	61
6	+	-	+	75
7	-	+	+	52
8	+	+	+	87

Table 3. Results of the example.

How to use these results? For each of the factors an effect has to be calculated. The effect shows (for this example) how the number of uncracked springs have been affected by a change from "-" to "+" for that factor. The calculation of effects is done by adding or subtracting the results according to the signs in the test matrix for a specific factor, divided by half the number of experiments. So, for this case the effect of factor S will be:

(result 2 + result 4 + result 6 + result 8 – result 1 – result 3 – result 5 – result 7)/4 =

(79+90+75+52-67-59-61-52)/4

When you perform an experiment as this, you will not only get information on the influence that each parameter has on the result, you can also get information on interactions between factors. The effects and interactions are found in table 4.

Exp no	S	O	C	SxO	SxC	OxC	SxOxC	results
1	-	-	-	+	+	+	-	67
2	+	-	-	-	-	+	+	79
3	-	+	-	-	+	-	+	59
4	+	+	-	+	-	-	-	90
5	-	-	+	+	-	-	+	61
6	+	-	+	-	+	-	-	75
7	-	+	+	-	-	+	-	52
8	+	+	+	+	+	+	+	87
effect	23	1,5	-5	10	1,5	0	0,5	

Table 4. Entire experiment matrix including results and effects.

If we look at factor S, steel temperature before hardening, the effect is 23. This means an increase in temperature from 830°C to 910°C is very beneficial: the amount of crack free springs will increase with 23. When you analyze an experiment like this you have to take into account the statistical uncertainty of the experimental results. Often you estimate a standard deviation of the original results which you compare your effects with. For this case, the standard deviation can be estimated to 3,6. From this a standard deviation for the effect can be calculated, here 2,5. This estimated error is used for comparison with the calculated effects to see if they are significant or the result of random variations. What you often do is to use a “null-hypothesis” for comparison. You assume that there is no real difference between the two levels of a factor, then the effect would have an expected value of 0 with (in this case) 2,5 as standard deviation. You would have a Gaussian distribution since all variations would be random. Again, looking at factor S, if you have Gaussian distribution (0;2,5) it is extremely unlikely that the effect 23 would result just from random variations, there has to be a real difference. The effect of factor O, however, which is 1,5 is rather likely to be a result of random variations. The factors where the effects are large enough to be a result of real differences are called active effects, while the others are called inactive effects. For this example we have two effects that are clearly active, S and SxO.

Lets look at SxO. This is an interaction between steel temperature and carbon content. When an interaction is active, this means that the effect of one of the factors (e.g. S) depends on the level of the other (O). If there was no interaction, the effect of S would be same regardless if O was at its low (-) or at its high (+) level. This means that when you have an active interaction, you should focus on the interpretation of the interaction effect, the individual factors in the interaction are not that interesting.

The conclusion of this example is that the most active factor, S, has been found and quantified. An active interaction, SxO, has also been discovered and quantified. All other factors and interactions were found to be insignificant. The active interaction would not have been found using one parameter at-a-time experiments.

Performed experiments: Now to the actual investigation that has been performed using DoE on shearography. As previously mentioned, the purpose was to see if DoE can be used to gain a better understanding of shearography and to evaluate if it ultimately can be used to optimize testing parameters.

Instrumentation and test object: The shearography equipment used was a standard Ettemeyer AG equipment. Heat loading was applied using a heat rig consisting of four halogen lamps, each with an effect of 500W. The test setup is shown in fig 1.

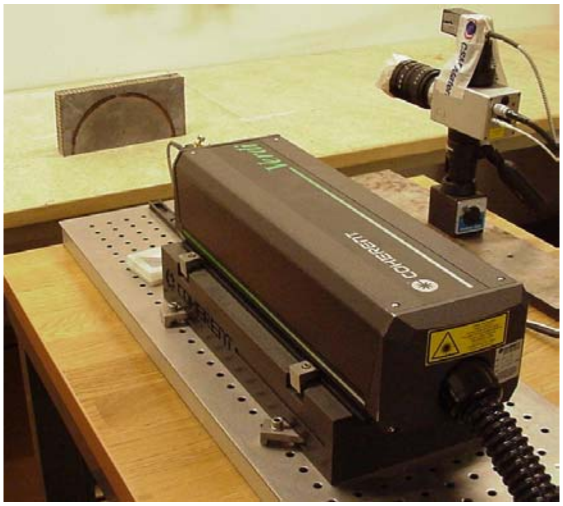

Fig 1. Test setup.

The sample used consists of carbon fibre skins (3mm thickness) and an aluminium honeycomb core (30mm thickness). There is a repair in the skin. The repair has been made by bonding a pre-cured repair patch into the skin. Schematically this is shown in fig 2. The repair was, however, not successful. The result is that there are a lot of debondings between skin and repair patch. In addition to this, artificial debondings between skin and core have been produced using a knife blade. The sample and defects are shown in fig 3.

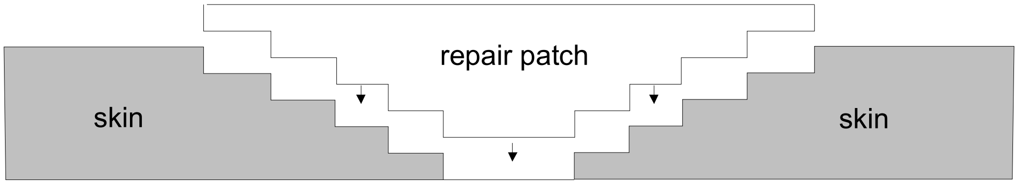

Fig 2. Schematic figure of the repair in the sample.

Fig 3. The used sample.

Identification of test factors: The first step is to identify possible factors that might influence the shearography inspection. A rather quick investigation resulted in the following set:

- Camera: aperture, shearing vector.
- Software: video gain, phase filter, phase calculation method.
- Load: amount, rate.
- Structure: material, thickness, core.
- Defect: size, location.
- Test configuration: distance camera-object, incidence angle camera-object.

Some of the factors can be further refined. When you end up with a large amount of factors you need to either chose factors for your experiment or divide the entire experiment in several smaller. Otherwise the experiment will be too large, since each additional factor will increase the amount of tests with a factor 2 for the experiment. For this test it was decided to use one specific sample and its defects. The factors and their respective levels for the first experiment are shown in table 5.

	A Heating time [s]	B Amount of heat [°C]	C Time to ref [s]	D Time ref – measurement [s]
-	15	2,4	2	5
+	30	4,5	5	10

Table 5. Factors and levels for the performed experiment.

<u>Heating time</u>: this factor was chosen to see how the heating rate will influence the shearography inspection.
<u>Amount of heat</u>: the increase in temperature of the surface of the test object compared to ambient.
<u>Time to ref</u>: the time interval from turning of the heat until the first image was taken, this image is called reference image (Ettemeyer terminology).
<u>Time ref – measurement</u>: the time interval between the reference image and the second image, called measurement image (again, Ettemeyer terminology).

Test matrix: The test matrix, including all interactions, is rather large, see table 6. Since we have four factors the experiment consists of 16 different tests.

Results and evaluation method: The results from a shearography inspection are as an image. Images can be used in DoE, it is however simpler and will normally give more reliable results if your results is some kind of figure. In the shearography software, it is possible to get a signal amplitude along a specified line. This amplitude will give the figure to put into the DoE calculations. Figs 4 and 5 show the results from the two extremes, i.e the two runs that produced the smallest and highest signals from the defects.

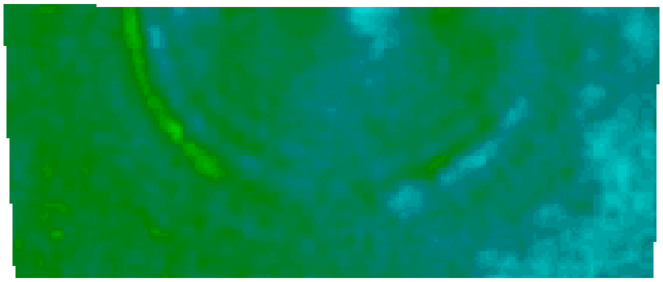

Fig 4. Result from run 2.

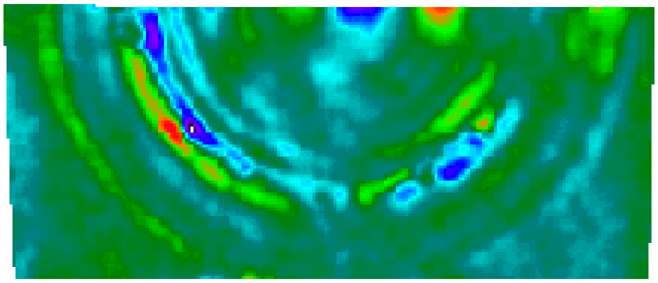

Fig 5. Results from run 11.

For the evaluation, two different spots were chosen. One spot with a defect close to the surface and one spot with the defect between skin and core. The spots are marked in fig 6, where the appearance of the signal amplitude also is shown.

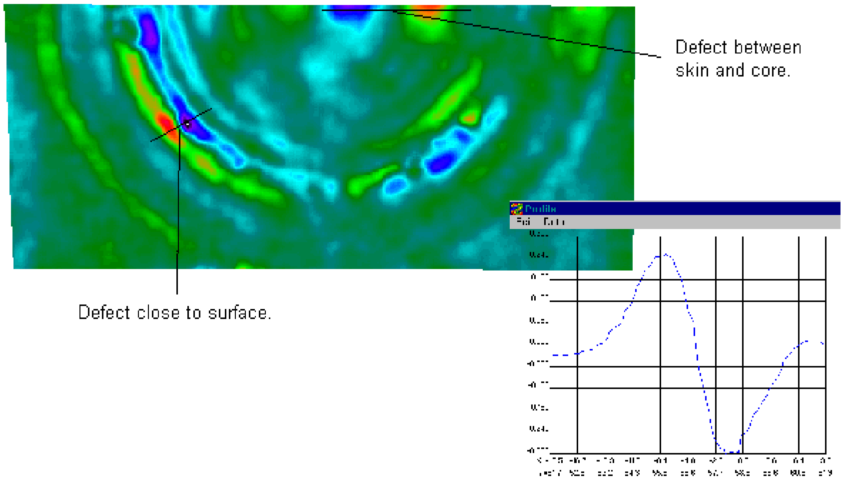

Fig 6. Evaluation spots and signal amplitude.

Calculated effects: The effects, calculated from the signal amplitudes, are found in table 7 for all individual factors and the most interesting interactions.

	A	B	C	D	AB	AC	AD	BC	BD	CD	surface	core
1	-	-	-	-	+	+	+	+	+	+	0,16	0,15
2	+	-	-	-	-	-	-	+	+	+	0,1	0,12
3	-	+	-	-	-	+	+	-	-	+	0,32	0,26
4	+	+	-	-	+	-	-	-	-	+	0,17	0,15
5	-	-	+	-	+	-	+	-	+	-	0,09	0,09
6	+	-	+	-	-	+	-	-	+	-	0,07	0,06
7	-	+	+	-	-	-	+	+	-	-	0,22	0,17
8	+	+	+	-	+	+	-	+	-	-	0,1	0,1
9	-	-	-	+	+	+	-	+	-	-	0,18	0,19
10	+	-	-	+	-	-	+	+	-	-	0,13	0,12
11	-	+	-	+	-	+	-	-	+	-	0,53	0,43
12	+	+	-	+	+	-	+	-	+	-	0,27	0,3
13	-	-	+	+	+	-	-	-	-	+	0,11	0,12
14	+	-	+	+	-	+	+	-	-	+	0,1	0,1
15	-	+	+	+	-	-	-	+	+	+	0,28	0,33
16	+	+	+	+	+	+	+	+	+	+	0,18	0,22
surface	-0,19	0,28	-0,18	0,14	-0,13	0,07	-0,02	-0,08	-0,08	-0,04		
core	-0,14	0,25	-0,13	0,18	-0,07	0,03	-0,02	-0,03	0,12	-0,01		

Table 6. Test matrix including results (the two columns to the right) and calculated effects (the two bottom rows).

Evaluation of the results: As mentioned in the introductory example, the calculated effects need to be compared against something to decide whether they are likely to be the result of coincidence or if they are significant. For this case it was chosen to use the measurement error at repetitive measurement to give a reference distribution. A null hypothesis was assumed, i.e a reference distribution with 0. Gaussian distribution was assumed.

Repetitive measurements produced an estimated standard deviation equal to 0,011. The reference distribution can thus be expressed as N(0;0,011).

From table 6 it can be seen that a number of factors and interactions are significantly larger than 0,011. One way to present this graphically which also will aid the evaluation is using a Gaussian distribution plot, see fig 7.

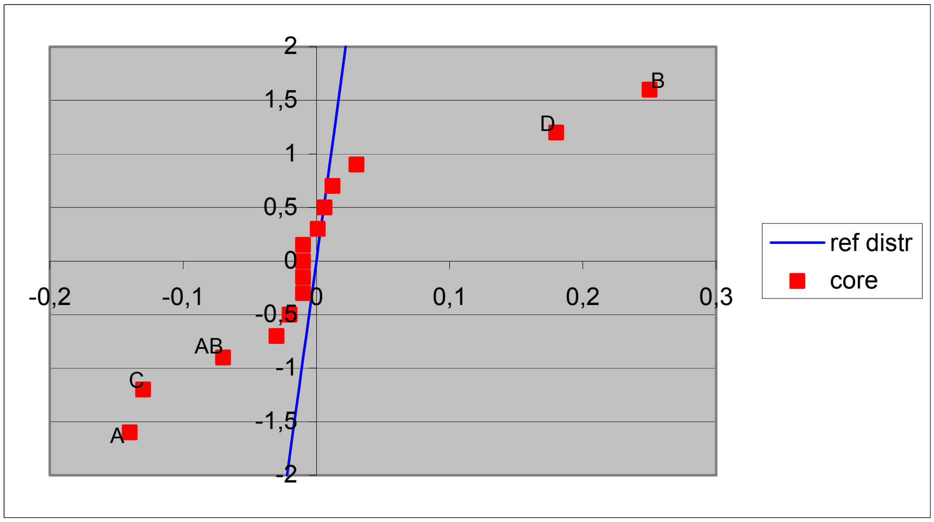

Fig 7. Gaussian distribution plot of the performed experiment.

The reference distribution is shown as the solid blue line. The calculated effects are the red dots. The further away the dots are from the reference line, the more active are the factors. It is obvious that all individual factors are active and that interaction AxB also is active.

A and B: part of the active interaction and will thus not be evaluated individually.

C: negative effect. This means that it is beneficial to have a short time between heating and the reference image.

D: positive effect. This means that it is beneficial to have a long time between reference image and measurement image.

AxB: negative effect. This means that A and B should be at their different levels. From the effects for A and B it is shown that it is beneficial to have short heating time and a large amount of heat.

Conclusions: For this work, the result of the actually performed experiment is not the most important issue. The results were as could be predicted. The most important learning is that DoE seems to work fine, also for shearography experiments. This means that there is a tool available that can be used to increase the understanding for shearography testing. DoE can also be used for easier and faster instrument settings.

References: [1] Industriell försöksplanering och robust konstruktion (in Swedish); Bo Bergman ; Studentlitteratur ; 1992.

[2] The Scientific Context of Quality Improvement ; Quality Progress ; 20 ; June 1987.