OPTIMISING OWN PV CONSUMPTION WITH PV ENERGY YIELD PREDICTIONS FROM MACHINE LEARNING ALGORITHMS AND WEATHER DATA

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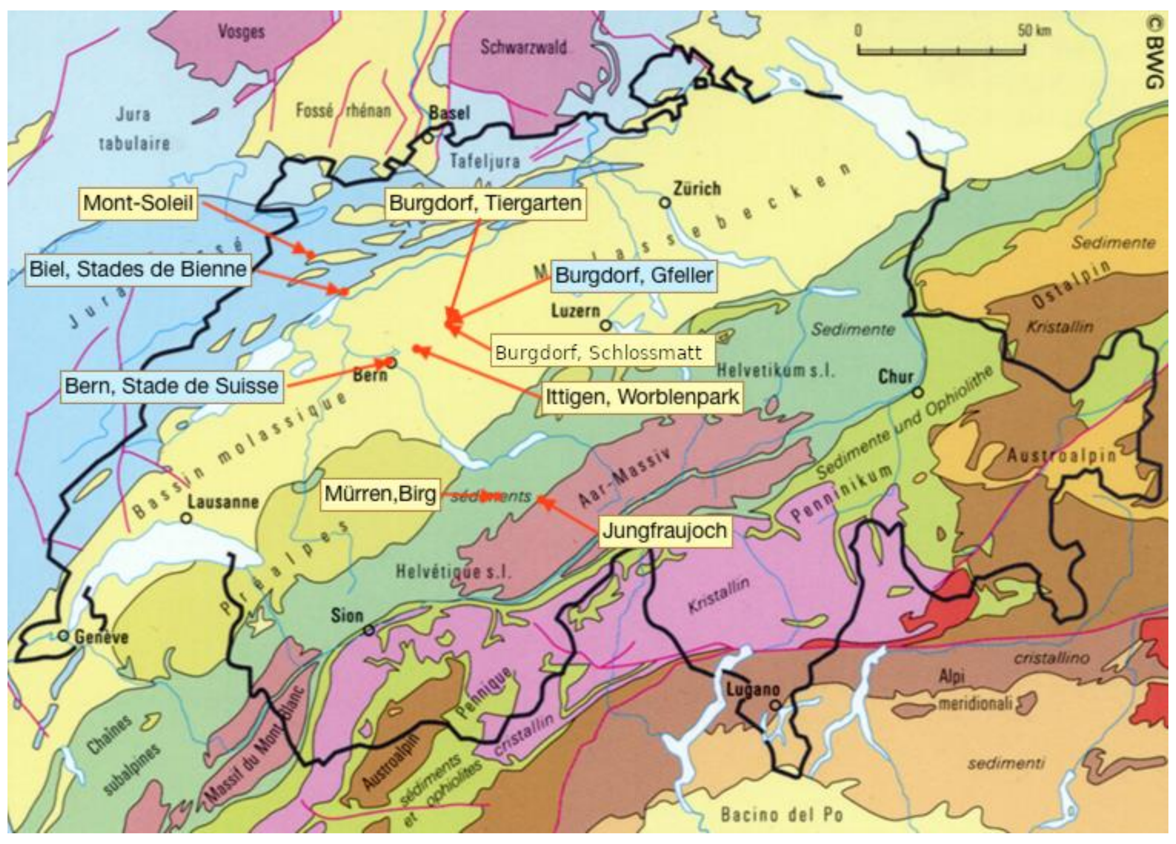
A tool to predict PV power is created. Machine learning algorithms (MLA) are developed and fed with data recorded at six PV plants in Switzerland and weather forecasts from two Swiss providers. The prediction precision is increased by 30% when additional weather parameters are included in the MLA learning process. Own PV consumption is expected to increase with good PV predictions.

Data

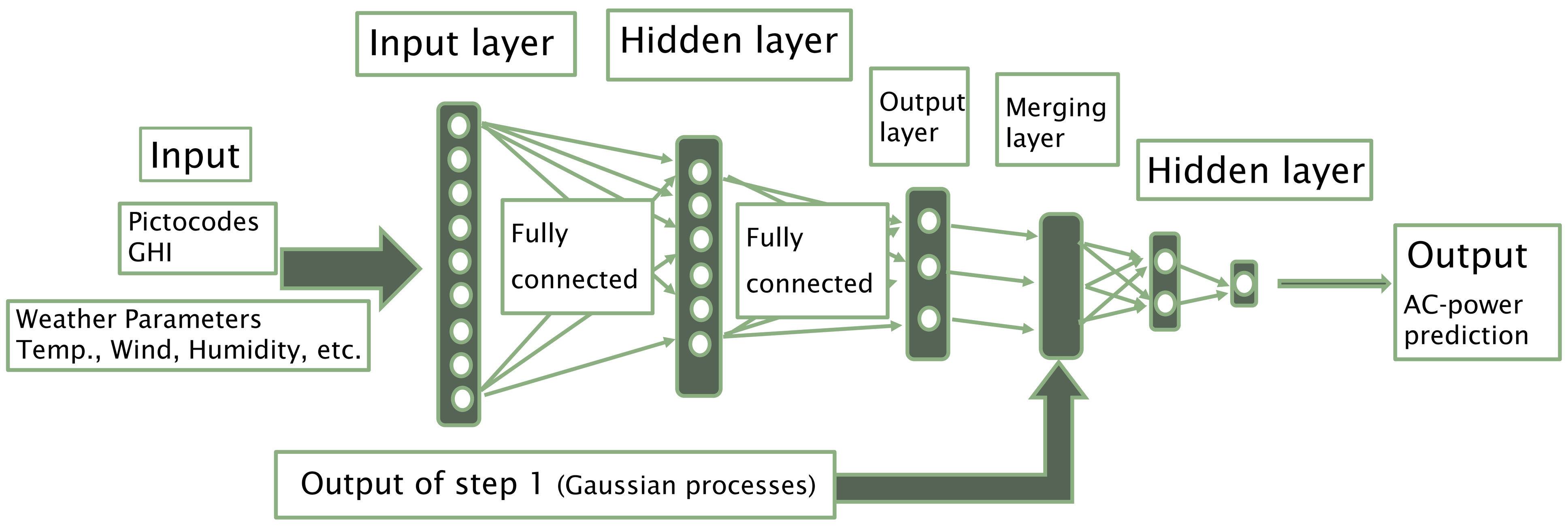
- AC-power records from 6/2016 to 6/2020
- 6 Swiss PV plants (3 urban, 3 alpine)
- Weather forecast data (0/2020-6/2020) provided by MeteoSuisse and Meteoblue



6 PV plant locations (yellow: used so far; blue: future use)

Algorithm

1st step: Gaussian Process
  Input: Measured AC-power at PV plants
2nd step: Neural Network
  Input: - Predictions from step 1
  - Basic NWP (Pictocode, GHI)
  - Additional weather parameters (temperature, wind, humidity, etc.)

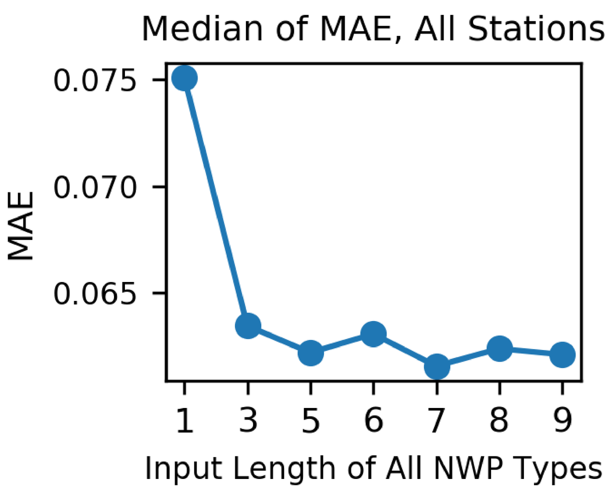


Results

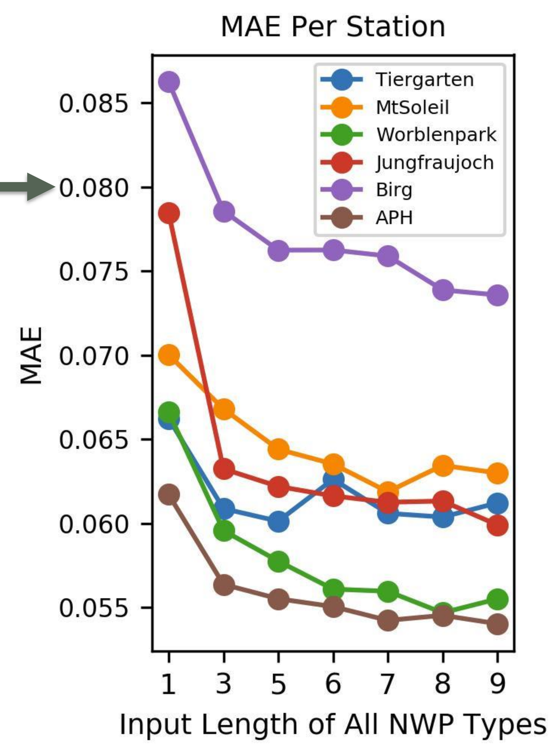
1. Input lengths of Pictocode/GHI

(Pictocode: Abstract description of weather situation, e.g., clear sky, cloudy, etc.)

More than 1 input value increases performance



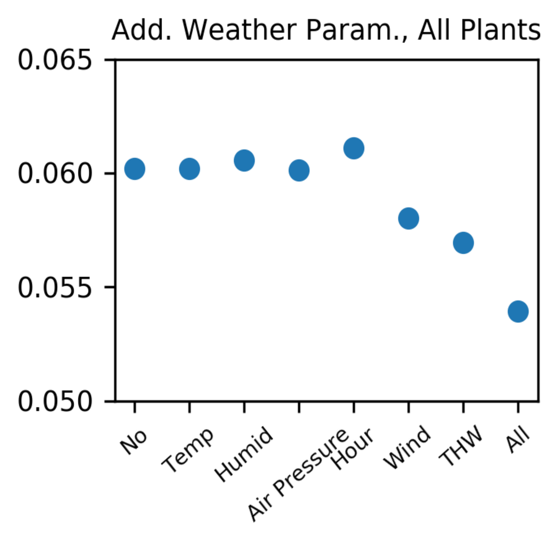
Alpine plants (red, yellow, purple) benefit more

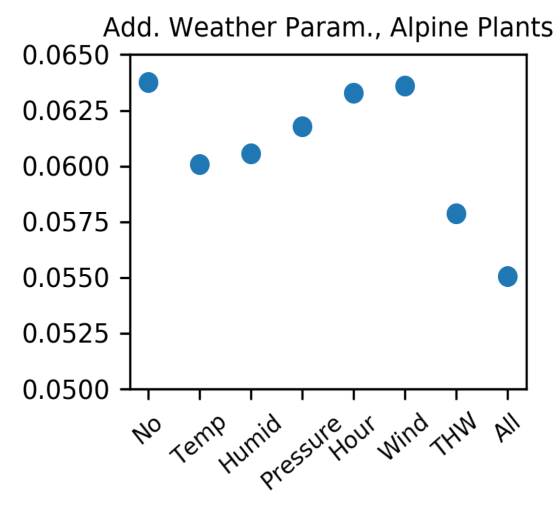


2. Weather Parameters

Additional weather parameters tested

- Temperature
- Humidity
- Pressure
- Wind
- Timestamp (hour)





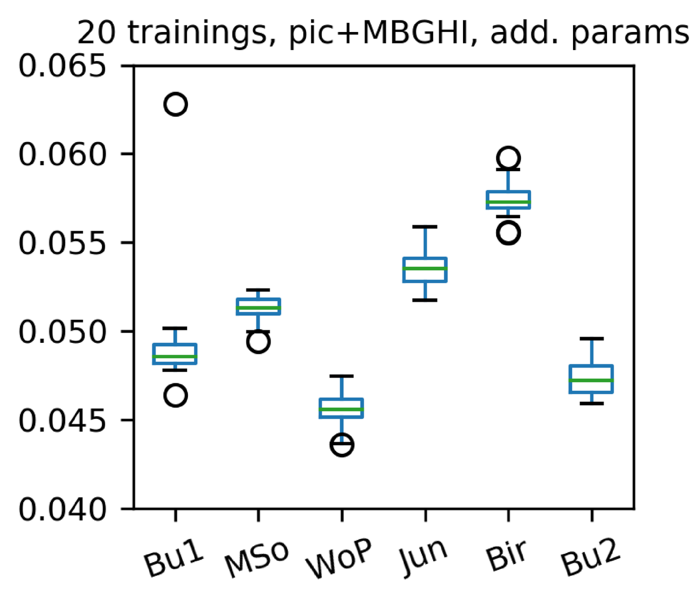
Alpine PV plants vs urban PV plants:
Temperature and humidity are more important for alpine than for urban PV plants.
Urban PV plants benefit from wind parameters.

Conclusions

- Future and past values of forecast for pictocode and GHI should be included as input.
- Further weather parameters such as temperature, wind, humidity, etc. improve the performance of the algorithm. The combination of parameters yields the best results.
- A performance increase of about 30% has been achieved so far.

Comparison of MAE for «First Try» (1 pictocode value as input) and «Optimised algorithm» (9 pict.+GHI values and additional weather param.)

Plant	First Try	Optim.	Diff.	Increase %
Burgdorf Tiergarten (Bu1)	0.0662	0.0486	0.0176	36 %
Mont Soleil (MoS)	0.0700	0.0513	0.0187	36 %
Worblenpark, Ittigen (WoP)	0.0666	0.0456	0.0210	46 %
Jungfraujoch (Jun)	0.0717	0.0535	0.0182	34 %
Birg (Bir)	0.0807	0.0573	0.0234	41 %
Burgdorf, Schlossmatt (Bu2)	0.0617	0.0472	0.0145	31 %



Test of 20 trainings per plant with optimal configuration

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