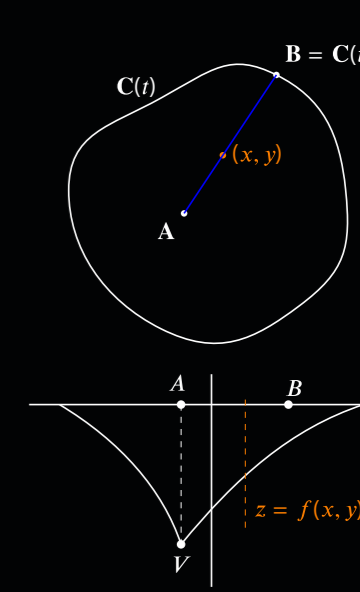


Problem and Motivation

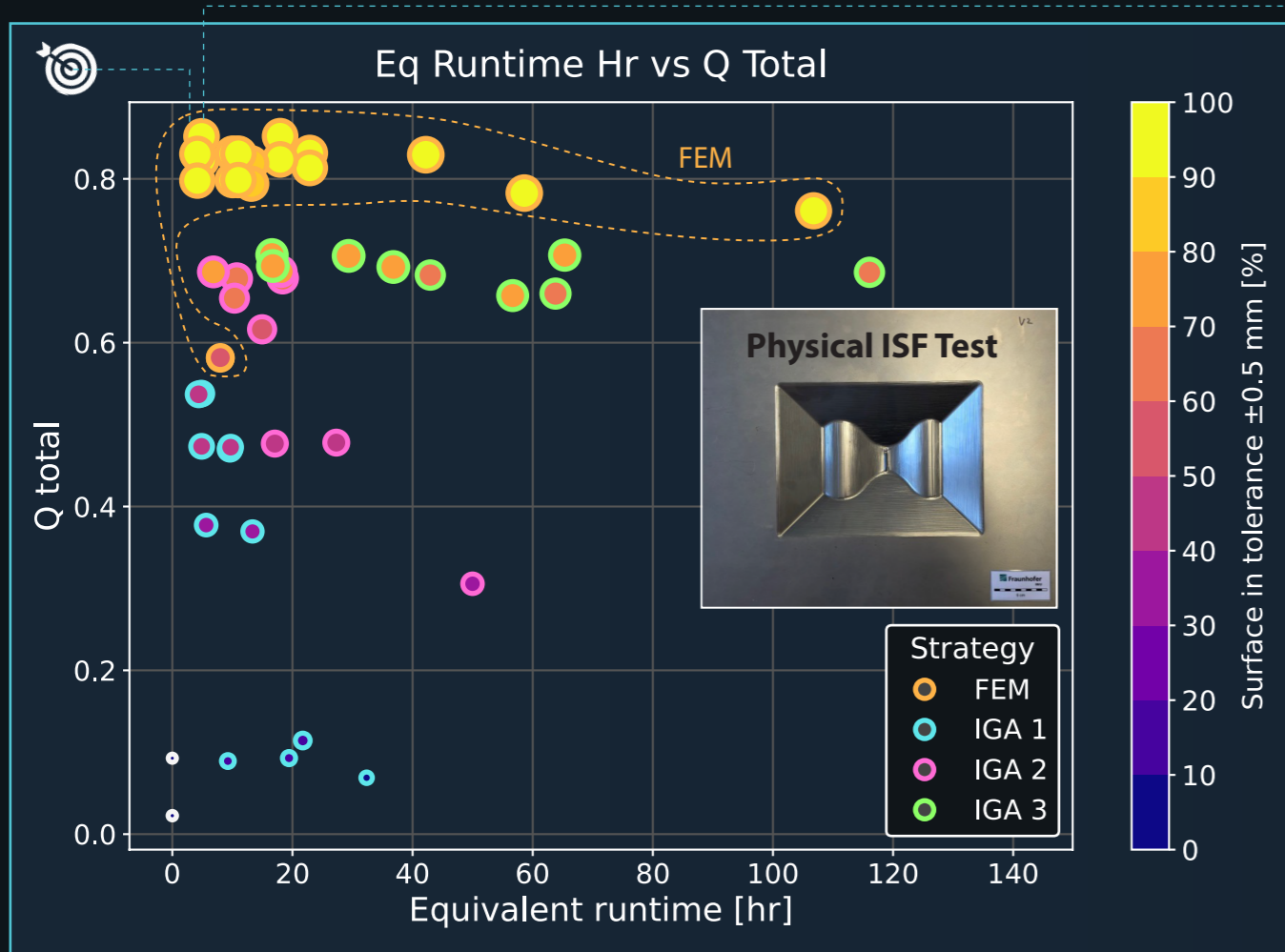
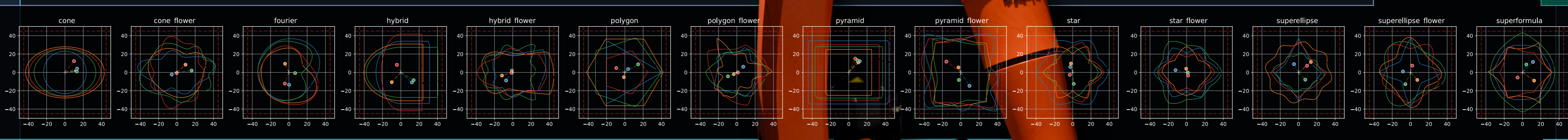
Incremental Sheet Metal Forming (ISMF) offers a flexible way to manufacture complex and customized metal parts without dedicated tooling, which is especially attractive for small-batch production and hybrid tooling concepts. However, the process is difficult to predict accurately because it involves strong nonlinear deformation, complex contact, material anisotropy, and springback. High-fidelity finite element simulations can capture these effects, but they are computationally too expensive for tasks that require evaluating many forming scenarios, such as toolpath optimization, process design, or die-shape compensation. This motivates the development of fast AI-based surrogate models trained on large-scale simulation data, enabling rapid prediction of sheet deformation while preserving the essential physical trends of the forming process.

1. Dataset Development

A fully automated data-generation pipeline was developed to create a large and structurally consistent ISMF dataset. For each sample, the die geometry was synthesized automatically, a corresponding Z-constant toolpath was generated, and all model components were converted into a complete LS-DYNA input deck with unified mesh, material, contact, and boundary-condition definitions.



Die Geometry and Shape Taxonomy

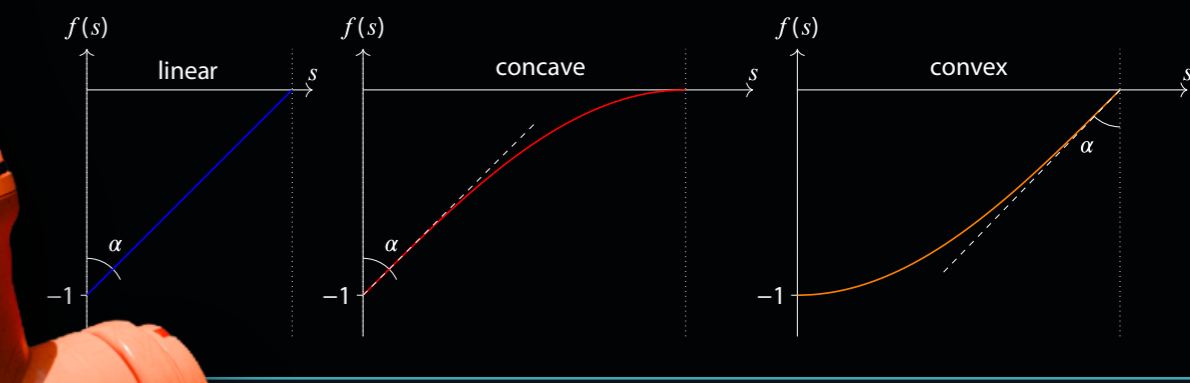


Strategies for acceleration of ISF simulation to identify the most efficient setup for rapid dataset generation.

- Multiple-tool: 1, 4, or 8 fictitious tools
- Parallelization setup: 4 SMP, or 4 / 16 MPI
- FEM or IGA with three different meshes
- Tool acceleration - mass scaling

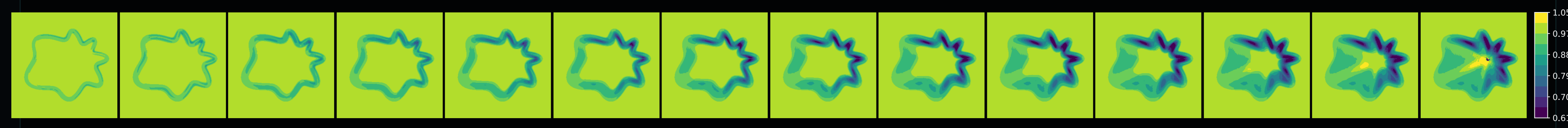
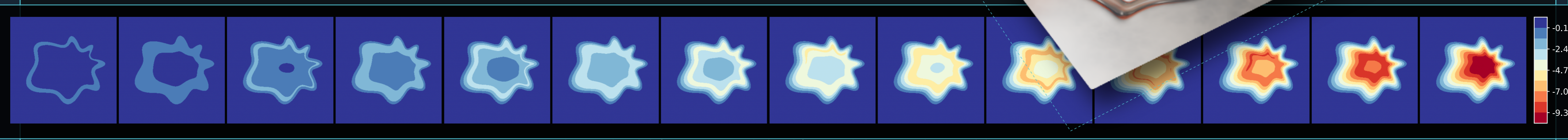
Set Strategy

Trajectory

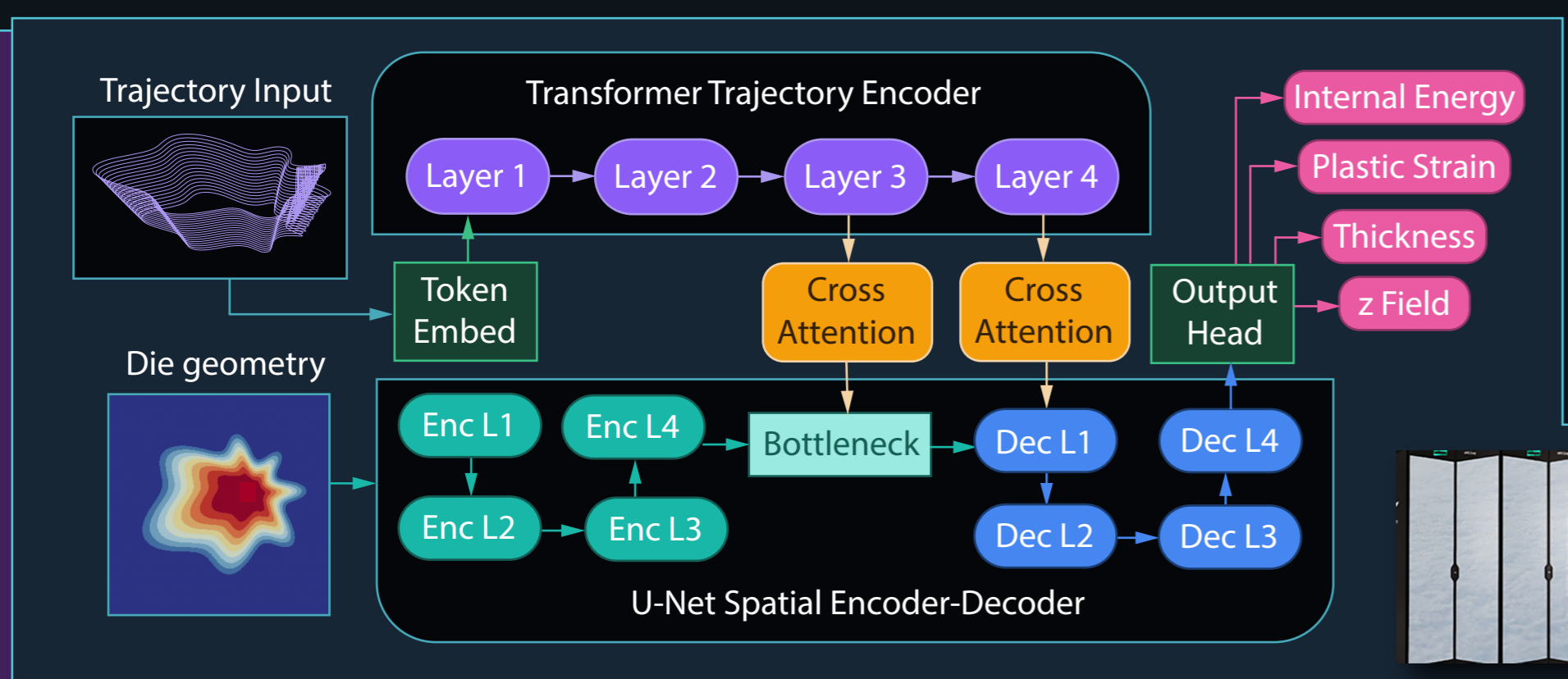


2. FEM Data Generation

The generated models were solved using high-fidelity explicit FEM simulations to capture the deformation of the sheet during forming. Automated post-processing then extracted intermediate and final geometries in a uniform format, producing a large-scale dataset suitable for training and validation of the surrogate AI model.



Transformer Cross Attention U-net



Model Generalization

The surrogate was trained on the full dataset containing both flat-bottom and wavy-bottom geometries

Training the surrogate only on samples with flat-bottom geometries and evaluating it on unseen wavy-bottom cases.

The dataset consists of 4,517 FEM simulations, of which 1,975 correspond to geometries with a flat-bottom die. The FEM simulations were performed on the Karolina cluster, while surrogate-model training was carried out on LUMI up to 160 GPUs.

TCAU variant model	Train dataset	Validation dataset	Test dataset	Total dataset	TCAU variant model	Number of GPUs	Peak VRAM [GiB]	Disk size [GiB]	Samples/s	Epoch time [min]	Epoch at target	GPU hours [h]
Final-time	4117 (91.14%)	200 (4.43%)	200 (4.43%)	4517 (100.00%)	Final-time	1	48.23	5.76	11.1	7.23	481	57.96
Fully time-resolved	15045338 (90.93%)	729681 (4.41%)	771047 (4.66%)	16546066 (100.00%)	Fully time-resolved	160	64.02	7407.1	201.5	986.38	5	13151.73

Dataset split used for training, validation and testing. Training-time memory usage, storage requirements, and computational cost of TCAU.

