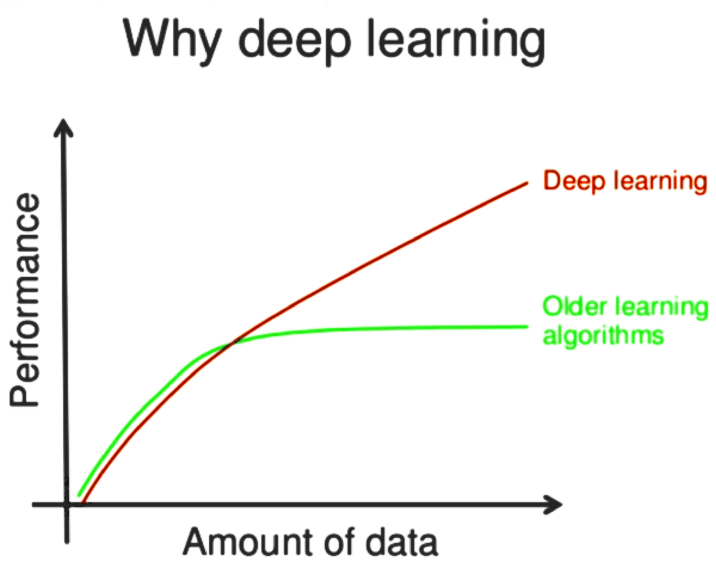
Development of a Digital Twin for Solar Tower Power Plants
Subsection: Heliostatfield Calibration

M. Pargmann*,[1], D. Maldonado[1], P. Schwarzbözl[1] , R. Pitz-Paal [1]
[1]German Aerospace Center (DLR), Institute of Solar Research, Cologne, Germany
*max.pargmann@dlr.de

Motivation

- The optimization potential of solar power plants cannot be exploited with existing simulation models
  - Approximations lead to deviations from reality
  - No approximations can lead to massive slowdown
  - Measuring all influencing factors can be expensive or might not be possible
- NNs continuously improve model behavior through sensor data and are superior to existing simulation models based on physical modeling
  - Trained models are extreme fast
  - No need for measuring complex influencing factors



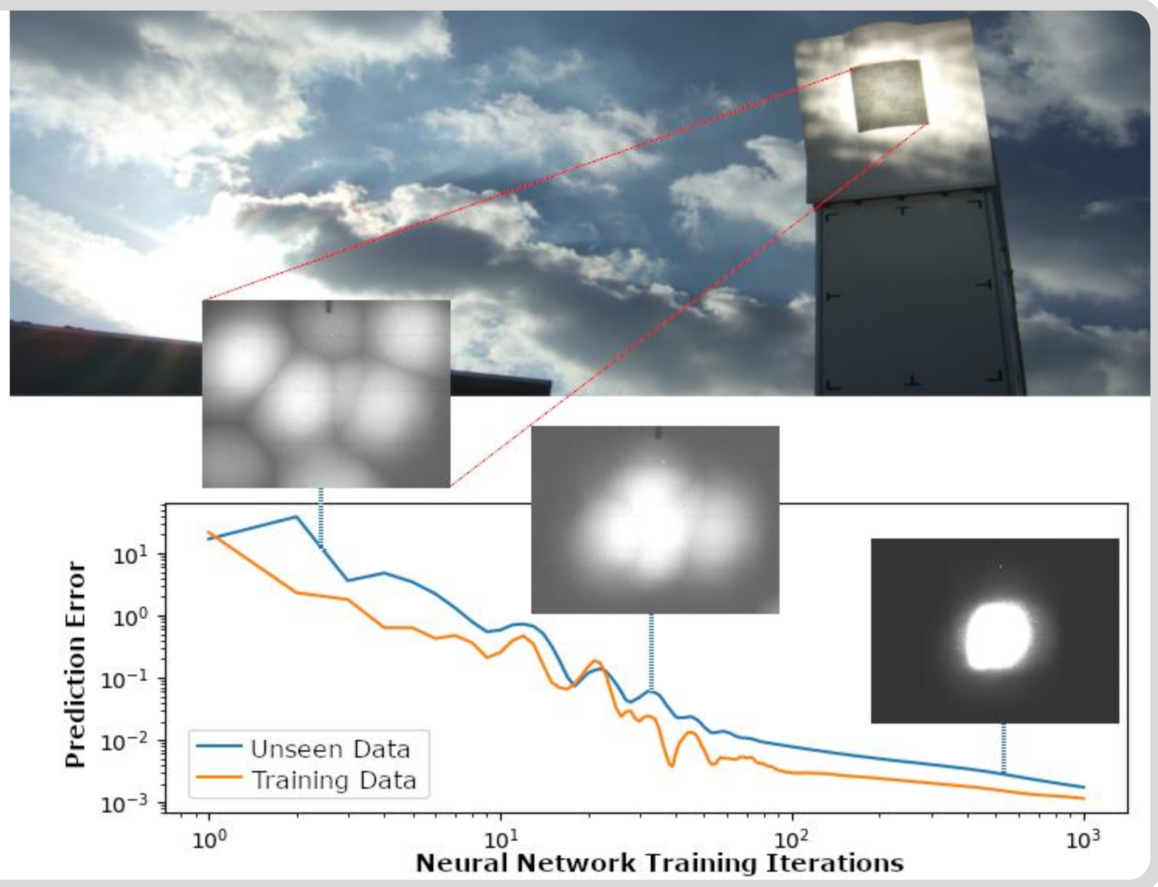
Objectives

- Scouting the possible applications of neural networks (NN) in solar tower power plants
- Apply the methods at the solar tower power plant at Jülich
- Evaluate the gain by comparison to existing approaches

Approach

Heliostat field as first approach for deep learning algorithms

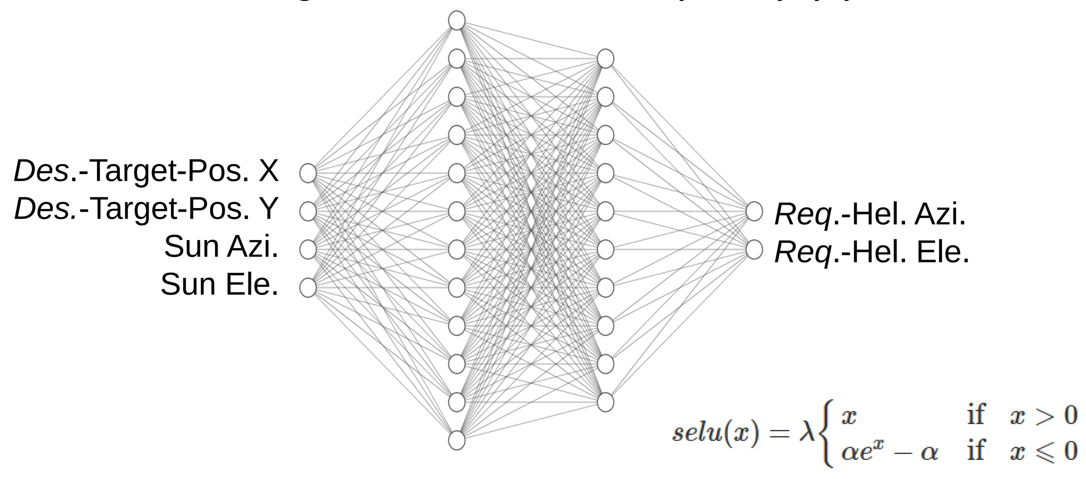
- A good calibration of heliostats is needed for higher energy output and to keep the costs per heliostat low.
- Also modern optimization algorithms needs high heliostat accuracy in sun tracking. Both are an key element of contemporary research (1)
- Classically a calibration is done by a parameter driven regression
  - Influencing factors are limited
  - New calibration does not necessary lead to better results
- By using NN the calibration can benefit from several features:
  - Every new calibration benefits from older measurements → fewer calibrations needed
  - Easy model extension with new system parameters e.g. local wind speed measurements
  - Time dependent or non linear parameters behavior can be captured
  - Possibility to parallelize the calibration process



Method & Results

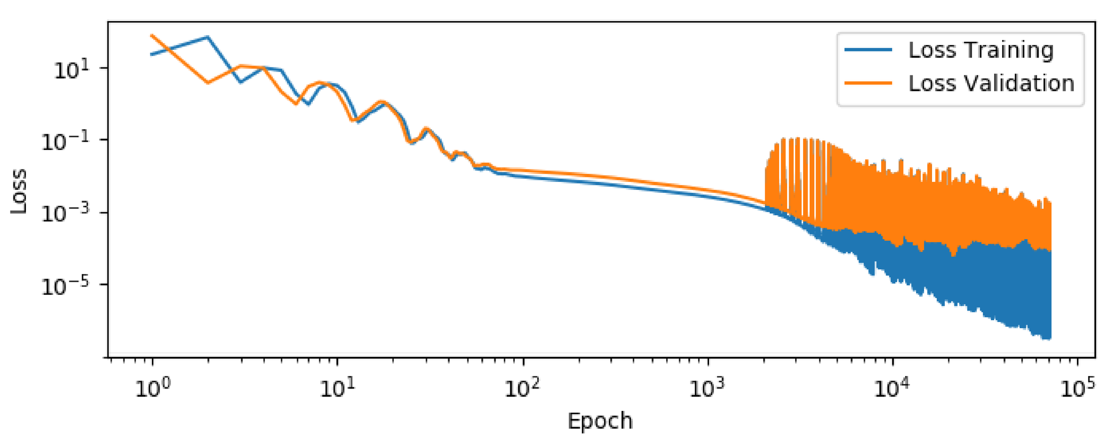
Search for neural networks which map the *desired* position on the target to the *required axes* positions of the heliostat with high accuracy. We found two types of networks that can handle this complex task:

<u>Self Normalizing Neural Networks (SNN) (2)</u>

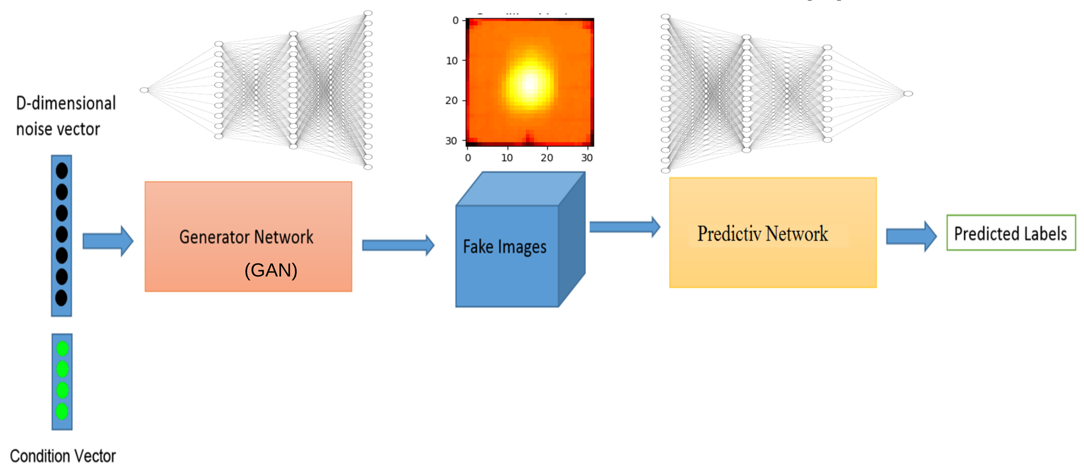


$$selu(x) = \lambda \begin{cases} x & \text{if } x > 0 \\ \alpha e^x - \alpha & \text{if } x \leqslant 0 \end{cases}$$

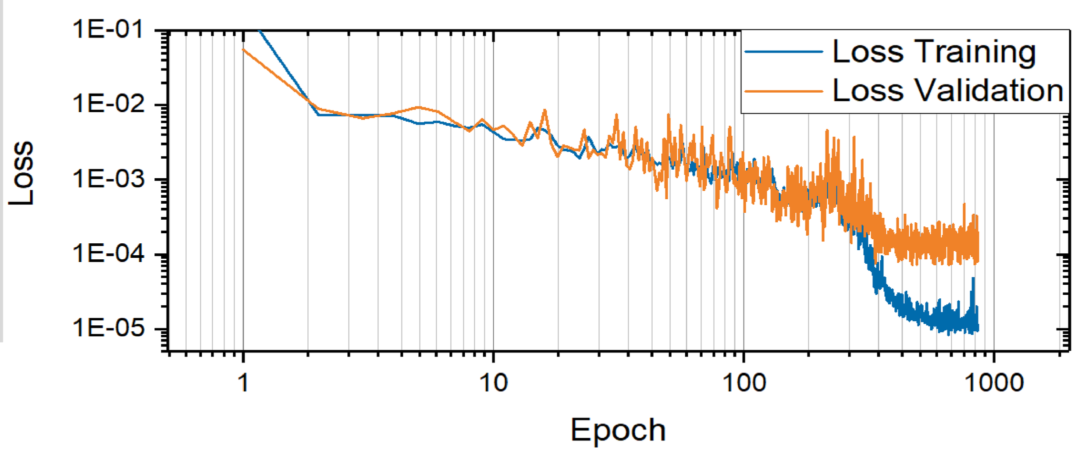
- Fast and Simple to train also for deep networks
- No Image and so no Imputation needed
- More training data needed as for GANs



<u>Shared-Loss GAN-Prediction Networks (3)</u>



- Need less data
- Faster than SNN for bigger networks
- Generator output can be used for other tasks, like parallelization , real error behaved raytracing or field network training



- Both methods are capable to reduce the error to a scale of 0.03mrad and below.
- We reach acceptable results for a dataset containing <800 data points for SNNs and <300 for GAN-Prediction networks.
- Due to *transfer learning* we can reduce the amount of needed data by a tenth and less.
  - First we train the Network with simulated Images, generated by a raytracer
  - Afterwards the data of the whole field can be used to adapt the networks to real world behavior.
  - The last step is to train the final network layers to its belonging Heliostat

Summary & Outlook

Key results

- Neural networks should be able to calibrate heliostats
- Calibration profits from surrounding heliostat data
- Follow-up Networks can Profit from GAN-Pictures,
- Generated GAN Pictures can speed up raytracers

Ongoing and future work

- Next step is to validate new method at solar tower in Jülich.
- Parallelization of the calibration process with the help of the shape analysis of image supported networks.
- Analysis of time dependent and not linear errors
- *Informed loss* for GAN-Prediction Network, to reduce error and amount of needed data

- Transferring the method to other components of the power plant, candidates are:
  - The receiver
  - The power plant circuit
  - The heat storage

References

(1) N. Sun, P. Shen, S. You 2019 “Heliostat correction system based on celestial body images and its method” Patent No US 10,309,691 B1
(2) G. Klambauer, T. Unterhiner, A. Mayr 2017. "Self-Normalizing Neural Networks" CoRR vol. 1706.02515
(3) M. Pargmann, D. Maldonado-Quinto, P. Schwarzbözl “Deep Learning Algorithms for Heliostat Field Calibration” in: SOLAR PACES 2019

Acknowledgements

Special thanks is owed to Kai Wieghardt and the whole SF-SKT for supporting this project

DLR Deutsches Zentrum für Luft- und Raumfahrt
German Aerospace Center