Cigré TAG 4, Working Group B2.59

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

PhD cand. Gabriela Molinar
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
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

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

These models are not considering vegetation effects along the line!


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

- Distributed sensor network
- Data collection
- Machine Learning
- Meteo-models
- DLR Forecast

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

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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Algorithm selection

Exploration
- Feedforward Neural Networks
- Recurrent Neural Networks
- Quantile Regression Forests
- Reinforcement Learning

Exploitation

Benchmark

Icons: www.flaticon.com
Evaluation of meteorological scales

Microscale (< 1 km)

\[ \Gamma = -\frac{dT}{dz} \]

Simple RNN Model

Combination of Mesoscale and Synoptic scale provides the best accuracy
## System design and benchmark

<table>
<thead>
<tr>
<th>Model</th>
<th>MAPE</th>
<th>MAE (t=48)</th>
<th>STD (t=48)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$t=1$</td>
<td>$t=24$</td>
<td>$t=48$</td>
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<tr>
<td>Persistence</td>
<td>21,75%</td>
<td>21,82%</td>
<td>23,68%</td>
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<tr>
<td>LSTM-SISO</td>
<td>18,66%</td>
<td>18,36%</td>
<td>18,49%</td>
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<tr>
<td>LSTM-Concat</td>
<td>13,40%</td>
<td>16,50%</td>
<td>17,67%</td>
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<tr>
<td>QRF</td>
<td>11,37%</td>
<td>16,52%</td>
<td>17,08%</td>
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Exploitation

Icons: www.flaticon.com
Benchmark: graphical representation

Ampacity forecast accuracy

<table>
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<th>Zeit (h)</th>
<th>Persistence</th>
<th>LSTM</th>
<th>QRF</th>
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<tr>
<td>t = 1 h</td>
<td>11,37%</td>
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Exploitation

Standard Deviation

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<td>LSTM</td>
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<tr>
<td>QRF</td>
<td>352,81 A</td>
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</tbody>
</table>

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
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Thank you for your attention

Questions?