Analysis of the Scatter of a Deploying Airbag

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Abstract

This paper discusses some of the challenges faced by the automotive industry in dealing with the natural variation in input parameters and environmental factors that lead to scatter in results. We describe how a lack of consideration of this variation can lead to surprises during testing, with the associated risk of unplanned cost, and present a technique using Principal Components Analysis to improve the robustness of CAE crash models.

In a purely virtual product development world, increasingly demanding functional requirements, and pressure on weight and cost, mean that analysis techniques must lead to designs that are robust with respect to external noise sources; large safety margins are no longer acceptable. Conventionally the CAE process has used nominal values for input parameters, and has been satisfied with single, deterministic solutions. However, virtual techniques have much to offer in understanding and managing scatter, and the consideration of variability in the CAE process is becoming more common-place. At the same time, the CAE method introduces its own issues associated with model stability, and these must also be addressed before design optimisation is attempted.

Frequently, analysis approaches used to improve design robustness can also be applied to issues of model stability, and we describe an example where Principal Components Analysis within the Diffcrash software package has been used to identify a source of instability in an airbag model. The mathematical background to the PCA method is presented, explaining its application to the analysis of variation, and showing how it can help in locating a source of scatter in results. The airbag example illustrates how this can be applied to allow changes to the modelling technique (or to the design) to be made to reduce the scatter. In this example, the source of the different airbag behaviours shown in figure 1 was identified as being a contact issue at an earlier point in time (figure 2), and a modification to the contact definition led to a reduction in the dispersion in results.

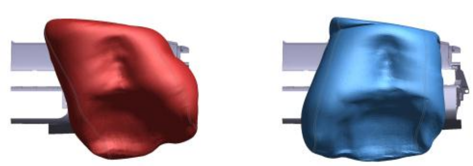

Figure 1. Airbag behavior modes at 85ms

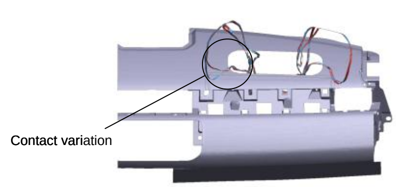

Figure 2. Airbag contact variability at 23ms

Lastly we offer insight into the requirements for deployment of such techniques, and describe how process integration is a fundamental necessity for a successful, sustained implementation.

Industrial Background

The current state of the art in the automotive industry sees almost all crash product development activity being carried out in the virtual world, with a final validation test taking place only after investment in tooling and facilities has been committed. The consequences of an unpleasant test surprise at this late stage can be very costly, particularly if design changes have to be made.

Since variability is present in all physical systems and operating environments, a consideration of robustness is an essential part of any CAE-based product development process. The assumption that there is a single, deterministic solution to a CAE analysis is bound to lead to a surprise when the product is tested, as a result of:

- Test to test variability
- Unwarranted assumptions as to input parameter values
- Non-robust CAE models

Because it is rare for identical tests to be carried out, there is little physical data relating to the test-to-test variability inherent in the product and its response to the operating environment. The probability that a future test will deliver the same result as a previous one is, therefore, unknown and, in a worst case, could lead to a false sense of security, with unexpected issues at a later date.

On the other hand, CAE techniques can produce useful insight into these concerns, as multiple versions of a design can be created and evaluated, and statistical tools can be used to understand and manage the variability. However, the CAE process itself introduces some robustness issues, which must be addressed before a design optimisation is attempted. A particular example is the instability of crash models subject to very small perturbations in input parameters, or even to purely numerical noise, and this will be discussed using the example of an airbag model. The methods described are equally applicable to the study of design robustness.

Traditionally, a common approach to the issue of variability has been the adoption of sufficiently large safety margins, but these are often associated with cost and weight penalties, which are no longer acceptable. The adoption by the industry of a structured approach to managing variability and robustness, using CAE techniques, has so far been the exception, and is only now starting to become more commonplace.

Sources of Unstable Crash Simulation Models

Explicit crash models are subject to two types of perturbation: modification of physical input parameters, and scatter resulting purely from noise inherent in the numerical process. This numerical variability is the consequence of a build-up of rounding errors leading to different responses from nominally identical models, when the individual calculations are carried out in a different order, for example when the model is run on different numbers of CPU. The degree of variation seen as a result of the numerical variation is model-dependent, and often reflects the sensitivity of the design to small changes in input parameters. Unless this spread is taken into account, any design decision based on a back-to-back comparison of two runs is unreliable and, potentially, misleading. Crash simulation is particularly susceptible to these effects, due to the ubiquitous use of multiple CPUs, and the large number of time steps involved, leading to a large opportunity to build up errors. As an illustration of this, figure 3 shows a set of time histories that were produced by thirty models that differed only in the order of calculations carried out.

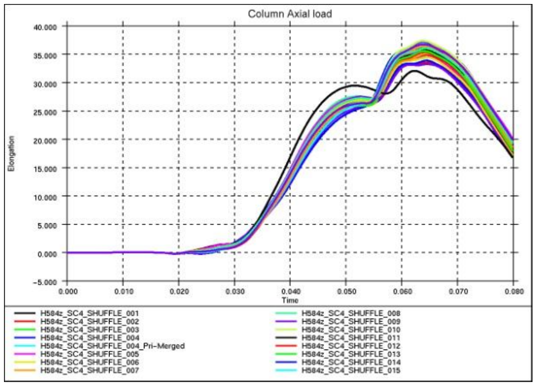

Figure 3. Scatter in time histories

This scatter in results called into question the validity of a design decision that had previously been taken based on a back-to-back comparison of two individual models, so the robustness analysis was repeated for the new design. As can be seen in the distributions of the curve maxima in figure 4, the design modification led to a large change in mean value compared with the spread of results, and the original decision appears to have been valid. On the other hand, the original analysis of the old design was optimistic, and the mean of the original distribution is worse than thought; the benefit indicated by the difference in means is greater than that indicated by the two original runs. In fact a back-to-back comparison of the two designs could, in an extreme case, indicate anything from a 0 to 8mm benefit, depending on where individual runs fell within the distributions, and without understanding the spread in the results, it would be invalid to compare the designs on the basis of individual runs. Interestingly, the model of the new design shows a smaller spread in results than the original, indicating that the design change has also led to a more robust design condition.

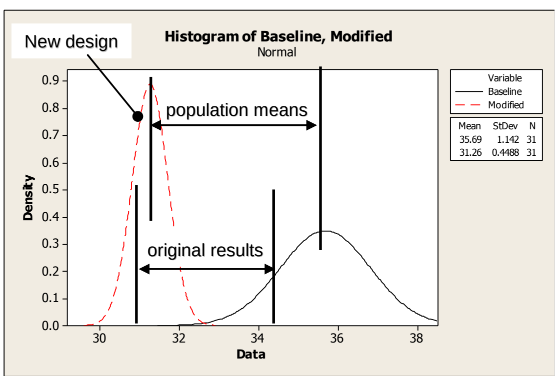

Figure 4. Distributions in results

Of course it is unrealistic to conduct a variability study for every design, and in practise it is necessary to reduce the scatter through improvement in modelling technique, or, remembering that model instability can be indicative of a lack of design robustness, by improving the design. Once this has been done, the remaining variability can be used as a measure of the precision of the model. On this basis, one design can only be considered statistically different from another if single results from each design differ by an amount greater than this precision.

Analysis of Robustness using Diffcrash

The Diffcrash software package allows a more in-depth analysis of sources of numerical variability. This software allows the user to identify distinct modes of behaviour from a variability study, and to track these modes to their time and point of origin. This provides information that can help to locate the cause of the variability, as an aid to improving the model. One of the mathematical analysis tools used by DIFFCRASH is Principle Component Analysis (PCA).

PCA Analysis for Crash Simulation Results

According to [1] Principle Component Analysis (PCA) was introduced by Pearson in the context of biological phenomena, and by Karhunen in the context of stochastic processes [2]. In [3] PCA was applied to full crash simulation results. Let

$X_i(p,t)$

be the displacement of simulation run *i* out of *n* simulation runs at node *p* and time *t*. If $\overline{(X)(p,t)}$ is the mean of all simulation runs, the covariance matrix *C* can be defined as

$C := [c_{i,j}]_{1\le i,j\le n}$ and $c_{i,j} := < X_i - \overline{X}, X_j - \overline{X} >_2$

The eigenvectors v_i of *C* form a new basis (principle components) and the $\lambda_1 i$ (square roots of the eigenvalues of *C*) provide a measure for the importance of each component.

If this method is applied to crash simulation results, n^2 scalar products between the simulations runs of length $3 * \#P * \#T$ have to be computed ($\#P$ number of points, $\#T$ number of time steps.)

From

$$\widehat{X}(a) := \sum_{i=1}^{n} a_i X_i \, ,$$

it follows that

$$\lambda_i = \left\|\widehat{X}(v)\right\|_2 \, .$$

The $\widehat{X}(v_i)$ show the major trends of the differences between the simulation results.

Difference PCA

Instead of considering the whole simulation results, correlation matrices can also be defined for the simulation results at parts of the model and for specific time steps. If *P* is a part of the model and T subset of the time steps, then $C_{P,T}$ can be defined as follows:

$C_{P,T} := \left[c_{i,j}^{P,T}\right]_{1 \le i,j \le n}$ and

$$c_{i,j}^{P,T} := \frac{1}{N_{P,T}} \sum_{p \in P, t \in T} \left(X_i(p,t) - \bar{X}(p,t)\right) * \left(X_j(p,t) - \bar{X}(p,t)\right).$$

($N_{P,T}$ denotes the size of P times the size of T .)
The intrinsic dimension of the set of simulation results can be defined as the number of major components in its differences (for more formal definitions see [4, Chapter 3]). Buckling or any other local instability in the model or numerical procedures increases the intrinsic dimension of simulation results at parts which are affected, compared to those that are not affected. Therefore, in the context of stability of crash simulation, those parts and time steps for which the intrinsic dimension increases are of particular interest.
Numerically this can be evaluated by determining eigenvectors and eigenvalues of

$$C_{P_1,T_1} - \tau\, C_{P_2,T_2}$$

for the covariance matrices of the simulation results at two different parts P_1 and P_2 and two different sets of time steps T_1 and T_2. If there are positive eigenvalues for a certain choice of τ (which separates noise from real signals), the simulation results at (P_1 , T_1) show additional effects compared to those at (P_2 , T_2). If v_{P_1,T_1} is the corresponding eigenvector, $\hat{X}(v_{P_1,T_1})$ shows the effect on (P_1 , T_1) and also the impact on the other parts of the model. Similar methods can be used to remove those effects from this result, which do not affect (P_1 , T_1) directly.
This approach has been filed for application of a Patent at the German Patent office (DPMA number 10 2009 057 295.3) by Fraunhofer Gesellschaft, Munich.

CURVES

Instead of variation of node positions a major interest of the design engineer may the analysis of scatter of curves (c.f. [5]). The analysis of curves can be included into the analysis by defining a matrix $C_{CV,T}$ for each curve *CV* and each time step *T* as follows:
Let

$$CV_i(k,t)$$

the scalar value of the k^th curve at time step t in simulation run *i*, then $C_{CV(k,T)}$ is defined as:
$C_{CV(k,T)} := \left[c_{i,j}^{CV(k,T)}\right]_{1 \le i,j \le n}$ and

$$c_{i,j}^{CV(k,T)} := \left(CV_i(k,t) - \overline{CV}(k,t)\right) * \left(CV_j(k,t) - \overline{CV}(k,t)\right).$$

$C_{CV(k,T)}$ may now be used in the analysis in the same way as $C_{P,T}$ before.

Airbag Example

In an airbag crash model, large differences were seen in occupant chest injury measures when the restraint system was subjected to small design changes. The model also exhibited significant variation in the kinematic behaviour of the airbag and occupant upper body. An assessment of the model stability was carried out, using purely numerical noise to excite variation in response. Use of numerical noise, rather than variation of a physical input variable, explicitly excludes the possibility that the change is driven by sensitivity to a design parameter, and is a useful way of demonstrating underlying model stability.

For thirty nominally identical models, which differ from each other only as a result of numerical noise, the dummy chest accelerations are shown in overlay in figure 5.

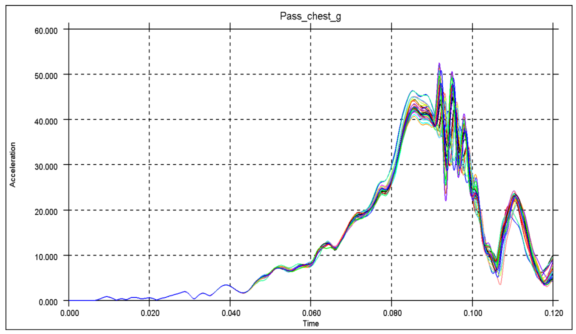

Figure 5. Dummy chest accelerations from thirty models

The responses show an unacceptable level of variation; differences of this magnitude could typically be used to guide design development, but it is not possible to ascribe a change in response to the value of a physical input parameter with this level of model instability. The gross instability beyond 90ms makes the model unusable beyond this time step.

The associated dispersion of dummy nodal coordinates for the thirty runs at 85ms, superimposed on a reference model, is shown in figure 6. This is consistent with the dispersion in chest acceleration.

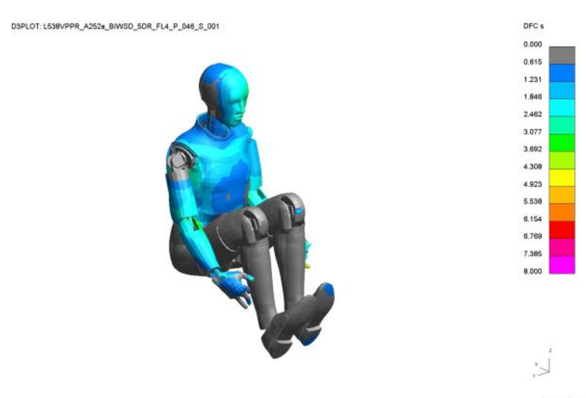

Figure 6. Dispersion in nodal coordinates of dummy at 85ms

Analysis of the results of the thirty runs, using PCA applied to the whole model, identified thirty characteristic scatter modes, where each run can be expressed as a linear combination of these modes. Further analysis showed that sub-set of 5 modes is responsible for 80% of the scatter. The most significant characteristic mode is best illustrated by the airbag deformed geometry as seen in figure 7, where the two plots represent the extremes of the scatter mode.

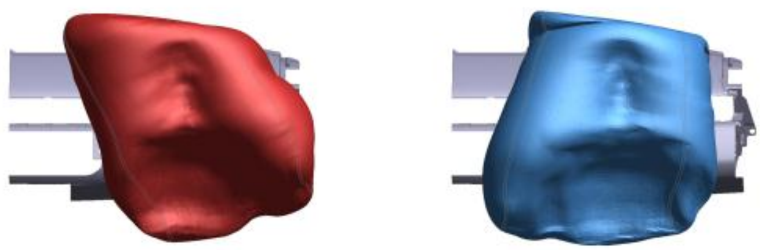

Figure 7. Most significant airbag scatter mode

Use of difference PCA allowed the origin of this characteristic mode to be traced to a specific part and point in time and indicated that the variation in behaviour at 85ms is initiated by a poor contact definition at 23ms relating to a strap in the airbag, as shown in figure 8.

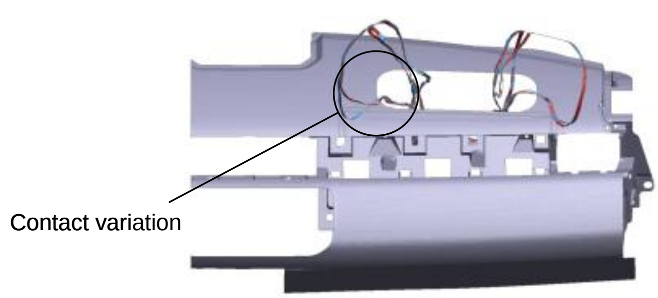

Figure 8. Variable contact of airbag strap at 23ms

Use of curve PCA further showed that the variation in occupant chest injury values is comprised of the same characteristic modes as the variation in the nodal positions, and 50% of the dispersion in occupant injury values was associated with the most dominant airbag scatter mode. This provided confidence that an improvement in the stability of the contact definition would lead to a reduction in scatter in the occupant injury values.

Following a modification to the contact definition of the airbag strap, and other minor changes to reduce the instability beyond 90 ms, a repeat of the original analysis, using the same method to introduce numerical noise, produced the results shown as an overlay in figure 9.

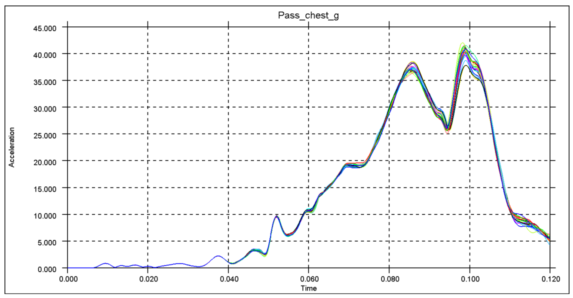

Figure 9. Dummy chest accelerations from thirty improved models

The variability has been significantly reduced, and the form of the curve after 85ms can be determined. The model is now stable enough to allow design optimisation. Further PCA could be expected to reduce this scatter further, but remaining residual variation must be considered to be a residual precision of the model, and any comparison of results must make reference to this.

Integration into Industrial Processes

As reliance on the CAE process becomes more firmly established as the only way to meet the timing, functional, and cost challenges of automobile development, it is clear from the foregoing that it is no longer satisfactory to work on the basis of nominal predictions, and one-to-one comparisons. Achieving a shift to a statistical and robustness-based product development process poses a number of challenges both of a technical and of a programme management nature, which must be met if it is to be seen as the norm, rather than as a potentially expensive, time-consuming extra. Traditionally a barrier to systematic application of variability analysis, IT infrastructure is becoming no longer the determining factor. However, the ability of current levels of processing power to produce large amounts of data makes automation and integration into standard processes essential; a continuing expansion of the CAE toolset is also desirable. The PCA process is an example of a technique that can be incorporated into existing process, making use of established pre and post-processing tools. In this way, traditional barriers to the roll-out of new techniques, such as learning thresholds, and compatibility with other process activities are minimised. The basic process elements as implemented at Jaguar Land Rover are shown in Figure 10. The standard post-processing environment continues to form the backbone of the process, while drag-and-drop access to the underlying PCA executables allows users to carry out PCA without leaving this environment.

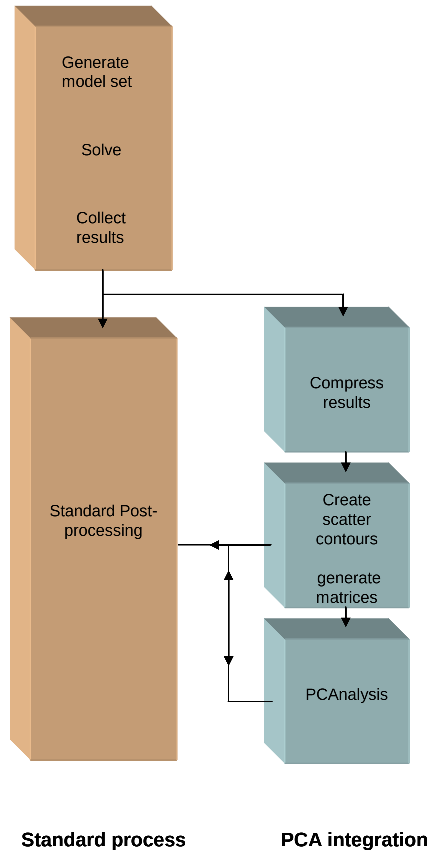

Figure 10. Process implementation

This has successfully allowed experienced users to apply a subset of these techniques, providing significant functionality. Full exploitation of the suite of utilities, however, remains the preserve of a small number of experts.

Summary

All physical products display variability as they respond to noise in input parameters, manufacturing processes, and operating environment. It follows that any single value from a CAE analysis is 'wrong' in the sense that it is only one possible outcome. As a consequence of this, it is inevitable that a test result will deviate from a single prediction, and that any following tests will deviate from both the prediction and the first test. Model stability is a case of variability without modification of input parameters, and adequate model stability is essential before design optimization is carried out. PCA has proved to be a useful tool in identifying locations and sources of model instability, and this has been demonstrated using an airbag example. The adoption of this methodology is dependent on infrastructure, process integration, and management factors, and must be driven by a consistent planned approach to usage.

References

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