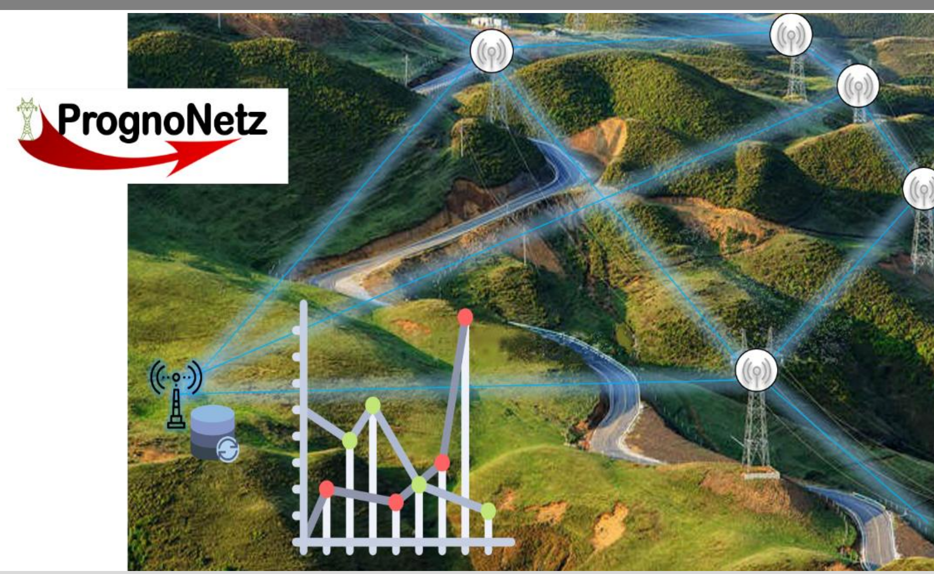
Institute for Information Processing Technologies

Cigré TAG 4, Working Group B2.59

Ampacity forecasting using machine learning: an approach based on distributed weather measurements

PhD cand. Gabriela Molinar

Institute for Information Processing Technologies (ITIV), Prof. Dr. rer. nat. Wilhelm Stork



Some background:
PhD cand. Gabriela Molinar

- Electronics Engineer from the Simon Bolivar University, Caracas – Venezuela
- Exchange year at the KIT in Karlsruhe – Germany
- Thesis written under the supervision of Prof. Wilhelm Stork

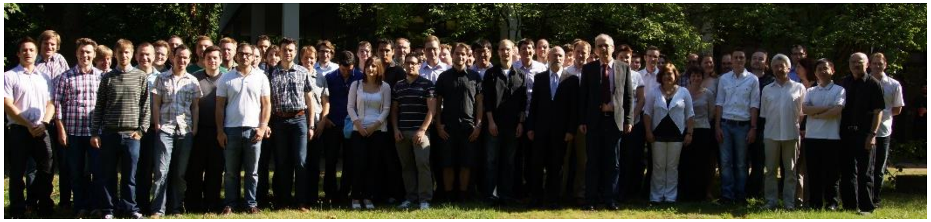
  → PhD position from April 2016

Institute for Information Processing Technologies at KIT

Karlsruher Institut für Technologie

Key competences:

- Systems Engineering (Prof. Sax)
- Embedded Systems (Prof. Becker)
- **Intelligent sensor networks, microsystems and Optics (Prof. Stork)**



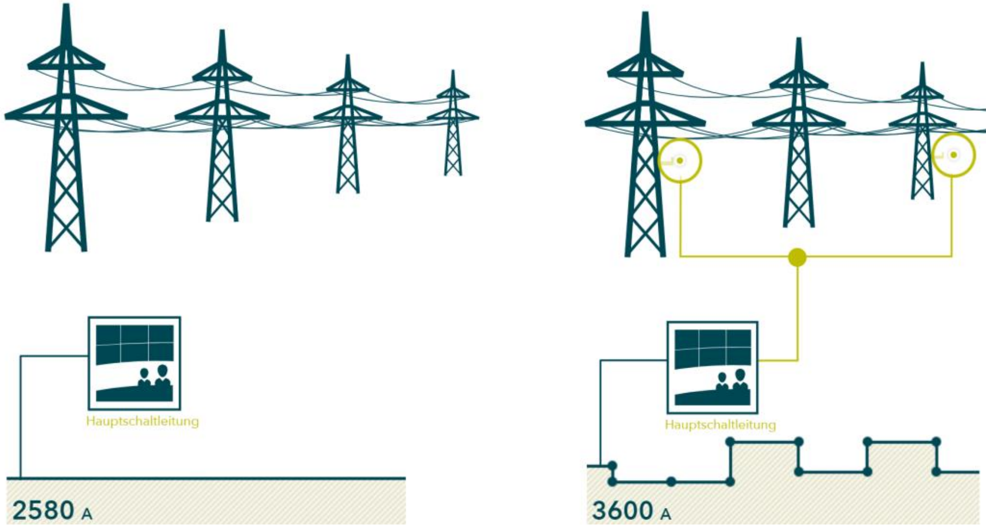
Research areas Prof. Stork:

- **Optical sensors and wearables for medical systems**
- **Virtual and Augmented Reality**
- **Sensor networks for indoor navigation**
- **Artificial Intelligence for automotive, medical systems, smart home and smart grid applications**

Motivation: NORE-Principle

Electrical Network Optimization, before Reinforcement, before Expansion

NOVA Prinzip, German Federal Network Agency

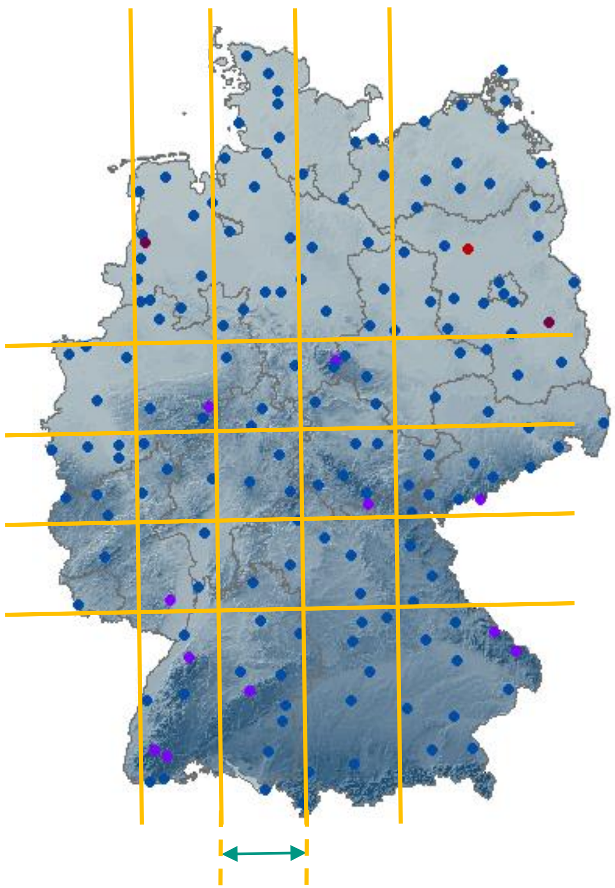


Dynamic Line Rating helps TSOs to optimize the use of the electrical network

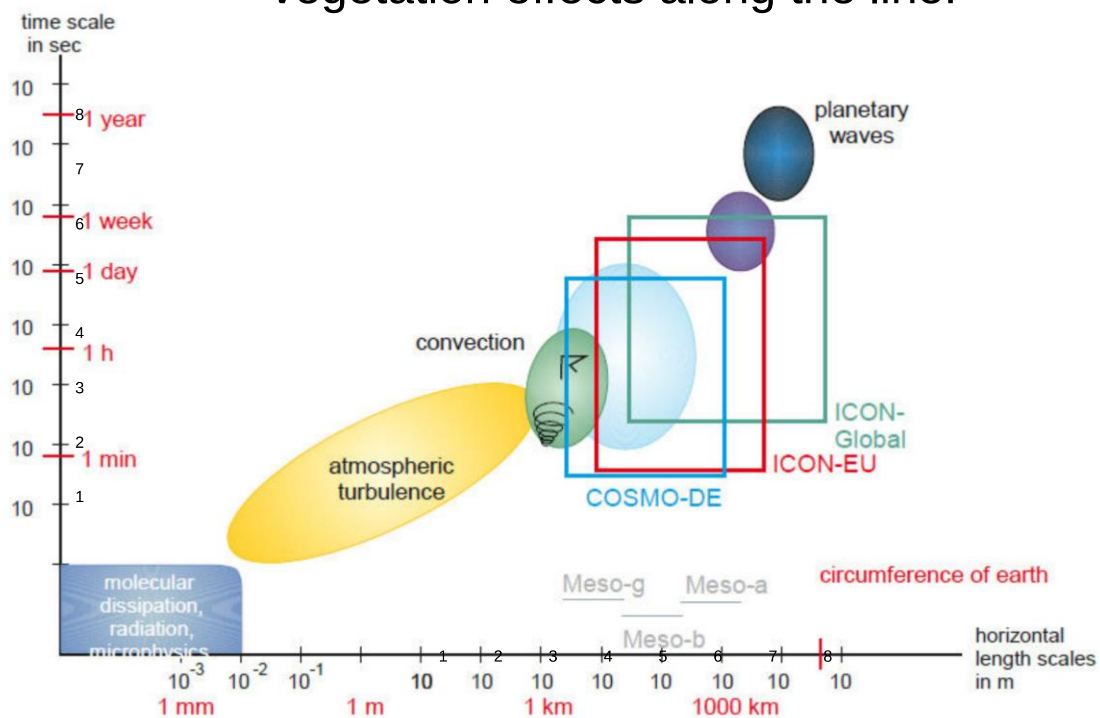
A DLR forecast is necessary!

TransnetBW, https://www.transnetbw.de/de/welt-der-energie/nova-prinzip

State-of-the-art: Numerical weather prediction



These models are not considering vegetation effects along the line!

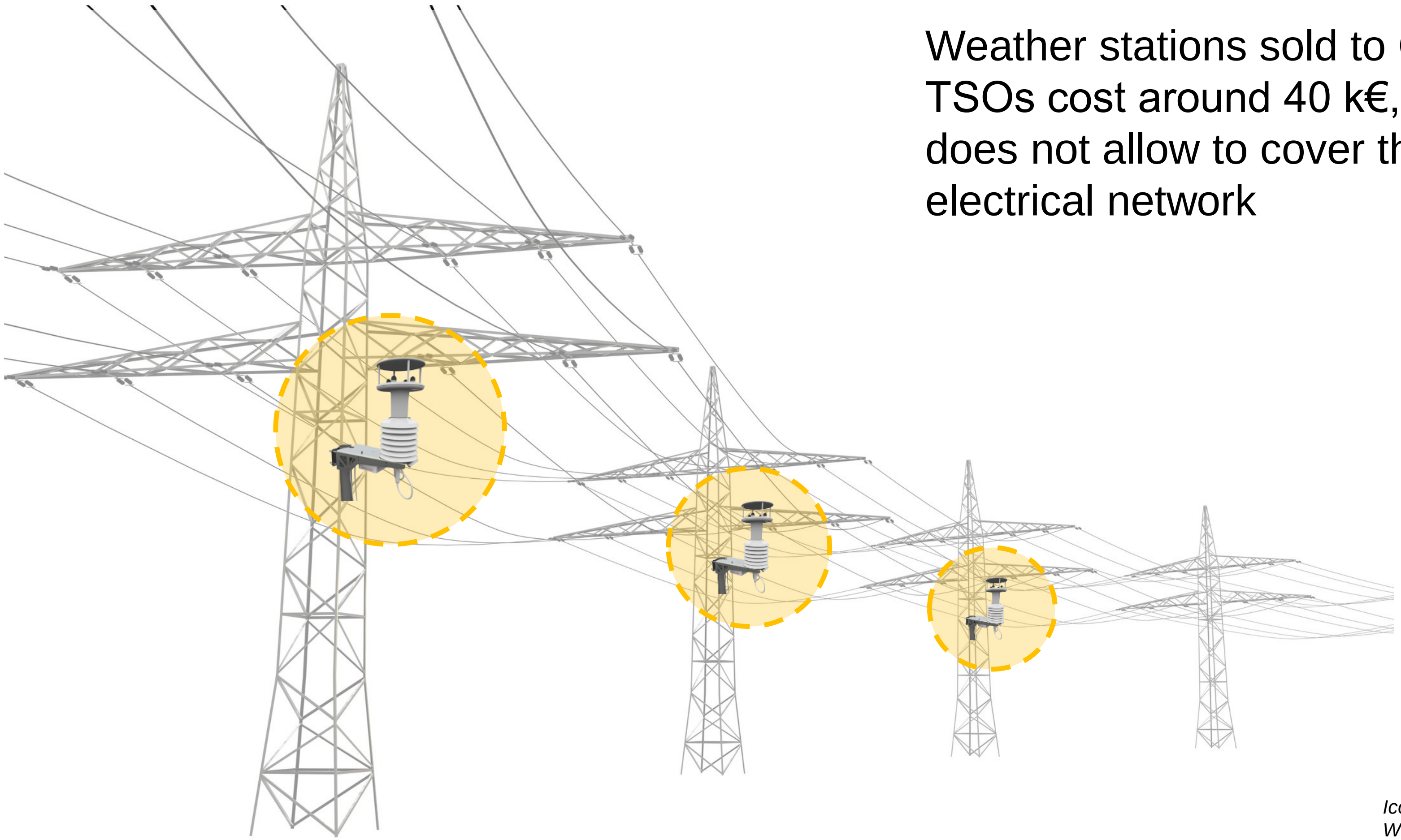


Spatial resolution up to 2.5 km → Not enough for DLR forecasting!

Deutscher Wetterdienst (DWD), "Wettermodelle," 2017.

G. Müller-Westermeier, "Verfügbarkeit und Qualität flächenbezogener Klimadaten," Deutscher Wetterdienst, Abteilung Klimaüberwachung. [Online]. Available: https://www.dwd.de/DE/leistungen/klimakartendeutschland/detailbeschreibung.html. [Accessed: 10-Feb-2019].

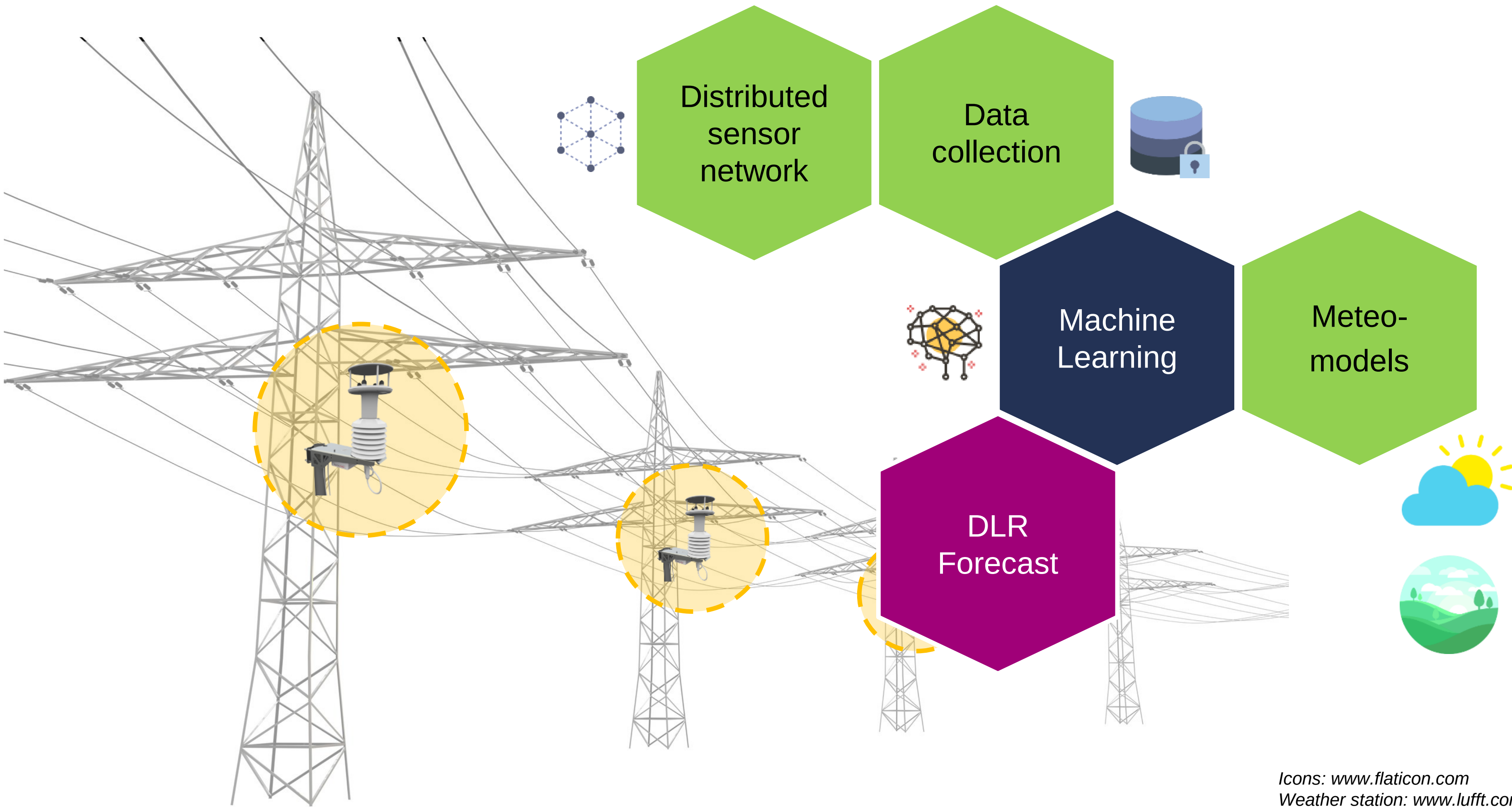
Solution: Distributed weather sensor network



Weather stations sold to German TSOs cost around 40 k€, which does not allow to cover the whole electrical network

Icons: www.flaticon.com
Weather station: www.lufft.com

Solution: PrognoNetz



Icons: www.flaticon.com
Weather station: www.lufft.com

PrognoNetz Project

Karlsruher Institut für Technologie

TRANSNET BW

UBIMET

unilab

wilmers

GWU

PrognoNetz

Supported by:

Federal Ministry
for Economic Affairs
and Energy

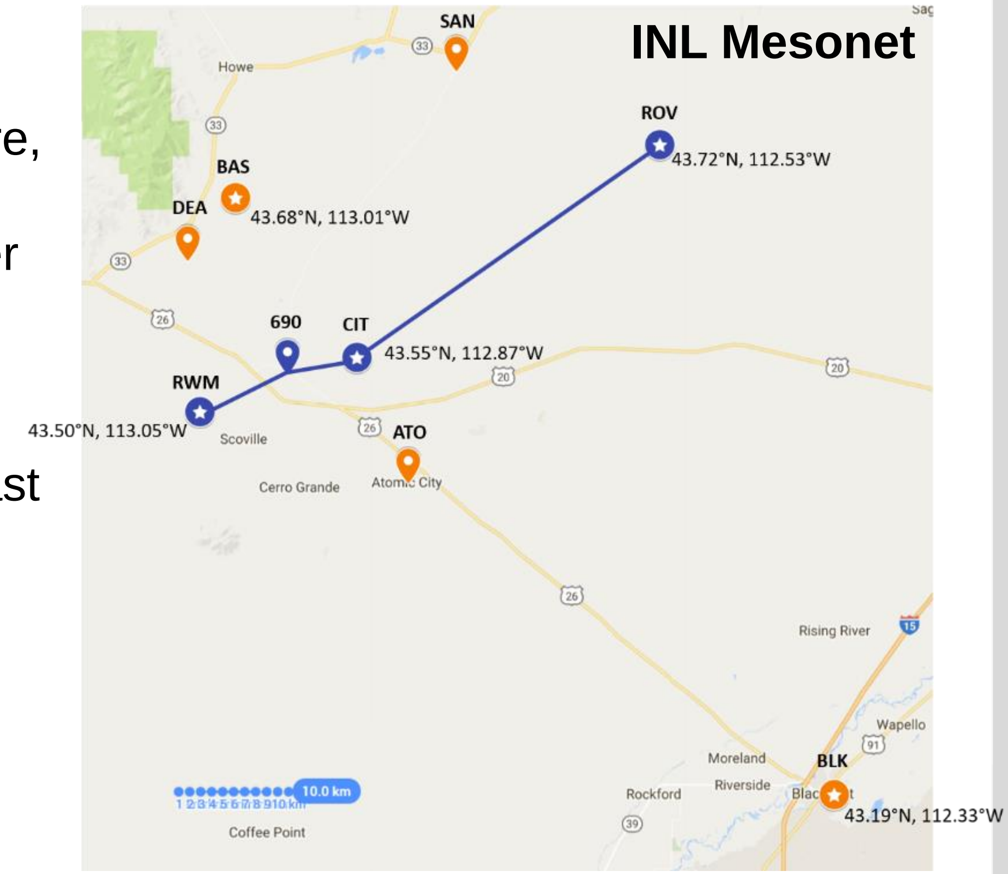
on the basis of a decision
by the German Bundestag

January 2019 – December 2021

Understanding the data

Criteria for database selection:

- Measured weather parameters:
  - ✓ For DLR calculation: Temperature, wind, solar radiation
  - ✓ Additional information for a better forecast: Pressure, relative humidity
- Geographical distribution:
  - ✓ Measurement at line level: at least 15 m
  - ✓ High spatial density sensor network
- Temporal coverage and resolution:
  - ✓ At least 3 years historical data (1 year for each: training, validation and test)
  - ✓ One hour resolution or better



Simulated overhead line, going along weather stations from the meteorological monitoring network from the Idaho National Laboratory (USA)

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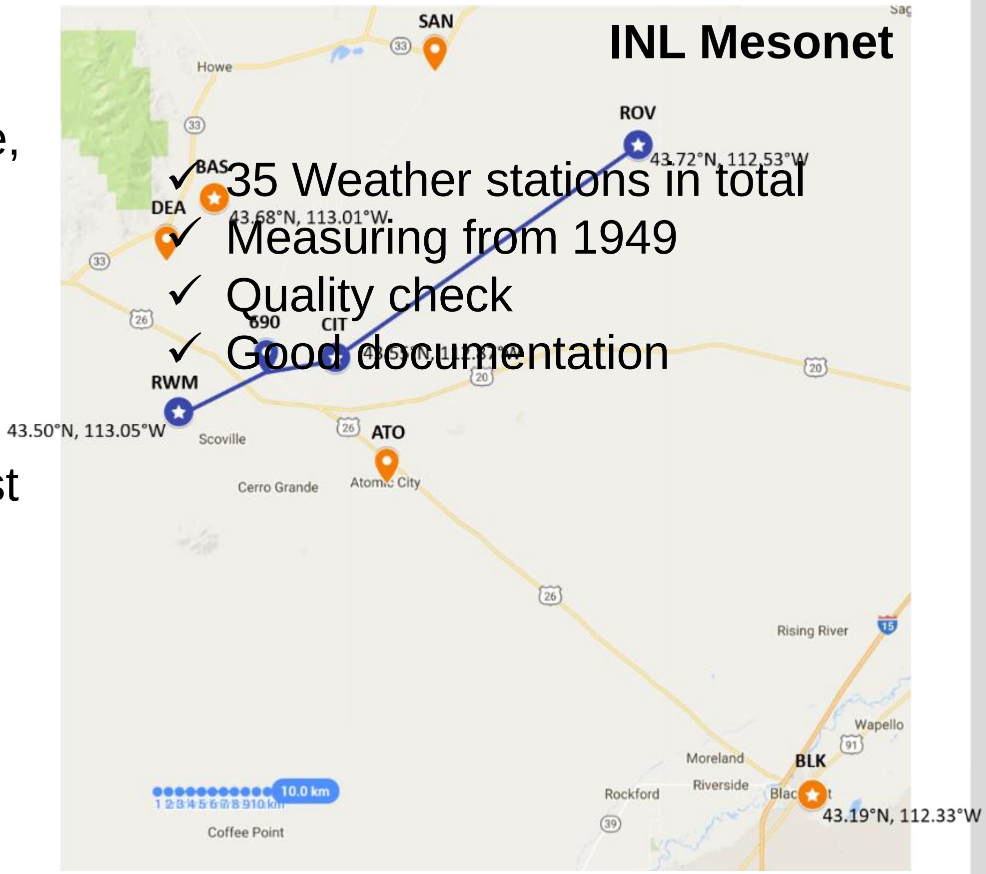
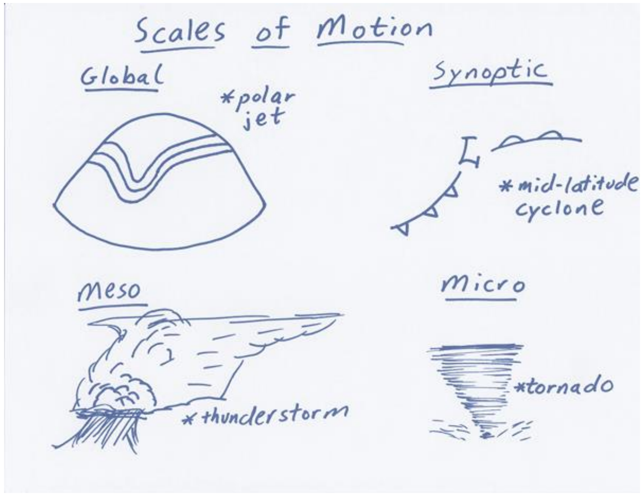


✓ 35 Weather stations in total
✓ Measuring from 1949
✓ Quality check
✓ Good documentation

Simulated overhead line, going along weather stations from the meteorological monitoring network from the Idaho National Laboratory (USA)

Algorithm selection

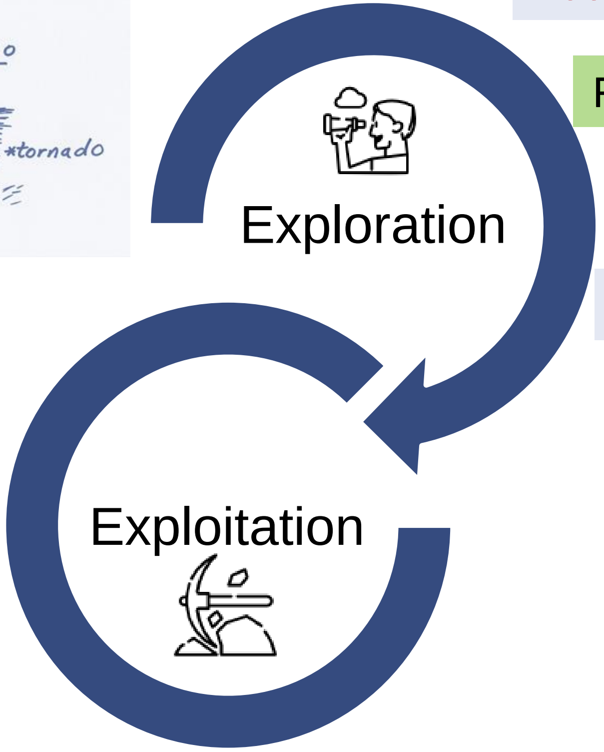


~~Feedforward Neural Networks~~

Recurrent Neural Networks

Quantile Regression Forests

~~Reinforcement Learning~~



Benchmark

Icons: www.flaticon.com

Scales of motion. Jeff Haby. http://www.theweatherprediction.com/habyhints3/733/

Evaluation of meteorological scales

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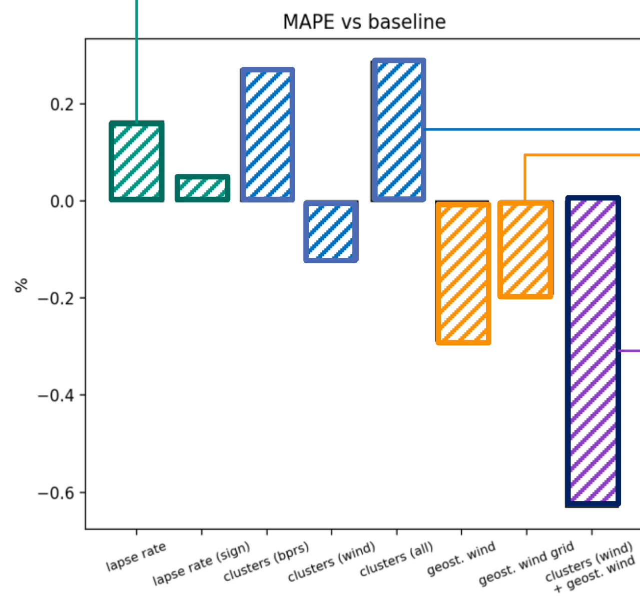
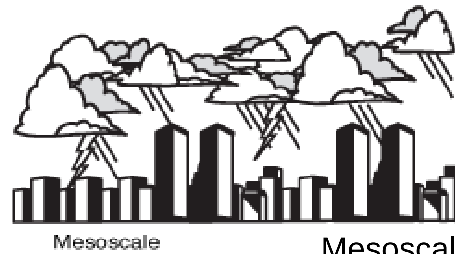
Microscale (< 1 km)

$$\Gamma = -\frac{dT}{dz}$$

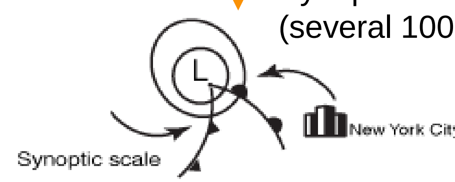
Simple RNN Model





Mesoscale (several 100 km)

Synoptic scale (several 1000 km)



Combination of Mesoscale and Synoptic scale provides the best accuracy

Icons: www.flaticon.com
Scales of motion. Jeff Haby. http://www.theweatherprediction.com/habyhints3/733/

System design and benchmark

Model	*MAPE*			*MAE (t=48)*	*STD (t=48)*
	t=1	*t=24*	*t=48*		
Persistence	21,75%	21,82%	23,68%	419,57 A	535,44 A
LSTM-SISO	18,66%	18,36%	18,49%	326,22 A	408,14 A
LSTM-Concat	13,40%	16,50%	17,67%	307,87 A	388,48 A
QRF	11,37%	16,52%	17,08%	284,11 A	352,81 A

Icons: www.flaticon.com

Benchmark: graphical representation

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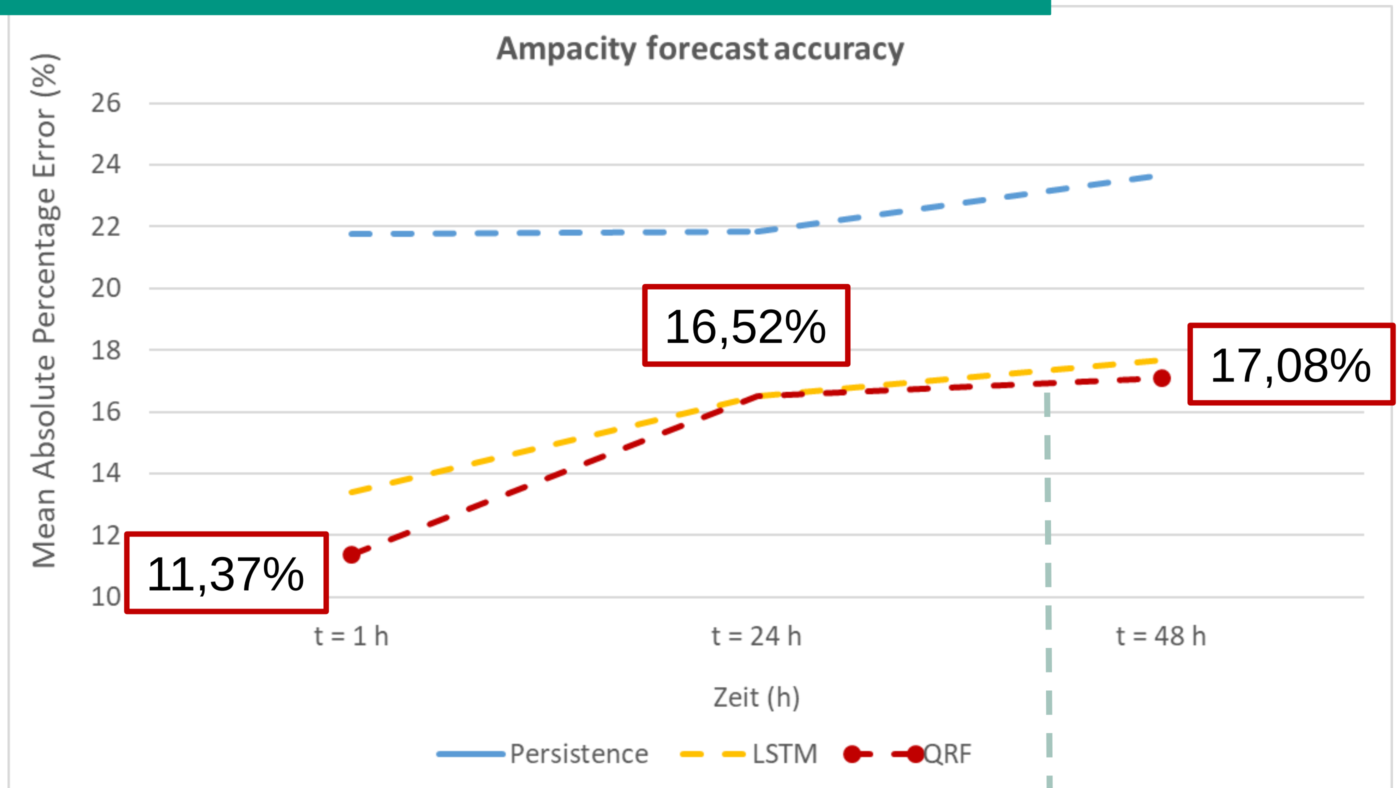

Standard Deviation

Persistence	535,44 A
LSTM	388,48 A
QRF	352,81 A

MAPE < 20%

Icons: www.flaticon.com

Summary and outlook

- Ampacity forecasting generated by historical and distributed weather data is possible
  - The accuracy can be smaller than 20% as expected
  - The standard deviation is in the order of 300 to 500 A

- As next steps:
  - Comparison with NWP-based ampacity forecasting
  - Combination of historical models with NWP models

Thank you for your attention

Questions?

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