KonKIS 2024

Power flow forecasts at transmission grid nodes using Graph Neural Networks

Dominik Beinert [1], Clara Holzhüter [1,2], Josephine M. Thomas [2], Stephan Vogt [2]
Kontakt: Dominik Beinert | Fraunhofer IEE | dominik.beinert@iee.fraunhofer.de

Fraunhofer IEE [1]
Universität Kassel [2]

Motivation

With the increasing integration of renewable energy and evolving power consumption patterns caused by new consumers like electric vehicles and heat pumps, power flows in the electricity grid have become more fluctuating and weather-dependent, challenging grid stability. Accurate power forecasts at grid nodes between voltage levels are essential for grid operators to ensure reliable grid calculations and planning.

The power flows within an electrical grid are not independent of one another; rather, they are interconnected, resulting in mutual influences at transformers at grid nodes (Fig. 1).

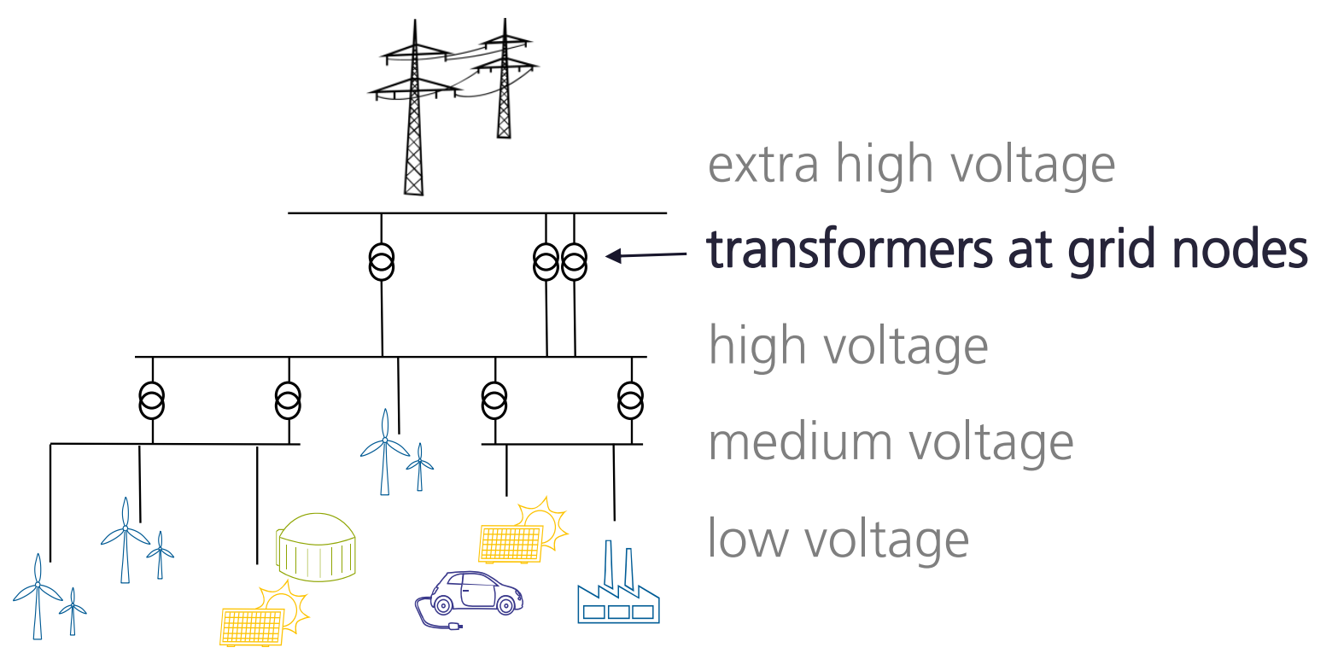

Fig 1: Schematic representation of the electric power grid with transformers at grid nodes between high voltage and highest voltage levels. Original image: [(1), 2022]

At the same time, power flows at individual grid nodes differ according to the connected power plants and consumers. Thus, it is not sufficient to train a machine learning model treating all grid nodes identically.

Objective

The objective is to calculate the desired node attribute (day-ahead forecast for the power value at the transformer) from existing local features (weather forecasts, calendar data, etc.) while considering the neighboring nodes.

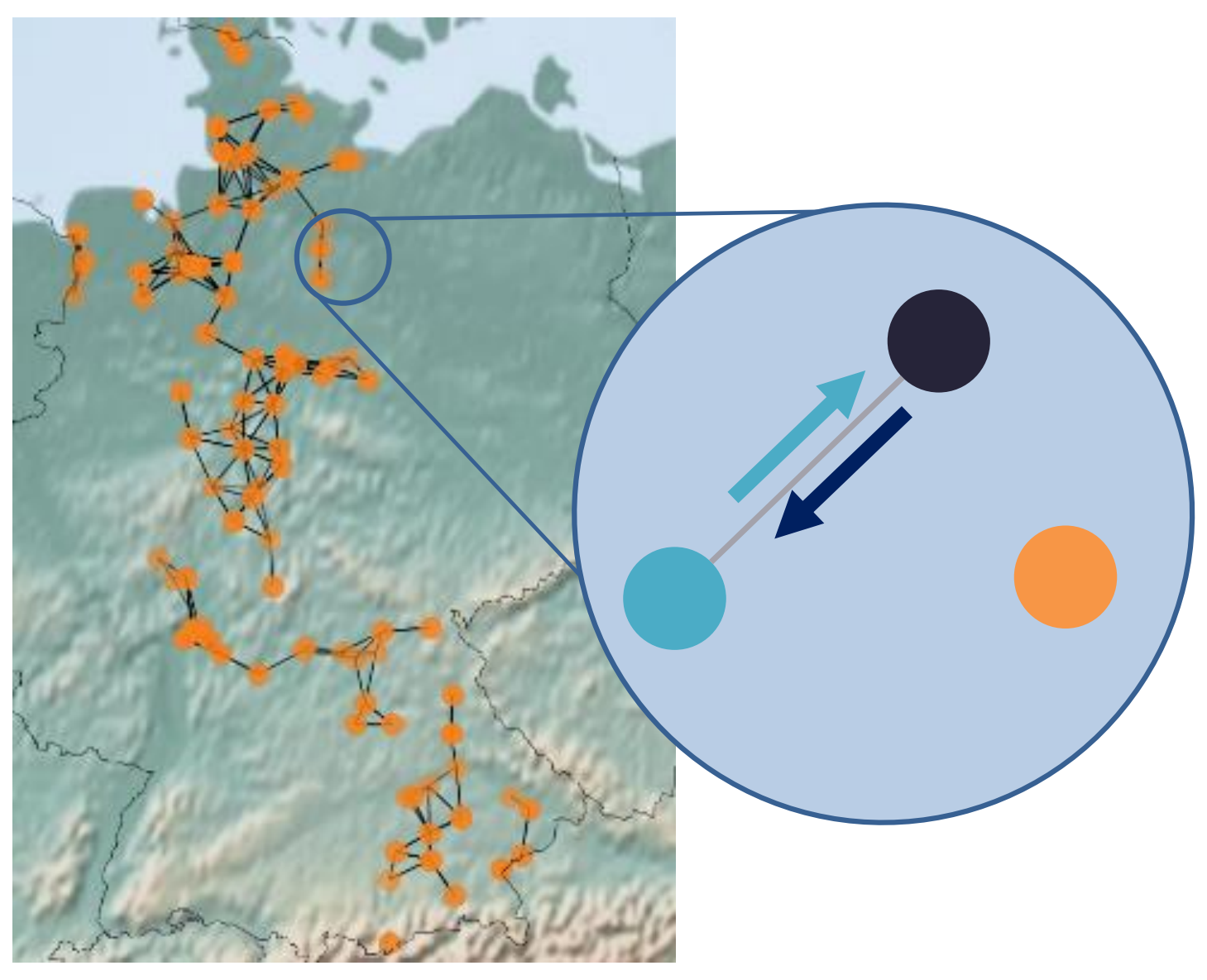

Fig 2: Location of transformers (= nodes) connecting high and extra high voltage levels in a grid zone controlled by German TSO TenneT. A graph can be defined by introducing edges between all nodes within a certain radius, as the real grid topology is unknown. Original image: [(2), 2023]

Methodology

We propose an approach combining a Graph Neural Network (GNN) with Multi-Task Learning (MTL). The GNN is employed to learn the interrelationships between transformers, while the MTL accounts for the individual node behavior.

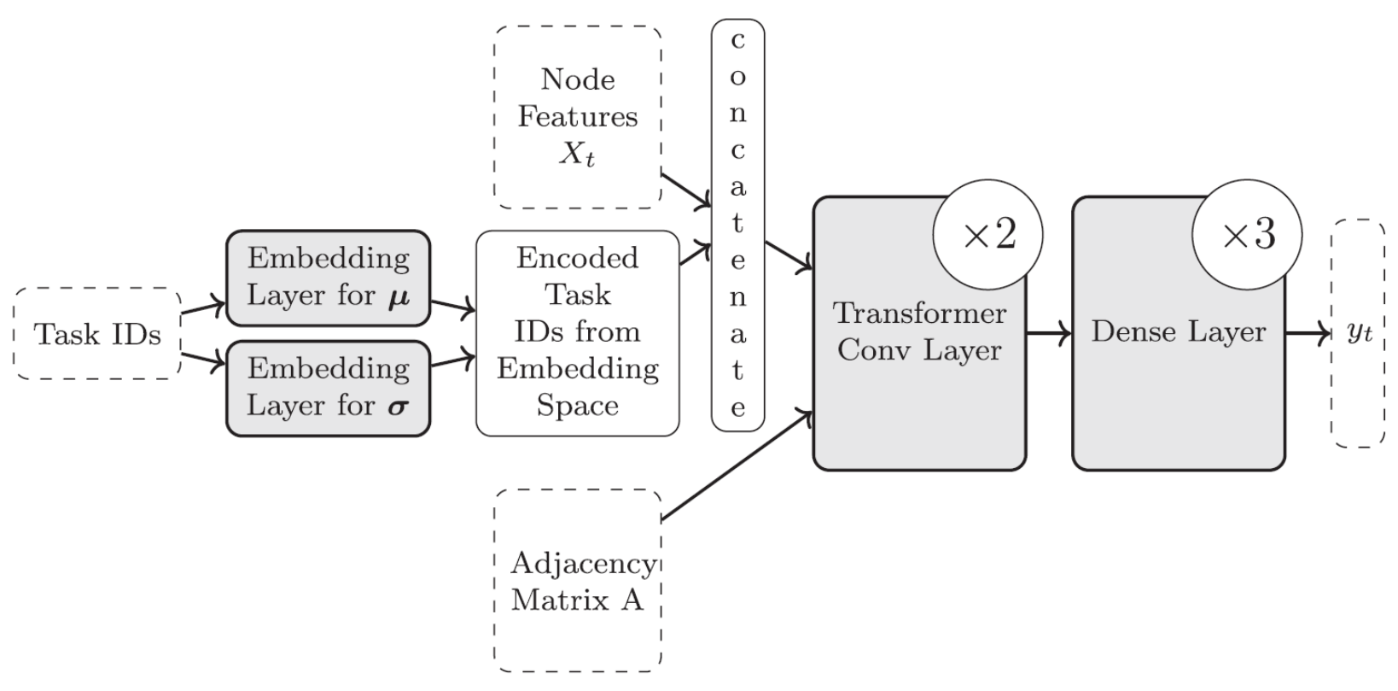

Fig 3: Proposed model architecture BEMTL-GNN. As an MTL approach a Bayesian embedding layer encoding characteristic node behavior is employed. The GNN is implemented by adding Attention Convolution layers (TransformerConv). Original image: [(2), 2023]

Case Study

- Two TSO data sets: 50Hertz (175 transformers), TenneT (176 transformers)
- Two years of data (one year training, two months validation, ten months test)
- Two experimental setups: Edges between nodes only if transformers are (1) located at the same substation, or (2) within a 50km radius of each other.

Results

The proposed BEMTL-GNN slightly reduced root mean square errors compared to a pure MTL model (BEMTL), and significantly reduced errors compared to a basic ANN and a standard GNN (Fig. 4). Experimental setup (2) with a higher number of edges further reduced errors.

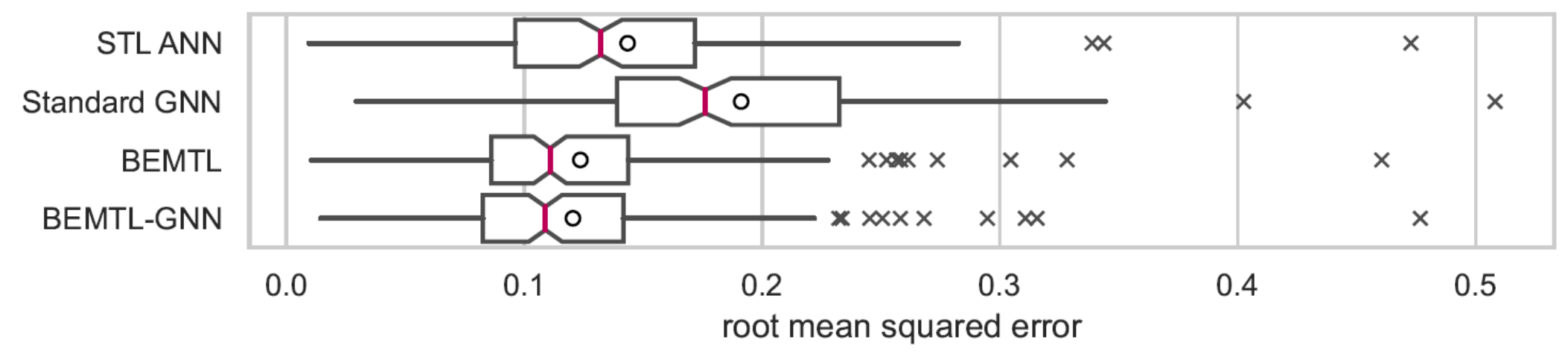

Fig 4: Root mean squared errors at transformers in TenneT control zone for experimental setup (1). Original image: [(2), 2023]

The advantage of BEMTL-GNN over a pure MTL model (Fig. 5) or a pure GNN (Fig 6.) is best observed by comparing predictions at example nodes.

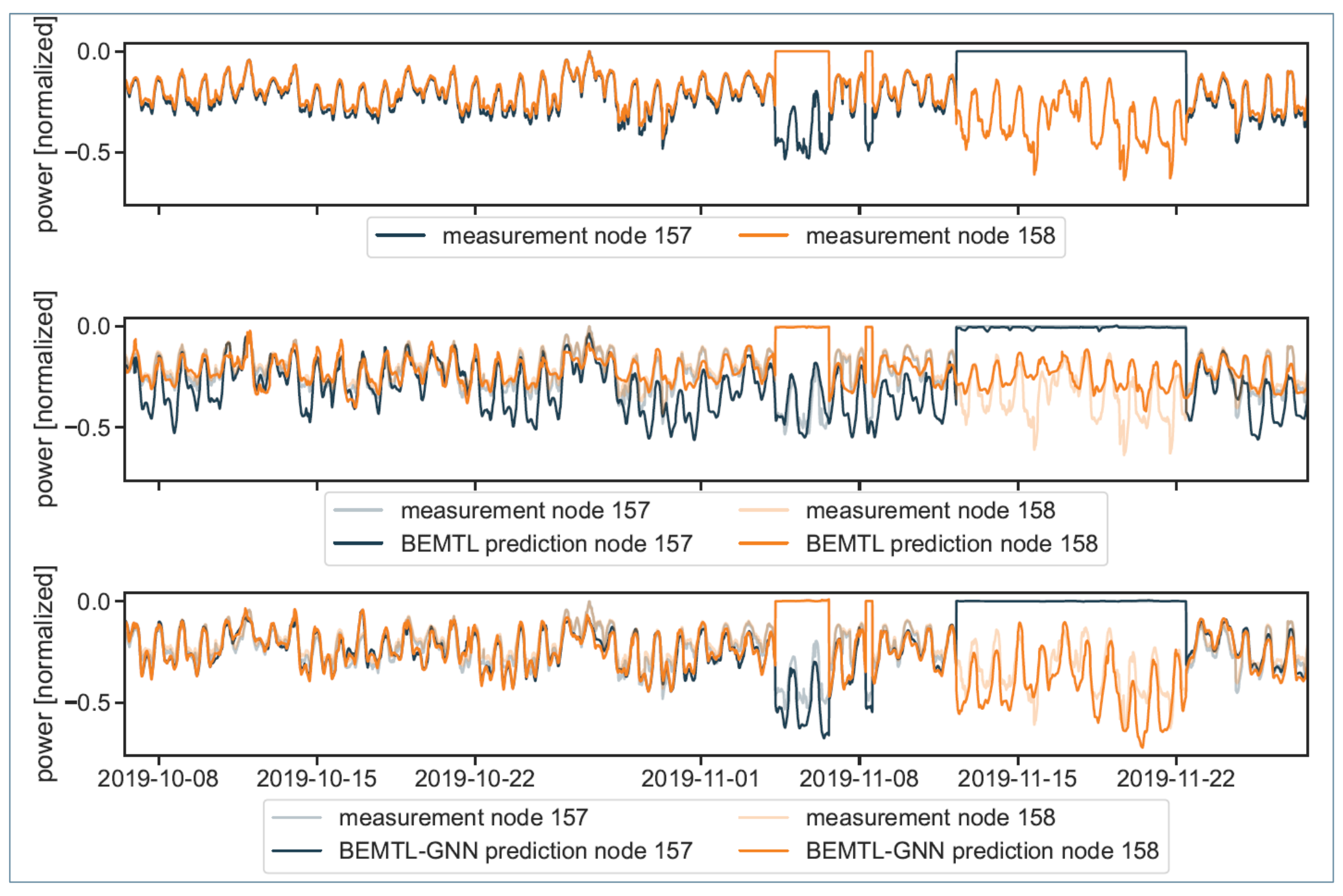

Fig 5: Measurements at pairwise connected transformers (top), pure MTL model prediction (middle) and predictions by the proposed model (bottom). The example illustrates the benefit of adding GNN layers to the model. Original image: [(2), 2023]

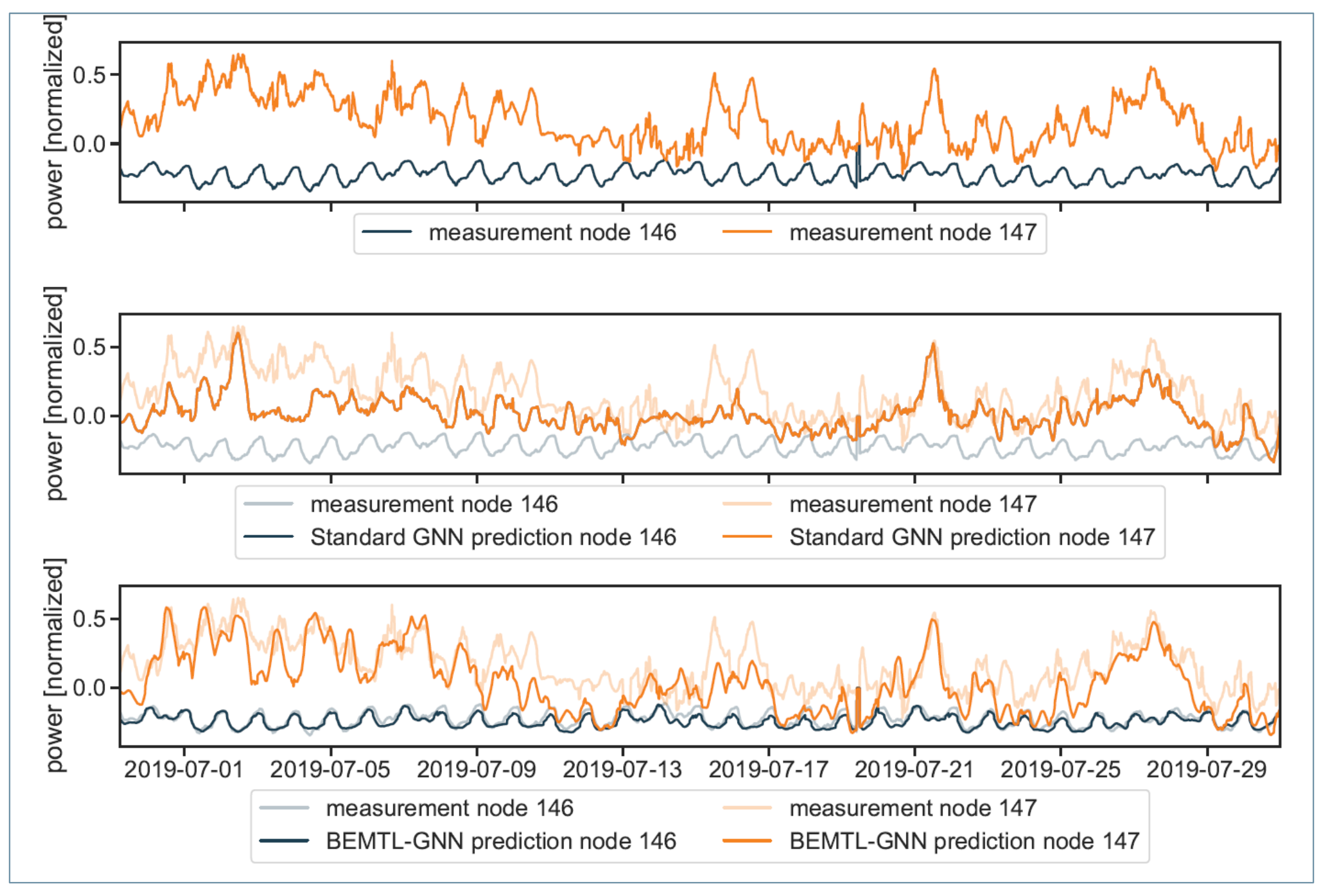

Fig 6: Measurements at pairwise connected transformers (top), standard GNN model prediction (middle) and predictions by the proposed model (bottom). The example illustrates the necessity of the embedding layer, enabling the model to create different predictions for node 146 and node 147. Original image: [(2), 2023]

Conclusion

The novel approach combining a GNN with MTL successfully learns individual characteristics of transformers, while also taking into account information from close-by transformers. Forecast errors can be reduced compared to benchmarks.

SPONSORED BY THE
Federal Ministry of Education and Research

This publication was supported by the Hessian Ministry of Higher Education, Research, Science and the Arts [511/17.001] and the German Federal Ministry of Education and Research [KISSKI, 01IS22093D] [TRANSFER, 01IS20020A] [GAIN, 01IS20047A].

(1) Dominik Beinert, Clara Holzhüter: PowerGraph – Prognose von Leistungsflüssen im elektrischen Netz mit Graph Neural Networks, Poster, https://s.fhg.de/PowerGraph-Poster
(2) Dominik Beinert, Clara Holzhüter, Josephine M. Thomas, Stephan Vogt: Power flow forecasts at transmission grid nodes using Graph Neural Networks, Energy and AI, Volume 14, 2023.