Surrogates for energy system modeling

Anurag Mohapatra

Center for Combined Smart Energy Systems (CoSES)

Technical University of Munich

EMT Colloquium

18.03.2026

CoSES at a glance

Prof. Dr.
Thomas Hamacher
Director

Dr. -Ing.
Anurag Mohapatra
Group Leader

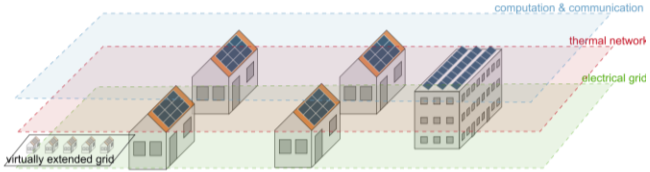
Leads

Integrated Multi-Energy Systems

- ❑ Active Distribution Grids
- ❑ Prosumers in District Heating Grids
- ❑ Energy Management Systems
- ❑ Data-driven techniques

Focus

Simulation / Emulation



Tools

CoSES at a glance

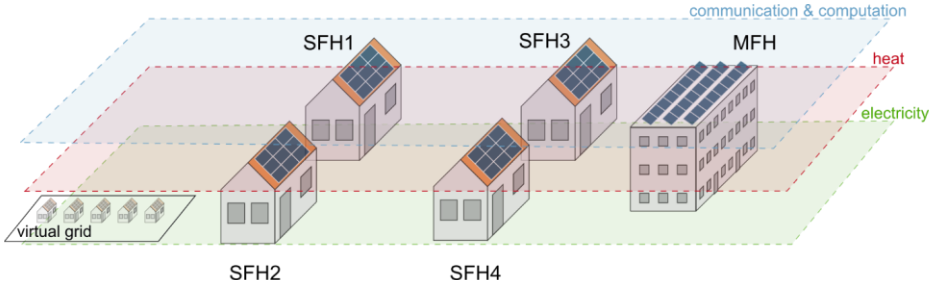
Sector-coupled microgrid at TUM

- Reconfigurable 1.5 km power grid
- Power Hardware-in-the-Loop – up to 250 KVA

- Prosumer emulation - heat and power
- PV, battery and charger for electric cars

- Decentralised control systems
- Unified programming interfaces

- API access to the lab



This talk will cover…

Publications

1. S. Candas, B. Reveron Baecker, A. Mohapatra, and T. Hamacher, "Optimization-based framework for low-voltage grid reinforcement assessment under various levels of flexibility and coordination," *Applied Energy*, vol. 343, Aug. 2023, doi: 10.1016/j.apenergy.2023.121147.
2. A. Mohapatra, M. Hock, B. Reveron Baecker, and T. Hamacher, "Surrogate Framework for Energy System Modeling," *2025 IEEE Kiel PowerTech*, Kiel, Germany, 2025, pp. 1-6, doi: 10.1109/PowerTech59965.2025.11180532.
3. G. Pjetri, A. Mohapatra, B. Reveron Baecker, M. Hock, and T. Hamacher, "Graph Neural Network Surrogates for Energy System Modeling", *2025 IEEE ISGT Europe*, Valletta, Malta, 2025, pp. 1-5, doi: 10.1109/ISGTEurope64741.2025.11305443.
4. H. Genena, A. Mohapatra, B. Reveron Baecker, and T. Hamacher, "Blending Surrogates for Energy System Modeling," accepted in *2026 IEEE PES General Meeting, Montreal, 2026.*
5. B. Reveron Baecker, S. Candas, D. Tepe, and A. Mohapatra, „Generation of low-voltage synthetic grid data for energy system modeling with the pylovo tool", *Sustainable Energy, Grids and Networks*, 41, 2025, doi: 10.1016/j.segan.2024.101617
6. B. Reveron Baecker, K. Kalkan, P. Buchenberg, A. Mohapatra, and T. Hamacher, "A Reproducible Open-Data Pipeline for Synthetic Low-Voltage Grid Generation in Germany ", *2025 IEEE PES Student Summit*, Munich, 2025, doi: 10.30420/566656008
7. E. Franz Hanser, A. Mohapatra, B. Reveron Baecker, and T. Hamacher, „Deep Learning Surrogates for Low-Voltage Grid Planning", accepted in *Power System Computation Conference (PSCC) 2026,* Limassol 2026

Master Thesis

1. Max Schulze, TUM EI, May 2023
2. Max Hock, TUM EI, October 2024
3. Gerild Pjetri, TUM Informatics, January 2025
4. Hussein Genena, TUM EI, September 2025
5. Elias Franz Hanser, TUM Physics, November 2025

PhD Thesis

1. Soner Candas, TUM ENS, December 2023
2. Beneharo Reveron Baecker, TUM ENS, *ongoing*

Motivation – High resolution modeling case for a **DSO**

- Majority of the new renewables are going to appear on distribution grids – predominanlty PV.
- Heatpumps and EV chargers will also contribute.

Der Ausbau der erneuerbaren Energien muss für eine weitgehend klimaneutrale Stromversorgung 2035 dramatisch beschleunigt werden. Binnen weniger Jahre müssen wir den PV-Ausbau in Deutschland auf 22 Gigawatt (GW) pro Jahr erhöhen. Mit dem EEG 2023 wurde dieses Ziel gesetzlich verankert und eine hälftige Verteilung auf Gebäude- und Freiflächenanlagen angelegt. Verglichen mit dem Niveau der bisherigen Boomjahre 2010 bis 2012,

V9. Ermöglichung netzbildender Eigenschaften im Verteilnetz

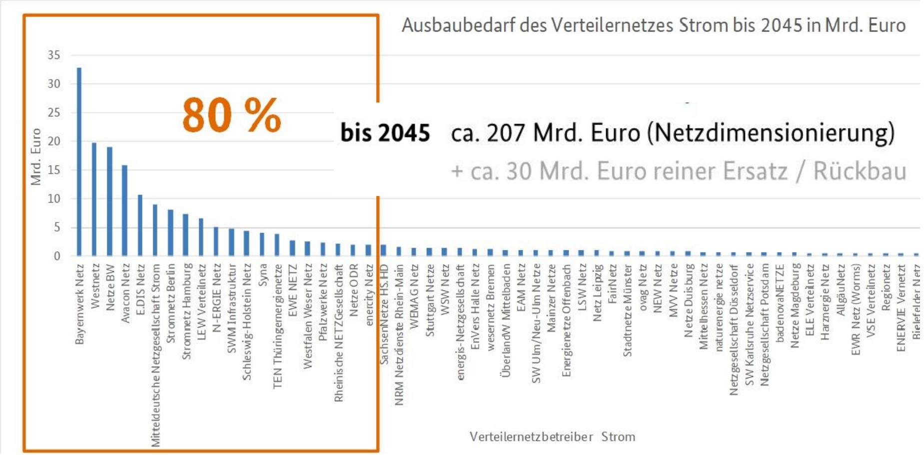
Zukünftig wird ein Großteil der Erzeugungsleistung auf Verteilnetzebene verortet sein. Um weiterhin einen stabilen und robusten Systembetrieb gewährleisten zu können, muss mindestens ein Teil dieser Anlagen netzbildende Eigenschaften aufweisen (zusätzlich zu ausgewählten Netznutzern im

RoadmapSystemstabilität 2023 Photovoltaic Strategy 2023

Motivation – High resolution modeling case for a **DSO**

- Majority of the new renewables are going to appear on distribution grids – predominanlty PV.
- Heatpumps and EV chargers will also contribute.
- The distribution grid will have to be upgraded – at a heavy cost!!

- DSO needs to know which grids are critical.
- Scheduling of capital upgrades in grids.

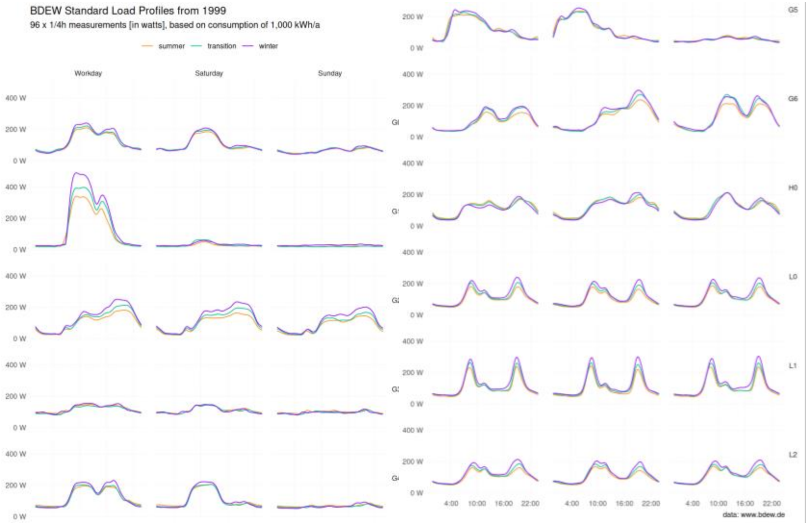


[BNetzA estimate for NAP24]

Motivation – High resolution modeling case for a **DSO**

- Majority of the new renewables are going to appear on distribution grids – predominanlty PV.
- Heatpumps and EV chargers will also contribute.
- The distribution grid will have to be upgraded – at a heavy cost!!

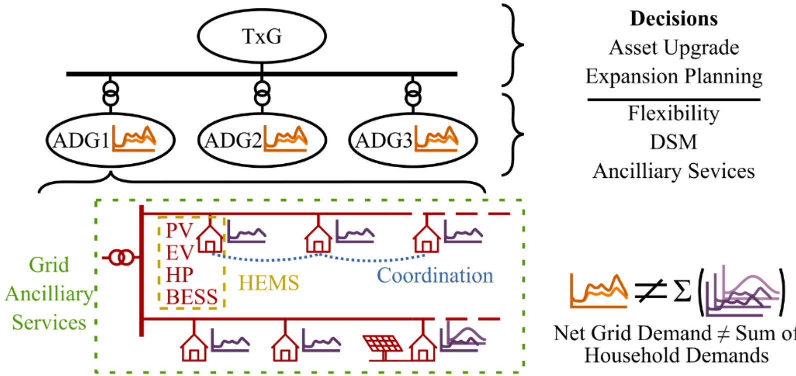
- Standard Load profiles will not be sufficient –
  - Home EMS
  - Grid side flexibility measures
  - Batteries as VPP
  - Sector-coupled consumer needs



https://flrd.github.io/standardlastprofile/

Motivation – High resolution modeling case for a DSO

- Majority of the new renewables are going to appear on distribution grids – predominanlty PV.
- Heatpumps and EV chargers will also contribute.
- The distribution grid will have to be upgraded – at a heavy cost!!

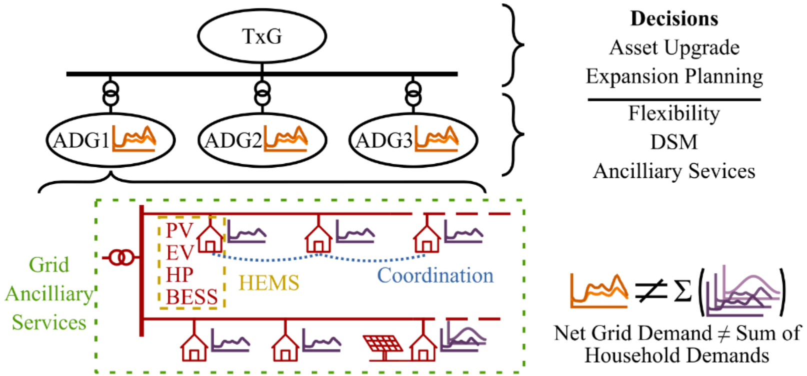


- Standard Load profiles will not be sufficient –
  - Home EMS
  - Grid side flexibility measures
  - Batteries as VPP
  - Sector-coupled consumer needs

- Transformer timeseries is <u>not an inelastic sum of standard load profiles</u>

Motivation – High resolution modeling case for a **TSO**

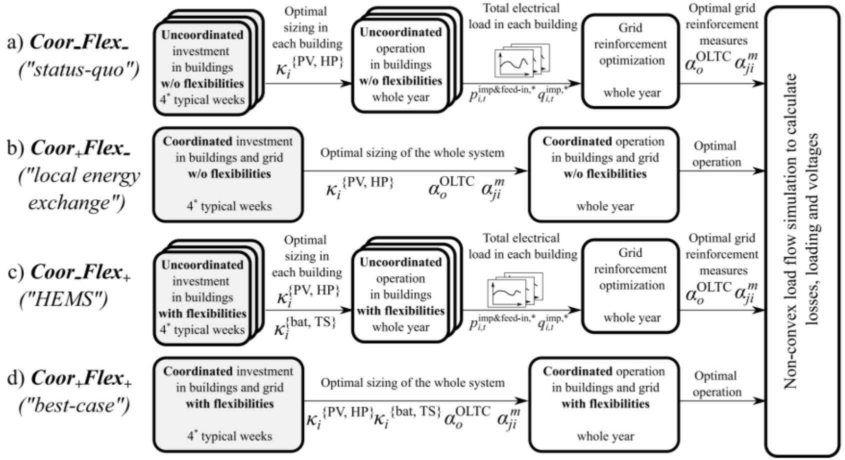
- Transformer timeseries is <u>not an inelastic sum of standard load profiles</u>
- Over 500,000 distribution grids transformers in Germany.
- TSO needs upstream grid asset upgrade to handle new renewables and sector-coupling below.
- Same argument for HV/MV transformers in a DSO grid.



Motivation – Model detail vs discrete decisions

- State-of-the-art approach is MILP modeling with hourly or 15m time-series.
- Typical days or in best case – one or multiple calendar years.

- Run through different flexibility paradigms
- Each node is an active entity.



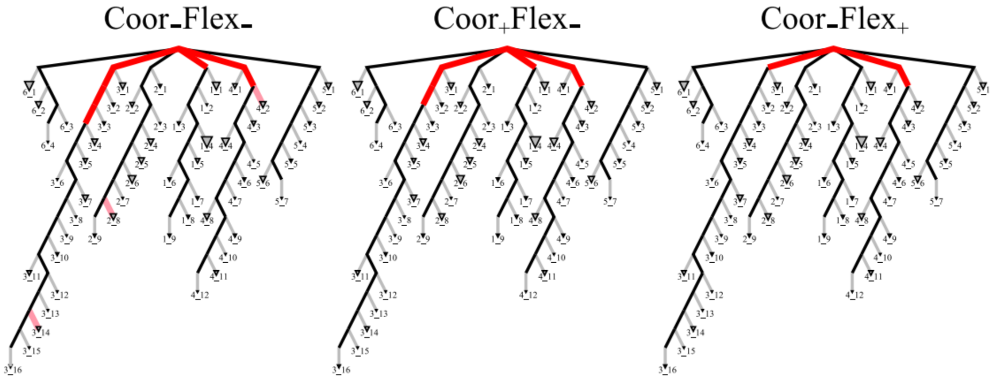
S. Candas, B. Reveron Baecker, A. Mohapatra, and T. Hamacher, "Optimization-based framework for low-voltage grid reinforcement assessment under various levels of flexibility and coordination," Applied Energy, vol. 343, Aug. 2023, doi: 10.1016/j.apenergy.2023.121147.

Motivation – Model detail vs discrete decisions

- State-of-the-art approach is MILP modeling with hourly or 15m time-series.
- Typical days or in best case – one or multiple calendar years.

- Run through different flexibility paradigms
- Each node is an active entity.

- Decide upon –
  - Grid reinforcement (discrete)
  - DER dispatch



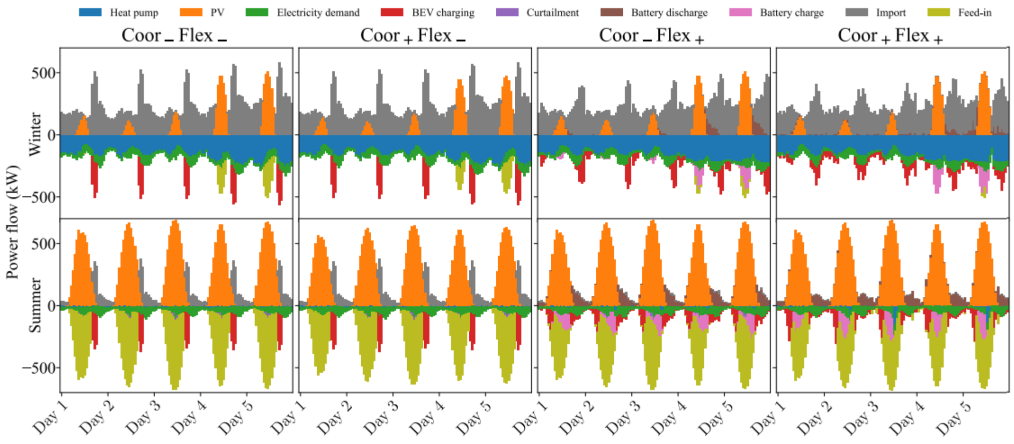
S. Candas, B. Reveron Baecker, A. Mohapatra, and T. Hamacher, “Optimization-based framework for low-voltage grid reinforcement assessment under various levels of flexibility and coordination,” Applied Energy, vol. 343, Aug. 2023, doi: 10.1016/j.apenergy.2023.121147.

Motivation – Model detail vs discrete decisions

- State-of-the-art approach is MILP modeling with hourly or 15m time-series.
- Typical days or in best case – one or multiple calendar years.

- Run through different flexibility paradigms
- Each node is an active entity.

- Decide upon –
  - Grid reinforcement (discrete)
  - DER dispatch



S. Candas, B. Reveron Baecker, A. Mohapatra, and T. Hamacher, "Optimization-based framework for low-voltage grid reinforcement assessment under various levels of flexibility and coordination," Applied Energy, vol. 343, Aug. 2023, doi: 10.1016/j.apenergy.2023.121147.

Motivation – Model detail vs discrete decisions

- State-of-the-art approach is MILP modeling with hourly or 15m time-series.
- Typical days or in best case – one or multiple calendar years.

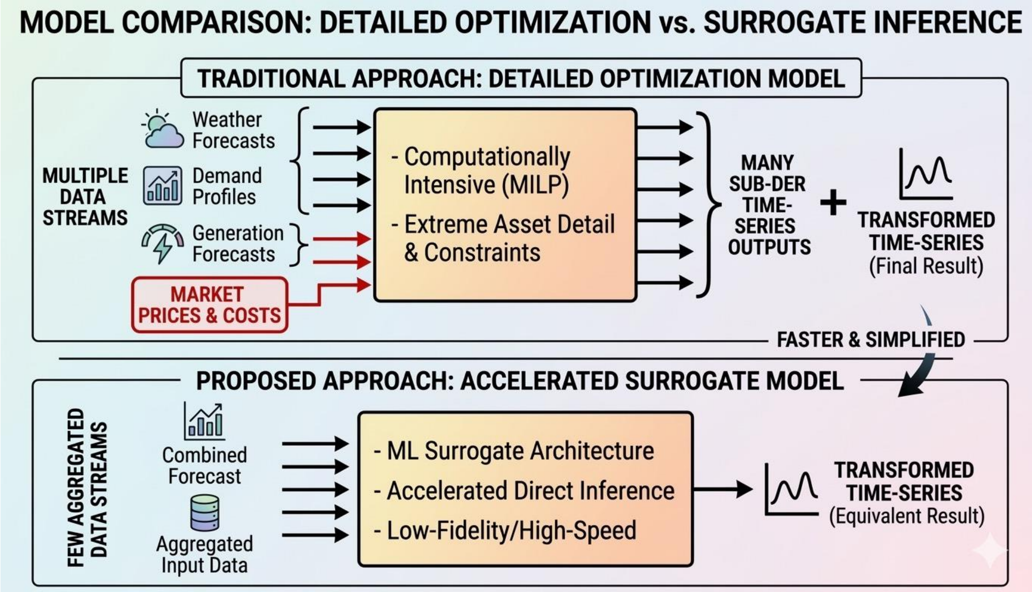
- Model setup takes a lot of time and turns intractable beyond few hundred nodes.
- Setup data collection is not trivial – difficult to haromize the assumptions from different datasets.

- The target timeseries of value aggregates from otherwise useless individual series.
  - but it costs RAM regardless!
- Transformer or cable upgrade is dependent on next larger available size.
  - decision is the same if the transformer is 1% overloaded or 10% overloaded.
- Every scenario is a separate model run.
  - Cannot solve a part of the model, however small the change. Inefficient use of computation.

MEP

Research Gap

- Can we replace the MILP model with ML surrogates for *rapid yet reasonable* estimates?



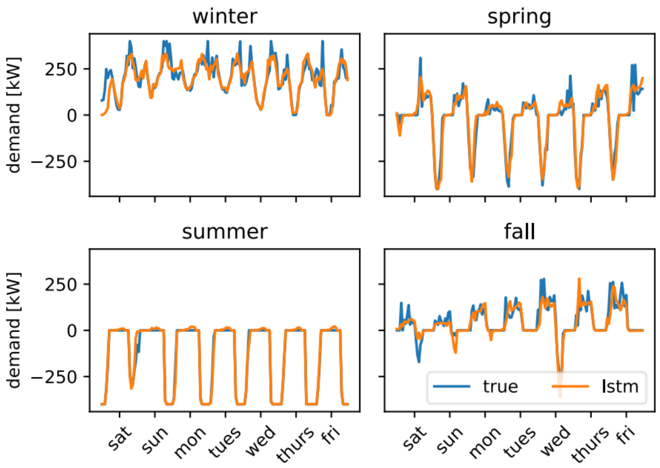
First attempt – May‘23

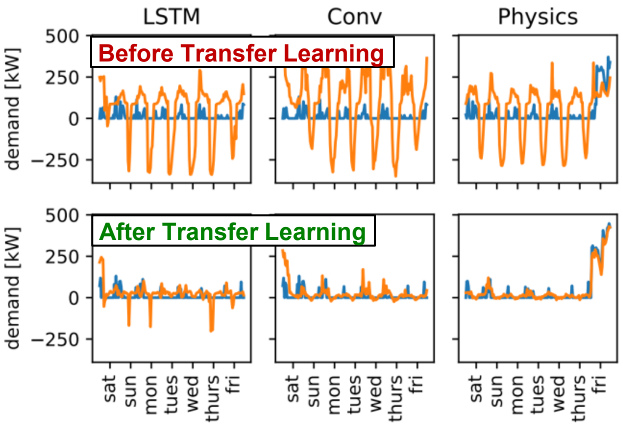
- Which architectures are best suited for the inference?
- Decide the input and output tuples for the dataset.
- Rules for splitting the training, validation and test datasets.
- Can the grids surrogate be transfered to a new grid with less data?

- Basic workflow
  - Generate 27 full runs from MILP model on a benchmark distribution grid.
  - Aggregate the time-series to create input-output tuples.
  - Two test datasets – one full scenario (one calendar year) + two composite scenario (4 weeks at random taken from other 26 scenarios)

First attempt – May’23 (Max Schulze MA)

- Which architectures are best suited for the inference?
- Decide the input and output tuples for the dataset.
- Rules for splitting the training, validation and test datasets.
- Can the grids surrogate be transfered to a new grid with less data?

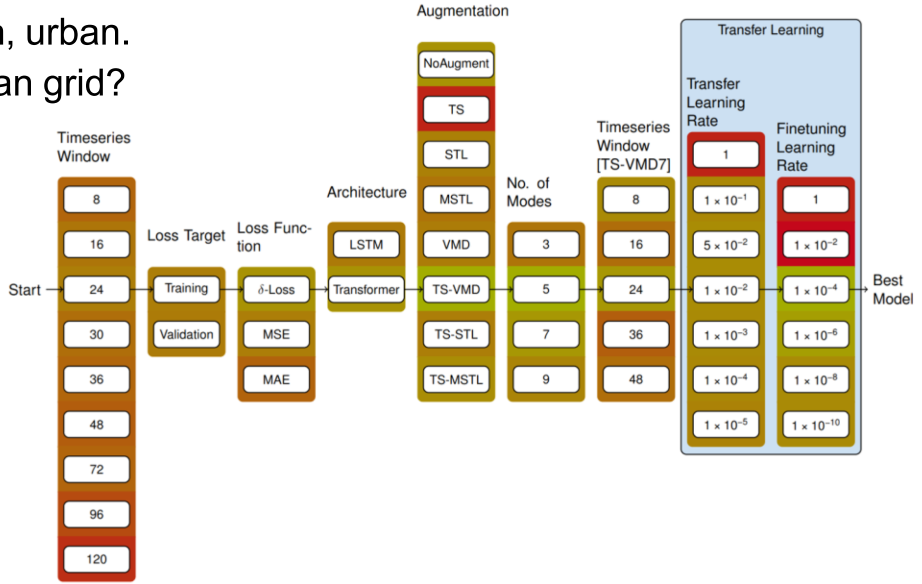




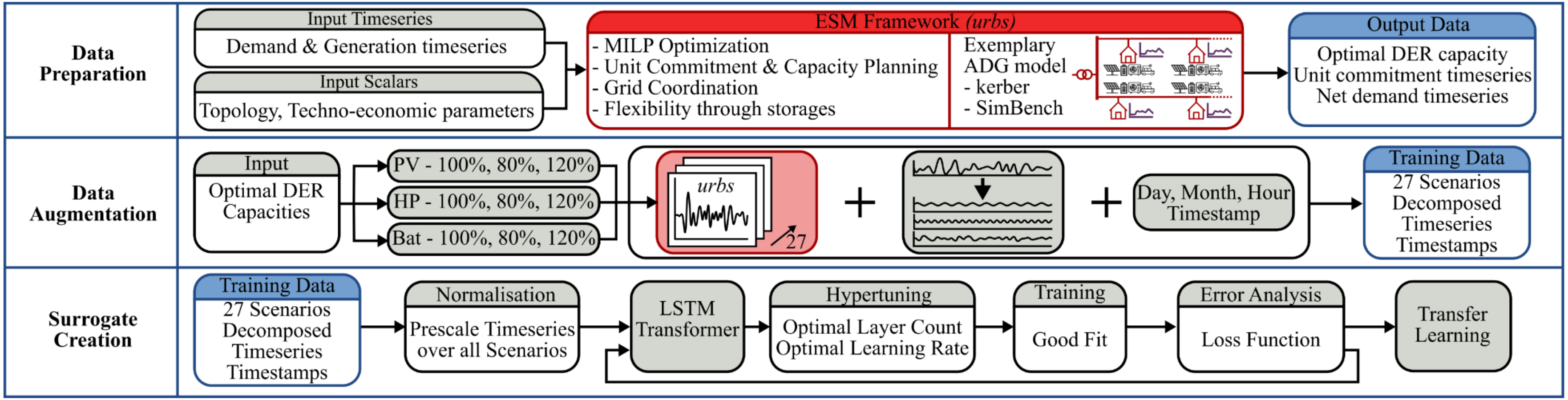
Error		LSTM	CNN	Physics
Agg. Demand [%]		5.6	10.3	1.5
	TL	0.5	1.1	0.5
Peak Demand [%]		3.3	3.0	3.8
	TL	14.6	9.2	1.1
Peak Feed-In [%]		0.01	0.2	0.4
	TL	29.7	33.1	22.3

Second attempt – October'24

- Hyperparameter tuning for LSTM and Transfomer architectures
- Feature engineering and data augmentation for better results.
- Archetypical benchmark grids – rural, semi-urban, urban.
- Does urban archetype transfer best to a new urban grid?



#1 – ML surrogates are fast, accurate and transferrable.



A. Mohapatra, M. Hock et.al, "Surrogate Framework for Energy System Modeling," *2025 IEEE Kiel PowerTech*, Kiel, Germany, 2025, pp. 1-6, doi: 10.1109/PowerTech59965.2025.11180532.

#1 – ML surrogates are fast, accurate and transferrable.

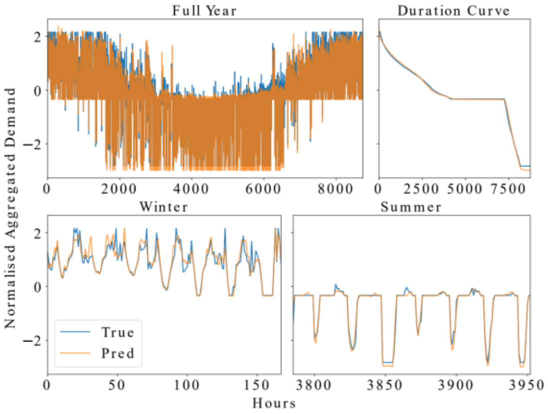
10 BEST-PERFORMING SURROGATE MODEL COMBINATIONS, SORTED BY PERFORMANCE ERRORS

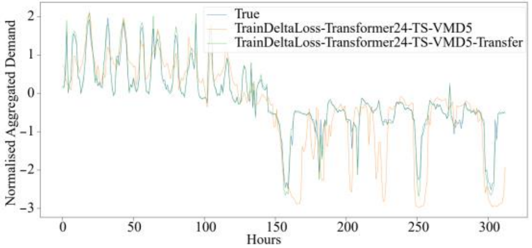
Label	MSE	MAE [kW]	Net Demand [%]	Peak Demand [%]	Peak Feed-in [%]	Hypertuning Time [h]	Training Time [h]	Evaluation Time [s]
TrainDeltaLoss_Transformer24_TS-VMD5	0.048	19.441	0.882	0.826	5.455	03:15:09	01:05:36	4.509
TrainDeltaLoss_LSTM24_TS-VMD5	0.049	19.238	7.985	1.404	1.461	03:07:20	00:59:42	4.047
TrainDeltaLoss_LSTM36_TS-VMD5	0.059	20.954	5.752	2.278	1.138	09:50:29	01:04:12	4.311
TrainDeltaLoss_LSTM24_TS-VMD7	0.047	18.991	8.819	5.536	1.947	06:01:53	01:04:28	3.919
TrainDeltaLoss_Transformer24_TS-VMD7	0.052	22.050	5.632	5.445	6.539	03:28:51	01:02:50	4.561
TrainDeltaLoss_Transformer24_VMD7	0.052	21.903	0.194	8.151	8.406	03:07:32	00:16:13	3.470
TrainDeltaLoss_Transformer24_NoAugment	0.062	23.004	3.765	1.994	10.636	01:12:08	00:16:55	3.572
TrainDeltaLoss_Transformer24_VMD3	0.049	20.246	3.507	12.485	8.785	03:15:57	01:05:42	4.413
TrainDeltaLoss_Transformer24_TS-MSTL	0.056	23.427	6.527	2.748	12.911	03:09:05	01:02:42	4.516
TrainDeltaLoss_LSTM36_NoAugment	0.060	21.154	6.225	9.521	3.893	01:10:20	00:15:47	2.865

Legend - Train: Training Data as loss target; DeltaLoss: Distance-weighted sum of MSE and MAE as loss function; TransformerXX/LSTMXX: Architecture type with a look-back window of size XX; TS/VMDX/MSTL: Data augmentation method, X indicates number of modes for VMD; NoAugment: No auxiliary inputs and modes

TRANSFER LEARNING ON 26 SCENARIOS WITH EACH SCENARIO CONSISTING OF 2 WEEKS OF DATA.

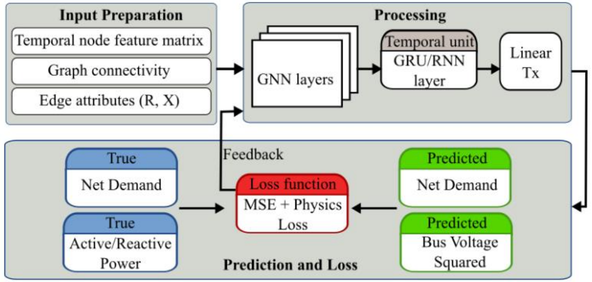
Label	MSE	MAE (kW)	Agg. Demand (%)	Peak Demand (%)	Peak Feed-In (%)
TrainDeltaLoss_LSTM24_TS-VMD5	0.042	6.270	0.397	2.819	12.874
TrainDeltaLoss_Transformer24_NoAugment	0.038	5.498	2.385	13.818	1.779
TrainDeltaLoss_Transformer24_TS-VMD5	0.050	6.169	2.808	8.439	1.131

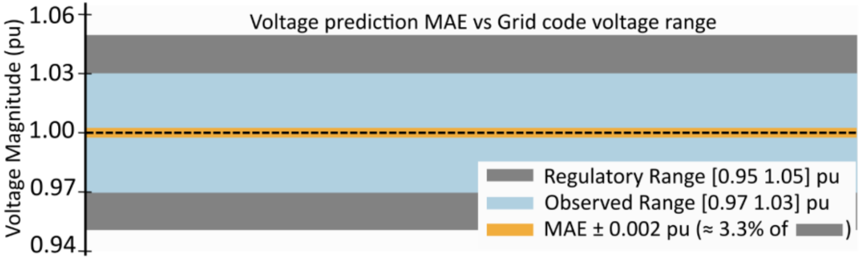




A. Mohapatra, M. Hock et.al, "Surrogate Framework for Energy System Modeling," *2025 IEEE Kiel PowerTech*, Kiel, Germany, 2025, pp. 1-6, doi: 10.1109/PowerTech59965.2025.11180532.

#2 – GNN surrogates take less data and predict voltages





NET DEMAND PREDICTION USING TGNN MODELS

Label	R^2	MSE	MAE [kW]	Net Demand [%]	Peak Demand [%]	Peak Feed-in [%]	Hypertuning Time [h]	Training Time [h]	Evaluation Time [s]
TGCN	0.85	0.02	38.834	0.19	9.31	2.77	22:15:20	03:52:42	4.081
TGAT	0.81	0.06	30.551	0.58	7.39	3.01	24:20:29	04:04:12	4.311
TGT	0.87	0.02	32.172	0.46	14.20	1.79	25:01:34	05:20:12	4.823
TGINE	0.79	0.05	32.320	0.80	13.06	1.32	21:28:40	04:02:50	4.452
PiTGAT	0.65	0.03	61.402	7.50	4.15	57.50	27:07:32	05:16:27	3.470
TrainDeltaLoss_Transformer24_TS-VMD5	-	0.048	19.441	0.882	0.826	5.455	03:15:09	01:05:36	4.509

Legend - TGCN: Temporal Graph Convolution Network, (no physics loss); PiTGAT: Physics-informed Temporal Graph Attention (LinDistFlow physics-informed loss included); TrainDeltaLoss Transformer24 TS-VMD5(TrainDeltaLoss: Distance-weighted sum of MSE and MAE on training data as loss function; Transformer24: Transformer with look-back window of size 24; VMD5: 5 mode variable mode decomposition);

G. Pjetri, A. Mohapatra et. al, "Graph Neural Network Surrogates for Energy System Modeling“, 2025 IEEE ISGT Europe, Valletta, Malta, 2025, pp. 1-5, doi: 10.1109/ISGTEurope64741.2025.11305443.

Checkpoint #1

- ML surrogates for existing MILP models are possible –
  - speed advantage for subsequent scenario runs.
  - Can be trained for multiple objectives.
  - Can work with only ten scenarios.
  - Can predict voltages using LinDistFlow equations.

But,

- MILP model should exist.
- Inference works so far for only one grid at a time.
- Data requirement is still high for setup.
  - Although far reduced than the full MILP model.

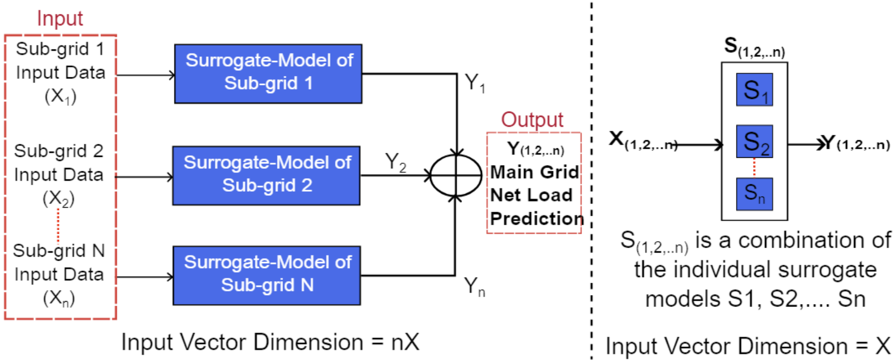
TRAINING DATASET CREATED WITH 8760 (1 YEAR) INPUT-OUTPUT PAIRS.

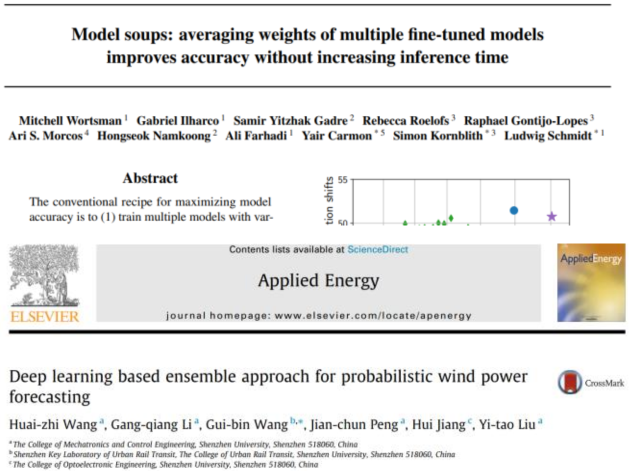
Type with units	**Spatial resolution**	**Temporal resolution**
Inputs		
Electrical demand, kWel	Sum over all households	Hourly
Domestic hot water demand, kWth		
Space heating demand, kWth		
Mobility demand, kWel		
Solar irradiation capacity factor	Weighted mean over all households	
Heat pump COP		
Charging station availability		
Battery capacity, kWel	Sum over all households	As installed
Rooftop PV, kWp		
Heat Pump, kWel		
Charging stations, kWel		
Output		
Net demand of the grid, kWel	Aggregated for grid	Hourly

A. Mohapatra, M. Hock et.al, "Surrogate Framework for Energy System Modeling," *2025 IEEE Kiel PowerTech*, Kiel, Germany, 2025, pp. 1-6, doi: 10.1109/PowerTech59965.2025.11180532.

Scalability is a concern

- Can we blend surrogates to make a composite surrogate at a higher level of grid abstraction?
- Can we work without the a full calendar year MILP run as ground truth?
- Can we use the surrogates themselves to create synthetic ground truth?





Model soups: averaging weights of multiple fine-tuned models improves accuracy without increasing inference time

Mitchell Wortsman [1] Gabriel Ilharco [1] Samir Yitzhak Gadre [2] Rebecca Roelofs [3] Raphael Gontijo-Lopes [3] Ari S. Morcos [4] Hongseok Namkoong [2] Ali Farhadi [1] Yair Carmon [*5] Simon Kornblith [*3] Ludwig Schmidt [*1]

Abstract

The conventional recipe for maximizing model accuracy is to (1) train multiple models with var-

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

ELSEVIER

Deep learning based ensemble approach for probabilistic wind power forecasting

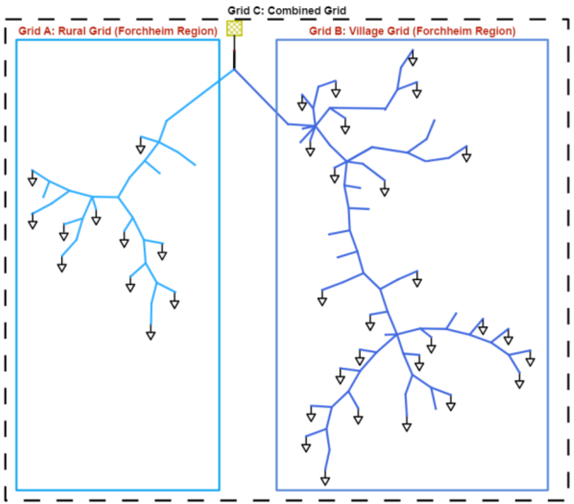
Huai-zhi Wang [a], Gang-qiang Li [a], Gui-bin Wang [b,*], Jian-chun Peng [a], Hui Jiang [c], Yi-tao Liu [a]

[a] The College of Mechatronics and Control Engineering, Shenzhen University, Shenzhen 518060, China
[b] Shenzhen Key Laboratory of Urban Rail Transit, The College of Urban Rail Transit, Shenzhen University, Shenzhen 518060, China
[c] The College of Optoelectronic Engineering, Shenzhen University, Shenzhen 518060, China

H. Genena, A. Mohapatra, et.al, "Blending Surrogates for Energy System Modeling," accepted in *2026 IEEE PES General Meeting, Montreal, 2026.*

Scalability is a concern

- Can we blend surrogates to make a composite surrogate at a higher level of grid abstraction?
- Can we work without the a full calendar year MILP run as ground truth?
- Can we use the surrogates themselves to create synthetic ground truth?



New workflow

- Use only a four type weeks instead of one calendar year
- Only one full MILP run scenario for Grids A, B and C
- Use the surrogates of Grid A and B to create more datasets for a combined Grid C.

- Assume there is no energy exchange between Grids A and B

H. Genena, A. Mohapatra, et.al, "Blending Surrogates for Energy System Modeling," accepted in *2026 IEEE PES General Meeting, Montreal, 2026.*

#3 – Uncoordinated grid surrogates can be blended without any original MILP modeling needed for the composite grid.

- 37 hours (MILP) vs 234 seconds (Surrogate) to generate 27 scenarios for training dataset.
- Training dataset for composite Grid C formed by combining equivalent (synchronous) or arbitrary (asynchronous) scenarios of Grid A and B.

EVALUATION OF MODEL BUILDING FOR GRID C AND D USING HYBRID AND SYNTHETIC DATASETS

Implementation Details	Grid	Testing Scenario	Loss Function[1]	Peak Demand [%]	Peak Feed-in [%]	R^2 Score	Peak Demand Mismatch [h][2]	Peak Feed-in Mismatch [h][3]
Implementation 1: Hybrid Datasets **(27 Synchronous + 1 Real)**	C	High	0.067	1.603	1.912	0.969	-2	0
		Low	0.061	0.461	3.327	0.954	0	0
Implementation 1: Hybrid Datasets **(140 Synchronous + 1 Real)**	C	High	0.064	0.077	2.404	0.968	-3	169
		Low	0.048	3.635	0.164	0.967	0	0
Implementation 2: Hybrid Datasets **(27 Asynchronous + 1 Real)**	C	High	0.057	6.293	1.662	0.973	-3	169
		Low	0.105	0.834	14.466	0.904	0	0
Implementation 2: Hybrid Datasets **(140 Asynchronous + 1 Real)**	C	High	0.065	2.719	1.406	0.968	-3	169
		Low	0.055	0.392	2.314	0.963	0	0
Implementation 3: Synthetic Datasets **(27 Synchronous)**	C	High	0.030	1.889	4.568	0.990	-3	0
		Low	0.033	3.424	2.264	0.985	0	-170
Implementation 4: Synthetic Datasets **(140 Asynchronous)**	C	High	0.061	0.982	1.628	0.970	-3	169
		Low	0.053	2.356	6.361	0.961	0	0
Implementation 1: Hybrid Datasets **(27 Synchronous + 1 Real)**	D	High	0.068	3.370	1.528	0.968	-3	169
		Low	0.062	1.352	3.224	0.955	0	169

[1] Loss Function = weighted combination of MSE and MAE; MAE = mean absolute error; MSE = mean squared error [2] Peak Demand Mismatch = Predicted- Actual Peak Demand Timing (in Hours) [3] Peak Feed-in Mismatch = Predicted - Actual Peak Feed-in Timing (in Hours)

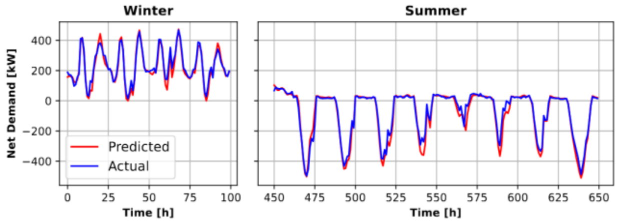


Fig. 7. Actual vs. predicted net demand for the high scenario on representative winter and summer days, using 141 datasets (140 synchronous + 1 real)

H. Genena, A. Mohapatra, et.al, "Blending Surrogates for Energy System Modeling," accepted in *2026 IEEE PES General Meeting, Montreal, 2026.*

Checkpoint #2

- Uncoordinated grids can be represented by a single composite surrogate made up of individual surrogates of downstream grids.
- No large MILP model needed for the composite grid to serve as ground truth

But,

- We still need a MILP model for the downstream grids to create their surrogates
- Model setup pain still exists for all these downstream grids
- We still need one surrogate per transformer.
- Uncoordinated assumption must hold for the studies using this technique.

- Can we make one surrogate for any distribution grid in the country and without the model setup pain??

Motivation – Open data & models for national energy studies

- National policy is underpinned by opaque studies with zero verifiability.

- Use of representative grids to model the whole country.
  - Real grids given by operator - impossible to access.
  - Synthetic grids - need access to propreitary datasets.
  - Almost arbitrary clustering to get representative set.

- MILP modeling is out of question due to the scale.
  - Arbitrary rules to abstract the optimisation step.

	Baseline scenarios		Sensitivities		
Variations for 2030	Basis KK	Basis KK+Gas	Dämm-	EMob-	Flex-
Assumptions	Coal consensus path (18.5 GW from coal-fired power plants)	Coal consensus path + switch from coal to gas	Lower insulation standard	Lower share of electric car use	No decentralized flexibility in heat pumps and electric cars**
Highest demand [GW]	17	11	20	21	10
Energy consumed [TWh]	36	22	42	43	16

Tabelle 6: Anteile der marktorientierten und netzorientierten Haushalte

in %	A 2037	B 2037	C 2037	A 2045	B 2045	C 2045
Anteil marktorientierte Haushalte	20	35	35	30	55	55
Anteil netzorientierte Haushalte	0	0	25	0	0	25

Quelle: Übertragungsnetzbetreiber

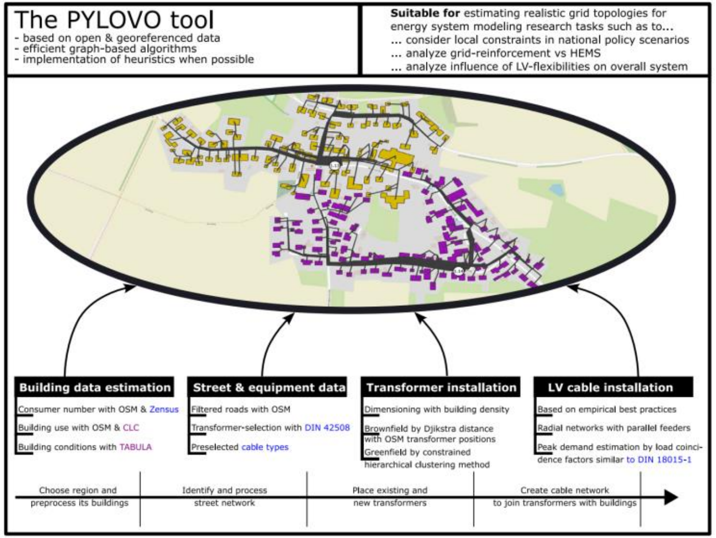
MEP

#4 – Open source synthetic LV grid models can be generated for whole Germany

- Brownfield and greenfield transformers
- Open source GIS datasets
- Government cadastral and census datasets
- DIN norms and equipment catalog
- Continuous improvement possible with new data

Before | After

AB: 27% - MFH: 24% - TH: 47% - SFH: 2% | AB: 85% - MFH: 7% - TH: 4% - SFH: 5%
Number of Transformers: 37 | Number of Transformers: 63



anurag.mohapatra@tum.de | https://www.mep.tum.de/mep/coses/

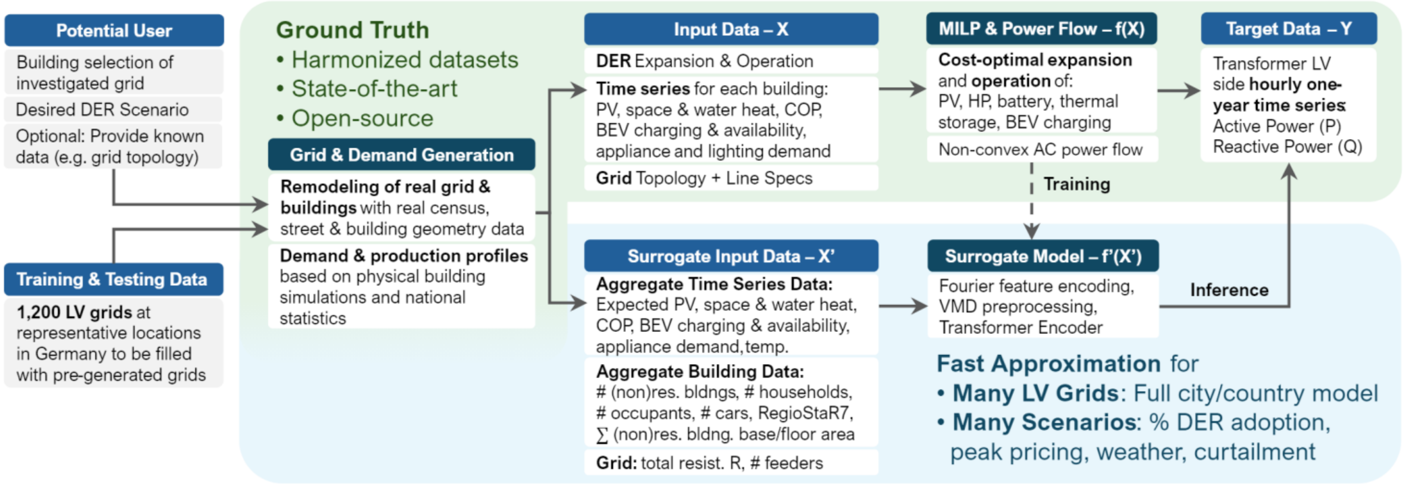
Reveron Baecker, B., Candas, S., Tepe, D., & Mohapatra, A, „Generation of low-voltage synthetic grid data for energy system modeling with the pylovo tool“, *Sustainable Energy, Grids and Networks*, 41, 2025, doi: 10.1016/j.segan.2024.101617

One surrogate for all German LV grids...

- A crisis of available data to learn across.
- We might have the synthetic grids but we need a full model setup for each grid
  - demand, generation, weather, prices at each node for each grid.

One surrogate for all German LV grids...

- A crisis of available data to learn across.
- We might have the synthetic grids but we need a full model setup for each grid
  - demand, generation, weather, prices at each node for each grid.

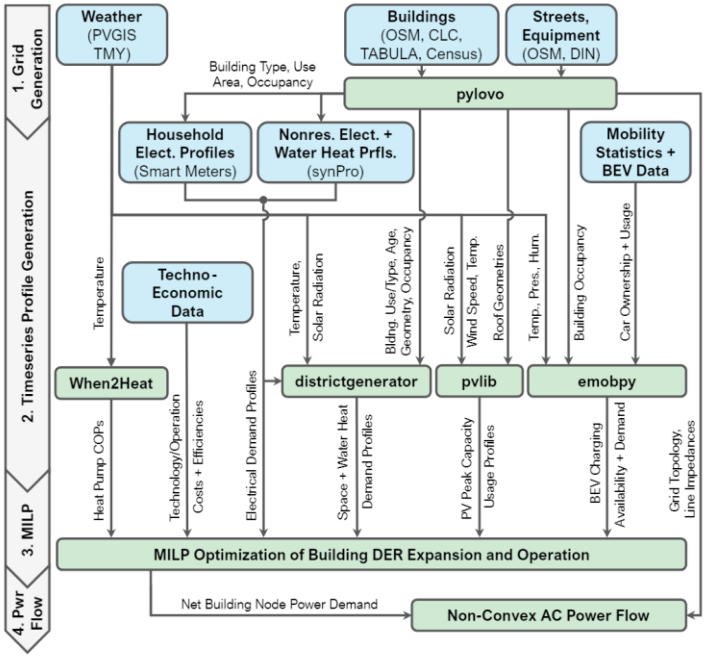


One surrogate for all German LV grids...

- Open-source MILP ground-truth tool.

- Using existing open-source demand tools.
- MILP optimization following HEMS paradigm
  - Houses are optimized individually for optimal DER size
- Full AC power flow to account for grid losses.

- Works for any German grid.



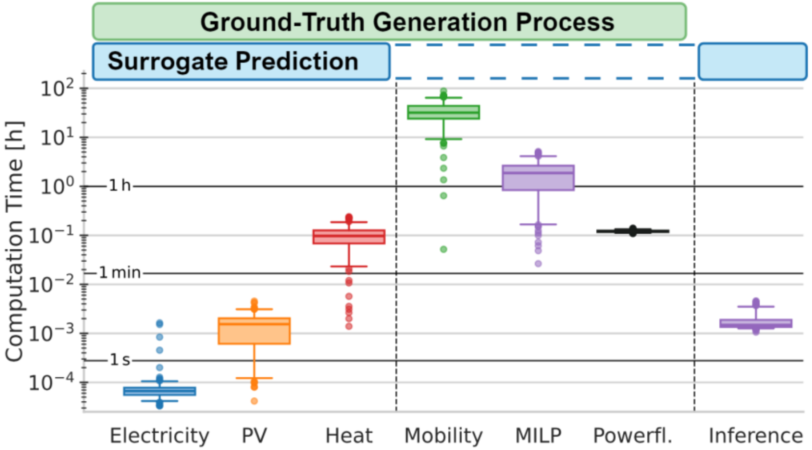
Franz Hanser, E., Mohapatra, A., et.al, „Deep Learning Surrogates for Low-Voltage Grid Planning “, accepted in *Power System Computation Conference (PSCC) 2026,* Limassol 2026

One surrogate for all German LV grids...

- Use computationally cheaper proxies as surrogate inputs
- Time taken to train Surrogate vs Time taken to generate inputs for surrogate inference.

SURROGATE MODEL TRAINING AND INFERENCE INPUT DATASETS.

Rationale	Input Features	Unit	Aggregation	Temp. Res.
Cheap Ground Truth	Electr. Demand	MW_{el}	Sum	Hourly
	Expect. PV Production	MW_{el}	Sum	Hourly
	Water Heat Demand	MW_{th}	Sum	Hourly
	Space Heat Demand	MW_{th}	Sum	Hourly
	Heat Pump COP	-	Weighted Avg.	Hourly
Mobility Proxies	Temperature	°C	Grid Wide	Hourly
	# Cars	-	Sum	Const.
	RegioStaR7 Region	-	Grid Wide	Const.
Power Flow Proxies	Grid Resistance	Ω	Transf. LV Side	Const.
	# Feeders	-	Sum	Const.
	# Buildings (Non-)Res.	-	Sum	Const.
Disagg.	Bldng. Base/Use Area	m^2	Sum	Const.
	# Households, # Occup.	-	Sum	Const.



Franz Hanser, E., Mohapatra, A., et.al, „Deep Learning Surrogates for Low-Voltage Grid Planning “, accepted in *Power System Computation Conference (PSCC) 2026,* Limassol 2026

#5 One surrogate possible for all German grids

- One surrogate hits < 10% accuracy on |S| at Transformer for all 200 test grids – no transfer learning.
- Completely open-sourced dataset and models.
- 500,000 German LV grids can be inferenced in 5.2 days – including surrogate input data generation.

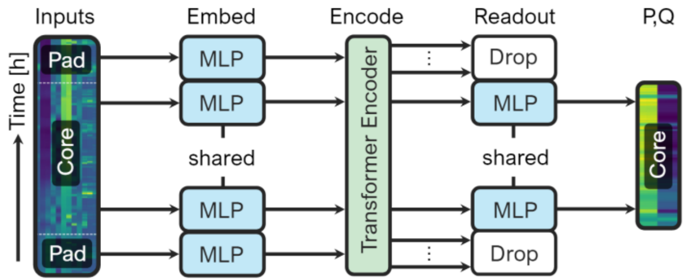


Fig. 6. Surrogate model architecture. The target time series is split into smaller, potentially padded, individually inferred core slices. A shared MLP embeds a multivariate input time step into a higher dimension. The transformer encoder architecture allows rich interaction encoding within a slice. Finally, a per-time-step, shared readout MLP reduces the output to a joint prediction of active and reactive power.

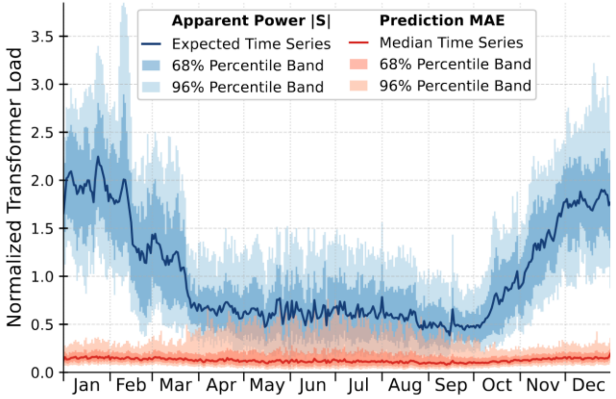


Fig. 8. Normalized transformer load ($|S|(t)/\langle|S|\rangle$) and normalized prediction MAE distributions for testing grids at daily aggregation over one year. The expected/median time series and percentile bands are obtained from each individual day's normalized load/error distribution over all grids.

Franz Hanser, E., Mohapatra, A., et.al, „Deep Learning Surrogates for Low-Voltage Grid Planning “, accepted in *Power System Computation Conference (PSCC) 2026,* Limassol 2026

#5 One surrogate possible for all German grids

- One surrogate hits < 10% accuracy on |S| at Transformer for all 200 test grids – no transfer learning.
- Completely open-sourced dataset and models.
- 500,000 German LV grids can be inferenced in 5.2 days – including surrogate input data generation.

MEDIAN ERROR METRICS OF THE SURROGATE MODELS.

	Metric	Agg.	MLP NMAE	Transformer NMAE	Transformer Peak
P	Agg. Feed-In MdAPE [%]	All	$9.7^{+34.8}_{-8.8}$	$12.1^{+28.9}_{-10.6}$	$11.0^{+39.1}_{-10.0}$
P	Agg. Import MdAPE [%]	All	$4.8^{+7.8}_{-4.5}$	$1.8^{+7.3}_{-1.6}$	$1.7^{+6.6}_{-1.6}$
P	Median NMAE [%]	1 h	$18.5^{+13.2}_{-3.8}$	$13.8^{+14.9}_{-3.6}$	$13.6^{+15.9}_{-4.0}$
P	Median NMAE [%]	24 h	$10.8^{+11.5}_{-3.5}$	$6.8^{+12.4}_{-2.5}$	$6.2^{+12.0}_{-2.4}$
P	Peak Feed-In MdAPE [%]	1 h	$16.8^{+24.3}_{-12.7}$	$23.4^{+17.3}_{-18.9}$	$14.4^{+18.9}_{-12.9}$
P	Peak Feed-In MdAPE [%]	24 h	$10.6^{+30.0}_{-9.4}$	$16.2^{+38.4}_{-13.3}$	$12.1^{+34.5}_{-11.4}$
P	Peak Feed-In Median Δt [d]	1 h	$22.0^{+48.2}_{-22.0}$	$19.0^{+53.0}_{-19.0}$	$16.0^{+48.3}_{-16.0}$
P	Peak Feed-In Median Δt [d]	24 h	$5.0^{+39.1}_{-5.0}$	$4.0^{+47.1}_{-4.0}$	$5.0^{+48.2}_{-5.0}$
P	Peak Import MdAPE [%]	1 h	$16.3^{+14.3}_{-12.4}$	$10.1^{+12.4}_{-8.2}$	$8.6^{+13.7}_{-7.5}$
P	Peak Import MdAPE [%]	24 h	$4.9^{+7.7}_{-4.5}$	$3.2^{+5.3}_{-2.8}$	$1.6^{+3.5}_{-1.4}$
P	Peak Import Median Δt [d]	1 h	$2.4^{+50.6}_{-2.4}$	$2.1^{+40.8}_{-2.1}$	$2.0^{+41.5}_{-2.0}$
P	Peak Import Median Δt [d]	24 h	$0.0^{+31.4}_{-0.0}$	$0.0^{+22.2}_{-0.0}$	$0.0^{+26.0}_{-0.0}$
Q	Agg. Feed-In MdAPE [%]	All	$3.2^{+6.5}_{-2.6}$	$1.9^{+4.2}_{-1.6}$	$1.6^{+5.2}_{-1.4}$
Q	Median NMAE [%]	1 h	$14.5^{+7.8}_{-3.4}$	$7.6^{+5.1}_{-1.9}$	$7.7^{+6.1}_{-2.1}$
Q	Median NMAE [%]	24 h	$8.2^{+4.1}_{-3.0}$	$3.4^{+3.5}_{-1.2}$	$3.7^{+5.0}_{-1.3}$
Q	Peak Import MdAPE [%]	1 h	$3.1^{+8.3}_{-2.8}$	$3.4^{+12.0}_{-3.2}$	$2.9^{+11.4}_{-2.6}$
Q	Peak Import MdAPE [%]	24 h	$3.8^{+7.1}_{-3.5}$	$2.6^{+6.5}_{-2.2}$	$1.6^{+4.7}_{-1.5}$
Q	Peak Import Median Δt [d]	1 h	$1.0^{+47.7}_{-1.0}$	$1.0^{+54.2}_{-1.0}$	$1.0^{+51.4}_{-1.0}$
Q	Peak Import Median Δt [d]	24 h	$0.0^{+27.1}_{-0.0}$	$0.0^{+17.7}_{-0.0}$	$0.0^{+27.0}_{-0.0}$
|S|	Agg. Import MdAPE [%]	All	$3.5^{+8.2}_{-3.0}$	$2.4^{+5.3}_{-2.2}$	$2.0^{+5.9}_{-1.9}$
|S|	Median NMAE [%]	1 h	$18.0^{+10.8}_{-3.6}$	$13.3^{+13.9}_{-3.5}$	$12.9^{+14.2}_{-3.7}$
|S|	Median NMAE [%]	24 h	$9.0^{+7.2}_{-2.9}$	$5.5^{+8.4}_{-1.7}$	$5.3^{+9.8}_{-1.9}$
|S|	Peak Load MdAPE [%]	1 h	$15.6^{+15.0}_{-11.9}$	$11.5^{+14.3}_{-8.8}$	$8.7^{+15.4}_{-7.8}$
|S|	Peak Load MdAPE [%]	24 h	$5.0^{+7.4}_{-4.6}$	$3.1^{+5.0}_{-2.6}$	$1.5^{+3.6}_{-1.3}$
|S|	Peak Load Median Δt [d]	1 h	$10.0^{+133.9}_{-10.0}$	$7.0^{+159.3}_{-7.0}$	$5.0^{+152.7}_{-5.0}$
|S|	Peak Load Median Δt [d]	24 h	$0.0^{+39.3}_{-0.0}$	$0.0^{+26.0}_{-0.0}$	$0.0^{+26.2}_{-0.0}$

Franz Hanser, E., Mohapatra, A., et.al, „Deep Learning Surrogates for Low-Voltage Grid Planning ", accepted in *Power System Computation Conference (PSCC) 2026,* Limassol 2026

Conclusion

1. ML surrogates are fast, accurate and transferrable.
2. GNN surrogates take less data and predict voltages
3. Uncoordinated grid surrogates can be blended without any original MILP modeling needed for the composite grid.
4. Open source synthetic LV grid models can be generated for whole Germany
5. One surrogate possible for all German grids

References

[1] Bundesministerium für Wirtschaft und Klimaschutz (BMWK), "Roadmap Systemstabilität: Fahrplan zur Erreichung eines sicheren und robusten Betriebs des zukünftigen Stromversorgungssystems mit 100 % erneuerbaren Energien," Berlin, Germany, Tech. Rep., Dec. 2023. [Online]. Available: https://www.bundeswirtschaftsministerium.de/Redaktion/DE/Publikationen/Energie/20231204-roadmap-systemstabilitaet.pdf

[2] Bundesministerium für Wirtschaft und Klimaschutz (BMWK), "Photovoltaik-Strategie 2023: Handlungsfelder für einen beschleunigten Ausbau der Photovoltaik," Berlin, Germany, Tech. Rep., May 2023. [Online]. Available: https://www.bundeswirtschaftsministerium.de/Redaktion/DE/Publikationen/Energie/photovoltaik-stategie-2023.pdf

[3] SMARD, "Update: Verteilernetze bis 2045," Bundesnetzagentur, Jan. 2024. [Online]. Available: https://www.smard.de/page/home/topic-article/444/215544/update-verteilernetze-bis-2045

[4] Bundesverband der Energie- und Wasserwirtschaft e.V. (BDEW) Standardlastprofil., "Standardlastprofile," GitHub repository, 2024. [Online]. Available: https://flrd.github.io/standardlastprofile/

[5] S. Candas, B. Reveron Baecker, A. Mohapatra, and T. Hamacher, "Optimization-based framework for low-voltage grid reinforcement assessment under various levels of flexibility and coordination," Applied Energy, vol. 343, Aug. 2023, Art. no. 121147, doi: 10.1016/j.apenergy.2023.121147.

[6] A. Mohapatra, M. Hock, et al., "Surrogate Framework for Energy System Modeling," in 2025 IEEE Kiel PowerTech, Kiel, Germany, 2025, pp. 1–6, doi: 10.1109/PowerTech59965.2025.11180532.

[7] G. Pjetri, A. Mohapatra, B. Reveron Baecker, M. Hock, and T. Hamacher, "Graph Neural Network Surrogates for Energy System Modeling," in 2025 IEEE ISGT Europe, Valletta, Malta, 2025, pp. 1–5, doi: 10.1109/ISGTEurope64741.2025.11305443.

[8] M. Wortsman et al., "Model soups: averaging weights of multiple fine-tuned models improves accuracy without increasing inference time," in Proc. 39th Int. Conf. Mach. Learn. (ICML), Baltimore, MD, USA, 2022, pp. 23965–23998. [Online]. Available: https://proceedings.mlr.press/v162/wortsman22a/wortsman22a.pdf

[9] H. Wang, G. Li, G. Wang, J. Peng, H. Jiang, and Y. Liu, "Deep learning based ensemble approach for probabilistic wind power forecasting," Applied Energy, vol. 188, pp. 56–70, Feb. 2017, doi: 10.1016/j.apenergy.2016.11.111.

[10] H. Genena, A. Mohapatra, B. Reveron Baecker, and T. Hamacher, "Blending Surrogates for Energy System Modeling," presented at the 2026 IEEE PES General Meeting, Montreal, Canada, 2026 (accepted).

[11] Übertragungsnetzbetreiber (ÜNB), "Netzentwicklungsplan Strom 2037/2045 (2025), Erster Entwurf," Mar. 2025. [Online]. Available: https://www.netzentwicklungsplan.de/nep-aktuell/netzentwicklungsplan-20372045-2025

[12] Agora Energiewende, "Wärmewende 2030: Schlüsseltechnologien zur Erreichung der mittel- und langfristigen Klimaschutzziele im Gebäudesektor," Berlin, Germany, Study, 2017. [Online]. Available: https://www.agora-energiewende.de/fileadmin/Projekte/2016/Sektoruebergreifende_EW/Waermewende-2030_WEB.pdf

[13] Langfristszenarien, "Enertile Explorer Dokumente," 2024. [Online]. Available: https://langfristszenarien.de/enertile-explorer-de/dokumente/

[14] Deutsche Energie-Agentur (dena), "Abschlussbericht dena-Leitstudie Aufbruch Klimaneutralität: Eine gesamtgesellschaftliche Aufgabe," Berlin, Germany, Oct. 2021. [Online]. Available: https://www.dena.de/fileadmin/dena/Publikationen/PDFs/2021/Abschlussbericht_dena-Leitstudie_Aufbruch_Klimaneutralitaet.pdf[

15] University of Wuppertal, "PubStadt – Planungs- und Betriebsgrundsätze für städtische Netze," Research Group for Network Structures and Network Planning. [Online]. Available: https://evt.uni-wuppertal.de/de/forschung/forschungsgruppe-netzstrukturen-und-netzplanung/pubstadt-planungs-und-betriebsgrundsaetze-fuer-staedtische-netze/.

[16] B. Reveron Baecker, S. Candas, D. Tepe, and A. Mohapatra, "Generation of low-voltage synthetic grid data for energy system modeling with the pylovo tool," Sustainable Energy, Grids and Networks, vol. 41, 2025, Art. no. 101617, doi: 10.1016/j.segan.2024.101617.

[17] B. Reveron Baecker, K. Kalkan, P. Buchenberg, A. Mohapatra, and T. Hamacher, "A Reproducible Open-Data Pipeline for Synthetic Low-Voltage Grid Generation in Germany," in 2025 IEEE PES Student Summit, Munich, Germany, 2025, doi: 10.30420/566656008.

[18] E. Franz Hanser, A. Mohapatra, B. Reveron Baecker, and T. Hamacher, "Deep Learning Surrogates for Low-Voltage Grid Planning," presented at the Power System Computation Conference (PSCC) 2026, Limassol, Cyprus, 2026 (accepted).

Contact

Dr. –Ing Anurag Mohapatra
CoSES Research Group
Technical University of Munich (TUM)
Lichtenbergstraße 4a
85748 Garching

Email - anurag.mohapatra@tum.de
Website - https://anuragmohapatra90.github.io/
Group - https://www.mep.tum.de/en/mep/coses/