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EP4.0

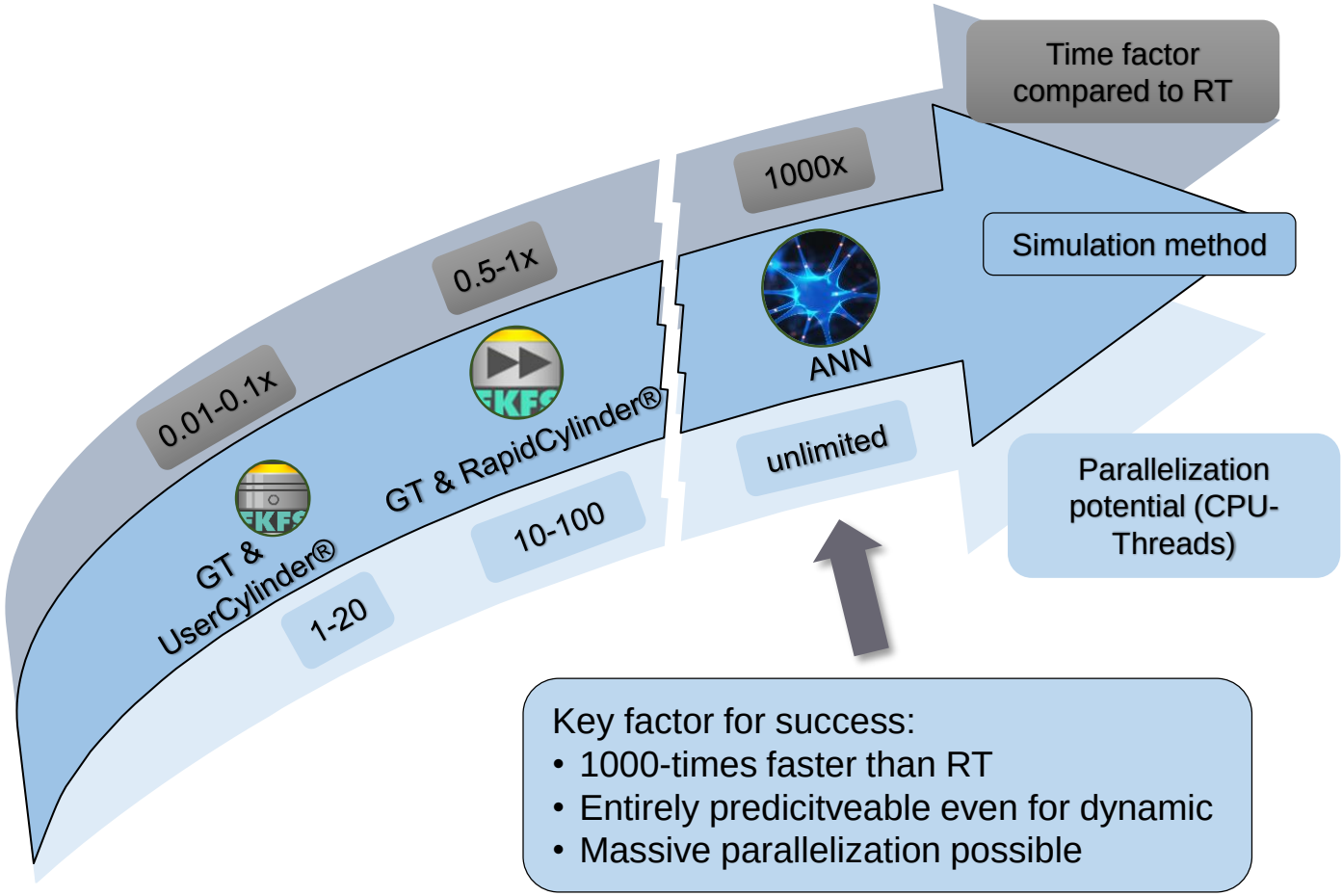
Long Short-Term Memory Networks for the Prediction of Fuel Cell Voltage and Efficiency

ITISE Meloneras

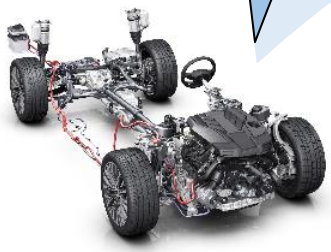
06/29/2022

Martin Angerbauer (FKFS)

Motivation: Ultra-Fast-Running Models



Key factor for success:
- 1000-times faster than RT
- Entirely predicitveable even for dynamic
- Massive parallelization possible



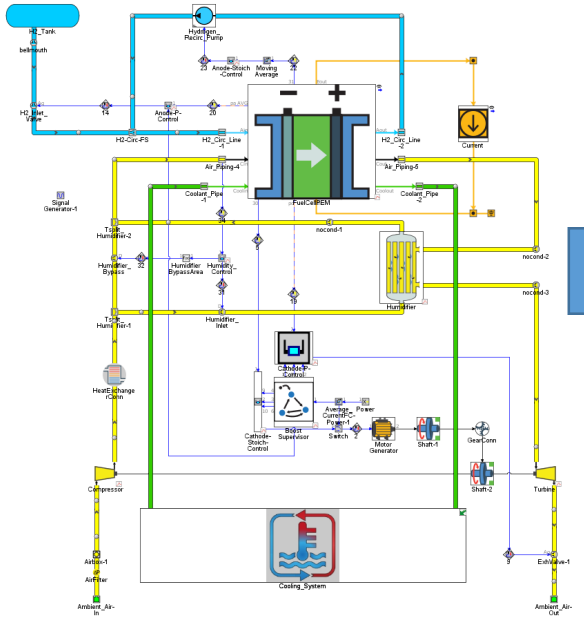
Possible applications for AI-based powertrain models

- Virtual pre-application
- Functional development & validation SiL
- Model-based controllers
- Reinforcement Learning: optimization of operating strategy
- Test of control units SiL & HiL
- Application on control units during operation
- Dimensioning of components
- Plausibilisation of measurement data

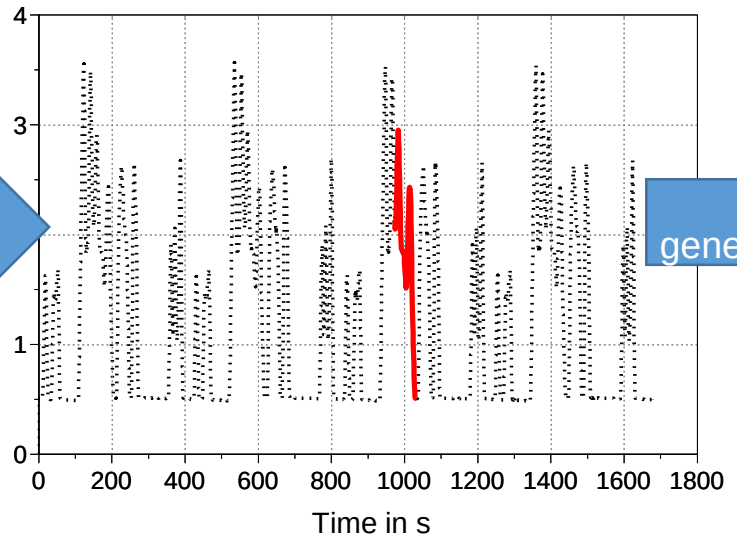
SiL: Software in the Loop
HiL: Hardware in the Loop

Our approach: AI-based models

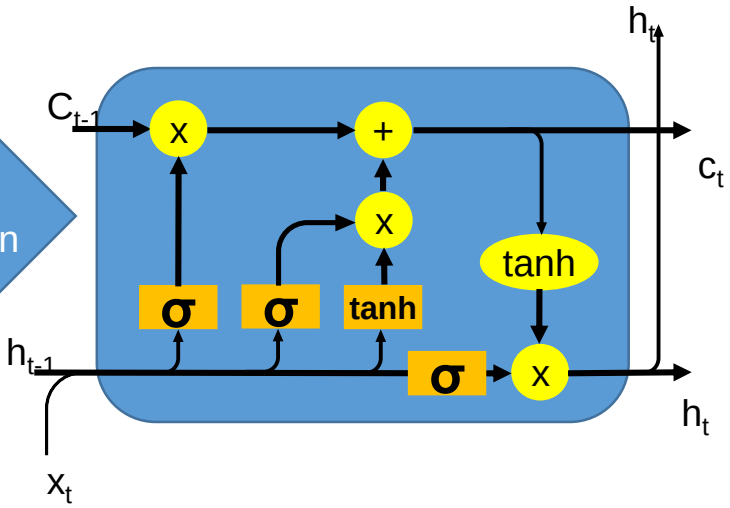
Application example: Fuel cell system



Data creation



Data generalization

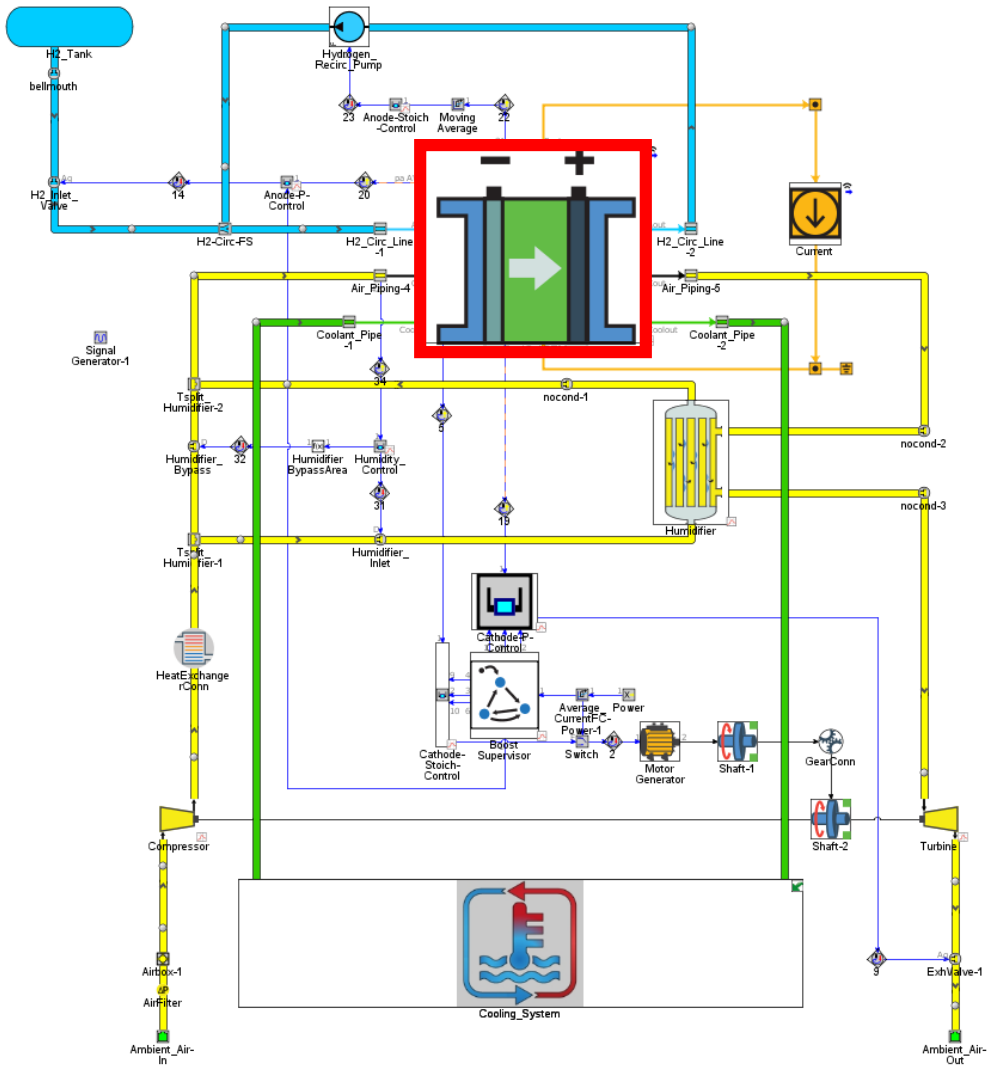


Detailed, but slow simulation model
- Calibrated by means of testbench data
- Wide spread of data
- Dynamic scenarios

Sequencing of simulation results
- Dynamic effects
- Length of sequences is part of investigation

LSTM network
- Short calculation duration
- Highly parallelisation
- No licensing

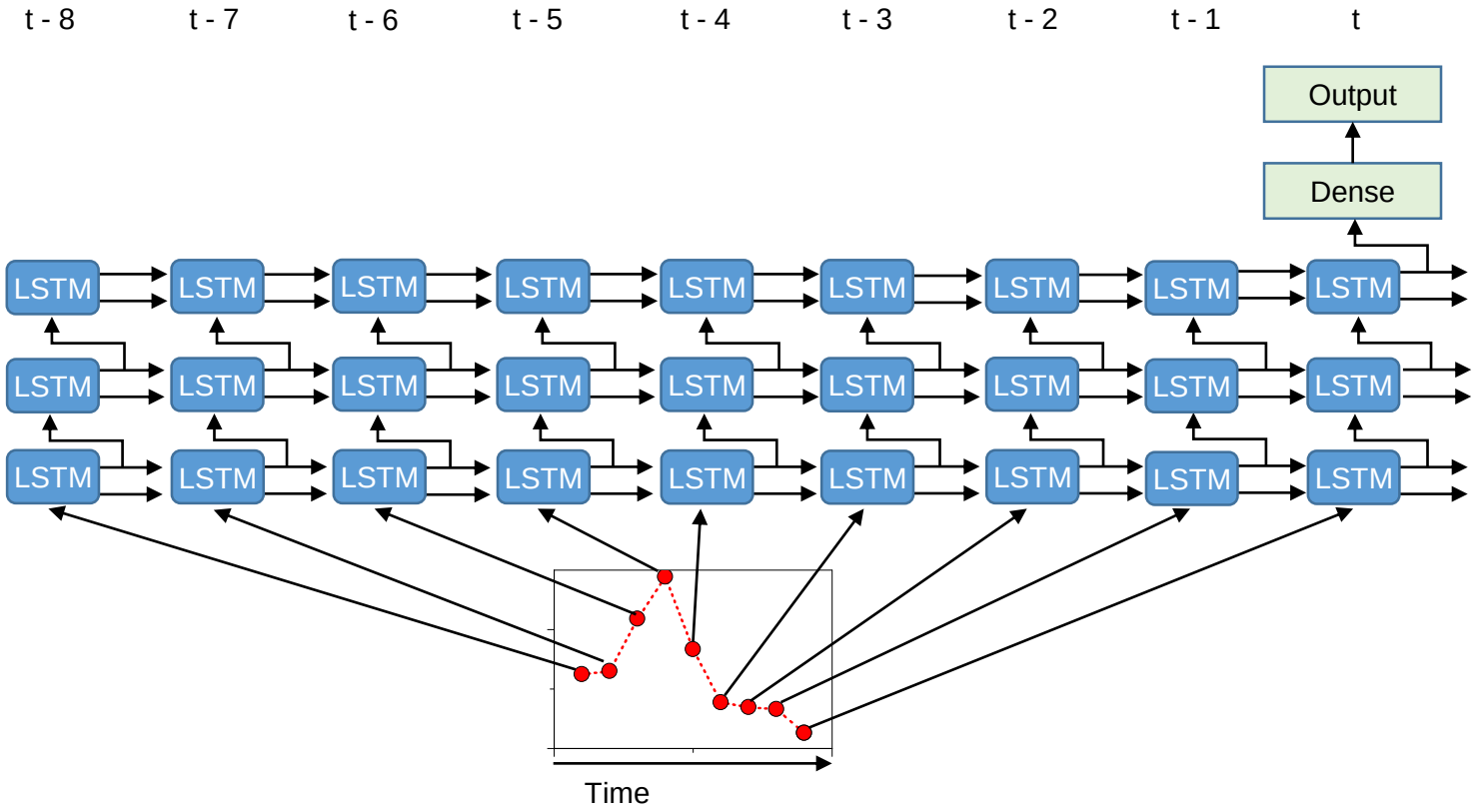
Application case: Modelling of the fuel cell



0d/1d simulation model of a fuel cell system

- Focus on the fuel cell stack
- Input values:
  - Stack temperature [K]
  - Current density [A/mm^2]
  - Anode pressure [bar]
  - Cathode pressure [bar]
  - Cathode stoichiometry [-]
  - Membrane humidity [%]
- Target values
  - Voltage [V]
  - Efficiency [%]

LSTM-Model Setup



Exemplaric unfolded LSTM structure with 3 layers for one input parameter

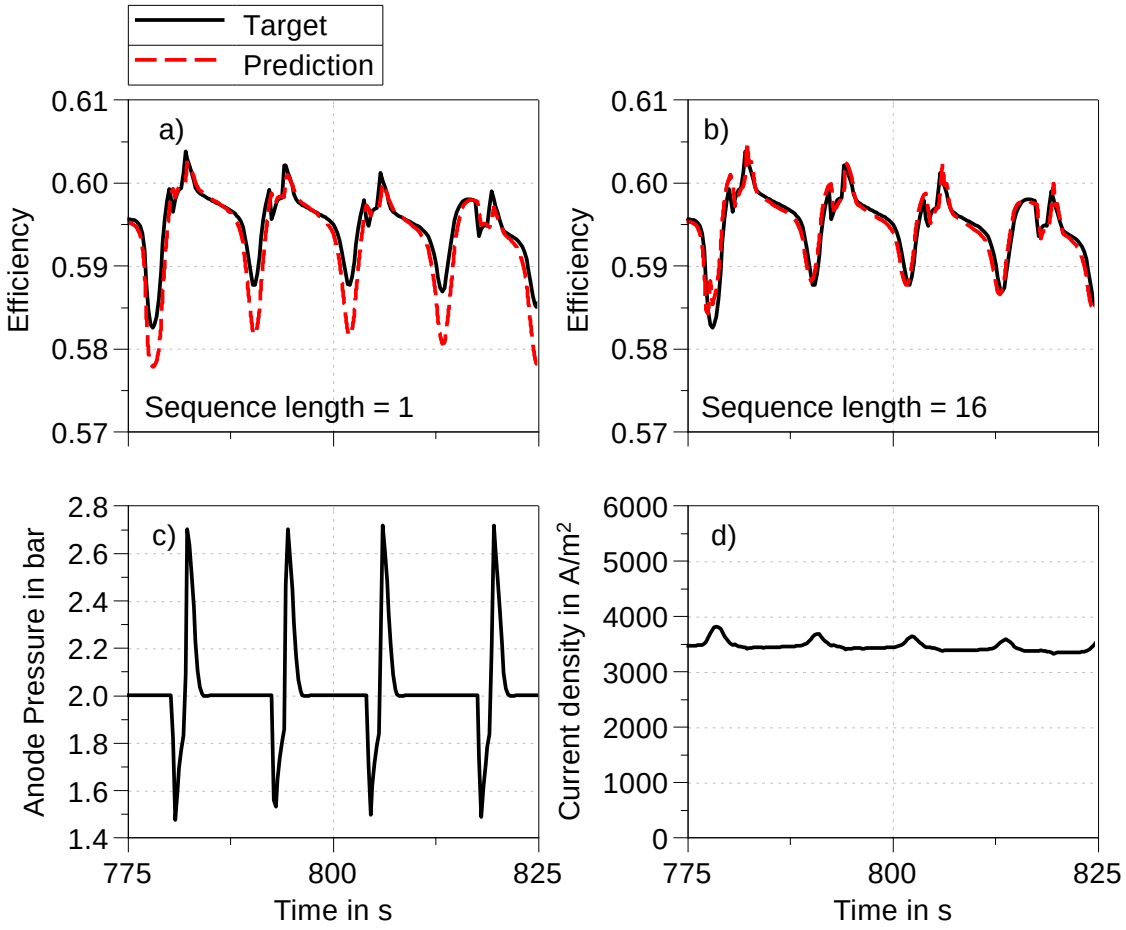
LSTM-Model setup

- 3 respectively 2 LSTM cells
- 50 - 100 cells per layer
- Prediction of one output value (voltage/efficiency) at the current time step t based on the last sequence
- Fully connected dense layer at the output
- 4 input points/second
- Stateful/Stateless initialisation of the hidden states

Results (Efficiency)

- Purge valve opening causes large instabilities at the anode side, while other values stay almost constant
- Significant increase of accuracy with longer input sequences

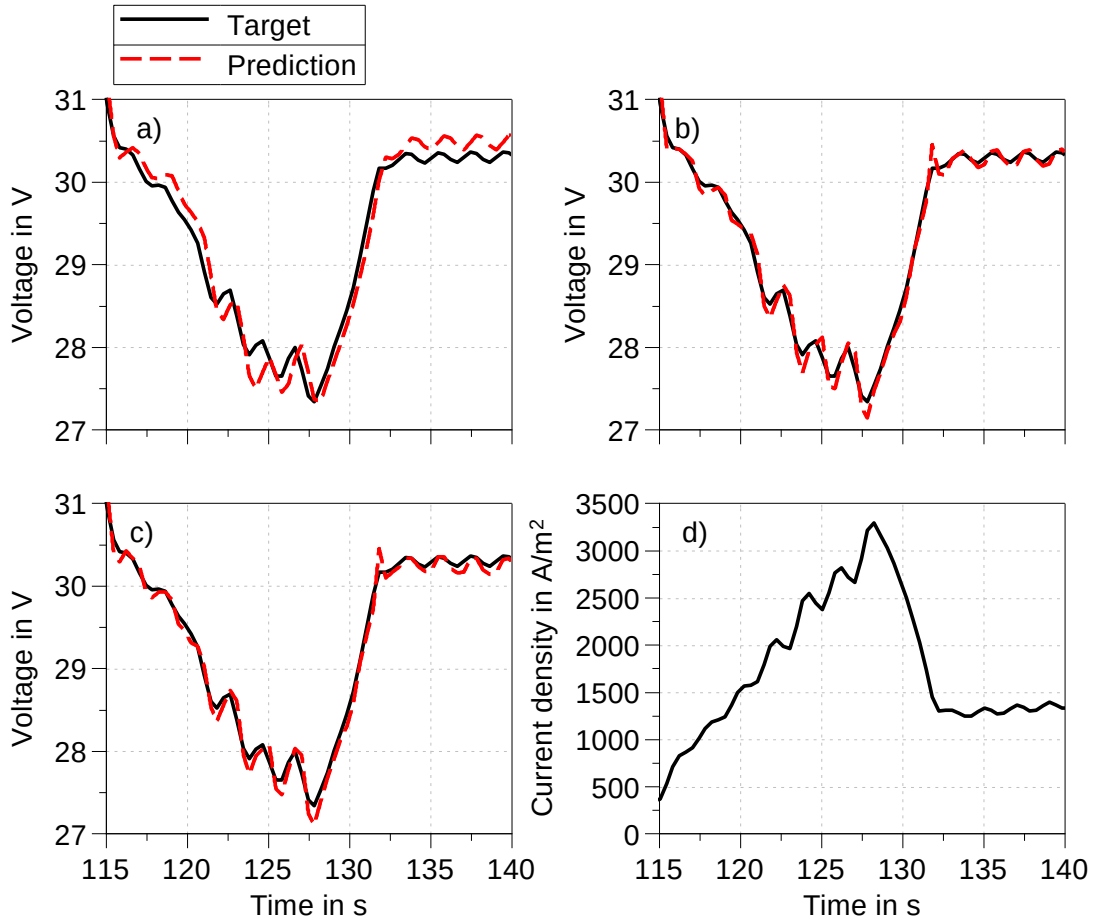
Plot	Layers	Neurons	Sequence length	RSME (absolute)	99 % percentile
a)	2	50	1	0.00518	0.040
b)	2	50	16	0.00227	0.0235



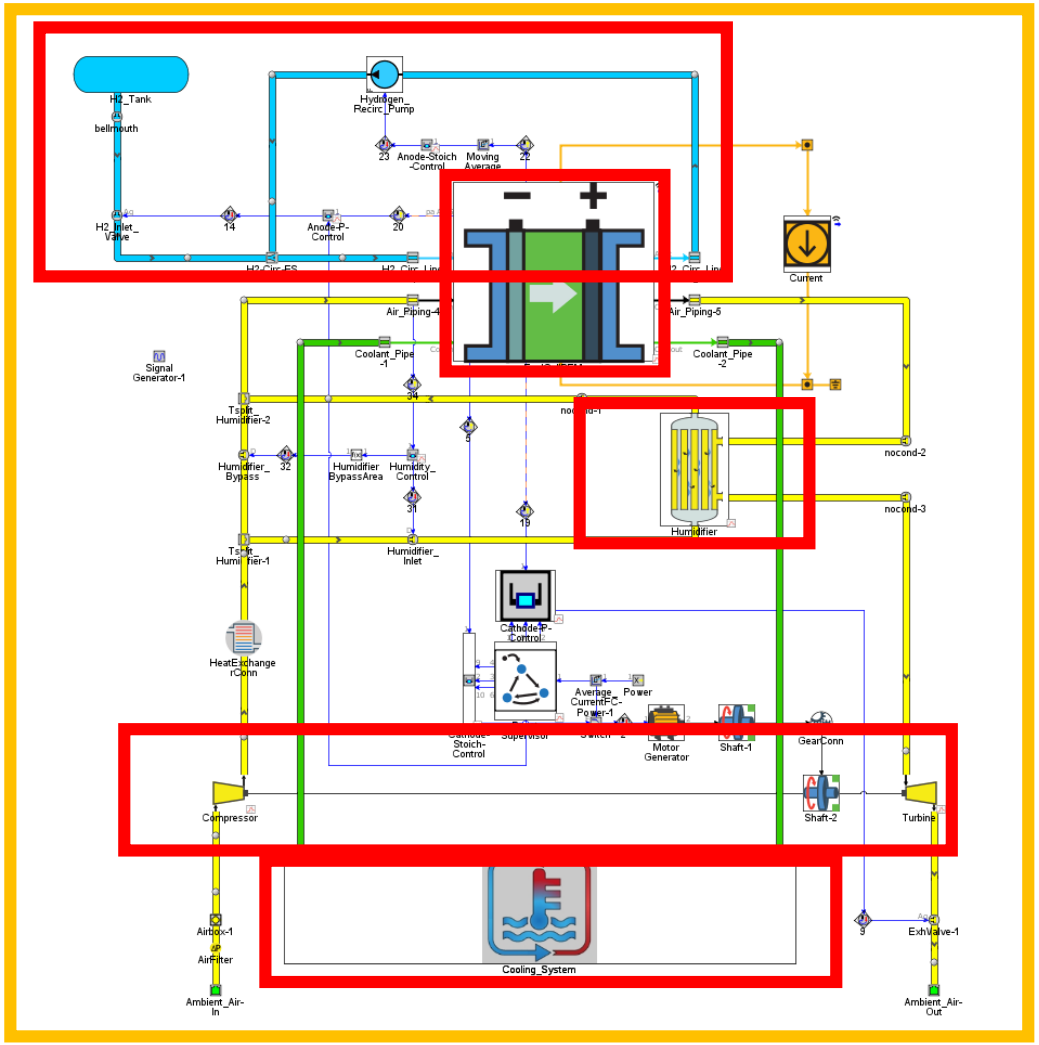
Results (Voltage)

- Section of the WLTC testcycle
- Stateful initialization is not beneficial
- Highest accuracy with a sequence length of 16 points

Plot	Stateful	Layers	Neurons	Sequence length	RSME (absolute)	99 % percentile
a)	No	3	50	1	0.161	0.537
b)	No	3	50	16	0.0616	0.289
c)	yes	2	50	8	0.0398	0.212



Outlook



- Combine various LSTM models to simulate the entire FC system
  - Abiliy to predict more values
- Also possible: One model for the entire system
- Optimization tasks:
  - Reinforcement learning
  - Model predictive control

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Thank you for your attention.

SEGULA Technologies GmbH
Dipl.-Ing. Frank Braunroth
Rugbyring 12
65428 Rüsselsheim am Main

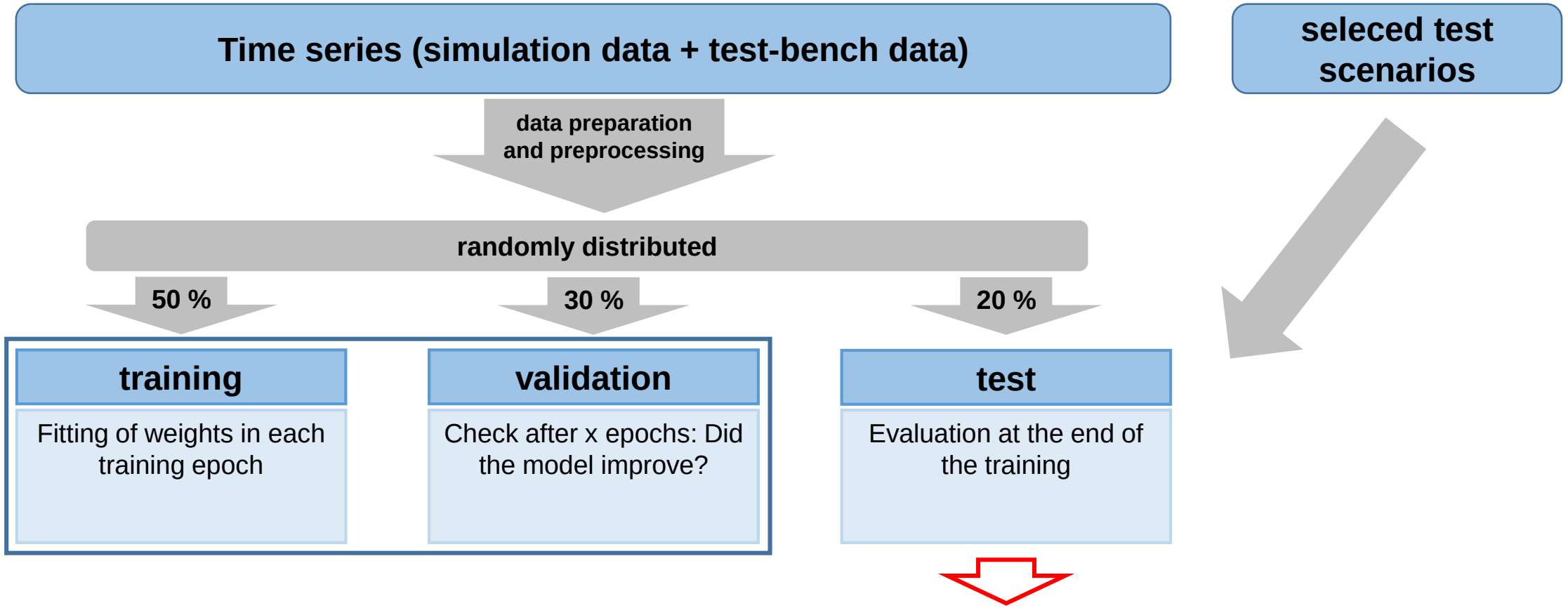
:em engineering methods AG
Dr. Marcus Krastel
Rheinstr. 97
64295 Darmstadt

Eigner Engineering Consult
Prof. Dr.-Ing. Martin Eigner
Höllhäuserweg 38a
76534 Baden-Baden

Forschungsinstitut für Kraftfahrwesen
u. Fahrzeugmotoren
Dr.-Ing. Martin Angerbauer
Pfaffenwaldring 12
70569 Stuttgart

Fraunhofer-Institut für Experimentelles
Software Engineering IESE
M. Sc. Oliver Bleisinger
Fraunhofer-Platz 1
67663 Kaiserslautern

Evaluation process: Model validation and model selection



Does the model satisfy the requirements regarding?

- Root squared mean error (RSME) of all test data → direct quantitative comparison
- Points of largest discrepancies are documented
- Special test scenarios (e.g. purge valve opening)
- Computaion speed