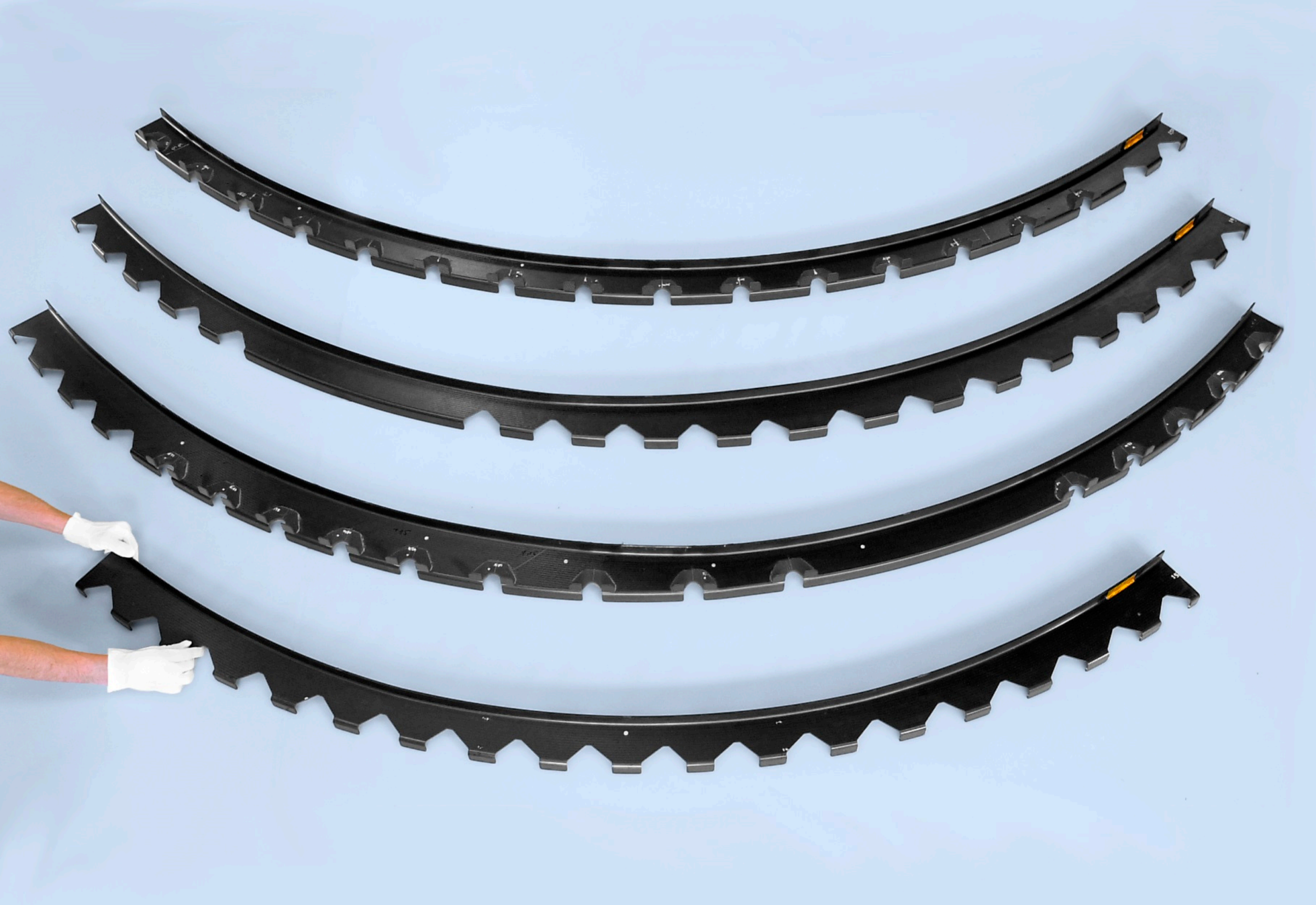
Inverse probabilistic analyses of composite part distortion

Customer

European Commission

NLR-TP-2015-303 - August 2015



__NLR__ – Dedicated to innovation in aerospace

National Aerospace Laboratory NLR
Anthony Fokkerweg 2
1059 CM Amsterdam
The Netherlands
Tel +31 (0)88 511 3113
www.nlr.nl

EXECUTIVE SUMMARY

Inverse probabilistic analyses of composite part distortion

Report no.
NLR-TP-2015-303

Author(s)
F.P. Grooteman

Report classification
UNCLASSIFIED

Date
August 2015

Knowledge area(s)
Construction and fabrication technology
Computational Mechanics and Simulation Technology

Descriptor(s)
Probabilistic Analysis
Inverse analysis
Composite Materials
Distortions
Spring-in

Problem area

Distortions in geometrical properties of composite components can result in a mismatch during assembly of the final aircraft structure. Composites are much less forgiving for such geometrical deficiencies than their metal counter parts and therefore require a higher manufacturing tolerance. Making the manufacturing process more robust therefore is important to achieve a higher product quality. In addition to this there are a wide variety of design and manufacturing factors that can potentially affect the curing processes leading to distortions.

Description of work

A probabilistic analyses scheme is presented by with which the most important scatter sources causing variation in the spring-in angle and thicknesses of a composite aircraft frame segment were qualitatively determined for an open-mould (vacuum infusion type of process) and closed-mould (resin transfer moulding) cure process. The approach is based on an iterative scheme consisting of a probabilistic sensitivity analysis, to determine the most important scatter sources, and an inverse

This report is based on a presentation to be held at the 13th International Probabilistic Workshop, Liverpool, November 4-6, 2015.

analysis, to improve the corresponding model parameter distribution functions.

Results and conclusions

The scatter in geometrical properties can most effectively be reduced by better control of the cure process. Especially, a good control of the resin and cure temperatures can yield much more stable product dimensions, but also variation in cure times have a significant effect. Although to a lesser extent, also control of the scatter in ply orientation of especially the outer plies, fibre volume fraction and cure times can yield a significant improvement.

Applicability

The result can be used to improve the geometrical distortions during curing and further direct an experimental programme to validate the current simulation results.

National Aerospace Laboratory NLR
Anthony Fokkerweg 2, 1059 CM Amsterdam,
P.O. Box 90502, 1006 BM Amsterdam, The Netherlands
Telephone +31 (0)88 511 31 13, Fax +31 (0)88 511 32 10, www.nlr.nl

Inverse probabilistic analyses of composite part distortion

F.P. Grooteman

Customer

European Commission

August 2015

This report is based on a presentation to be held at the 13th International Probabilistic Workshop, Liverpool, November 4-6, 2015.

This publication has been refereed by the Advisory Committee AEROSPACE VEHICLES.

Customer	European Commission
Contract number	FP7-GA-2012-314003
Owner	NLR
Division NLR	Aerospace Vehicles
Distribution	Unlimited
Classification of title	Unclassified
Date	August 2015

Approved by:

Author	Reviewer	Managing department
F.P. Grooteman	W.M. van den Brink	H.G.S.J. Thuis
Date 17-08-'15	Date 17-08-2015	Date 17-08-2015

Summary

Distortions in geometrical properties of composite components, due to residual stresses build-up during the cure process, can result in a mismatch during assembly of the final aircraft structure. Composites are much less forgiving for such geometrical deficiencies than their metal counter parts and therefore require a higher manufacturing tolerance. Making the manufacturing process more robust therefore is important in achieving a higher product quality. In addition to this, there is a wide variety of design and manufacturing factors that can potentially affect the curing processes leading to distortions.

To determine the importance of the various scatter sources that are present during the cure process they need to be characterised. The problem is that little to no information is available to characterise the variability in the various process parameters. To overcome this issue, a special approach was applied. From measured distribution functions of geometrical properties such as thickness and spring-in angle, the distribution functions for the model parameters were computed in a so-called inverse probabilistic analysis. With this inverse probabilistic analyses scheme the most important scatter sources causing variation in the main geometrical distortions (spring-in angle and thicknesses) of a composite aircraft frame segment were qualitatively determined for an open- and closed-mould cure process.

Content

Abbreviations

Acronym	Description
COV	Coefficient Of Variation
DLR	Deutschen zentrums für Luft- und Raumfahrt
FEM	Finite Element Modelling
LOCOMACHS	LOw COst Manufacturing and Assembly of Composite and Hybrid Structures
NLR	National Aerospace Laboratory NLR
RAP++	Reliability Analysis Program
RTM	Resin Transfer Moulding
TANGO	Technology Application to the Near term business Goals and Objectives of the aerospace industry

This page is intentionally left blank.

1 Introduction

Within the EU-project TANGO (Technology Application to the Near term business Goals and Objectives of the aerospace industry), NLR has manufactured Z-shaped composite frames for a composite aircraft fuselage which were composed of four different segments, see Figure 1, representing a non-circular aircraft cabin structure:

- **Bottom** frame with an included angle of 72.0°
- **Top** frame with an included angle of 90.2°
- **Right** hand side frame with an included angle of 97.7°
- **Left** hand side frame with an included angle of 100.1°

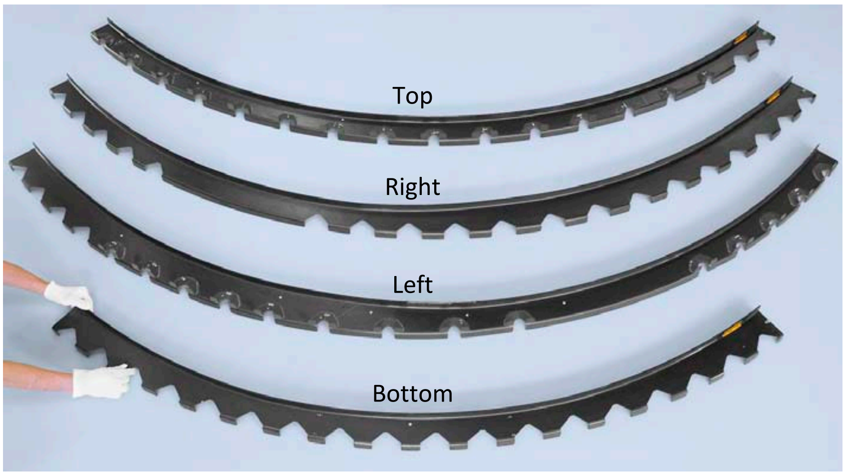


Figure 1: TANGO frames

For all these frames, four geometric parameters were measured, see Figure 2, where:

- **α** is the outside flange angle
- **t-inn** is the thickness of the inside flange
- **t-out** is the thickness of the outside flange
- **t-web** is the thickness of the middle section of the frame

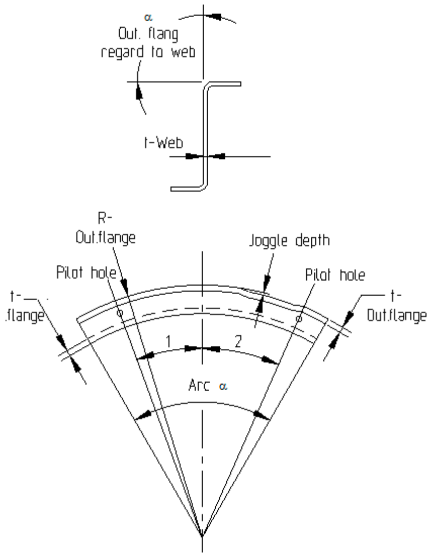


Figure 2: TANGO frame geometric parameters

Due to residual stresses build-up during the autoclave process, distortions will be present in the final product geometry such as spring-in (reduction of enclosed angles in frame cross section) and warpage of flat sections. These distortions can result in a mismatch during assembly of the final aircraft structure. Composites are much less forgiving for such geometrical deficiencies than their metal counter parts and therefore require a higher manufacturing tolerance.

For the TANGO frames the spring-in is the main distortion. Spring-in is caused by differential thermal expansion between fibres and matrix and by the evolution of mechanical properties of the resin during processing and therefore strongly depends on the timing of events during curing [Albert and Fernlund (2002)]. The spring-in angle can be corrected on average by adjustments made in the mould. The TANGO frame mould had a spring-in compensation angle of 1.2 degrees, i.e. the angle of the mould is 91.2 degrees, which was also applied in the finite element model. This compensation angle was determined on a small resin transfer moulding (RTM) of a section of the composite frame. The measured angle α therefore characterises the variability in the “spring-in effect”. Reduction of the amount of scatter, i.e. making the manufacturing process more robust, is important to achieve a higher product quality.

The deviation from the nominal value of these four geometric parameters is caused by variations (scatter) in the different parameters of the manufacturing process. Determination and characterization of the most important scatter sources that cause the majority of the scatter in especially the spring-in angle was the main objective of this work performed within the EU-project LOCOMACHS**.**

Within the LOCOMACHS project also a cure model was developed by NLR [Brink, van den (2014)], consisting of a thermal model to compute the temperature distribution during the cure cycle and a mechanical model to compute the final product dimensions. For both models special user-subroutines were implemented for this purpose. This deterministic model was verified on L-shaped specimens and a TANGO frame and was applied in the probabilistic analyses to examine the influence of the various scatter sources on the scatter in the product dimensions of the composite part. This offers a huge advantage over experimental methods. Apart from the huge costs involved in an experimental programme to characterise the various scatter sources, several of the parameters are hard or even impossible to measure, e.g. volumetric chemical shrinkage in rubber or glassy state, heat generated during curing process or coefficient of thermal expansion at glassy state.

2 TANGO frames spring-in angle distribution

For each of the 4 different TANGO frame segments, 5 frames were manufactured by NLR and for each frame the angle and thicknesses, see Figure 2, were measured at 9 different locations. An example of the measured data is given in Figure 3.

Based on this dataset, distribution functions can be fitted to the data. The larger the dataset, the higher the confidence in the resulting distribution fit parameters. Hence, it would be beneficial to pool the data for the different frame segments, as well as for the different thicknesses (web and two outer flanges) yielding more accurate distribution fit.
Whether the datasets obtained for the different frames can be pooled or not can be determined by means of statistical tests. For instance, the T- and F-tests are applied to determine if the difference in mean, respectively, standard deviation between both sets is insignificant, i.e. whether both sets are extracted from the same distribution. In that case both sets can be pooled to form a larger dataset. It turned out that the spring-in data of all frames could be pooled yielding a dataset of 4*5*9=180 data values.

Frame 1914	Drawing 5845-24c			Arc α 100,018°		
Position	t-Out.flange (mm)	t-Inn.flange (mm)	t-Web (mm)	α Out.flange regard to web. (°)	R-Out.flange (mm)	Joggle-depth (mm)
1	3,461	3,556	3,67	90,250	1974,425	
2	3,440	3,554	3,74	90,000	1974,787	
3	3,461	3,557	3,75	90,250	1975,143	
4	3,497	3,587	3,76	90,250	1975,284	
5	3,480	3,574	3,69	90,250	1973,192	1,808
6	3,473	3,576	joggle	90,167	1972,431	2,569
7	3,450	3,556	3,73	90,167	1973,556	1,444
8	3,420	3,460	3,62	90,167	1974,810	
9	3,396	3,383	3,56	90,250	1974,779	

Figure 3: Example of available TANGO frame measurement data

Before fitting a distribution to the pooled dataset, first outlier analyses were performed to check for data values in each dataset that deviated too much from the rest of the data. These outliers should be removed before fitting a distribution function since they can heavily affect the result. No outliers were found for the spring-in angle.

For the distribution fit many distribution types, e.g. Normal; Lognormal; Weibull, can be applied. Here a Normal distribution turned out to fit best, which might be expected since the variation in geometrical dimensions often can be modelled well by this distribution type (no preference for a higher or lower value, i.e. symmetrical distribution).

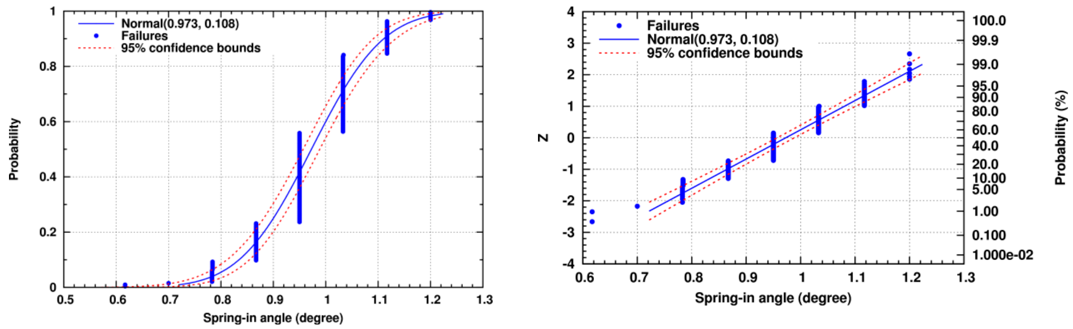


Figure 4: Cumulative distribution function (left) and Normal probability paper (right) for spring-in angle

Figure 4 provides the distribution obtained for the spring-in angle. The right figure shows a straight line that corresponds to the sigmoidal shape of the cumulative distribution function depicted in the left picture, which can be achieved by proper transformations. This type of plot is called a (Normal) probability paper plot, and better reflects whether the distribution type is appropriate to represent the underlying dataset than the cumulative distribution. This was further supported by the outcome of several goodness-of-fit tests.

The red-lines denote the 95% confidence bounds in between which the true distribution lies with 95% probability. The larger the dataset the narrower the confidence bounds.

The spring-in angle plots shows vertical lines of equal valued (random) points caused by the limited accuracy of the measured data values, yielding discrete sets of points.

The spring-in angle can thus be represented by a Normal distribution function with mean of 0.973 degrees and standard deviation of 0.11 degrees. The variability in the spring-in angle for the TANGO frames is thus very low, being the main purpose at the time of manufacturing that directed, amongst others, the selection of the fibre and mould material. Nevertheless, the dataset can be used to examine which scatter sources contributed most to the scatter in the spring-in angle, identifying the most critical process parameters.

3 Inverse probabilistic approach

To determine the importance of the various scatter sources that are present in the cure process they need to be characterised. The problem now is that little to no information is available to characterise the variability in the different process parameters and for various parameters even difficult or impossible to measure. To overcome this issue, a special approach was applied. Instead of computing the distribution functions for the final geometrical properties (output, e.g. spring-in angle) from known distribution functions for the model parameters (input) in a probabilistic analysis, as presented at the end of this paper, here the inverse is applied. From the measured distribution functions of the spring-in angle (output), the distribution functions for the model parameters (input) are computed in a so-called Inverse Analysis, schematically depicted in Figure 5. For this purpose, values are randomly drawn from the known spring-in angle distribution and for each value an optimisation analysis is performed to determine the corresponding values of the model parameters. Each spring-in angle value thus results in a slightly different set of model parameter values, for instance the cure time. Repeating this inverse analysis for 50 random spring-in values, yields a random dataset of 50 values for each model parameter to which a distribution function can be fitted, representing the required scatter that cause the scatter in the spring-in angle.

The underlying assumption here is that the optimum found in each inverse analysis corresponds to the model parameter values in the real cure process. This at least requires that the cure model is reasonable accurate, i.e. can predict the average spring-in angle, which is the case. Furthermore, the number of model parameters that are allowed to vary (called design variables in the optimisation analysis) should be kept to a minimum (only the parameters that matter) to obtain a useful optimum and in an acceptable amount of computational time. The optimisation scheme has to converge to a nearby optimum (set of parameter values that yields the correct spring-in angle) in the neighbourhood of the initial point (the spring-in angle obtained for the mean parameter values), which is an unconstraint nonlinear optimisation. To prevent that a faraway solution in one-direction is obtained, a gradient based optimisation scheme is not suitable. Instead, the Nelder-Mead simplex algorithm is an appropriate choice. The algorithm first makes a simplex around the initial point by adding 5% of each component and using these vectors as elements of the simplex in addition to the initial point. Then, the algorithm modifies the simplex repeatedly until an optimum is reached.

If a distribution function can be fitted to the resulting datasets, i.e. being random sets, this is an indication that the above assumption might be valid. It is furthermore assumed that there is no significant statistical correlation between the different important model parameters since this can only be determined from a set of experimental data which is lacking, although any correlation affects the obtained distribution functions.

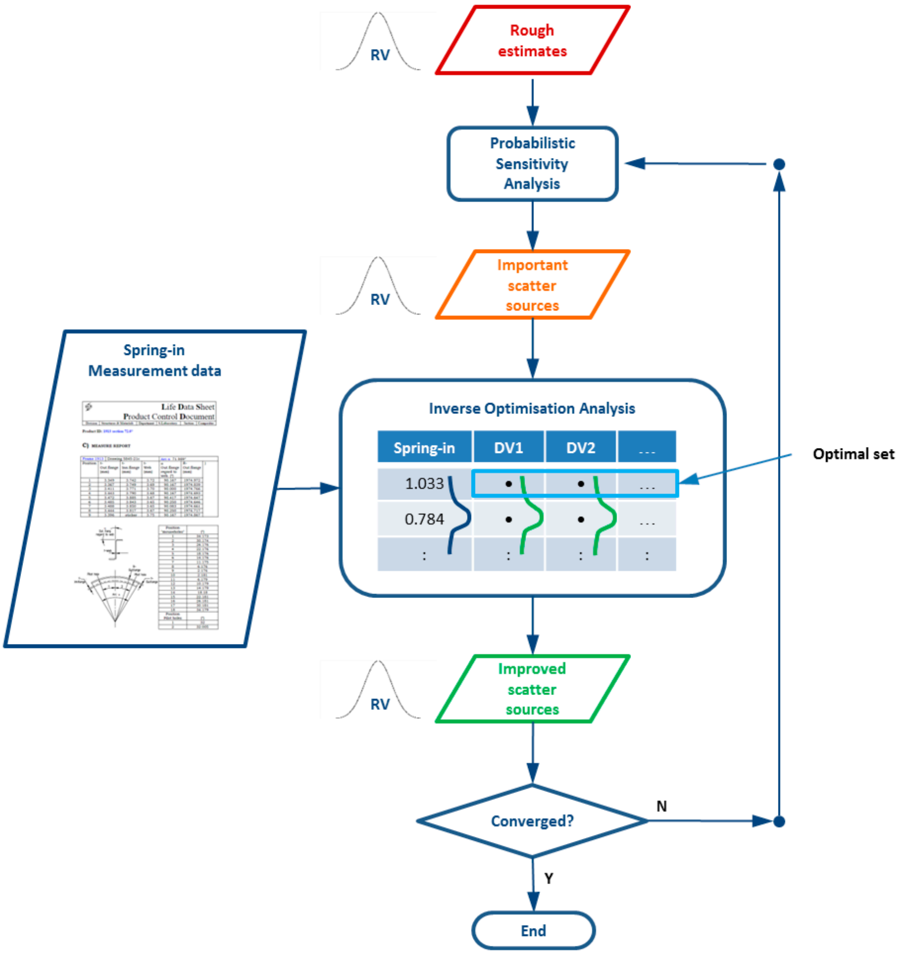


Figure 5: Schematised inverse analysis

The cure model consists of a large number (89) of model parameters, too many to be taken into account as design variables in the inverse analysis. Hence, first a selection is made of the most important ones. These are the model parameters for which their scatter causes most of the scatter in the product dimensions. This can be determined by means of a probabilistic sensitivity analysis, which calculates how much of the scatter in a response value (here the product dimensions like spring-in angle) is caused by the scatter in the various model parameter. For this, approximate distributions suffice. Many of the model parameters will not cause any significant scatter in the spring-in angle, even if the amount of scatter in the parameter itself is large. This immediately rules out a substantial set of parameters as candidates in the inverse analysis. The problem again is the unknown distribution functions for the various cure model parameters. This can be overcome by an iterative approach, schematically depicted in Figure 5. First, approximate distribution functions are estimated based on the known mean value and a conservative estimate of the coefficient of variation, assuming a Normal distribution. These are used in a sensitivity analysis to determine the most important scatter sources (random variables). The corresponding model parameters are subsequently used in an inverse optimisation analysis as the design variables for which a random dataset is computed with which the scatter in the spring-in angle can be explained. Subsequently, this random dataset is used to determine new distributions for these model parameters. The resulting distribution functions based on the random datasets are better approximations for the true scatter in these model parameters and are used in a second sensitivity analysis. At first this can result in a somewhat different set of important model parameters for which again an inverse analysis is performed. After a few iterations this process converges.

It should be noted here that approximate distributions suffice for a probabilistic sensitivity analysis since the objective is to determine the cause of variation around the mean and rank the random variables according to their influence on the scatter in the product dimensions, which only depends on the global behaviour of the various distribution functions around the mean. This in contrary to a reliability analysis to compute the probability (of failure), for which accurate distribution functions are required, especially for the distribution tails.

The above analysis scheme is applied for an open-mould as well as a closed-mould RTM process. Based on the final distributions, guidelines can be formulated for the manufacturing of composite components minimising the variation in geometrical properties.

The NLR in-house probabilistic tool RAP++ (Reliability Analysis Program) [Grooteman, 2011] is applied for the probabilistic sensitivity analysis. RAP++ is a general probabilistic tool that can be easily interfaced with any deterministic tool, adding the probabilistic layer. The program has for instance been applied to: ABAQUS (FEM); NASTRAN (FEM); PAM-CRASH (FEM); NASGRO (crack growth), using a very simple user-friendly interfacing approach and is written in C++ (fully object oriented) to enhance maintainability and especially extendibility. The main features of RAP++ include: 1) Data Analyses such as comparison, correlation, outlier analysis and distribution fits; 2) Sensitivity Analysis; 3) Reliability analysis; 4) Deterministic optimisation analysis and 5) Reliability based optimisation.

4 Deterministic model

During the RTM process the resin material experiences several changes. Before the process starts the resin material is uncured and behaves like a viscous liquid at room temperature. During the cure phase the polymer cross links with the other chains forming large polymer chains. When a cure rate of ~0.7 called the α_{gel} is reached the large chains/cross links are restraining the free motion to such an extent that a “rubber-state” is reached which is called gelation.
The fibre properties are relatively constant while the resin properties drastically change during the cure cycle as the resin polymerizes, in which the semi-crystalline matrices shrink, i.e. the crystals have higher density then the amorphous phase. Hence, the development of residual stresses heavily dependents on the processing history.
A dedicated cure model was developed and verified by NLR, see for details [Brink, van den (2014)], which was applied in the probabilistic simulations by NLR of the TANGO frames depicted in Figure 1. The cure simulation model consists of two sequential analyses starting with the thermal cure simulation where the cure rate and heat generation from the exothermal reaction of the resin is calculated. After this thermal analysis the sequential mechanical analysis for spring-in is performed. The simulations are performed within the finite element package Abaqus 6.13-1, which is extended with the cure and spring-in user subroutines (HETVAL, USDFLD, UEXPAN).

The probabilistic analyses, but especially the inverse analysis, being an optimisation analysis, require a large number of simulations, which is time consuming. Hence, the original TANGO frame finite element model (FEM) was reduced to an L-shape (Figure 6) with the same geometry, stacking sequence, material properties and boundary conditions as the full TANGO frame FE model resulting in similar spring-in angle and thickness values. This is justified by the fact that the spring-in and thickness are local effects and do not strongly depend on the circumferential dimensions of the frame. Hence, an L-shaped section can be cut-out of the frame as depicted in Figure 6. The L-shape also corresponds to the sample geometry often applied in spring-in tests.

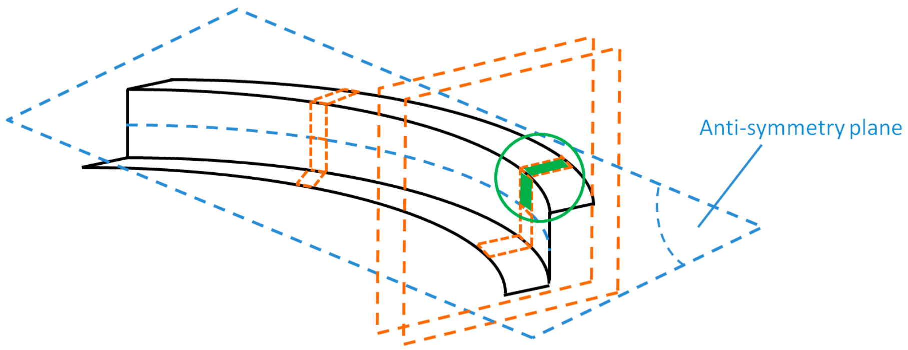


Figure 6: Schematised TANGO frame and L-shape detail

Based on the L-shape an open- and a closed-mould model version was created with different boundary conditions. The mould included the 1.2 degree spring-in compensation as applied in the real RTM moulds. The mesh for both models was optimised for computational efficiency and accuracy and consisted of linear heat transfer elements for the cure phase and quadratic stress elements for the mechanical model. The total analysis time to evaluate the open- and closed-mould model was approximately 1, respectively, 3 minutes while this was 14 minutes for the full TANGO frame model.

5 Results

The inverse approach was examined for an open- and closed-mould model showing similar results. The results presented here are obtained for the open-mould model. Figure 7 presents the results of the initial sensitivity analysis for the 30 (out of 89) most important model parameters (see Table 1 for the meaning) in the form of a Pareto plot. The Pareto plot shows a bar-diagram expressing in descending order the contributions of the scatter in the individual model parameters on the scatter in the response (here the spring-in angle). A green colour reflects a positive correlation, i.e. an increase in the parameter value results in an increase in the response value, and a red colour a negative correlation. The solid line shows the summation of the different contributions adding up to 100%.

The most important scatter sources determined in this initial sensitivity analysis are in the order of importance: initial temperature of the resin (TRESINT), fibre volume fraction (VFF), final curing temperature (DWELL2), volumetric chemical shrinkage in rubber state (EPSCHEM_RUB), coefficient of thermal expansion at rubber and glassy state (CTE_R2 and CTE_G2).

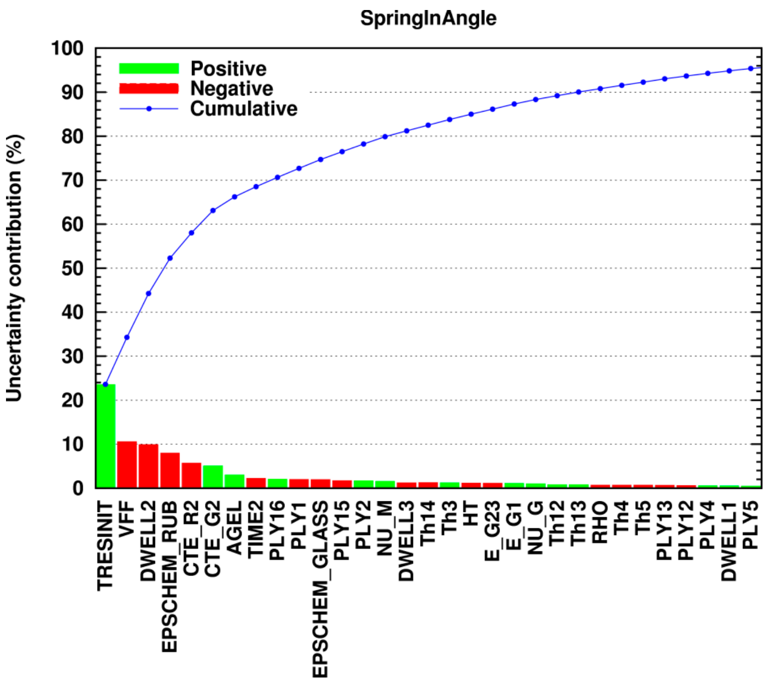


Figure 7: Pareto plot for the spring-in angle of the initial sensitivity analysis results for 30 most important model parameters

The first 15 model parameters, ranging from TRESINT (initial temperature of the resin) up to DWELL3 (post-curing temperature), were selected and taken into account in the first inverse analysis as design variables covering 81 % of the observed scatter. The other 74 model parameters cause the remaining 19 % of the scatter of which 45 contributed less than 0.1 %.

For 30 spring-in angles, randomly selected from the measured distribution, an inverse optimisation analysis was performed yielding 30 values for each of the 15 model parameters. On average it took 224 cure simulations per optimisation run to reach an absolute error of 0,001. A distribution function could be fitted to each of the datasets, indicating the randomness of the datasets. For all important parameters a Normal distribution proved to be appropriate supporting the initial choice. Figure 8 depicts four example distribution fits on Normal probability paper showing a straight blue-line for the sigmoidal shape of the cumulative distribution function. Ideally, the points should be scattered around the blue-line, which is the case for the plots shown.

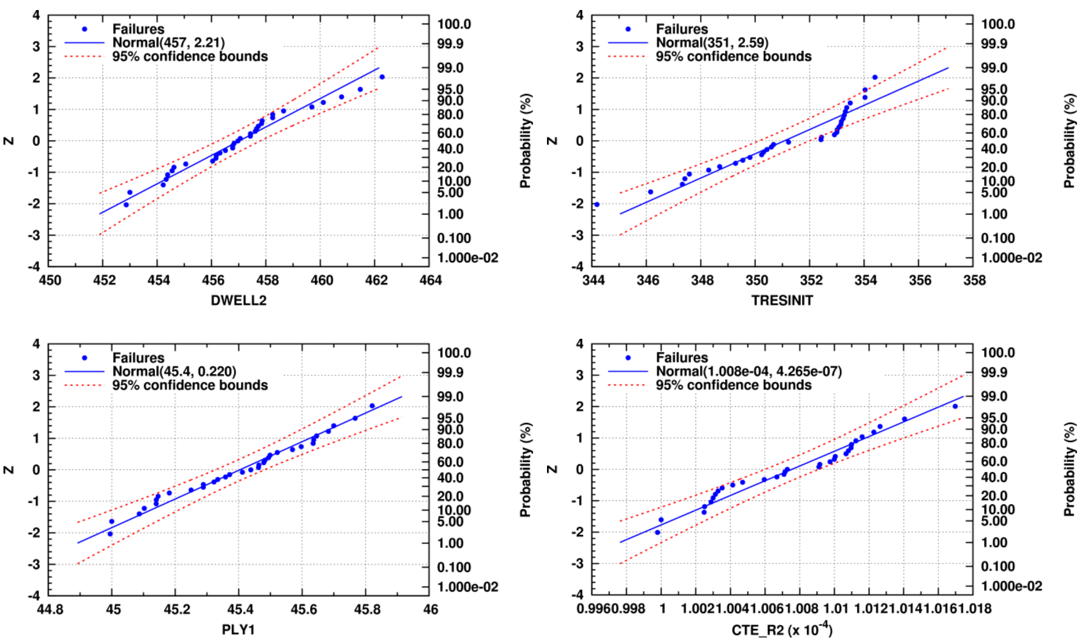


Figure 8: Example distributions resulting from the third inverse analysis

The resulting distribution functions, based on the model parameter values obtained in the first inverse analysis, are shown in Table 1 (denoted with index 1). The table also provides the initial estimated distributions (denoted with index 0) and the distributions based on the results from the last (third) inverse analyses (denoted with index 3).
The improved estimates for the model parameter distributions from each inverse analysis were applied in the next sensitivity analysis to improve the initial results. Moreover, for related parameters the initial estimated scatter was also set to the value of a corresponding parameter of the inverse analysis, e.g. all ply orientations were given the same standard deviation of 0.2

degrees and all Poisson's ratios a COV of 0.3. Besides this, for a number of other parameters showing minor influence, the initially very high COV was also somewhat adjusted to prevent unrealistic dominance by these parameters.

The resulting set of important parameters only slightly differs from the initial one, denoted by the blank cells in Table 1. A few of the previous dominant scatter sources shifted to lower positions in the ranking (e.g. EA and NU_M) and a number of parameters became more dominant (e.g. CP, RHO).

Table 1: Open-mould cure model inverse analyses results

Model parameter	Name	Mean0	Std0	COV0	Mean1	Std1	COV1	Mean3	Std3	COV3
AGEL	Degree-of-cure at gelation	0.7	0.04	5	0.7	2.50E-03	0.35	0.7	2.50E-03	0.35
CP	Specific heat	1.30E+09	1.30E+08	10				1.30E+09	5.70E+06	0.45
CTE_G2	CTE at glassy state	5.50E-05	2.80E-06	5	5.40E-05	1.90E-07	0.34	5.50E-05	4.80E-07	0.87
CTE_R2	CTE at rubber state	1.00E-04	5.00E-06	5	1.00E-04	9.90E-07	0.97	1.00E-04	4.30E-07	0.42
DWELL1	Initial curing temperature	413	4.13	1				413	1.61	0.39
DWELL2	Final curing temperature	453	4.53	1	453	1.58	0.35	457	2.21	0.48
DWELL3	Post-curing temperature	293	2.93	1	294	0.93	0.32	296	1.4	0.47
E_G1	Stiffness modulus at glassy state	1.20E+05	9.60E+03	8				1.20E+05	929	0.77
E_G23	Stiffness modulus at glassy state	8.00E+03	640	8				8.10E+03	54.7	0.68
EA	Activation energy of the Arrhenius' law	6.90E+04	6.90E+02	1	6.90E+04	267	0.38			
EPSCHEM_GLASS	Volumetric chemical shrinkage glassy state	-0.02	1.10E-03	5	-0.022	7.40E-05	0.34	-0.022	1.20E-04	0.56
EPSCHEM_RUB	Volumetric chemical shrinkage rubber state	-0.04	1.80E-03	5	-0.035	2.50E-04	0.72	-0.035	3.60E-04	1.05
HT	Heat generated during curing process	4.30E+11	4.30E+10	10				4.00E+11	3.10E+09	0.72
K1	Thermal conductivity	0.43	0.02	5				0.22	1.20E-03	0.57
NU_M	Poisson's coefficient of the matrix	0.37	0.01	3	0.37	1.10E-03	0.29			
PLY1	Ply 1 orientation	45	1	2	45.1	0.18	0.39	45.4	0.22	0.48
PLY2	Ply 2 orientation	45	1	2	-45.1	0.13	0.28	-45.4	0.2	0.44
PLY15	Ply 15 orientation	-45	1	2	-45.1	0.24	0.53	-44.8	0.25	0.56
PLY16	Ply 16 orientation	-45	1	2	45.1	0.18	0.4	44.8	0.24	0.54
RHO	Density	1.60E-09	6.40E-11	4				1.60E-09	7.00E-12	0.43
TIME2	Cure time	1.80E+04	540	3	1.80E+04	73.2	0.4			
TRESINIT	Initial temperature of the resin	353	14.12	4	347	3.21	0.93	351	2.59	0.74
VFF	Fibre volume fraction	0.55	0.03	5	0.56	7.10E-03	1.26	0.56	3.20E-03	0.57

Most of the previous important parameters remained important. With this new set of most important model parameters a second inverse analysis was run and similarly a final third iteration was performed before sufficient convergence was reached. A number of observations can be drawn from the table.

- Only a limited number (23) of model parameters are active over the three inverse analyses and the resulting distribution functions are similar for the last iterations giving confidence in the results, indicating good overall convergence.
- The distribution estimates from the inverse analyses show much less scatter (around 1%, expressed by the COV values) than originally assumed (around the 5-10%). Low values for the COV of important scatter sources were expected, because the amount of scatter in the experimentally determined spring-in distribution is low as well having a COV of 0.11 %, due to the measures taken at that time. High initial values for the COV were selected to rule out many of the model parameters as potential scatter sources, i.e. if a high amount of scatter does not cause any significant scatter in the spring-in angle it can be left out as potential scatter source.

A final sensitivity analysis was performed with the results from the third iteration shown in Figure 9. The most important scatter sources causing the majority of the scatter in the spring-in angle are in descending order:

- Final curing temperature (DWELL2)
- Initial temperature of the resin (TRESINIT)
- Volumetric chemical shrinkage in rubber state (EPSCHEM_RUB)
- Coefficient of thermal expansion at glassy state (CTE_G2)
- Post-curing temperature (DWELL3)

Scatter in parameters that still have a significant influence are:

- Ply orientation of last, 45 degree, ply (PLY16)
- Ply orientation of second to last, -45 degree, ply (PLY15)
- Heat generated during curing process (HT)
- Fibre volume fraction (VFF)
- Time to increase temperature from initial to cure temperature (TIME1)
- Ply orientation of first, 45 degree, ply (PLY1)
- Ply orientation of second, -45 degree, ply (PLY2)
- Initial curing temperature (DWELL1)
- Coefficient of thermal expansion at rubber state (CTE_R2)
- Cure time (TIME2)

- Thermal conductivity (K2)
- Volumetric chemical shrinkage glassy state (EPSCHEM_GLASS)

Scatter in the top plies (higher ply number), having a larger radius, causes more spring-in than bottom plies. Furthermore, scatter in the 0 degree (fibres in length direction of L-shape) plies caused less scatter than plies at an angel.

For the web and flange thickness the same scatter sources as for the spring-in angle cause the scatter in the thicknesses as well, apart from the scatter in the ply angle orientations which were not important, although in a somewhat different order of importance. Moreover, most scatter is caused by a smaller set of parameters than for the spring-in angle.

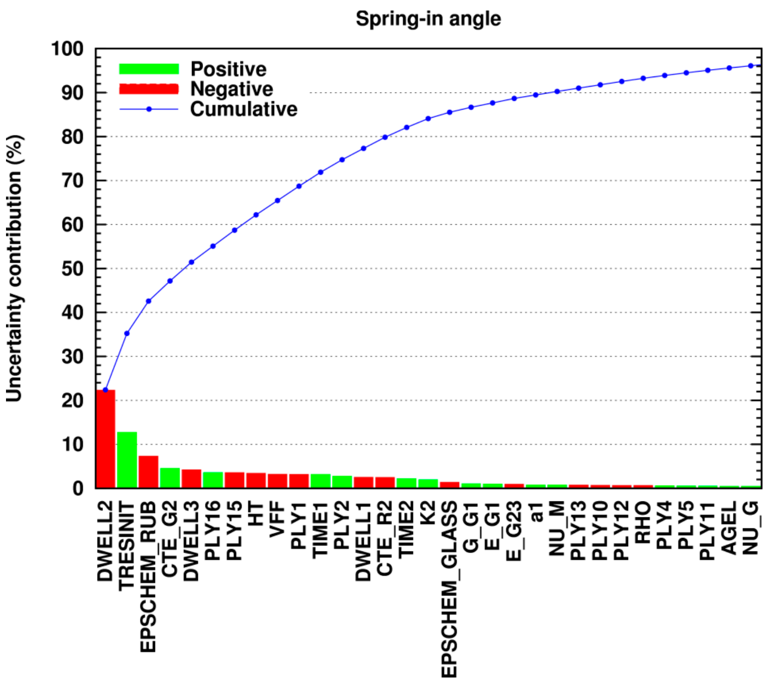


Figure 9: Pareto plot for the spring-in angle of the final sensitivity analysis results for 30 most important model parameters

It should be stated that the current results are based on simulations only and are of a qualitative sense only. Nevertheless, the results are in-line with experimental results performed by DLR in LOCOMACHS on a limited number of samples [Danilov and Opitz (2014)], where an increase of the fibre volume fraction (VFF) and a longer injection temperature dwell time (TIME1) resulted in a significant decrease in the spring-in angle. An increase in the injection temperature (TRESINIT) resulted in both an increase and decrease of the spring-in angle.

With the final distributions resulting from the inverse analysis, the scatter in the spring-in angle can be computed again by means of a probabilistic analysis. If this distribution is comparable with the original experimental data it also gives confidence in the applied methodology.
A Monte-Carlo analysis of 50 simulations was performed with RAP++ for the open- and closed-mould model to compute the spring-in distribution. In each simulation, values for each scatter source are randomly drawn from the corresponding model parameter distributions for which the spring-in angle is computed. Subsequently, a distribution function is fitted on the resulting 50 spring-in values. Figure 10 shows the computed distribution (blue-line) as well as the measured distribution (red-line). It can be seen that both distributions show reasonable correlation (mind the scale on the x-axis). The mean value in both cases is close to the measured value, but the scatter is underestimated.

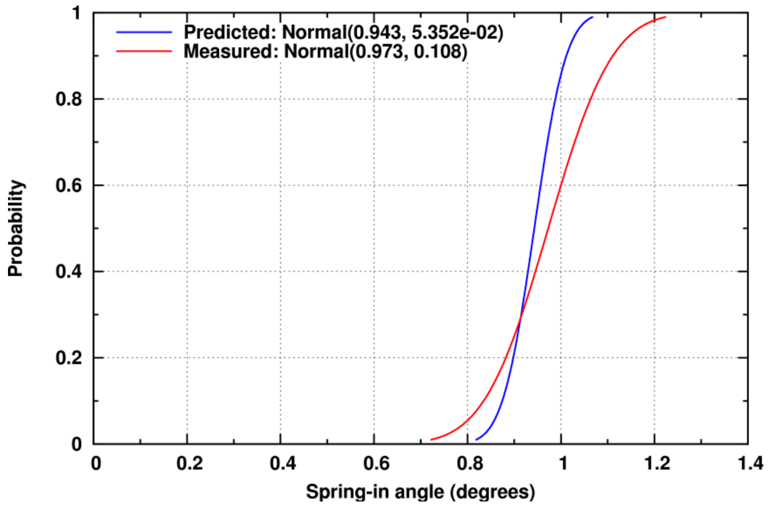


Figure 10: Measured and predicted scatter in spring-in angle for the open-mould cure model

6 Conclusions

The scatter in spring-in angle and thicknesses, and possibly in other geometrical parameters as well, can be reduced by better control of the cure process to arrive at more geometrical robust composite components for aircraft structures. Especially, a good control of the resin and cure temperatures can yield much more stable product dimensions, but also variation in cure times have a significant effect. This accounts for temperature variations within the product as well, which was not taken into account in the probabilistic part of the current analysis. Although to a lesser extent, also control of the scatter in ply orientation of the outer plies, fibre volume fraction and cure times can yield a still significant improvement. The volumetric chemical shrink, coefficient of thermal expansion and heat generated during curing cannot or not easily be controlled. Selection of a different resin showing less scatter may here be an option.
A variable hardly showing any influence (around 0.1%) is the initial cure state. Beforehand it was expected that this parameter would have a larger effect, since it can show considerable variation due to storage and out-of-freezer time. Even with a 10% COV the contribution to the overall scatter was neglectable.
The results were also not very sensitive for the length of the web and flanges, supporting the fact that spring-in is mainly caused by the curved areas for thicker laminates. This is different for thin laminates were significant warpage (curvature) of the initial straight web and flanges significantly increase the total spring-in. The analyses results presented here are based on one thickness, flange and web length, yielding consistent results, i.e. not requiring a warpage correction.

The current result can be used to direct an experimental programme to validate the results obtained for the controllable parameters.

7 Acknowledgements

The research leading to these results has received funding from the European Union's Seventh Framework Programme FP7 (FP7/2007-2013) under grant agreement n°314003 LOCOMACHS (www.locomachs.eu).

8 References

1. Albert, C. and Fernlund, G. (2002). *Spring-in and warpage of angled composite laminates*, Composites Science and Technology, V62, pp 1895–1912.

2. Brink, W.M. van den, Vankan, W.J. and Vrie, G. van de (2014). *Manufacturing process simulation and structural*, National Aerospace Laboratory NLR, NLR-TP-2014-442.

3. Danilov, M. and Opitz, M. (2014). *Sensitivity report*, LOCOMACHS deliverable D11.2.

4. Grooteman, F.P. (2011). *Reliability Analysis Program RAP++ User Manual V3.1*, National Aerospace Laboratory NLR, NLR-TR-2007-007.

WHAT IS NLR?

NLR is a Dutch organisation that identifies, develops and applies high-tech knowledge in the aerospace sector. The NLR's activities are socially relevant, market-orientated, and conducted not-for-profit. In this, the NLR serves to bolster the government's innovative capabilities, while also promoting the innovative and competitive capacities of its partner companies.

NLR, renowned for its leading expertise, professional approach and independent consultancy, is staffed by client-orientated personnel who are not only highly skilled and educated, but also continuously strive to develop and improve their competencies. The NLR moreover possesses an impressive array of high quality research facilities.

***NLR** – Dedicated to innovation in aerospace*