Deep Learning Surrogates For Low-Voltage Grid Expansion Planning

Elias Franz Hanser, Anurag Mohapatra, Beneharo R. Baecker, Thomas Hamacher

Center for Combined Smart Energy Systems (CoSES)

Technical University of Munich

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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,

Bundesministerium für Wirtschaft und Klimaschutz

Photovoltaik-Strategie

Handlungsfelder und Maßnahmen für einen beschleunigten Ausbau der Photovoltaik

Stand 05.05.2023

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

Bundesministerium für Wirtschaft und Klimaschutz

Roadmap Systemstabilität

Fahrplan zur Erreichung eines sicheren und robusten Betriebs des zukünftigen Stromversorgungssystems mit 100 % erneuerbaren Energien

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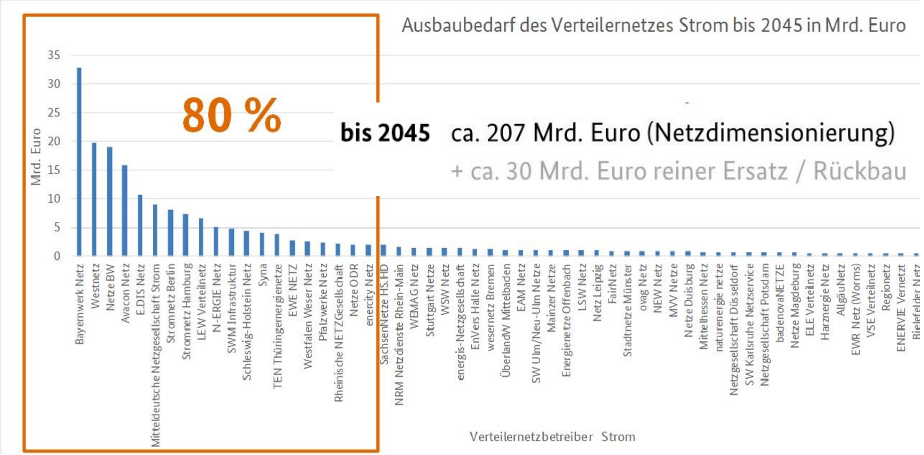
- Majority of the new renewables are going to appear on distribution grids – predominanlty PV.
- Heatpumps and EV chargers will also contribute.
- The distribution grid will have to be upgraded – at a heavy cost!!

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



[BNetzA estimate for NAP24]

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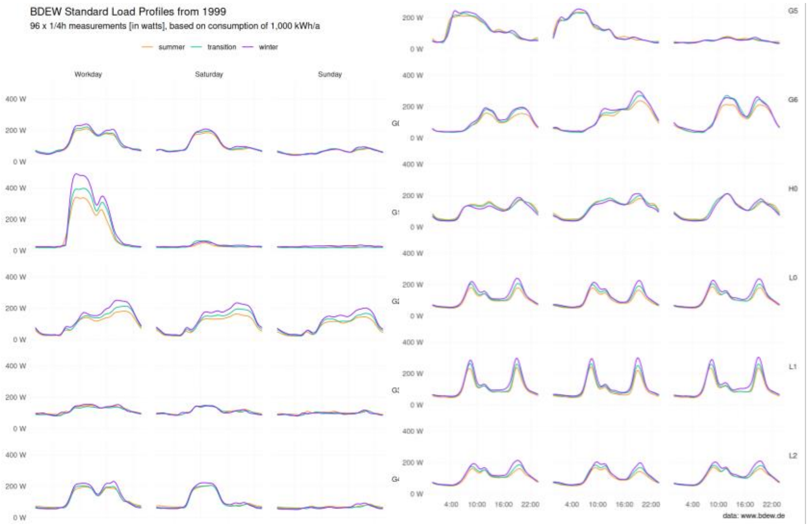
- Standard Load profiles will not be sufficient –
  - Home EMS
  - Grid side flexibility measures
  - Batteries as VPP
  - Sector-coupled consumer needs



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

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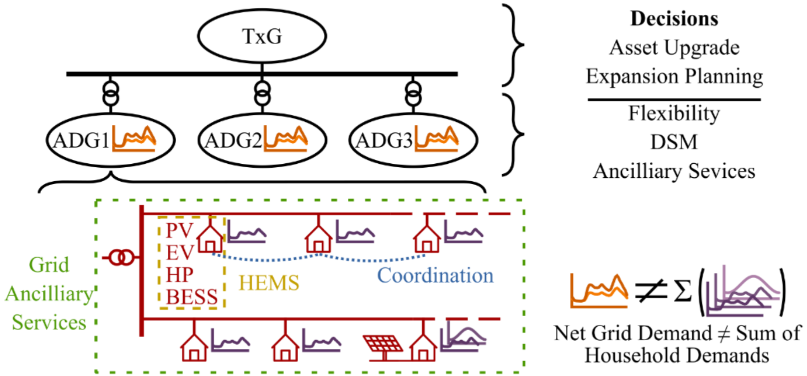

- Standard Load profiles will not be sufficient –
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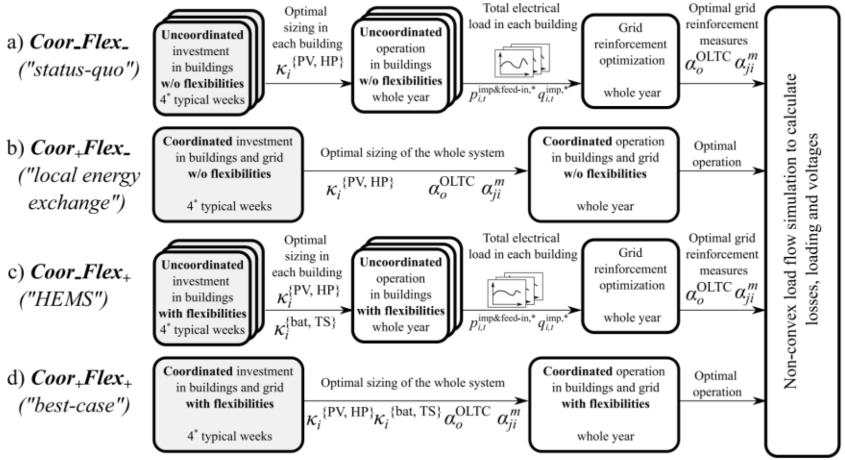
  - Grid side flexibility measures
  - Batteries as VPP
  - Sector-coupled consumer needs

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

Motivation – 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.



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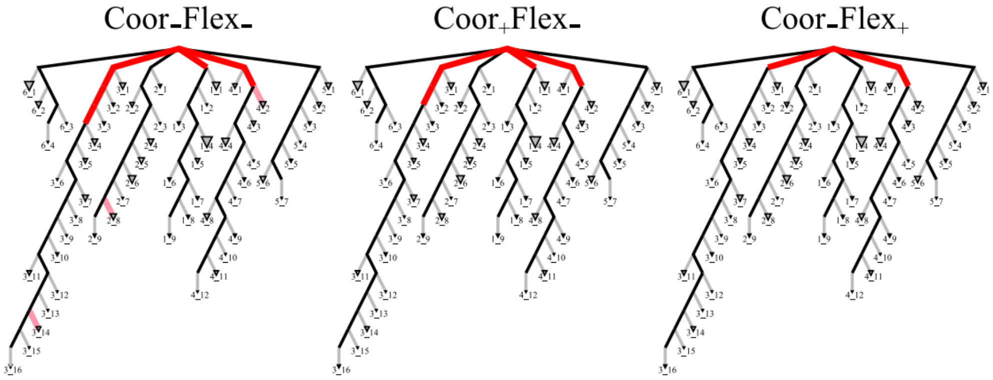
  - DER dispatch



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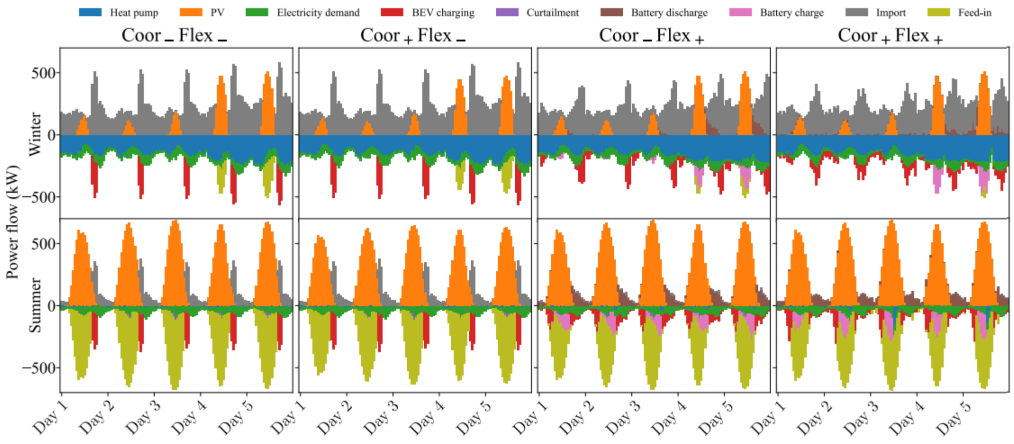

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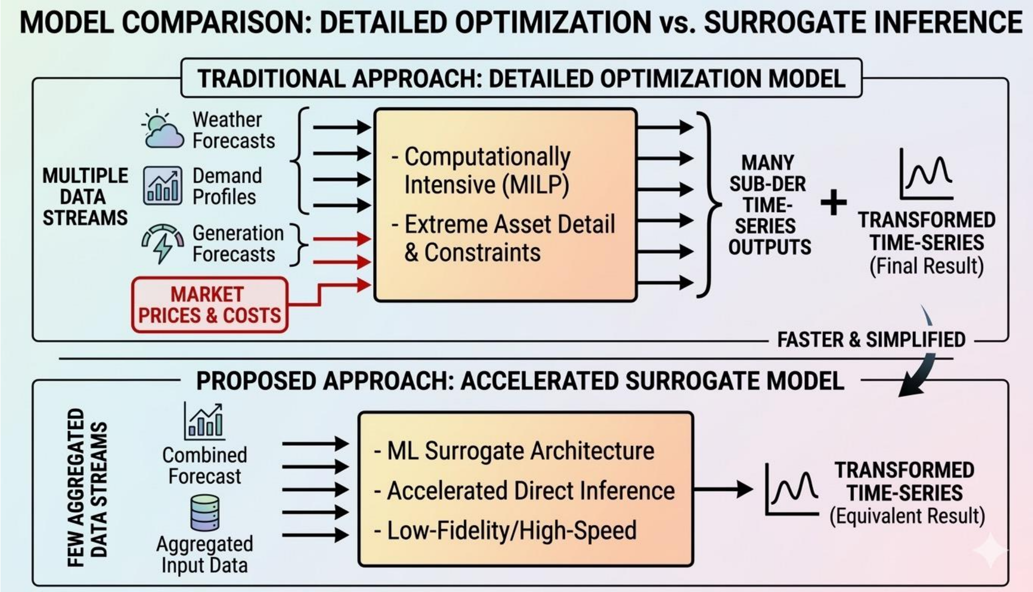
- Model setup takes a lot of time and turns intractable beyond few hundred nodes.
- Setup data collection is not trivial – difficult to haromize the assumptions from different datasets.

- 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.

Research Gap

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



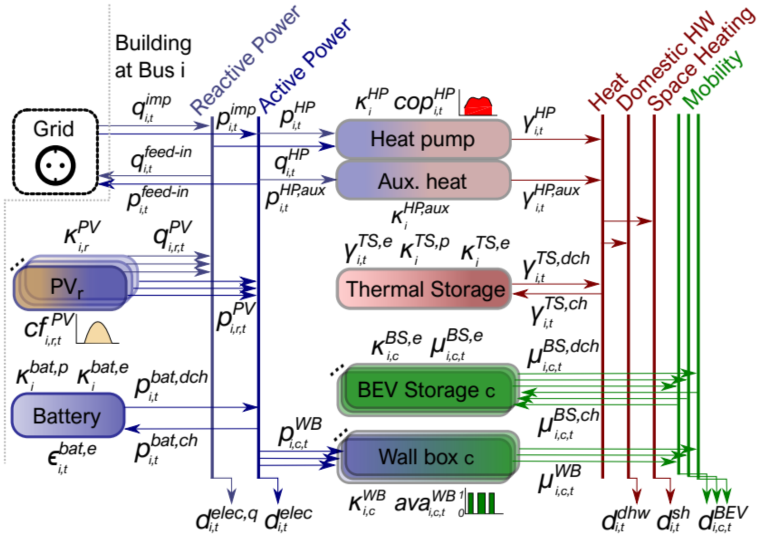
*Totally not made by AI

ML surrogates are fast, accurate and transferrable.

- Focus on hyperparameter tuning for LSTM and Transfomer architectures
- Feature engineering and data augmentation for better results.
- Archetypical benchmark grids – rural, semi-urban, urban.

- 30 scenarios – 1h resolution for 1yr model

- Pre-trained model can be *transfer learnt* to new grids
- Requires less than 4% of the original dataset.



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.

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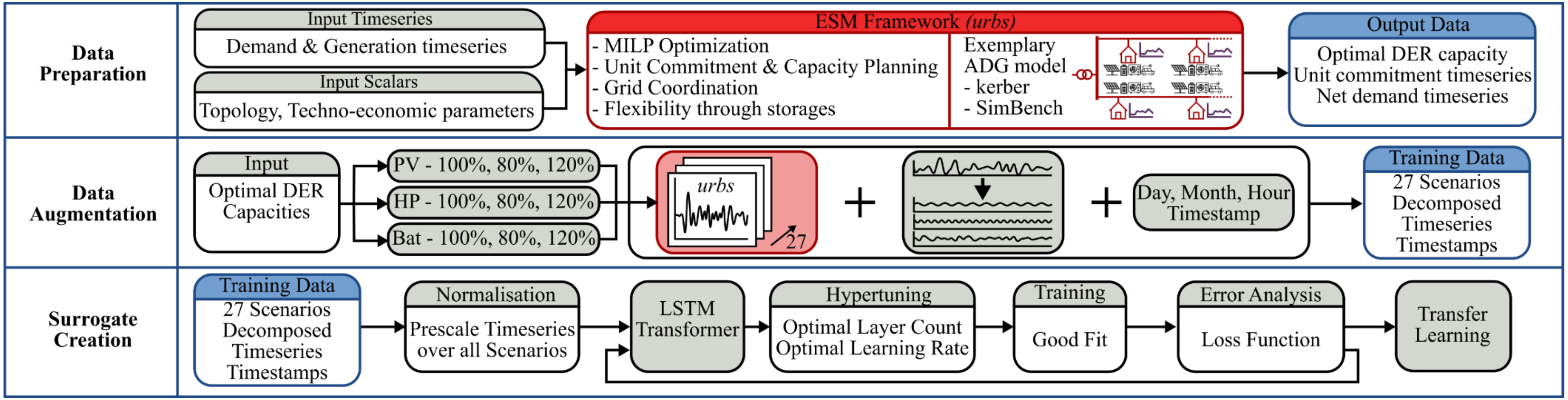

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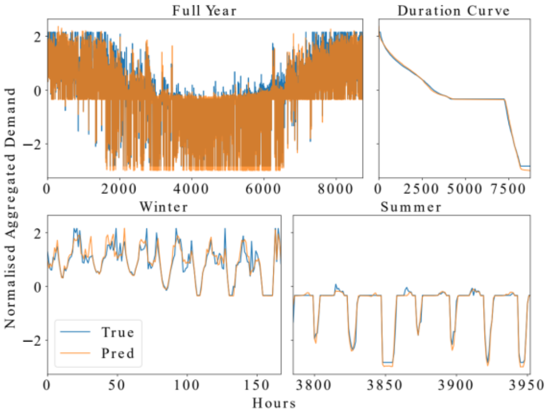
10 BEST-PERFORMING SURROGATE MODEL COMBINATIONS, SORTED BY PERFORMANCE ERRORS

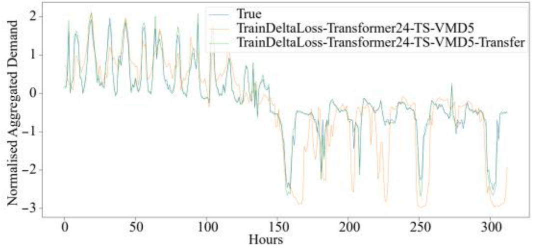
Label	MSE	MAE [kW]	Net Demand [%]	Peak Demand [%]	Peak Feed-in [%]	Hypertuning Time [h]	Training Time [h]	Evaluation Time [s]
TrainDeltaLoss_Transformer24_TS-VMD5	0.048	19.441	0.882	0.826	5.455	03:15:09	01:05:36	4.509
TrainDeltaLoss_LSTM24_TS-VMD5	0.049	19.238	7.985	1.404	1.461	03:07:20	00:59:42	4.047
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





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But actually…

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

No Data, No Party….

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

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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

The *actual* gap…

- A crisis of available grid 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...

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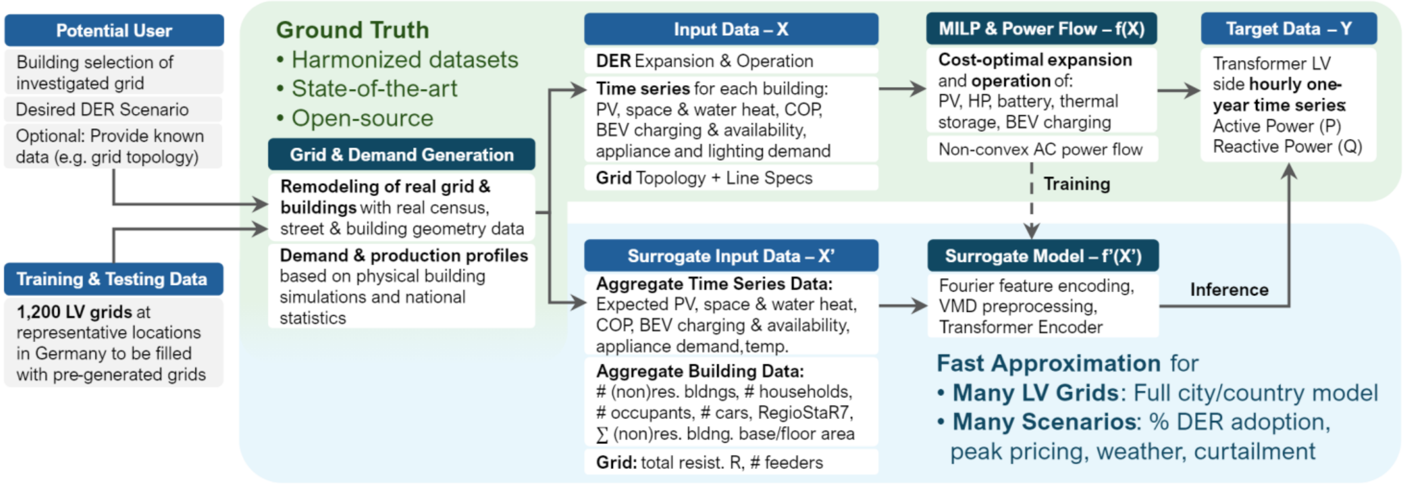
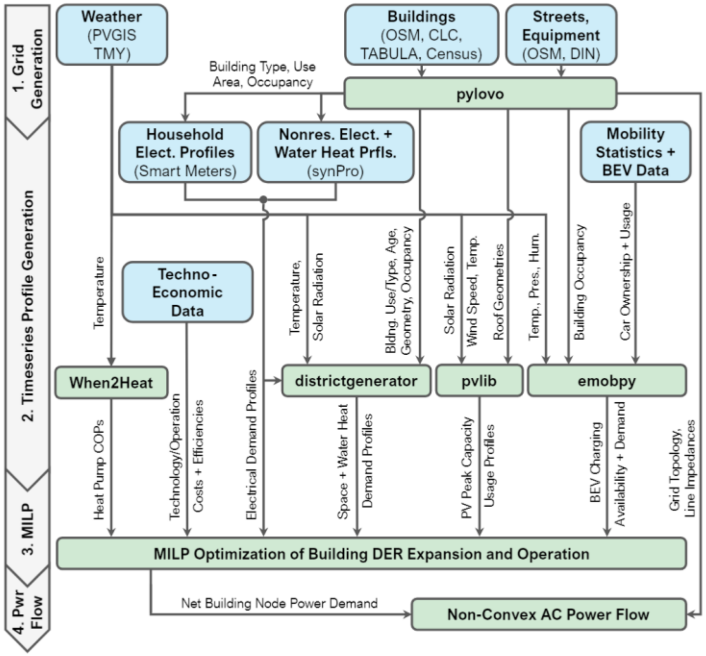


Result #1 – Fully open-source MILP ground truth tool

- Using existing open-source demand tools.
- MILP optimization following Home EMS paradigm
  – Houses are optimized individually for optimal DER size
- Full AC power flow to account for grid losses.
- LV grids generated synthetically with our tool - *pylovo*



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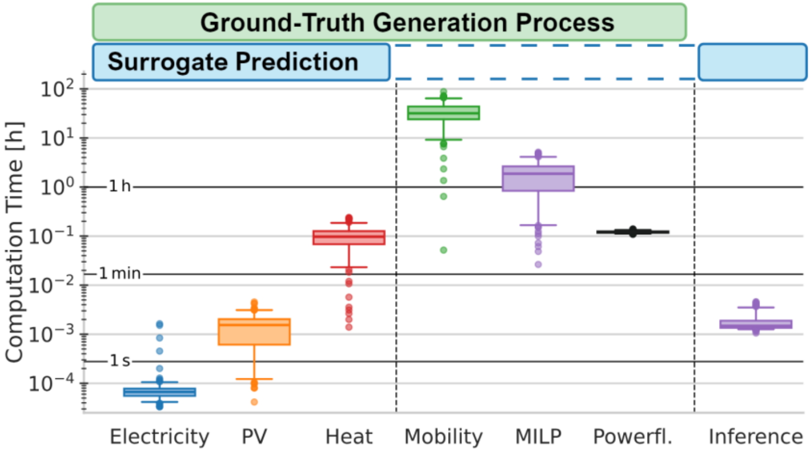
Result #2 – Inference with proxies instead of time-series

- 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.



Result #3 – 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.

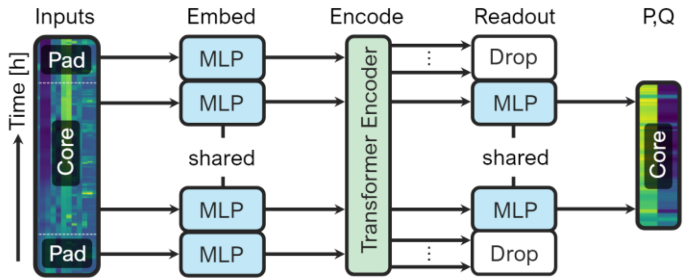


Fig. 6. Surrogate model architecture. The target time series is split into smaller, potentially padded, individually inferred core slices. A shared MLP embeds a multivariate input time step into a higher dimension. The transformer encoder architecture allows rich interaction encoding within a slice.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

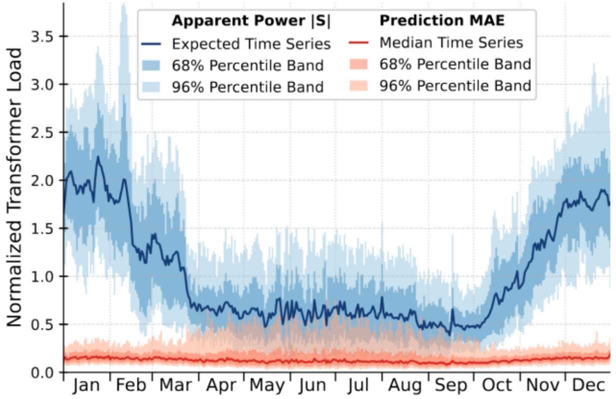


Fig. 8. Normalized transformer load ($|S|(t)/\langle|S|\rangle$) and normalized prediction MAE distributions for testing grids at daily aggregation over one year. The expected/median time series and percentile bands are obtained from each individual day's normalized load/error distribution over all grids.

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MEDIAN ERROR METRICS OF THE SURROGATE MODELS.

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

MEP TUM

Conclusion

1. ML surrogates for energy system models are fast, accurate and transferrable.
2. Open source synthetic LV grid models can be generated for whole Germany.
3. One surrogate *possible* for all German grids.
   I. Fully open-source MILP ground truth tool.
   II. Inference with proxies instead of time-series.

SurroGrid Repo →

SurroGrid

SurroGrid is a research codebase that combines two workflows:

1. **GridExpand**: a 4-step pipeline to generate *grid-level simulation data* for low-voltage (LV) distribution grids.
2. **GridForecast**: preprocessing + machine learning models (MLP and Transformer) to train **surrogate forecasters** on the GridExpand outputs.

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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/