HOW CAN NEXT-GENERATION TECHNOLOGIES SERVE HELIOSTAT METROLOGY?

Marc Röger, Michael Nieslony, Alexander Schnerring, Rafal Broda, Eduardo Saez, Niels Algner, Jan Lewen, Max Pargmann, Daniel Maldonado Quinto

SPIE Optics + Photonics, San Diego, CA, Aug. 06, 2025

DLR

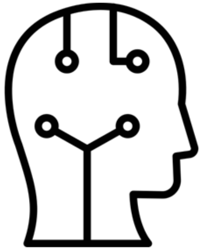
Introduction
How can next-generation technologies serve heliostat metrology?

Industrial Revolutions:

- 1st: Hand production → machines
- 2nd: Mass production, assembly lines and electricity
- 3rd: Automation and electronics in manufacturing, computers

The way this presentation was prepared ….

- 4th: Integration of Artificial Intelligence, robotics, Internet of Things (IoT), and biotechnology



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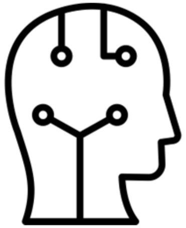


Icon: https://www.flaticon.com/free-icons/creative-user. Icon created by VectorPortal – Flaticon

Increased availability of

Computing resources to process and store data
&
Data

allows →

Increased use of

Artificial Intelligence/ Machine Learning,
&
Digital Twins

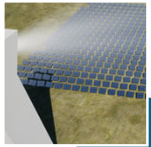
speeds-up → Development cycles

reduces → Risks and costs

creates → more accurate, efficient, and innovative systems

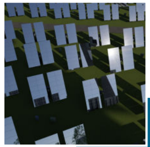
Overview of Talk
How can next-generation technologies serve heliostat metrology?

- Three examples of DLR work for the use of AI or digital twins in central receiver technology:



Example 1

- How we develop an airborne heliostat metrology system in a fast and safe manner without the necessity to fly in a real power plant ?



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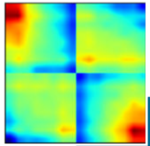
- How we train an AI network without having large amounts of labelled data ?



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- How well work data-driven AI models compared to physical models in the case of heliostats?

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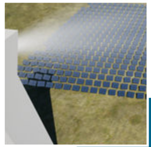

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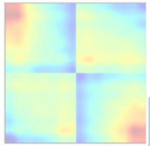


Example 3

- How well work data-driven AI models compared to physical models in the case of heliostats?

Example 1: UAV based system development with a digital twin

- Challenge: The classical development of metrology with unmanned airborne vehicles (UAV) is often time-consuming and dangerous, especially in CST and when mirror reflections are used
- Solution: Implementation and validation of a digital twin of UAV and CST plant and its use for metrology development

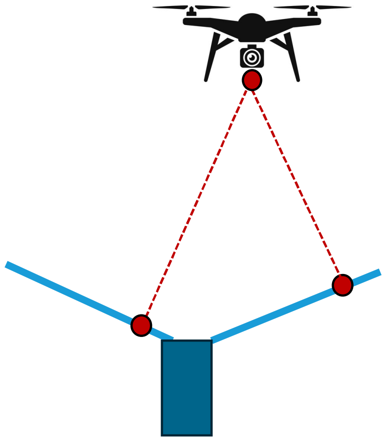
Work from:
Schnerring, A., Broda R., Winter, A., Nieslony, M., Krauth, J., Röger, M., Kallio, R., Pitz-Paal, R., A Simulation Environment for UAV-Based Real-Time Condition Monitoring of Central Receiver Solar Tower Power Plants, Solar Energy, accepted, 2025

Schnerring, A., Broda R., Nieslony, M., Algner, N., Saez, E., Röger, M., Kallio, R., Pitz-Paal, R., ARTSCORE: Airborne Real-Time Solar Concentrator Orientation Estimation, paper, in preparation

Example 1: UAV based system development with a digital twin
Components of the digital twin

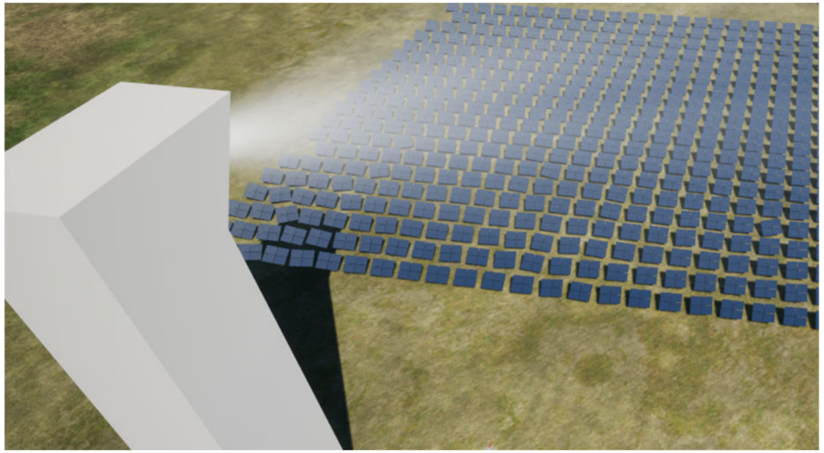
- ***Component 1: Scenery and Camera***
  - Heliostat geometric and kinematic model
  - Point light source reflection model
  - Camera model

  Uses Python



- ***Component 2: Perception Model***
  - Includes UAV flight physics and flight commands in simulation loop
  - Creates photorealistic images together with component 1

  Uses Unreal Engine + AirSim + ArduPilot SITL



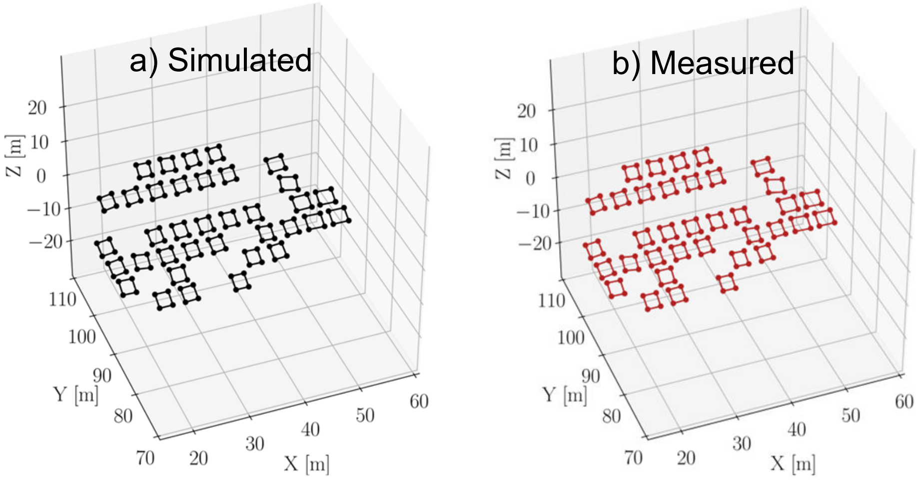
Example 1: UAV based system development with a digital twin

Validation of the digital twin

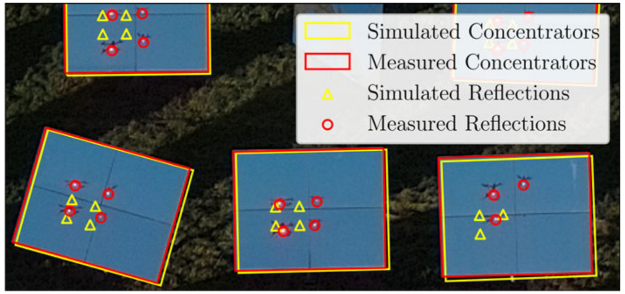
- Heliostat kinematic model: Simulated concentrator corner points match the measured points up to

$$\mathbf{RMSE} \approx \mathbf{24mm}$$

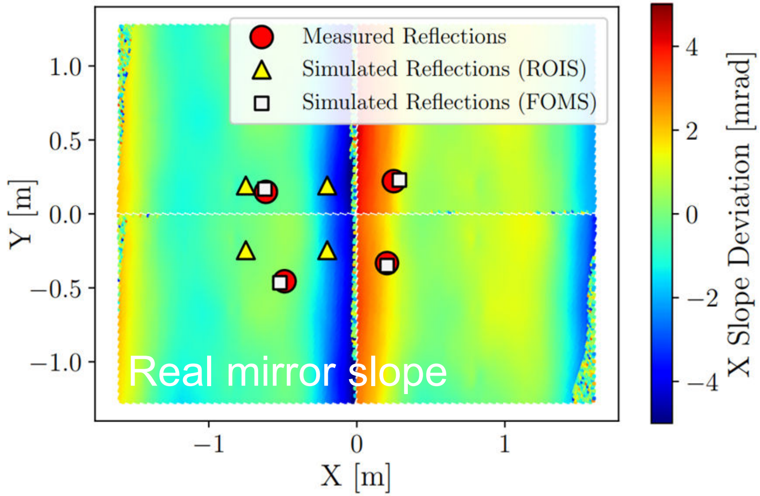
3D concentrator corner points



- Simulated point light reflections match the measured reflections up to
  - $\mathbf{RMSE_X \approx 0.35mrad}$
  - $\mathbf{RMSE_Y \approx 0.22mrad}$



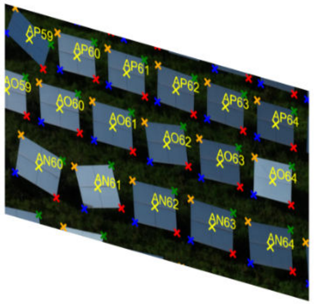
Flat mirror facets assumed



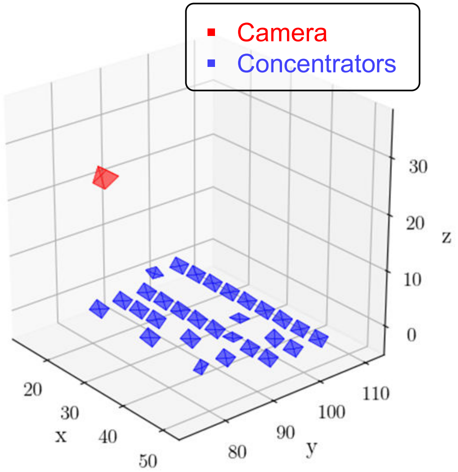
Example 1: UAV based system development with a digital twin
Development 1: Coarse calibration system

Pre-calibration / coarse system (accuracy in ~3-10mrad range)

- Estimate coarse concentrator orientations and camera pose in **real-time** using
  - Detected concentrator corner points
  - & known heliostat positions, kinematic system and geometry (patent pending)
- System was developed in digital twin and tested on real data
- Applicable to single image, or averaging over multiple images



Step 1:
Imagewise concentrator orientation estimation



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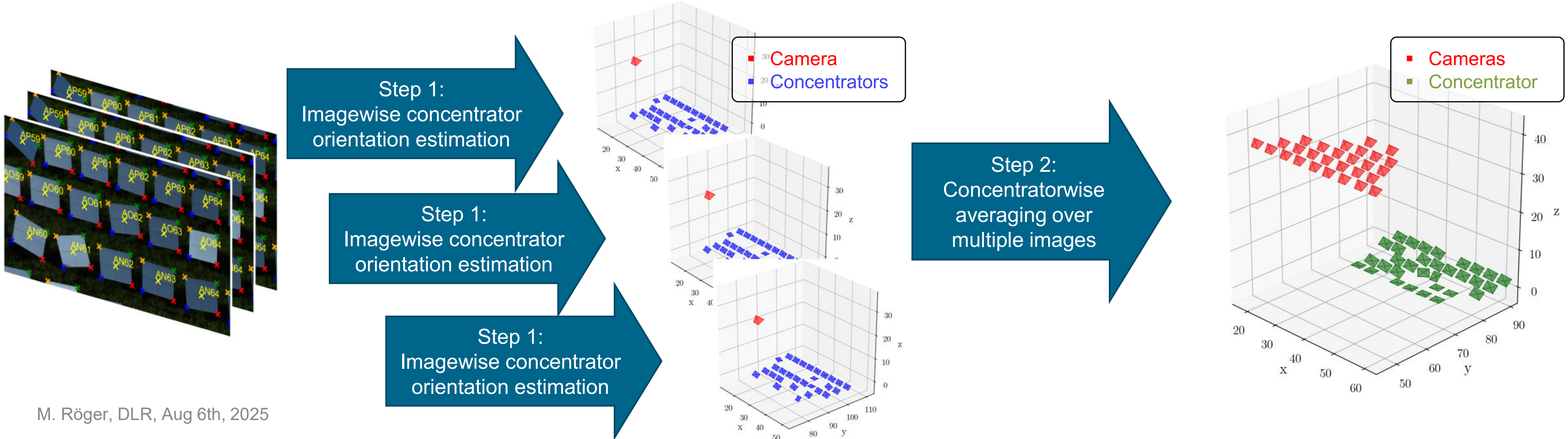
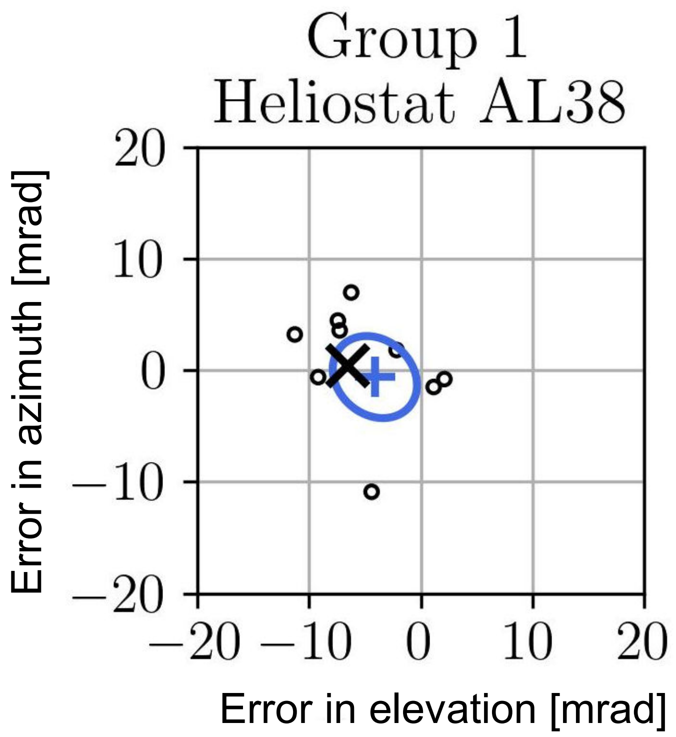


Example 1: UAV based system development with a digital twin
Development 1: Coarse calibration system - Validation

- Digital twin enables statistical analysis by exploring many scenarios in Monte-Carlo simulations

Black: Results of validation flight
Blue: Results of Monte-Carlo simulations

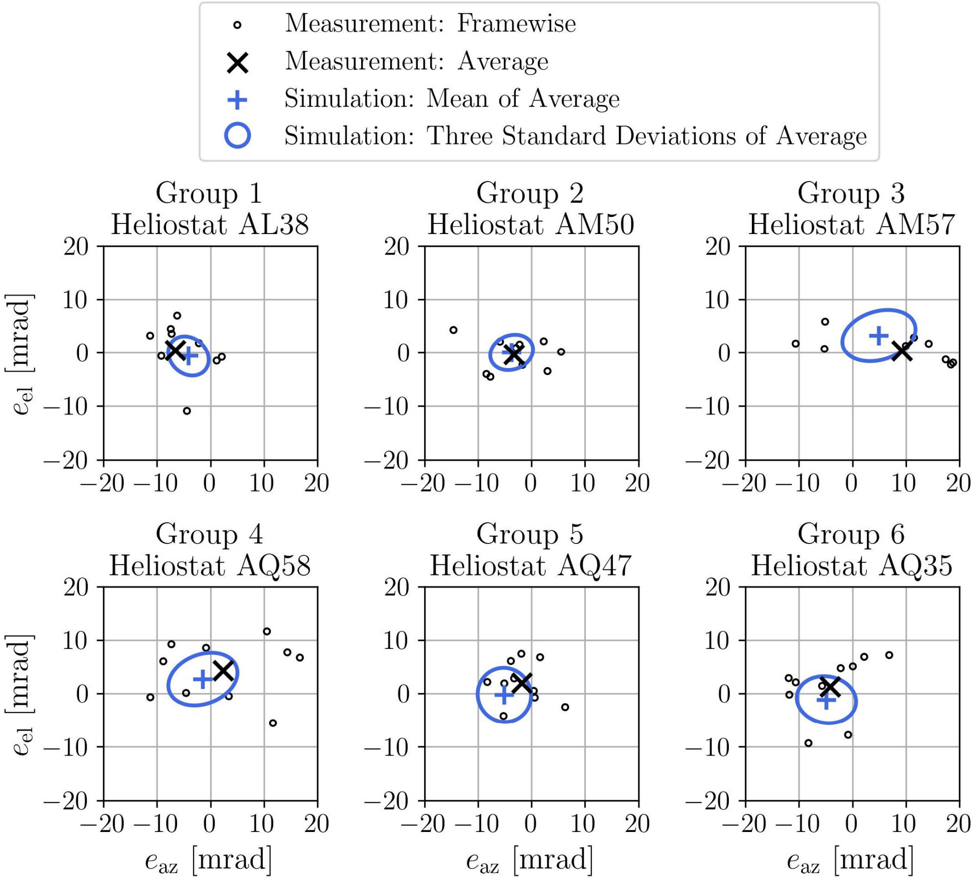
Measurement: Framewise
Measurement: Average
Simulation: Mean of Average
Simulation: Three Standard Deviations of Average



Example 1: UAV based system development with a digital twin
Development 1: Coarse calibration system - Validation

Digital twin

- helped to develop the system, and
- correctly predicts orientation and uncertainties

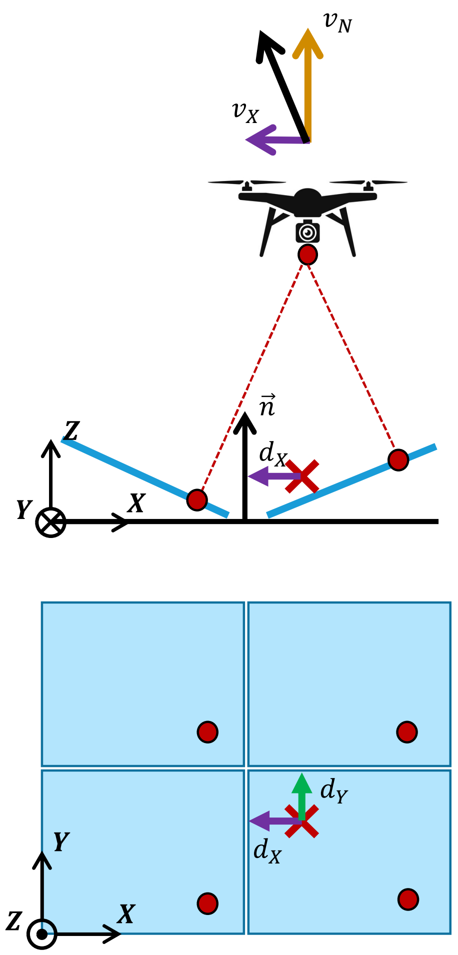


Validation data shows only one outcome, which may not reflect system variability

Example 1: UAV based system development with a digital twin
Development 2: Fine calibration system

Regular or fine calibration system (accuracy ~0.1-0.3mrad)

- Measure a calibration point in fine calibration accuracy in < 2 minutes without prior knowledge of orientation
- Measurement principle: Control loop, where UAV flight commands are derived from LED reflex (patent pending)



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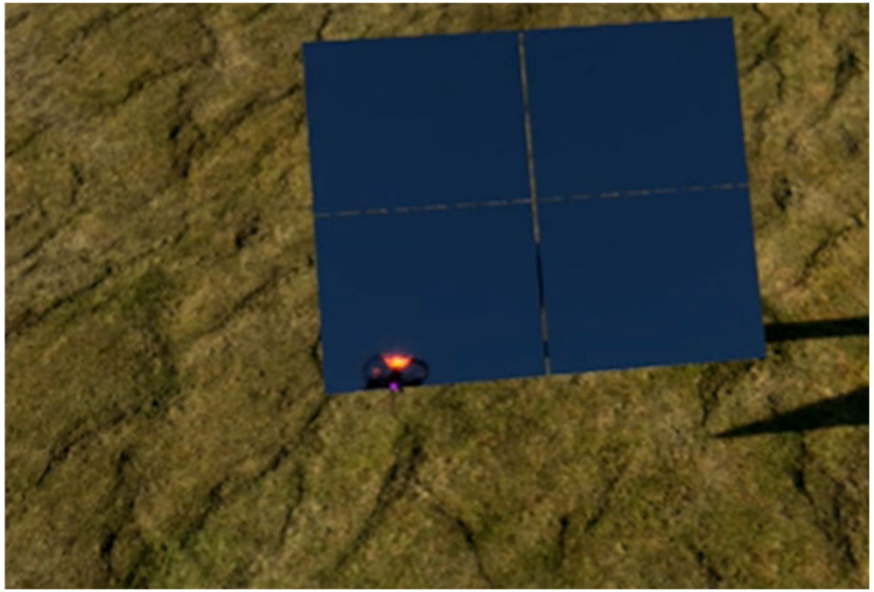
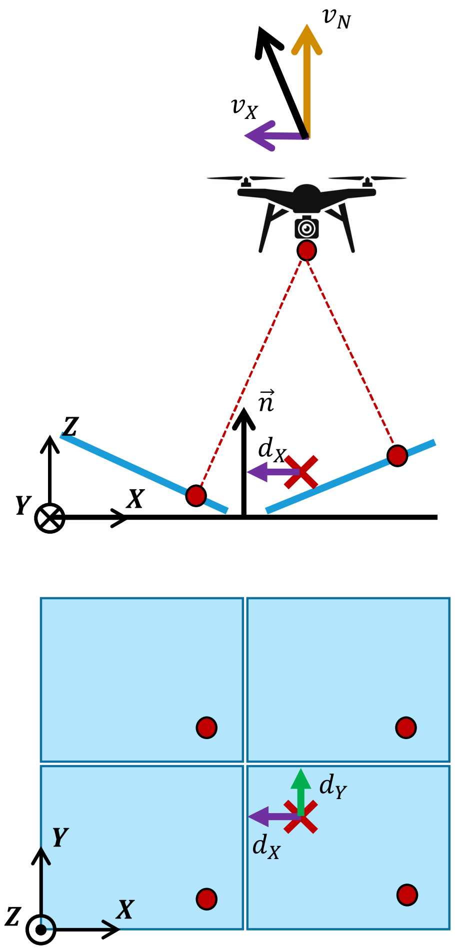
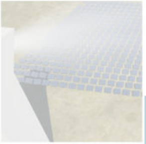


Digital twin

- helped to develop the system, e.g. the tuning of the parameters of the flight controller



Overview



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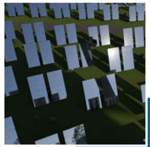

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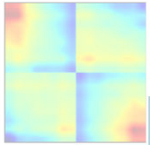


Example 3

- How well work data-driven AI models compared to physical models in the case of heliostats?

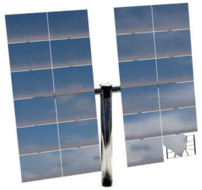
Example 2: Training of AI for image processing with a digital twin

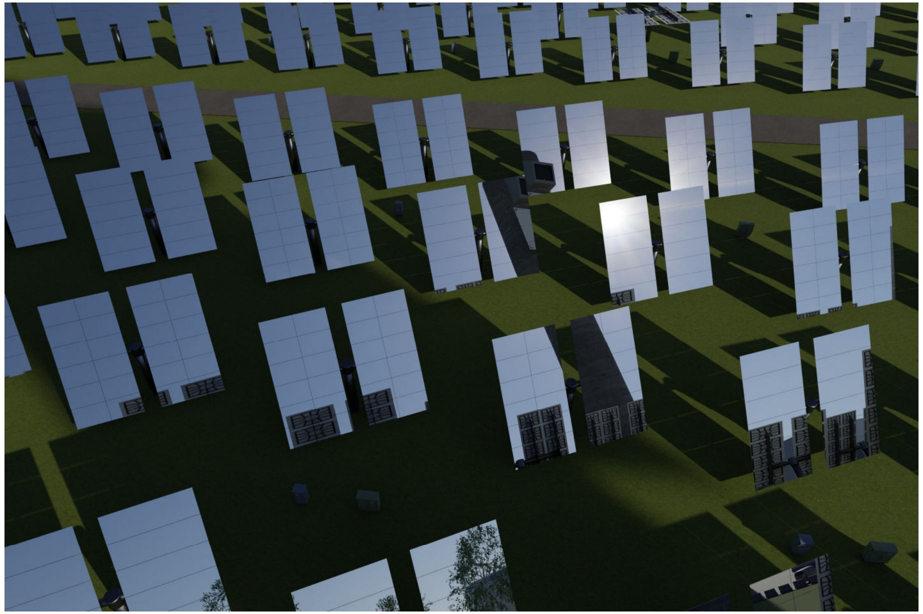
- Challenge: Creating different input data and labeling it to train a machine learning (ML) model is time-consuming and therefore very expensive
- Solution: Create a digital twin to create data (fotos & labels)
- Example: Data to train a ML model for image processing

Work from:
Broda R., Schnerring, A., Schnaus., D., Nieslony, M., Krauth, J., Röger, M., Kallio, S., Triebel, R., Pitz-Paal, R., Bridging the sim2real Gap: Training Deep Neural Networks for Heliostat Detection with Purely Synthetic Data, Solar Energy, Volume 300, 1 November 2025, 113728, https://doi.org/10.1016/j.solener.2025.113728

Example 2: Training of AI for image processing with a digital twin
Components of digital twin

- Digital twin and dataset creation using **Blender** and **BlenderProc**
  - Parametric heliostat model
  - Various objects and textures
  - Rendering of images and labels

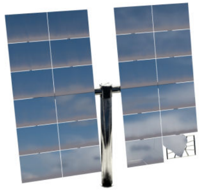




Rendered Blender image

Labels: Bounding boxes around collectors

Example 2: Training of AI for image processing with a digital twin
Components of digital twin



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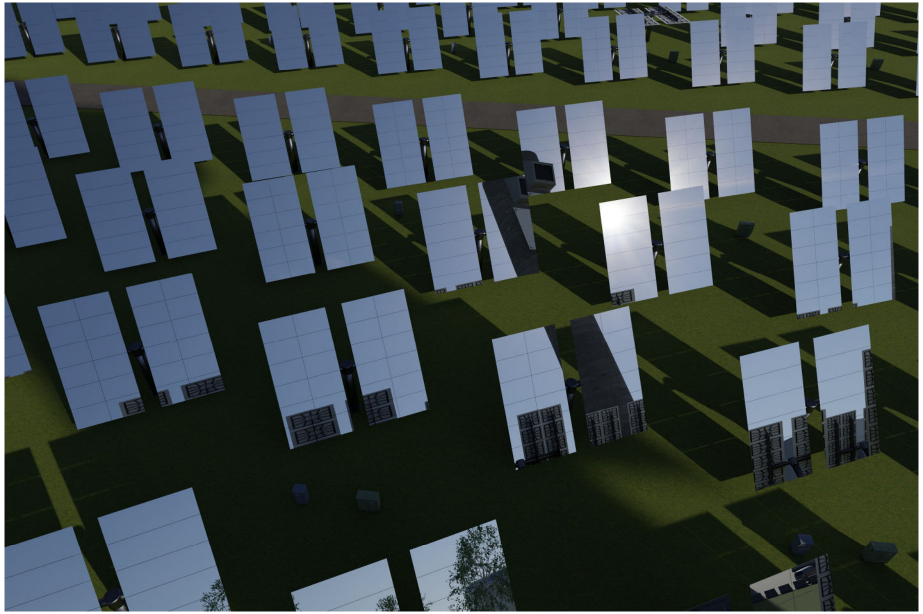
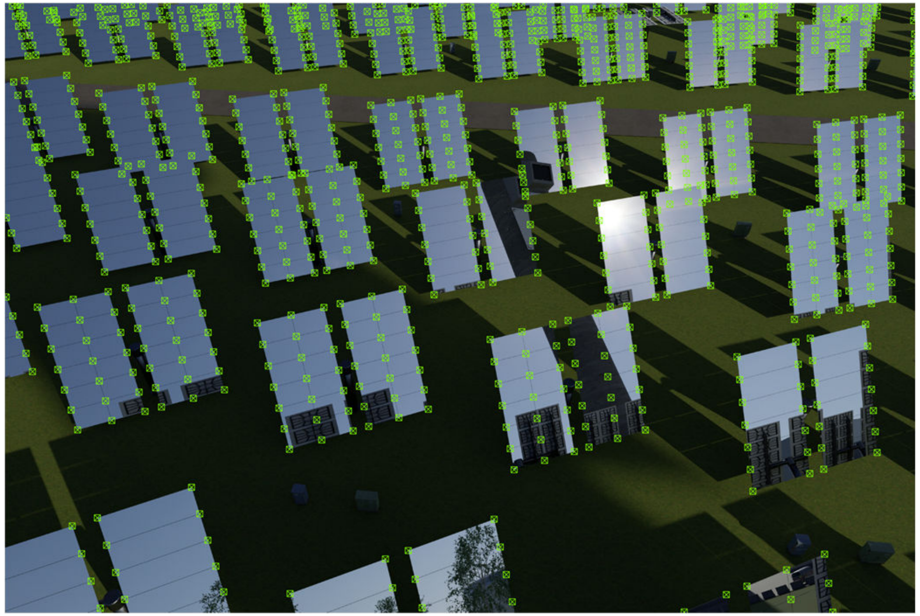


Rendered Blender image



Labels: Mirror corner points

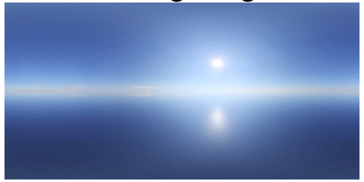
Example 2: Training of AI for image processing with a digital twin

Creating images with digital twin

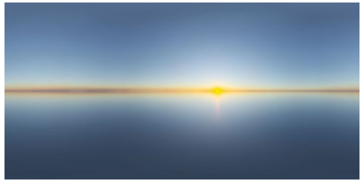
powered by terrabyte

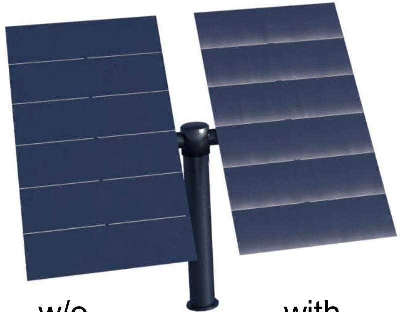
- Variation of scene parameters for **sim2real** study
  - *Appearance*
    - Simple vs. randomized ground textures
    - Constant vs. varying lighting
    - No soiling vs. soiling on mirrors
  - *Content*
    - No distractor objects vs distractor objects added
    - Reasonable vs. random object positions
    - Reasonable vs. random object orientations

Constant lighting



Varying lighting

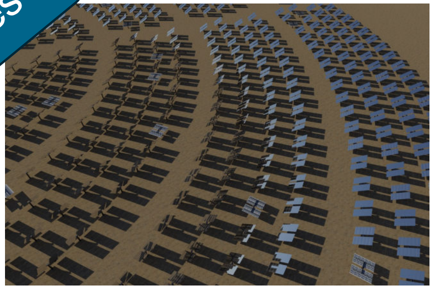


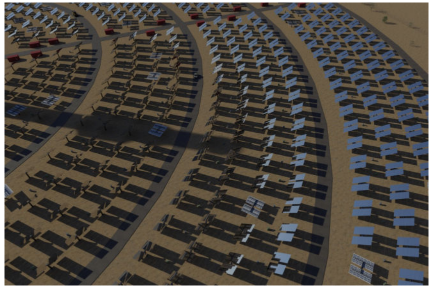


w/o soiling

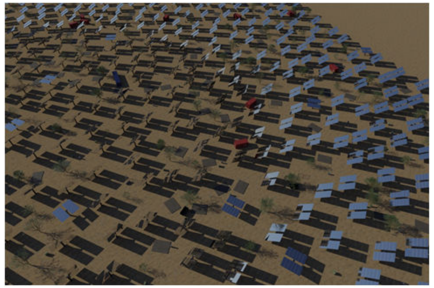
with soiling

Rendered images

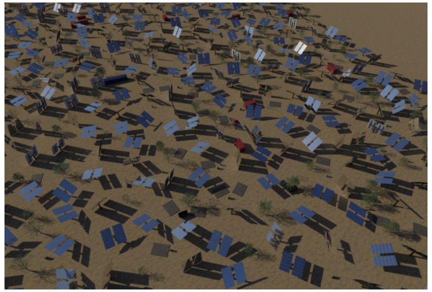




& Distractor objects



& Distractor objects
& Random positions



Distractor objects
& Random positions
& Random orientations

Example 2: Training of AI for image processing with a digital twin
Sim2real Study: Best training

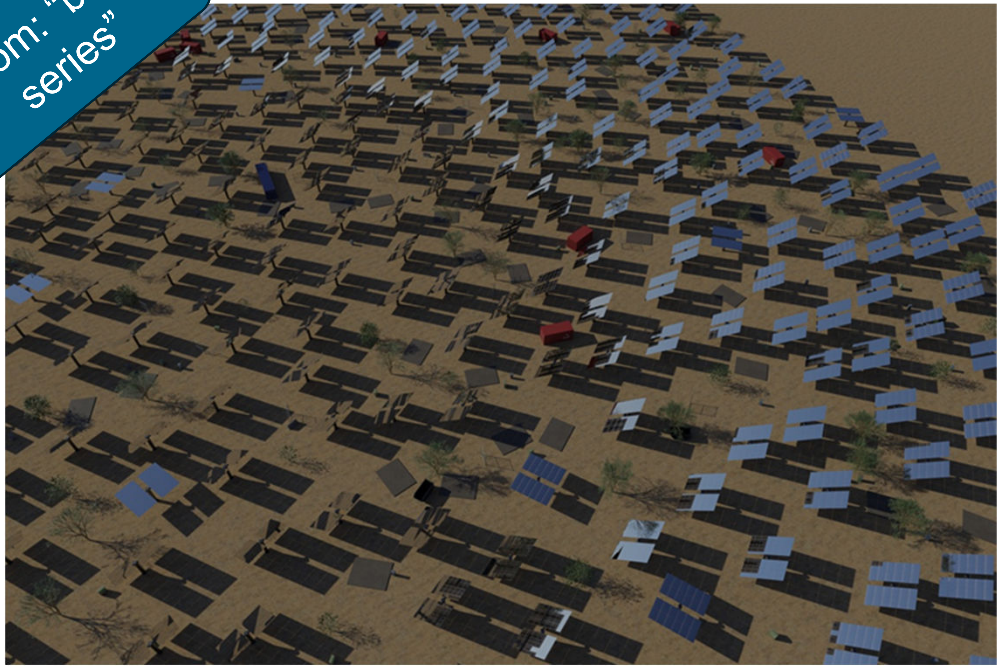
- **Sim2real** Study: Transfer of AI model from simulation to reality
  i.e. training with purely synthetic image data and evaluation/application on real-world images
  Best way of training?
- Considered metrics
  - Average precision (AP): Heliostat detection performance
  - Percentage of correct keypoints (PCK): Mirror corner detection performance
- Best identified scene configuration after 15 exp.

  Appearance
  - Randomized ground textures
  - Constant lighting
  - Soiling on mirrors

  Content
  - Distractors added,
  - Random object positions,
  - but reasonable object orientations

as in “reality”, but no field pattern

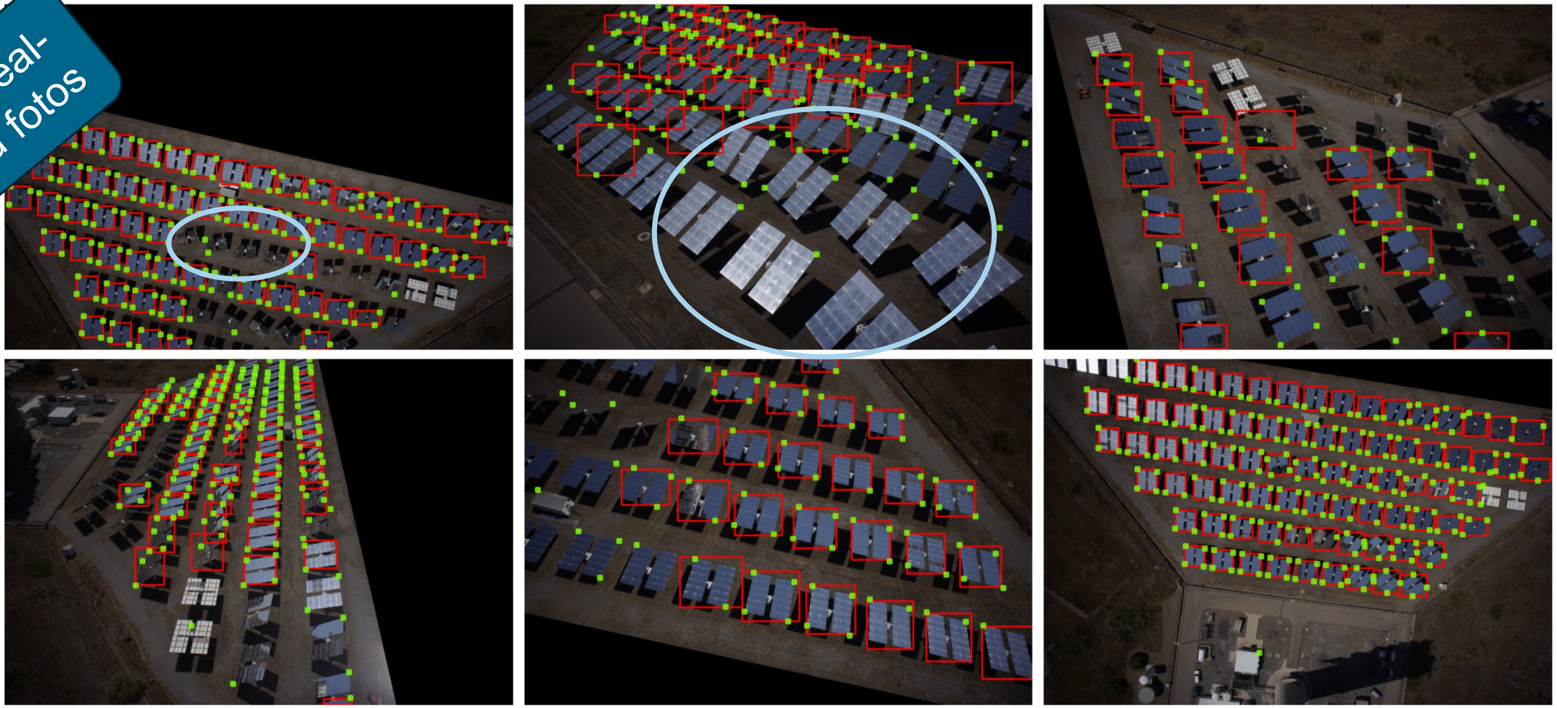
From: “best series”



Example 2: Training of AI for image processing with a digital twin
Sim2real Study: Performance with optimal image series

- Model trained with optimal scene configuration **detects 61% of mirror corners** in test dataset
- Proven simple **heliostat geometry transfer → Training with synthetic data is useful.**

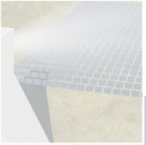
AI on real-world fotos



Model predictions on real-world drone images of CESA-1, PSA
(PSA owned and operated by CIEMAT)

Transfer to Solar Tower Jülich (STJ)

Overview



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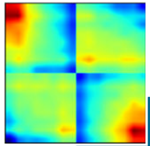


Example 3

- How well work data-driven AI models compared to physical models in the case of heliostats?

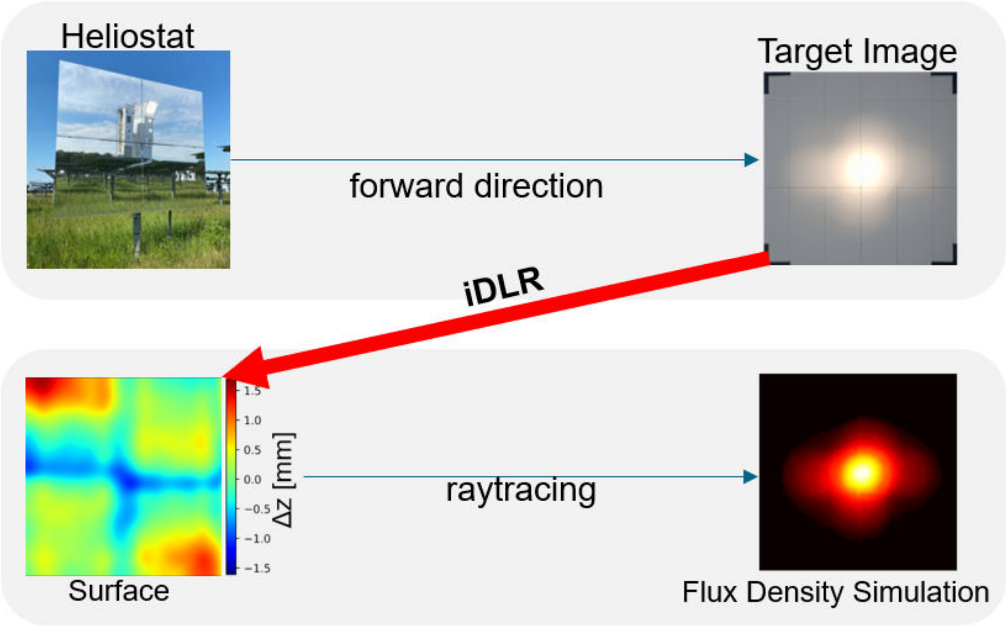
Example 3: Data-driven AI models for heliostat shape

- Challenge: Derive heliostat slope deviation data with low effort
- Solution: Train a data-driven model to create a digital twin of the heliostat for slope deviation using only target images of focal spots originally taken for calibration

Work from:
Jan Lewen, Max Pargmann, Mehdi Cherti, Jenia Jitsev, Robert Pitz-Paal,
Daniel Maldonado Quinto, Inverse Deep Learning Raytracing for heliostat surface prediction,
Solar Energy 289 (2025) 113312, https://doi.org/10.1016/j.solener.2025.113312

Jan Lewen, Max Pargmann, Mehdi Cherti, Jenia Jitsev, Robert Pitz-Paal, Daniel Maldonado Quinto,
Scalable heliostat surface predictions from focal spots: Sim-to-Real transfer of inverse Deep Learning Raytracing,
Solar Energy 300 (2025) 113726, https://doi.org/10.1016/j.solener.2025.113726

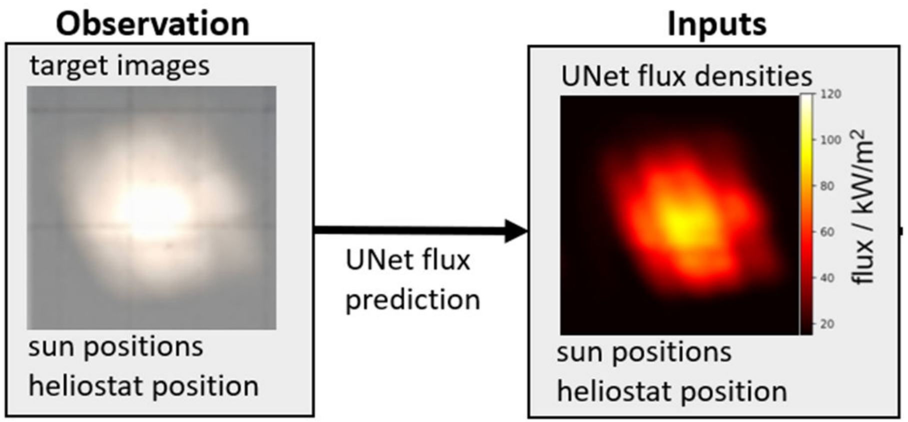
Example 3: Data-driven AI models for heliostat shape
Problem and solution



iDLR
=inverse Deep Learning Raytracing

- Inverse raytracing using flux maps is an underdetermined problem → Generative deep learning
- Generative deep learning models acquire domain-specific knowledge during training, and can generate new instances!
- To control the output, we use additional input which condition the output
  → conditional generative modeling

Example 3: Data-driven AI models for heliostat shape
Training and AI architecture



Inference data:

- Target images of focal spots on a Lambertian Target
- Preprocessing using the UNet Deep Learning approach of Kuhl et al. 2024 for flux density extraction

Mathias Kuhl, Max Pargmann, Mehdi Cherti, Jenia Jitsev, Daniel Maldonado Quinto, Robert Pitz-Paal,
In-situ UNet-based heliostat beam characterization method for precise flux calculation using the camera-target method
https://doi.org/10.1016/j.solener.2024.112811.

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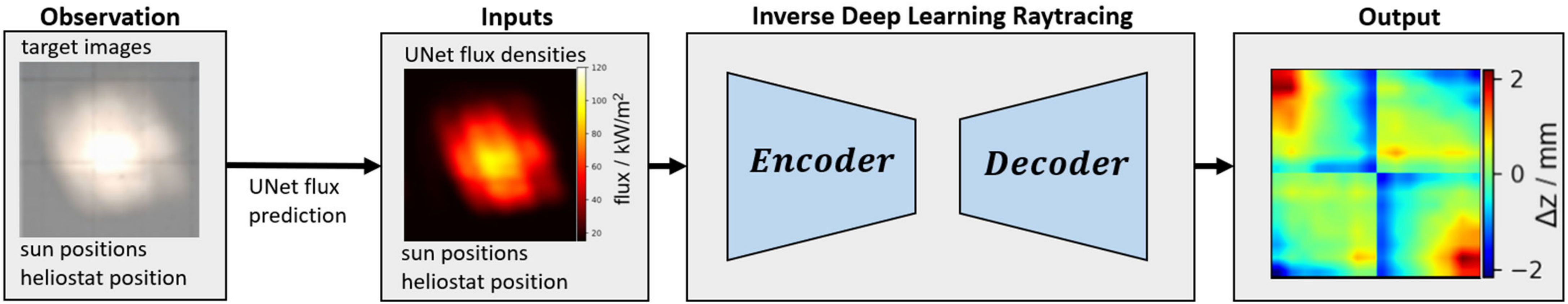

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Training data:

- Sun and Heliostat Position
- up to 8 **flux maps** over day, calculated by raytracing using the shape of
  - **Deflectometry** measurements of 458 heliostats (428 training + 32 validation)

    Data augmentation to 160’000 shapes by 1. rotating maps 180° and 2. weighted average between two randomly selected shapes

Objective of Training:

- Minimize MAE betw. surface height points *z* of prediction and known ones from deflectometry

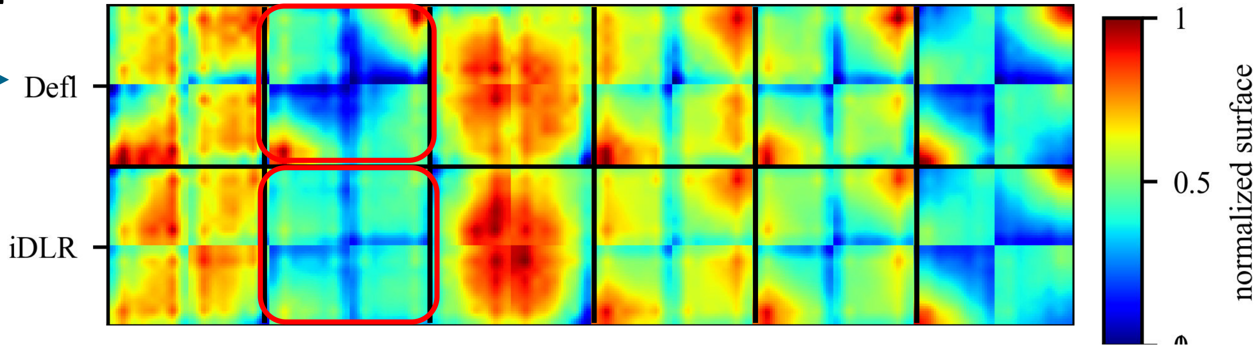
Example 3: Data-driven AI models for heliostat shape

Validation with deflectometry measurements and flux maps

Results

Concentrator surface height deviation from ideal shape (Δz)

Ground Truth



<u>Deviation Defl-iDLR:</u>

MAE: 0.14mm

min: ~-2mm

max: 2mm

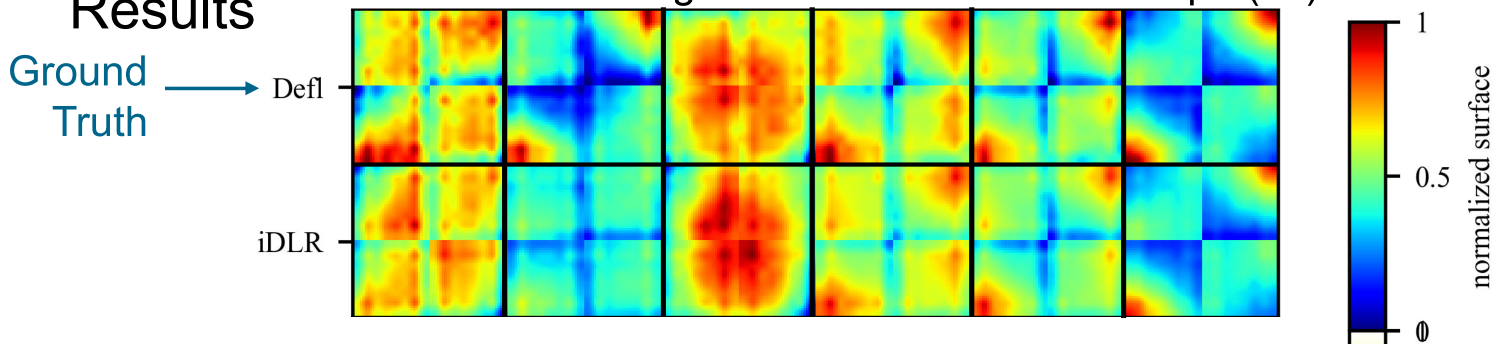
<u>Surface Misspredictions:</u>

10 of 63 (~16%) validation heliostats from STJ were misspredicted (two left heliostats)

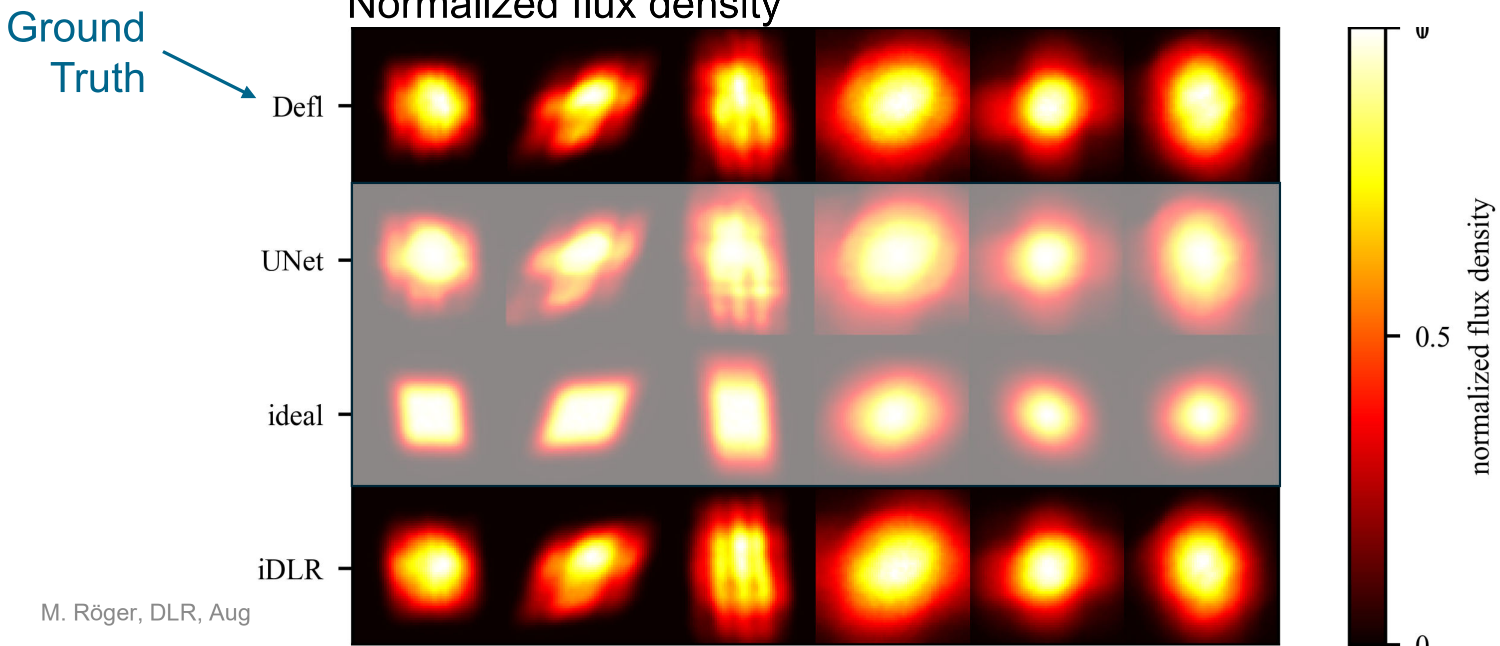
Example 3: Data-driven AI models for heliostat shape
Validation with deflectometry measurements and flux maps

Results

Conc. surface height deviation from ideal shape (Δz)



Normalized flux density



Deviation Shape (Defl-iDLR):
MAE: 0.14mm
min: ~-2mm
max: 2mm

Surface Misspredictions:
10 of 63 (~16%) validation heliostats from STJ were misspredicted (two left heliostats)

Deviation Flux (Defl-iDLR):
Median accuracy: 90-92%

Despite some surface misspredictions, good flux density predictions because of ill-posedness

Thank you !

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