Optimization and robustness of complex material model simulations with modeFRONTIER

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Summary:
Experimental quasi-static and dynamic tests were conducted over different types of advanced material samples, such as composite sandwich, in order to derive both mechanical and numerical input parameters for LS-DYNA material models. The characterization of models addressed to reproduce the behaviour of real materials takes great importance in order to simulate accurately complex phenomena such as crash tests and impact events.

This work deals with an innovative procedure aimed to calibrate the constitutive parameters of LS-DYNA advanced material models, and use them for prediction, design optimization and robustness analysis, hence reducing the need of further expensive experimental tests. This kind of approach allows also to understand the influence of physical and geometrical variables on composite dynamic structural response, or to get improved solution for industrial case studies.

More in details, the available experimental data were imported in the modeFRONTIER Process Integration and Design Optimization software. An efficient stochastic optimization algorithm performed the calibration of the mechanical and numerical parameters of the existing LS-DYNA models, with a fully automated process. Such models could then be handled by modeFRONTIER to steer LS-DYNA simulation campaigns improving the design of composite and sandwich laminates. Any kind of free parameters to be investigated can be included in such a process, and the constraints to be respected and the multiple objectives to be pursued too. A short description of the most innovative techniques to do that will be given.

An experimental-numerical procedure example from Automobili Lamborghini Composite Technical Department is shown.

Keywords:
Calibration, modeFRONTIER, LS-DYNA material models, design optimization, robustness analysis.

1   The rationale

The procedure proposed here allows to define reliable material numerical models needed to predict accurately the static and dynamic behaviour of real components (even complex-geometry ones), without performing dedicated experimental test campaigns. In particular, in this activity two different composite materials, "RTM 1400" and "PREPREG 977- 6", have been investigated with the ultimate aim to exploit the calibrated material models in impact events of automotive structural components. The main difference between the two composite materials is the manufacturing technique. The most common type of material used for the fabrication of composite structures is the pre-impregnated tape, or "PREPREG". In prepreg preparation, fibres are subjected to a surface treatment so that the resin will adhere to them. They are then placed in a resin bath and rolled into tapes or sheets. The resin is partially cured in order to give handling to the pre-impregnated pre-forms during the positioning inside the mould. Resin Transfer Moulding (RTM) is a composites processing method that offers a high potential for customization, but is currently limited to low-viscosity (easily flowing) thermosetting polymers. In RTM, a textile pre-form (made by braiding, weaving, or knitting fibres together in a specified design) is placed into a mould, which is then closed and injected with a resin. After curing, the mould is opened and the part removed. Pre-forms can be made in a wide variety of architectures, and several can be joined together during the RTM process to form a multi-element pre-form offering reinforcement in specific areas and load directions.

Here, only the "RTM 1400" modelling with "MAT 58" LS-DYNA material card is described, but the procedure generality has been validated by applying it also to the "PREPREG 977- 6", yielding to similar results in terms of numerical model accuracy.

The main objective of the paper, in fact, is to establish a procedure to calibrate the constitutive parameters (i.e. material constants) of LS-DYNA advanced material models. With the aim to get a good and robust numerical-experimental correlation, the parameters calibration has to be performed taking into account the material behaviour in different load conditions: therefore there are different objective functions, representing the material responses, to be achieved simultaneously. Hence, the calibration process can be tackled as an optimization challenge, with material constitutive parameters as input variables to be optimized accordingly to different conflicting goals. To this purpose, LS-DYNA has been coupled with modeFRONTIER, a Process Integration and Design Optimization tool able to explore the design space (i.e. the free parameters dominions) and find the configurations satisfying several objective functions (i.e. the specimen response in different loading conditions). This tool allows also to assess the smaller set of experimental tests needed to achieve a reliable static and dynamic mechanical characterization, by means of its sensitivity analysis capabilities. On top of such approach, modeFRONTIER and LS-DYNA can be applied together in the design phase (as well as with other disciplines' models in the loop), with the aim of optimize overall assembly parameters respect to multiple attributes, such as impact behaviour, manufacturing cost, weight, size, etc.

CFRP composites have been used in Lamborghini since 1983, at first for esthetical and exterior parts. From 90's till nowadays the main challenge switched on manufacturing structural parts and in the recent years also on simulating their behaviour. Simulation can be cost-effective, saving time and money respect to real testing of big components. Because of CFRP composites behaviour is not implemented in any software and because it depends on the manufacturing method, Lamborghini adopted a campaign of testing on a small scale in order to calibrate the response of the software and enable a correct Finite Element (FE) prediction of the dynamic tests. Cooperation with EnginSoft has been settled up for a combined activity of experienced manufacturing and FE technical support in the creation of the material model. After a full calibration on the material is done, that means when all the variables have been investigated (manufacturing method, fibre percentage, layup orientation, thickness,...), it is possible to rely on the simulated analysis. This has been the approach adopted, adding analytic value to the experimental know-how. From Lamborghini Composite Division, LS-DYNA has revealed as a powerful instrument to analyse advanced material models and to make prediction on complex CFRP structures.

2   Preliminary steps

As mentioned above, defining a procedure to characterize the dynamic structural response of advanced materials (e.g. composite sandwich) by simple and cheap experimental tests is a challenging topic. However, it enables a design process that does not require further specific and more demanding tests, even for complex structures. In defining such a procedure, some operations are crucial, and will be described in the next sections:

- selection of a set of simple experimental tests to obtain proper data to be fitted;
- building of a robust Finite Element Model (FEM) with respect to the real working conditions, and choose a "baseline" material card to calibrate: LS-DYNA is the suitable tool to do that;
- capability to handle simultaneously several parameters, both input and output ones, to correlate the numerical model: modeFRONTIER is the suitable tool to do that.

2.1   Selection of the experimental tests

The experimental tests should describe in an accurate way the different material behaviours under different loading conditions. On the other hand, it's necessary to avoid information redundancy, for time and costs sake: in other words, they have to be uncorrelated.

To these purposes, a set of tests has been selected, taking into account the phenomena to be reproduced: since here the main application field is related to impact, quasi-static and dynamic tests are selected.

To get homogeneous data between the different tests, the same ASTM D 790 specimen geometry has been used: a rectangular cross section bar, with dimensions of 100mm length, 16 (or 25) mm width, and 3 mm depth.

Summarizing, to perform the calibration of the constitutive parameters able to wrap both dynamic and static behaviour of the RTM 1400 composite material model, the following four destructive flexural and Charpy pendulum tests have been selected:

- Three Points Bending Test (16mm width specimen);
- Three Points Bending Test (25mm width specimen);
- Four Points Bending Test;
- Charpy Pendulum Test.

For the bending tests, the crosshead motion rate has been set up to 5.5 mm/min, in order to match the typical design working condition of composite material components. Therefore, the Four Points Bending Test and the Three Points Bending Test are able to characterize accurately the material flexural behaviour: in particular, the effects of a pure bending moment and of a bending moment / shear condition respectively. The equipment used for the bending tests was a "LR5KPlus (Fig. 1, left). The Charpy Pendulum tests are characterized by an impact velocity of 3.8 m/s, and a total energy of 25 Joule. Being the velocity of 10 m/s a typical value for crash purposes, the chosen setup represents a good compromise between the need to represent accurately the material dynamic behaviour, and the simplicity of the test itself, considering the available equipment ("Pendulum IMPats15", Fig. 1, right).

Fig. 1- The Bending Test machine (left) and the Charpy Pendulum Test machine (right)

The details of the implementation of such experimental test campaign are beyond the scope of the present paper, however, as final result of such an activity, authors obtained a complete set of data for the RTM 1400 composite sandwich specimen, regarding the following physical measurements:

- Global Stiffness and Total Absorbed Energy, provided by the 3 and 4-Points Bending tests;
- Absorbed Energy and Local Failure Mode, provided by the Charpy Pendulum tests.

These data are then the basis for the LS-DYNA material model calibration.

2.2   Setup of robust numerical models

Amongst the LS-DYNA's material models, MAT 58 (MAT_LAMINATED_COMPOSITE_FABRIC) has been selected as the most suitable to describe the RTM 1400 composite sandwich, and its constitutive parameters will be the subject of the calibration procedure. In fact, the MAT 58 may be used to model composite materials with unidirectional layers, complete laminates and woven fabrics.

The build up of the finite element models has been addressed with the aim to get accurate results within reasonable computation times. For these reasons, a preliminary FEM robustness investigation has been performed for each one of the four numerical models corresponding to the physical tests. Goal is to assure that the model behaviour gets independent from the mesh element size, loading rate and contacts typology. Regarding to the mesh convergence, the mesh element size has been set to 8x8 mm: besides the accuracy of the results, this value is similar to the ones used in real-components analyses. In fact, the idea is to exploit the calibration results in FEM real components models, where it

is unlikely to have extremely refined meshes (even if they would be viable for the current stand-alone experimental test correlations).

The four different LS-DYNA models, arranged to simulate the experimental tests mentioned in Chapter 2.1 , are sketched respectively in Fig. 2 left, centre and right.
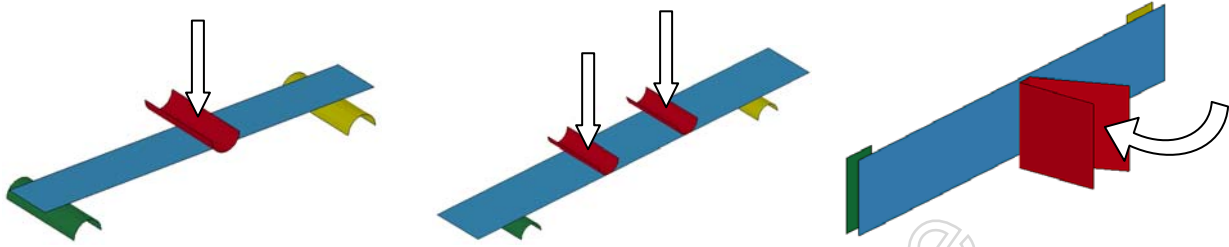

Fig. 2 – Three Points Bending test, Four Points Bending test, Charpy Pendulum test

The typical CPU times span from about 40 seconds to simulate the Charpy Pendulum test, to about 1 minute for the Three Points Bending Tests, to more than 3 minutes for the Four Points Bending Test (on an AMD Athlon workstation, 64x2 Dual Core Processor 6000+ at 3.00 GHz, with 3.37 GB RAM). Computational times are very important in the definition of the procedure to tackle the material model calibration in the most time-efficient way.

2.3   Numerical model calibration process details: process integration and optimization

As mentioned in the introduction, the material model calibration process can be described as a proper optimization challenge, with material constitutive parameters as input variables to be optimized accordingly to the different goals, namely the minimization of the numerical prediction error respect to all the experimental data.

2.3.1 MAT 58 simulation results to be correlated with experiments ("objectives" for the optimization)

Each one of the experimental measurement represents a target to be reached by the corresponding numerical model simulation. Hence, an independent objective function, to be minimized, has been assigned to each one of them by using the following relative error index formulation:

$$\frac{\left| F^{j}_{FEM} - F^{j}_{exp} \right|}{F^{j}_{exp}} \times 100 \tag{1}$$

where F^{j}_{FEM} is the numerical value for the jth physical data, and F^{j}_{exp} is the experimental one.

Summarizing, the nine objectives are:
Charpy pendulum (16mm width ASTM D 790 specimen)
-   "c_d_Energy" , the corresponding % deviation on the specimen's Absorbed Energy
-   "c_d_BreakTime" , the corresponding % deviation on the Failure Time
-   "c_d_Zforce" , the corresponding % deviation on the Maximum Force
Three Points Bending test (16mm width ASTM D 790 specimen)
-   "p1_d_E_val" , the corresponding % deviation on the Maximum Force @ Maximum Deflection
-   "p1_d_MaxForce" , the corresponding % deviation on the Absolute Maximum Force
Three Points Bending test (25mm width ASTM D 790 specimen)
-   "p2_d0_E_val" , the corresponding % deviation on the Maximum Force @ Maximum Deflection
-   "p2_d0_MaxForce" , the corresponding % deviation on the Absolute Maximum Force
Four Points Bending test (25mm width ASTM D 790 specimen)
-   "p3_d_E_val", the corresponding % deviation on the Maximum Force @ Maximum Deflection
-   "p3_d_MaxForce", the corresponding % deviation on the Absolute Maximum Force

The purpose to get a flexible, all-round material model set-up, requires to handle these objective without any a priori assumption on their relative priorities. This should be done by avoiding the classical approach of building an overall "fitness function" to be minimized, such as their weighted sum. Instead, by relying on the modeFRONTIER Multi-Objective optimization algorithm, such nine

objectives can be considered as independent and minimized simultaneously, using the Pareto Dominance criteria [1] without the need to specify any weighting factor.

2.3.2 MAT 58 constitutive parameters to be fitted ("input variables" for the optimization)

The MAT 58 embeds several parameters that can be customized. They include "classic" mechanical parameters, easy to be assessed through conventional tests or even found in literature: Young modulus, Poisson ratios, tensile strengths, etc. A second group is made up by other mechanical parameters, such as the shear and compressive strengths and strains, that need specific experimental tests. Finally, other parameters are purely numerical, hence they could be freely tuned.

Therefore, the available parameters have been subdivided in three clusters, accordingly to their physical meaning and the available engineering knowledge on the material itself. Table in Fig. 3 lists them (more information in [2]), and displays the range of variations around the suggested nominal values that has been investigated in the correlation process (unless specified, values are expressed in terms of the following units: mm, ton, sec, N). This corresponds to the definition of the input variables' domain, the scope of the search for the current optimization challenge: globally the possible parameters combinations are billions.

	Variable Name	Description	Range
Group 1 (8 var.s)	EA	Young's modulus – longitudinal direction a	50000-55000 MPa
	EB	Young's modulus – transverse direction b	55000-60000 MPa
	ERODS	Maximum effective strain for element layer failure	0.01-0.03
	GAB	Shear modulus ab	4400-4600 MPa
	XC	Longitudinal compressive strength	650-710 MPa
	XT	Longitudinal tensile strength	800-880 MPa
	YC	Transverse compressive strength	720-770 MPa
	YT	Transverse compressive strength	870-950 MPa
Group 2 (10 var.s)	E11C	Strain at longitudinal compressive strength	0.02-0.08
	E11T	Strain at longitudinal tensile strength	0.01-0.10
	E22C	Strain at transverse compressive strength	0.02-0.10
	E22T	Strain at transverse tensile strength	0.01-0.10
	SLIMC1	Factor to determine the min. stress limit after max. stress (fiber compr.)	0.01-0.10
	SLIMC2	Factor to determine the min. stress limit after max. stress (matrix compr.)	0.01-0.10
	SLIMS	Factor to determine the min. stress limit after max. stress (shear)	0.01-0.10
	SLIMT1	Factor to determine the min. stress limit after max. stress (fiber tension)	0.01-0.10
	SLIMT2	Factor to determine the min. stress limit after max. stress (matrix tension)	0.01-0.10
	SOFT	Softening reduction factor for strength in the crashfront	0.01-0.21
Group 3 (5 var.s)	GAMMA1	Strain limit of the first slightly nonlinear part of shear stress/shear strain curve	0.08-0.10
	GMS	Strain at shear strength	0.15-0.21
	SC	Shear strength	90-110 MPa
	TAU1	Stress limit of the first slightly nonlinear part of shear stress/shear strain curve	70-90 MPa
	Thick_01	Thickness of a ply (all the plies have the same thickness)	0.32-0.38 mm

Fig. 3 – Constitutive parameters summary table, including scope of the search

Note that the "almost" mechanical parameters (e.g. EA, EB, …) could have been set to a fixed values, but to take into account the bias affecting these ones (such a problem for composite materials is more relevant), a small range was investigated. This approach is the same applied for the plies thickness. Some variables requested the setup of dedicated constraints to the optimization problem: the shear strength "SC" has to be greater than the stress limit of the first nonlinear part, "TAU1" (see Fig. 4), as well as "GMS" and "GAMMA1". Also a constraint for the slope of the linear part ("SLIMS" and "SC") has been set up.
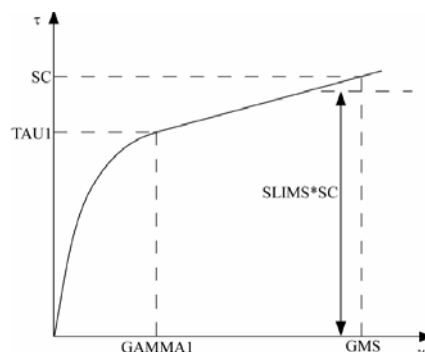

Fig. 4 – Stress Vs. Strain diagram for shear: the variables of group three [2]

2.3.3 Process Integration and Design Optimization

From the given description of the LS-DYNA material model calibration process, it is clear that it cannot be solved by simple trial-and-error procedure. In fact, the number of parameters and goals to pursue simultaneously is too high: such an approach is simply not viable.
The efficient method proposed here, instead, takes advantage of the modeFRONTIER Process Integration and Design Optimization capabilities.

The "Process Integration" part is all about describing the calibration process activity by means of a chart, a workflow (see Fig. 5). This chart represents a sort of "high-level" programming language to describe a generic design process. It's made up by pre-defined blocks (called "nodes"), that represent the fundamental components of any process. In modeFRONTIER such nodes can be drag-and-dropped from a library, and linked, to build up a network following simple rules: it's the same procedure anyone uses when combining alphabet letters to build up words and phrases. Hence, Fig. 5 simply describes the current calibration process.
From top to bottom, following the blue links, there's the representation of the so-called "Data Flow". The green blocks at the top define the input variables of the challenge (the constitutive parameters to be calibrated) with their original value and the range of variations around it to be explored. Each time a new combination of their values is proposed by the modeFRONTIER internal optimization strategy, the MAT 58 material card file is updated (node "mat_inp" in Fig. 5) and passed to the four LS-DYNA models of the quasi-static and dynamic tests. Such computations produce outputs that are post-processed (grey blocks) and finally give numerical forecasts of the nine physical responses that should be fitted to the available experimental results. To that purpose, there are nine independent objective nodes (red blocks at the bottom of Fig. 5): each one of them assign the goal to minimize a deviation as defined by Equation 1.
From left to right of Fig. 5, the so-called "Logic Flow" is represented: it is the sequence of operations that modeFRONTIER will automate, and the logic driving them. First, the two blocks at the left side. "DOE" stays for Design Of Experiments: such node simply defines one or more configurations (combinations of input variable values) that are the starting set of the design improvement search. "Scheduler" node contains the "search strategy" itself (the "Design Optimization"). Then, going to the right side, the four LS-DYNA runs should be started sequentially and completed to evaluate any single design variant.
Therefore, the workflow is a picture of a step of the process it describes, while the strategy to solve it iteratively, is enclosed in the DOE and Scheduler blocks. Hence, changing approach/strategy to solve the same design process more efficiently, does not require any change on the workflow structure.
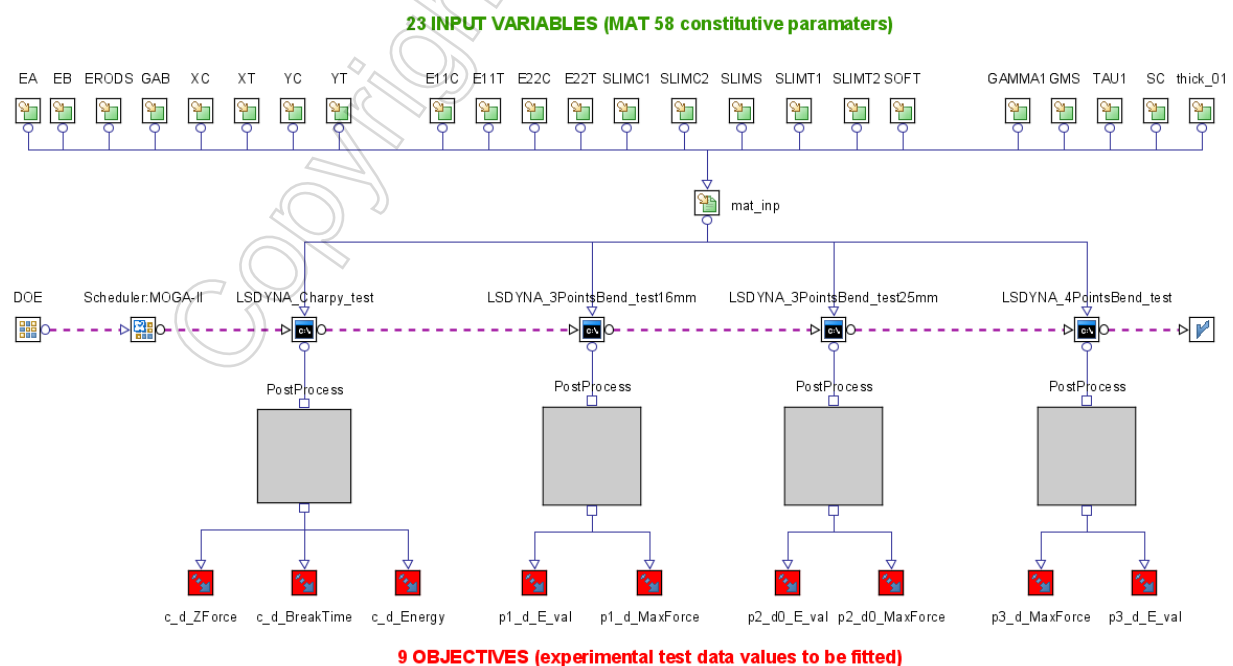

Fig. 5 – The calibration process as described by the modeFRONTIER's workflow, integrating the four LS-DYNA test models

Once the workflow is completed, modeFRONTIER is able to link the LS-DYNA models and automate the process: it acts as a robot, and carries out automatically the material parameter value modifications, the CAE model runs and the results extraction.

The procedure automated by the above described "Process Integration", repeated for each input parameter combination, has to be driven by an efficient "Design Optimization" logic. This can be any combination of the available optimization algorithms and advanced tools (such as interpolant Response Surface Models -RSM-) available in modeFRONTIER, and aims to improve all the assigned objectives simultaneously.

This approach guarantees a strong reduction of the needed engineering-time, thanks to the automation of all the repetitive operations. High-qualified human resources can instead concentrate into data analyses and decision-making. Also the pure computational time needed to solve most of the today's typical engineering challenges (with typical hardware/software resources) can be strongly reduced, thanks to the efficiency of the optimization strategies. In fact, modeFRONTIER offers the state-of-the-art mechanisms to generate DOEs, more than eighteen optimization algorithms, as well as RSMs to speed up optimum search when computational time is high. [3]

3   The material model calibration procedure

The approach proposed here, that can be adapted to any material model calibration, once proper experimental data are available, is made up by a few fundamental steps.

- Reduction of the calibration challenge size, by detecting correlated input variables (here between the 23 constitutive parameters) and correlated outputs (here the four tests all together yield to 9 objectives): "numerical model parameters' sensitivity check".

- Calibrate (using a Multi-Objective optimization algorithm) only the most sensitive input variables by running (and comparing with corresponding experimental data) only the LS-DYNA models that give the uncorrelated outputs: "reduced numerical model correlation".

- Check the best solutions of the previous point (each one is a particular set of values for the 23 input variables), by running their whole set of four LS-DYNA models and comparing the whole 9 outputs with the corresponding experimental results: "validation of the best results of the reduced calibration".

In particular, the first phase grants major saving in computational time by reducing the number of constitutive parameters to be tuned, and simultaneously the number of CAE models to be run. This way, the subsequent model numerical correlation phase (optimization) is reduced in terms of number of LS-DYNA model runs, and hence much faster. The more the challenge is complex, in terms of number of constitutive parameters to tune (inputs) and number of static/dynamic tests to fit (outputs), the higher is the advantage of this approach.

3.1   Numerical model parameters' sensitivity check

The complexity of any optimization process depends mainly on the number of independent input variables and considered objectives. As previously pointed out, the present calibration process is initially defined by 23 constitutive parameters and 9 objectives. By means of a statistically significant but affordable-sized Design Of Experiment (DOE) sampling, it's possible to check whether a problem reduction is possible, by:

- "freezing" the least-sensitive (on all the objectives simultaneously) input variables;
- reducing the number of independent objectives, by detecting correlated ones.

The DOE strategy used in this case, relies on a combination of three separated 2-levels Full Factorial samplings [1], one for each group of input variables presented in Chapter 2.3.2, for a total number of 1312 design variant evaluations. This is a limited number of variants, taking into account the total number of possible combinations for the inputs. Anyhow, with the hardware resources mentioned in

Chapter 2.2, performing all the four test simulations for such a number of configurations would take five days, even with modeFRONTIER automating the process. More than half of this time is due to the 4-Points Bending Test simulation.

Hence, the idea is to carry the above described DOE test campaign connecting modeFRONTIER only to the LS-DYNA models of the Charpy and the 3-Points Bending tests, abating the computational effort to slightly more than two days. Any consideration that will arise from this campaign will be then cross-checked with the results of a smaller-sized second DOE (a 480-design reduction of the previous 1312 one), focused only on the the 4-Points Bending Test simulation. The latter requires an additional day only, and such results could then be added to complete the previous database and the final conclusions taken. This two-step procedure is described in the following subsections.

3.1.1 Full Factorial DOE (only Charpy and two 3-Points Bending tests)

An efficient DOE scheme should uniformly sample the space of all the possible input variable combinations, and avoid self-correlation between the variables themselves in the chosen configuration set. A 2-level Full Factorial DOE satisfies such properties, and allows to detect main effect and interactions between factors and responses. Its main drawback is the number of design evaluations, that grows with the number of variables with a 2^{nVar} law. Here a good compromise between completeness of information and sample size has been achieved by creating three different Full Factorial schemes: they are generated separately over each one of the three variables' group mentioned in Chapter 2.3.2, and then merged. This means taking advantage of the engineering knowledge that leaded to such a grouping, by reducing the sampling from more than 8 millions combinations (2^{23} of the coupled 23-variable sampling) down to only 1312 ($2^8+2^{10}+2^5$ by merging the decoupled groups sampling). Without such an additional knowledge, an alternative way to proceed without de-coupling the input variables could have been relying on a "Reduced Factorial" or "Latin Square" DOE scheme: they are good compromises between statistical information quality and sampling size. As mentioned, merging the three 2-levels Full Factorial schemes gave 1312 designs to be evaluated: $2^8+2^{10}+2^5$, adding the three groups of 8,10 and 5 variables respectively. In the generation of each one of them, the variables not belonging to the group under investigation have been "frozen" at their central value. The average self-correlation between the input variable on the merged set is more than acceptable: around 0.07 on a scale from 0 (perfectly uncorrelated set) to 1 (perfect correlation). This guarantees the global validity of the conclusion that will arise.

Two different statistical analysis tools have been used to the purposes described above, after completion of the 1312 variants LS-DYNA computations.

modeFRONTIER has been used to complete a correlation analysis and a Student's t-test based on the DOE set available.
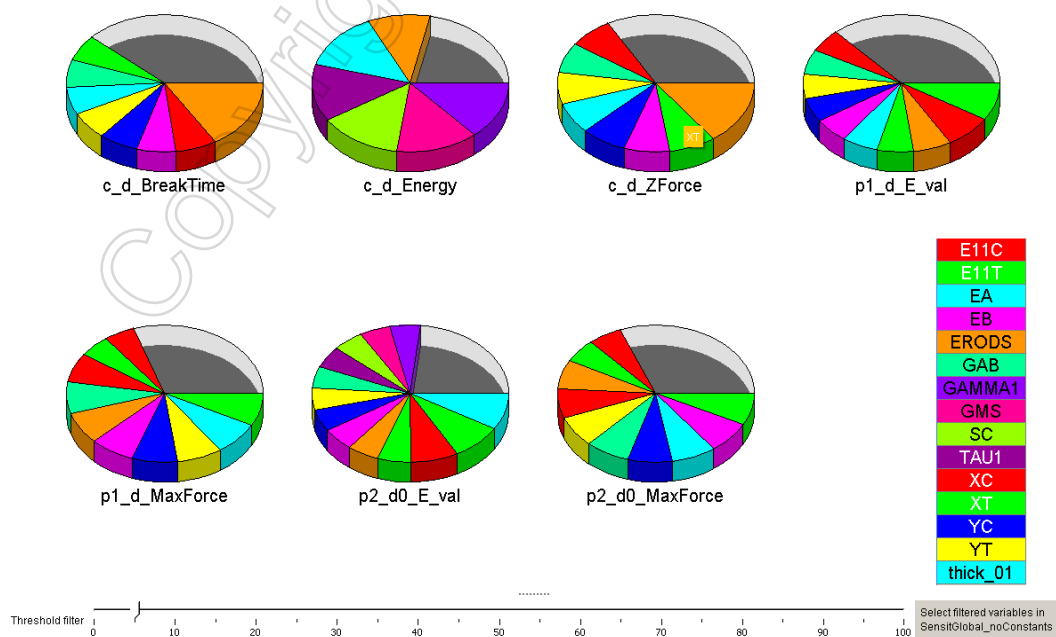

Fig. 6 – Student-t analysis: for each objective, a pie chart depicts the most sensitive input parameters

Results are displayed on a pie chart with filtering functionality (see
Fig. 6). This chart is extremely useful to easily detect the input variables that are the least-sensitive ones over the set of the seven objectives considered, simultaneously. In fact they're hided from the table at the right side of the picture (and grey-shaded in the pie charts), after moving the "threshold filter" at the bottom of the picture. This way, eight variables of the second group (E22C, E22T, SLIMC1, SLIMC2, SLIMS, SLIMT1, SLIMT2, SOFT) have been detected as least-sensitive respect to all the objectives simultaneously, and hence are candidates to be "frozen" to constant values in the final calibration process. ERODS (belonging to the first group of parameters) is the variable that most affects the considered objectives simultaneously. Moreover, an inverse correlation has been detected with all the objectives: increasing ERODS value seems to generally decrease the deviations between simulations and experimental data, for all the tests considered so far. Between the first-group of parameters, also EA and XT seems influent. For EA a globally inverse correlation with all the objectives exists, while for XT such correlation seems direct (decreasing it value reduce the deviations). In the second-group of parameters, E11C is the most sensitive one with an inverse correlation with all the output, unless for "c_d_Energy" that seems directly correlated.

The second idea was to search for correlated objectives, in order to reduce the number of tests to be simulated to calibrate the material. From the above described results, the fact that some of the most important input parameters are simultaneously correlated with all the objectives, suggests that such redundancies might exist. Fig. 7 shows the objectives' correlation matrix, based on the DOE results. The first-order correlation between two entities is expressed by means of a normalized index spanning from −1 to +1: a value equal to +1 (-1) denotes a full direct (inverse) correlation, while a low absolute value means low correlation.
It turns out that the objectives associated with the outputs of the two 3-Points Bending test are strongly directly correlated between themselves: see the violet dotted box in Fig. 7. Moreover, "c_d_Energy" output of the Charpy test seems to be generally uncorrelated with respect to the other tests (blue dotted box), while "c_d_BreakTime" and "c_d_Z_Force" are mildly correlated.
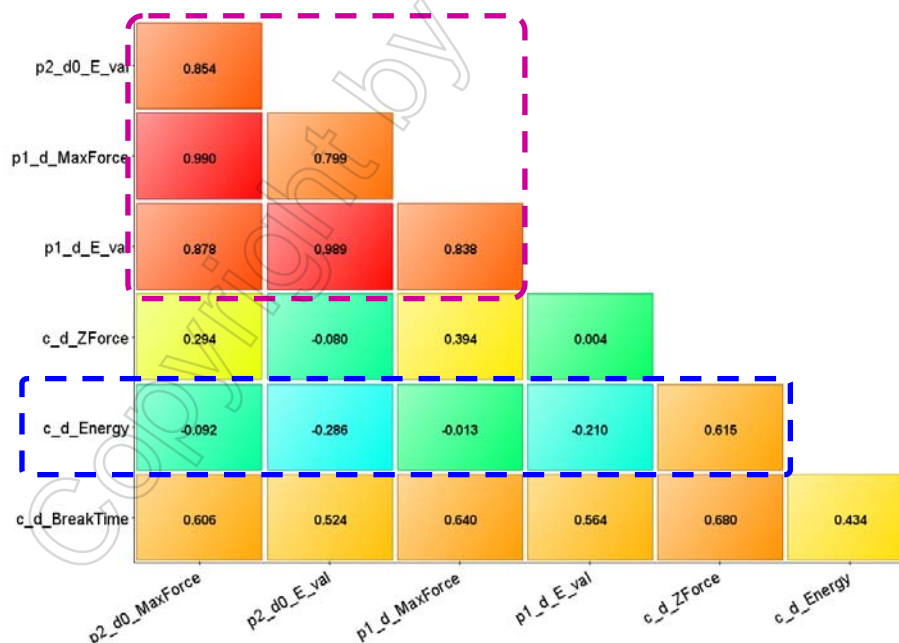

Fig. 7 – Correlation indexes between the deviations of numerical to experimental Charpy and 3-Poins Bending test results, based on the Design Of Experiments campaign

These observations, involving both input and output variables, seems to suggest the following calibration challenge simplifications:

- reduction of input variables from 23 to 15 (by freezing the 8 least sensitive parameters);
- simulating only the Charpy test, plus only one 3-Point Bending test (e.g. the 16 mm's one);
- reducing the number of independent objectives related to the Bending Tests down to one.

As mentioned, such considerations needs to be validated by including also the missing 4-Points Bending test in the results' database.

3.1.2 4-Points Bending test simulations on a subset of the Full Factorial DOE

To the purpose mentioned above, the most meaningful (in terms of input variable distribution) subset of 480 design configurations should be selected between the previous 1312-ones, and its outputs' evaluation completed by adding the 4-Points Bending test simulations. This has been done by using the modeFRONTIER D-Optimality DOE filtering capability [3]: the lower self-correlated 480-elements subset has been selected out of the 1312 available input variable combinations. The 4-Points Bending test has been simulated for this relatively small and un-correlated set of configurations. Such results have been added to the ones relative to the 3-Points bending Tests and the Charpy test. All the statistical analyses described in Chapter 3.1.1 have been repeated, now including also the 4-Points Bending test data. The conclusions of Chapter 3.1.1 regarding the relevance of the input variables have been confirmed also for the two additional objectives. Regarding the 4-Points Bending test outputs themselves, "p3_d_E_val" is correlated with the outputs of the 3-Poins bending tests, while "p3_d_MaxForce" seems to be independent.

Hence, this preliminary phase has been effective in reducing the challenge:

- independent input variables reduced from 23 to 15;
- only the Charpy test and the 4-Point Bending test will be simulated;
- independent objectives reduced to four: "c_d_BreakTime" (correlated to "c_d_Z_Force") and "c_d_Energy" for the Charpy test; "p3_d_MaxForce" and "p3_d_E_val" (correlated to all the results of the 3-Points Bending tests) for the 4-Points Bending test.

3.2 Reduced numerical model calibration

The workflow of Fig. 5 has been simplified accordingly to the above mentioned findings, and the multi-objective optimization campaign launched. The modeFRONTIER Multi-Objective-Optimization-Algorithm MOGA-II has been used, starting the search from the best performing solutions found during the sensitivity analyses already performed. The "Pareto Optimality criteria" has been applied, and the multi-objective problem handled without any a-priori definition of weighting factors. Thanks to the challenge simplification and to the efficiency of the algorithm, optimal solutions have been found with slightly less than 4000 design variant evaluations, over the billions of possible combinations. Considering that only Charpy and 4-Points Bending test LS-DYNA simulations have been included in the computational chain, this required less than ten days of calculations with the available workstation.
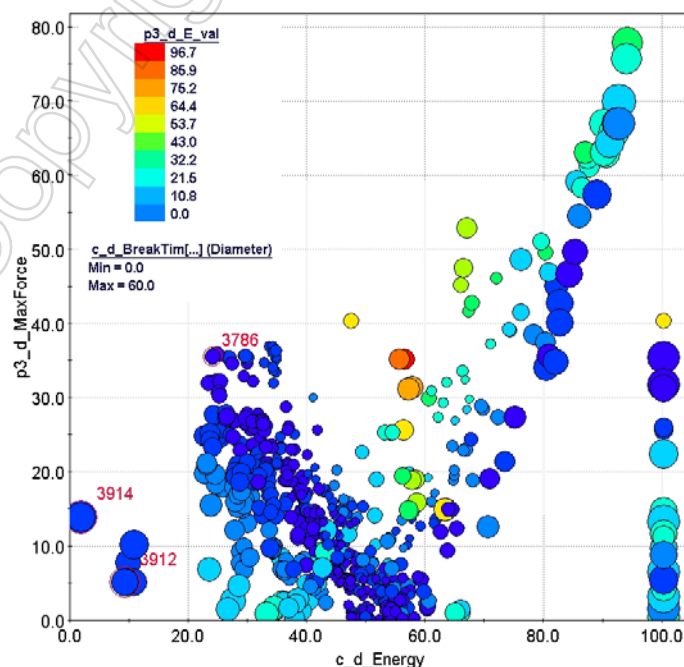

Fig. 8 – Four-dimensional bubble cart

Three promising constitutive parameter sets have been found: they're red-framed in Fig. 8, where each solution is represented by a bubble in the 4-D plane of the objectives. An ideal configuration should stay bottom left in the chart (low "c_d_Energy" and "p3_d_MaxForce" deviations from experimental data), should be cold-coloured (low "p3_d_E_val") and small-sized bubble (low "c_d_BreakTime"). Selected configurations number 3786, 3912 and 3914 are good compromises between the simultaneous reduction of the four un-correlated percentage deviation indexes, selected from the Charpy and 4-Bending Points tests.

3.3 Validation of the best results of the reduced calibration

With the aim to validate the three candidate solutions found in Chapter 3.2 in terms of the whole set of four experimental tests, they were inserted in the complete workflow of Fig. 5, and evaluated with a few minutes of additional computational effort. One-digit percentage deviations from experimental values have been confirmed also by the other five objectives.

This has been judged as very satisfying, especially taking into accounts the large number of considered parameters, simultaneous un-correlated objective functions, and the experimental data scattering itself.

4 Conclusions

A material model calibration procedure has been proposed, by coupling LS-DYNA and modeFRONTIER. Such a procedure has been tested for RTM1400 composite modelling with MAT58 material card, giving good results within a two-weeks timeframe (once experimental data available), on an ordinary workstation. Moreover, the method allows also to identify the minimum set of experimental tests needed to characterize the material model, out of a set of available (and potentially redundant) ones: in the described example, they are the Charpy and the 4-Points Bending tests.

The calibration of whichever material model can be tackled by using such a procedure: starting from a complete set of standard experimental tests and material card parameters, assessing the crucial objectives and inputs, and finally achieving a fast and accurate model calibration that can be then validated with reduced additional effort. The whole procedure is relatively simple to implement. In fact, modeFRONTIER embeds a wizard to suggest the best optimization strategy, while the usage of the data post processing tools is very intuitive. On the other hand, LS-DYNA's FEM modelling is simple and proved to be reliable. Therefore, this methodology has been easily integrated into the Lamborghini design chain.

5 Acknowledgements

6 Literature

[1]   Rao, S.S.: "Engineering Optimization, 3rd ed.", Wiley Interscience, 1996.
[2]   "LS-DYNA Key User's Manual, Version 971", 2007.
[3]   "modeFRONTIER User's Manual, Version 4.1.1", 2009.