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Vacuum bag leak detection with geometry-informed machine learning

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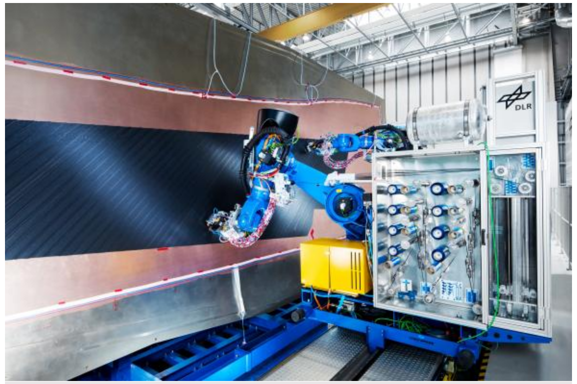
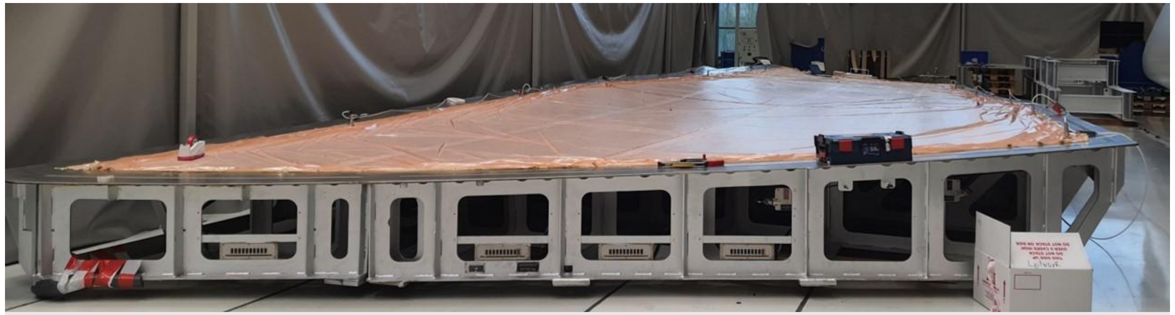
Motivation: Vacuum leak detection in CFRP manufacturing

- AFP- or ATL-laid prepreg laminate is vacuum-bagged on the mold prior to autoclave curing
- The vacuum bag is evacuated while heat and external pressure are applied in the autoclave
- Leaks in the vacuum bag can reduce laminate compaction and promote void formation, degrading the mechanical performance of the part
- Therefore, all vacuum leaks must be detected and repaired before the autoclave cure cycle begins



AFP / ATL

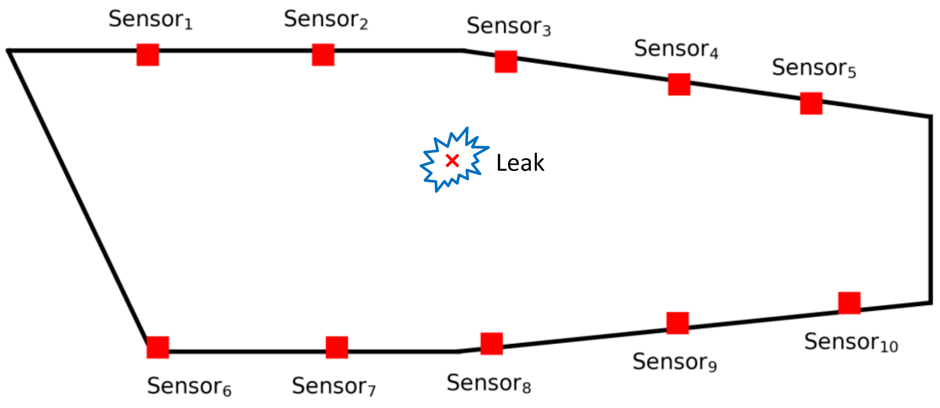
Autoclave curing



Vacuum bagging

Data-driven leak detection

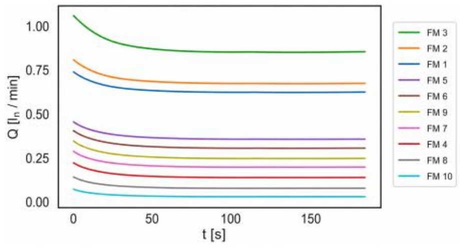
- Manual approaches (e.g., helium, ultrasonic, and thermographic leak testing) can be slow, making leak detection a potential bottleneck [Haschenburger & Heim2019]
- Flow meters can monitor the air flow at different vacuum connections, providing data that can be used to automate leak detection [Haschenburger et al.2021]
- Hand-crafted and machine learning-based approaches have been proposed in recent years [Haschenburger2022, Haschenburger et al.2022, Brauer et al.2022, Naveenachandran2023]



Wing cover mold with flow meters at vacuum connections

Mass flow meter

AI-generated symbolic image, no actual device



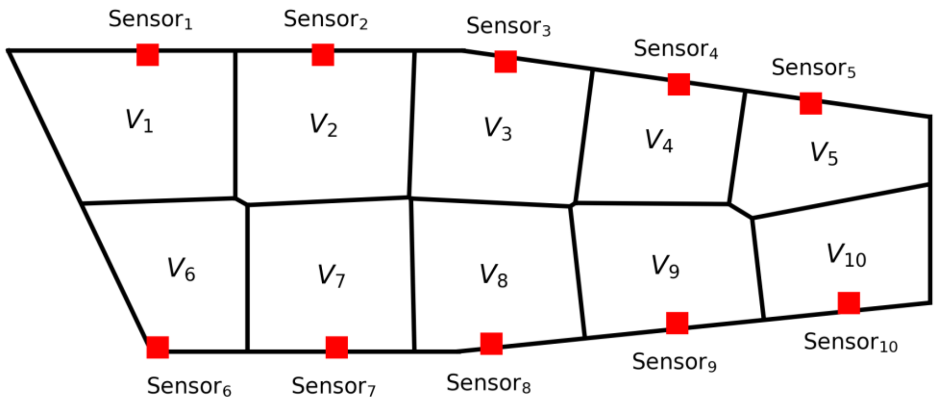
Flow measurements

Voronoi diagrams for leak detection

- The approach of [Haschenburger et al.2019] implicitly relies on the assumption:

If there is a leak, it will be closest to the vacuum port with the largest air flow.

- This assumption can be formalized using a well-known concept from discrete geometry: **Voronoi diagrams** [Brauer et al.2026]
- A Voronoi diagram partitions the mold surface into Voronoi regions V_k, each containing the locations closest to a particular vacuum connection

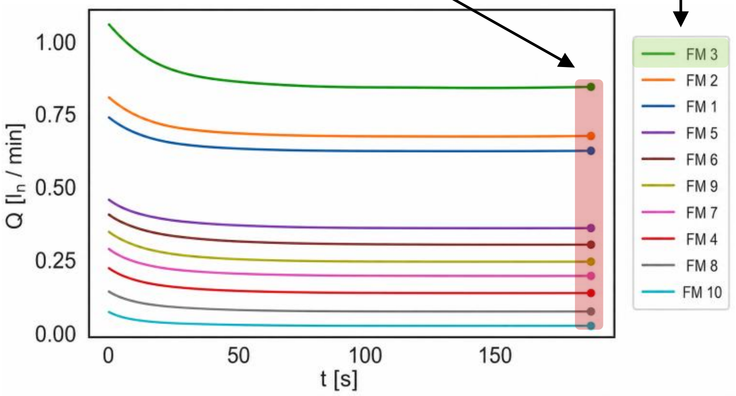


Voronoi diagram of sensor positions on the mold geometry

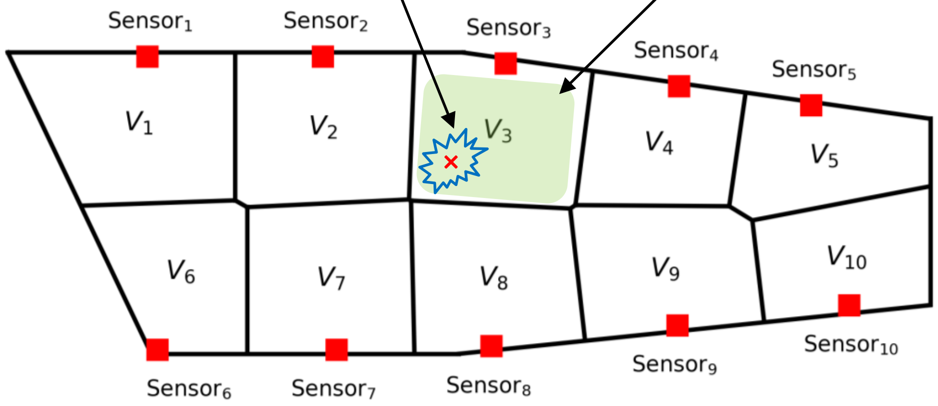
$$V_k := \{\boldsymbol{y} \in \mathbb{R}^2 \mid \|\boldsymbol{y} - \boldsymbol{p}_k\| \leq \|\boldsymbol{y} - \boldsymbol{p}_l\| \ \text{ for all } \ l \neq k\}$$

Voronoi-informed regression

$\boldsymbol{x} = (x_1, \ldots, x_d)$ $\quad$ $\mathrm{argmax}(\boldsymbol{x})$



$f_{\boldsymbol{\theta}}(\boldsymbol{x}) = (y_1, y_2) \quad \in \quad V_{\mathrm{argmax}(\boldsymbol{x})}$

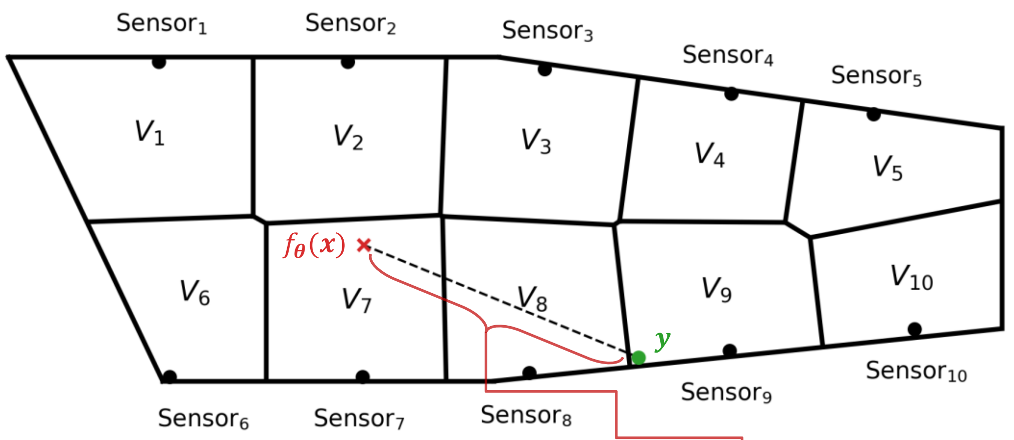


Train a machine learning model $f_{\boldsymbol{\theta}}$ that predicts two-dimensional leak coordinates subject to the following logical rule:

$$\boxed{\mathrm{argmax}(\boldsymbol{x}) = k \implies f_{\boldsymbol{\theta}}(\boldsymbol{x}) \in V_k}$$

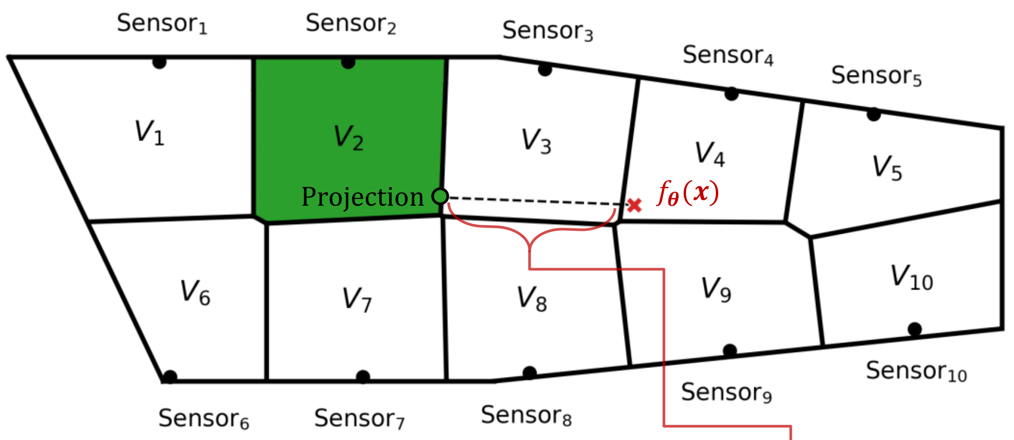
Incorporating the rule into the model

Data fidelity loss term



$$\mathrm{MSE}_{\mathrm{data}} = \frac{1}{|\mathrm{data}|} \sum_{(\boldsymbol{x},\boldsymbol{y})\in \mathrm{data}} \|\boldsymbol{y} - f_{\boldsymbol{\theta}}(\boldsymbol{x})\|^2$$

Knowledge-based loss term



$$\mathrm{MSE}_{\mathrm{info}} = \frac{1}{|\mathrm{samples}|} \sum_{\boldsymbol{x}\in \mathrm{samples}} \left\| \mathrm{proj}_{V_{\mathrm{argmax}(\boldsymbol{x})}}\big(f_{\boldsymbol{\theta}}(\boldsymbol{x})\big) - f_{\boldsymbol{\theta}}(\boldsymbol{x}) \right\|^2$$

$$\boxed{\underset{\boldsymbol{\theta}}{\mathrm{minimize}} \quad \lambda_{\mathrm{data}}\mathrm{MSE}_{\mathrm{data}} + \lambda_{\mathrm{info}}\mathrm{MSE}_{\mathrm{info}}}$$

from suitable input distribution $\mathcal{D}$

Empirical data collection

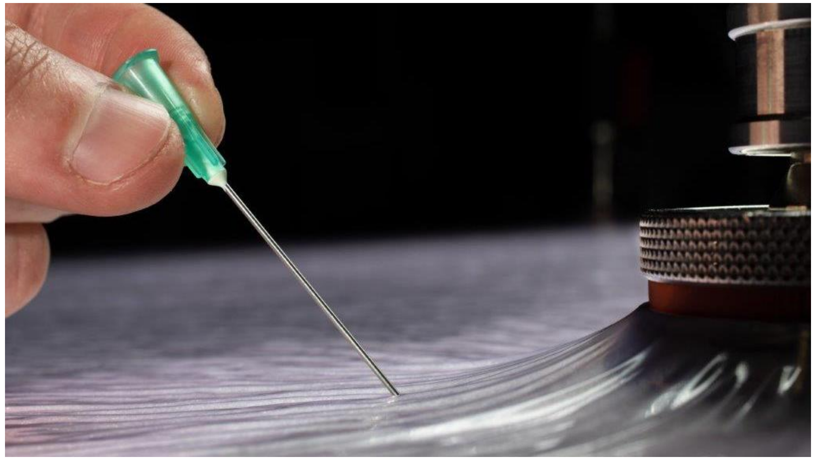
Wing cover

- 16 x 5.2 m
- 512 input-output pairs $(\boldsymbol{x}, \boldsymbol{y})$
- 420 train, 47 validation, 45 test
- Used by [Naveenachandran2023, Brauer et al.2026]

Square

- 1.5 x 1.5 m
- 317 input-output pairs $(\boldsymbol{x}, \boldsymbol{y})$
- 256 train, 47 validation, 45 test
- Used by [Haschenburger2022, Haschenburger et al.2022, Brauer et al.2022]

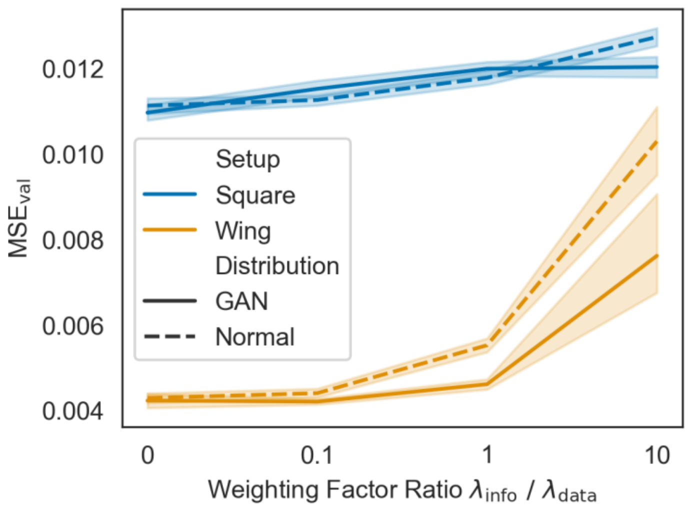
Process



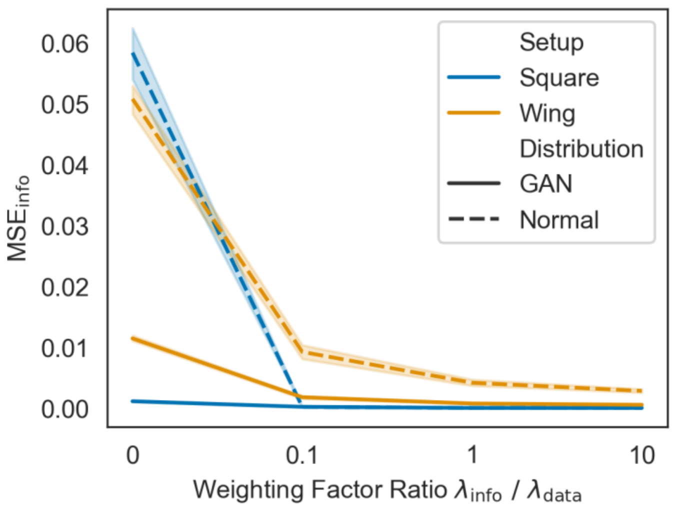
- Start with tight vacuum
- Introduce a leak using a hypodermic needle
- Record leak position and flow measurements
- Patch leak and repeat

Numerical results

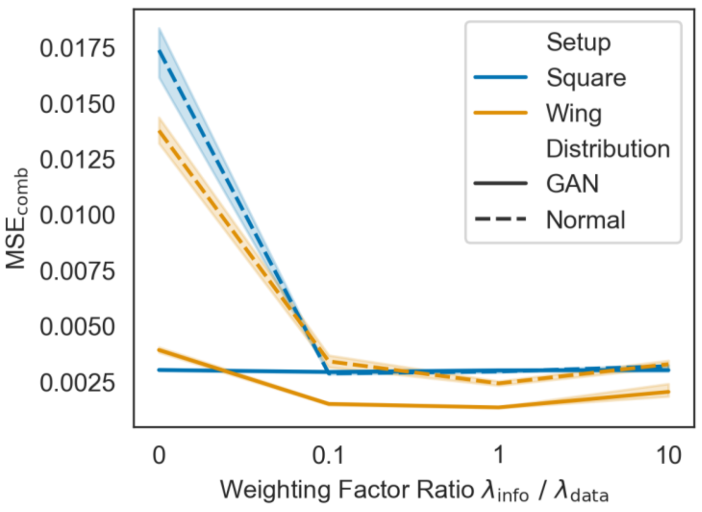
Data fidelity loss



Knowledge-based loss

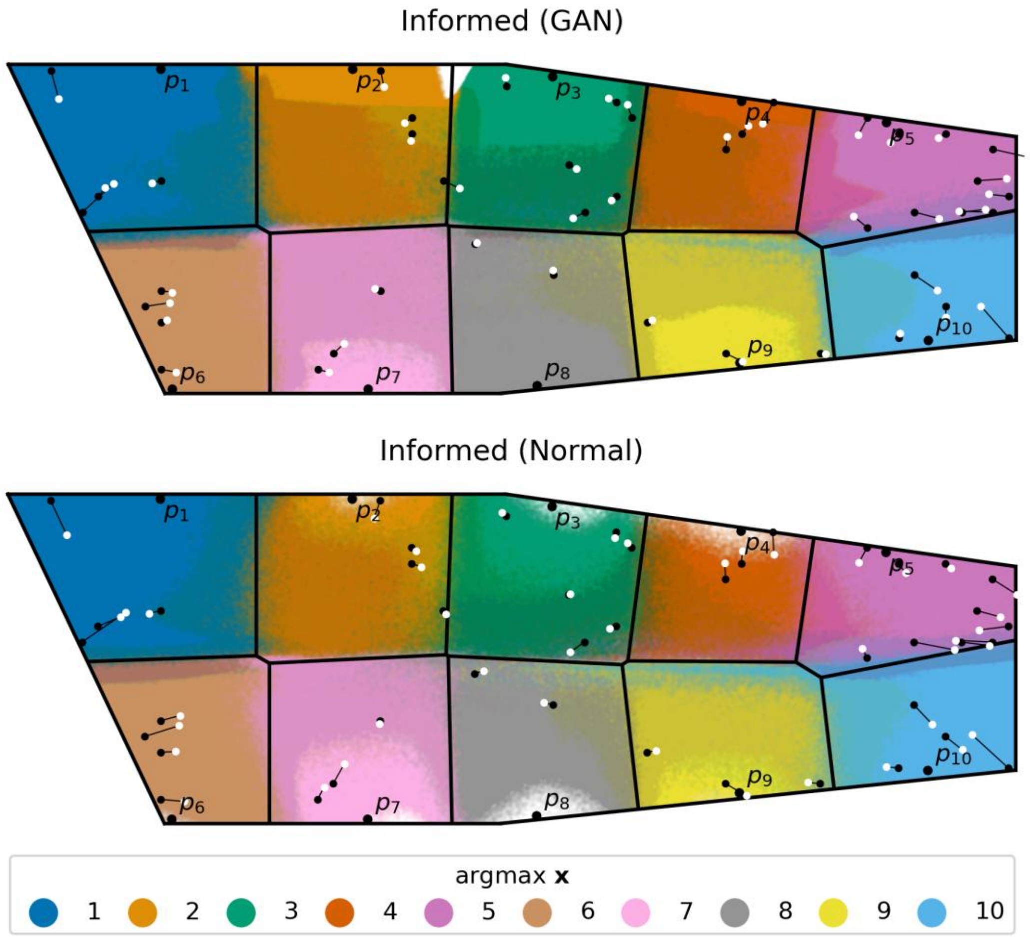


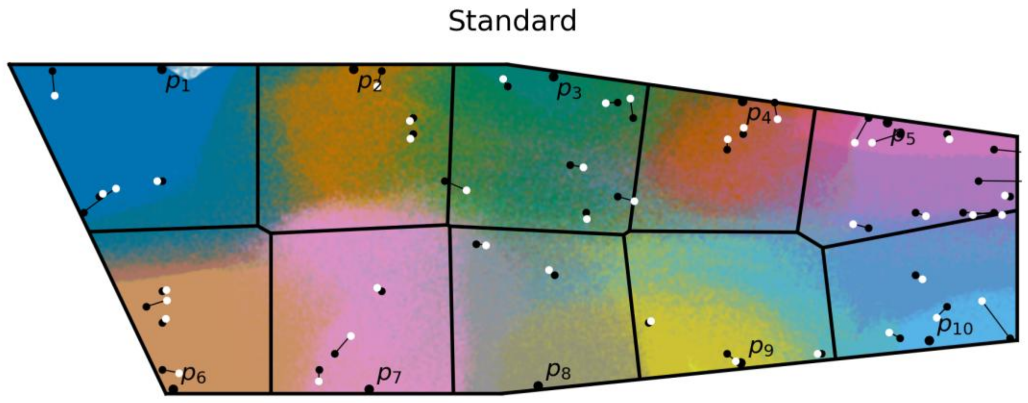
Both combined (50 / 50)



- Trained **100 neural networks** for each combination of {Square, Wing} x **{GAN input distribution, Normal input distribution}**
- 100 models = **10 trials** for each combination of **3 positive weighting ratios** and **3 batch sizes**, plus **10 uninformed models**
- Selected three best-performing uninformed and informed models for each dataset based on combined metric

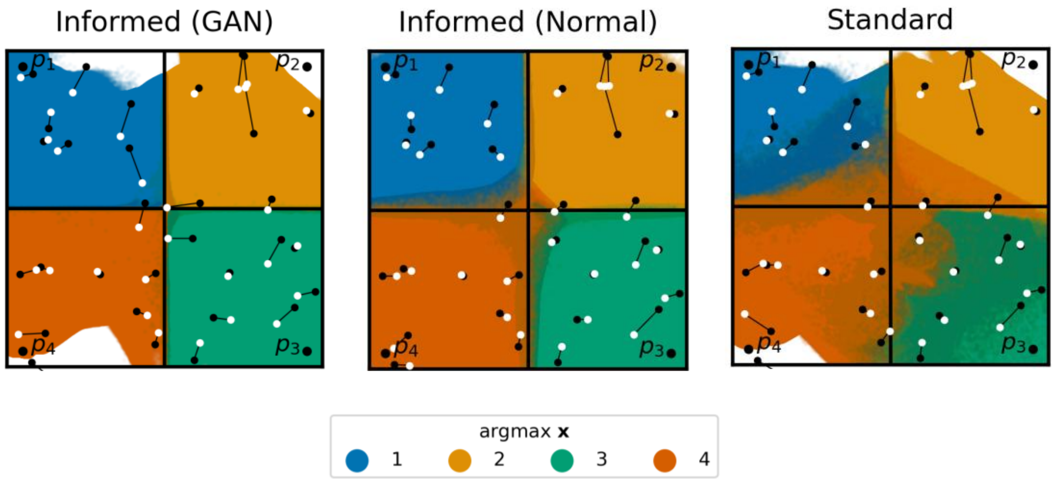
Selected models wing experiment





Distr.	$\frac{\lambda_{\text{info}}}{\lambda_{\text{data}}}$	b_{info}	MSE_{test}	MSE_{info}	MSE_{comb}
-	0	-	0.006176	0.012433	0.004652
Normal	1	64	0.007841	0.002491	0.002583
GAN	1	32	**0.005996**	**0.000634**	**0.001658**

Selected models square experiment



Distr.	$\frac{\lambda_{info}}{\lambda_{data}}$	b_{info}	MSE_{test}	MSE_{info}	MSE_{comb}
-	0	-	0.015540	0.001198	0.004185
Normal	0.1	64	**0.013971**	0.000047	**0.003505**
GAN	10	64	0.019991	**0**	0.004998

Takeaways

- Voronoi diagrams mitigate the leakage detection bottleneck in composite manufacturing
- Voronoi-informed regression models consistently outperform standard neural network models
- Future work: multi-leak scenarios, anisotropic flow, curved surfaces, and adaptive Voronoi diagrams

References

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[Brauer et al.2026] C. Brauer, A. Hindersmann, T. de Wolff, Voronoi-based vacuum leakage detection in composite manufacturing, arXiv:2603.29980 (2026).

Code: https://github.com/chrbraue/leakage_detection

THANK YOU!

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