The effectiveness and advantages of deep learning based surrogate models in the real-time prediction of as-stamped component thickness fields

Imperial College London

Dyson School of Design Engineering

Haosu Zhou, Peter R N Childs, Nan Li

Dyson School of Design Engineering, Imperial College London, Exhibition Road, London, SW7 2AZ

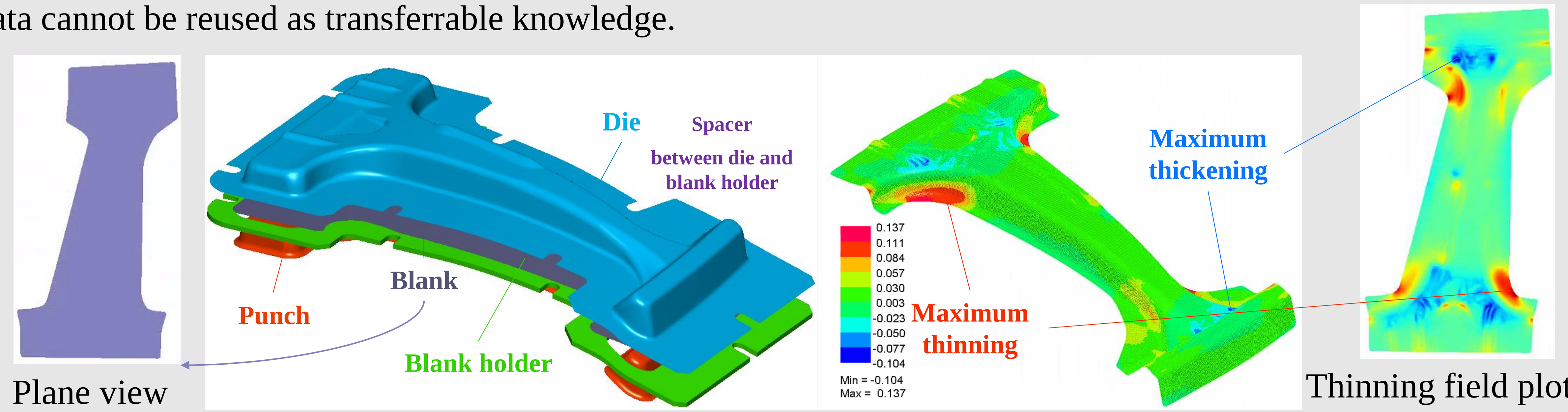
1. Introduction: To design a manufacturing-feasible blank shape for a hot-stamped B-pillar component

Since manual trial-and-error design iterations are very time-consuming and unreliable, a deep learning based surrogate model is developed to accurately replicate finite element simulations and optimise the arbitrary blank shape in real time, which is compared with the results obtained using traditional surrogate models.

2. Manual trial-and-error design iterations

- **Step 1:** Empirically design or update a blank shape.
- **Step 2:** Conduct hot stamping simulation in PAM-STAMP. In this research, maximum thinning/thickening values of the blank after stamping are selected to be the **manufacturability indicators**. In industrial practice, the acceptable upper limits of maximum thinning/thickening are 0.15/0.1.
- **Step 3:** If the maximum thinning/thickening values do not satisfy these manufacturability criteria, return to Step 1 and repeat this 1-3 design iterations until satisfaction.

This design iteration pipeline purely relies on the expertise and intuition. Two weeks are typically required even by senior engineers to tailor a manufacturing-feasible blank shape, without ensuring the optimality. Historic simulation data cannot be reused as transferrable knowledge.



Plane view of the blank before stamping

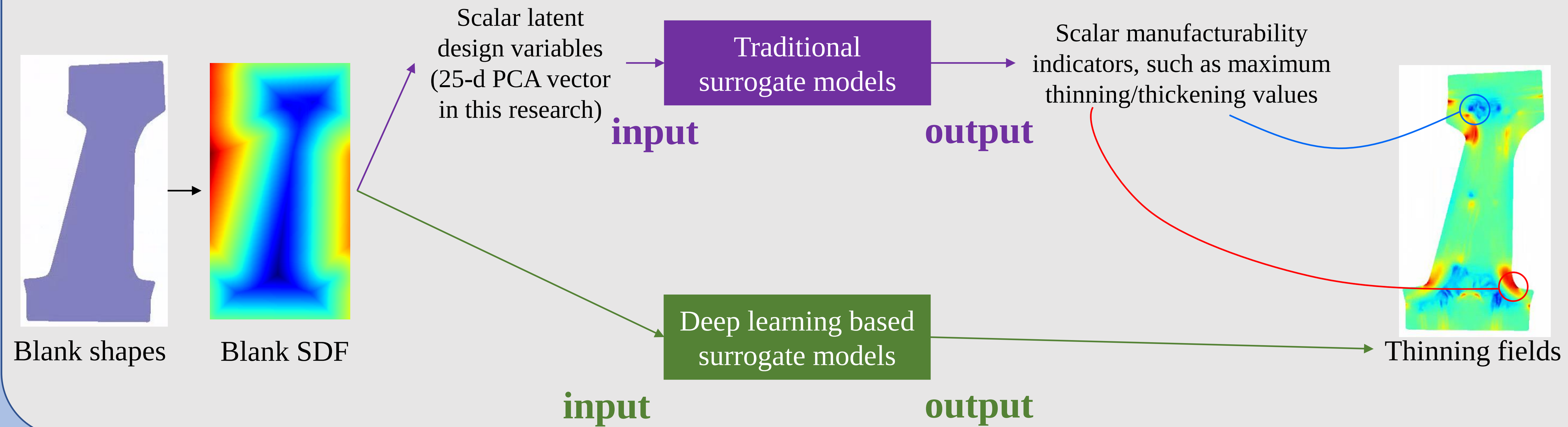
Hot stamping simulation setup PAM-STAMP

Thinning field plotted on the deformed blank configuration

Thinning field plotted on the undeformed blank configuration

3. Traditional (non-deep-learning) and deep learning based surrogate models

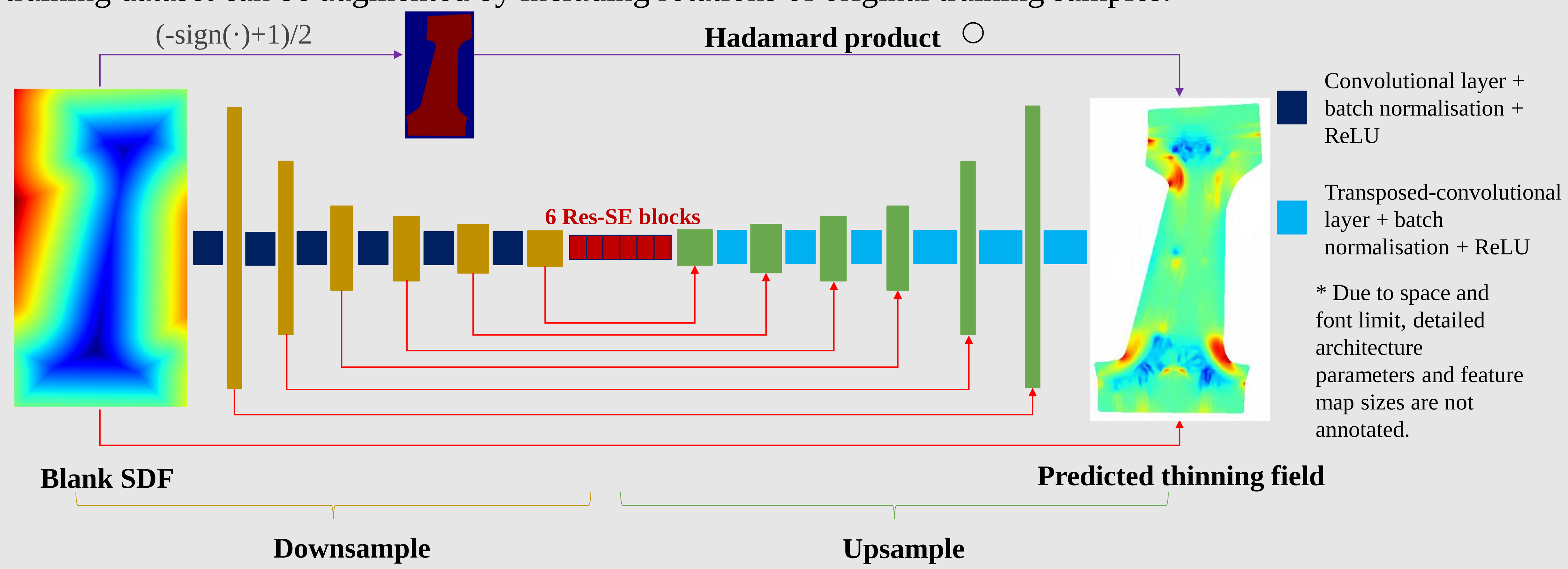
- Surrogate models, trained with a given simulation dataset, can predict the manufacturability indicators in real-time and automatically optimise the blank shape in a differentiable way.
- Traditional methods, such as Kriging (equivalent to Gaussian Process), only take scalar latent design variables as inputs, and output scalar manufacturability indicators (maximum thinning/thickening values). Due to the scalar input form, they cannot directly handle multiple-parameterised blank shapes.
- In contrast, deep learning based surrogate models utilise the natural structure of simulation data, with whole blank signed distance fields **(SDF)** as inputs and thinning fields as outputs. They can significantly enhance the accuracy, generalisability, informativeness of the surrogate models, as well as reduce the data requirement.



* The disadvantages of traditional surrogate models, when compared with deep learning based surrogate models, might be attributed to the information loss of scalar latent design variables and manufacturability indicators.

4. SDFMask-Res-SE-U-Net as a deep learning based surrogate model

- A specially-tailored CNN architecture, namely SDFMask-Res-SE-U-Net, takes an arbitrary blank SDF as input, and predicts the corresponding thinning field plotted on the undeformed blank configuration.
- Residual, squeeze-excitation blocks and skip connections, which are generally used in modern CNN architectures, can significantly enhance the performance of surrogate models.
- Non-blank regions of the rectangle output map are masked to be 0 using the input SDF.
- Training and test datasets comprise of a certain number of pairs of different blank SDFs and thinning fields. The training dataset can be augmented by including rotations of original training samples.



* Due to space and font limit, detailed architecture parameters and feature map sizes are not annotated.

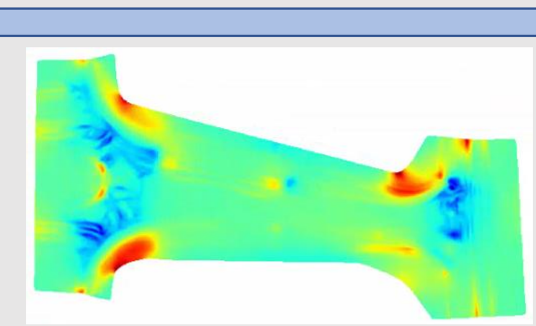
5. Comparing the prediction accuracy of maximum thinning/thickening

- SDFMask-Res-SE-U-Net outperforms Kriging even though the maximum thinning/thickening prediction is extracted from the predicted thinning field, rather than directly predicted.
- SDFMask-Res-SE-U-Net can achieve industrial-acceptable performance (both Mean AREMAT and AREMIT below 10%) using only 64 training samples, which indicates **the small-data learning nature of engineering AI tasks**. For details, please check https://openreview.net/forum?id=qvxJBCp7aji.
- Data augmentation (from 64 to 256 through 90deg, 180deg, 270deg rotation in this research) can significantly boost the prediction performance especially under small data.

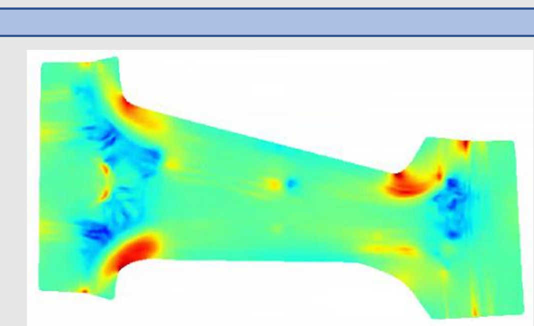
MREMAT: Mean relative error of maximum thinning on test samples
MREMIT: Mean relative error of minimum thinning on test samples

Model	Kriging	SDFMask-Res-SE-U-Net			
Training set size	256	64		256	
Test set size	1020 pairs of ground truth SDFs and simulation fields				
Augmentation	Augmentation not available	No	Yes	No	Yes
MREMAT	24.0%	10.1%	7.44%	5.79%	4.70%
MREMIT	41.7%	10.2%	9.77%	8.35%	8.04%

6. Visualisation of a test sample thinning field



Ground truth (simulation)



Deep learning prediction

Deep learning model accurately captures the thinning localisation and wrinkle behaviour.

Acknowledgement

SHOUGANG