Application of Machine Learning technique to incorporate manufacturing and Testing variation for Robust BIW design for Crash performance

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1 Abstract

In vehicle development CAE plays crucial role in arriving at optimum structural design to meet various vehicle performance targets in different domain such as Crash, NVH, Durability etc. Accurate CAE methodology can aid in reducing the number of physical tests & reducing overall vehicle development time. However, there are instances where there are gaps observed between test results and CAE predictions. These gaps get amplified in crash simulations as the event is highly dynamic and non-linear behavior simulation is always challenging. In order to enhance CAE methodology, it was decided to incorporate the effect of manufacturing and testing variations in crash CAE simulations. Manufacturing process accounts for variations due to inherent variation in material properties, spot weld nugget diameter, manufacturing processes such as stamping etc. whereas Physical Testing houses variation in barrier positions, test speed etc. within specified tolerance defined by regulatory bodies. These variations affect structural performance and negating these issues in early design phase will help to arrive at robust structural design.
In this paper, the CAE based approach for accommodating manufacturing and testing variation in crash CAE simulation for arriving at robust BIW design is described. In the current work, unsupervised machine learning based CAE approach is used to identify variations in structural performance arising out of manufacturing and testing variations. This paper also describes accuracy verification of this CAE approach based upon its comparison with quasi-static experimental test.

Keyword : Crash, Robustness, Diffcrash, unsupervised ML,PCA,DPCA

2 Introduction

Computer-Aided Engineering (CAE) plays a significant role in the development of vehicles. CAE allows manufacturers to simulate and analyze various scenarios before physical prototypes are built. This reduces the need for expensive and time-consuming physical tests, resulting in cost & overall model development time. CAE enables automakers to quickly iterate designs, evaluate performance, and make necessary improvements without the need for physical prototypes. CAE tools help to optimize vehicle performance by simulating and analyzing various aspects such as NVH, aerodynamics, structural integrity in Crash, thermal management, and vehicle dynamics etc.

CAE simulation becomes utmost important for Passive safety domain by reducing number of destructive physical test. Passive safety refers to the measures taken to protect vehicle occupants during a crash or collision by providing sufficient survival space and efficiently restraining occupant to prevent injuries. CAE aids automakers to simulate different crash scenarios in virtual environment and analyzing the results, identify potential safety risks and develop effective countermeasures to minimize occupant injuries by optimizing the vehicle structural design and ensuring structural integrity. With efficient CAE methodologies vehicle structures can be optimized with effective energy-absorbing materials, deformation patterns, and crumple zones to ensure the vehicle can safely absorb and dissipate crash energy.

CAE methodologies are derived by establishing best practices for FE modelling of parts, accurate material modelling and defining boundary conditions etc. The standardized methodologies prove to provide consistent results and product development can revolve around these methodologies for meeting performance requirements. However, instances are there where CAE predictions do not match with physical test. Since CAE is a virtual simulation that uses computational models and algorithms to predict the behavior and performance of a vehicle before it is physically built and tested however, there are possibilities of variation with physical test because of the following reasons:

- Accuracy of CAE Process/Methodology (modelling, Boundary condition, failure criteria etc.)

- Variation in Part Manufacturing (Forming, welding, assembly etc.)
- Variation in inherent properties of raw material.
- Variation in physical testing condition.

The above-mentioned parameters are difficult to control & can affect the crash performance of vehicle due to change in deformation modes, abnormal crushing etc. Hence, to counter the manufacturing and testing variation it becomes important to arrive at robust BIW design during initial stage of vehicle development to get consistent performance even if there are variations in production or test within limits decided by OEMs.

In this study, new approach in Crash CAE simulation methodology is described wherein effect of manufacturing variation such as panel thickness variation, spotweld nugget diameter variation along with physical testing variation such as test velocity, barrier position are integrated in existing CAE methodology to arrive at a robust BIW design.

DOE based CAE approach creates set of iteration considering variation in manufacturing and testing parameters with predefined limits. The output of DOE was used to identify robustness sensitive parts in the event of 64kmph frontal offset crash (BNCAP condition). Manual approach of identifying robustness sensitive parts out of set of iterations is tedious and this is where Machine learning was used. ML in CAE offers opportunities to enhance the accuracy and efficiency in analysing large datasets. In this study DiffCrash tool developed by SIDACT GmbH that uses unsupervised ML method to identify robustness sensitive parts was used.

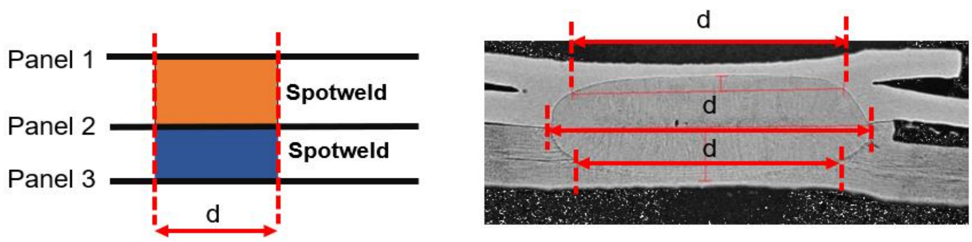
3 Crash CAE Robustness Analysis

Crash Robustness analysis refers to the process of testing and evaluating the ability of vehicle structure to provide consistent performance in the event of crash by handling variability in manufacturing, testing, material properties etc. within OEM permitted tolerance limits. Vehicle BIW need to be designed in such a way that irrespective of these variations the vehicle performance in terms of structural integrity, energy absorption and survival space of occupant is not compromised. Crash robustness analysis helps identify vulnerabilities and weaknesses in the design and enables designers to make necessary improvements to enhance its crash resilience.

In this study the BIW robustness for crash performance is evaluated by considering variation in manufacturing and Testing. The variations considered for manufacturing are spotweld nugget diameter & Sheet metal thickness whereas for Physical testing its test velocity, barrier position & barrier orientation.

3.1 Manufacturing Variations

Spotweld representation in CAE is done using Hexahedral elements to capture the actual behavior of spotweld. The size of spotweld in CAE is taken as reference from design data and all the spotwelds are modelled with standard diameter as per OEM standard. However, physical spotweld diameter may vary depending upon manufacturing parameters such as weld current, welding time, hold time, electrode force etc. It further depends upon the fusion of different grades of material. Cross section comparison of spotweld in CAE and physical vehicle is shown in Fig-1.



CAE Spotweld nugget diameter

Physical spotweld nugget diameter

Fig.1: CAE Vs Physical Spotweld section Comparison

From Fig-1 shows cut-section of 3ply spotweld in CAE and physical model. It can be seen that in CAE, spotweld diameter is constant whereas in physical spotweld the diameter of spotweld is maximum at the center and reduced on top and bottom surfaces. Change in spotweld nugget diameter results in variation the spotweld strength. As BIW consists of numerous spotwelds, these variations in nugget diameter can lead to discrepancies in CAE and Test results.

Another aspect of manufacturing variance is steel sheet thickness from raw material supplier. Steel sheet thickness can vary from base thickness with tolerance specified by OEM. Conventional CAE model is generated as per design thickness. Similar to spotweld nugget diameter variation, variation in BIW panel thickness can also lead to gap between Test & CAE results.

3.2 Physical Test Variations

In physical tests, regulatory bodies permit permissible tolerance for deviation in test. These include misalignment of barrier, Impact velocity etc. Figure-2 shows the permissible limits of ODB barrier misalignment limit in lateral and vertical direction as specified in BNCAP.

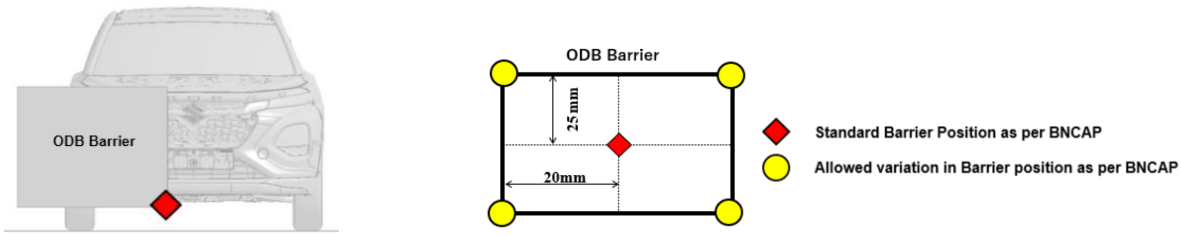


Fig.2: ODB Barrier position variation as per BNCAP

Conventional CAE simulation is performed with standard barrier position & velocity as specified by regulation. These variations in test condition leads to variation in impact loads which result in variation in deformation mode and magnitude of deformation resulting in overall differences in Test and CAE.

4 Numerical Robustness Analysis – Set up

Studying the effect of individual variation and its effect was possible. However, to study the combined effects, manual method is not practical. Combining these variations will lead to infinite numbers of combinations and studying these combinations manually was cumbersome & hence it was decided to perform DOE study with appropriate sampling approach to maximize the utilization of variation. In this study Latin Hypercube sampling (LHS) approach was used for sampling. Latin hypercube sampling is a statistical technique used for sampling from a multidimensional parameter space. Latin hypercube sampling ensures the following:

- Entire parameter space is sampled more evenly, reducing the risk of missing important regions.
- Minimizes the sampling error by ensuring that each parameter is sampled multiple times.
- LHS requires fewer samples than traditional random sampling methods to achieve the same level of accuracy, making it more resource efficient.

Sl. No	Variable	Base	Min Variation	Max Variation
1	Spotweld Nugget diameter (mm)	A	-E% (A)	+ E% (A)
2	Panel Thickness (mm)	B	-F% (B)	+F% (B)
3	Impact Velocity (Kmph)	64	63	65
4	Barrier Lateral position (mm)	C	-20	+20
5	Barrier vertical position (mm)	D	-25	+25

Table 1: Parameters considered for DOE Study

Table -1 represents some of parameters considered in DOE study for evaluating the effect of variation. The variation level was defined considering permissible tolerance defined by OEM in production processes and tolerances defined by regulatory bodies (BNCAP) for physical test. Using an in-house developed tool, DOE setup was done. The number of iterations were determined to build desired database so that ML based tool used for post-processing can accurately identify robustness sensitive parts and design flaws. Figure-3 shows the representation of DOE model for vehicles evaluated under BNCAP condition for 64kmph ODB crash.

Fig.3: DOE setup for Robustness analysis

In this DOE, the variation in spotweld nugget diameter is simulated by varying spotweld strength. Panel thickness variation is applied to nodal thickness as per OEM specified tolerance in CAE. These DOE iterations are solved using LS-Dyna solver and post-processing of DOE results for robustness sensitive part identification and root cause are performed using DIFFCRASH software. Evaluation of the robustness analysis was based on deformation modes of long members, Dash panel intrusions, acceleration profile etc.

4.1 Numerical Robustness Analysis-Result Processing

DOE iteration creates significant data set and analyzing these data to arrive at meaningful conclusions manually is tedious. To expedite this process an unsupervised ML approach was preferred. In unsupervised learning, the machine learning algorithms are provided with instances without their respective labels, here the algorithm aims to identify hidden patterns in the dataset. Unsupervised learning algorithms can be used to classify, label and group the data points contained within data sets without requiring any external guidance in performing a particular task. Advantages of applying unsupervised ML in CAE process are as follows:

Pattern Discovery
- Identify patterns in data set

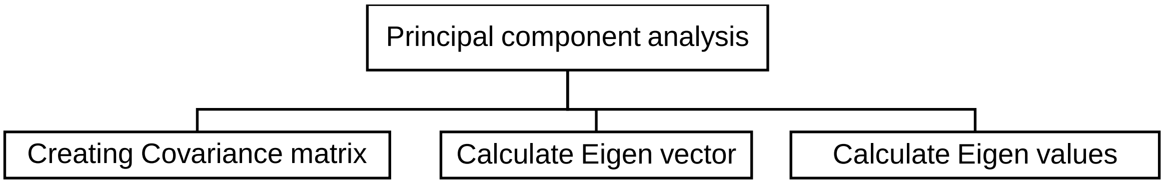
Irregularity Detection
- Identify irregularity in CAE data, which is leading to potential issues in designs

Dimensionality Reduction
- Dimensionality reduction techniques like PCA can simplify data while retaining important information.

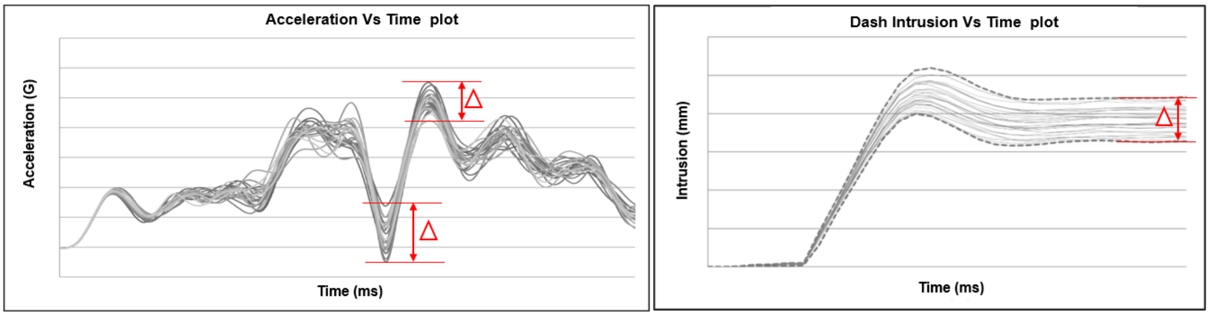
Clustering
- Group similar CAE simulations of large datasets aiding engineers

Reduce manual effort
- Automates the analysis process reducing manual effort in analysing larger data set

In this study, unsupervised ML tool i.e. DIFFCRASH was used to evaluate the DOE outputs. DIFFCRASH is a variation visualization tool developed by SIDACT GmbH. DiffCrash allows to identify variation in modes from the set of data. It further aids engineers to identify the time state from which variation initiates. DiffCrash works on a mathematical tool called Principal Component Analysis (PCA). PCA works in following steps:



Before getting into DiffCrash, it was necessary to gauge the amount of variation in vehicle structure. Quick reference for variation was drawn by plotting vehicle acceleration vs time plots for all set of iterations as shown in Figure-4.



4a. Acceleration Vs Time plot *4b. Dash Intrusion Vs Time plot*

Fig.4: Result summary of DOE iterations

From Figure-4a it can be seen that vehicle structure is experiencing significant variation in acceleration profile. These variations in vehicle pulse indicates variation in deformation pattern of vehicle structure. From Figure-4b, it can also be seen that dash intrusions had significant variations. This variations in dash intrusion adversely affects occupant response leading to gap in CAE prediction and physical test output. Dash intrusions are primarily governed by deformation of front long member and powertrain interaction with dash panel. Since powertrain is mounted on front long member, the deformation mode of long member becomes critical. Using DiffCrash, the long member deformation modes were analyzed.

5a. Importance factor Vs Mode plot *5b. Scatter plot for long member*

Fig.5: Diffcrash analysis of long member deformation mode

DiffCrash reduces dimensions of all nodal coordinates by using PCA approach. The PCA method helps to visualize extreme results from the set of CAE simulations. Maximum information of variation in data set is mapped into first principal component. From Figure-5a, it can be seen that the first principal component i.e.mode-1 is having maximum contribution to the variation. Therefore, it was possible to estimate the cause of variation by checking the deformation of the two extreme cases of the first principal component.

Figure-5b shows scatter plot for DOE iterations plotted with two major principal components i.e. Mode-1 & Mode-2. The abscissa of scatter plot represents mode-1 & ordinate represent mode-2. Iteration at extreme end of abscissa i.e. mode-1 in Figure-6 carries maximum variation and those are iteration X & Y . These two iterations were studied to evaluate the variation levels along with root cause.
The long member deformation mode in iteration X & Y is shown in Figure-8.

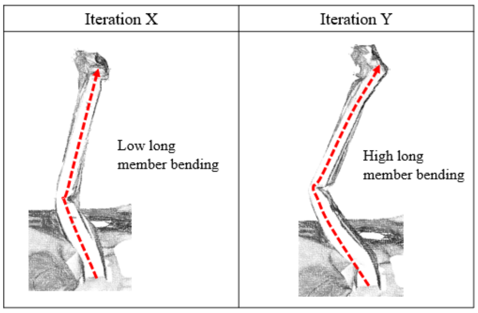


Fig.6: Long member deformation mode comparison

Bending of long member is very low in iteration X compared to iteration Y. It can be seen that in iteration X, long member undergo axial compression thus limits overall bending whereas in iteration Y, front end of long member does not get axial crushing rather forms a Z-shaped lateral bending profile.

In order to stabilize the mode of long member, it is necessary to identify the origin of variation. DiffCrash offers method to identify origin of variation by plotting mode over time state plot.

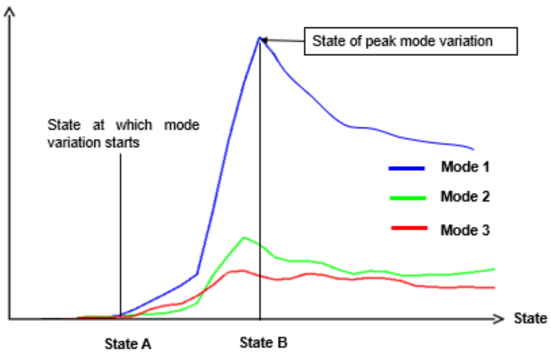


Fig.7: Mode Vs Time state plot

Figure 7 shows the mode-1 variation with respect to time state. Till state A, there is no variation in long member deformation. At state A, variation in long member mode initiates and at state B variation has reached maximum value.

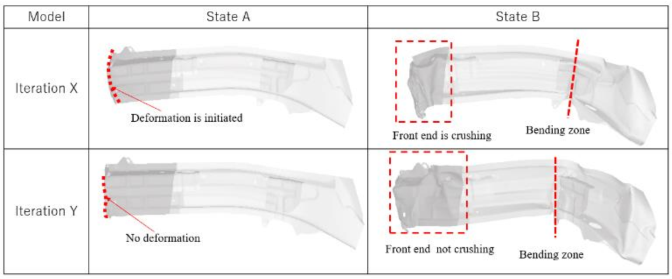


Fig.8: Variation in long member mode w.r.t. time state

Figure-8 shows long member deformation mode at time state A & B. At time state A, front end of long member starts to deform in iteration X whereas in iteration Y no deformation is observed. At time state B, the variation in deformation mode was at peak and it can be seen in figure-8, the long member bending location & magnitude in iteration X & Y are different. These variations in long deformation mode leads to variation in dash intrusion and hence it becomes very important to stabilize long member deformation modes. To identify the root cause for variation, DiffCrash offers extension of PCA approach called DPCA (Difference Principal Component Analysis). DPCA uses the correlation matrices created during PCA to identify relation in variation of target part with trigger part based on degree of correlation between target part and trigger part.

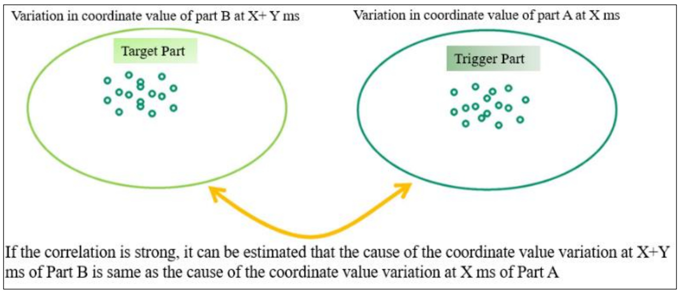


Fig.9: DPCA method for variation analysis [6]

Figure-9 shows how the nodal coordinate variation of trigger part is correlated with nodal coordinates variation of target part. Based on this principal, root cause for variation in long member was identified. DiffCrash DPCA results show high correlation between long member (target part) deformation variation & deformation of long member front end components (trigger part).

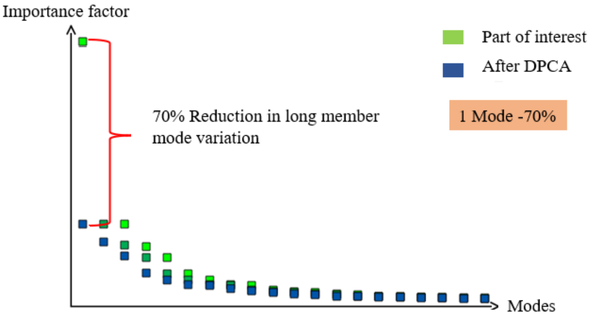


Fig.10: Front end variation contribution in long member mode variation

Figure-10 indicates contributions of variation in long member front end components to variation of long member mode. It can be seen that by controlling variation of long member front end components, variation in long member deformation mode can be reduced by 70%. The variation in deformation of front end could be because of variation in panel thickness, spotweld strength, test conditions but design for long member must be such that it gives consistent results. With this objective countermeasure study was conducted.

5 Numerical Robustness Analysis-Design Improvement

In order to stabilize long member deformation mode, the entire long member is categorized into two zones shown in Figure-11.

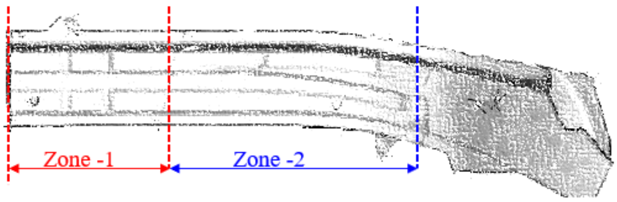


Fig.11: Design improvement for long member mode stabilization

Zone -1: Improve crushing of front end to reduce overall load transferred to long member rear end and initiate long member bending from design location.

Zone -2: Long member bending location stabilization. Long member bending from design location will help to reduce variation in dash intrusions which will help to achieve robust design of occupant compartment.

Design improvement of long members includes design features such as beads/crush initiators, addition of reinforcement for controlling the collapse and bending location. The improved design was further evaluated for robustness performance and results were compared.

6 Numerical Robustness Analysis-Result Analysis with Improved Design

Improved design was further evaluated with all the variation conditions. The results of DOE were further studied using DiffCrash. Figure -12 shows the long member deformation mode comparison of initial design and improved design.

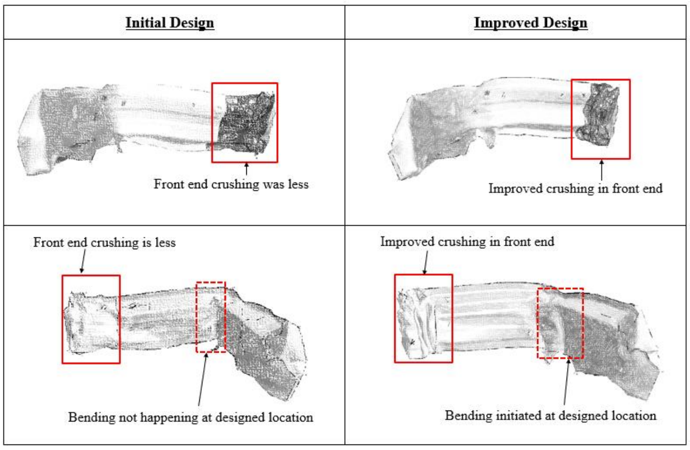


Fig.12: Long member deformation mode comparison

With improved design the deformation mode of long member has enhanced. The front end of the long member was getting crushed and bending at rear end of long member was observed at design location.

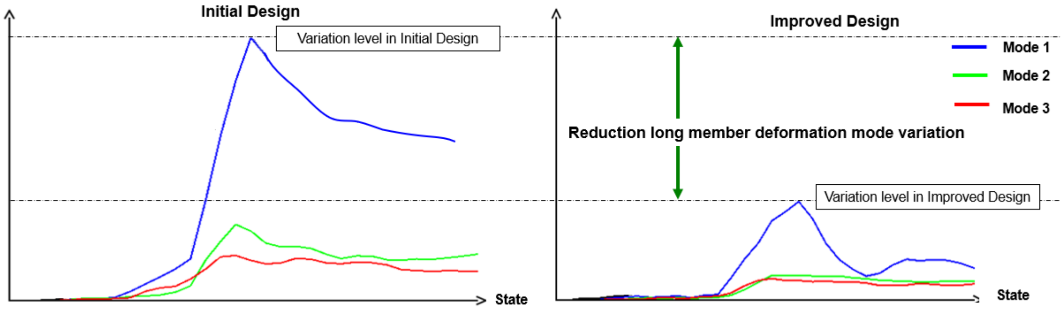


Fig.13: Long member variation comparison Initial Vs Improved design

With improved design, significant reduction in long member deformation variation is achieved as shown in Figure-13. The design changes made on long member design resulted in robust performance of long member and same can be visualized in Figure-14.

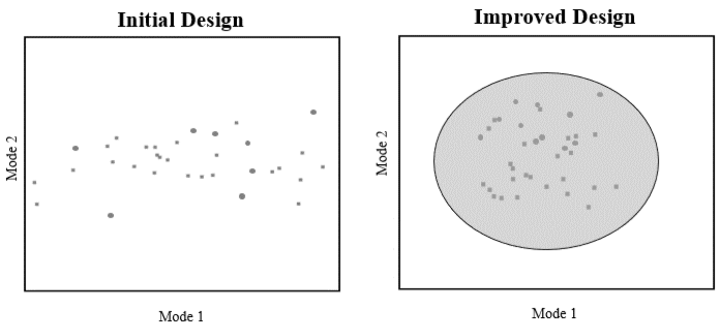


Fig.14: Correlation cluster for long member Initial Vs Improved design

Figure-14 shows correlation cluster for long member deformation mode. It can be seen that deformation mode in initial design of long member was scattered whereas with improved design, modes are clustered together with very less variation. Further improvement in reduction of variation was not required in this study as the improved design had no concerns with respect to survival space for occupant protection and other crash performance requirements.
This numerical robustness analysis methodology has helped to achieve robust BIW design. In order to implement the methodology in model development it was necessary to validate the CAE methodology by correlating the same with physical test to assess the accuracy of overall process.

7 Numerical Robustness Analysis-Methodology Validation

For validating the CAE methodology, it was decided to perform an experimental quasi-static test considering local area of BIW as it was not feasible to build complete BIW with above mentioned variation and cost associated with vehicle level destructive test for methodology validation. Local area of BIW was made with production variation of panel thickness based on steel sheet thickness received from supplier, spotweld nugget diameter by altering weld parameters and same is shown in Figure 15

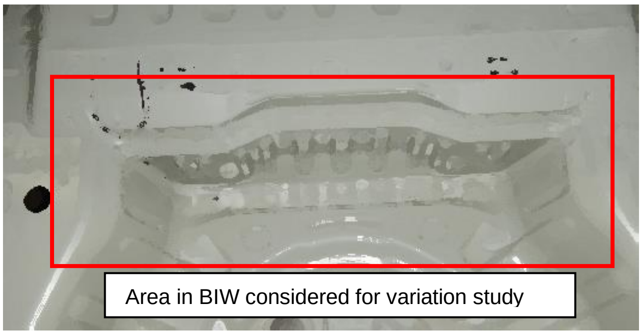


Fig.15: BIW with production variance for experimental test

The BIW structure was tested as per standard seat belt anchorage test condition. A similar test was also performed on BIW structure with standard production configurations without variation. Both these BIW structures responded differently to the test. The BIW with production variation resulted in panel crack whereas BIW without variation sustained the load without any crack or spotweld rupture as shown in Figure-16. From the experimental test it was evident that variation in production and test variation can result in substantial variation in vehicle response.

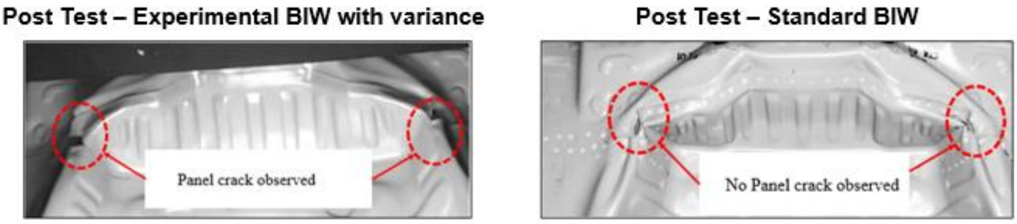


Fig.16: BIW deformation variation in experimental test

To validate the CAE methodology, CAE model was built for simulating the experimental test. In the CAE model production and test variations were applied using DOE approach as described in earlier section of paper and all DOE iterations were solved using LS-Dyna. The DOE iterations once solved were processed using DiffCrash which helped to identify iterations which produced similar results to the experimental test. Out of X iterations performed, several iterations shown panel crack very much similar to the test. Figure-17 shows panel crack observed in CAE simulation.

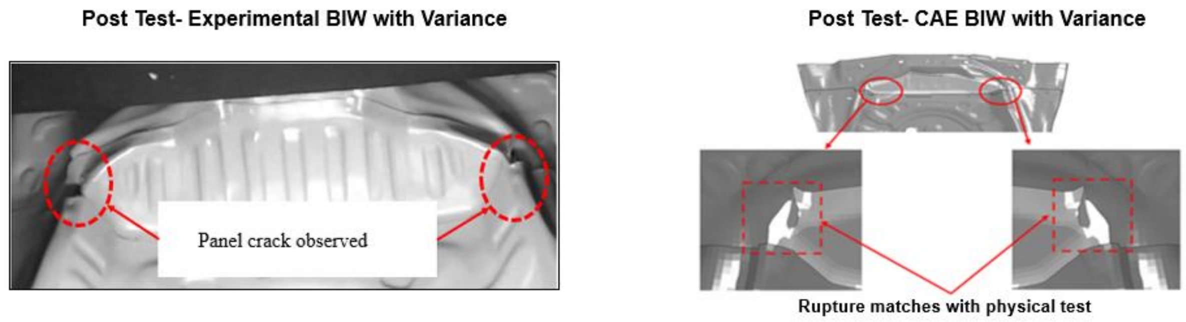


Fig.17: Experimental Test Vs CAE deformation comparison

CAE methodology accuracy is validated with very high correlation of CAE results with physical test and gives confidence for implementation of CAE process in product development cycle.

8 Summary

The robustness analysis CAE methodology mentioned in this paper can be used to effectively identify critical areas in vehicle which require strict production control and monitoring. During design phase additional provisions to prevent failures in physical test can be accommodated by using this CAE robustness analysis methodology.

Unsupervised ML approach effectively reduced human effort in processing large data set. DiffCrash software was efficient in identifying patterns in set of data, variation origin and root cause of variation.

This CAE methodology help in developing robust BIW structure to meet crash performance with production and test variation as per OEM production and BNCAP test tolerance limits.

9 Future Scope

The robustness analysis CAE methodology mentioned in this paper can be further improved by considering variation in material properties such as yield strength, failure strain etc. and Variation in spotweld position.

Current study was limited to evaluate structural robustness performance. The scope of this methodology can be further increased to investigate occupant injury mechanism based on variation in occupant position, restraint system configuration etc.

10 Literature

[1] Masahiro Okamura “A process for Robust Design of a Vehicle Front Structure using Statistical Approach”, 14th International LS-DYNA Users conference

[2] Ckenebs-August Thole “ Advanced Mode Analysis for Crash Simulation Results”, 11th International LS-DYNA Users conference

[3] Johannes Will, Uli Stelzmann "Robustness Evaluation of Crashworthiness using LSDYNA and optiSLang", 25th CAD-FEM Users Meeting 2007

[4] Johannes Will, Hans Baldauf, Christian Bucher, “Robustness Evaluations in Virtual Dimensioning of Passive Passenger Safety and Crashworthiness”, 3rd Weimar optimization and Stochastic Days 2006

[5] Masahiro Okamura “Robustness Analysis of a Vehicle Front Structure Using Statistical Approach” 10th European LS-Dyna Conference 2015, Wurzburg ,Germany

[6] DiffCrash 6.1.24 User manuals.