Automated Generation of Robustness Knowledge for selected Crash Structures

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1. Introduction

Maintaining or even improving vehicle safety whilst vehicle mass is reduced and safety regulations are tightened is a key challenge in vehicle design. Mastering scatter of material properties, manufacturing tolerances and load condition variations requires sophisticated robustness analysis, in order to gain knowledge about the behavior of the car under typical uncertainties. In order to condensate the knowledge in the crash simulation data much better than just doing casual statistics, advanced pattern recognition techniques are needed.
Uncertainties are usually modeled with probabilistic distributions, which are then used in a robustness analysis. The most common first step is to observe the scatter of the responses of interest and check whether unacceptable violations occurred. In case of a violation, it can be very difficult and time demanding to find the causes for the violation due to high nonlinearity, bifurcations and concatenation of effects. Even though humans are having extremely flexible pattern recognition capabilities in combination with the usage of previous knowledge, the mind itself still struggles with recognizing patterns within large amounts of data, namely “Big-Data”.
In order to face these challenges, a new knowledge generating approach was developed. This process is outlined in figure 1 and comprises geometric model reduction, results mapping, similarity calculation and finally knowledge generation through visualization, outlier detection, clustering and cluster importance ranking.

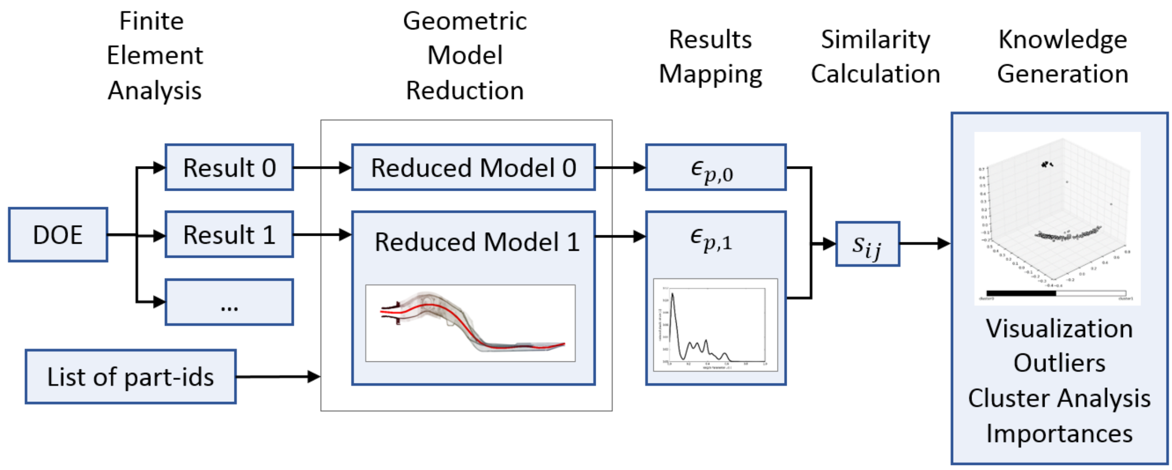

Fig.1: Proposed process flow

2. Data Reduction and Knowledge Generation

The data reduction and knowledge extraction procedure shall be outlined briefly here and is described more detailed in [9].

2.1 Geometric Simplification

The first step in the process flow of figure 1, after the Finite Element Analysis (FEA), is a geometric model reduction. Various techniques have been proposed in order to compare geometries [1-3,7], but these are either computationally expensive, need parametric adjustement to the specific problem or need recalculation if new data is added. To mitigate these challenges, a novel technique for geometric model reduction was developed, which simplifies a selected group of parts to either a 1D line or 2D plane, which generically reflects beam or sheet structures in technical applications (see figure 2). The line or plane is fitted to the geometry with a parametric Bézier-Polynomial.

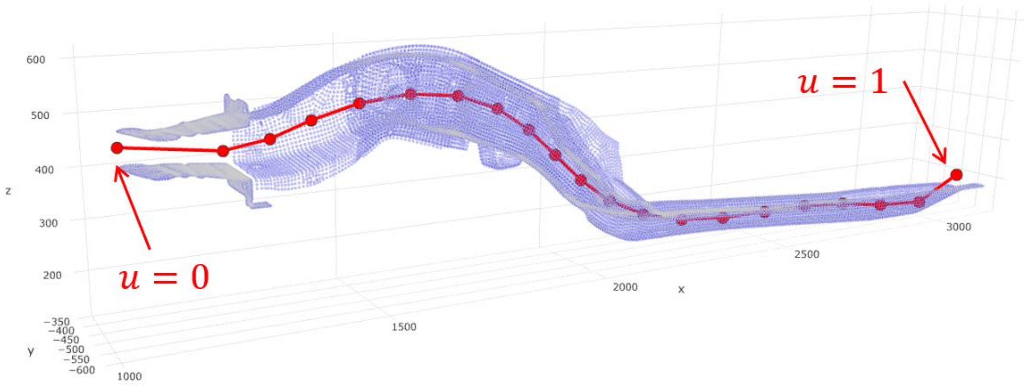

Fig.2: An example for geometric simplification. The geometry is simplified to a curve, so that each element has only a one-dimensional coordinate u on the curve.

2.2 Results Projection and Smoothing

Thereafter the results of the individual FEA runs, such as plastic strain, are mapped to the reduced geometry. The equivalent plastic strain was chosen as it describes large deformations. Since the mapping is done with a smoothing kernel, the result is a continuous function of reduced plastic strain along the parametric coordinates of the reduced model geometry (see figure 3). This function is calculated for each simulation run of the investigation.

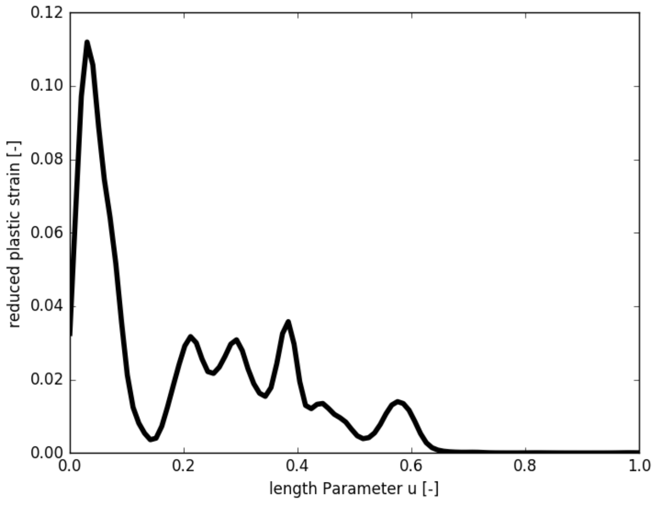

Fig.3: Function of reduced plastic strain along the length coordinate of the regression in figure 2. The smoothing was done with a Gaussian kernel as distance weight for the elements plastic strain.

2.3 Similarity Computation

In the next step, the similarity of two individual FEA runs represented by the above functions of reduced plastic strain needs to be quantified. The metric $\langle \cdot | \cdot \rangle$ for calculating the similarity s_{ij} between two functions of reduced plastic strain is the dot product for continuous functions [6]

$$s_{ij} = \frac{\langle f_i | f_j \rangle}{\sqrt{\langle f_i | f_i \rangle \cdot \langle f_j | f_j \rangle}} \in [0,1] \tag{1}$$

$$\langle f_i(u,v) | f_j(u,v) \rangle = \iint f_i(u,v) \cdot f_j(u,v) \cdot d(u,v) . \tag{2}$$

Since the comparison of curves is computationally very cheap, it can be applied to all runs of the robustness study, resulting in a symmetric similarity matrix, which contains the similarities of all runs to each other. The similarity value is normalized and can be seen as a percentage of equivalence of the distribution of plastic strain, where 1 stands for identical and 0 for totally different.

2.4 Clustering of Simulations

Finally, the knowledge intrinsically hidden/embedded in the data needs to be extracted. For data visualization and cluster analysis, the similarity matrix is fed to machine learning algorithms. Visualization of the similarities enables recognizing patterns in the data, such as clusters of similar behavior, and hence enables the extraction of the underlying knowledge. The high-dimensional nature of the similarity data requires lower dimensional embedding techniques [4,5] to generate plots. Here Multidimensional Scaling (MDS) was used, which reconstructs coordinates in lower dimensions from the similarity matrix. In order to find statistically conspicuous samples, outlier detection and cluster analysis find groups of simulations with similar behavior. The agglomerative clustering [10] is hierarchical, so that finer substructures may be analyzed too. The association of a simulation sample with a behavior cluster represents knowledge and is saved in a knowledge database. An example plot for the clustering with visualization can be found in figure 4 and 6.

2.5 Finding important Variables triggering simulation clusters

In order to find the most important variables for each cluster, importance ranking was used, quite similar to correlation between a continuous input variable and a continuous response. The importance ranking of variables is realized by decision tree algorithms [8], which allows association of individual clusters with its own sensitive variables. The variables responsible for the generation of undesired behavior clusters, such as certain buckling modes, may represent sensitive knobs to turn in order to make a specific design robust to input variations.

3. Example 1 : Buckling Location of a Rail

The first example is a longitudinal component, which consists of a U-profile which is bolted along the flanges to another sheet metal so that it closes the U-profile. The component is additionally connected at the upper and lower end by two plates with seamlines (see figure 4). The boundary conditions constrain the lower end, while an impactor is dropped onto the upper end. The parametric uncertainty was modelled with probabilistic distributions of properties, such as length, width, bolt position, bolt strength, material and so on. In total the parametric model contains 175 variables, but most of these originate from the 26 bolts. In order to get a statistical sufficient impression, 1000 simulation samples were drawn from the probabilistic distributions in combination with a latin-hypercube-design. All simulations were sent to a HPC and reduced to curves of plastic strain and compared against each other in order to get a quadratic similarity matrix of size 1000. The low dimensional embedding of the similarities in 3D is shown in figure 4, where each simulation is colored according to its corresponding cluster.

The data reveals that there are two obvious clusters and two outliers. The small cluster contains 2% of the simulations. All of these simulations did buckle at the constrained lower end, despite being hit at the top. Almost all simulations (98%) did buckle in the upper half, but the spread of the cluster reveals, that about 10% did buckle towards the mid. Since the large cluster is continuous, there is a transition between the state at the left and the right end of the cluster. The first outlier has a buckling location in an area where no other sample did buckle. Additional simulations did show, that this event is just extremely rare. The second outlier is a sample, which showed some bending to the side due to buckling at the top and the bottom at the same time.

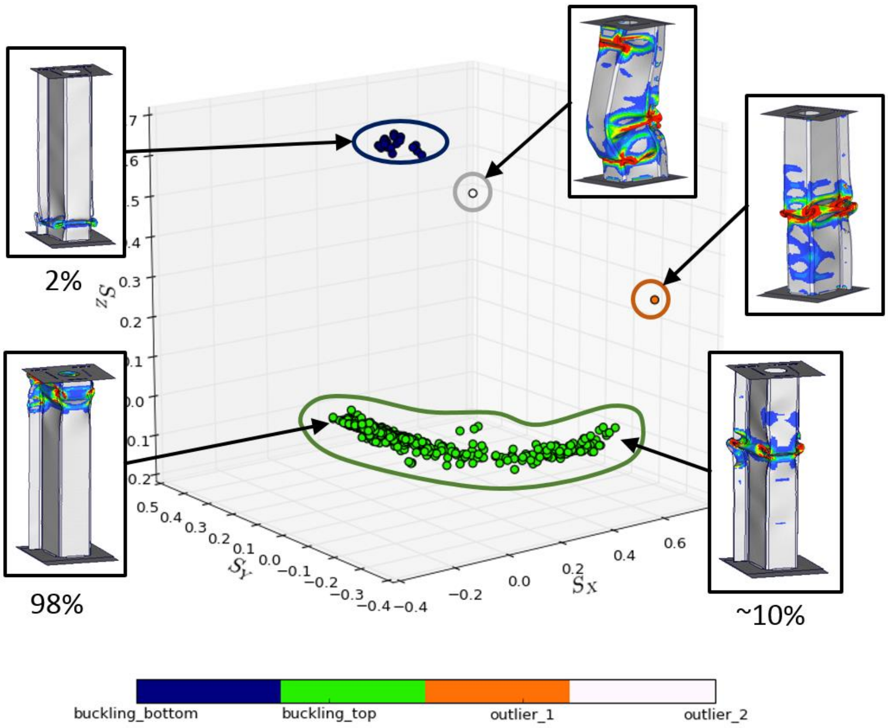

Fig.4: Visualization of the similarity of 1000 simulations with a MDS in 3D. The data originates from a virtual drop-tower test. Watching only 5 representative simulations is enough to understand the behavior of all 1000 simulations

4. Example 2 : Ball Impact on a Plates Edge

The second example is an impact of a ball onto the edge of a sheet metal plate. The setup resembles a cantilever beam (see figure 5), which is constrained at the left end and hit with a ball upwards. The edge of the plate is covered by a small flange like a frame with a width of 10mm, which stabilizes the structure a little bit. In this example only 6 uncertainties where used, which are the balls velocity vector, as well as the position of impact. The impact offset of the ball (PY) was varied minimally, in order to trigger slightly different contact situations numerically.

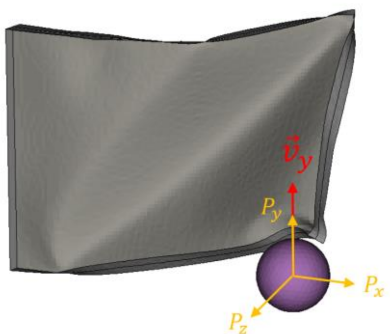

Fig.5: The plate is hit with a ball upwards at its lower edge. The velocity vector and the initial ball position were varied.

Since the structure is obviously 2D, a planar model reduction scheme was applied, in contrary to the previous example. The results of the clustering and the low-dimensional embedding in 3D can be seen in figure 6.

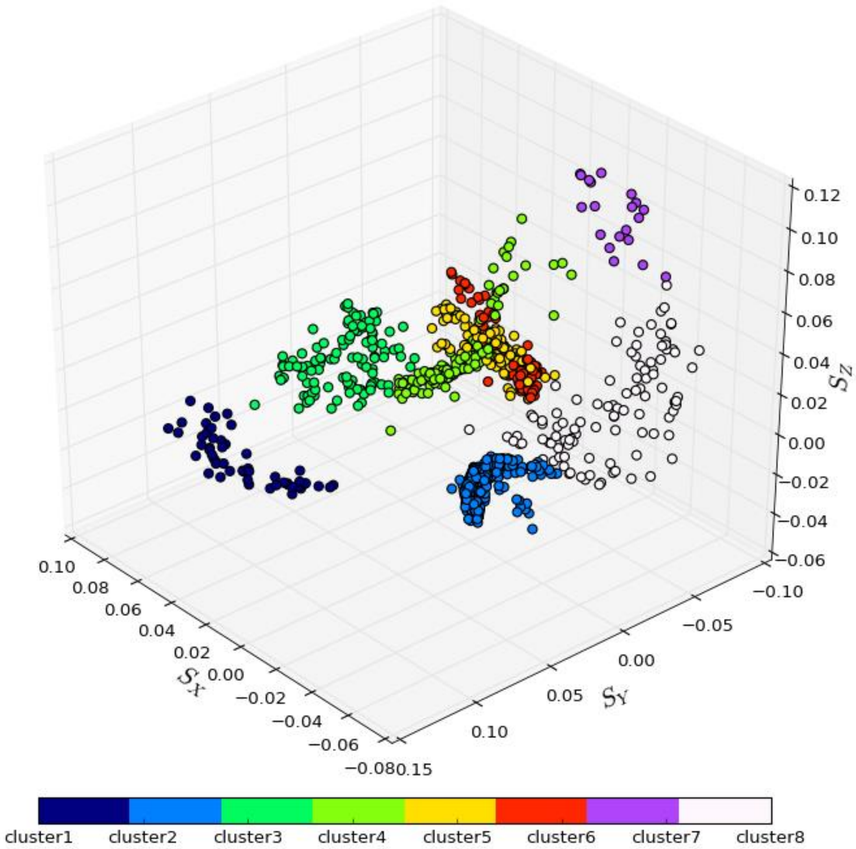

Fig.6: Low dimensional space embedding of 1400 simulations. The structure is very twisted in 3D, but reveals 3 major groups and about 8 minor.

The behavior cloud is much harder to understand than the previous example, since the buckling itself has many different states and transitions. Since the structure itself seems to be complex, the automated clustering helps understanding the structure of the data, even though it also struggles with the entangled section in the middle. There are roughly about 3 unconnected large clusters, which themselves may be separated into a total of 8, in order to achieve a good partition. Even though the behavior seems to be complex, it is not arbitrary. Having to watch only 8 out of 1400 simulations is already a large reduction of work, in order to see all of the major buckling modes of the component. Figure 7 shows a representative simulation for each of the 8 clusters. If an engineer has further interest into a certain behavior cluster, he may watch more samples of it.

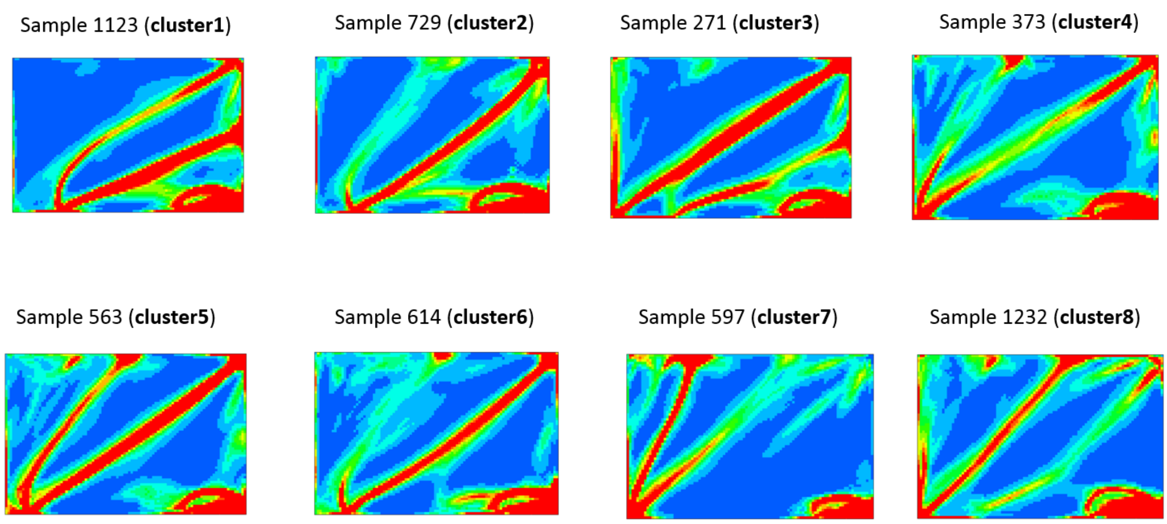

Fig.7: Picture of one representative simulation for every cluster. The samples are colored with the effective plastic strain at the last timestep. Note the large red zone on the lower right, which is the location of impact of the ball.

The interesting fact is, that some of these 8 clusters are connected in between, so that transition zones exist, such as between cluster 3 and cluster 4 even though they look very different. By choosing a path in the cloud from the center of cluster 3 to cluster 4 reveals the intermediate states, see figure 8. In this particular case did the lower buckling line of the component vanish, whereas at the same time a buckling line is appearing in the upper region. Watching such transitions can be used by an engineer, in order to validate the pure statistical procedure of the algorithm quite nicely.

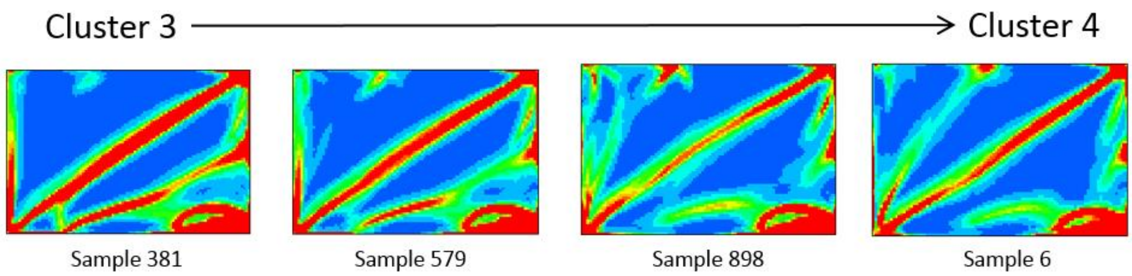

Fig.8: Transition from cluster 3 on the left to cluster 4 on the right. Two additional representative samples in between reveal the intermediate behavior.

The application of the importance ranking scheme on any cluster proposes the planar position of the ball underneath the edge of the plate (namely PX and PZ in figure 5) to be the most important variables. The variation of the velocity vector seems to be too small in order to make any significant contribution. Plotting the variables PX versus PZ and coloring each simulation with its cluster reveals zones in the input space, which lead to a certain behavior cluster (figure 9). Note that some the borders are not continuous transitions, but may represent jumps in the buckling mode. This can be checked in the low dimensional space embedding of the similarities (watch cluster 1 in figure 6 and figure 9).

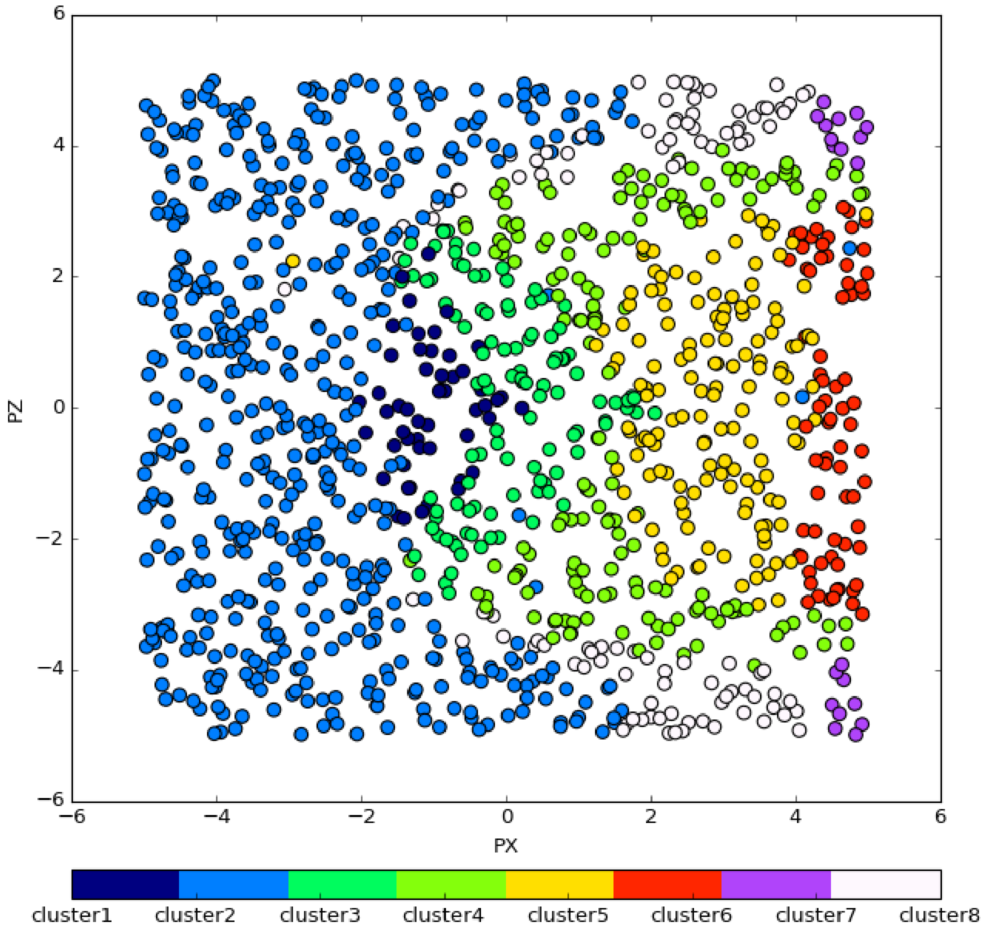

Fig.9: The initial planar position of the ball (PX and PZ) underneath the plate determines the deformation behavior. The few "outliers" within certain zones were wrongly assigned by the clustering algorithm.

5. Outlook

An important bottleneck for meaningful statistical analysis is the need for a large number of samples. This is particularly true for the huge computational effort for full vehicle crash simulations. Hence investigations have to be made on the performance of the procedure regarding smaller sample numbers. Furthermore, decision tree learning may be used to give automatic solution proposals as a next step for certain behavior clusters. Lastly a modification of the process may enhance the segmentation of different bending directions, which cannot be treated with the efficient plastic strain well.

6. Literature

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