upscale

Upscaling **P**roduct development **S**imulation **C**apabilities exploiting **A**rtificial inte**L**ligence for **E**lectrified vehicles

D5.9 Final report containing proposal for further use of the new methods

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The UpScale Project

UPSCALE is the first EU project with the specific goal of integrating Artificial Intelligence (AI) with traditional physics-based Computer Aided Engineering to reduce the development time and increase the performance of electric vehicles (EVs).
Nowadays High-Performance Computing (HPC) and Computer Aided Engineering (CAE) play a decisive role in vehicle development processes, thus the two most HPC and CAE intensive parts of the development, which are vehicle aero-thermal and vehicle crash performance, have been chosen as use cases for the endeavour.
Through the combined effort of universities, research laboratories, European automotive OEMs, software companies and an AI-SME specialized in Machine Learning (ML), the UPSCALE, project will provide a unique and effective environment to produce novel AI-based CAE-software solutions to improve the competitiveness of the automotive industry.

The UpScale Consortium

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ABSTRACT

The present deliverable describes the assessment of the researched and developed methodologies within the crash part of UPSCALE. The integration of the methods into a full vehicle crash simulation is described as well as a robustness analysis. Three methods are investigated. The first is the AI model for predicting the short circuit risk which was finally delivered from WP5.1. Second, the integration of load case parameters into a reduced order model was delivered in WP5.2. Third, the AI model predicting the stiffness of the battery cell jellyroll which was delivered in WP5.3. Finally, the future application fields of the methods are discussed.

Revision History

The following table describes the main changes done in the document since it was created

REVISION	DATE	DESCRIPTION	AUTHOR (ORGANIZATION)
0	28.03.2022	Template	Andres (Volkswagen)
1	26.04.2022	Draft Version	Andres (Volkswagen)
2	29.04.2022	Review	Dumon (ESI)
3	29.04.2022	Final version	Andres (Volkswagen)

Disclaimer

Abbreviations

AI	Artificial Intelligence
CPU	Central processing unit
DoE	Design of Experiment
FEA	Finite Element Analysis
FEM	Finite Element Method
HPC	High Performance Computing
LHS	Latin Hypercube Sampling
ROM	Reduced Order Model
RVE	Representative Volume Elements
SC	Short Circuit
sPGD	Sparse Proper Generalized Decomposition
VPS	Virtual Performance Solution

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1 Executive Summary

The present deliverable describes the assessment of the researched and developed methodologies within the crash part of the UPSCALE project. The methodology and the resulting models have been set up during the project period within the work packages 1, 3 and 5. The integration of the methods into a full vehicle crash simulation is described here. The main focus lies on the assessment of the AI based model for predicting the internal risk of short circuit within a battery cell during a full vehicle crash scenario. But also the integration of load case parameters in a reduced order model using the sPGD method and the prediction of the stiffness of the battery cells' jellyroll by an AI based model integrated to full vehicle crash simulations are discussed. For each of the three models/methods the integration into the full vehicle model is explained in detail.

In chapter 2 a small introduction is presented to get a better understanding of the subsequent chapters. In chapter 3 the integration of the AI based model for predicting the short circuit risk into the vehicle simulation model is explained. The model was finally delivered in WP5.1 by Ensam and ESI. The prediction of the model is discussed. A robustness study is presented. Finally, improvements for future work are recommended. In chapter 4, the integration of load case parameters into a reduced order model using the sPGD method is assessed. The method was delivered in WP5.2 by ESI. It is applied to some side pole crash scenarios with four changing parameters. The interpolation result file allows the user to investigate intermediate solutions by interpolation within one file. The interpolation of the risk of short circuit is discussed as well as further possible application areas. Chapter 5 is dedicated to the AI model predicting the stiffness of the battery cell jellyroll which was delivered in WP5.3 by ESI. The integration to the full vehicle model is explained. The assessment of the method is presented and recommendations for improvements and further usage are given. Finally, chapter 6 deals with the conclusion and a discussion on deviations in time and content.

At this point the authors want to emphasize, that the results of the full vehicle simulations may not be used in order to assess the safety or performance of the present vehicle or even a real vehicle which may look similar. First of all, the load cases are adjusted in such a way, that no legal or consumer test may be valid anymore. Second, the vehicles themselves are not based on real vehicles as they only exist as FE models for research reasons. Furthermore, a comparison with existing vehicles, whether they are now available or in the future, is strictly prohibited.

The vehicle model has been derived from a battery electric vehicle model that was used in the national project SMILE (SysteM-Integrated multi-material Lightweight concept for E-mobility) funded by the German Federal Ministry of Education and Research from 2014 to 2017. The battery concept and parts of the battery models are used from the project ALIVE (Advanced high volume affordable LIghtweighting for future electric VEhicles) which was co-funded by the European Community's 7th Framework Programme from 2012 to 2016. The vehicle type is comparable to an e-Golf type.

2 Introduction

The AI and ROM models developed within the crash part of the UPSCALE project have been implemented into the Volkswagen battery electric vehicle model, see Figure 1. The model has been already described in deliverable D5.2 in detail. Here, the authors just want to repeat the relevant parts, i.e. the battery assembly, in order to ensure a better understanding of the implementation process. The FE model consist of 5 million shell elements (2D) and 2.5 million solid elements (3D), where the majority of solid elements is located in the battery cells' jellyroll. For all simulations 40 contour plots (element variables) and 1000 time history plots (e.g. measured forces) were stored in the result file, leading to an average non-compressed main output file size of around 9.1GB. This file size is usually much smaller, as the amount of output variables is reduced and the files are compressed but in this research project the authors decided to have more output in order to improve the assessment of the model and the methods and to locate possible issues which occurred during the implementation.

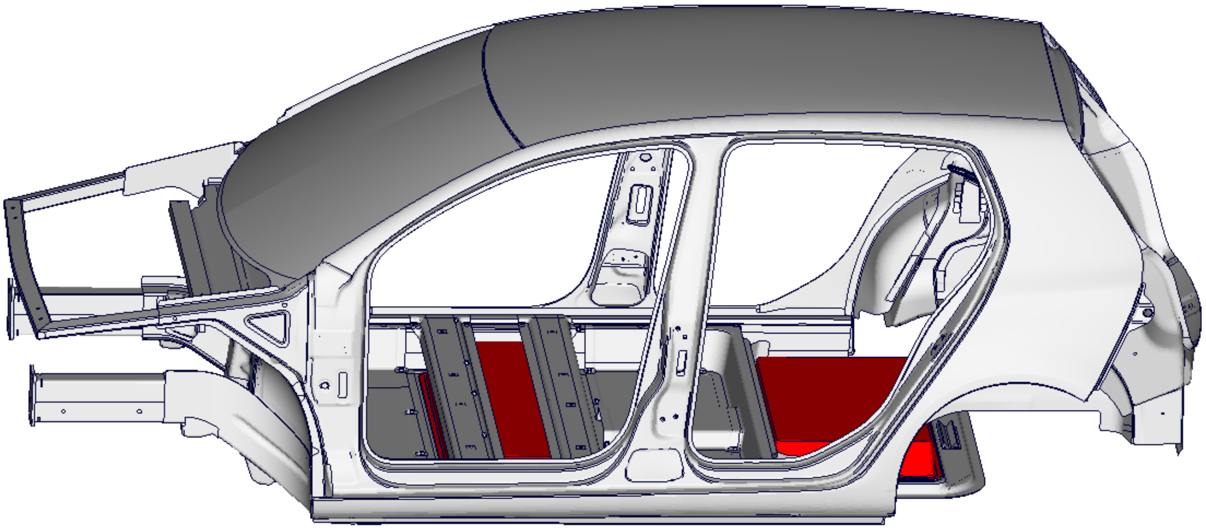
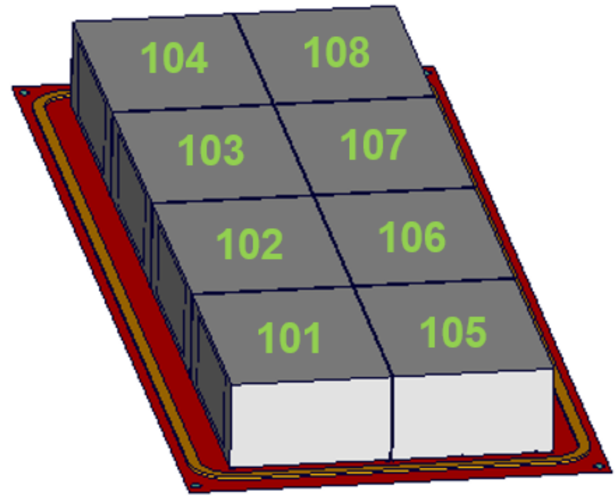


Figure 1: Body-in-white of the vehicle model, battery packages are highlighted in red

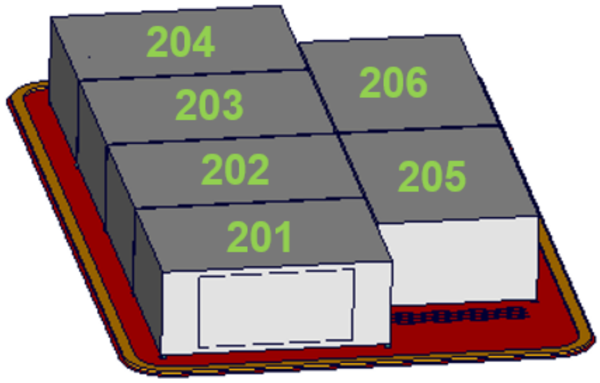
The battery modules and the battery cells are assembled by using the VPS modular input, see [1]. This allows the reuse of an FE model without causing issues with the node or element numbering. Figure 2 shows an overview of the front and rear battery package and the battery modules and battery cells incorporated. Only one FE model for the battery modules and one for the battery cells is used leading finally to 14 battery modules and 210 battery cells in the vehicle model.

The post-processing is not affected by the modular input, as the unique numbering of each battery module or cell allows a convenient location within a post-processor. Figure 3 shows the deformation field of the battery packages after a severe side pole impact and the location of a battery cell within ESI post-processor Visual Viewer.

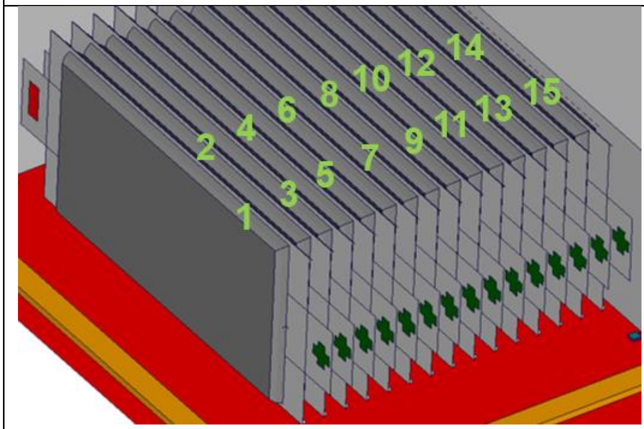
Finally, Figure 3 (b) also shows the jellyroll of the battery cell. This is the main focus of the assessment of the methods, described in the subsequent chapters. The jellyroll consists of 6600 solid elements leading to a total of around 1.4 million solid elements for all jellyrolls in the FE model.



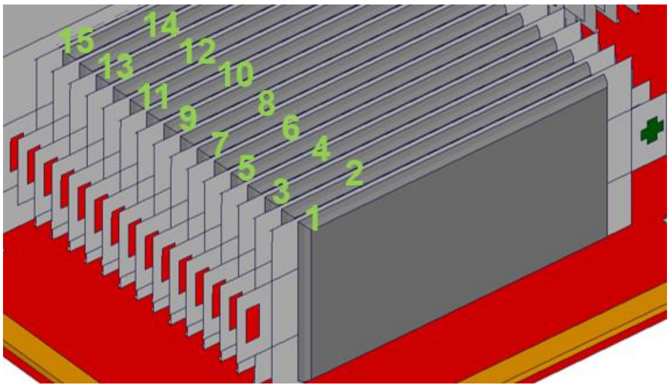
(a) Front battery package



(b) Rear battery package

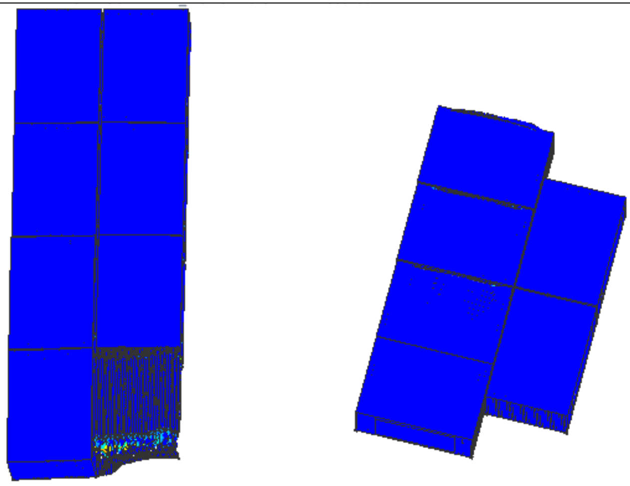


(c) Battery cells of module 101

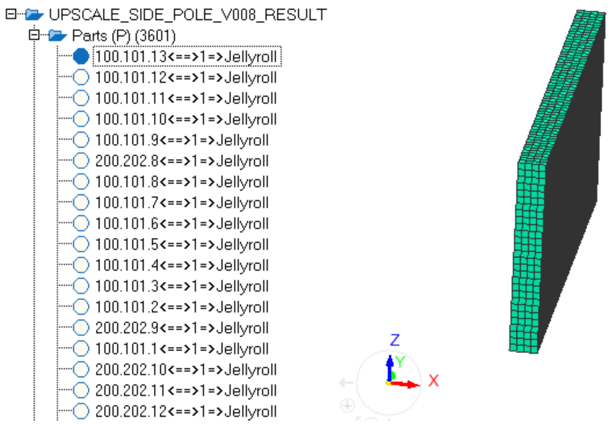


(d) Battery cells of module 201

Figure 2: Overview of the battery packages, modules and cells and its numbering using VPS modular input



(a) Deformation field of the battery packages



(b) Post-processing within ESIs Visual Viewer

Figure 3: Post-processing of the battery packages undergoing a severe side pole impact

3 Assessment of the AI based model predicting the risk of short circuit in a full vehicle crash load case

Within the UPSCALE project two AI based models for predicting the internal risk of short circuit in a battery cell FE model have been set up. The first one is using the basic full vehicle simulation result exhibiting the battery cells' jellyroll which is modelled with a homogenized Honeycomb material, i.e. MAT42 in VPS. After the simulation is finished a python based post-processing tool which has the AI based model implemented is applied to the output file and creates a new output file containing a new element variable for the jellyroll solid elements being the risk of short circuit. The training of the AI model has been described in deliverable D3.2.

At Volkswagen the implementation of the post-processing tool has met some issues, as the utilized versions of the python tool and the python libraries included were different to the versions of the Volkswagen environment. To circumvent this issue ESI has prepared a compiled version of the post-processing tool, including all necessary libraries. This allows the usage of the first method on a windows operating system. As the post-processing of a vehicle model is performed on Linux operating systems at Volkswagen the python tool cannot be added to this procedure, the crash engineer would need to perform an additional post-processing step for each simulation. Due to this reason, the first approach was not assessed by Volkswagen.

However, the second AI based method is circumventing this additional post-processing step, as the AI based risk is directly implemented to the material model of the jellyroll. This is realized within the VPS plugin user material framework with MAT85. User libraries usually define a mechanical material law based on the FE integration points of the solid elements, with access to element internal variables. The selected AI based internal short circuit risk uses elements strain state and so can be added in VPS user material framework, as shown by Greve et al [2].

ESI has implemented the Honeycomb material together with the evaluation procedure of the AI model, which is simple linear algebra plus the application of analytic functions. For the short circuit AI model, the Support Vector Machine (SVM) classifier and regression parameters have been added to the material model via lookup tables. In this way, the AI model parameters can be changed by the user. As the training of the AI model is still possible with the above described windows version, the user is able to exchange the AI model coefficients by his own needs. This fact is a big advantage, as the material is not a typical black box material which can be changed by ESI only.

The plugin material is implemented in a special user library, which can be compiled independently of the main VPS code. This allows the usage of stable versions of the VPS main code, in this case VPS version 2020.52. The additional user library is integrated using the environment variable PAMSHARE which is set to the folder, where the user library is located. The main code is checking the folder for present user libraries and thus the MAT85 material cards used within the FE model can be read correctly by the main code.

On average the simulation with the AI based short circuit risk model took 6.5 hours on the cluster using 64 CPUs. This time includes already the time for file upload and download. Compared to the times using the homogenized Honeycomb material, which was 5.9 hours on average, the time increase is acceptable. Without dummies and airbags, which was the case in the investigation phase, the simulation times could be reduced to 4.3 hours on average. The time step stayed stable at 0.5 µs. The simulation times show, that the first objective of the project is already met, namely the possibility to assess the risk of short circuit at reasonable cost. Dealing with simulations of around 6.5 hours, the crash engineer has the possibility to assess two variants of the vehicle model per working day. Please note, this is the case for side crash. Other crash scenarios will have its own typical computation times. But the fact, that the simulation times using the AI model are similar than with the initial model using a homogenized Honeycomb material for predicting the stiffness of the jellyroll only, indicates that the times for front or rear crash will be similar as well. The authors want to emphasize, that the usage of a user material library comes along with a larger computation time, as the VPS main code needs to interact with the additional user library. Simple tensile tests, using only one material law, have shown, that the overhead by using user material libraries in VPS compared to an equivalent material from the main code can be up to 30%. Here, the implementation of the MAT85 to the main code of VPS by ESI will lead to a decrease of simulation time in future releases.

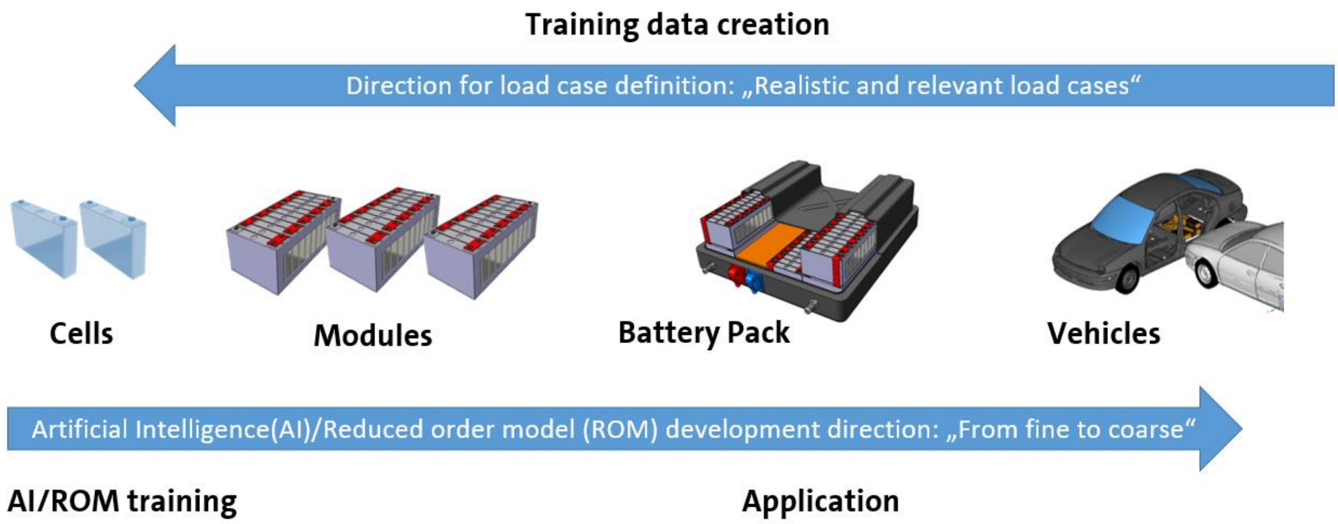


Figure 4: Visualization of the methodology for creating the AI based model predicting the risk of an internal short circuit in a battery cell

The proof of concept for the developed methodology, see Figure 4, is depicted in Figure 5. This is one of the first simulations, which terminated without an error. Please note again, the deformation of the vehicles' body-in-white must not be compared to some real vehicles or real legal or consumer tests. The risk of short circuit is computed correctly and may be visualized in typical post-processors, in this case animator4 by GNS.
The first DoEs have shown a high number of instabilities leading to early error terminations of the simulations of up to 50% of the runs. For this reason, the model was investigated in more detail. The instability problems occurred mostly in some of the jellyrolls during the simulations. Comparing the deformation of the jellyroll solids and the hourglass energy within each jellyroll, the hourglass energy has been identified as the main reason for the instabilities. This was proven by a simulation with selective reduced integration (SRI) scheme, showing no hourglass effects at all. As the SRI scheme is much more time consuming, it is only used for debugging in full vehicle models. As the material law has changed from MAT42 to MAT85, the hourglass prevention mode has been changed from the viscous method using hourglass base vectors (ISHG=0) to the stiffness method using hourglass shape vectors (ISHG=2). Figure 6 shows the comparison of the hourglass energy in the jellyrolls using the three different integration schemes and hourglass prevention modes. This change has solved the instability problems. In a further DoE only one out of forty simulations has terminated with an error but not originated from the jellyroll.

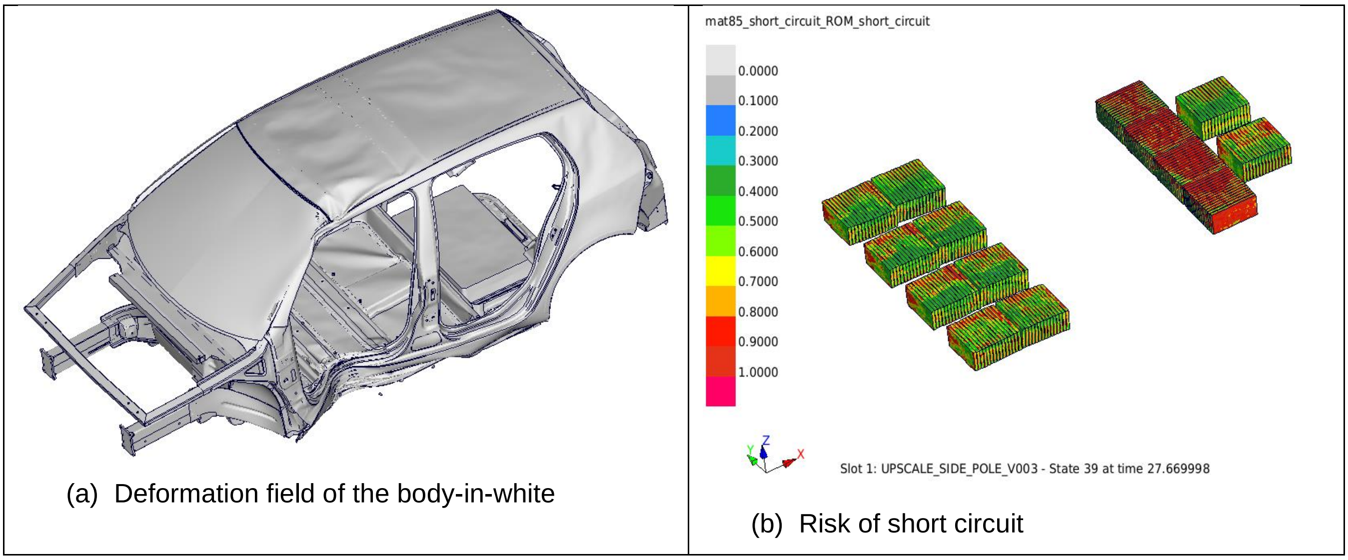


Figure 5: Visualization of the risk of short circuit within the jellyrolls of the battery cells (b) after loaded by a severe side pole crash load (a)

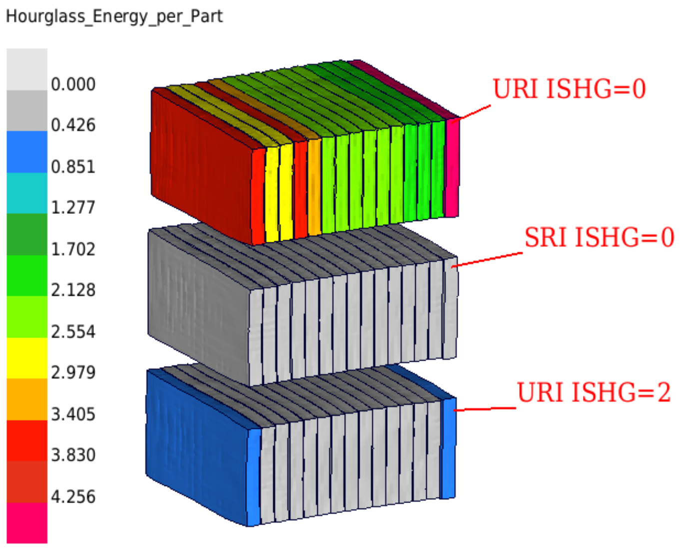


Figure 6: Comparison of the hourglass energy in the jellyroll using different integration schemes and hourglass prevention modes

Concerning the assessment of the AI based model the risk shown in Figure 5 (b) is not plausible, as the risk is reaching high values in the rear battery pack, although the pole is indenting near the front battery pack. The risk is starting already at some positive values of around 0.1, which is caused by the AI model. After some time steps, the risk is then increasing to values up to 0.95, which is already critical. This increase in the early phase of the simulation is not physical, as the battery cells are not yet deformed. To identify the reason for this unphysical behavior the model has been investigated further. As the battery cell is under pressure, the first idea was, that the pressure is causing the high increase of the risk. But a simulation without the pressure in the battery cells did not solved the issue. A second approach was to reduce the contact among the cells. This was realized by decreasing the number of battery cells within the module in the sense that every second cell was excluded from the FE model. But this also did not solved the issue.

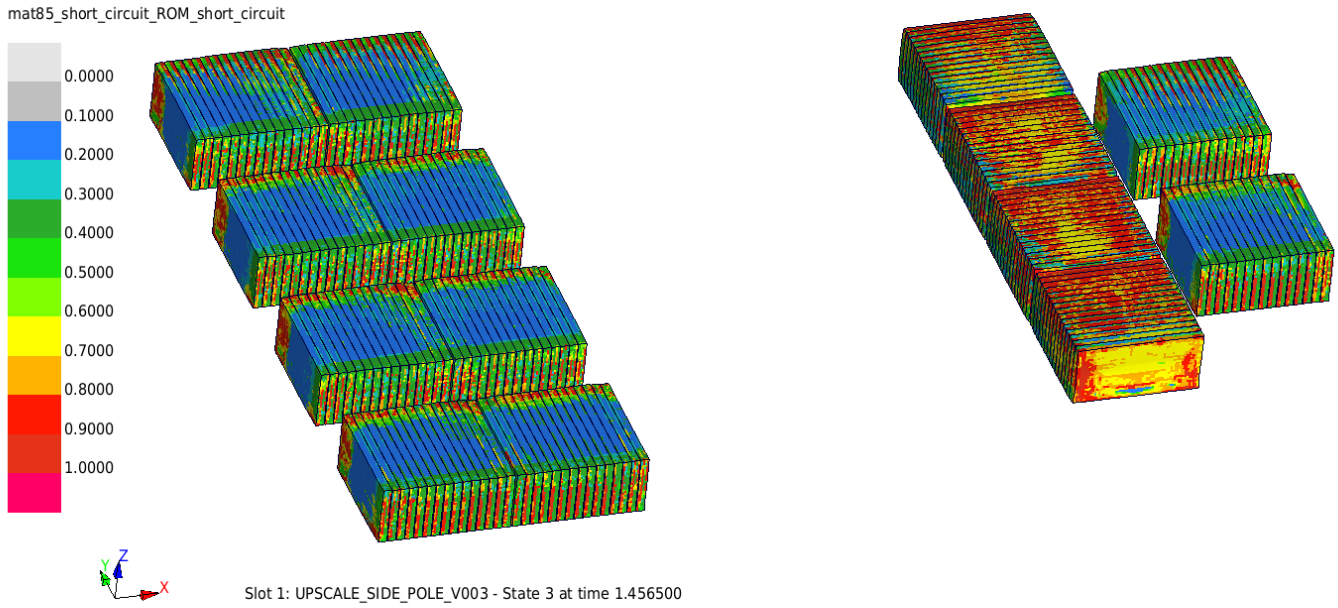


Figure 7: Risk of short circuit in the battery cells for a simulation with 50km/h initial velocity

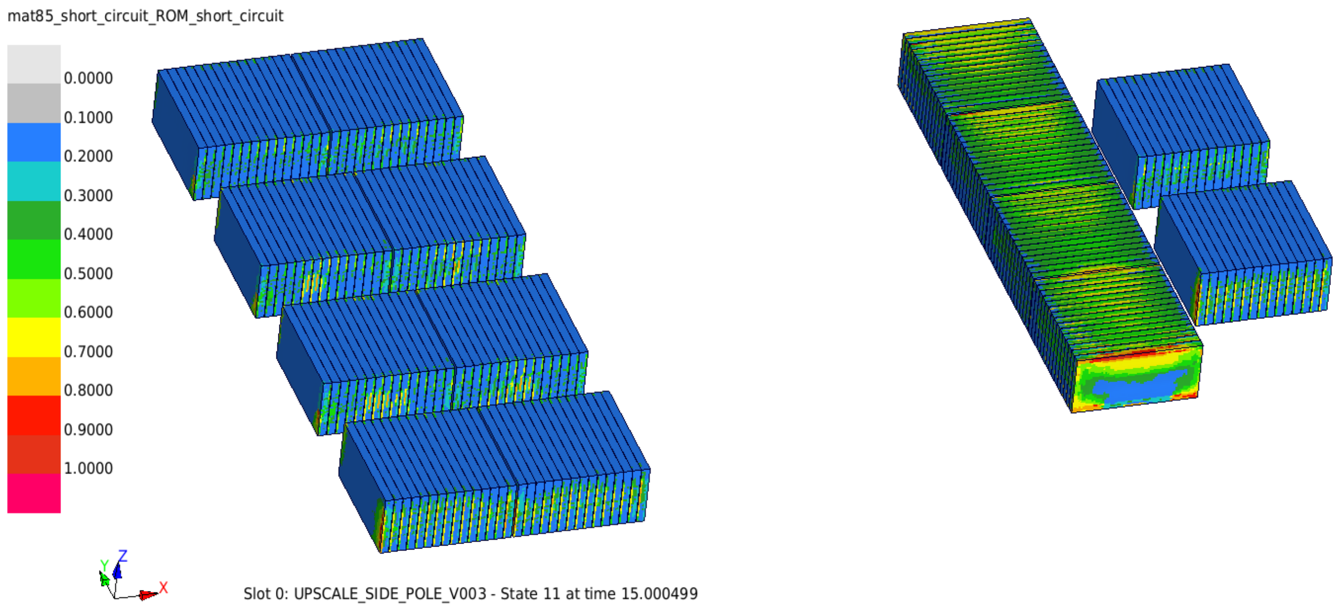


Figure 8: Risk of short circuit in the battery cells for a simulation with 5km/h initial velocity

Finally, the dynamics of the load case were expected to cause the high increase of the risk of short circuit variable in the early phase of the simulation. For this reason a simulation of the side pole crash was performed at a velocity of 5km/h. A comparison of the risk of short circuit variables for the slow side pole crash with a simulation with 50km/h initial velocity shows, that the dynamics play a significant role. Figure 7 shows the risk of short circuit at an early stage for the simulation with 50km/h whereas Figure 8 show the variable for the simulation with 5km/h initial velocity. Here, the effect of the dynamics can be seen quite clear, as the risk of short circuit is way more severe in the fast simulation than in the slow one, although the indentation of the pole is almost the same for both simulation, i.e. the fast simulation was evaluated at 1.45ms and the 10 times slower simulation was evaluated at 15ms. As shown in Figure 9, the deformation of the battery at this early stage has not yet started. The whole body-in-with structure is still undeformed. The only influence on the battery cells comes from the pulse caused by the first contact of the car with the pole due to the initial velocity. Of course, the risk of short circuit is still reaching non-physical values at the early stage, but compared to a quasi-static case, the slow simulation with initial velocity of 5km/h is still 1000 times faster, as the simulations for the unit-cell test, i.e. the three-point-bending test, the cylindrical and spherical indentation and the folding test are in the range of some few millimeters per second. As the time for investigating the methods in a stable environment and with robust versions was very short, further improvements in the training and/or structure of the AI model were not possible. This comes from the fact, that the whole methodology has been built up from scratch during the project. The battery models had to be developed as well as the vehicle models, that needed an adjustment to the new battery geometry. The whole subsequent procedure of training data generation from the full vehicle DoEs with homogenized macro scale battery cells, via the meso-scale cell simulations to the creation of the AI based models has been performed. The integration of the AI based models to the full vehicle simulations finally took more iterations than expected, such that the investigation on the AI models itself was limited. Nevertheless the proof of concept is shown in this chapter.

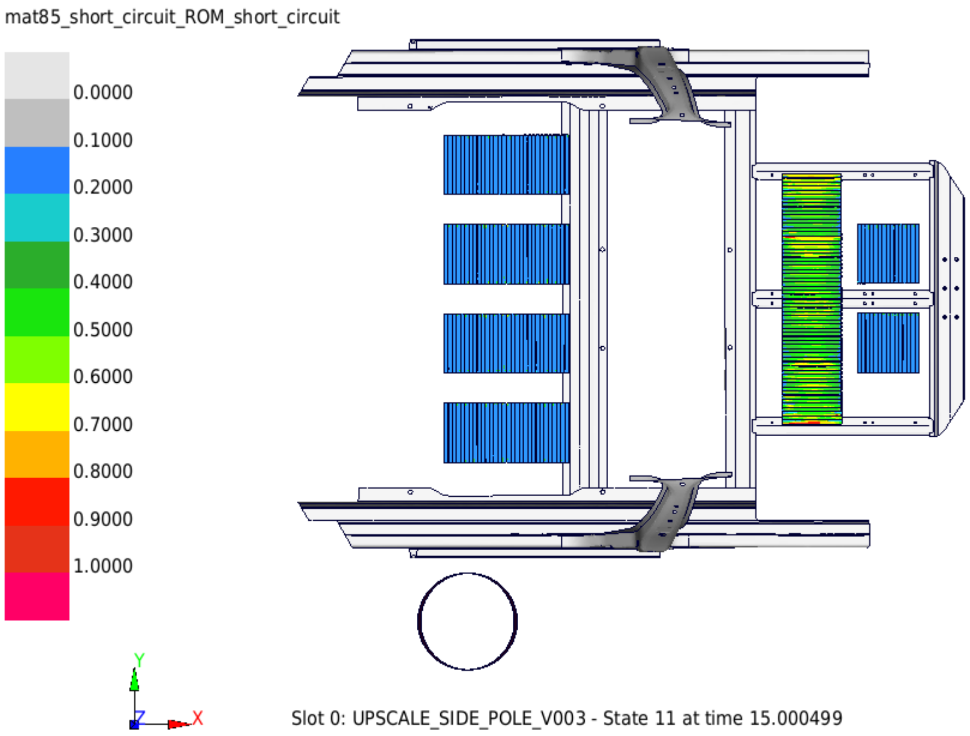
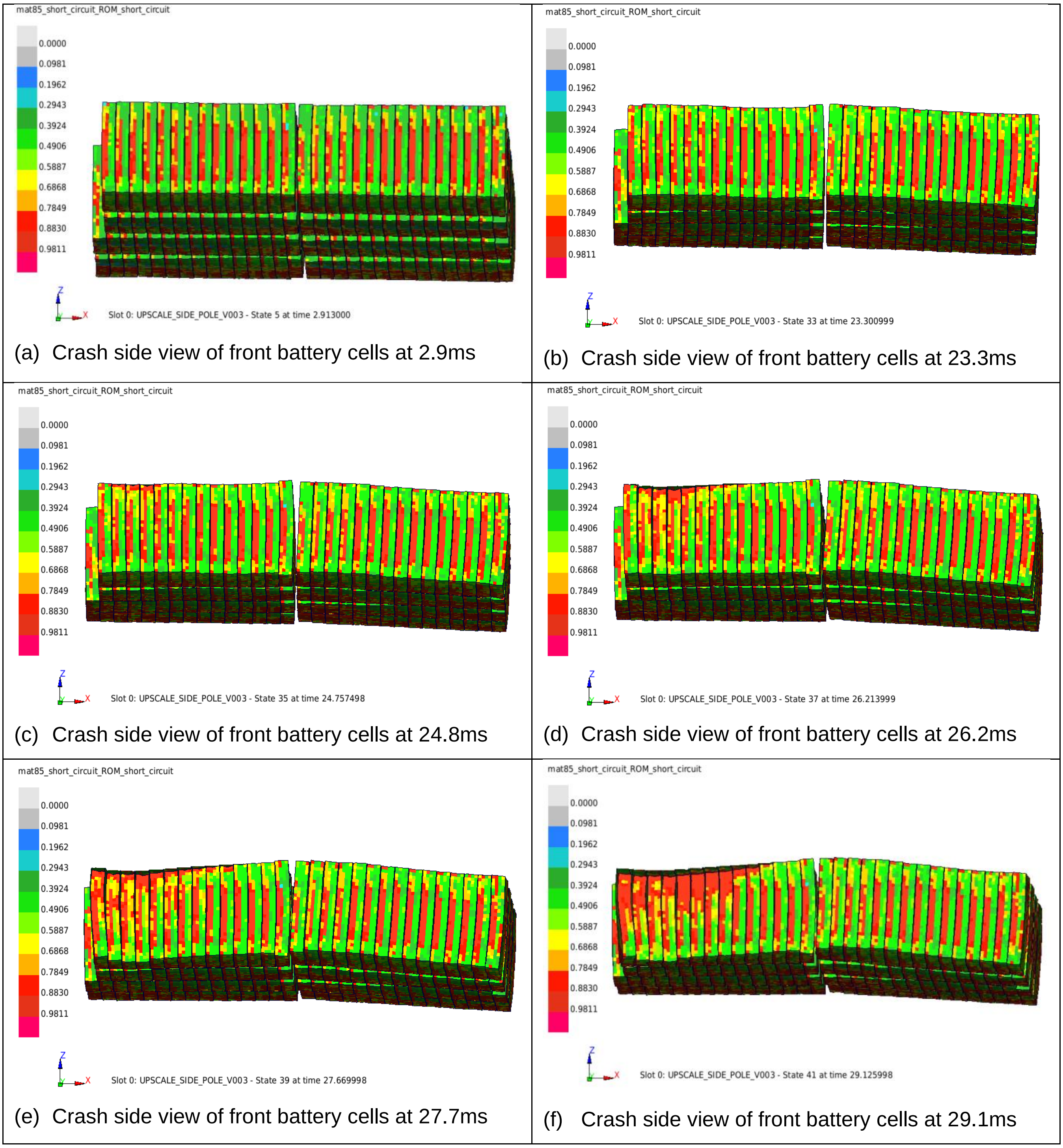


Figure 9: Top view of the slow simulation (5km/h) including the pole, side rocker and b-pillar

Knowing the fact, that the risk of short circuit is increasing non-physically in the beginning of the simulation, this initial error can be dismissed. This strategy was applied to two load cases, a severe side pole crash scenario with 55km/h initial velocity and a moderate side pole crash scenario with 36km/h initial velocity. Please note, that the two simulations have not been used to train the AI based model for predicting the risk of short circuit. The pole is positioned such that it indents the vehicle more or less at the same point as for the slow side crash in Figure 9.

For the severe crash scenario Figure 10 shows the risk of short circuit in the front battery cells viewed from the crash side. After the risk is increasing due to the dynamics in the early stage of the simulation up to 3ms, see Figure 10 (a), the risk stays almost unchanged for the next 20ms, see Figure 10 (b). At 24ms, Figure 10 (c), suddenly the risk is increasing at the top of the battery cells positioned in the left battery module, i.e. the first cells 1-6 in module number 101, see Figure 2. The increase of the risk proceeds until 29ms, where a distinct area of high risk can be identified, see Figure 10 (f). For this reason, a risk of short circuit is indicated. On the other hand, the battery cells in the right module, i.e. module number 105 in Figure 2, exhibit no changes in the risk during the whole time period from 3ms up to 29ms. Here, no risk of short circuit would be expected.



(a) Crash side view of front battery cells at 2.9ms

(b) Crash side view of front battery cells at 23.3ms

(c) Crash side view of front battery cells at 24.8ms

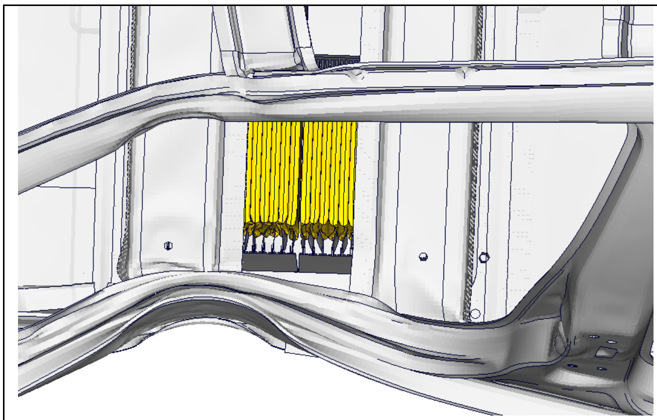
(d) Crash side view of front battery cells at 26.2ms

(e) Crash side view of front battery cells at 27.7ms

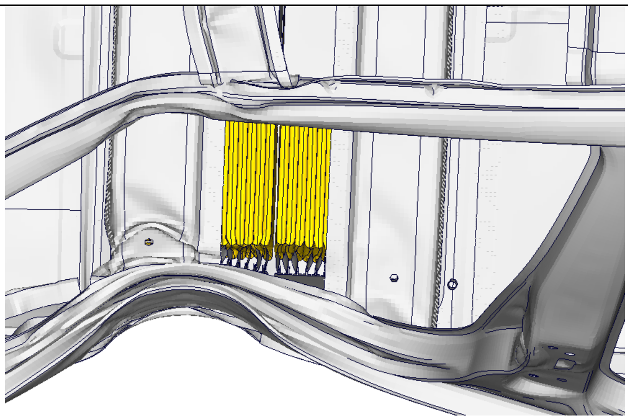
(f) Crash side view of front battery cells at 29.1ms

Figure 10: Risk of short circuit evolution in the front battery cells

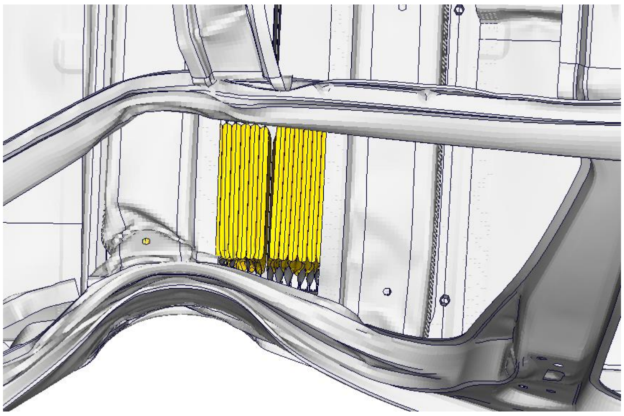
To check if this assessment is reasonable, the deformed structure of the body-in-white and the battery package is analysed. In Figure 11(a)-(c) the evolution of the deformation is visualized. It can be seen, that the front cross member, positioned above the front part of the front battery package, i.e. above the front part of the battery module number 101, see Figure 2, is hit by the pole and starts to fold downwards into the battery package. As a consequence, the battery package is pushed inwards at the front side which thus indents the battery module that has been identified as critical in Figure 10. This is shown in Figure 11(d), where the battery package cover is highlighted in red. For this reason, the identified high risk of short circuit in the front battery module is reasonable and would lead to necessary adjustments of the structure in order to improve the battery safety.



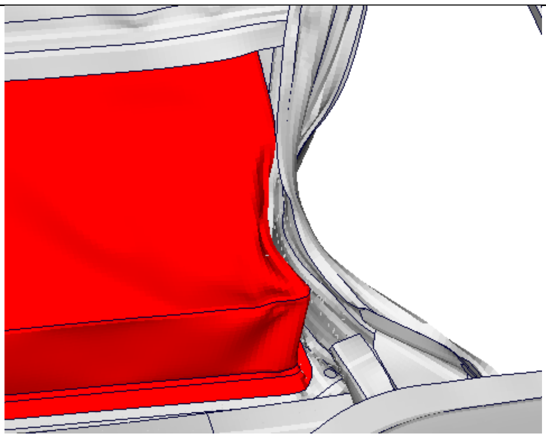
(a) Top view of front battery package at 20.4ms



(b) Top view of front battery package at 24.8ms



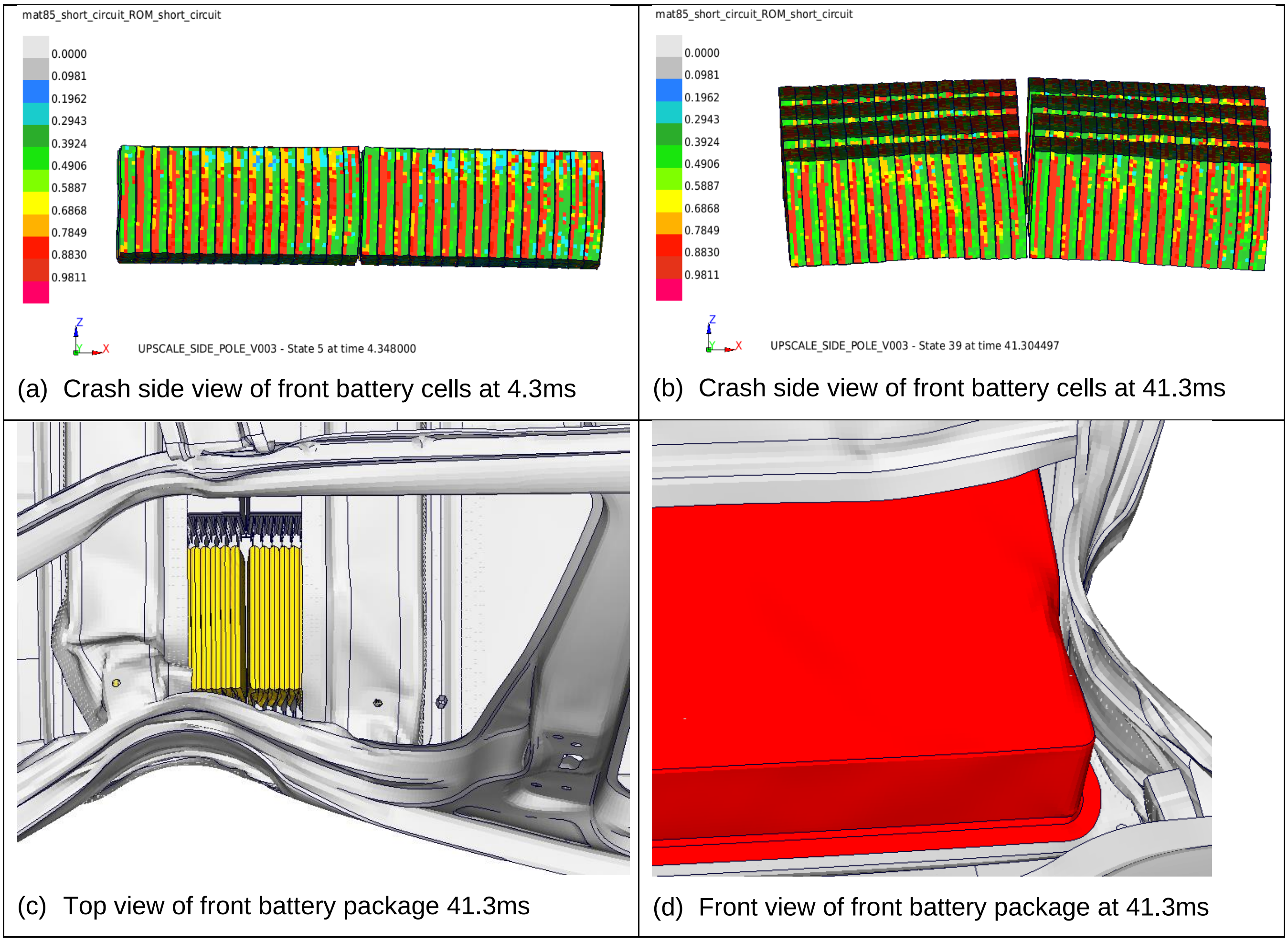
(c) Top view of front battery package at 27.7ms



(d) Front view of front battery package at 27.7ms

Figure 11: Deformed structure of the vehicle in the area of the front battery package, battery cells are highlighted in yellow, battery package cover is highlighted in red

Looking at the moderate load case with 36km/h initial velocity, the risk of short circuit stays almost constant within the time from 4ms up to 41ms, see Figure 12 (a) and (b). Thus, no severe risk of short circuit would be expected. Looking at the deformed structure, there is also a fold of the front cross member positioned above the front battery package, see Figure 12 (c), but the fold is not too severe and does not indent the battery package significantly, as can be seen in Figure 12 (d). Here, no relevant risk of an internal short circuit within one of the battery cells is expected. Therefore, no adjustments of the structure would be performed due to battery safety reasons. Please note, the authors just concentrated on the assessment of the battery safety for all load cases. Passenger safety was not assessed as it is not part of the project. Of course, all necessary safety aspects would need to be assessed in real life vehicle projects.



(a) Crash side view of front battery cells at 4.3ms

(b) Crash side view of front battery cells at 41.3ms

(c) Top view of front battery package 41.3ms

(d) Front view of front battery package at 41.3ms

Figure 12: Risk of short circuit in the front battery cells (a9 and (b) and deformed structure of the vehicle in the area of the front battery package (c) and (d), battery cells are highlighted in yellow, battery package cover is highlighted in red

Having the AI based model integrated to a full vehicle simulation, the assessment of battery safety can be performed faster and even more reliable. The crash engineer does not need to check the whole structure, surrounding the battery packages. Furthermore, the deformation field does not give a value, that can be assessed. It is always a subjective assessment, when looking at deformation fields. With the new developed AI based model predicting the risk of short circuit, the crash engineer does not need to rely only on the deformation fields anymore. The shaping of some areas with high risk of short circuit gives him a hint, where to look at. This will definitely speed up the time for battery safety assessment and thus the time of the virtual vehicle development.

At this point the authors want to give an advice for future research projects. As the dynamics of full vehicle crash simulations have been identified to cause an early increase of the risk of short circuit variable computed by the AI model, this aspect should be addressed in future research projects. In detail, the authors believe, that the structure of the AI model would need to be adjusted. The trained classifier should not be trained on quasi-static deformation modes only. A consideration of different load scenarios, at different crash velocities could lead to a much better performance of the AI model in the beginning of a full vehicle simulation. Instead of deformation modes, the classifier could be trained on specific stress or strain states using invariants as the stress triaxiality or others.

4 Assessment of the sPGD method applied to the load case parameters in full vehicle crash load cases and representing the battery cells of the corresponding electric vehicle

In the beginning of the project, a prototype tool with integrated SSL PGD method enabling the user to train the model based on his own training data has been installed at Volkswagen. Several restrictions on the environments and the hardware lead to restrictions in the usage due to security reasons at Volkswagen. For this reason the tool could not be used on a computer that was online. This restriction made the work with the tool tedious. As ESI has then developed the new sPGD method, the project partners decided to switch to this method and leave the training and the evaluation at ESI.

The sPGD method has already been described in deliverable D5.5. in detail. Here, the authors just want to give a summary of the methodology together with the assessment of the method, when applied to the full vehicle simulations with the AI based model for the prediction of short circuit. For creation of training data a DoE was performed changing four load case parameters, that are the initial velocity ranging from 32km/h to 64km/h, the shift of the x-position of the pole ranging from -500mm to 220mm, the impact angle ranging from 60° to 90° and the diameter of the pole scaled by a factor ranging from 0.7 to 1.5. The parameter sets are shown in Figure 13 also highlighting the simulation runs that were used for training. Figure 14 visualizes the parameter settings in a top view on the vehicle model. Of course only x-position and pole diameter are visible. In total 12 simulation runs were used for the training which means 3*n with n being the number of parameters. This means, that the number of necessary training data is not increasing exponentially but linear with the number of parameters. Especially for problems with several parameters this is superior to e.g. Monte Carlo type methods. If for example 10 parameters were used, the simulation of the corners of the 10-dimensional parameter interval would demand 1024 simulations, whereas the training data set for the sPGD method consists of only 30 simulations.

	initial velocity of vehicle	shift x-position of pole	impact angle	scaling factor for width of pole
	[32,64][km/h]	[-500,300][mm]	[60,90][°]	[0.5,1.5][-]
DoE-run	0	1	2	3
run002	44.26667	-246.66667	64.5	1.25000
run003	36.80000	-326.66667	72.5	1.15000
run004	54.93333	-273.33333	88.5	1.18333
run007	35.73333	-140.00000	69.5	0.71667
run008	34.66667	-433.33333	67.5	0.85000
run009	42.13333	-86.66667	81.5	0.98333
run010	40.00000	-406.66667	71.5	0.55000
run011	43.20000	180.00000	73.5	1.08333
run012	46.40000	-300.00000	89.5	0.61667
run013	51.73333	-353.33333	74.5	0.58333
run015	45.33333	126.66667	75.5	1.35000
run016	41.06667	-193.33333	60.5	1.31667
run017	32.53333	20.00000	61.5	0.88333
run021	56.00000	-380.00000	86.5	0.68333
run022	33.60000	73.33333	63.5	0.78333
run023	38.93333	153.33333	78.5	1.28333
run024	63.46667	-166.66667	87.5	0.91667
run025	53.86667	100.00000	79.5	1.21667
run027	37.86667	-486.66667	83.5	1.48333
run028	47.46667	-113.33333	68.5	0.81667
run029	49.60000	206.66667	80.5	1.38333

Figure 13: DoE matrix showing the parameter setting for each DoE run, the simulation runs that were used for training are marked in green, the simulations for validation are marked yellow

For the post-processing the jellyrolls of the battery cells in the four battery modules, that are nearest to the crash side have been chosen. This means, 60 parts of the vehicle model have been trained with the sPGD method in order to create a single solution file, which is able to show the deformation of the battery cells but also the risk of short circuit. The chosen parts are depicted in Figure 15.

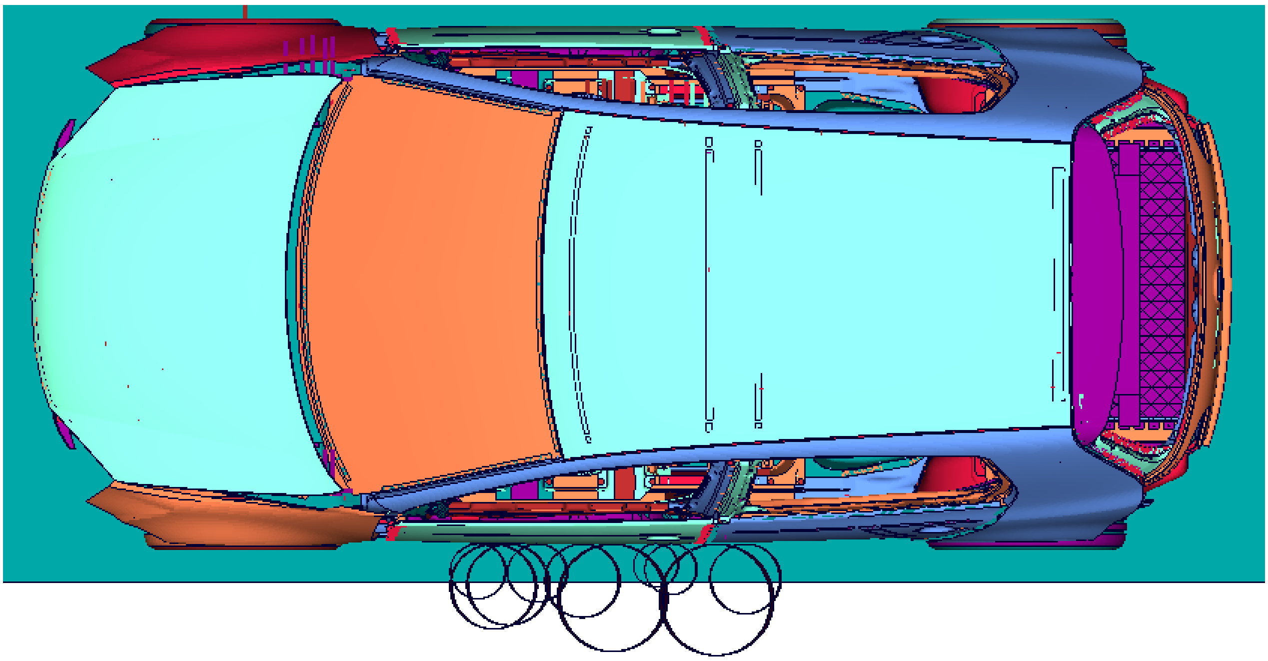


Figure 14: Overview of the DoE runs

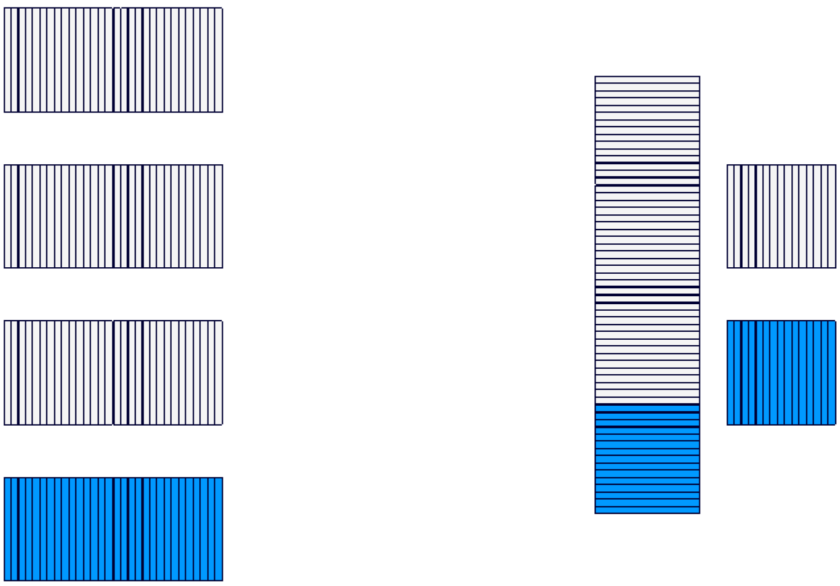
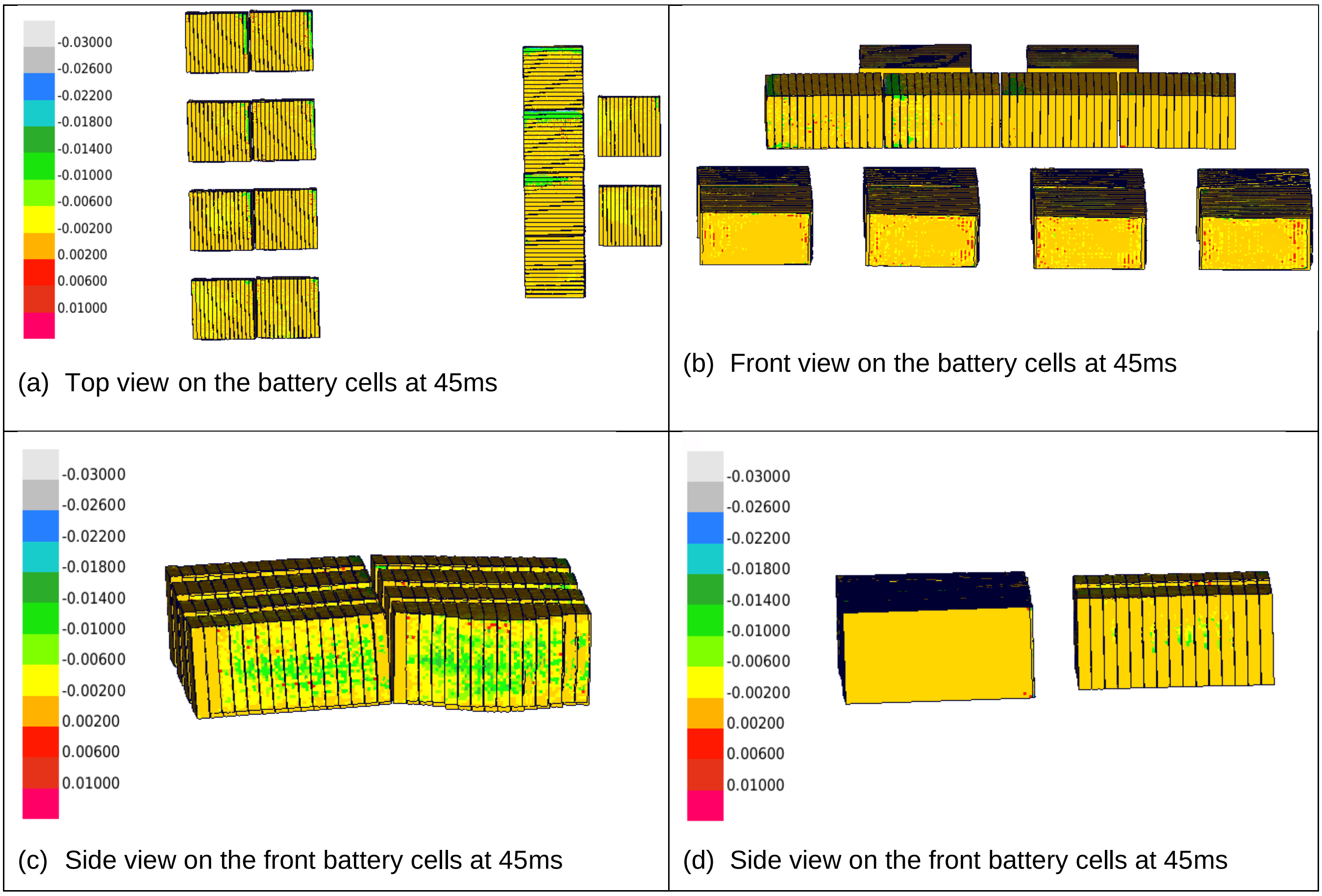


Figure 15: Overview of the battery cells' jellyrolls (highlighted blue) that have been used for training the sPGD model

Due to the non-physical behaviour of the risk variable, as explained in chapter 4, the results with the sPGD method are not representative. This is explained by the non-continuous behaviour of the risk variable caused by the dynamics of the load cases. When looking at the deformation field, the interpolation of the sPGD method gives good results when compared to the validation tests, as was already shown in deliverable D5.5.

5 Assessment of the AI based model predicting the stiffness of the battery cells' jellyroll material in full vehicle crash load scenarios

In this chapter the AI based model predicting the stiffness of the battery cells' jellyroll material is investigated. As the new developed methodology would need to be implemented in a new VPS release, the authors decided to follow the same approach as for the AI based model predicting the risk of short circuit in chapter 3. This means, that the AI based stiffness model has been integrated to a VPS user plugin material. The benefit is, that the development is independent of the main VPS code development. As it is a logical step, the AI model predicting the short circuit risk was implemented in the same user material library. The simulation time for the model took on average 4.5 hours, where the model was running without dummies and airbags. Compared to the AI based model predicting the short circuit only, the time is almost equal, 4.3h vs. 4.5h. As already mentioned in chapter 3, the use of user materials comes along with an overhead in simulation time. This means, that the time effort may be decreased in the future when the material model is implemented to the main code.



(a) Top view on the battery cells at 45ms

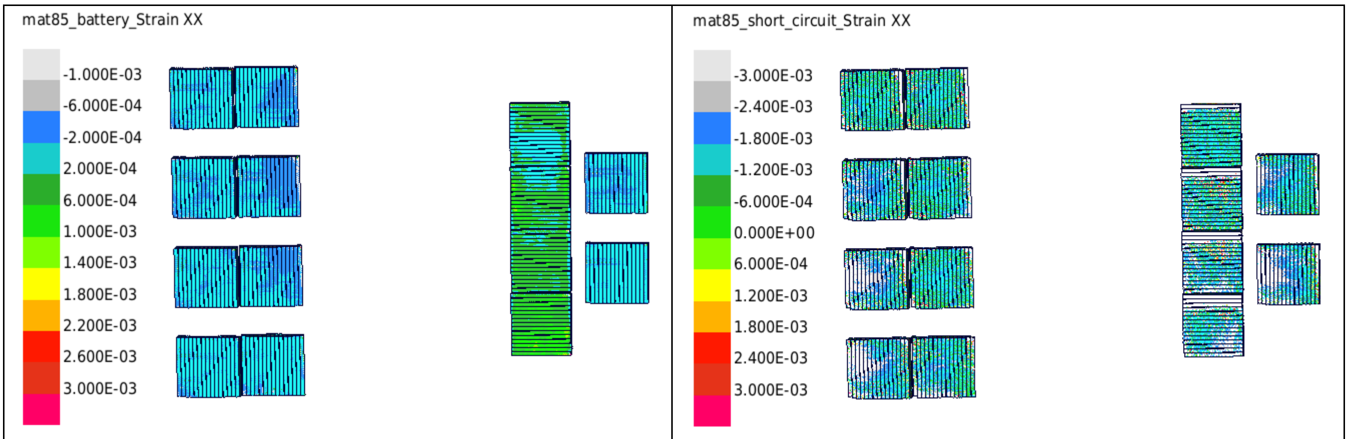
(b) Front view on the battery cells at 45ms

(c) Side view on the front battery cells at 45ms

(d) Side view on the front battery cells at 45ms

Figure 16: Comparison of the global deformation of the battery cells between AI based model for predicting the risk of short circuit from chapter 3 and the AI based model predicting the stiffness. The contour visualizes the strain in x-dircetion.

Figure 16 shows the comparison of the two AI based models, i.e. the model to predict the risk of short circuit, as presented in chapter 3, and the model predicting the stiffness. The figure shows an overlay of both simulations for a side pole crash with initial velocity of 38km/h at the end of the simulation. The global deformation for both models is very similar. In order to check the performance of the AI based model predicting the stiffness, the two models from Figure 16, are displayed next to each other in Figure 17. The figure shows the strain in x-direction. One can see, that the AI based model predicting stiffness exhibits lower strains by a factor of 3. Thus it can be deduced, that the model predicts a stiffer material than the homogenized Honeycomb material model.



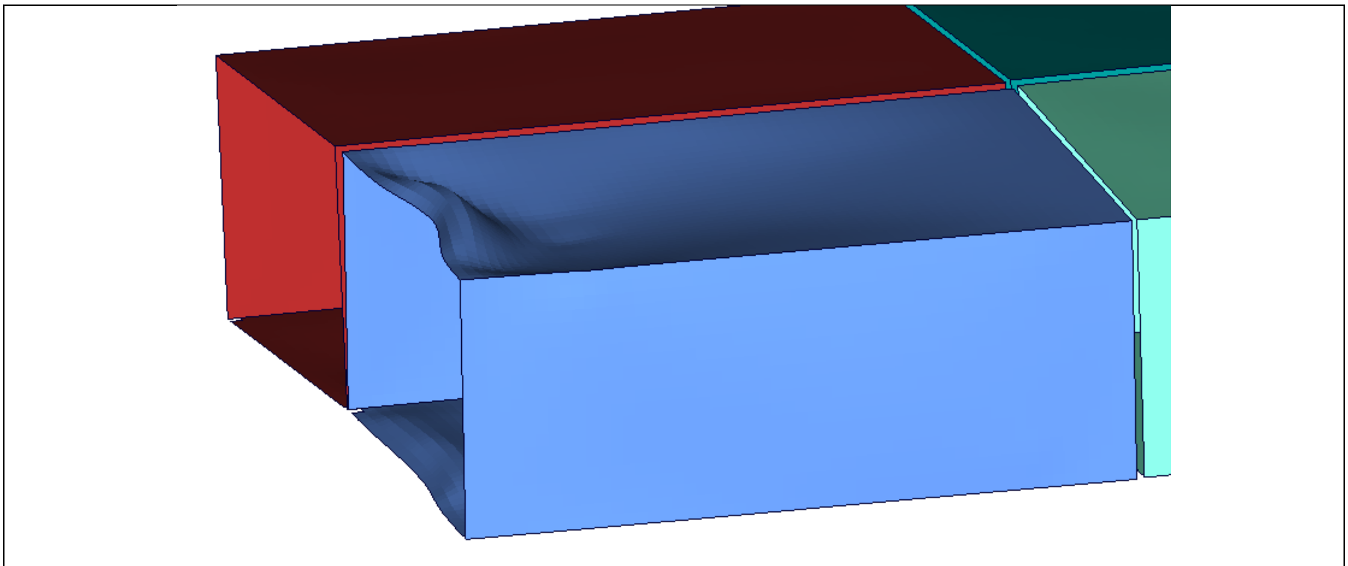
(a) Battery cells using the AI based model for predicting the stiffness at 45ms

(b) Battery cells using the AI based model for predicting the risk of short circuit at 45ms

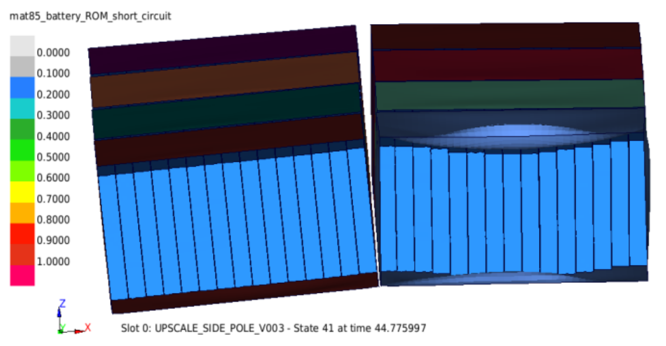
Figure 17: Comparison of the strains for both AI based models

Due to this, the risk of short circuit, which is based on element strains is not showing the initial increase in the early phase of the simulation. This is shown in Figure 18 (b) and c), where the risk of short circuit is compared to each other. Based on the deformation of the battery modules' cover, shown in Figure 18 (a), a slight increase in the risk variable would have been expected. Here, the AI based model fails due to the higher stiffness in the jellyroll elements.

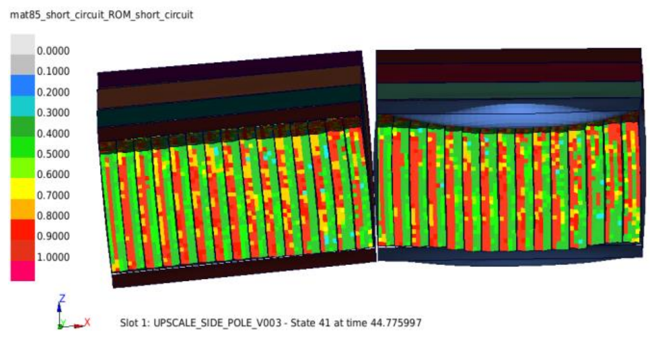
Local comparison on unit cell tests from deliverable D3.2 (i.e. three point bending, indentation, punch, folding) of the AI based model predicting stiffness against the Honeycomb law shows similar properties in-plane but higher stiffness in the out-of-plane directions. The AI based model predicting the risk of short circuit was trained based on the response of the Honeycomb law. Possible improvements for a consolidated material with both AI based models would be an update of the representative volume element model, as it is explained in the deliverable D5.7, used to train the AI based model for stiffness in order to reduce the differences between the AI based stiffness model and FEA mechanical behavior.



(a) Deformation of the battery modules' cover in the front battery package at 45ms



(b) Battery cells using the AI based model for predicting the stiffness at 45ms



(c) Battery cells using the AI based model for predicting the risk of short circuit at 45ms

Figure 18: Comparison of the risk of short circuit for both AI based models

6 Conclusion and future work

The proof-of-concept of the methodology as shown in Figure 4 has been shown. The authors achieved their objective to show, that the complete path from full electric vehicle simulations creating the inputs for the meso-scale battery cell models creating the training data for the AI models and finally integrating the trained models to the full electric vehicle is suitable.

The assessment of the AI models has shown, that an improvement of the prediction quality could be made. Here, the time for a comprehensive investigation on vehicle level was not sufficient, as the project has started to set up the methodology from scratch and the work on the AI based models could not start at the beginning of the project period. In the AI based model predicting the risk of an internal short circuit a non-physical initial increase of the risk is observed. The authors have shown, that the non-physical behavior is caused by the dynamics of the vehicle load cases. The use of a classifier based on unit-cell tests showing well defined deformation modes and performed quasi-statically is not suitable when dealing with highly dynamic full electric vehicle simulations. Maybe a classification based on the present stress state or some other stress and strain invariants would lead to better results. Unfortunately, the authors had not enough time to start this kind of investigation. The authors therefore suggest that this research question should be answered in a future research project. This could lead to a better understanding of the AI models. Similarly the performance of the AI model predicting the battery cell stiffness could be improved in the future.

Nevertheless, the developed AI model is suitable to identify scenarios where a risk of internal short circuit is expected to appear due to deformation of the battery structure. But it is also suitable to identify scenarios, where the battery safety is ensured despite of slight deformations of the battery structure.

The computation times for the full vehicle model simulations are equal to those without AI based models incorporated. Optimization of the simulation times have been identified. First, the material models could be implemented to the main source code of VPS. In this case the overhead time for using user material libraries could be spared. Furthermore, the authors decided to use a fine FE mesh for the jellyroll. A coarsening is not expected to affect the deformation behavior significantly but would lead to faster computation times.

If the problem with the initial increase of the risk could be solved, the authors believe that the crash engineer would be able to develop a new electric vehicle variant faster than today. Using the AI based model the assessment of the battery cells comes immediately with the simulation results. A subjective and more elaborated post-processing could be circumvented, as the risk variable shows the hot spots, where the crash engineer needs to look at in more detail. Finding the critical areas earlier leads to an earlier new variant. Optimally, the engineer could assess the vehicle simulations that were performed overnight faster, such that new variants submitted to the cluster could be assessed at the same day. At least for side crash scenarios, this is possible. Furthermore, some sPGD applications could lead to faster optimizations of the body-in-white. Here, the parametrization of the x-position of the pole could be combined with e.g. the parametrization of the thicknesses of the parts in the side rocker in order to combine the requirements on battery safety with a lightweight optimized structure.

Further fields of application for the AI based models may be human body models where complex and expensive material models could be exchanged. Furthermore, the use of AI methods in addition or in place of the Smoothed Particle Hydrodynamics (SPH) or the Finite Pointset Method (FPM) that are used for airbags could be investigated. Finally, the application of AI based stiffness models for barriers seems promising. For all three application areas the AI models could help to speed up simulations and lead to deeper insights in the future.

7 References

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8 Figures

9 Acknowledgement

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