Data Driven Voltage Control – Perspectives from Germany

Anurag Mohapatra

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Technical University of Munich

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26.11.2025

CoSES at a glance

Prof. Dr.
Thomas Hamacher
Director

Dr. -Ing.
Anurag Mohapatra
Group Leader

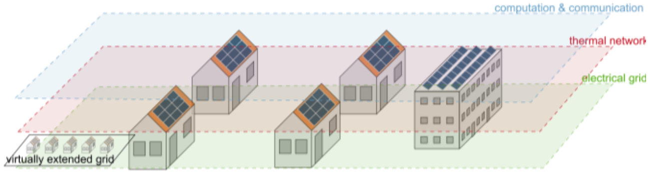
Leads

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

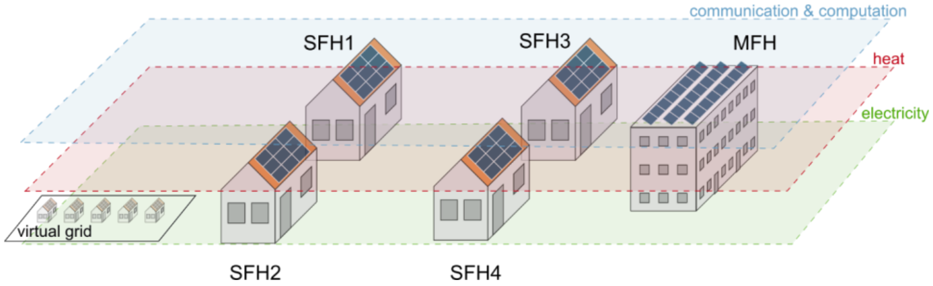
Sector-coupled microgrid at TUM

- 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



CoSES at a glance

Directly at CoSES
- 6 PhD students
- 1 Post-doc

Associated with CoSES
- 7 PhD students
- Chair of Power Transmission and Distribution.
- TUM Smart Grid Initiative

Frequent Guest Researchers

Outline

- State-of-the-art for data driven control in distribution grids
- Our work at CoSES on data driven control.
- Unique challenges of working in the German distribution grid context
- Our focus area and benchmarking within these constraints.

MEP

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Inverter Control Ideas

- Famous results on how to design inverter controllers
  - Grid following, forming, support…

- Concepts of emulating synchronous machines on IBRs

- However!!!!!!
  - Require grid knowledge
  - R/X ratio

- Bigger concern in distribution grids
  - Less live data, grid knowledge
  - R >> X does not hold for most real distribution grids

34 IEEE TRANSACTIONS ON POWER ELECTRONICS, VOL. 27, NO. 11, NOVEMBER 2012

Control of Power Converters in AC Microgrids

Joan Rocabert, *Member, IEEE*, Alvaro Luna, *Member, IEEE*, Frede Blaabjerg, *Fellow, IEEE*, and Pedro Rodríguez, *Senior Member, IEEE*

(Invited Paper)

Virtual Synchronous Machine

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Dipl.-Ing. Ralf Hesse
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Institute of Electric Power Technology (IEE
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[1] Rocabert, J., et al. "Control of Power Converters in AC Microgrids," in IEEE Transactions on Power Electronics, vol. 27, no. 11, pp. 4734–4749, 2012.
[2] H. Beck, R. Hesse, "Virtual synchronous machine," in 2007 9th International Conference on Electrical Power Quality and Utilisation, 2007, pp. 1–6.

Grid Agnostic Control

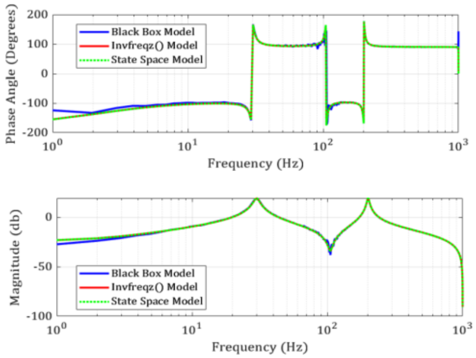
- State estimation based control / Probing based control
  - Perturb the system and estimate eigen modes
  - Online and offline versions

2462 IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 36, NO. 3, MAY 2021

Roles of Dynamic State Estimation in Power System Modeling, Monitoring and Operation

IEEE Task Force on Power System Dynamic State and Parameter Estimation

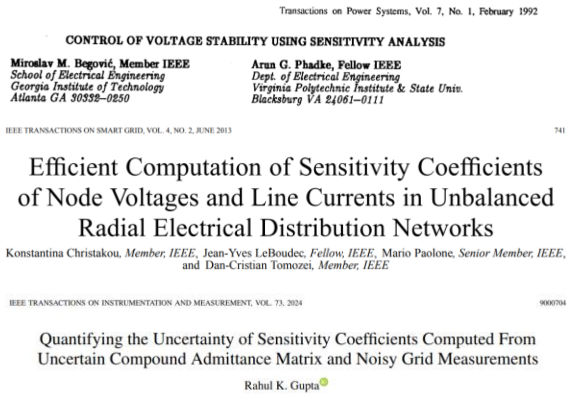
Junbo Zhao (TF Chair), *Senior Member, IEEE*, Marcos Netto, *Member, IEEE*, Zhenyu Huang, *Fellow, IEEE*, Samson Shenglong Yu, *Member, IEEE*, Antonio Gómez-Expósito, *Fellow, IEEE*, Shaobu Wang, *Senior Member, IEEE*, Innocent Kamwa, *Fellow, IEEE*, Shahrokh Akhlaghi, *Senior Member, IEEE*, Lamine Mili, *Life Fellow, IEEE*, Vladimir Terzija, *Fellow, IEEE*,



[3] Zhao, J., et al. "Roles of Dynamic State Estimation in Power System Modeling, Monitoring and Operation," in IEEE Transactions on Power Systems, vol. 36, no. 3, pp. 2462–2472, 2021.
[4] Chakraborty, R., et al. "A review of active probing-based system identification techniques with applications in power systems," *International Journal of Electrical Power and Energy Systems*, vol. 140, Art. no. 108008, 2022

Grid Agnostic Control

- Sensitivity parameter based control
  - Change in P, Q correlated to change in V,I
  - Calculated from Jacobian and measurements
  - Mature literature on efficient computation and robustness



Transactions on Power Systems, Vol. 7, No. 1, February 1992

CONTROL OF VOLTAGE STABILITY USING SENSITIVITY ANALYSIS

Miroslav M. Begović, Member IEEE
School of Electrical Engineering
Georgia Institute of Technology
Atlanta GA 30332–0250

Arun G. Phadke, Fellow IEEE
Dept. of Electrical Engineering
Virginia Polytechnic Institute & State Univ.
Blacksburg VA 24061–0111

IEEE TRANSACTIONS ON SMART GRID, VOL. 4, NO. 2, JUNE 2013 741

Efficient Computation of Sensitivity Coefficients of Node Voltages and Line Currents in Unbalanced Radial Electrical Distribution Networks

Konstantina Christakou, *Member, IEEE*, Jean-Yves LeBoudec, *Fellow, IEEE*, Mario Paolone, *Senior Member, IEEE*, and Dan-Cristian Tomozei, *Member, IEEE*

IEEE TRANSACTIONS ON INSTRUMENTATION AND MEASUREMENT, VOL. 73, 2024 9000704

Quantifying the Uncertainty of Sensitivity Coefficients Computed From Uncertain Compound Admittance Matrix and Noisy Grid Measurements

Rahul K. Gupta

[5] M. Begovic, A. Phadke. "Control of voltage stability using sensitivity analysis," in IEEE Transactions on Power Systems, vol. 7, no. 1, pp. 114–123, 1992.
[6] Christakou, K., et al. "Efficient Computation of Sensitivity Coefficients of Node Voltages and Line Currents in Unbalanced Radial Electrical Distribution Networks," in IEEE Transactions on Smart Grid, vol. 4, no. 2; 2013
[7] Gupta, Rahul K., "Quantifying the Uncertainty of Sensitivity Coefficients Computed From Uncertain Compound Admittance Matrix and Noisy Grid Measurements," *IEEE Transactions on Instrumentation and Measurement*, vol. 73, Art. no. 10371404, 2023

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Grid Agnostic Control

- Data driven predictive control (DeePC)
  - Constrained optimization to calculate stabilizing feedback
  - Ensures guaranteed behaviour

A note on persistency of excitation

Jan C. Willems[a], Paolo Rapisarda[b], Ivan Markovsky[a,*], Bart L.M. De Moor[a]

[a]ESAT, SCD/SISTA, K.U. Leuven, Kasteelpark Arenberg 10, B 3001 Leuven, Heverlee, Belgium
[b]Department of Mathematics, University of Maastricht, 6200 MD Maastricht, The Netherlands

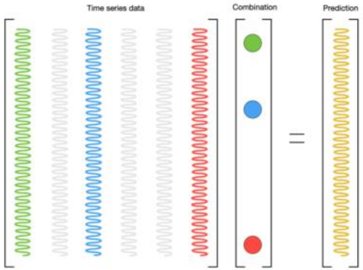
Received 3 June 2004; accepted 7 September 2004
Available online 30 November 2004

Data-Enabled Predictive Control: In the Shallows of the DeePC

Jeremy Coulson John Lygeros Florian Dörfler

Data-Enabled Predictive Control for Grid-Connected Power Converters

Linbin Huang, Jeremy Coulson, John Lygeros and Florian Dörfler



<u>sufficiently exciting input</u> signal allows us to <u>completely determine the system</u>'s behaviour from a <u>finite number of input-output</u> data points

https://control.ee.ethz.ch/research/theory/data-enabled-predictive-control.html

[8] Willems, J., et al. "A note on persistency of excitation," in *Systems & Control Letters*, vol. 54, no. 4, pp. 325–329, 2005.
[9] J. Coulson, J. Lygeros, F. Dörfler, "Data-Enabled Predictive Control: In the Shallows of the DeePC," in 2019 18th European Control Conference (ECC), 2019, pp. 307–312.
[10] Huang, L., et al, "Data-Enabled Predictive Control for Grid-Connected Power Converters," in 2019 IEEE 58th Conference on Decision and Control (CDC), 2019, pp. 8130–8135.

Grid Agnostic Control

- Online Feedback Optimization
  - Solve an optimization problem online – with tricks…
  - Constrained optimization to calculate stabilizing feedback
  - Use real measurement for feedback, no plant model needed

Online Optimization in Closed Loop on the Power Flow Manifold

Adrian Hauswirth, Alessandro Zanardi, Saverio Bolognani, Florian Dörfler, and Gabriela Hug
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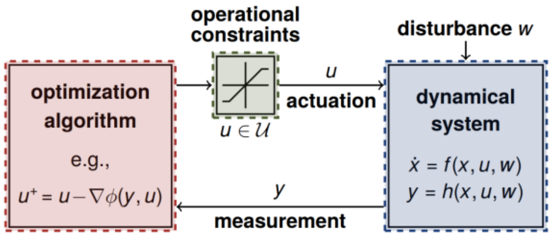
ELSEVIER
Electric Power Systems Research
journal homepage: www.elsevier.com/locate/epsr

Experimental validation of feedback optimization in power distribution grids☆

Lukas Ortmann*, Adrian Hauswirth, Ivo Caduff, Florian Dörfler, Saverio Bolognani
ETH Zurich, Zurich 8092, Switzerland

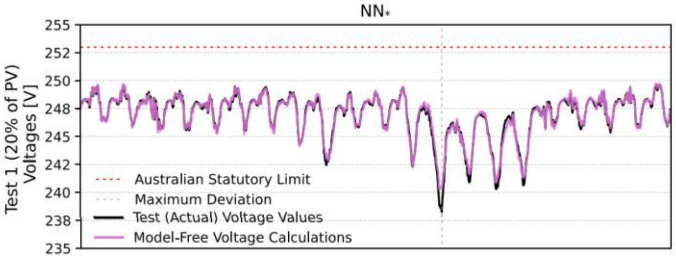


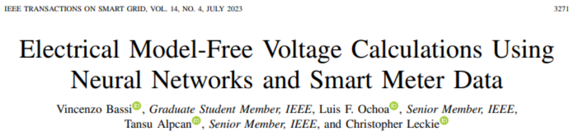
https://speakerdeck.com/floriandoerfler/online-feedback-optimization-73d52898-e8fb-4956-8453-eb4f09d44101

[11] A. Hauswirth, A. Zanardi, S. Bolognani, F. Dörfler, and G. Hug, "Online optimization in closed loop on the power flow manifold," in *2017 IEEE Manchester PowerTech (PTC)*, 2017, pp. 1-6
[12] L. Ortmann, A. Hauswirth, I. Caduff, F. Dörfler, and S. Bolognani, "Experimental validation of feedback optimization in power distribution grids," *Electr. Power Syst. Res.*, vol. 189, Art. no. 106782, 2020

Grid Agnostic Control

- Neural Networks
  - Feedforward MLPs are fast and reliable for voltage prediction
  - Reinforcement Learning can be useful





IEEE TRANSACTIONS ON SMART GRID, VOL. 14, NO. 4, JULY 2023 3271

Electrical Model-Free Voltage Calculations Using Neural Networks and Smart Meter Data

Vincenzo Bassi, *Graduate Student Member, IEEE*, Luis F. Ochoa, *Senior Member, IEEE*, Tansu Alpcan, *Senior Member, IEEE*, and Christopher Leckie

IEEE TRANSACTIONS ON SMART GRID, VOL. 13, NO. 1, JANUARY 2022 149

Deep Reinforcement Learning Enabled Physical-Model-Free Two-Timescale Voltage Control Method for Active Distribution Systems

Di Cao, *Student Member, IEEE*, Junbo Zhao, *Senior Member, IEEE*, Weihao Hu, *Senior Member, IEEE*, Nanpeng Yu, *Senior Member, IEEE*, Fei Ding, *Senior Member, IEEE*, Qi Huang, *Senior Member, IEEE*, and Zhe Chen, *Fellow, IEEE*

[13] V. Bassi et al., "Electrical Model-Free Voltage Calculations Using Neural Networks and Smart Meter Data," *IEEE Transactions on Smart Grid*, vol. 14, no. 4, Jul. 2023
[14] D. Cao et al., "Deep Reinforcement Learning Enabled Physical-Model-Free Two-Timescale Voltage Control Method for Active Distribution Systems," *IEEE Transactions on Smart Grid*, vol. 13, no. 1, pp. 642-655, Sep. 2021

Grid Agnostic Control

	Sys ID	Sensitivity	DeePC	OFO	NN
Mathematically rigorous	↔	↔	↑	↑	↓
Online/Real-time	↑	↑	↓	↔	↑
Data Requirement	↓	↑	↔	↔	↔
Low effort setup	↔	↔	↓	↑	↓
Robust to changes	↓	↔	↔	↑	↔
Experimentally validated in real DG	↔	↑	↓	↑	↑

↑ Good ↓ Bad ↔ Meh…

MEP TUM

Data Driven Predictive Control at CoSES

- First implementation of DeePC on real inverter, real distribution grid
  - Optimal predictor in low data regimen
  - Fits on a microcontroller
  - Grid was „LTI enough“

The Transient Predictor

Keith Moffat, Florian Dörfler, and Alessandro Chiuso

Grid-Connected, Data-Driven Inverter Control, Theory to Hardware

Sebastian Graf,* Keith Moffat,* Anurag Mohapatra,‡ Alessandro Chiuso,† Florian Dörfler*

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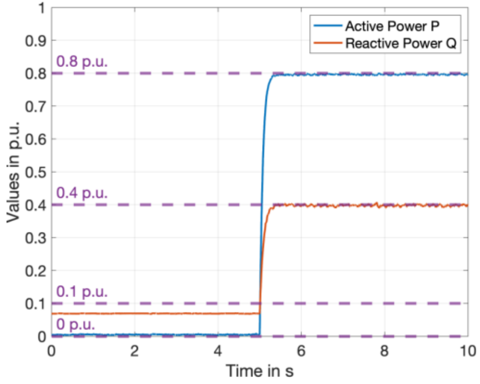
Email: anurag.mohapatra@tum.de



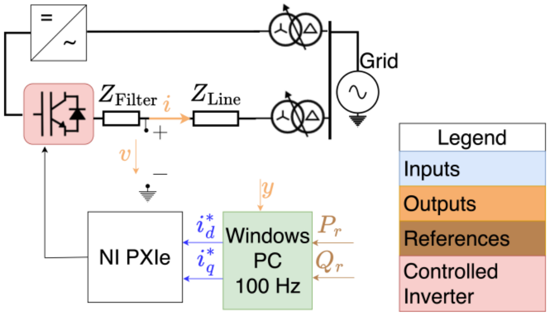


Fig. 4. Schematic of the experiments at TUM's CoSES Lab [18]

[15] K. Moffat, F. Dörfler, and A. Chiuso, "The Transient Predictor," in *2024 IEEE 63rd Conference on Decision and Control (CDC)*, 2024, pp. 1871–1876
[16] S. Graf et al., "Grid-Connected, Data-Driven Inverter Control, Theory to Hardware," in *2025 IEEE PowerTech*, 2025

Data Driven Predictive Control at CoSES

- RL and OFO based voltage control from data-driven state estimators
  - Live substation measurement with historical smart meter data.
  - Control individual prosumers at downstream nodes.
  - Collaboration with Siemens

Low-Voltage Grid Control Based On Data-Driven State Estimation and Reinforcement Learning

Hakan Özlemiş[1,2], Edwin Mora[1], Jano Schubert[1,3], Anurag Mohapatra[2], Mathias Duckheim[1], Stefan Niessen[1,3]
[1] Siemens AG, Erlangen, Germany
[2] Technical University of Munich, Munich, Germany
[3] Technical University of Darmstadt, Darmstadt, Germany
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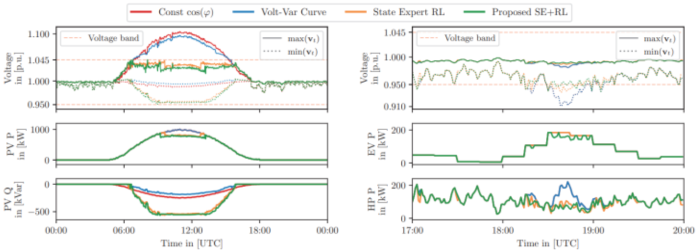
Towards Automatic Parameterization of Online Feedback Optimization for Autonomous Low-Voltage Distribution Grids

Jano Schubert[1,2], Albi Allmeta[1,3], Edwin Mora[1], Anurag Mohapatra[3], Mathias Duckheim[1], Stefan Niessen[1,2]
[1] Siemens AG, Erlangen, Germany
[2] Technical University of Darmstadt, Darmstadt, Germany
[3] Technical University of Munich, Munich, Germany
{jano.schubert, edwin.mora-gil, mathias.duckheim, stefan.niessen}@siemens.com, {albi.allmeta, anurag.mohapatra}@tum.de



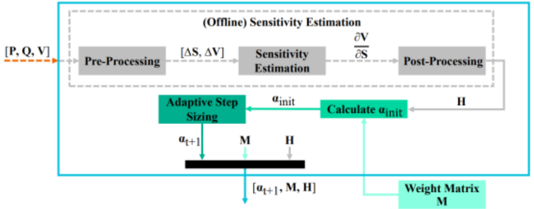
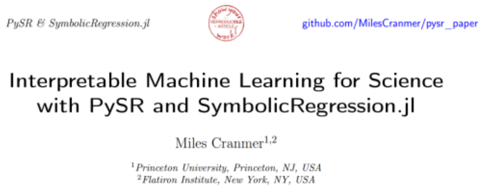


Fig. 2: Proposed automatic parameterization of OFO.

[17] H. Özlemiş et al., "Low-Voltage Grid Control Based On Data-Driven State Estimation and Reinforcement Learning," in *2024 IEEE Power & Energy Society General Meeting (PESGM)*, 2024
[18] J. Schubert et al., "Towards Automatic Parameterization of Online Feedback Optimization for Autonomous Low-Voltage Distribution Grids," in *2025 IEEE Kiel PowerTech*, 2025

Symbolic Regression at CoSES

- Introduced Symbolic Regression for voltage control
  - Introduced Physics informed SR for voltage estimation
  - Derive analytical functions for node voltages from bus injections


PySR & SymbolicRegression.jl github.com/MilesCranmer/pysr_paper

Interpretable Machine Learning for Science with PySR and SymbolicRegression.jl

Miles Cranmer[1,2]

[1] Princeton University, Princeton, NJ, USA
[2] Flatiron Institute, New York, NY, USA

[19] M. Cranmer, "Interpretable Machine Learning for Science with PySR and SymbolicRegression.jl," arXiv, arXiv:2305.01582, May 2023.

Symbolic Regression at CoSES

- Introduced Symbolic Regression for voltage control
  - Introduced Physics informed SR for voltage estimation
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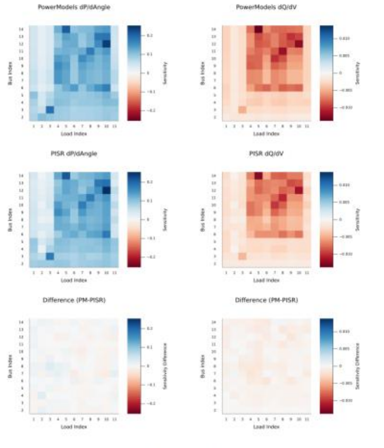

Figure 17: Comparison of $\frac{\partial P}{\partial \theta}$ sensitivity matrices: PowerModels (top), PISR (middle), and difference (bottom)

Figure 18: Comparison of $\frac{\partial Q}{\partial V}$ sensitivity matrices: PowerModels (top), PISR (middle), and difference (bottom)

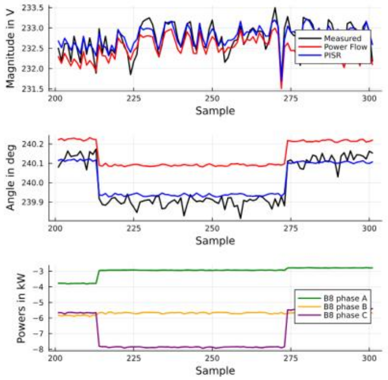

Fig. 6: Voltage magnitude (top) and angle (middle) prediction for Bus B8, Phase B, with all three phase power injections (bottom)

PISR: Physics-Informed Symbolic Regression for Predicting Power System Voltage

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Anurag Mohapatra, Technical University of Munich, Munich, Germany, anurag.mohapatra@tum.de
Christoph Goebel, Technical University of Munich, Munich, Germany, christoph.goebel@tum.de

PHIL Validation of Physics-Informed Symbolic Regression for Power System Voltage Prediction

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Anurag Mohapatra, *Technical University of Munich, Munich, Germany*, anurag.mohapatra@tum.de
Ehimare Okoyomon, *Technical University of Munich, Munich, Germany*, e.okoyomon@tum.de

$$\texttt{line\_current}(V_{send} \in \mathbb{C}, S \in \mathbb{C})\ \textbf{return}\ \overline{S/V_{send}}$$

$$\texttt{voltage\_drop}(I \in \mathbb{C}, Z \in \mathbb{C})\ \textbf{return}\ I \cdot Z$$

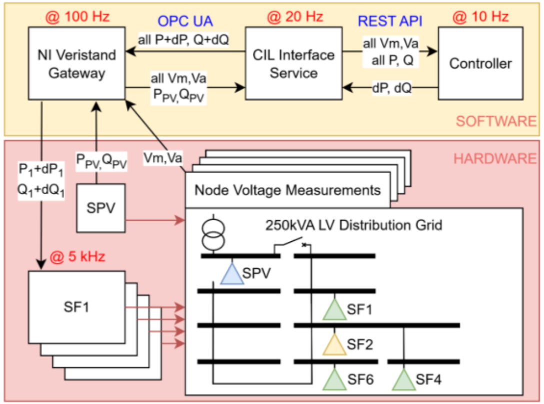
[20] S. Eichhorn et al., "PISR: Physics-Informed Symbolic Regression for Predicting Power System Voltage," in *Proceedings of the 16th ACM International Conference on Future and Sustainable Energy Systems*, 2025
[21] S. Eichhorn et al., „PHIL Validation of Physics-Informed Symbolic Regression for Power System Voltage Prediction," in *2025 IEEE ISGT Europe*, 2025

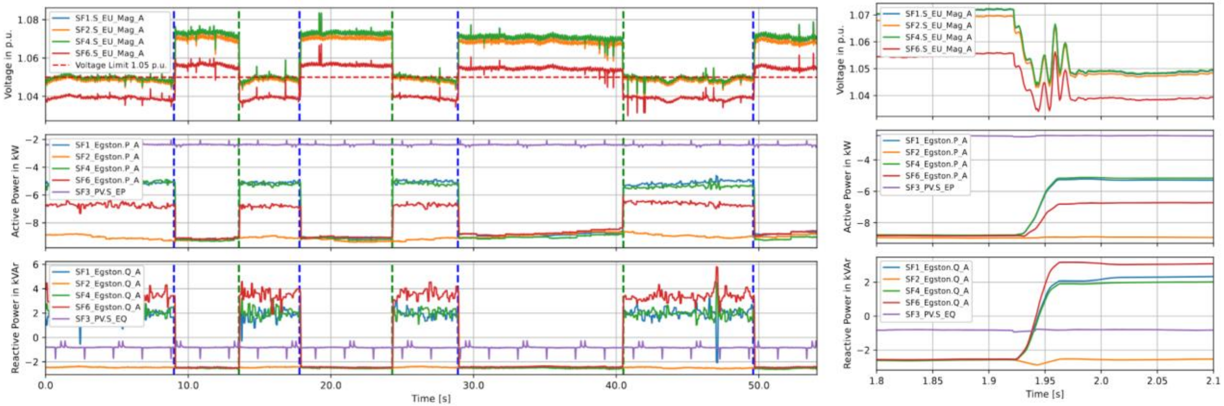
Symbolic Regression at CoSES

- Introduced Symbolic Regression for voltage control
  - First SR based voltage controller in a real LV grid
  - Used standard MPC but based on a SR surrogate of the grid
  - Open loop control; doesn‘t care if grid is LTI or not

Fast, Interpretable, and Agnostic - PISR Voltage Control on a Low-Voltage Grid

Sebastian Eichhorn [1,2], Anurag Mohapatra[2], Reinaldo Tonkoski[1]
[1]Chair of Electric Power Transmission and Distribution, Technical University of Munich, Munich, Germany
[2] Center for Combined Smart Energy Systems, Technical University of Munich, Munich, Germany
{sebastian.eichhorn, anurag.mohapatra, reinaldo.tonkoski}@tum.de





[22] S. Eichhorn, A. Mohapatra and R. Tonkoski, “Fast, Interpretable, and Agnostic - PISR Voltage Control on a Low-Voltage Grid”, Zenodo, Oct. 2025. doi: 10.5281/zenodo.17395966

MEP

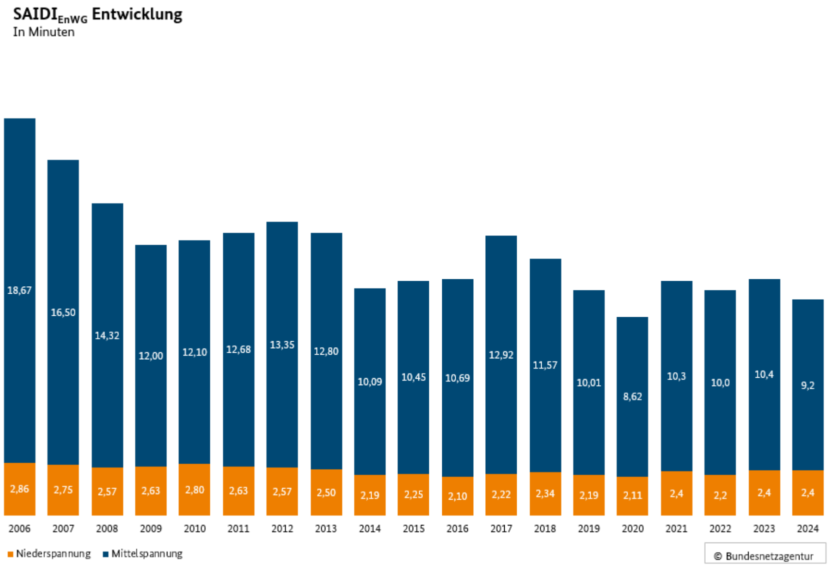
Grid Agnostic Control (Updated)

	Sys ID	Sensitivity	DeePC	OFO	NN	PISR
Mathematically rigorous	↔	↔	↑	↑	↓	↑
Online/Real-time	↑	↑	↑	↔	↑	↑
Data Requirement	↓	↑	↔	↔	↔	↔
Low effort setup	↔	↔	↑	↔	↓	↑
Robust to changes	↓	↔	↔	↑	↔	↔
Experimentally validated in real DG	↔	↑	↑	↑	↑	↑

↑ Good ↓ Bad ↔ Meh…

Distribution grids in Germany

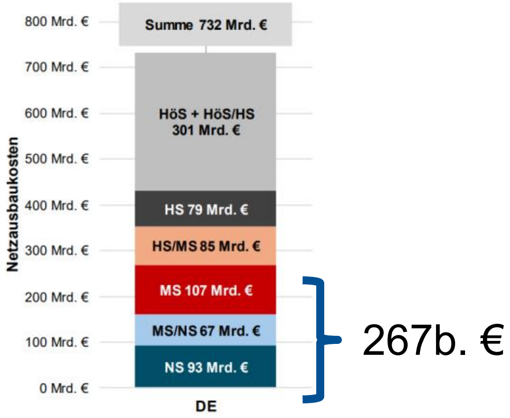
- 883 distribution grid operators
- Distribution grid 1.7m km vs HV grid 37k km
- 80% underground cables
- One of the most reliable distribution grids worldwide

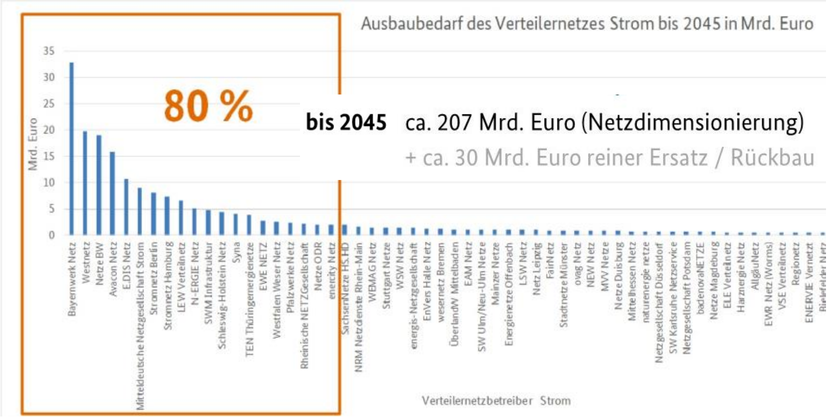


MEP TUM

Distribution grids in Germany

- 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!!
- Distribution grid automation and HEMS based self-consumption is critical





Netze Südwest estimate for NEP23 BNetzA estimate for NAP24

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A Brief Look at the German Smart Meter Landscape

- Germany did not install smart meters for billing automation
- Smart Meters entered the market as a „control“ entity – data flows both ways

- Customers above 6000 kWh annual consumption OR who have a controllable load MUST have the *iMSys* (Intelligent Measurement System)
- 15% roll out among qualifying homes, as of March 31, 2025.

- Total smart meter penetration – 2.8% as of March 31, 2025

- Slow…but we will get there….
- However this presents a research opportunity!

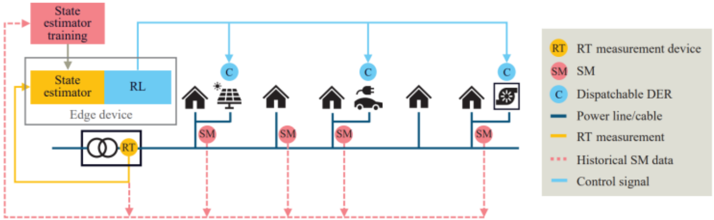
https://www.ffe.de/en/publications/how-is-the-german-smart-meter-rollout-progressing/

State Estimation in German Distribution Grids

- One day…we will have 100% smart meter rollout.
- BUT, the live data will *probably* be impossible.

- Only live measurement point – ADMS at Transformer
- Work with historical smart meter data

- Can we predict *live node voltages* with this setup?



Distributed State Estimation in Digitized Low-Voltage Networks

Dr. Thomas Werner[1], Wiebke Fröhner[1], Dr. Mathias Duckheim[2], Dr. Dieter Most[2], Dr. Alfred Einfalt[3]

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[2] Siemens AG, Corporate Technology, Guenther-Scharowsky-Str. 1, 91058 Erlangen, Germany
[3] Siemens AG Österreich, Siemensstr. 90, 1210 Wien, Austria

[23] T. Werner, W. Froehner, M. Duckheim, D. Most and A. Einfalt, "Distributed State Estimation in Digitized Low-Voltage Networks," *NEIS 2018; Conference on Sustainable Energy Supply and Energy Storage Systems*, Hamburg, Germany, 2018

MEP

TUM

State Estimation in German Distribution Grids

- Can we predict *live node voltages* with this setup? - Yes!

- LSTM based; MLP for benchmark
- Noisy data
- Comprehensive analysis

Data-Driven Visibility: Nodal Voltage Estimation from Limited Substation Data

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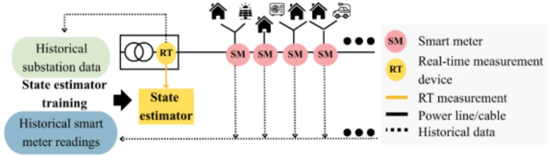


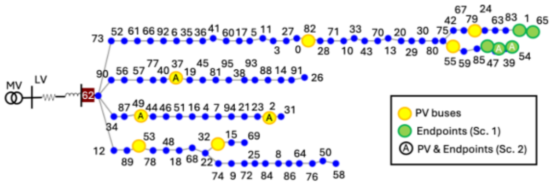
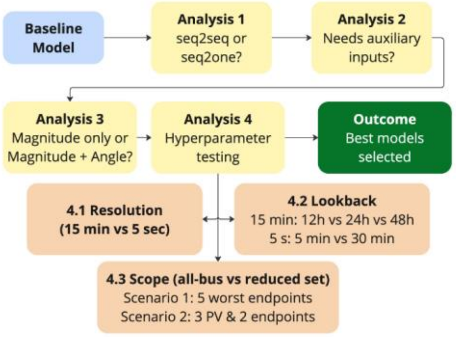


TABLE II
STATE ESTIMATION RESULTS FOR ANALYSIS 1-3. ALL VALUES ARE $\times 10^{-4}$. THE MAE IS SHOWN FOR THE WORST PERFORMING BUS.

Category	Model	Magnitude (p.u.)		Angle (°)	
		RMSE	MAE	RMSE	MAE
Benchmark*	MLP	3.5	4.9	64	90
	LSTM	2.8	3.8	54	72
#1: Seq2Seq vs Seq2One	LSTM_Seq2Seq	2.9	4.1	55	72
	LSTM_Seq2One	13.0	13.0	360	340
#2: Time or not	VMVA_Seq2Seq	2.7	3.4	54	69
#3: Only Magnitude	LSTM_Seq2Seq_time	2.7	3.5	–	–
	MLP_time	3.2	4.6	–	–

These models are trained with 100 epochs. The highlighted model is chosen as the baseline for further analyses.



[24] A. D. Larasati, A. Mohapatra, T. Hamacher, “Data-Driven Visibility: Nodal Voltage Estimation from Limited Substation Data”. Zenodo, Nov. 25, 2025. doi: 10.5281/zenodo.17714508.

MEP

TUM

HEMS Benchmarking for Germany

PhyLFlex

Gefördert durch:
Bundesministerium für Wirtschaft und Energie
aufgrund eines Beschlusses des Deutschen Bundestages

- HEMS Finder - a project to compare all available HEMS being sold in Germany
  - Second annual survey is currently out – open-access report here
  - More information can be found on the website – https://hems-finder.org/
- Current comparison is limited to a manufacturer survey through a questionnaire.
- A true benchmarking requires subjecting HEMS to test conditions.
- But what are these conditions?

HEMS Benchmarking for Germany

Gefördert durch:
Bundesministerium für Wirtschaft und Energie
aufgrund eines Beschlusses des Deutschen Bundestages

- There are separate standards for benchmarking – a tale of three worlds.

	Research world	**Regulations world**	**Real world**
Motivation	What ***could*** be possible?	What ***should*** be possible?	What ***is currently*** possible?
Focus	Algorithms and forecasts	Discrimination free access, privacy by design, grid stability	Ease of implementation, converging on interoperable solutions.

- Research project PhyLFlex (2025-2028) is focused on this problem.
  - How to evaluate various HEMS strategies?
  - Can there be a universal methodology?

HEMS Benchmarking for Germany

Gefördert durch:
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- Validation strategy for laboratory and demonstrator

CoSES Laboratory, TUM

ÜZW Grid section

EMS benchmarking suite

1. Rule based
2. MPC
3. Reinforcement Learning
4. Physics based (combination of above)

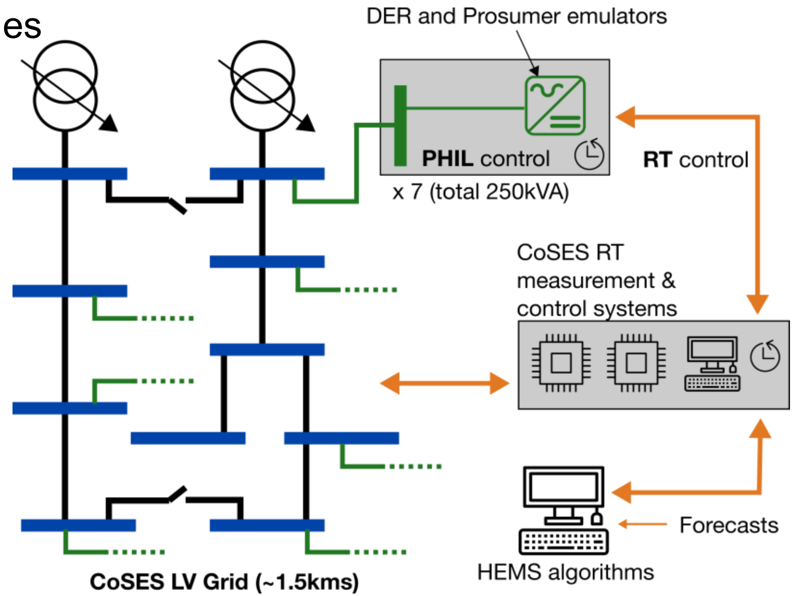
PhyLFlex HEMS Benchmarking Suite

The research benchmark – What ***could*** be possible?

Gefördert durch:
Bundesministerium für Wirtschaft und Energie
aufgrund eines Beschlusses des Deutschen Bundestages

- Reference demand, generation profiles
- Reference objective functions
- Complete emulation

- To test:
  - Different algorithms
  - Forecasts
  - Control windows



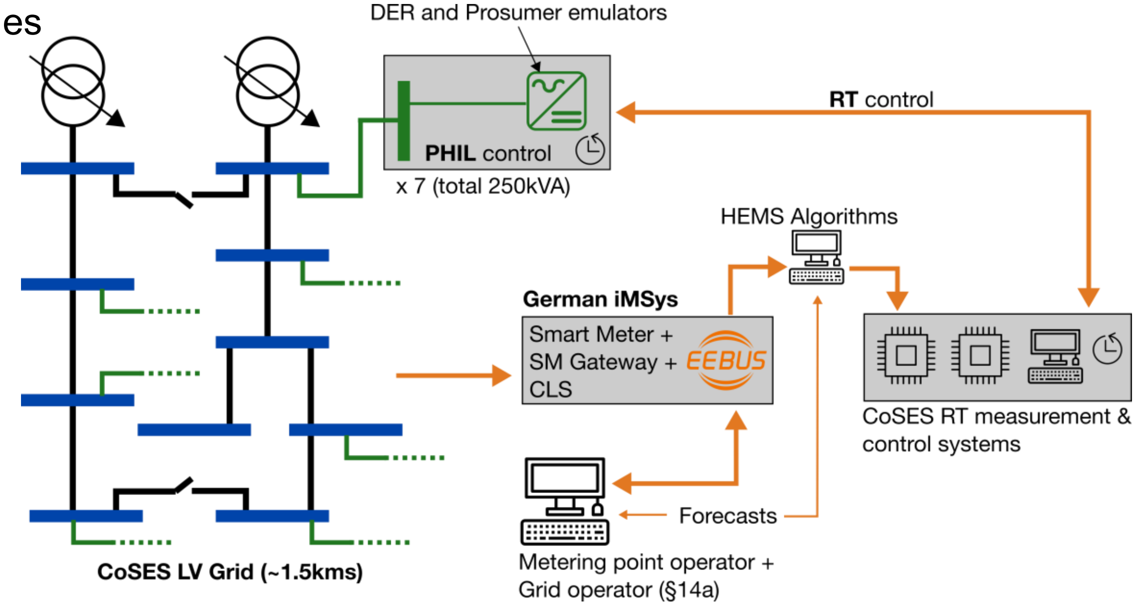
PhyLFlex HEMS Benchmarking Suite

The iMSys benchmark – What ***should*** be possible?

Gefördert durch: Bundesministerium für Wirtschaft und Energie aufgrund eines Beschlusses des Deutschen Bundestages

- Reference demand, generation profiles
- Reference objective functions
- iMsys-in-the-loop
- DERs and prosumers emulated

- To test:
  - §14a signal efficacy
  - Max. utility from iMsys + FNN
  - Grid friendly EMS



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PhyLFlex HEMS Benchmarking Suite

The real-world benchmark – What ***is currently*** possible?

PhyLFlex

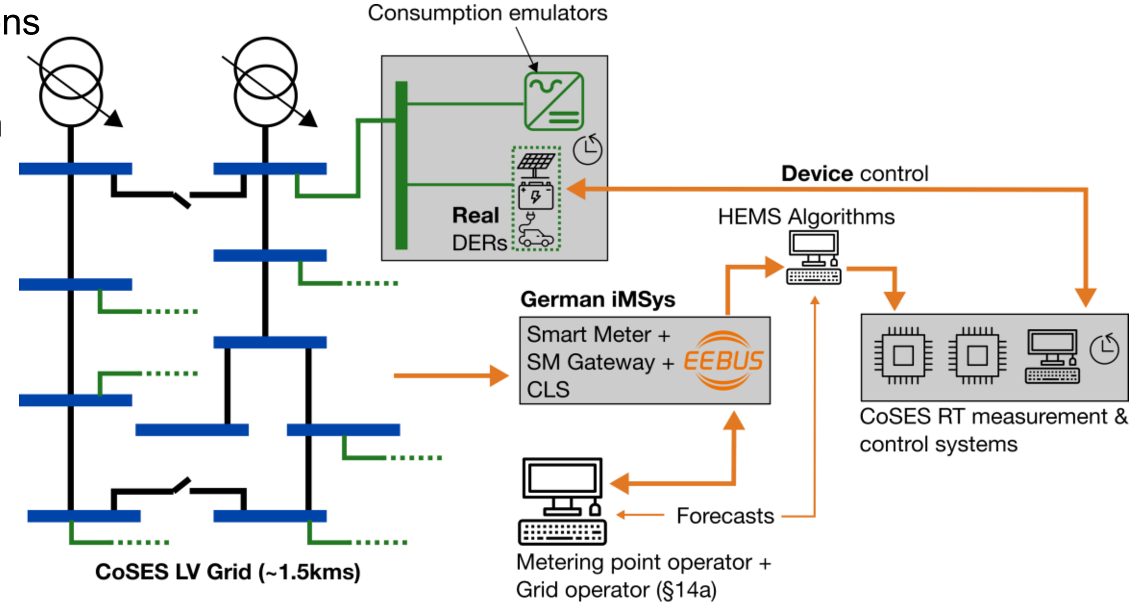
Gefördert durch: Bundesministerium für Wirtschaft und Energie aufgrund eines Beschlusses des Deutschen Bundestages

- Reference demand, objective functions
- iMsys-in-the-loop
- Real DERs + Emulated consumption

- To test:
  - Device interoperability
  - HEMS → DER protocols
  - Claims vs Reality
- Further demonstrations at

HOCHSCHULE ANSBACH — **10+ DER manufacturers**

ÜZW NETZ — **10 houses in ÜZW grid**



Conclusion

- Forget the grid model, embrace the data – will work everywhere.
- There is no *Magic Bullet* method for data driven grid control – horses for courses.
- Real grid testing for data driven methods are still rare – we are trying to beat that in CoSES.
- Smart meter data in Germany is scant and never live – methods must adapt to that.
- Benchmarking is necessary for acceptance – but there isn't one metric to rule them all.
- This stuff is fun – get into it if you can ☺

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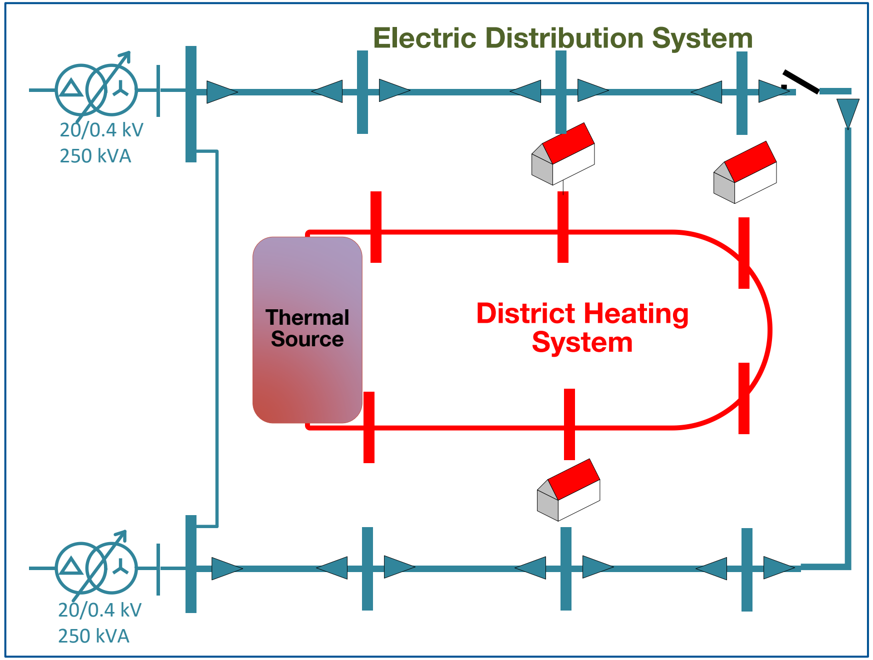
Appendix – Electrical Equipment

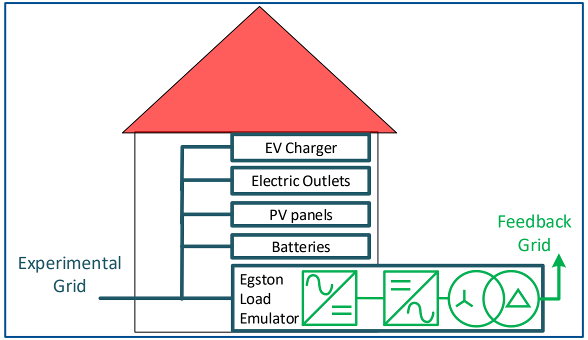
Transformers	2 x MV/LV OLTC, 250 KVA; 1 x MV/LV 630KVA for feedback loop
LV Grid	12 x Power cables, 10 Lv Busbars, 2 x LV circuit breaker (to change the network topology)
Prosumers	Egston Compiso, 7 x bidirectional 4 leg inverters, SFP interface for control, 250KVA (total), 100KVA (single cabinet)
DERs	18KWp PV divided into 3 inverters, 2 x 13KWh battery storage, 2 x 22KW car chargers.

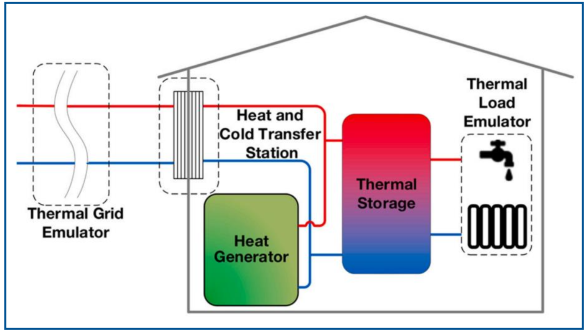
Appendix – Thermal Equipment

	Haus 1	Haus 2	Haus 3	Haus 4	Haus 5
Thermal generators	CHP (2 kW_{el}, 5,2 kW_{th}) Boiler (20 kW_{th}) Solar thermal (9 kW_{th})	Boiler (20 kW_{th}) Heat pump (19 kW_{heat}, 9 kW_{cold}) Solar thermal (9 kW_{th})	Ground source heat pump (19 kW_{heat}) Solar thermal (9 kW_{th})	Stirling Engine (1 kW_{el}, 6 kW_{th}) Boiler (20 kW_{th})	CHP (5 kW_{el}, 11,9 kW_{th}) CHP (18 kW_{el}, 34 kW_{th}) Boiler (50 kW_{th})
Thermal storage	800 l	785 l	1000 l	1000 l	2000 l
Domestic hot water	Fresh water storage (500 l)	Fresh water storage	Fresh water storage	Internal heat exchanger	Fresh water storage
Transfer stations	Bidirectional transfer station (30 kW_{th}) Booster heat pump (19 kW_{heat}, 14 kW_{cold})	Bidirectional transfer station (30 kW_{th})	Bidirectional transfer station (30 kW_{th})	Bidirectional transfer station (30 kW_{th})	Bidirectional transfer station (60 kW_{th})
Thermal loads	30 kW_{heat}, 9 kW_{cold}	30 kW_{heat}, 9 kW_{cold}	30 kW_{heat}, 9 kW_{cold}	30 kW_{heat}	60 kW_{heat}

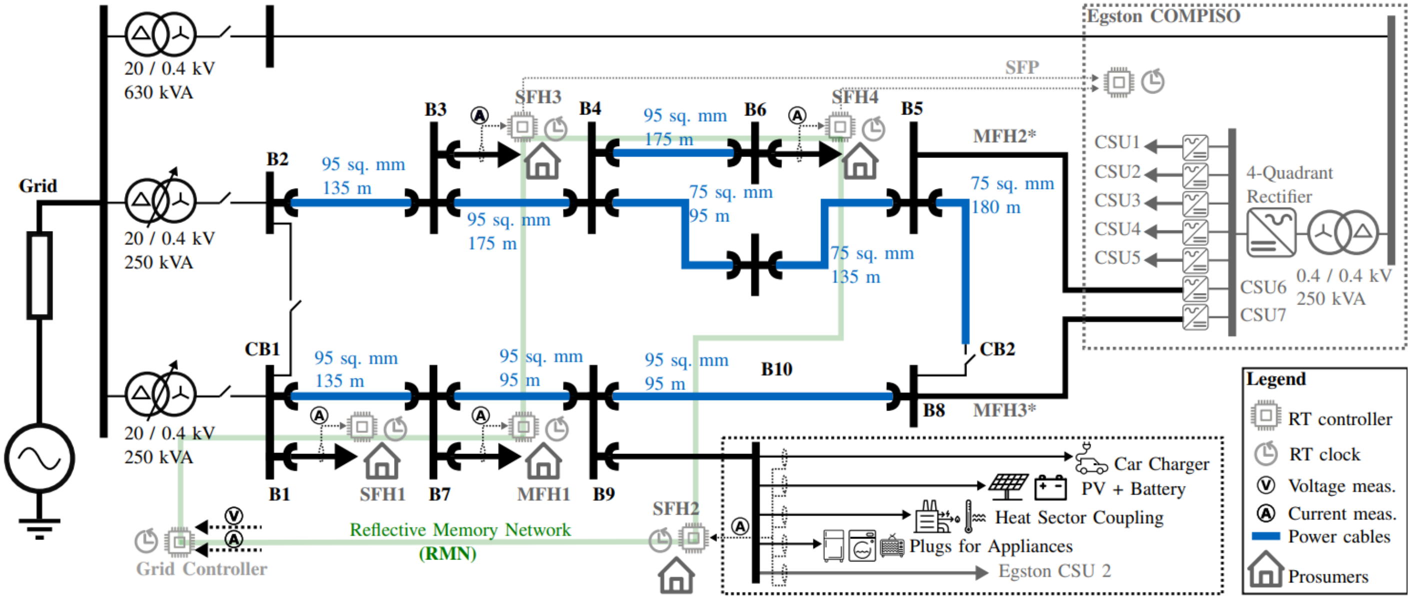
CoSES Lab - Overview

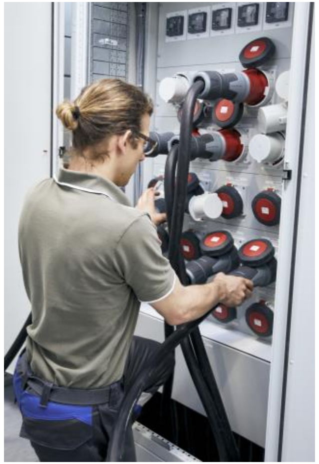




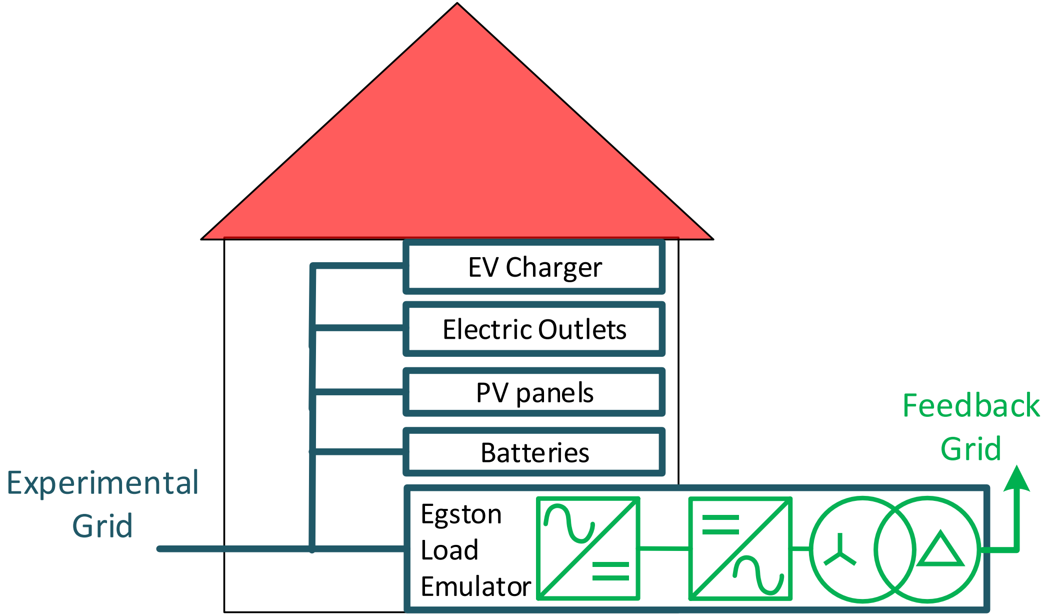


Electric Grid

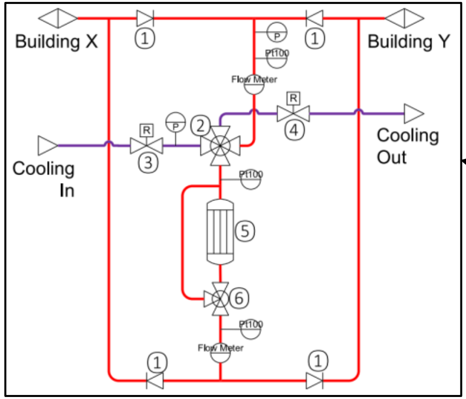




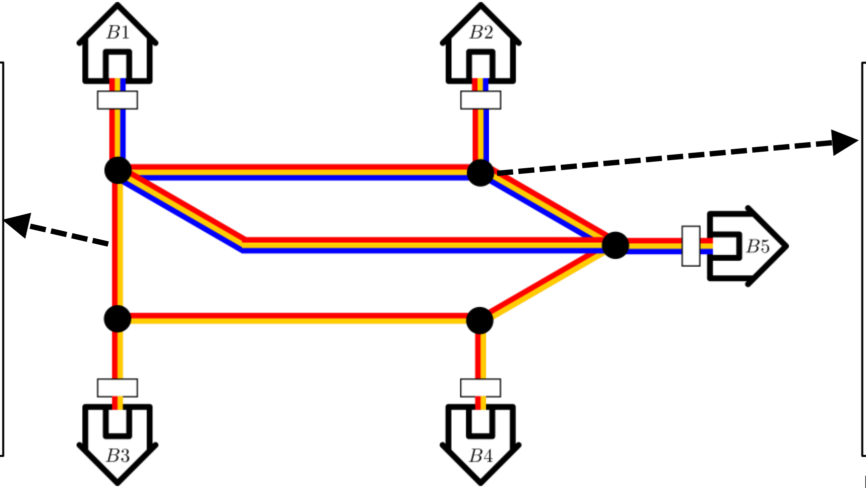
Electric Building Emulator



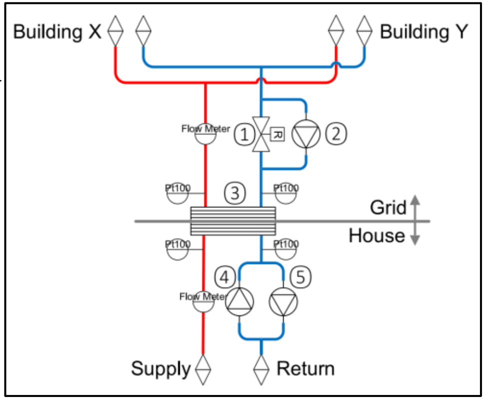
Thermal Grid



thermal network emulator /
pipe emulator

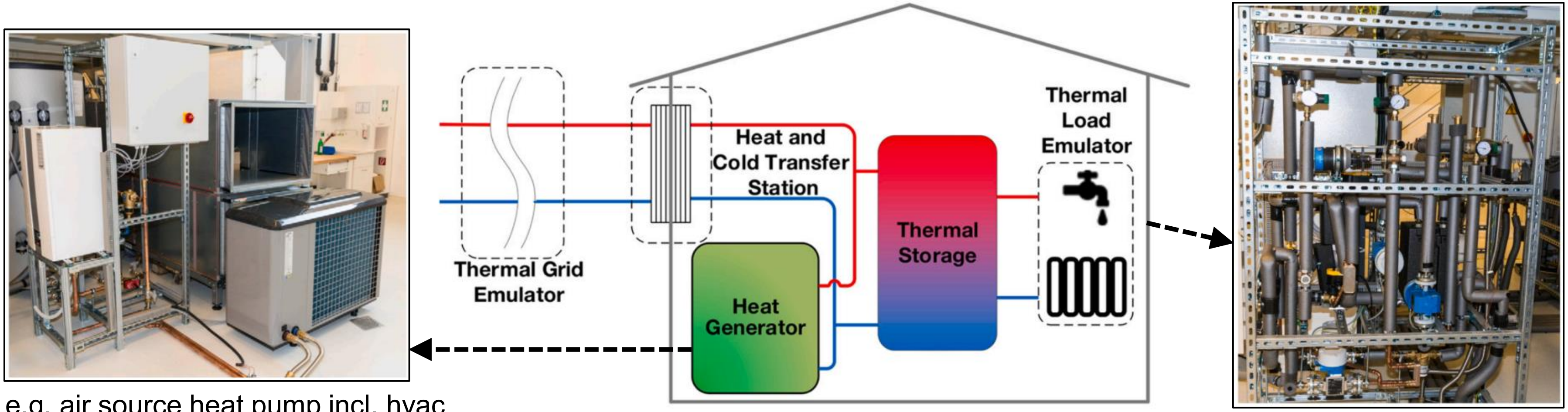


bidirectional thermal network with prosumers



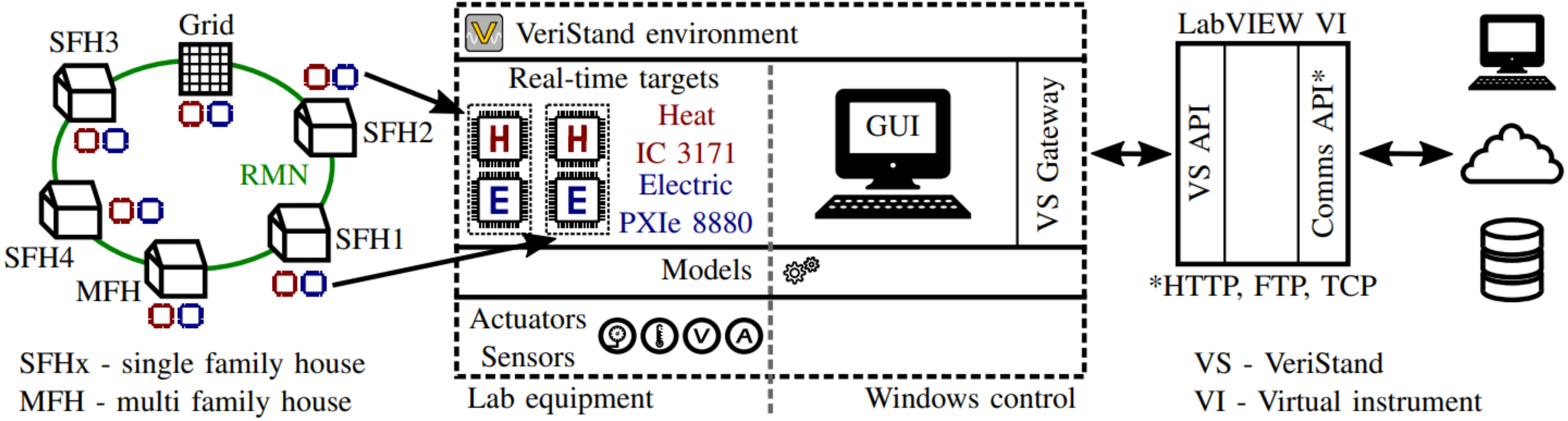
bidirectional heat transfer station

Thermal Building Emulator



e.g. air source heat pump incl. hvac system for ambient emulation

Computation and Communication



SFHx - single family house
MFH - multi family house

VS - VeriStand
VI - Virtual instrument

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