Ansys SimAI^{TM} Application in Stamping Die Engineering

Li Zhang, Junyan He, Amit Nair, Ethan Rabinowitz, Ethan Thompson

Ansys, Part of Synopsys

1 Introduction

For thirty-five years, the most important parts of modern stamping die engineering consisted of die face design (binder and addendum creation) using CAD and ensuing simulation using FEA simulation software. It will all change now with Ansys SimAI^{TM} [1]– Artificial Intelligence for Simulation.
Ansys SimAI^{TM} is Ansys' new cloud-based AI platform for Simulation that is leveraging all the modern Deep Learning technologies in an in-house developed architecture. With Ansys SimAI^{TM}, one can train AI models with (this paper) or without parameterized geometry using historical, pre-existing die designs and simulation results. Once the AI models are trained, formability across design changes can be predicted within seconds, faster than any specialized forming software on the market. These design changes can be simply new product designs (without any die face) or they can be complete new die surface designs. It is physics-neutral, and software-neutral, meaning results from any fluid, structures, electromagnetics, optics simulation, and from any software can be used to train the AI surrogate models. It can be applied across all industry segments, such as Aerospace, Automotive, Semiconductor, Consumer Electronics, etc. Once the AI models are trained, they can be used by designers, process planning (method) engineers, or full-time FEA simulation specialists, greatly lower the entry barrier for high fidelity simulation results.

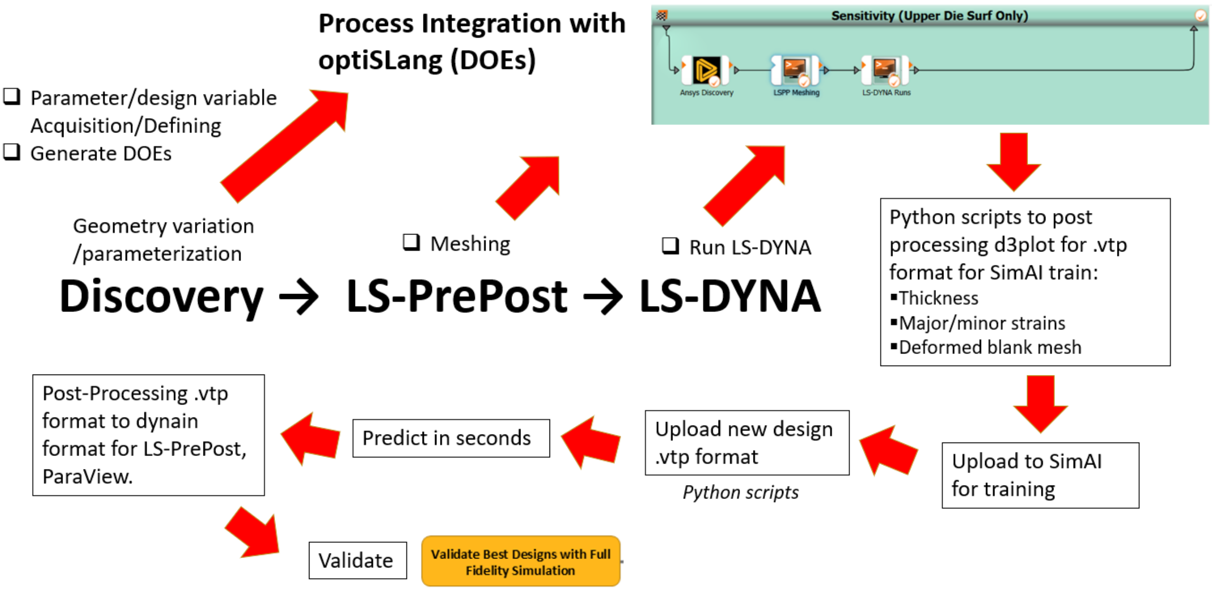


Fig.1: Ansys SimAI^{TM} model training workflow.

As shown in Fig.1, parameterized designs can be generated in Ansys Discovery. Using Ansys optiSLang as a process integration tool and simple scripts, the resulting parameterized geometries from Discovery can be automatically meshed in LS-PrePost, combined with parameterized simulation input deck, and submitted for LS-DYNA runs. After LS-DYNA runs, Python scripts are used to convert the d3plot results including formed sheet thickness, strain tensors, and deformed blank mesh to .vtp format for SimAI training. Scripts are used to upload and ensure all the training data are in the project folder for SimAI training. Training and test sets are automatically assigned and typically are 90% for training and 10% for testing. Customized training and test sets can also be defined using scripts through the open-source python SDK named PySimAI [2] (https://simai.docs.pyansys.com/). Once the training/test sets are uploaded, a simple GUI allows for choosing the inputs and outputs of the model, and selection of three different training durations. Global Coefficients are high-level, scalar metrics derived from the complete simulation field to provide a quick and quantitative assessment of a design's performance. Rather than analyzing complex, detailed 3D field data like thickness, strain and displacement, one can use these single-value coefficients for rapid evaluation and optimization of the designs. The user input here is minimum, and in stamping die engineering application, typically can be all defined within one minute. A summary report will be generated after the training is finished, which can be used to assess model performance. New designs can be uploaded for prediction using the trained Deep Learning model, and the resulting surface VTPs can be converted using in-house Python scripts to dynain format for post-processing thickness and FLD (Forming Limit Diagram) results using LS-PrePost.

In this paper, the NUMISHEET 2005 Crossmember (modified) was parameterized in Ansys Discovery. By varying controlling bottom die and top punch radii (Fig.2), a total of 49 simulations were generated by optiSLang with the full factorial design of 7 levels. To prevent severe uneven blank edge draw-ins on either side of the hat-section, two punch radii were kept the same and changed from R=3 to R=20mm; likewise, two die shoulder radii were kept the same and ranged from R=5 to R=30mm. The following different cases/scenarios were studied,

- CASE A –Trim panel prediction on trim panel surrogate model:
  - Thickness:
    - Training Input: deformed sheet blank only in final trimmed state including thickness.
    - Prediction Input: new product geometry; Output: thickness.
  - Strains/FLD:
    - Training Input: deformed sheet blank only in final trimmed state including strain tensor.
    - Prediction Input: new product geometry; Output: strains/FLD.
- CASE B - Trim panel prediction on draw panel surrogate model:
  - Training Input: deformed sheet blank only in final drawn state (before trimming) including thickness.
  - Prediction Input: new product geometry; Output: thickness.
- CASE C - Transient with 10 states each for one DOE (a total of 490 training/test sets):
  - Training input: ten states from each DOE of sheet metal deformed blanks (before trim) and rigid die set, including thickness.
  - Prediction Input: initial flat blank and die geometry; Output: draw panel breakdowns and thickness.

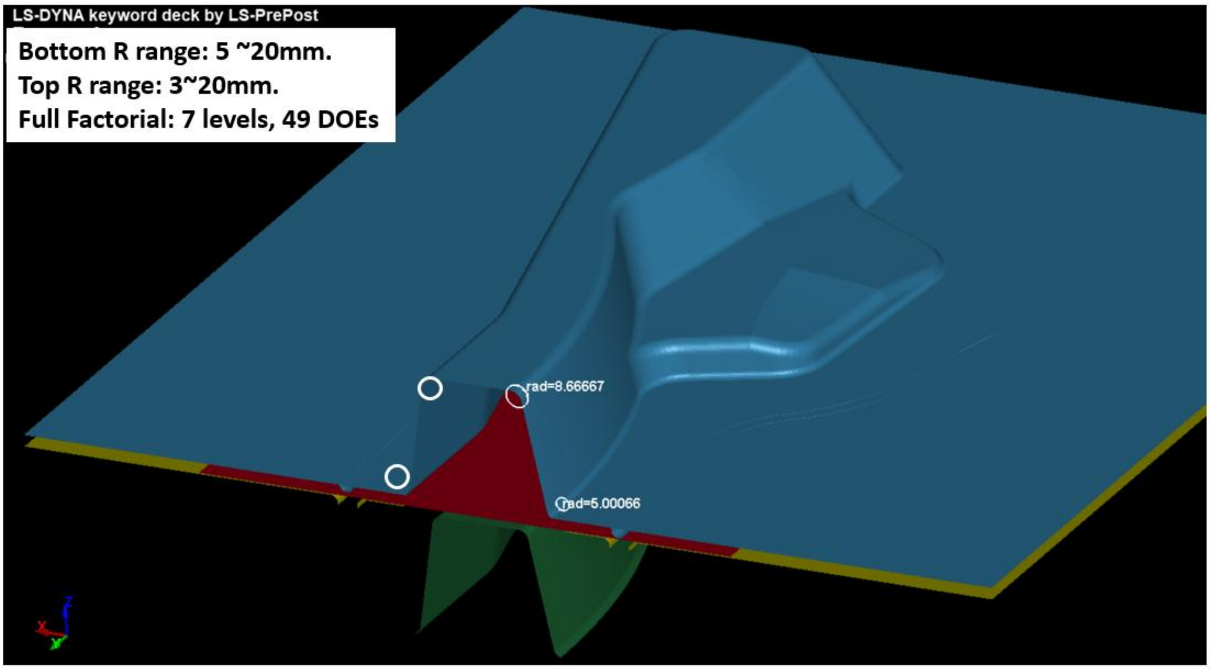


Fig.2: Design variables to generate full factorial design in Discovery and optiSLang.

The DOEs generated covered formability ranged from the most formable (safe to make, Fig.3 right, upper bound design) to the least formable scenario with multiple locations of failure (Fig.3 left, lower bound design). Wrinkles also varied from mild to severe. The DOEs allowed for a thorough test of SimAI prediction capabilities.

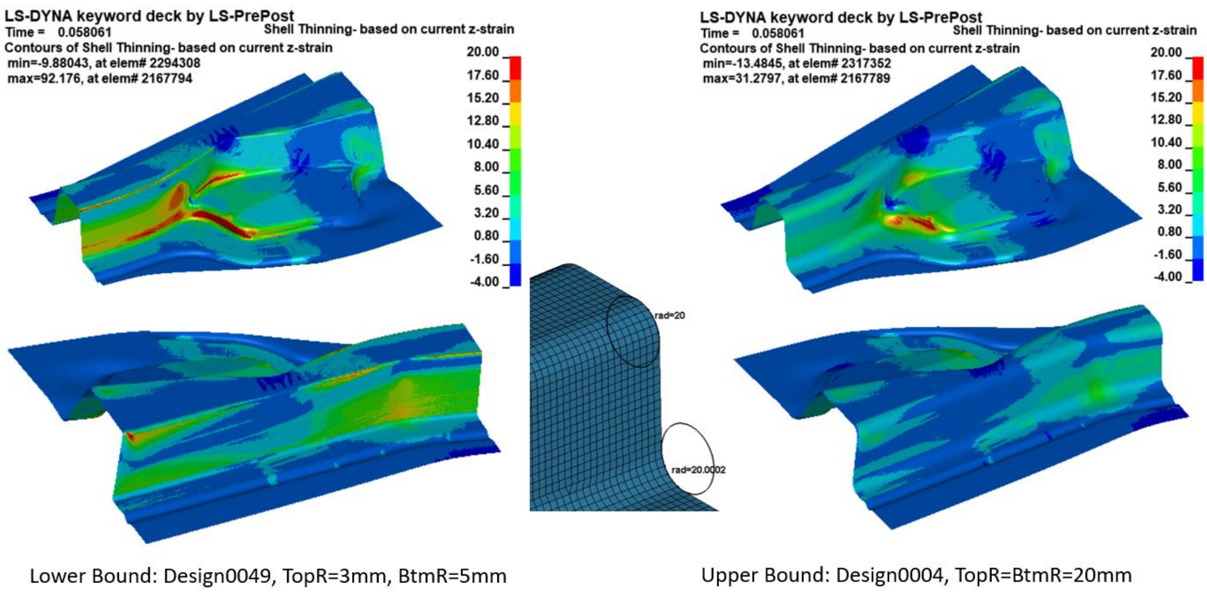


Fig.3: Formability coverage of the 49 DOEs.

2 Results

In this section three case studies will be discussed in detail.

2.1 CASE A – Thickness Prediction

In this case, referring to Fig.4 left, trim panels from draw forming include final deformed/trimmed mesh and associated thickness in .vtp format were used to train the surrogate model. Once the training was done, new product geometry (Fig.4 middle) in .stl or .vtp format can be uploaded for prediction. Prediction output included mesh and thickness, also in .vtp format. Python scripts were used to convert from .vtp to dynain format so it can be post-processed in LS-PrePost. Alternatively, .vtp format file can be viewed directly using ParaView. The global coefficient was defined as thickness=mean(thickness). Typically, in one SimAI model, fewer the global coefficients defined the better the model performance. Therefore, strains/FLD prediction were done in a separate model.

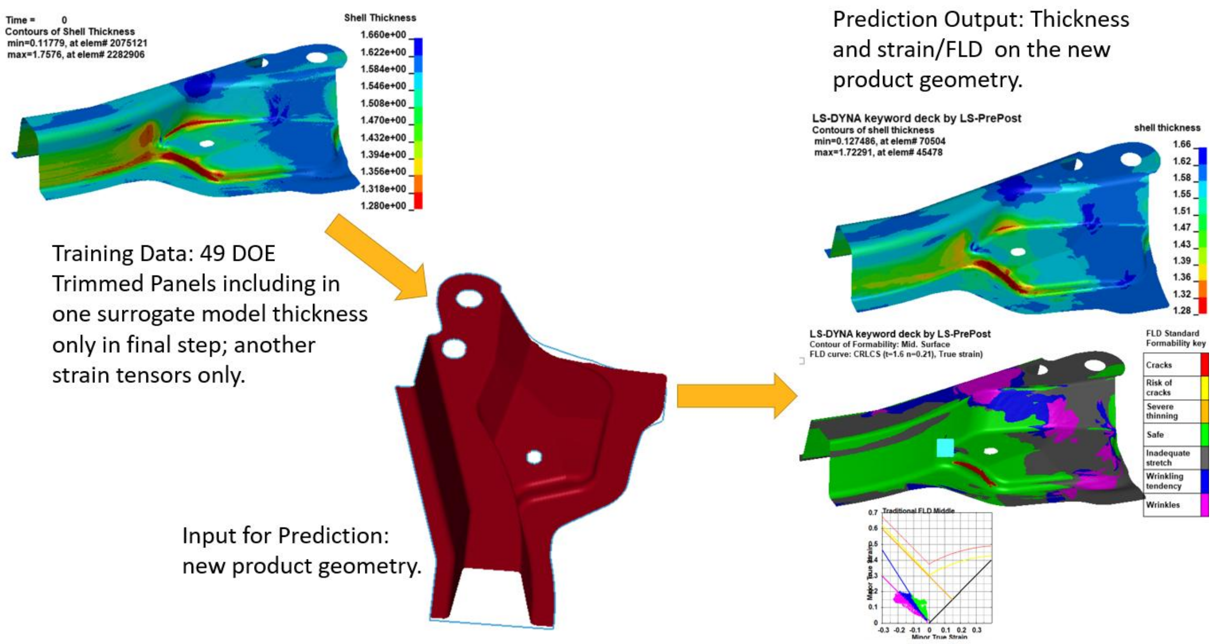


Fig.4: CASE A workflow.

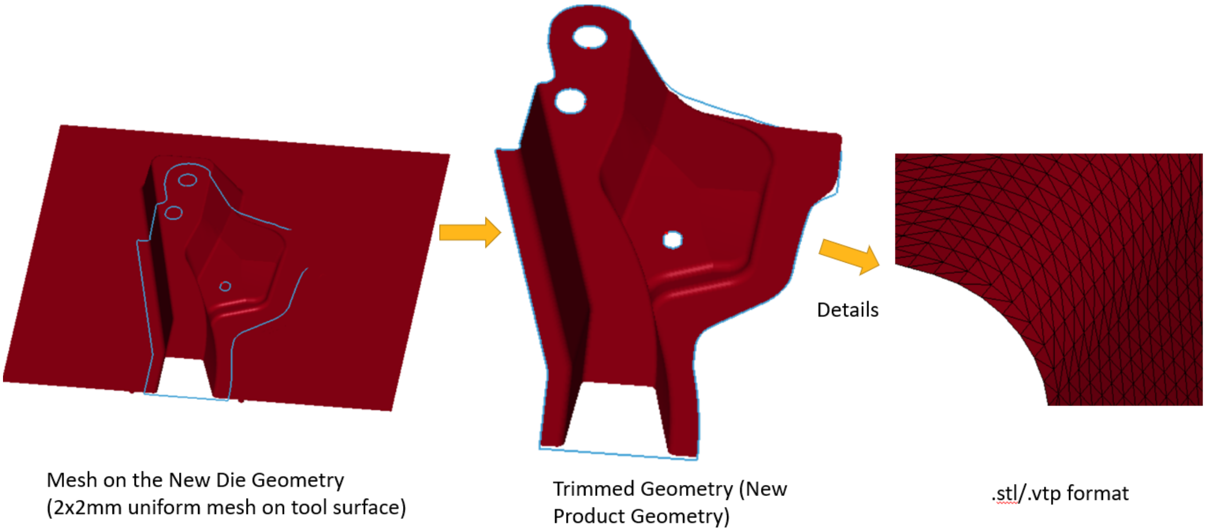


Fig.5: Input to surrogate model for prediction.

To prepare for a new prediction with geometry that was not a part of the original DOEs, die/punch radii are changed on the die, trimmed, offset to mid-plane, and output (in LS-PrePost) in .stl format file to upload for SimAI prediction, shown in Fig.5.
A summary report was automatically generated after SimAI training was done. One of the tables listed "Confidence score" of the test sets as shown in Fig.6, where both "Precise Build" and "More/Most Precise Build" (two separate models) were shown. The "Confidence score" was calibrated to be between 0 and 1 with the following key values:

• 2/3 (0.66) at the 95th percentile of the distribution.
• 1 at the 5th percentile of the distribution.

A prediction with a confidence score lower than 0.66 was labeled as 'Low'; greater than 0.66 was labeled as 'High'.
To show the divergence between the estimated and target global coefficients, the auto-generated report also included thickness trend comparison plot (SimAI value vs. Solver value) and thickness trend order plot (Fig.7). In the order plot, the cases were ordered such that the solver values were in ascending order, facilitating the visualization of the range of possible values, their distribution, and associated errors simultaneously. The test numbers were labeled in red in both plots. Note the three test sets (blue) Refs.17, 18, and 40 having the low confidence scores from Fig.6 were noticeably deviated from solver value (orange).
Also included in the report were thickness surface field plots for the test sets predicted by the SimAI prediction, the solver target and the difference between the two, shown in Fig.8.
The best way to determine for certain what the low confidence score cases really mean, of course, was to compare the thickness distribution manually in LS-PrePost. In Fig.9, a detailed markup for two areas of interest was done for Reference 17 / DOE24 (Fig.6), which had the lowest score of 0.14. The maximum difference occurred in the area where the front-facing draw wall meets the raised platform, the SimAI (most precise setting) underpredicted thickness compared with solver value by over 100%. Multiple high thinning areas in close proximity might have contributed to the large deviation. In practice, since both values (0.795 prediction vs. 0.384mm solver) were well below the safe limit (1.28mm) it might not matter too much. The lowest thickness on the back draw wall was predicted as 1.38mm vs. the 1.36mm solver, with the relative error at 0.6%. This proves to be the trend as more case studies revealed that SimAI predicts the thickness very well for the areas with no extreme severe thinning; note the failure thickness is at 1.28mm.

Precise Build

Reference	Confidence score
17	Low (0.31)
18	Low (0.62)
40	Low (0.56)
46	High (0.86)

Most Precise Build

Reference	Confidence score
17	Low (0.14)
18	Low (0.51)
40	Low (0.5)
46	High (0.81)

Case name	Reference
XmbrTrimPnl_LastState_TD24	17
XmbrTrimPnl_LastState_TD25	18
XmbrTrimPnl_LastState_TD45	40
XmbrTrimPnl_LastState_TD6	46

Fig.6: Three "low confidence" test sets: Ref. # and the corresponding DOE #.

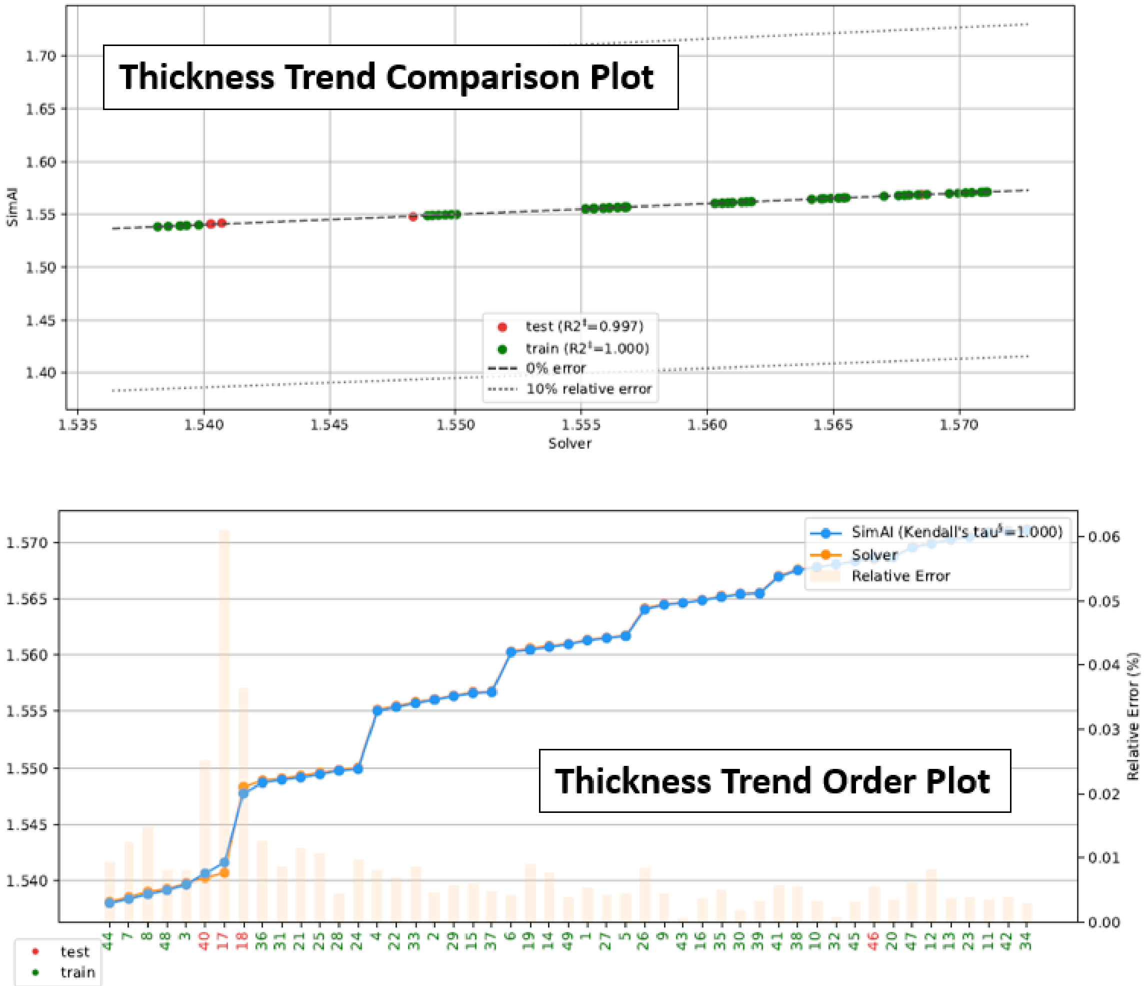


Fig.7: Divergence between estimated and target global coefficients.

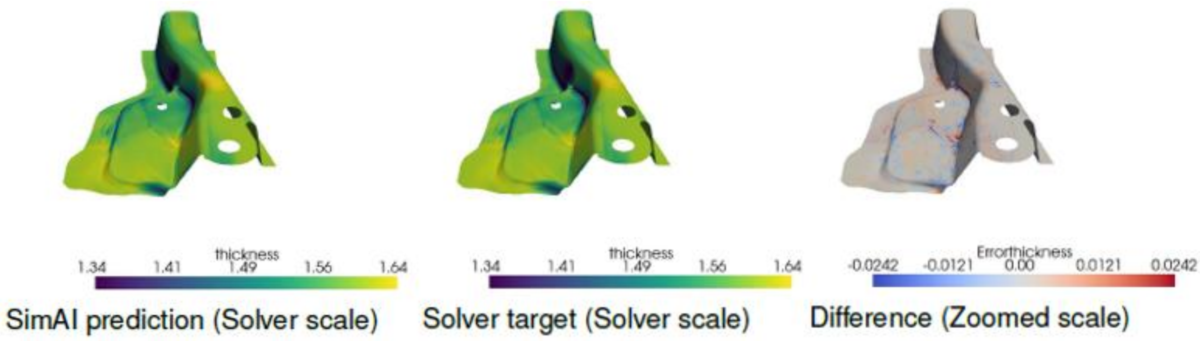


Fig.8: SimAI auto-generated thickness comparison from one of the test set.

To test the surrogate model further, four additional predictions were made with die geometry that were not a part of the original DOEs. The four predictions were selected to be evenly spaced in the design space, each was between two existing DOEs, as shown in Fig.10. The same four additional predictions were used for CASE B and CASE C as well. Detailed thickness contour plots were made for the precise build, most precise build, and solver (ground truth), as shown in Fig.11 through Fig.14. Detailed thickness values from the front and back draw walls were listed in Table 1. Noticeably, prediction 4 also did not predict extreme thinning on the front draw wall well, as was the case in Ref.17/Design 24. This was expected as these two designs have a similar top and bottom radii and were in the lower confidence region. Relatively high percentages of difference in these cases might not be meaningful, as both cases predicted failure well below the limit. Similar to Ref.17/Design 24, Multiple areas of failure with high thinning in close proximity at the front draw wall might also have contributed to the high relative % difference in Prediction 4. The remaining three predictions came in with maximum relative error of ~10%. Prediction 2 underpredicted thickness by 10%, which at 1.22mm, was close to the thickness limit of

1.28mm. Note the closest DOE to Prediction 2 is #48 which had small relative error (Fig.7) with respect to solver. All predictions did well at the back draw wall, with the maximum relative error of 2.8%. The four additional predictions again predicted thickness well for regions that do not have extreme, severe thinning. CASE A also indicated (Table 1) the "Most Precise" build was still better than the "Precise" build as shown in Design24, where the "Precise" build predicted front wall thickness safe, while the "Most Precise" build showed it was well below the limit. The "Most Precise" build is therefore recommended.

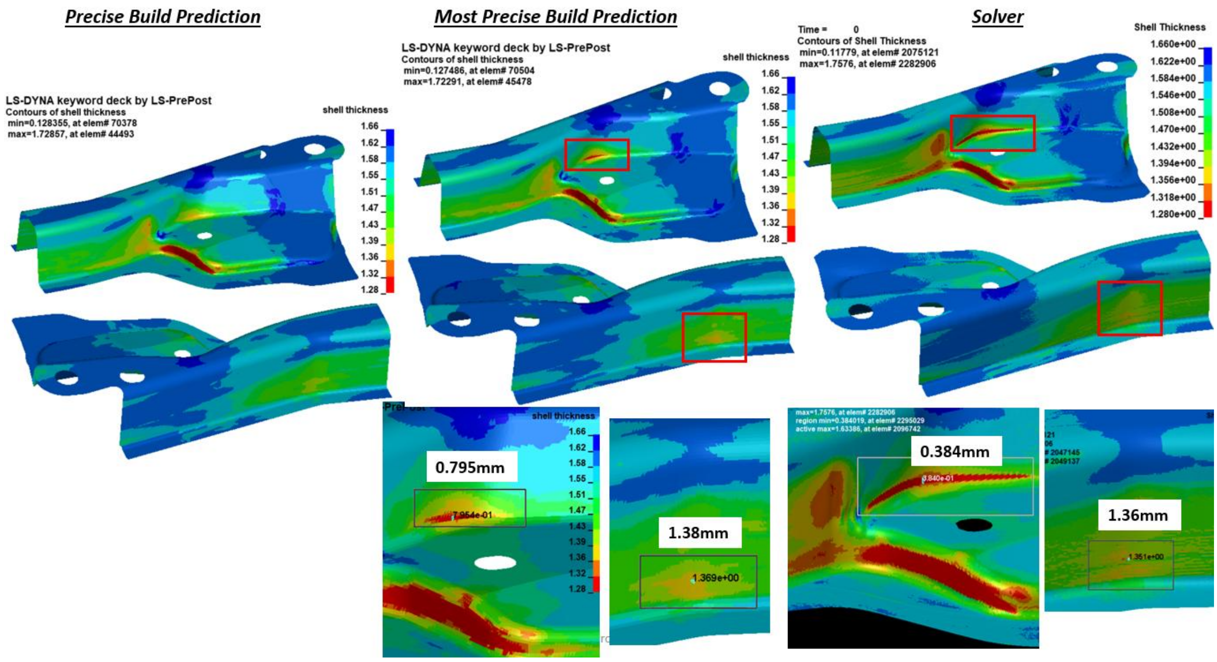


Fig.9: Checking on Ref. 17 (DOE24) with lowest confidence score of 0.31 (precise) and 0.14 (most precise), with R_{top}=20mm and R_{bottom}=5mm.

Additional Prediction Runs (new geometry) not a part of the Original DOEs:

Id	Feasible	Duplicates	Status	bottom	top
0.8	true		Succeeded	5	11.5
0.11	true		Succeeded	5	14.3333
0.15	true		Succeeded	5	5.83333
0.16	true		Succeeded	5	8.66667
0.24	true		Succeeded	5	20
0.45	true		Succeeded	5	17.1667
0.49	true		Succeeded	5	3
0.25	true		Succeeded	7.5	3
0.28	true		Succeeded	7.5	11.5
0.30	true		Succeeded	7.5	20
0.31	true		Succeeded	7.5	14.3333
0.34	true		Succeeded	7.5	17.1667
0.37	true		Succeeded	7.5	8.66667
0.41	true		Succeeded	7.5	5.83333
0.10	true		Succeeded	10	11.5
0.12	true		Succeeded	10	3
0.22	true		Succeeded	10	17.1667
0.29	true		Succeeded	10	5.83333
0.35	true		Succeeded	10	14.3333
0.39	true		Succeeded	10	8.66667
0.42	true		Succeeded	10	20
0.1	true		Succeeded	12.5	14.3333
0.9	true		Succeeded	12.5	11.5
0.13	true		Succeeded	12.5	20
0.14	true		Succeeded	12.5	3

Prediction Run #4:
Rbtm=6.25, Rtop=18.5

3 Lower confidence Designs in red boxes.

Prediction Run #1:
Rbtm=9, Rtop=6

Id	Feasible	Duplicates	Status	bottom	top
0.21	true		Succeeded	12.5	8.66667
0.26	true		Succeeded	12.5	5.83333
0.33	true		Succeeded	12.5	17.1667
0.17	true		Succeeded	15	5.83333
0.23	true		Succeeded	15	11.5
0.32	true		Succeeded	15	3
0.36	true		Succeeded	15	17.1667
0.40	true		Succeeded	15	14.3333
0.44	true		Succeeded	15	20
0.48	true		Succeeded	15	8.66667
0.5	true		Succeeded	17.5	14.3333
0.6	true		Succeeded	17.5	17.1667
0.18	true		Succeeded	17.5	8.66667
0.27	true		Succeeded	17.5	20
0.38	true		Succeeded	17.5	11.5
0.43	true		Succeeded	17.5	5.83333
0.46	true		Succeeded	17.5	3
0.2	true		Succeeded	20	5.83333
0.3	true		Succeeded	20	11.5
0.4	true		Succeeded	20	20
0.7	true		Succeeded	20	3
0.19	true		Succeeded	20	14.3333
0.20	true		Succeeded	20	8.66667
0.47	true		Succeeded	20	17.1667

Prediction Run #2:
Rbtm=14, Rtop=9

Prediction Run #3:
Rbtm=19, Rtop=10

Fig.10: Four additional predictions were run with designs that are not part of the original DOEs.

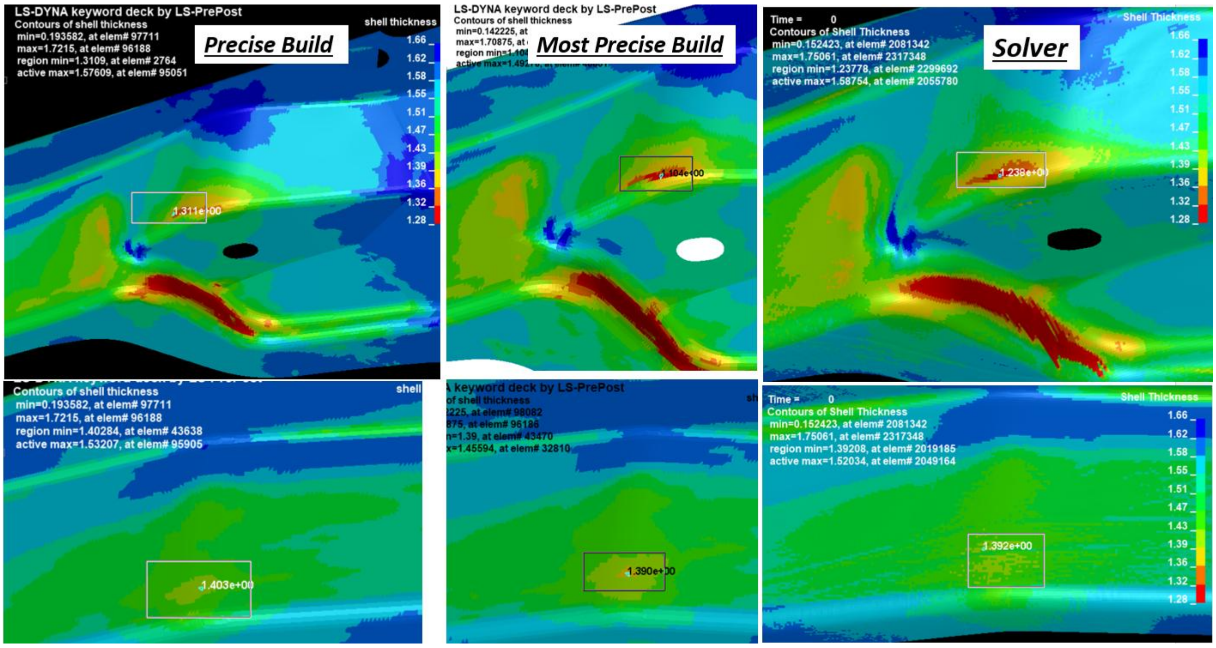


Fig.11: Extra prediction #1, with R_{top}=6mm and R_{bottom}=9mm.

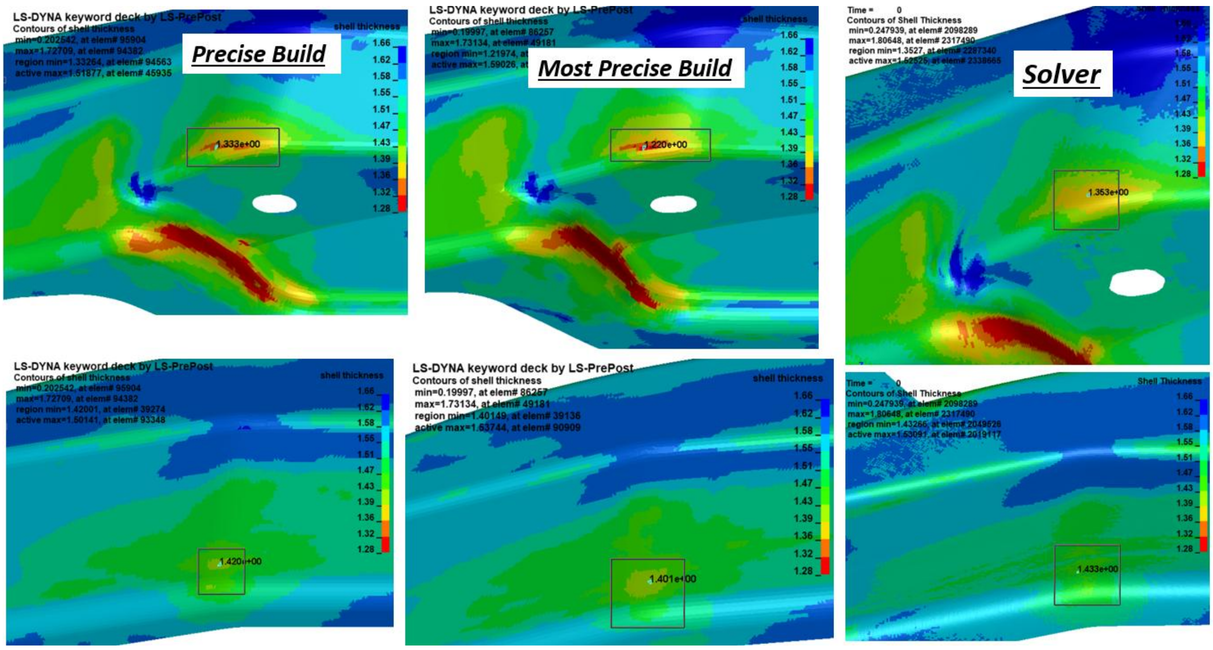


Fig.12: Extra prediction #2, with R_{top}=9mm and R_{bottom}=14mm.

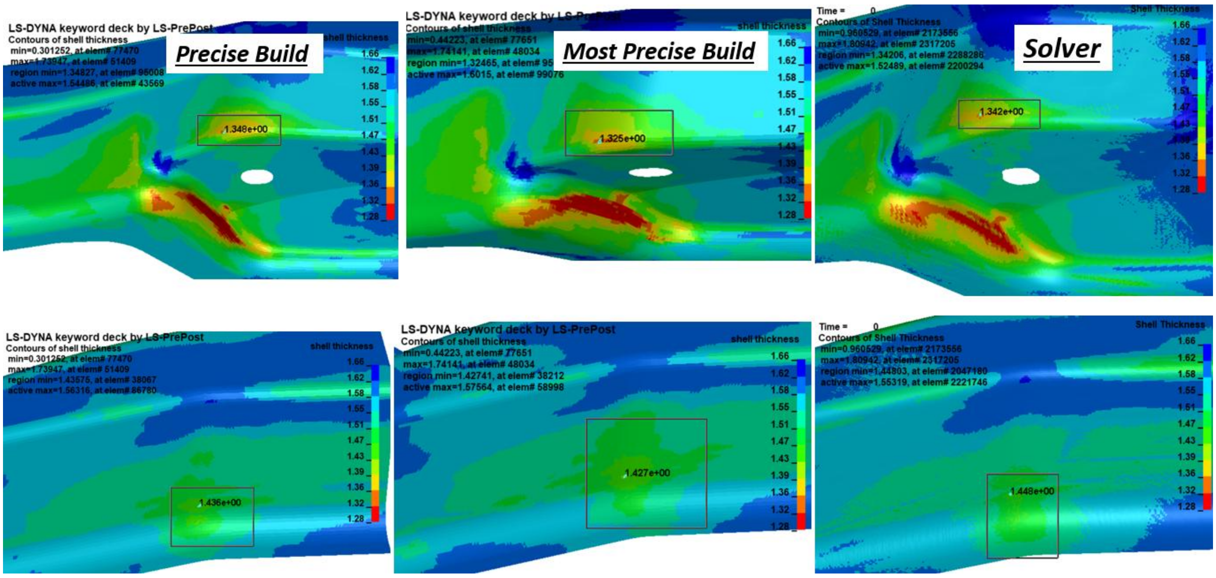


Fig.13: Extra prediction #3, with R_{top}=10mm and R_{bottom}=19mm.

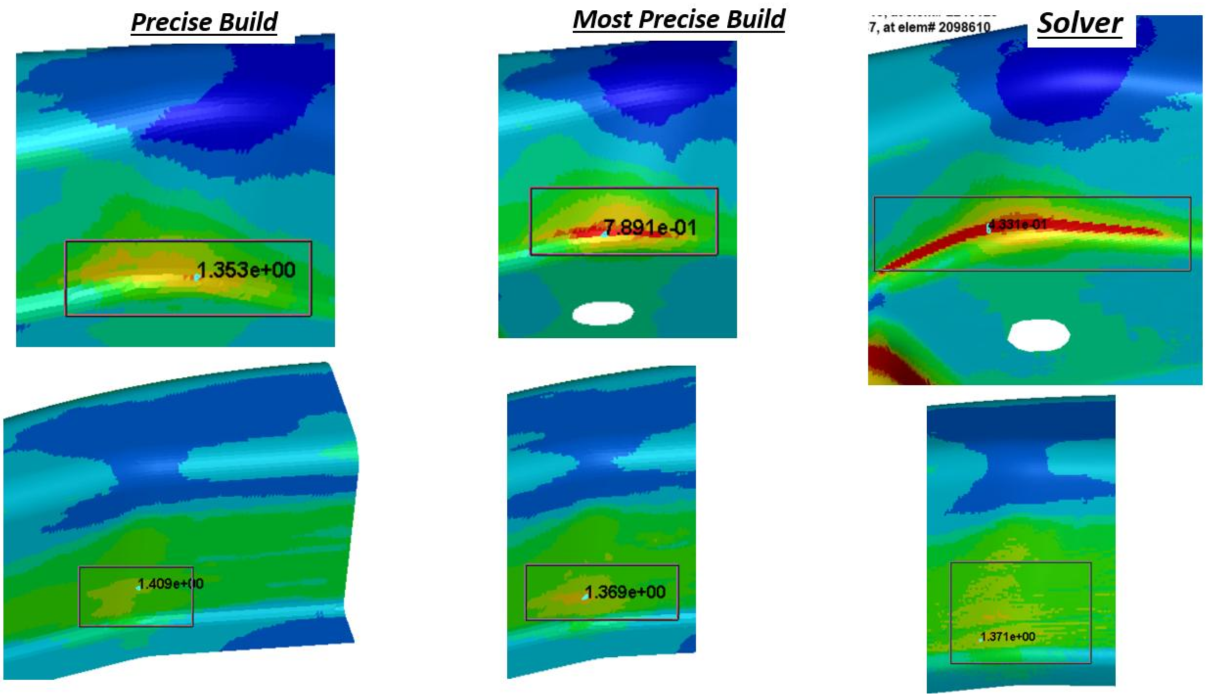


Fig.14: Extra prediction #4, with R_{top}=18.5mm and R_{bottom}=6.25mm.

Prediction Cases	Front Draw Wall Thickness (mm)			%Difference To Solver		Back Draw Wall Thickness (mm)			%Difference To Solver	
	Precise	Most Precise	Solver	Precise	Most Precise	Precise	Most Precise	Solver	Precise	Most Precise
Design24/Ref.17	Too high	0.795	0.384	x	107.0	x	1.369	1.361	x	0.6
Prediction 1	1.311	1.104	1.238	5.9	-10.8	1.403	1.39	1.392	0.8	-0.1
Prediction 2	1.333	1.22	1.363	-2.2	-10.5	1.42	1.401	1.433	-0.9	-2.2
Prediction 3	1.348	1.325	1.342	0.4	-1.3	1.436	1.427	1.448	-0.8	-1.5
Prediction 4	1.353	0.7891	0.433	212.5	82.2	1.409	1.369	1.371	2.8	-0.1

Table 1: CASE A detailed thickness comparison between predictions and solver.

2.2 CASE A – Strain/FLD Prediction

This case was very similar to CASE A thickness prediction. In place of the thickness, strain tensors were used to train the AI model. The global coefficients defined for the six strain tensors were (naming convention might not be indicative of the actual meaning),

- emid1x=mean(E11).
- emid1y=mean(E22).
- emid1z=mean(E33).
- emid2x=mean(E12).
- emid2y=mean(E23).
- emid2z=mean(E13).

Python script was used to convert SimAI generated surface VTP file into dynain files, which was used to plot FLD in LS-PrePost.
In Fig.15, snapshots of three of the global coefficients were automatically generated. Overall, the test sets did well, with a maximum of relative error at a little over 5% for test set 44. A detailed comparison similar to Fig.9 was made but not shown here. Instead, detailed comparisons of FLD on failure and wrinkling patterns were shown in Figs.16 to 19 for one of the four additional predictions with die geometry not part of the original DOEs. Fig.16 showed FLD formability plots for “Precise”, “Most Precise” and “Solver” for one of the failure locations. Both predictions predicted failure location as in the “Solver” and FLD spread patterns were very similar, with the “Precise” one being a bit closer to the “Solver” one than the “Most Precise” one, but both were acceptable. In Figs.17 and 18, wrinkling predictions using FLD were compared for two different areas, with blue being “potential wrinkle” and purple being "severe wrinkle”. These predictions showed wrinkles were very well predicted for areas “A” and “B”, which had severe wrinkles visible from the shaded plot in Fig.19 from LS-PrePost. For area “C” (FLD plot not shown), the blue color patterns from Figs.17 and 18 also correlated well with the slight wrinkles in Fig.19.

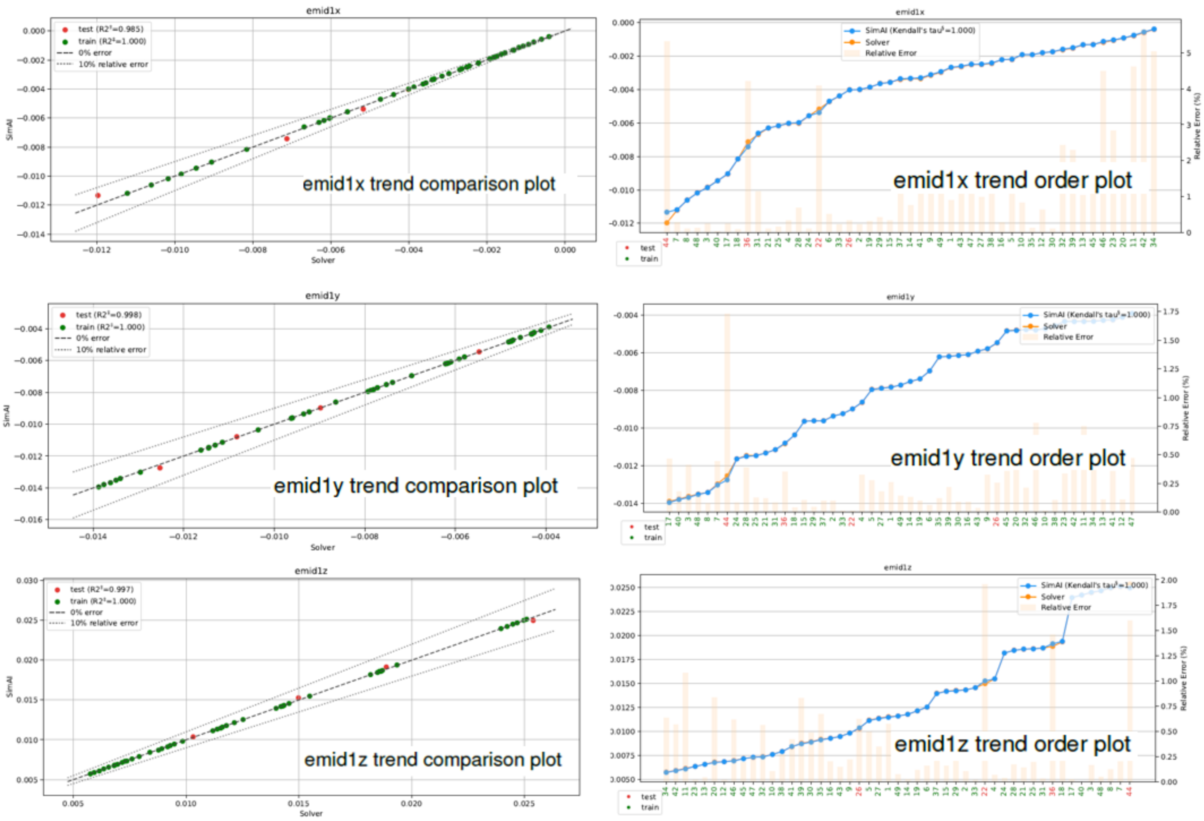


Fig.15: Divergence between estimated and target global coefficients.

In Table 2, two “low confidence” from training and test sets, along with the four additional predictions were summarized. FLD Predictions in terms of failure and wrinkles were excellent, as all failure and wrinkling locations were predicted, even in cases where multiple areas of severe straining were present in close proximity. Furthermore, a low confidence score might not mean a bad prediction in this case. Both “Precise” and “Most Precise” builds did equally well. Overall, strain prediction results were better than thickness prediction results.

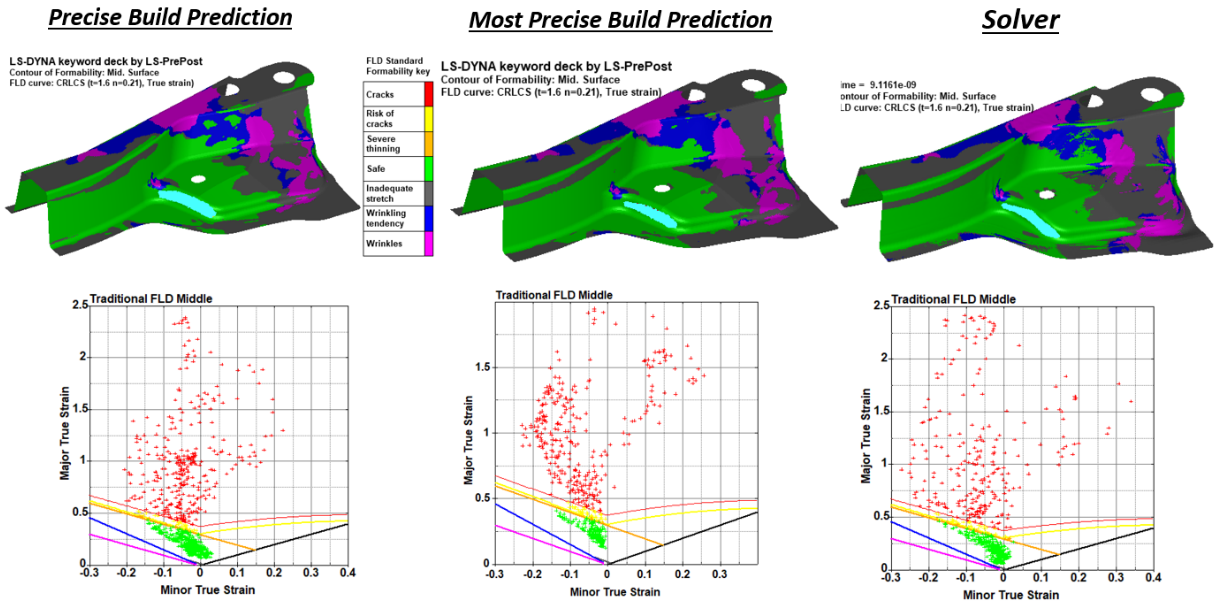


Fig.16: Failure prediction: an extra prediction #1 that is not a part of the original DOEs, R_{top}=6mm and R_{bottom}=9mm.

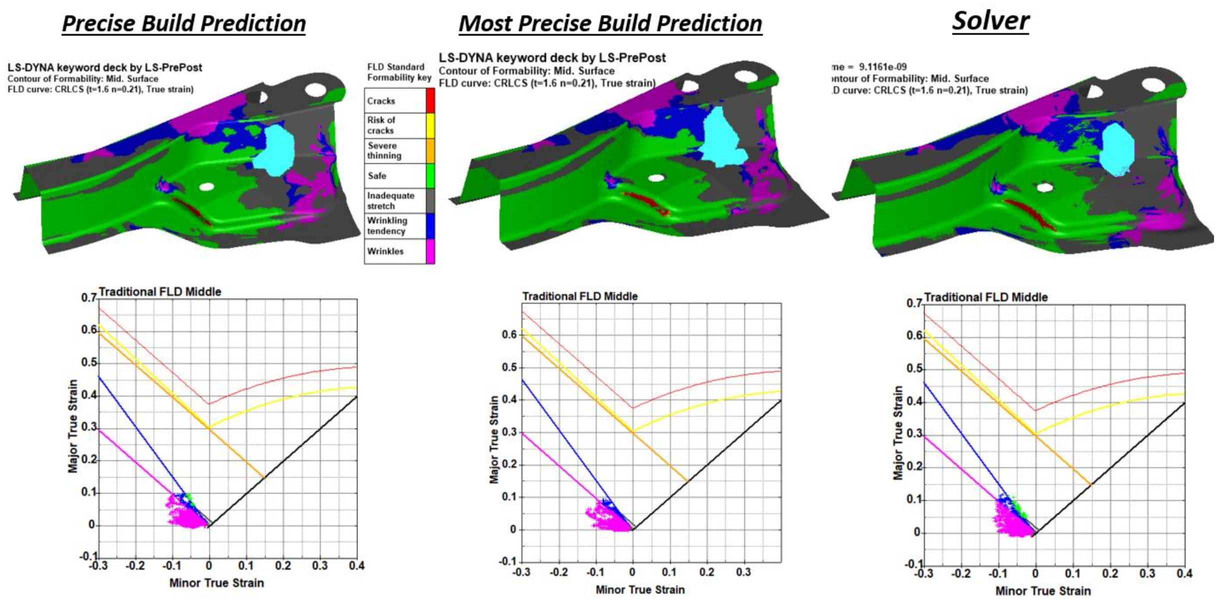


Fig.17: Wrinkling prediction: an extra prediction #1 that is not a part of the original DOEs, R_{top}=6mm and R_{bottom}=9mm.

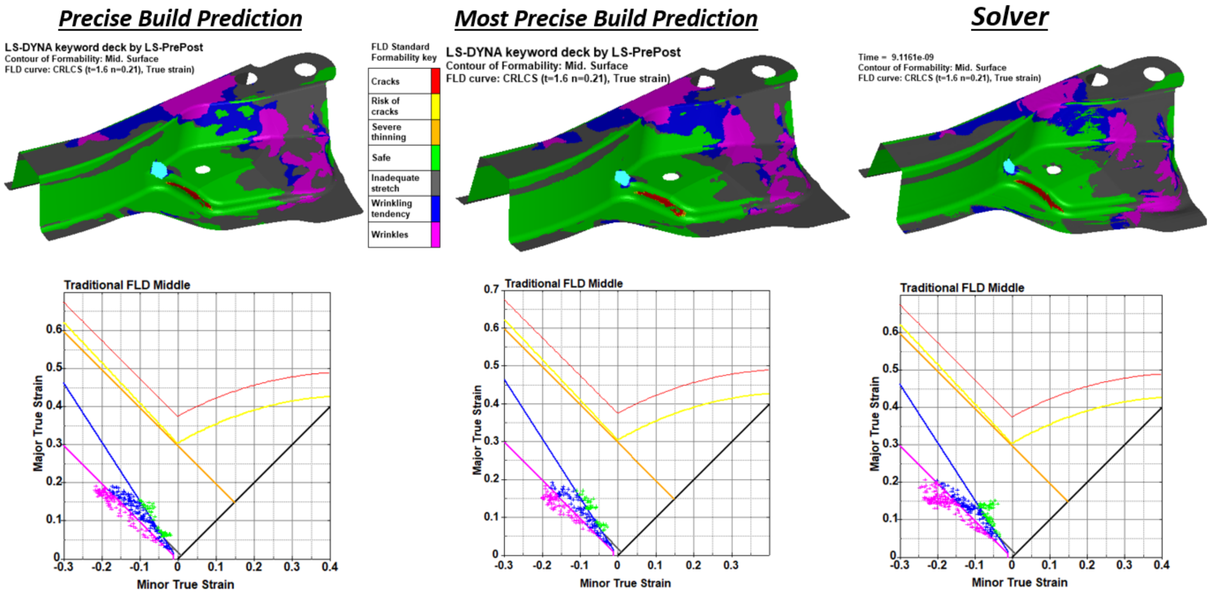


Fig.18: Wrinkling prediction: an extra prediction #1 that is not a part of the original DOEs, R_{top}=6mm and R_{bottom}=9mm.

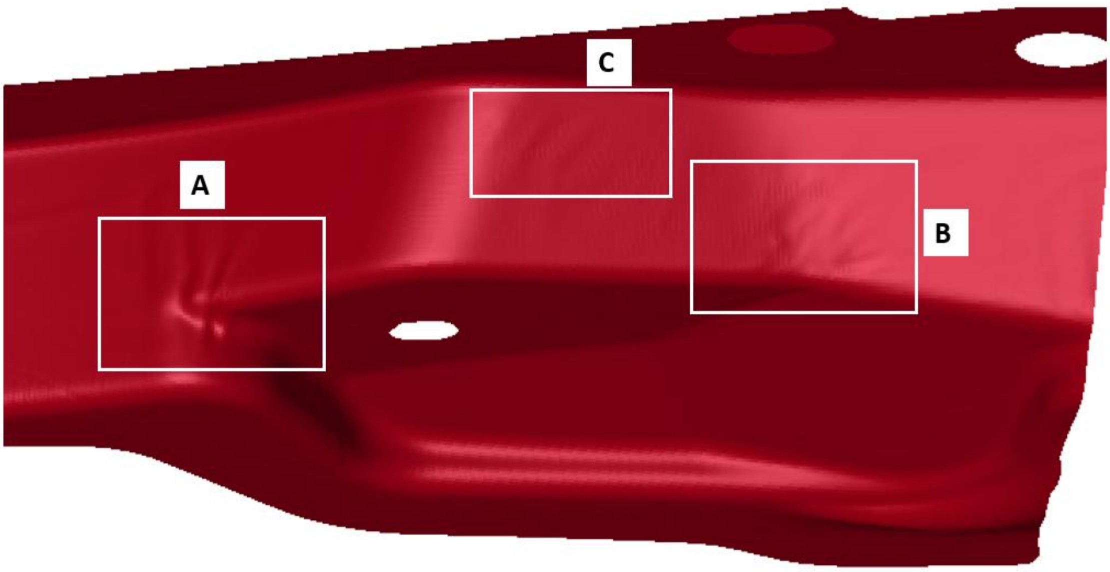


Fig.19: Wrinkling pattern from Solver results (ground truth).

Prediction Cases	Front Draw Wall/radius Failure Prediction			Front Die Radius/PO Failure Prediction			Front Wrinkling (small area) Prediction			Front Wrinkling (larger area) Prediction		
	Precise	Most Precise	Solver	Precise	Most Precise	Solver	Precise	Most Precise	Solver	Precise	Most Precise	Solver
Design29	Safe	Safe	Safe	Fail	Fail	Fail	Yes	Yes	Yes	Yes	Yes	Yes
Design49	Fail	Fail	Fail	Fail	Fail	Fail	Yes	Yes	Yes	Yes	Yes	Yes
Prediction 1	Safe	Safe	Safe	Fail	Fail	Fail	Yes	Yes	Yes	Yes	Yes	Yes
Prediction 2	Safe	Safe	Safe	Fail	Fail	Fail	Yes	Yes	Yes	Yes	Yes	Yes
Prediction 3	Safe	Safe	Safe	Fail	Fail	Fail	Yes	Yes	Yes	Yes	Yes	Yes
Prediction 4	Fail	Fail	Fail	Fail	Fail	Fail	Yes	Yes	Yes	Yes	Yes	Yes

Table 2: CASE A detailed FLD failure prediction comparison.

2.3 CASE B – Thickness prediction

In practice, the most likely scenario was the drawn panel results would be used for training, and new product geometry (trim panel) to be used as input for prediction. The output from the prediction would be displayed on the new product geometry, as shown in Fig.20. In this section, the same 49 DOEs drawn panels before trimming were used for training. The global coefficient was defined as thick=mean(thickness). The thickness trend comparison plot and thickness trend plots for the global coefficients were shown in Fig.21. The maximum relative error is at 0.014% with respect to the solver result for Ref.12 (DOE 2). A detailed look at fringe contour difference was shown in Fig.22 for Ref.12, where maximum difference in thickness in the front draw wall is 5% for the “Most Precise” prediction. Again, four additional predictions were made with new designs that were not a part of the original DOEs, and two of the predictions were given in Figs.23 and 24.

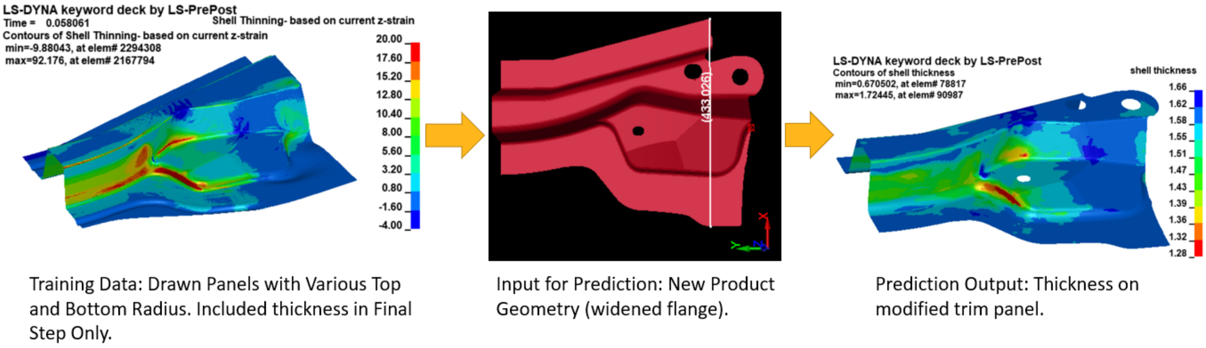


Fig.20: Input and output for prediction.

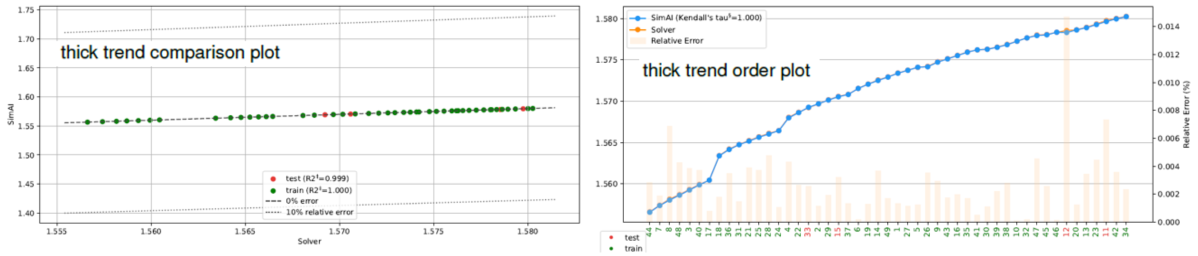


Fig.21: Divergence between estimated and target global coefficients.

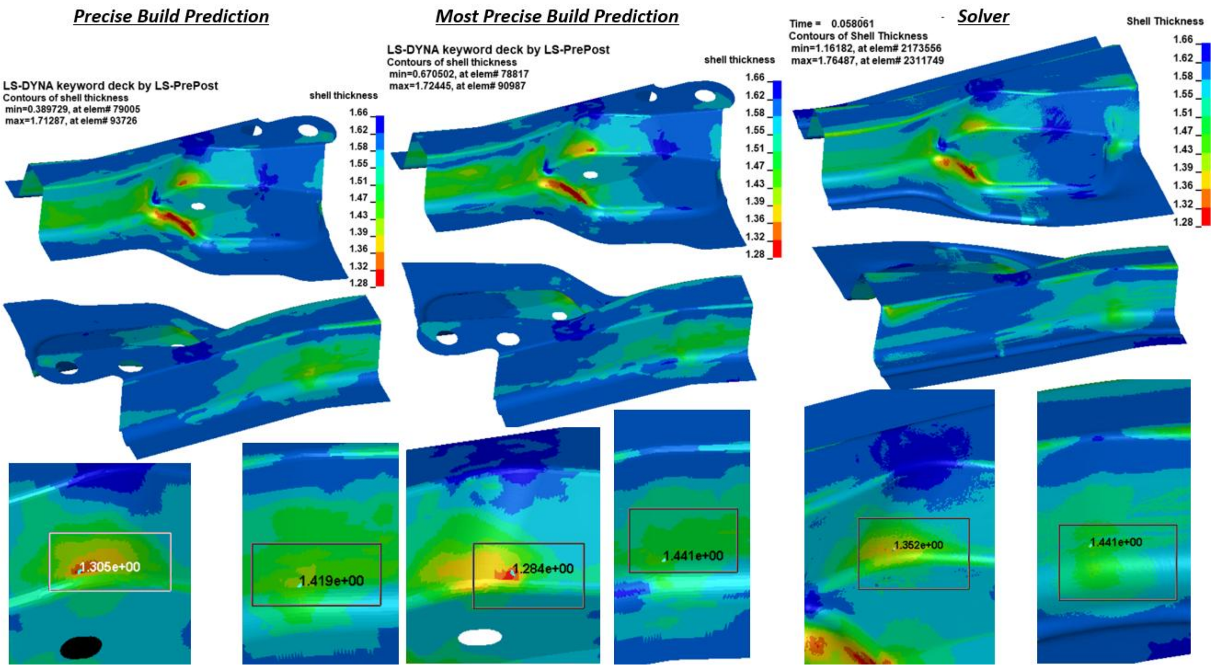


Fig.22: Ref. 12 (Design 0002, Lower Confidence), R_{top}=5.833mm, R_{bottom}=20mm.

Table 3 listed measured values in all comparisons. In the “Most Precise” setting, Prediction 3 had a relative percentage of error (4.8%) similar to Ref.12(Design0002 at 5.0%) as both were close to each other in the DOE space. Prediction 4 had the highest 84% relative error compared to the solver results, which was very similar to the same prediction in CASE A thickness prediction(Fig.14). Multiple higher thinning areas in close proximity might have confused predictions, nevertheless, failure is predicted in the front draw wall. Predictions 1 and 2 had relative errors of 14.9% and 10.7%, respectively, while both predictions showed in the trend order plot (Fig.21) having very low relative errors (41 with 0.0004% and #48 with 0.004%, respectively).

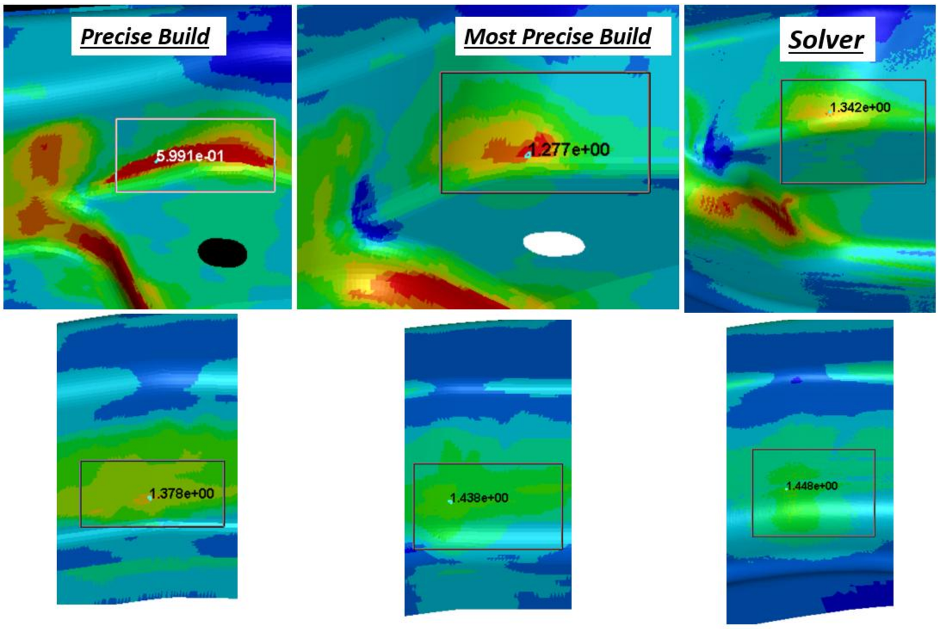


Fig.23: Prediction Run #3: Rbtm=19, Rtop=10 (new geometry), closest to Ref.12 (Design 0002, Lower Confidence)

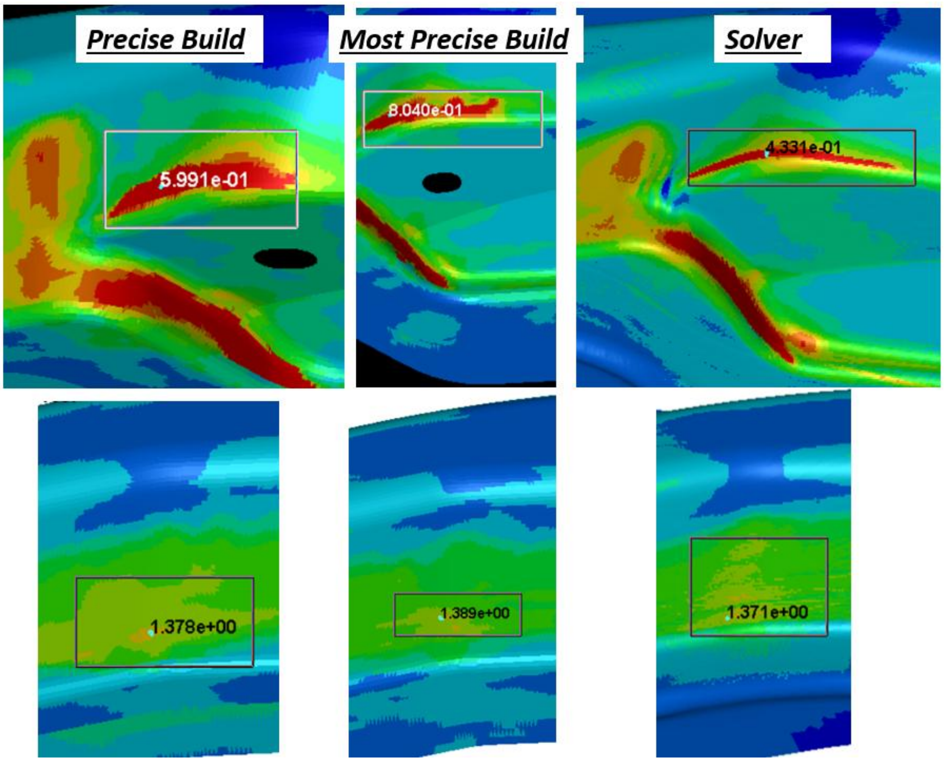


Fig.24: Prediction Run #4: Rbtm=6.25, Rtop=18.5 (new geometry), which has the largest relative error compared to Solver.

Prediction #2 also predicted failure at the front draw wall giving the thickness as 1.208mm in the area, well below the failure thickness of 1.28mm, while the solver results indicated a safe forming thickness (1.353mm). Perhaps the size difference between prediction input and trained model made error relatively large. Overall, it could also be concluded that the "Most Precise" predictions performed better than the "Precise" ones.

Prediction Cases	Front Draw Wall Thickness (mm)			%Difference To Solver		Back Draw Wall Thickness (mm)			%Difference To Solver	
	Precise	Most Precise	Solver	Precise	Most Precise	Precise	Most Precise	Solver	Precise	Most Precise
Design0002	1.305	1.284	1.352	-3.5	-5.0	1.419	1.441	1.441	-1.5	0.0
Prediction 1	0.933	1.054	1.238	-24.6	-14.9	1.399	1.382	1.392	0.5	-0.7
Prediction 2	1.197	1.208	1.353	-11.5	-10.7	1.413	1.417	1.433	-1.4	-1.1
Prediction 3	0.599	1.277	1.342	-55.4	-4.8	1.378	1.438	1.448	-4.8	-0.7
Prediction 4	0.599	0.801	0.433	38.4	85.0	1.378	1.389	1.371	0.5	1.3

Table 3: CASE B detailed thickness comparison between predictions and solver.

2.4 CASE C – Transient with 10 states.

The training data used in this case were 490 DOEs, with 49 different designs and each including 10 deformation states and associated thickness. The global coefficients defined were:

- thick= mean(thickness).
- dx=mean(displacement[X]).
- dy=mean(displacement[Y]).
- dz=mean(displacement[Z]).

As indicated in the workflow in Fig.25, drawn panels along with rigid tools for each state (10 states total) per DOE were used for training, for a total of 490 training and test sets (49 DOEs). Input for prediction was the initial blank and tools in its initial position in one .stl format file. Prediction output included thickness and sheet blank deformation. Likewise, similar to CASE A, strains/FLD could also be trained in a separate model. Given the experiences from prior cases, only the "Most Precise" setting was investigated and discussed here.

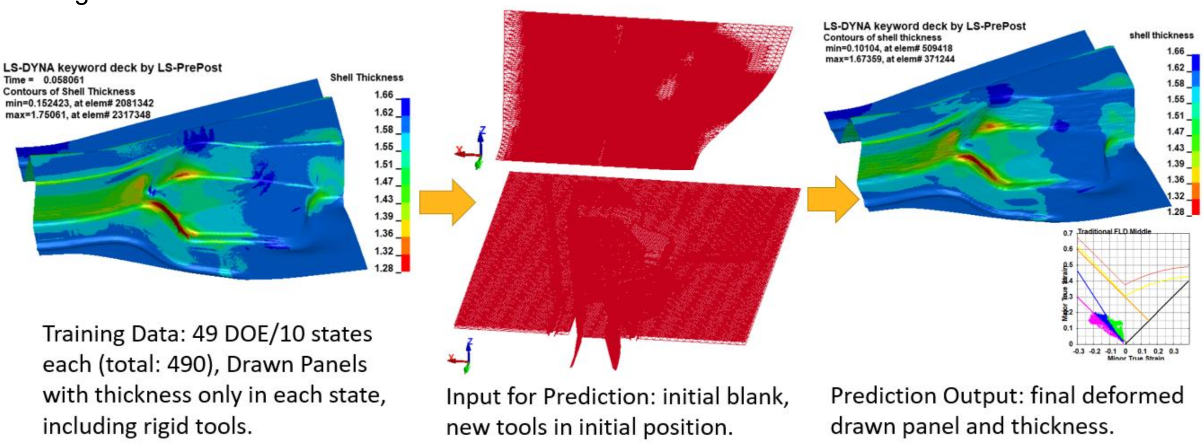


Fig.25: CASE C workflow.

The estimated and target global coefficients comparisons were shown in Fig.26. The thickness trend order plot showed nearly all the training/test sets consistently deviated from the solver results with localized spikes on the left side. The UX and UY trend order plots also showed comparatively high relative errors, with UX being particularly higher. Note the UX direction was perpendicular to the draw wall and was the controlling factor in affecting the draw wall smoothness.

Four more predictions were made with die geometries that were not a part of the original DOEs, one of which (Prediction #4) was shown in Fig.27. Thickness was predicted to be 1.339mm (safe) at the front draw wall while the solver result was 0.433mm (fail), with a large relative error. A further look at the original DOE training set #420 (Fig.28), which was the closest to Prediction #4 in the design space indicated the error was a result of the training.

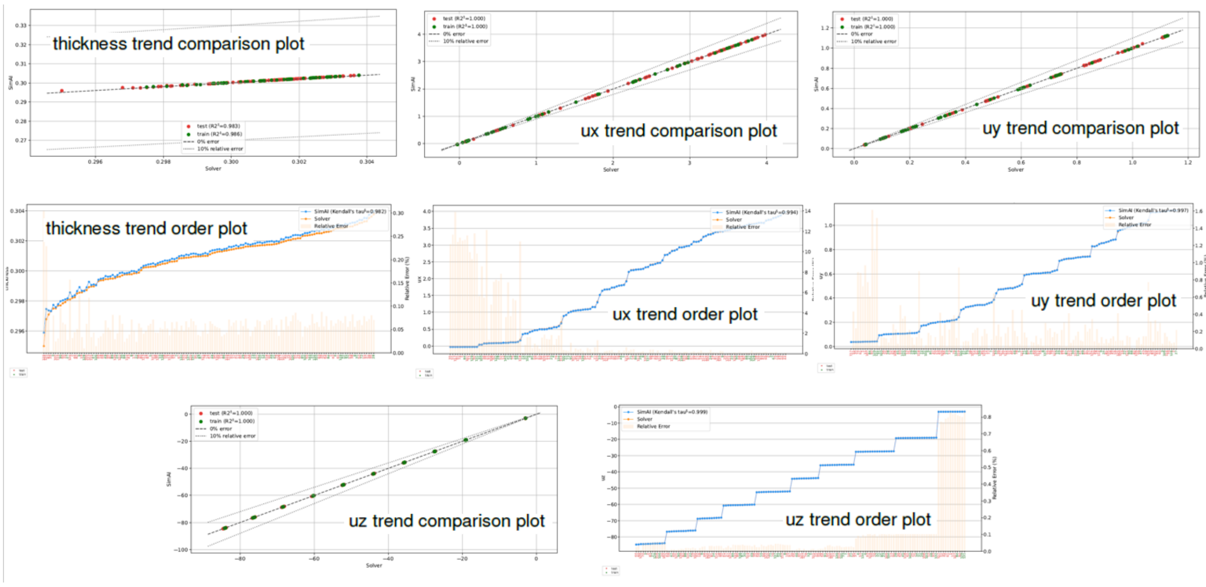


Fig.26: Divergence between estimated and target global coefficients.

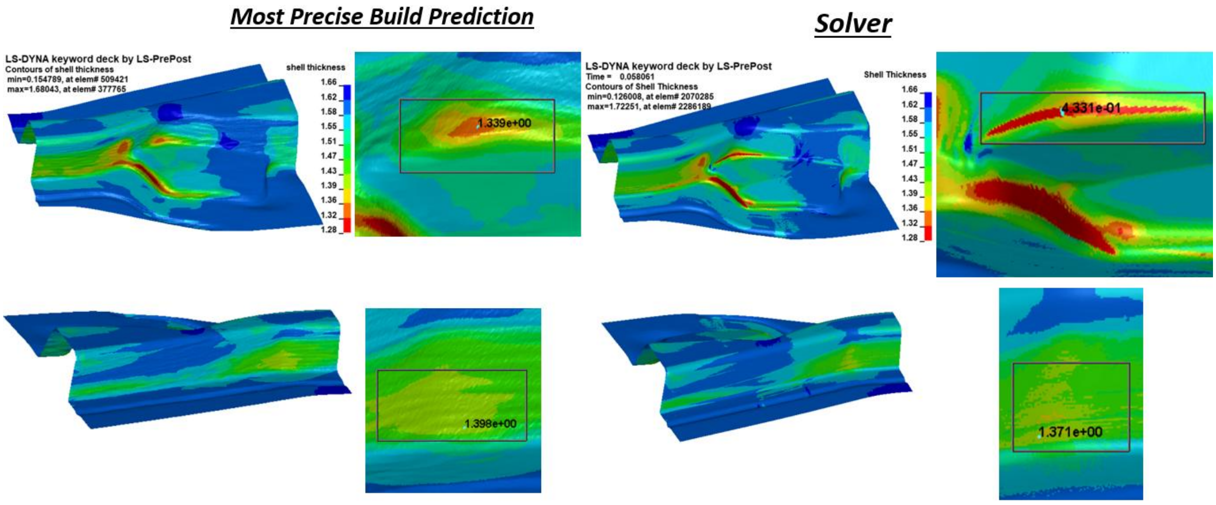


Fig.27: Prediction/Solver comparison for Prediction Run #4 with R_{top}=18.5mm, R_{bottom}=6.25mm, which is not a part of the original DOEs used for training.

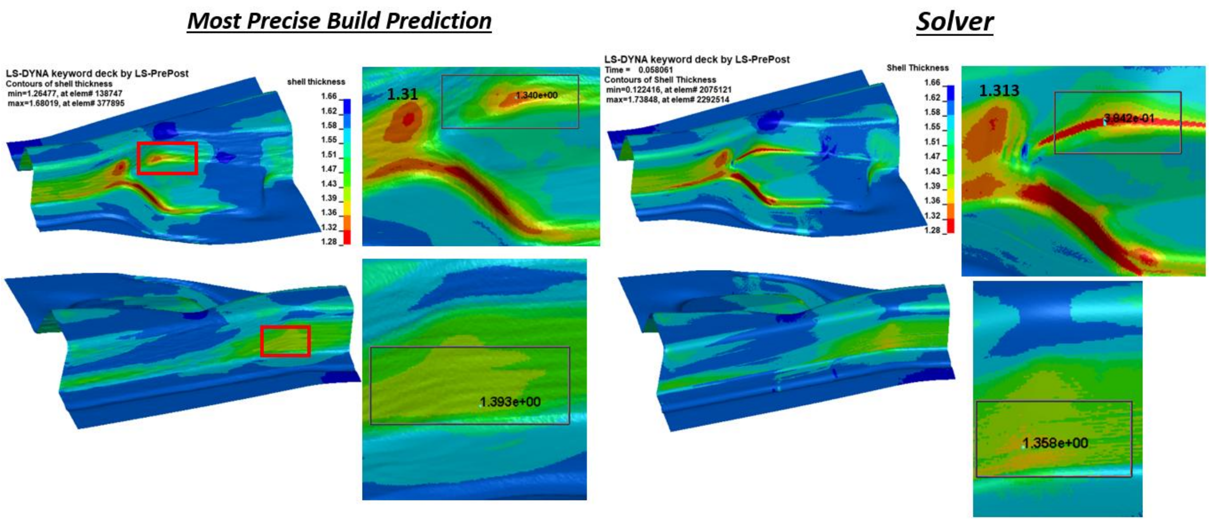


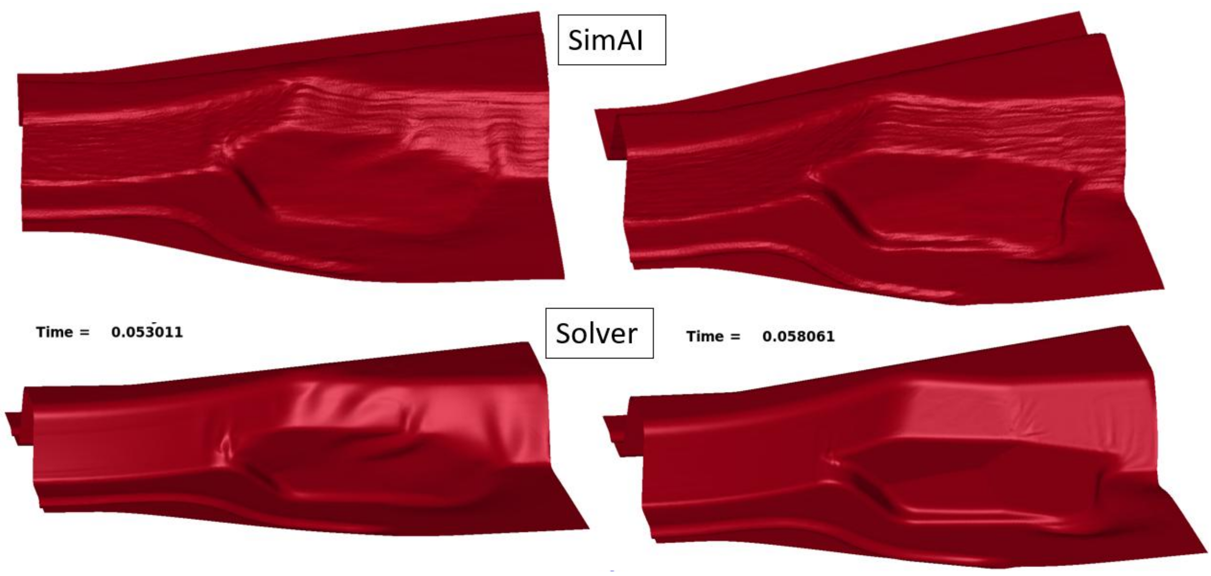
Fig.28: Prediction/Solver comparison for Design0045 (#420), R_{top}=17.166mm, R_{bottom}=5mm – Closest to Prediction #4

In Table 4, results from all additional predictions were listed in detail. Aside from Prediction 4 (and Design0045/#420), all three other predictions did very well, with the maximum of relative error of 8.4% for Prediction 1 on the front draw wall, and 2.8% at the back draw wall for Prediction 3. A further look at the training (and predictions) indicated the rigid body thickness predications were included in the model, as indicated in the global coefficient thickness trend order plot (Fig.26) as well. In sheet metal stamping multiple tools modeled as rigid bodies typically have more elements/thickness than the sheet blank itself, the inclusion of rigid body thickness in the training could possibly obscure and overwhelm the thickness prediction on the sheet blank.
In Fig.29, draw panel breakdowns were selected for comparison for two of the draw depths. Prediction of breakdown wrinkles during drawing were of great interest in the stamping community. At time=0.053011sec, about 5mm away from home position, although not a one-on-one match, wrinkles on the front draw wall were mostly visible in a few areas in the prediction compared to the solver. In the back draw wall, the prediction mostly missed the wrinkle patterns and fine details such as skid marks. At time=0.058061sec (home position), no wrinkles (front draw wall) or skid marks were visible from the prediction.

Prediction Cases	Front Draw Wall Thickness (mm)			%Difference To Solver		Back Draw Wall Thickness (mm)			%Difference To Solver	
	Precise	Most Precise	Solver	Precise	Most Precise	Precise	Most Precise	Solver	Precise	Most Precise
Prediction 1	x	1.342	1.238	x	8.4	x	1.418	1.392	x	1.9
Prediction 2	x	1.35	1.353	x	-0.2	x	1.461	1.433	x	2.0
Prediction 3	x	1.361	1.342	x	1.4	x	1.488	1.448	x	2.8
Prediction 4	x	1.339	0.433	x	209.2	x	1.398	1.371	x	2.0
Design0045(#420)	x	1.31	0.384	x	241.0	x	1.358	1.441	x	-5.8

Table 4: CASE C detailed thickness comparison between predictions and solver.

Perhaps more prominently displayed were the artificial wrinkles/noises that overpowered the real wrinkles/skid marks. The global coefficient UX trend order plot in Fig.26 mostly affects the artificial noises on the draw wall.



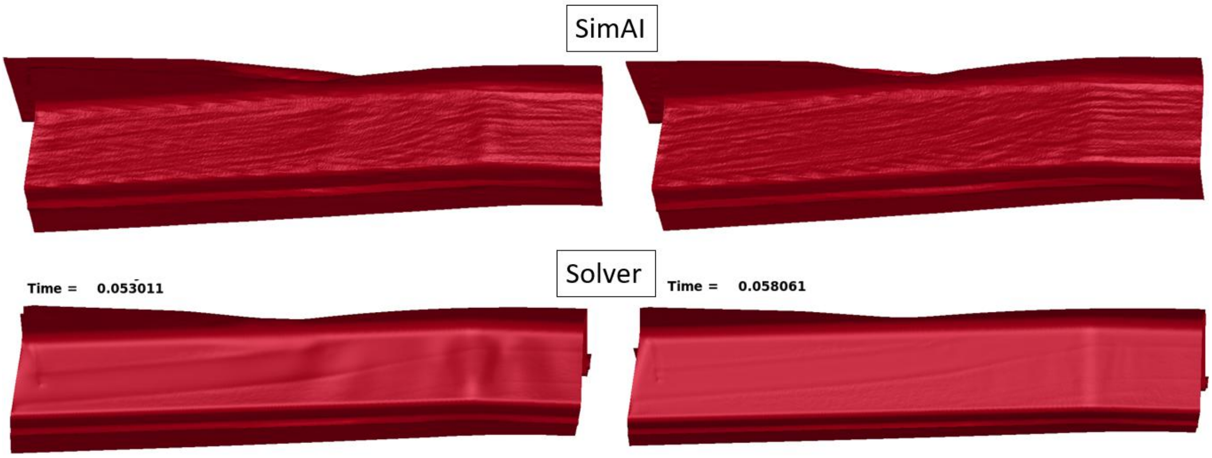


Fig.29: Breakdown panels wrinkle comparison.

3 Summary/Discussion

In this paper, Ansys SimAI™ was used for the following sheet metal forming case studies,

- CASE A (only need final trim panel formed results for training):
  - Failures were very well predicted with FLD plot, for both “Precise” and “Most Precise” builds, for both low and high strains, even in cases where severe strains were present in multiple areas of close proximity.
  - Wrinkling prediction is excellent via FLD plot.
  - The “Most Precise” setting is recommended for thickness prediction and both “Precise” and “Most Precise” settings could be used for strains/FLD build.

CASE A represents the best of both worlds, combining the speed of “one-step” prediction (in seconds) and the accuracy of incremental simulation. Extrapolated design predictions are not recommended.

- CASE B (only need final drawn panel formed results):
  - Thickness prediction was not as good as in CASE A.
- CASE C “Transient”:

Thickness predictions were not as good as CASE A. It might have something to do with rigid body thickness being included in the global coefficient of thickness. The total of four global coefficients defined (but necessary) might have also caused higher relative error on thickness prediction. Deformation predictions somewhat captured wrinkling patterns from the solver in some areas but difficult for robust predictions on wrinkles, skid marks and impact marks, etc. Extrapolated design predictions were not recommended.

Note the above conclusions were made based on the study only for this crossmember. Performance may vary for other stamping parts. Generally speaking, for thickness prediction, parts with reasonable thinning are expected to have very good predictions; parts with severe thinning and multiple areas of severe thinning in close proximity may have higher relative errors. For strains and FLD predictions, failure and wrinkles can be very well predicted regardless of parts’ formability situations.

Based on more studies, the strategy for stamping die engineering application using Ansys SimAI™ is proposed as follows,

- Use CASE A/B “Most Precise” build for strain/FLD prediction in stamping die engineering to predict both failure (large strains) and wrinkling for structure members such as pillars, underbody rails/crossmembers, etc. which give excellent results on interpolated designs. This should cover most of the formability issue predictions in stamping die engineering for the draw dies.
- Use CASE A/B “Most Precise” build for strain/FLD prediction for exterior, class-A surface panel stretch prediction (lower strains) in stamping die engineering and for downstream engineering applications such as denting/oil canning, pedestrian head impact, etc.
- Use CASE A/B “Most Precise” build for thickness (and effective plastic strain) prediction for downstream engineering applications, such as in durability, fatigue, reliability, crash, safety, etc.
- Use CASE C “Most Precise” for additional visualization of panel breakdowns for potential wrinkling areas during punch travel.

Well-trained AI models using large numbers of historical/legacy incremental stamping simulation for each class of panels (Fig.30), e.g. hood outer/inner, fender outer/inner, decklid inner/outer, etc. can be deployed in all product design (including evaluation of multiple early clay design concepts manufacturability), stamping die process and die development stages. It can be used for prediction by product designers with little or no stamping die experience or FEA knowledge, and by die process

engineers with no in-depth FEA experience, and even by full-time stamping FEA specialists for advance and fast stamping feasibility assessment of new product designs without the need to develop binder and addendum, required for full incremental FEA simulation. CASE A is especially useful as it is easier to extract data, upload, train and predict; it is faster for prediction than any forming software available on the market.
One of the best features of SimAI™ is it can grow and improve the Deep Learning models by adding additional training data to the existing trained model, so a new build does not have to start from scratch. It should be possible to automatically build trained Deep Learning models directly from an accurate forming simulation software as digital process of design and simulations are being conducted, often in an iterative fashion to arrive at a feasible solution. The history of going from multiple failed designs to a finally successful design which may include binder and/or addendum modifications, blank size change, trimline adjustments, cam directions, product changes, etc. is such a natural learning process and the best training data for SimAI™.
At the early product design stage, draw die simulation typically does not have physical beads to restrain and control the blank edge flow. Instead, curved/line beads are used as it is easier to set up and faster to run. Draw bead force needs to be specified for each segment of the simplified bead. Such a draw bead force can be predicted using SimAI™ in seconds. Design variables can include draw bead shapes, controlled by four corner radius, side clearance between upper and lower beads, bottom clearance, binder slope, binder gap, blank thickness, and material type/grades. Global coefficients for Deep Learning training can include draw bead restraining force, uplifting force, edge flow amount, etc. In most cases, the training data already exist in automotive OEMs, and the simulation results usually are meticulously correlated with carefully designed and executed physical draw bead tests (DOEs). However, the number of DOEs may not be enough to capture fine increments which may be needed to prescribe draw bead forces. SimAI™ can be a perfect tool in this scenario.
Although the focus of this paper is on stamping dies, it has a much wider application potential; essentially, as we have already seen, that any simulation with deformable bodies driven by rigid bodies (e.g. drilling and sealing, etc.) can be trained in SimAI™, covering oil and oil service industry, semiconductor, consumer electronics, automotive, aerospace, medical services, etc.

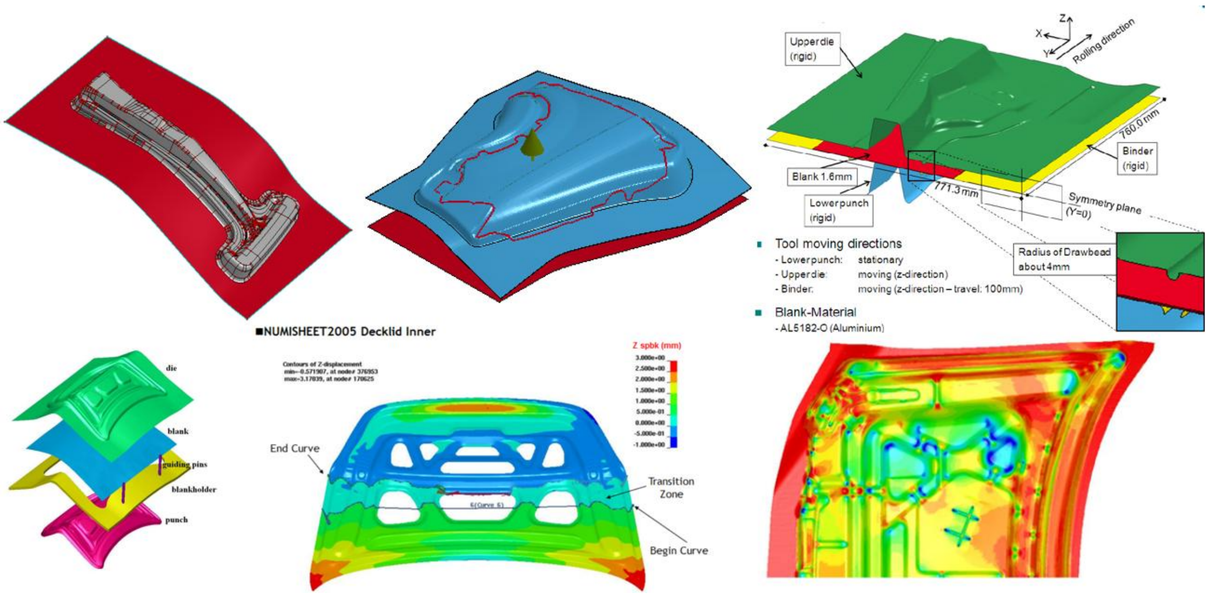


Fig.30: Pretrained SimAI models can be built for each classes of different stamping panels using legacy/historical simulation data.

4 Literature

[1] https://www.ansys.com/products/simai
[2] https://simai.docs.pyansys.com/