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Usage of Machine Learning for Subtopology Detection in Wire and Arc Additive Manufacturing

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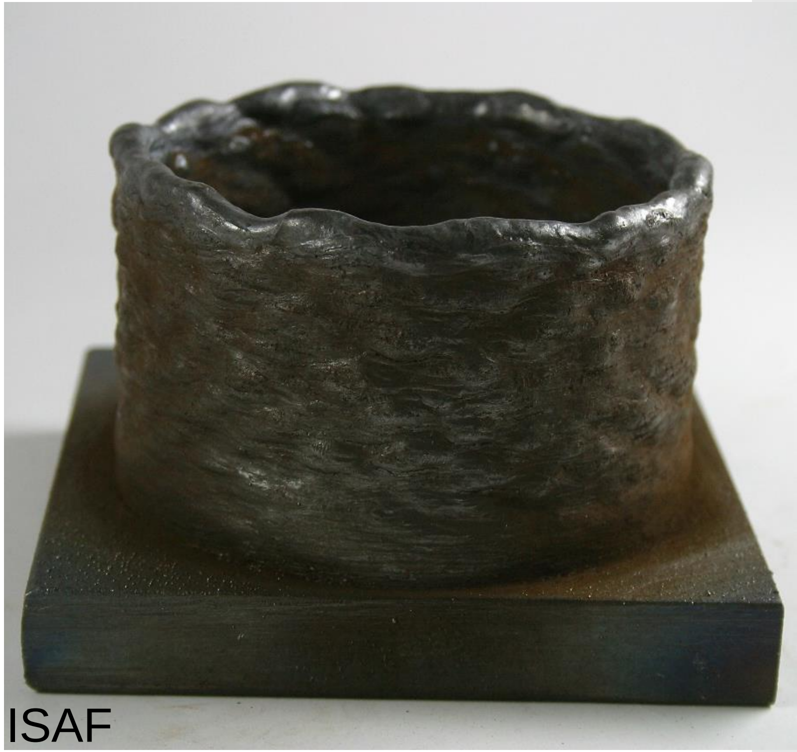
Introduction

- Motivation: Wire Arc Additive Manufacturing
- Multilayer welding
  - Geometry deviation propagate
- In-situ compensation possible
  - But detection required
- Monitoring with sensors (e.g. [6-9])
  - Additional sensors necessary
  - Costs, complexity of the system

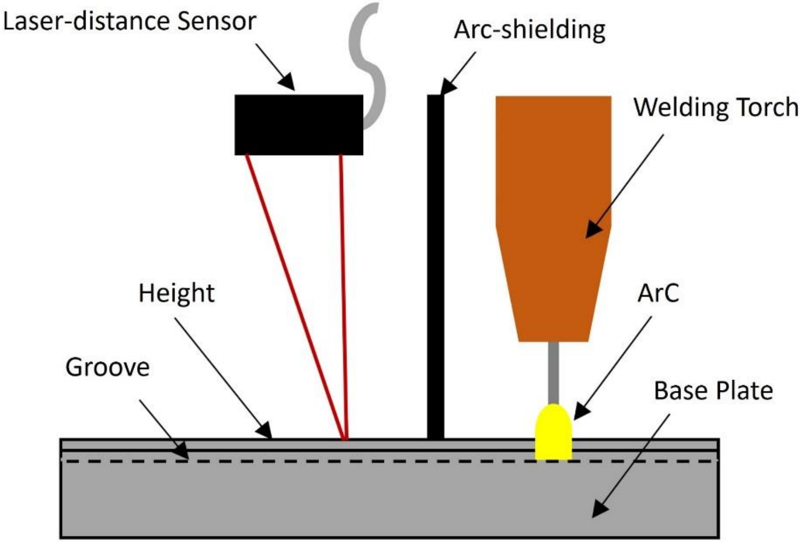


Einleitung

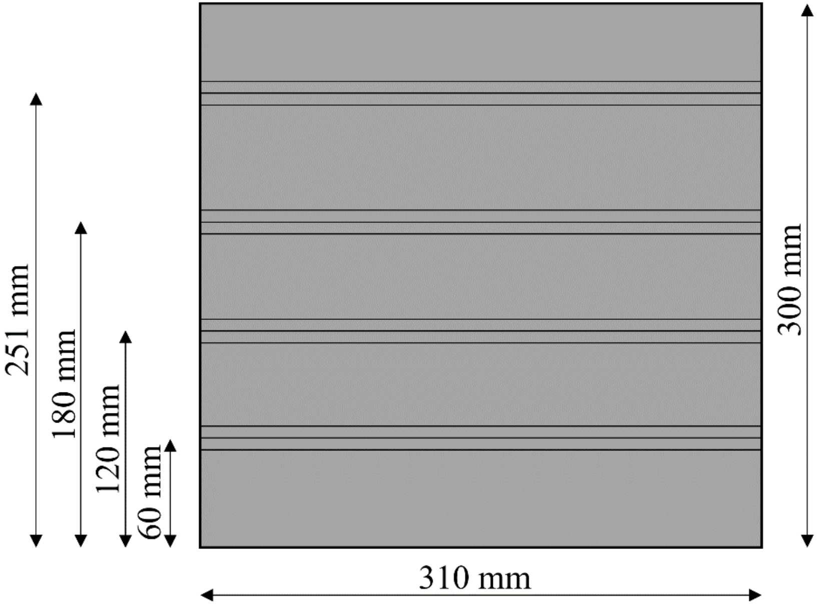
- Our approach:
  - Subtopology detection
  - Based on current and voltage
  - Use of artificial intelligence with memory (LSTM)

- Artificial intelligence for the welding process [12 - 22].
  - Mostly static consideration
  - Current/voltage (t) -> Subtopology (t): not yet considered.

principle sketch of the experiment

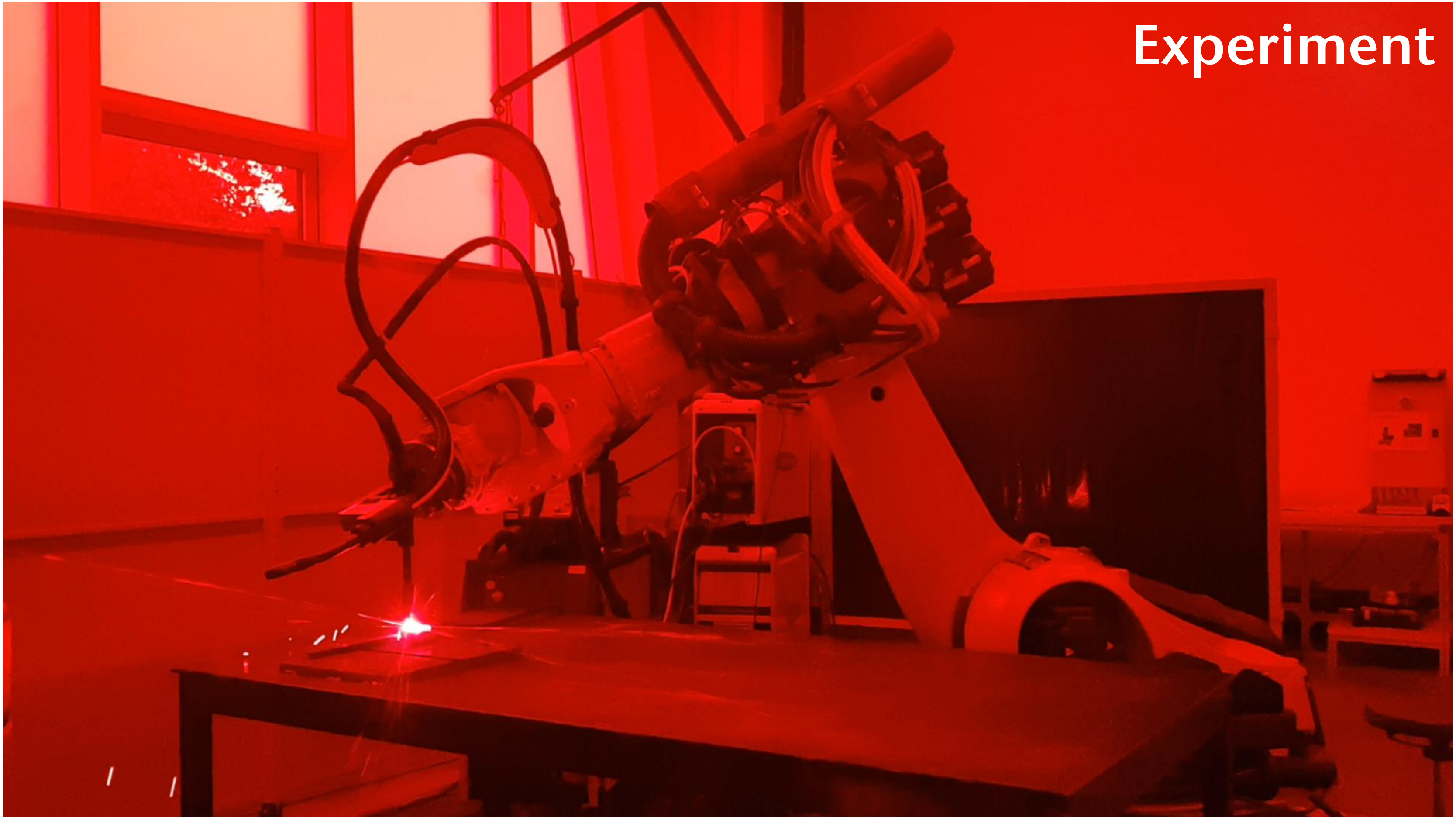


experimental setup



substrate plate

Experiment

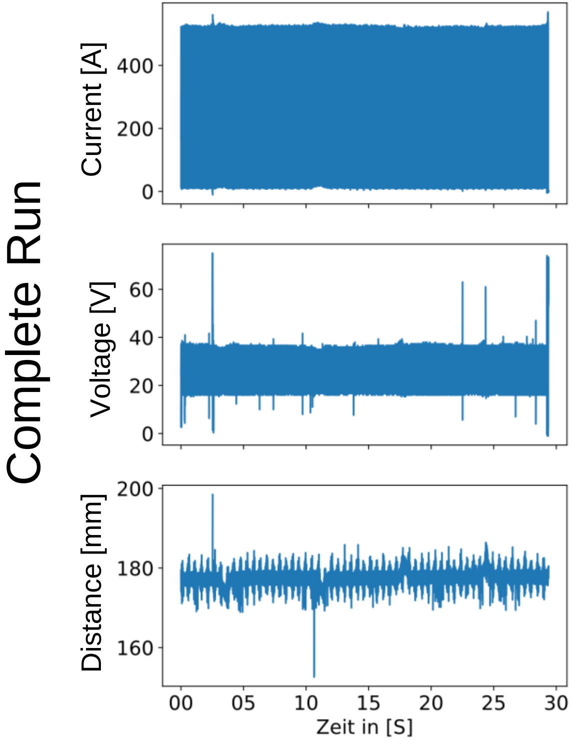


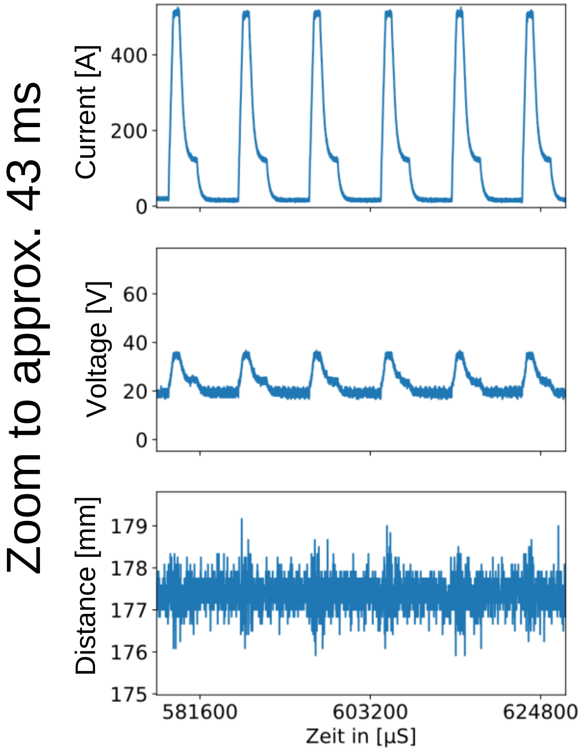
Experimental Conditions

Run. Nr.	Wire feed speed	Current	Voltage	Welding Mode
1	4,5	93	17,0	Impulse
2	4,5	93	17,0	Impulse
3	4,5	93	17,1	Impulse
4	4,8	136	14,5	Standard
5	4,8	136	14,5	Standard
6	4,8	136	14,6	Standard
7	7,0	171	16,2	Standard
8	1,7	37	14,7	Impulse
9	1,7	37	14,2	Impulse
10	1,7	37	15,2	Impulse

Experiments – Welds

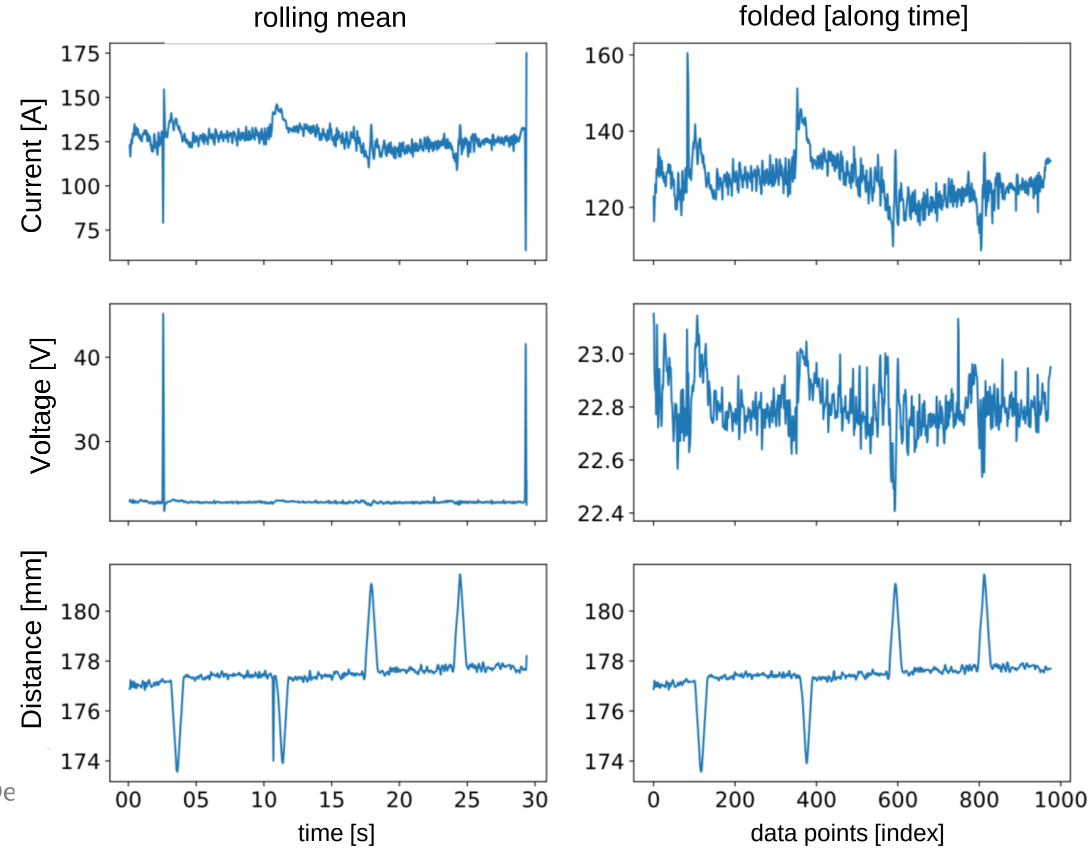
Aquired Data



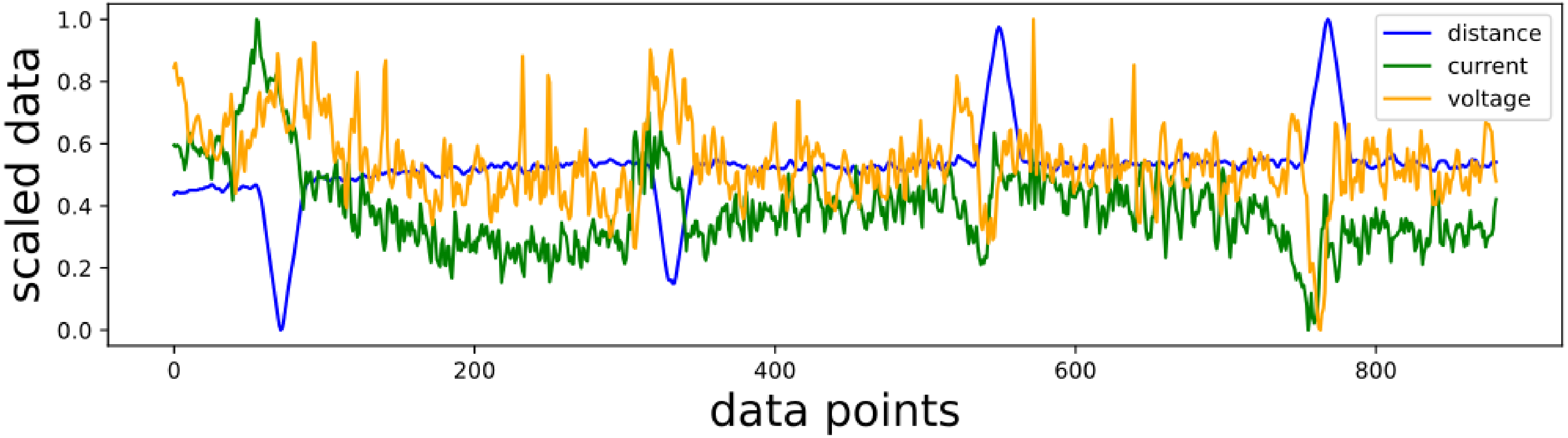


Methodology: Artificial Intelligence - Preprocessing

- **Smoothing:** rolling mean
- **Reduction:** folding of data along time



Methodology: Artificial Intelligence - Preprocessing

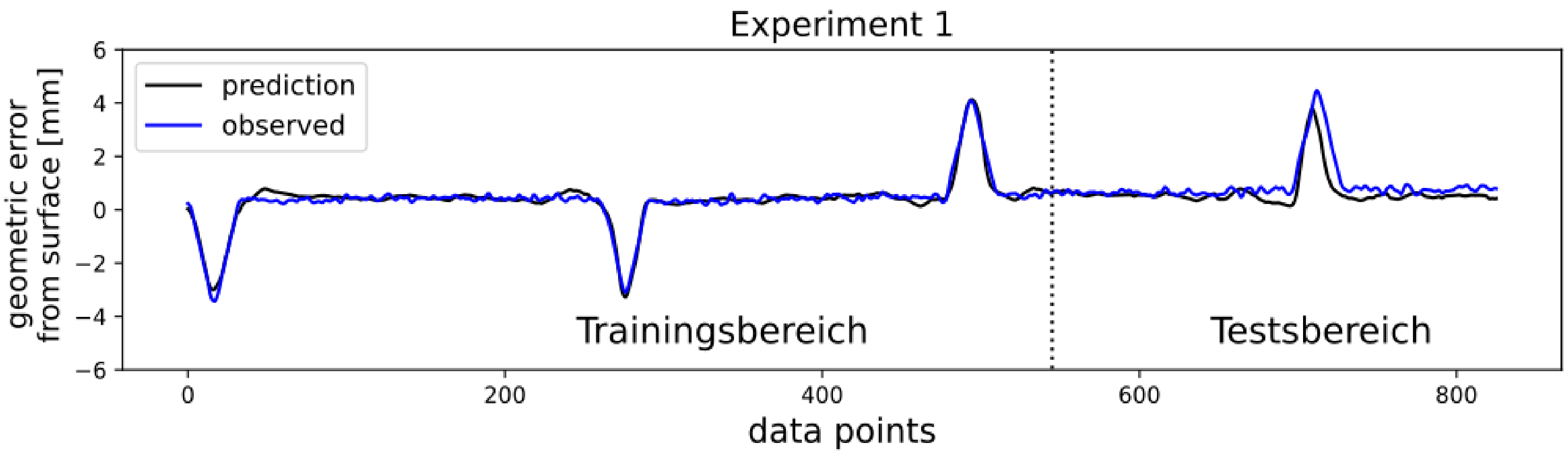


Methodology: Artificial Intelligence

Layer	N	Description
Input	50x2	history **current/voltage**
Hidden 1	50	LSTM
Hidden 2	20	LSTM
Output	1	Prediction of **distance**

- Loss function : Mean Squared Error (MSE)
- Optimizer for training : ADAM
- Regularization (model 8 only) : L2 = 0.1
- Software Framework : KERAS; Python

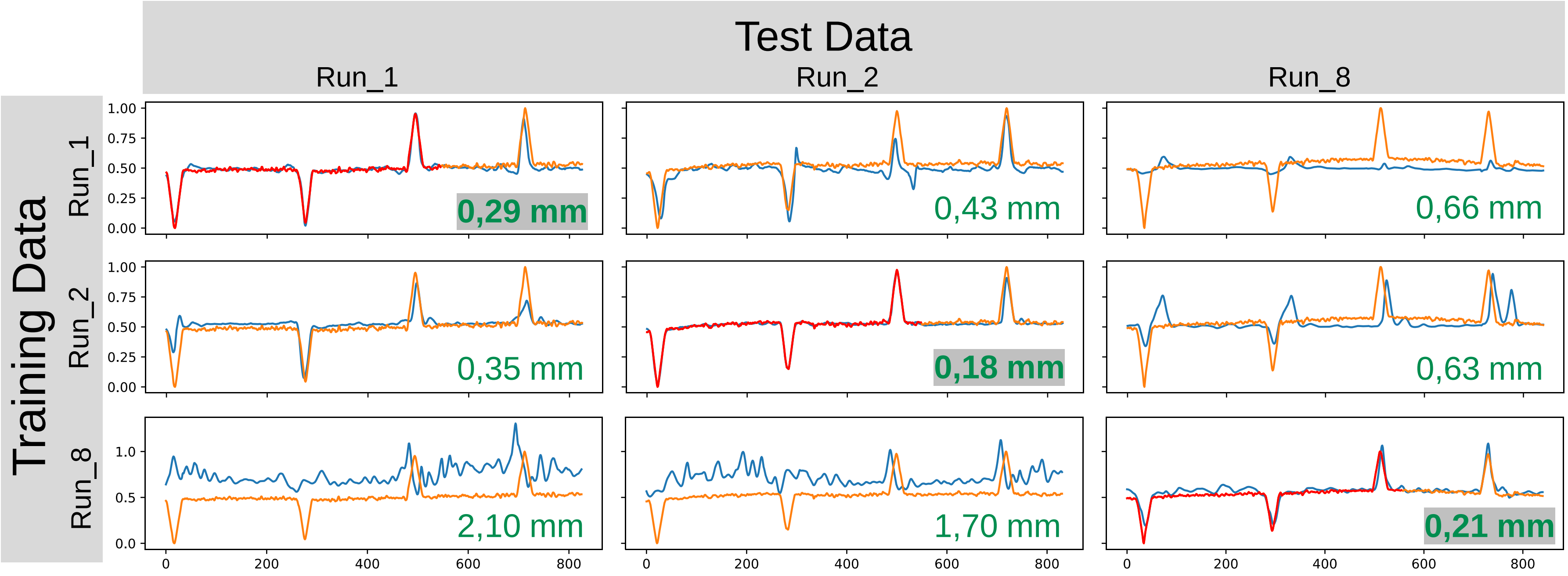
Results


Experiment 1
prediction
observed
geometric error
from surface [mm]
6
4
2
0
−2
−4
−6
Trainingsbereich
Testsbereich
0
200
400
600
800
data points

Results - Standard Welding

Mean Squared Error

Results – Impulse Welding



Mean Squared Error

Conclusion

- Neural networks for geometry detection in MSG welding
  - High accuracy (<0.3mm) possible when predicting the subtopology
  - Evaluation in real time
  - Only limited database necessary
  - Learned models partially transferable to modified process parameters

- Long-term goal:
  - Application to wire arc additive manufacturing
  - Spectrum of the arc as additional input
  - Preciction of further quality properties

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