DEEP LEARNING INVERSION OF A RAYTRACER FOR HELIOSTAT SURFACE PREDICTIONS

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DLR

Outline

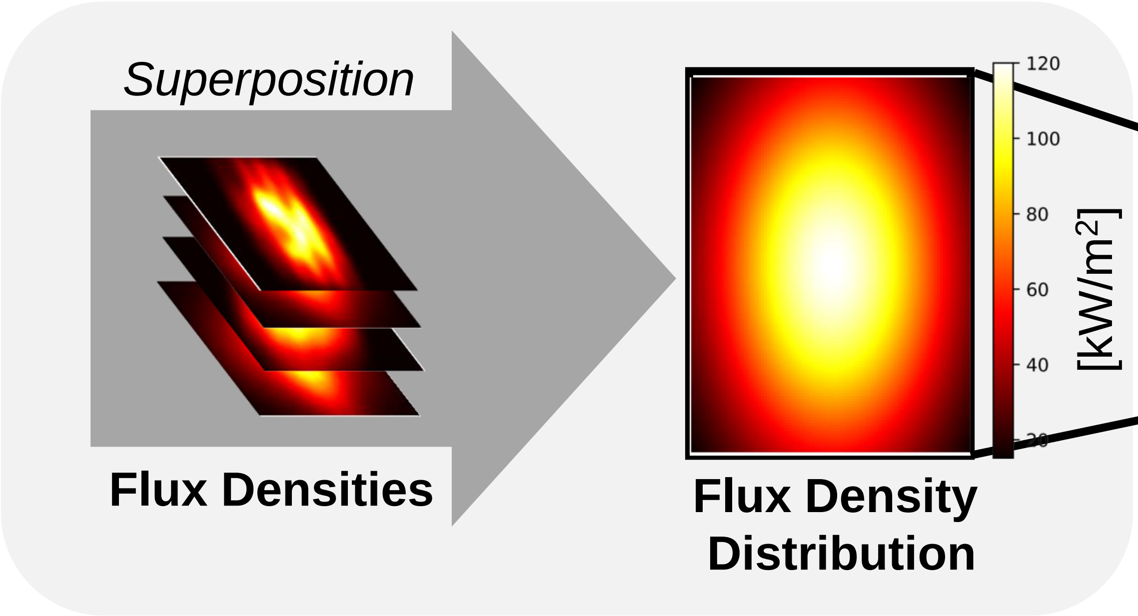
- Motivation
- Method: Deep Learning Inversion of a Raytracer
- Results: Heliostat Surface and Flux Density Prediction
- Conclusion
- Outlook

MOTIVATION

Flux density distribution

Flux Density Distribution

- most important control parameter
- superposition of single flux densities



Solar Tower Jülich

Flux density distribution

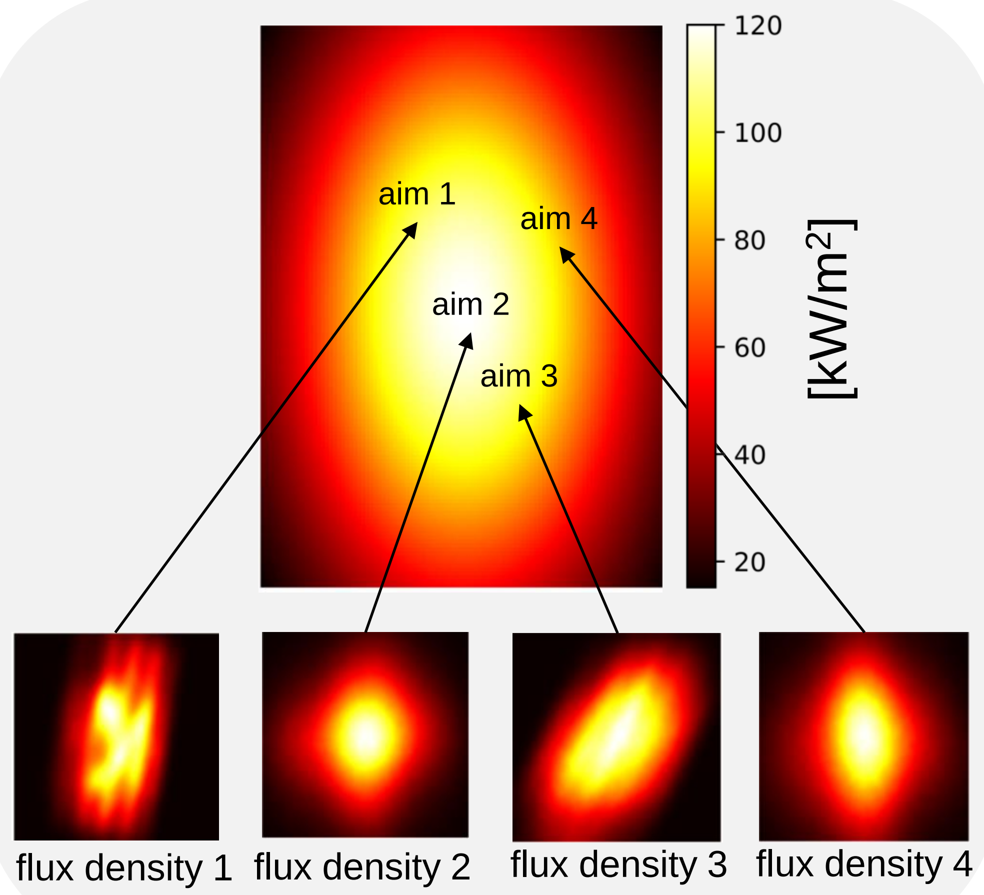
Flux Density Distribution

- most important control parameter
- superposition of single flux densities

Aim Point Control

- optimizes the flux density distribution
- mass center of flux density at designated aim point (*tracking*)
  - ➢ fully automatic calibration is established
- flux density shape should be incorporated in aim point control
  - heliostat specific
  - depends on sun position

  ➢ **currently no fully automatized, cheap and reliable method to predict flux density shapes**



Potential of Automatized Flux Density Prediction

Goal of the Work

Effect of the Work

Automatized Flux Density Prediction → Enhanced Aim Point Control → Optimized Flux Density Distribution → Enhanced Power Plant Efficiency

- more save and reliable power plant operation
- reduction of safety limits during operation leads to higher yield

Potential of Automatized Flux Density Prediction

Goal of the Work | **Effect of the Work**

Automatized Flux Density Prediction → Enhanced Aim Point Control → Optimized Flux Density Distribution → Enhanced Power Plant Efficiency

Goal of the Work

- minimal-cost method
- data-driven approach
- using only data from regular power plant operation

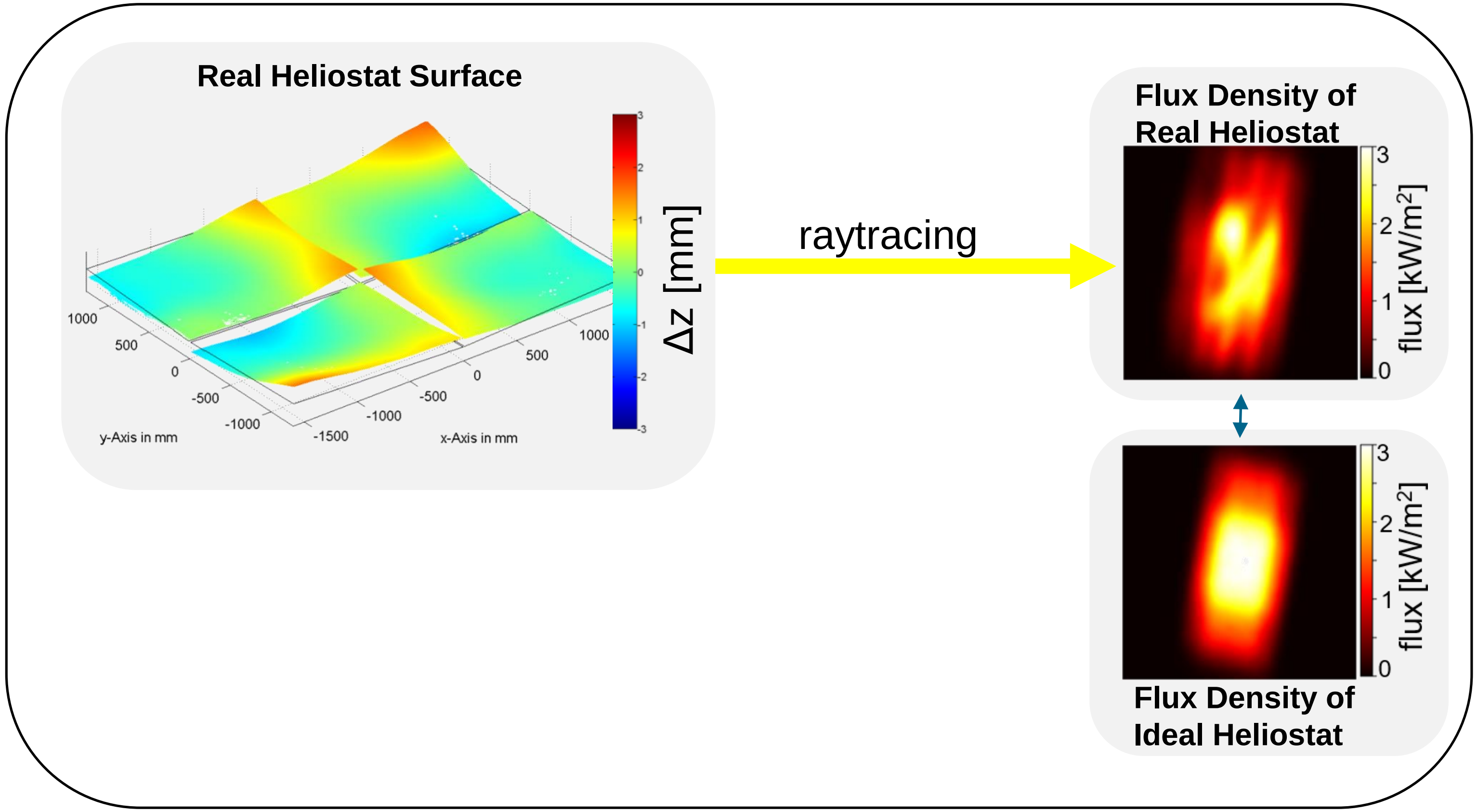
Effect of the Work

- more save and reliable power plant operation
- reduction of safety limits during operation leads to higher yield

Heliostat Surface Shape

Heliostat Surface Shape

- mirror surface shapes
- facet alignment
    - ➢ heliostat flux density is non-ideal



Deflectometry Measurement

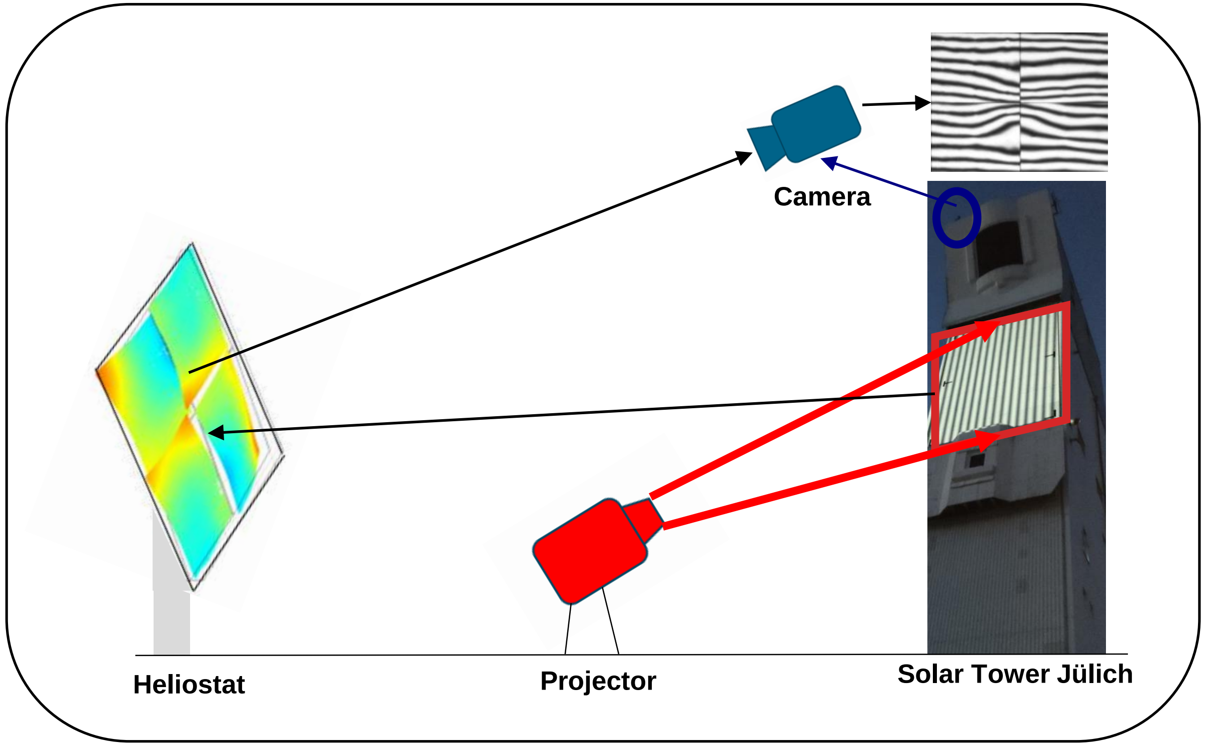
Heliostat Surface Shape
- mirror surface shapes
- facet alignment
  - ➢ heliostat flux density is non-ideal

Deflectometry Measurement
- precise measurement of heliostat surface shape

- not used at commercial power plants for automatized flux density prediction:
  - expensive in material and execution
  - error prone to weather conditions

➢ **Is it possible to replace the Deflectometry Measurement by a Deep Learning model?**

Sketch Deflectometry Measurement



METHOD

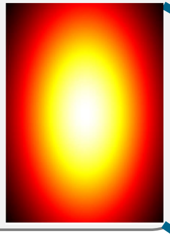
Digital Twin of a Heliostat | State of the Art

SOTA
- geometry model from calibration
- ideal heliostat assumption

Aim Point Control

Raytracing

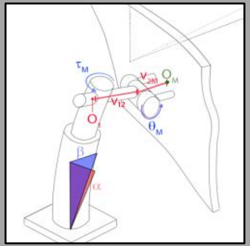
Optimized Flux Density Distribution
- reduced *tracking error*



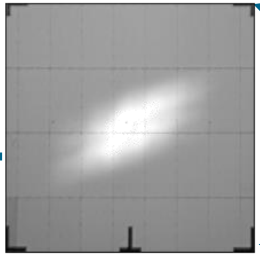
Heliostat Digital Twin

Ideal Heliostat Assumption

Geometry Model



Fully Automatized Calibration



Target Images
shape changes over the course of a day!

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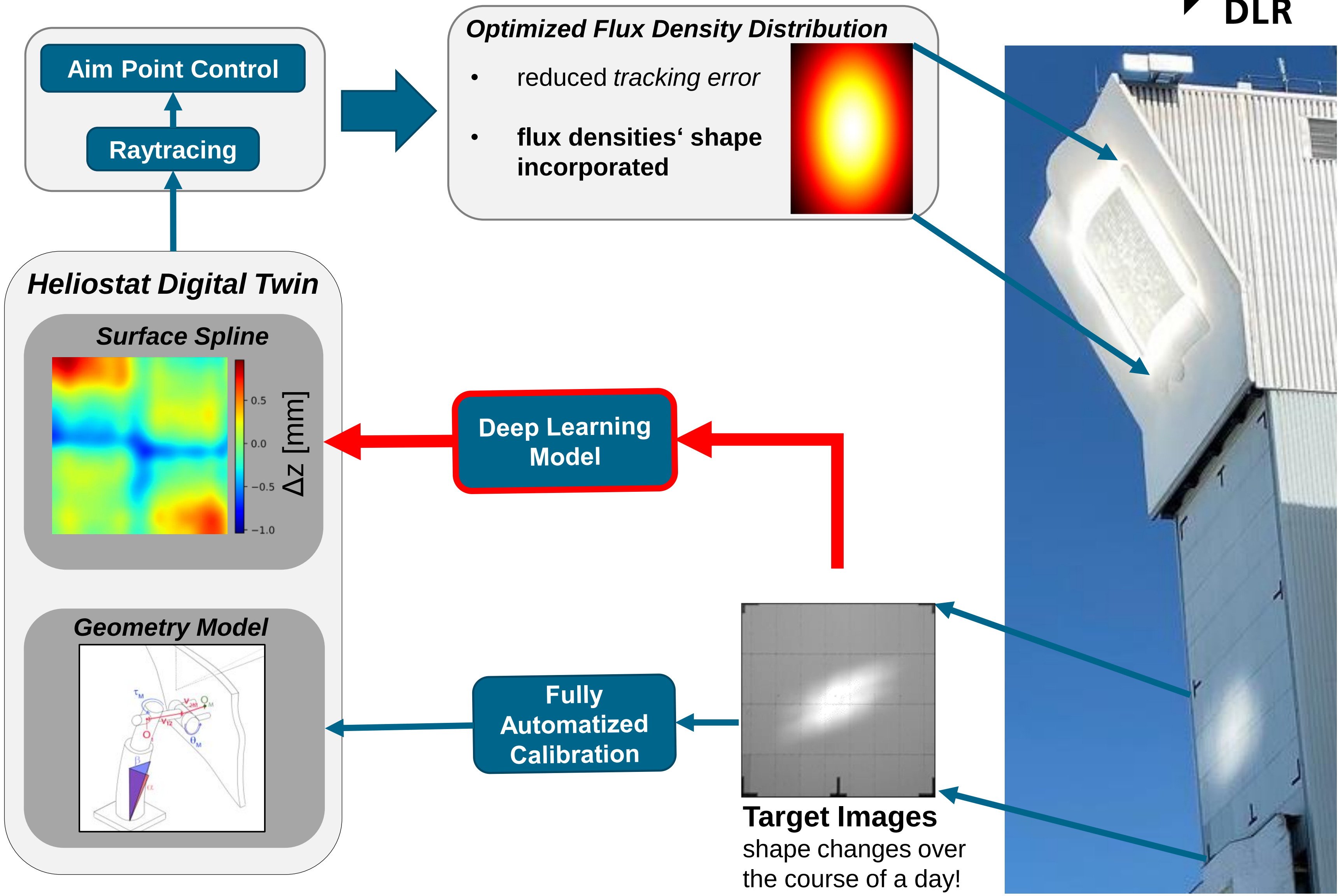
Digital Twin of a Heliostat | Deep Learning Enhanced

SOTA

- geometry model from calibration
- ideal heliostat assumption

Deep Learning Enhanced

- model predicts heliostat surface shape from target images
- flux density shape predictable for all sun position
- heliostat surface shape described by a spline
- no new hardware necessary
  - ➢ minimal-cost



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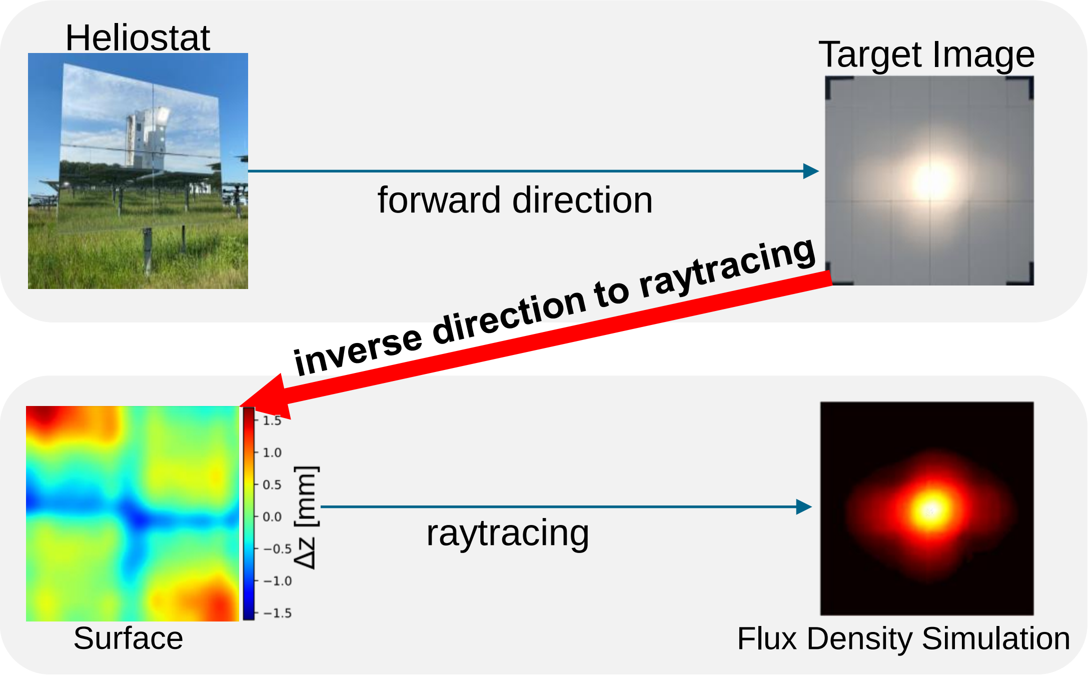
Deep Learning Inversion of a Raytracer

Raytracing
- accurate description of physics
- high similarity between target image and simulated flux density when scene known

Deep Learning Inversion of a Raytracer
- predicting the heliostat surface from a target images is the inverse problem to raytracing
- training data can be simulated with a raytracer



Generation of Artificial Training Data

Deflectometry → Surface Splines

- 371 Heliostats
- at Solar Tower Jülich

Random Surface

Random Environment Parameters

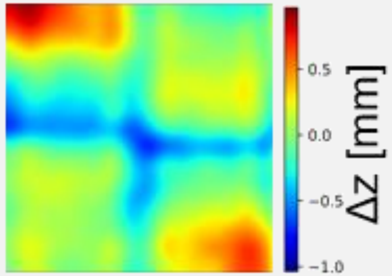
Raytraced Flux Densities

repeat one million times

save

Training Data

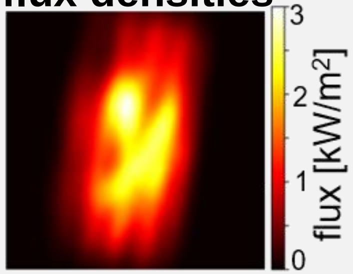
surfaces



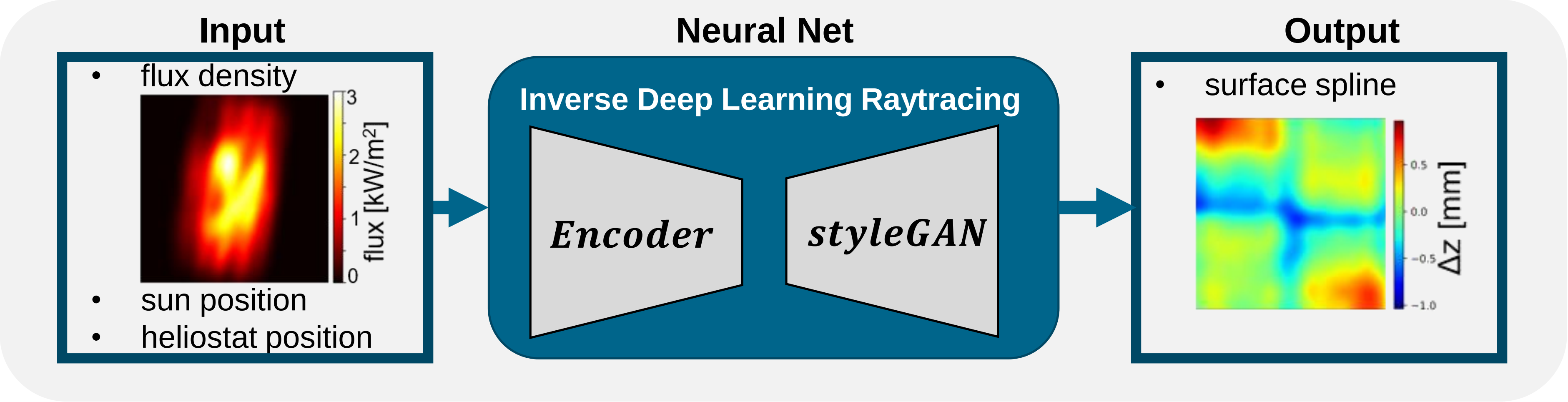
scalar data

- sun positions
- heliostat position

flux densities



Deep Learning Model



Neural Net

- Encoder-Decoder structure
- styleGAN-Generator as Decoder

Training

- with simulated raytracer dataset
- on JUWELs at Research Center Jülich

RESULTS: SIMULATIVE DATA

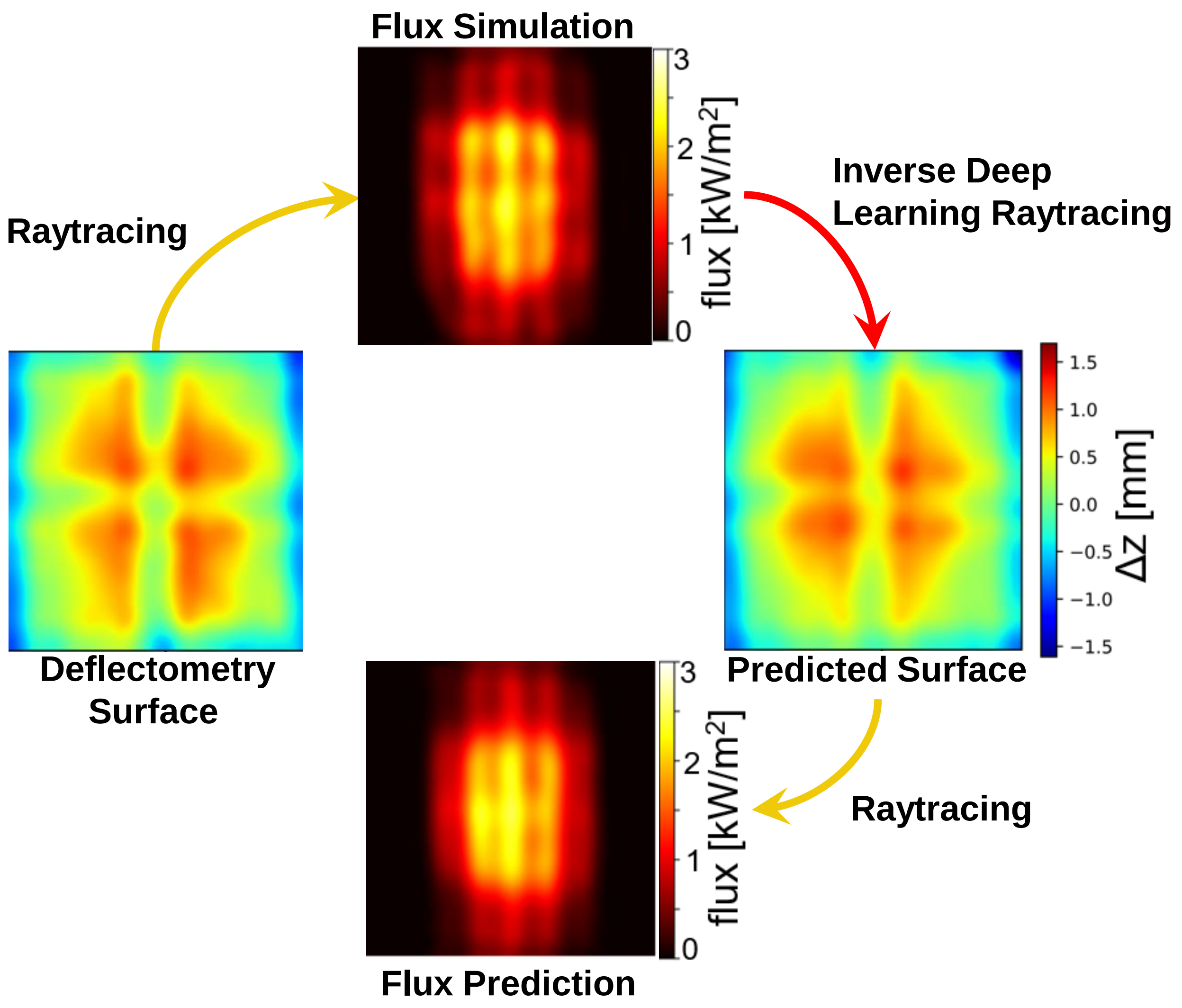
Results

Validation Set

- deflectometry measured surfaces of heliostats at Solar Tower Jülich
- raytracing to obtain simulated flux densities as input for the deep learning model

Inverse Deep Learning Raytracing

- surface prediction
- comparison with the deflectometry surface
- flux density prediction for all sun position possible

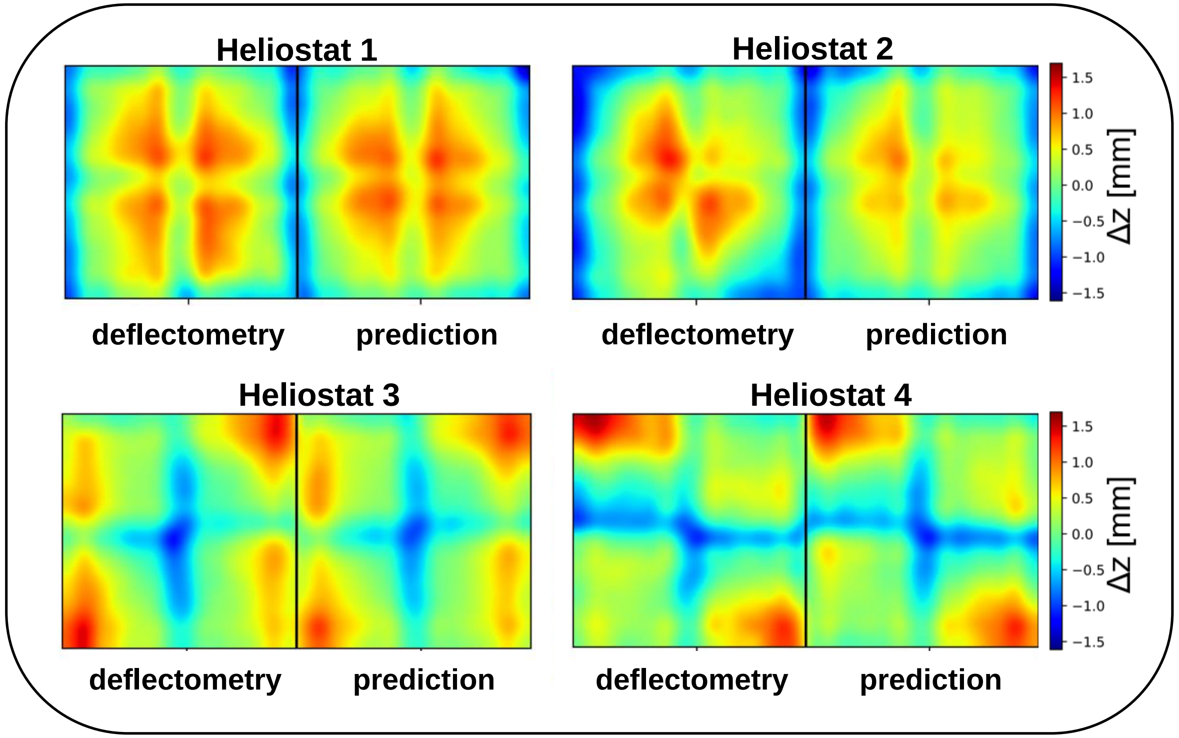


Results Surface Prediction

Inverse Deep Learning Raytracing

- very precise surface prediction
- deviations are possible (Heliostat 2)
- mean absolute error:
  - ➢ MAE = 0.18 ± 0.08mm
- surface deviation range: 2-4mm

Examples of the Surface Prediction (validation set)

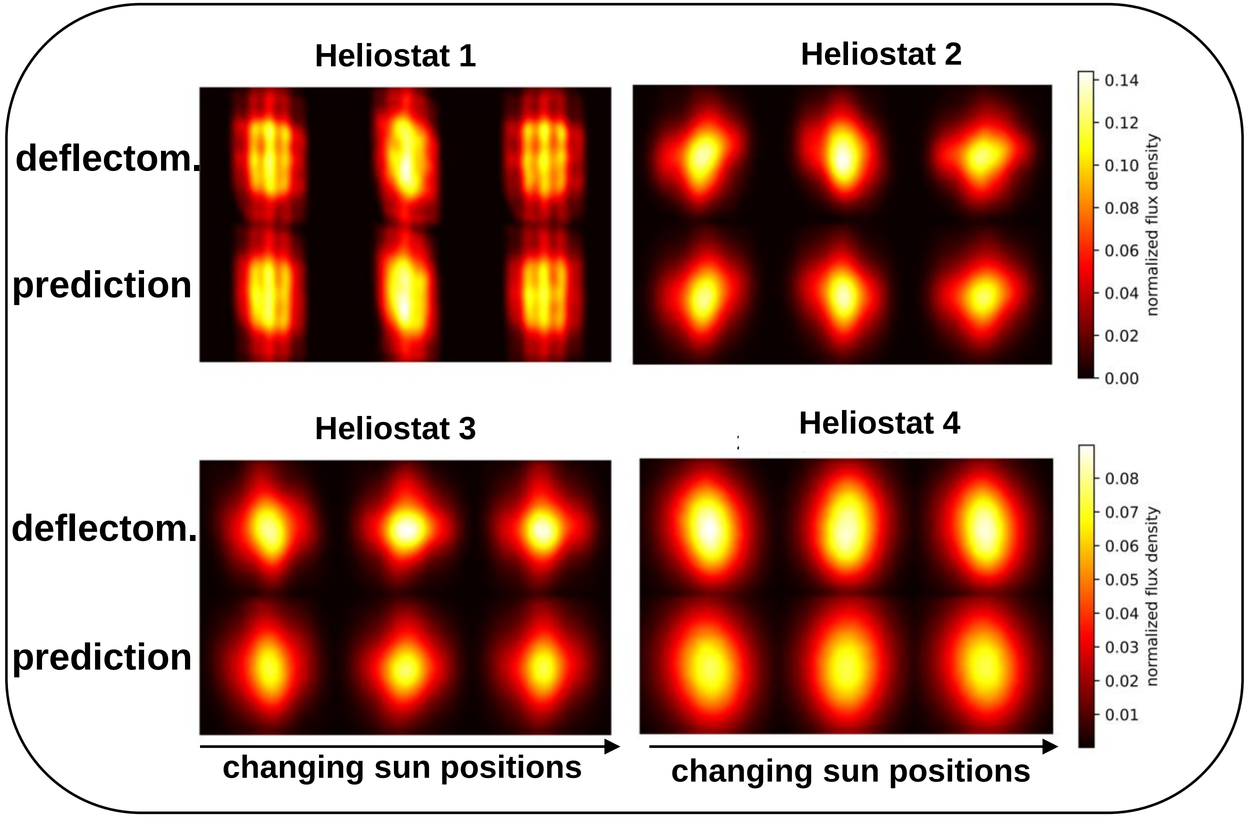


Results Flux Density Prediction

Raytracing the Predicted Surface

- very precise flux density prediction
- even details can be predicted with high accuracy
- less accurate surface predictions can still result in good flux density prediction (Heliostat 2)

Examples of the Flux Density Prediction (validation set)



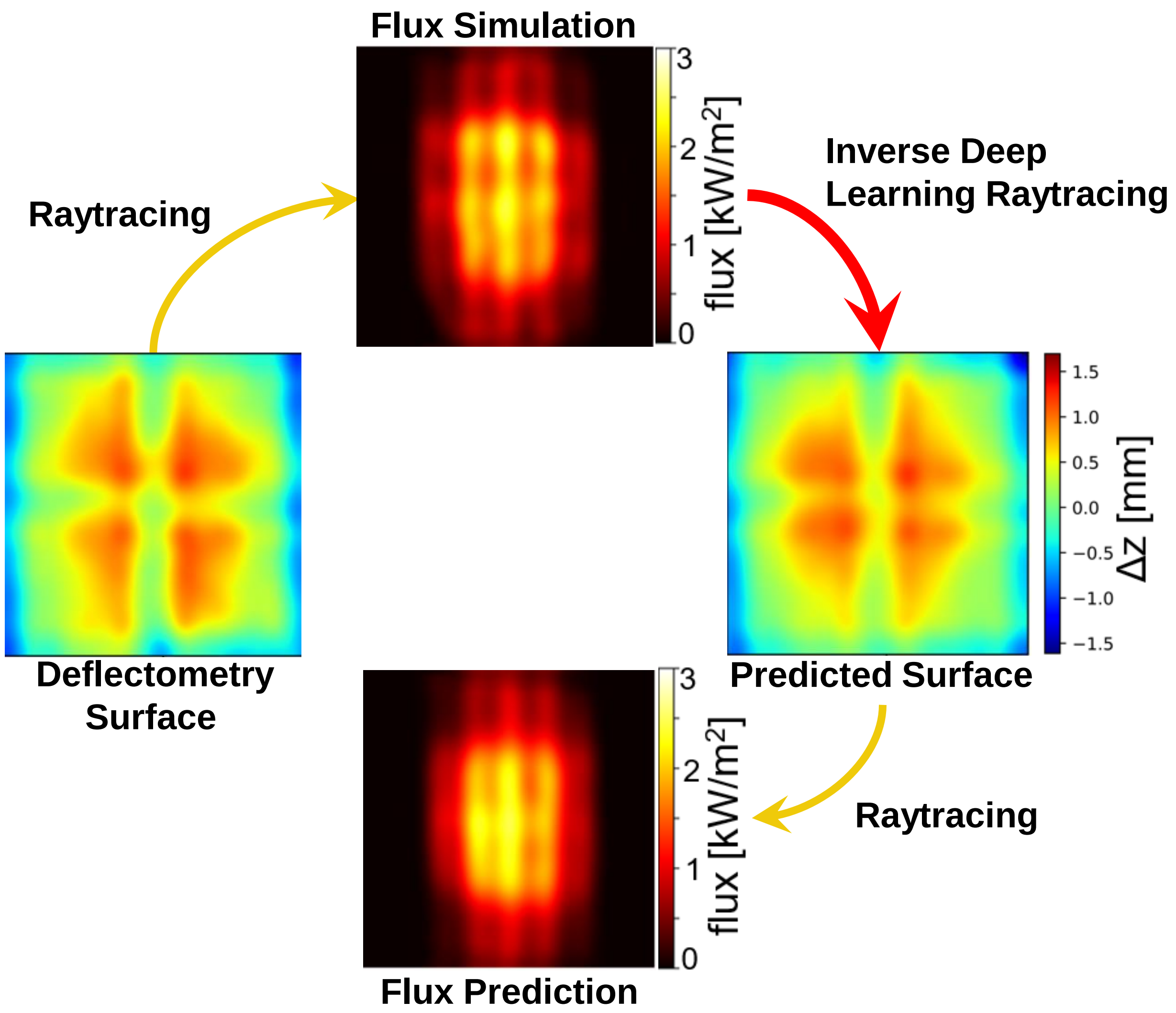
Summary

Deep Learning Inversion of a Raytracer

- minimal-cost deep learning approach to predict heliostat surfaces from target images

- model performs very good in simulative condition
  - ➢ mean absolute error = 0.18 ± 0.08mm

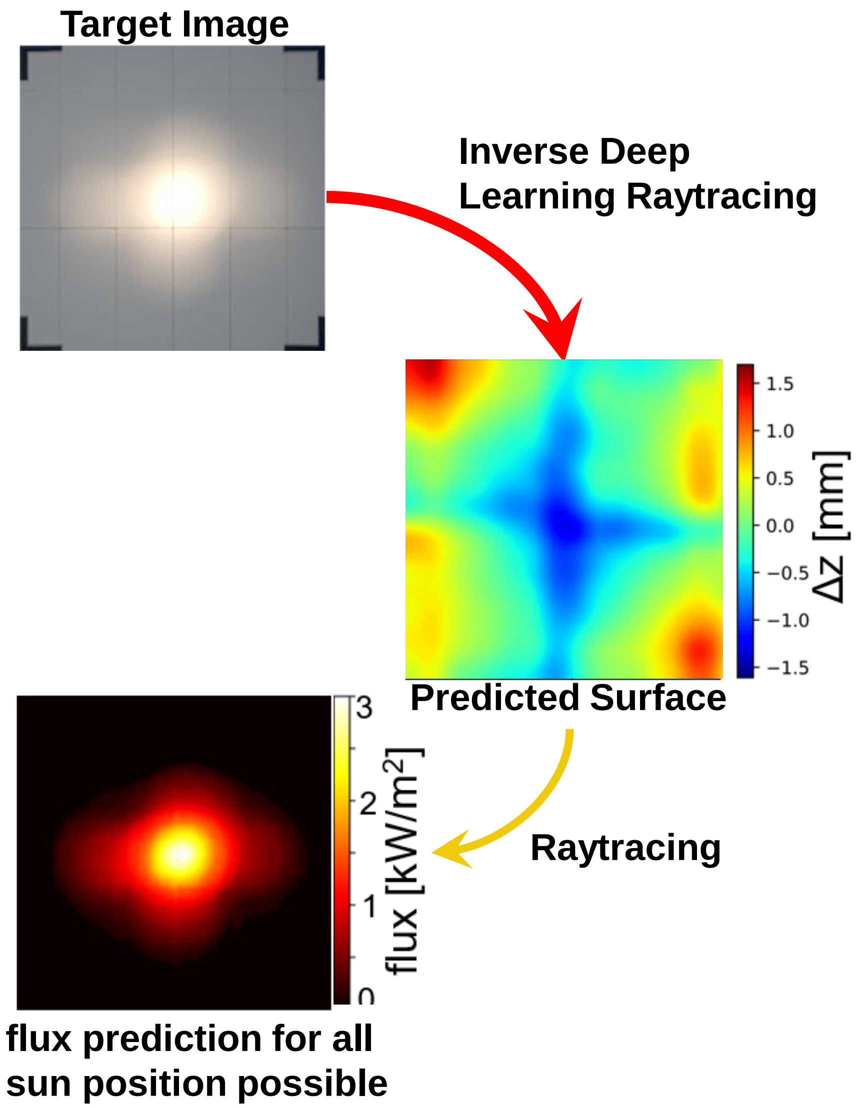
- allows modern aim points strategies reducing the safety margins and hence increase the power plants yield



Outlook

Sim2Real Transfer

- transfering the simulative model to real data
- target images replace the simulated flux density as input
- zero-shot sim2real transfer



Outlook

Sim2Real Transfer

- transfering the simulative model to real data
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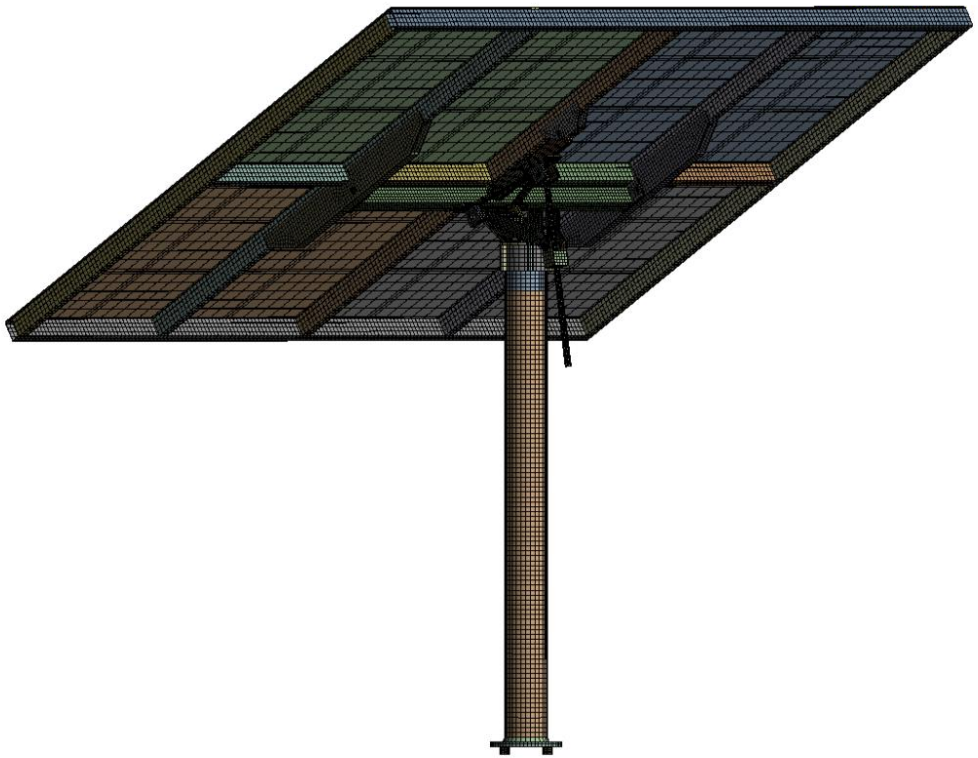
- zero-shot sim2real transfer

Training without Deflectometry Data

- deflectometry not available for all power plants
- replace deflectometry data by FEM simulation of possible heliostat deformation



FE Model of a Heliostat
taken from *Vásquez Arango 2016 „Dynamic wind loads on heliostats“*

THANK YOU FOR YOUR ATTENTION!