Hochschule
München
University of
Applied Sciences

Faculty of Electrical
Engineering and Information
Technology (FK04)

Institute for Sustainable
Energy Systems (ISES)

Artificial neural network (ANN) based optimal feedforward torque control (OFTC) of electrically excited synchronous machines (EESM)

Niklas Monzen, M.Sc. and Prof. Dr.-Ing. habil. Christoph M. Hackl

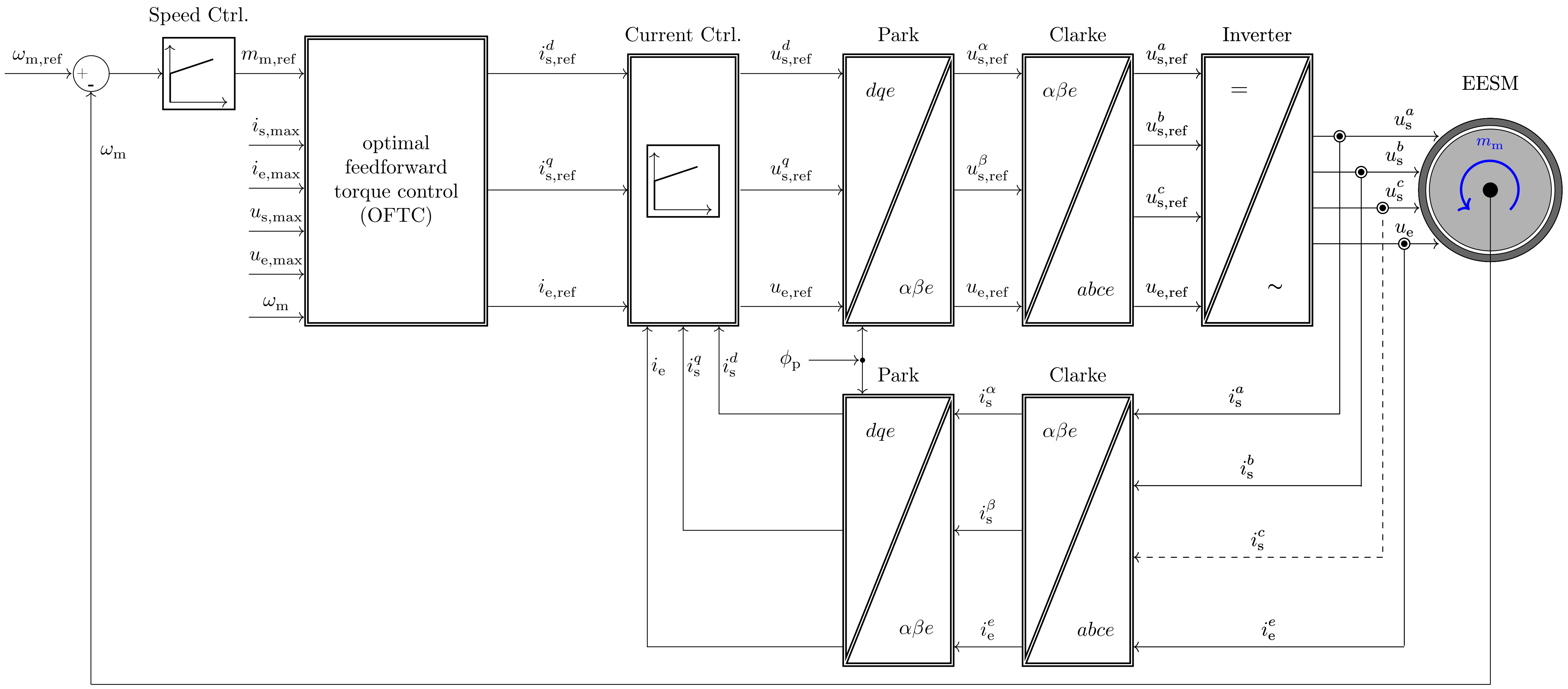
IEEE 32nd International Symposium on Industrial Electronics (ISIE)
Aalto University, Helsinki-Espoo, Finland
June 19th – June 21st, 2023

Niklas Monzen, 2023/06/19

HM ISES

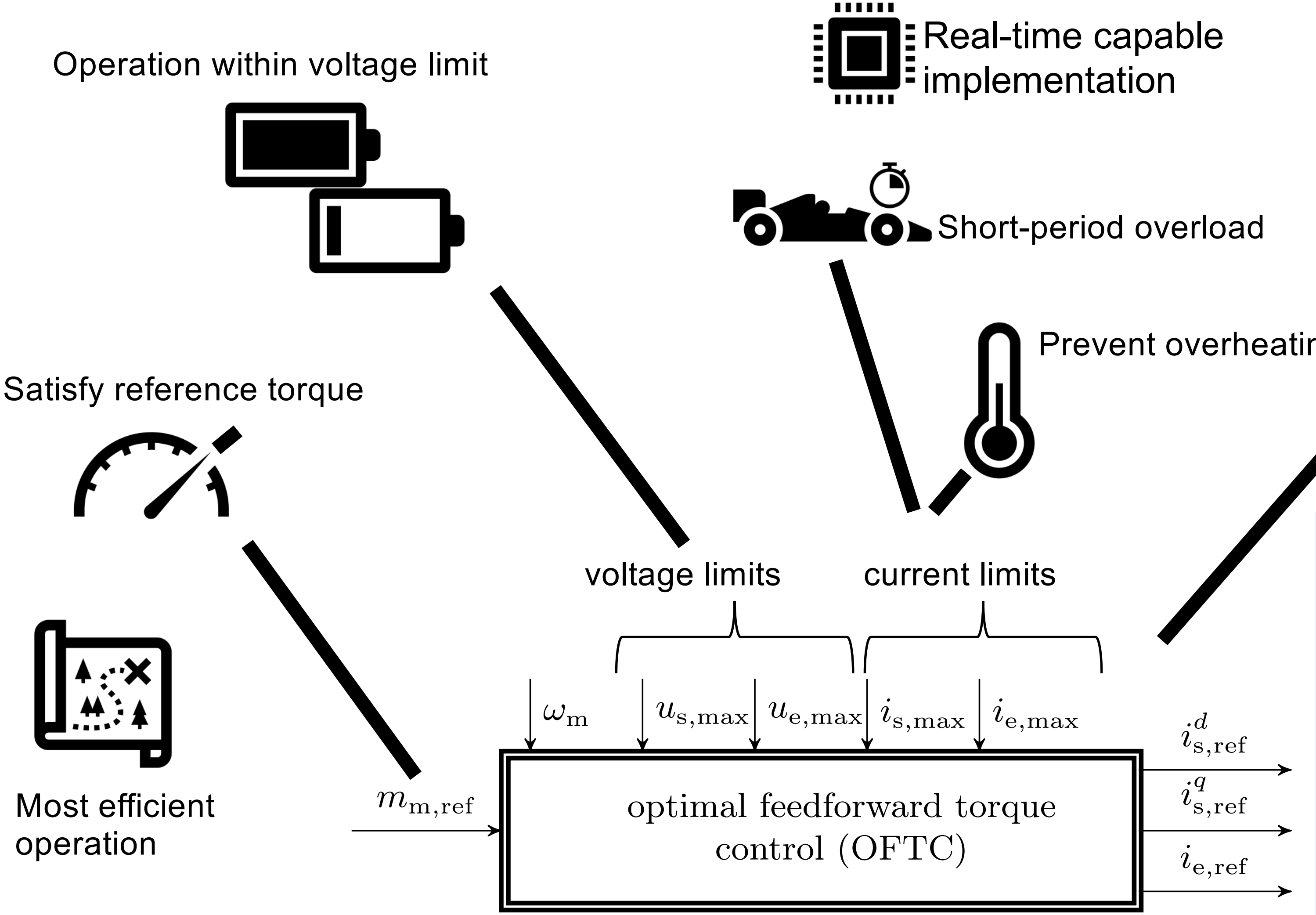
Where is OFTC used?

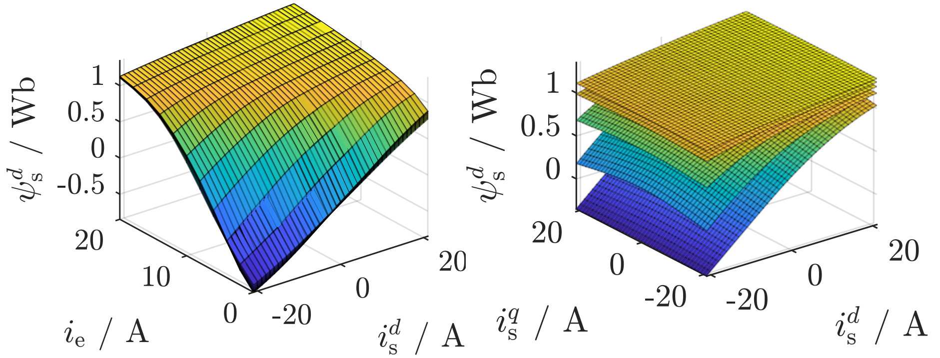
Motivation
Control of an electrically-excited synchronous machine (EESM) with optimal feedforward torque control (OFTC)



What are the main goals of OFTC?

Motivation
Problem formulation & proposed solution





Nonlinear flux linkages, iron and copper losses

⇒ computationally intensive nonlinear optimization problem (NLP)

Proposed Solution:

ANN-based OFTC for EESM

1. Dataset creation
2. Training of suitable ANN-topologies
3. Validation and choice of an optimal ANN

ANN-based OFTC of EESM

Dataset creation

For the k-th input sample

$$\boldsymbol{x}[k] \coloneqq \left(m_{\mathrm{m,ref}}[k], \omega_{\mathrm{m}}[k], u_{\mathrm{s,max}}[k], i_{\mathrm{s,max}}[k], u_{\mathrm{e,max}}[k], i_{\mathrm{e,max}}[k]\right)^{\mathrm{T}}$$

the corresponding output vector

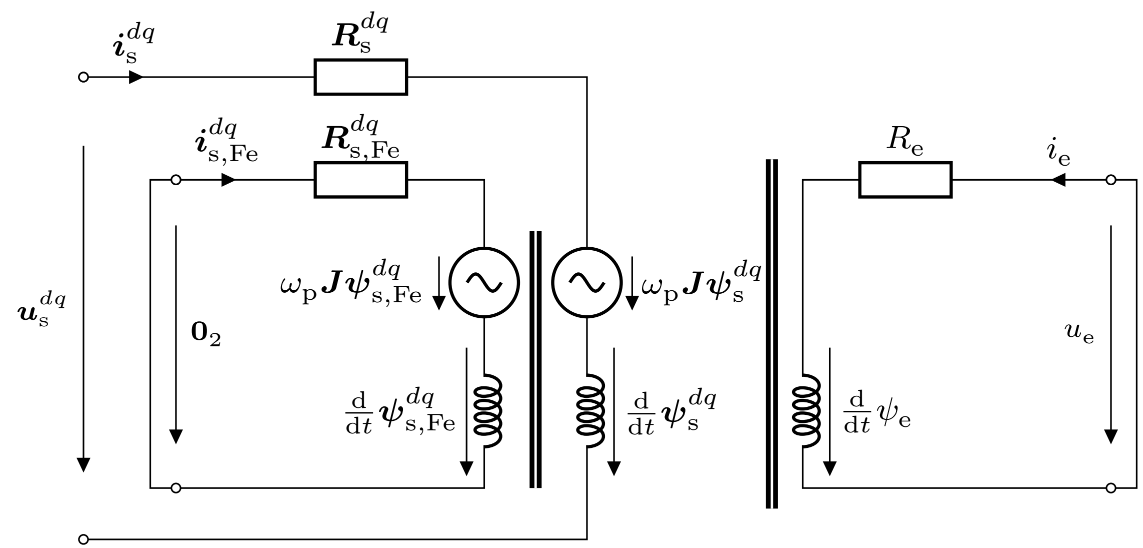
$$\boldsymbol{y}[k] \coloneqq \left(i^{d}_{\mathrm{s,ref}}[k], i^{q}_{\mathrm{s,ref}}[k], i_{\mathrm{e,ref}}[k]\right)^{\mathrm{T}}$$

is the solution of the nonlinear optimization problems (NLP)

$$\begin{aligned}
\boldsymbol{i}^{dqe}_{\mathrm{s,e,ref}}[k] = \underset{\boldsymbol{i}^{dqe}_{\mathrm{s,e}}[k]}{\arg\min}\ & p_{\mathrm{L}}\left(\boldsymbol{i}^{dqe}_{\mathrm{s,e}}[k]\right)\\
\text{s.t.}\ \left\|\boldsymbol{u}^{dq}_{s}\left(\boldsymbol{i}^{dqe}_{\mathrm{s,e}}[k]\right)\right\| &\le u_{\mathrm{s,max}}[k],\\
\left\|\boldsymbol{i}^{dq}_{s}\left(\boldsymbol{i}^{dqe}_{\mathrm{s,e}}[k]\right)\right\| &\le i_{\mathrm{s,max}}[k],\\
\left|u_{\mathrm{e}}\left(\boldsymbol{i}^{dqe}_{\mathrm{s,e}}[k]\right)\right| &\le u_{\mathrm{e,max}}[k],\\
\left|i_{\mathrm{e}}[k]\right| &\le i_{\mathrm{e,max}}[k],\\
m_{\mathrm{m}}\left(\boldsymbol{i}^{dqe}_{\mathrm{s,e}}[k]\right) &= \underset{m_{\mathrm{m,max}}}{\mathrm{sat}}\ m_{\mathrm{m,ref}}[k]
\end{aligned}$$

$$\begin{aligned}
m_{\mathrm{m,max}}[k] = \max_{\boldsymbol{i}^{dqe}_{\mathrm{s,e}}[k]}\ & m_{\mathrm{m}}\left(\boldsymbol{i}^{dqe}_{\mathrm{s,e}}[k]\right)\\
\text{s.t.}\ \left\|\boldsymbol{u}^{dq}_{s}\left(\boldsymbol{i}^{dqe}_{\mathrm{s,e}}[k]\right)\right\| &\le u_{\mathrm{s,max}}[k],\\
\left\|\boldsymbol{i}^{dq}_{s}\left(\boldsymbol{i}^{dqe}_{\mathrm{s,e}}[k]\right)\right\| &\le i_{\mathrm{s,max}}[k],\\
\left|u_{\mathrm{e}}\left(\boldsymbol{i}^{dqe}_{\mathrm{s,e}}[k]\right)\right| &\le u_{\mathrm{e,max}}[k],\\
\left|i_{\mathrm{e}}[k]\right| &\le i_{\mathrm{e,max}}[k].
\end{aligned}$$

→NLP can not be solved online in real-time!
→But offline to create a dataset with $k \in \{1, \dots, K\}$ samples.



$$\boldsymbol{u}^{dq}_{s} = \boldsymbol{R}^{dq}_{\mathrm{s}}\boldsymbol{i}^{dq}_{\mathrm{s}} + \boldsymbol{\omega}_{\mathrm{p}}\boldsymbol{J}\boldsymbol{\psi}^{dq}_{\mathrm{s}} + \frac{\mathrm{d}}{\mathrm{d}t}\boldsymbol{\psi}^{dq}_{\mathrm{s}}$$

$$u_{\mathrm{e}} = R_{\mathrm{e}}i_{\mathrm{e}} + \frac{\mathrm{d}}{\mathrm{d}t}\psi_{\mathrm{e}}$$

$$\boldsymbol{0}_2 = \boldsymbol{R}^{dq}_{\mathrm{s,Fe}}\boldsymbol{i}^{dq}_{\mathrm{s,Fe}} + \boldsymbol{\omega}_{\mathrm{p}}\boldsymbol{J}\boldsymbol{\psi}^{dq}_{\mathrm{s}} + \frac{\mathrm{d}}{\mathrm{d}t}\boldsymbol{\psi}^{dq}_{\mathrm{s}}$$

$$p_{\mathrm{L}} = \underbrace{\frac{2}{3\kappa^2}\left(\boldsymbol{i}^{dq}_{\mathrm{s}}\right)^{\mathrm{T}}\boldsymbol{R}^{dq}_{\mathrm{s}}\boldsymbol{i}^{dq}_{\mathrm{s}} + R_{\mathrm{e}}i^2_{\mathrm{e}}}_{\text{copper losses}} + \underbrace{\frac{2}{3\kappa^2}\left(\boldsymbol{i}^{dq}_{\mathrm{s,Fe}}\right)^{\mathrm{T}}\boldsymbol{R}^{dq}_{\mathrm{s,Fe}}\boldsymbol{i}^{dq}_{\mathrm{s,Fe}}}_{\text{iron losses}}$$

$$m_{\mathrm{m}} = \frac{2n_{\mathrm{p}}}{3\kappa^2}\left(\boldsymbol{i}^{dq}_{\mathrm{s}} + \boldsymbol{i}^{dq}_{\mathrm{s,Fe}}\right)^{\mathrm{T}}\boldsymbol{J}\boldsymbol{\psi}^{dq}_{\mathrm{s}}$$

Neuron's output (i-th neuron of the j-th layer):

$$\hat{y}_{j,i} = \Phi_{j,i}\left(\boldsymbol{w}_{j,i}^{\mathsf{T}} \boldsymbol{x}_j + b_{j,i}\right) \in \mathbb{R}$$

Layer's output (j-th layer):

$$\hat{\boldsymbol{y}}_j = \begin{pmatrix} \hat{y}_{j,1} \\ \vdots \\ \hat{y}_{j,n_j} \end{pmatrix} = \begin{pmatrix} \Phi_{j,1}\left(\boldsymbol{w}_{j,1}^{\mathsf{T}} \boldsymbol{x}_j + b_{j,1}\right) \\ \vdots \\ \Phi_{j,n_j}\left(\boldsymbol{w}_{j,n_j}^{\mathsf{T}} \boldsymbol{x}_j + b_{j,n_j}\right) \end{pmatrix} \in \mathbb{R}^{n_j}$$

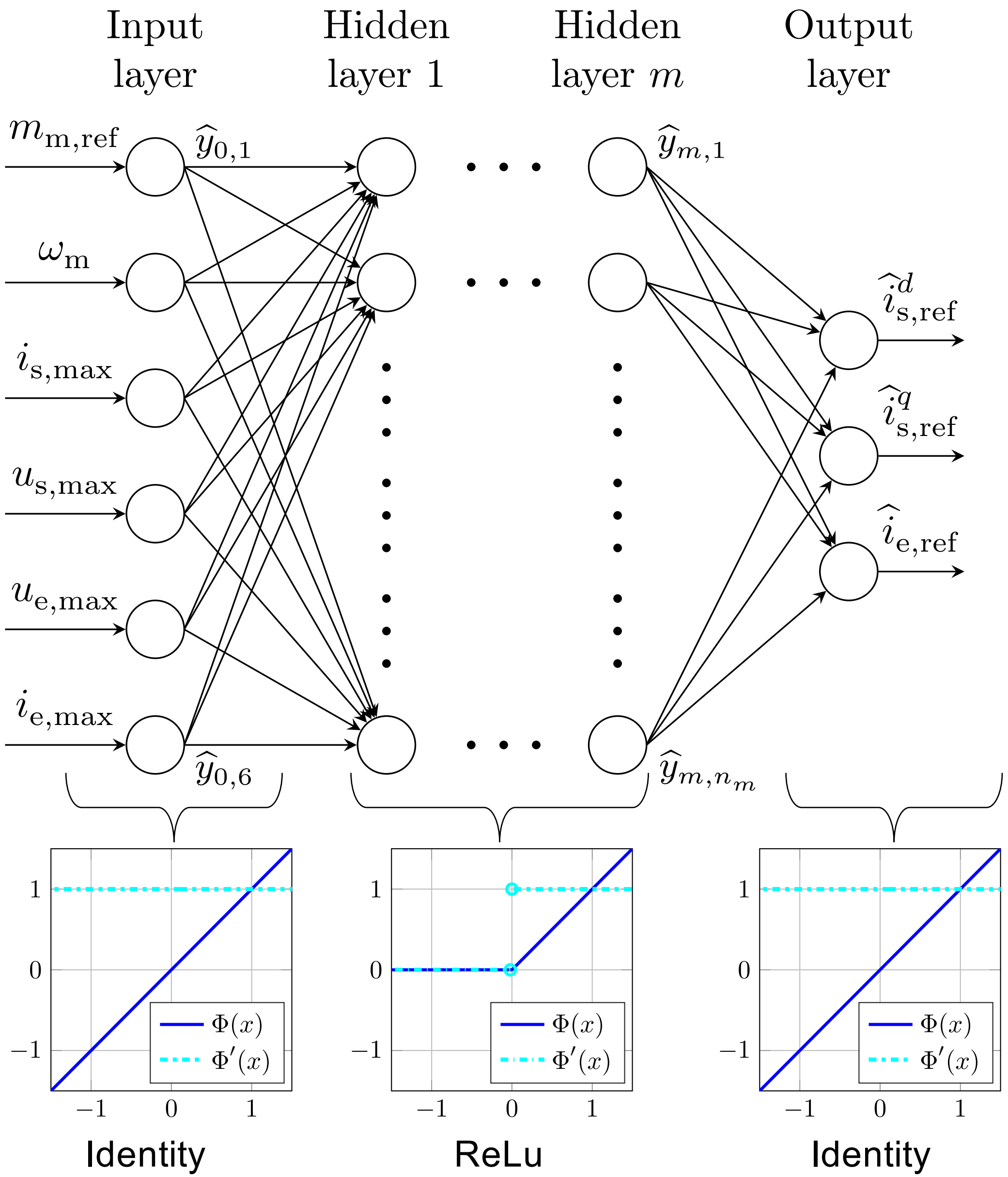
ANN output:

$$\hat{\boldsymbol{y}}[k] \coloneqq \left(\hat{\imath}_{\mathrm{s,ref}}^{d}[k], \hat{\imath}_{\mathrm{s,ref}}^{q}[k], \hat{\imath}_{\mathrm{e,ref}}[k]\right)^{\mathsf{T}} = f(\boldsymbol{x}, \boldsymbol{w}, \boldsymbol{b})$$

Training:

$$(\boldsymbol{w}^*, \boldsymbol{b}^*) = \underset{(\boldsymbol{w},\boldsymbol{b})}{\arg\min} \frac{1}{K} \sum_{k=1}^{K} \|\boldsymbol{y}[k] - \hat{\boldsymbol{y}}[k]\|^2$$

Different ANN topologies can be trained
→ Which one is the *best* trained ANN?



ANN-based OFTC of EESM

Choice and validation of an optimal ANN design

$$e_{u_s} = \frac{1}{K}\sum_{k=1}^{K} \max\left(0, \left\|\hat{u}_s^{dq}[k]\right\| - u_{s,\max}[k]\right)^2$$

$$e_{u_e} = \frac{1}{K}\sum_{k=1}^{K} \max\left(0, |u_e[k]| - u_{e,\max}[k]\right)^2$$

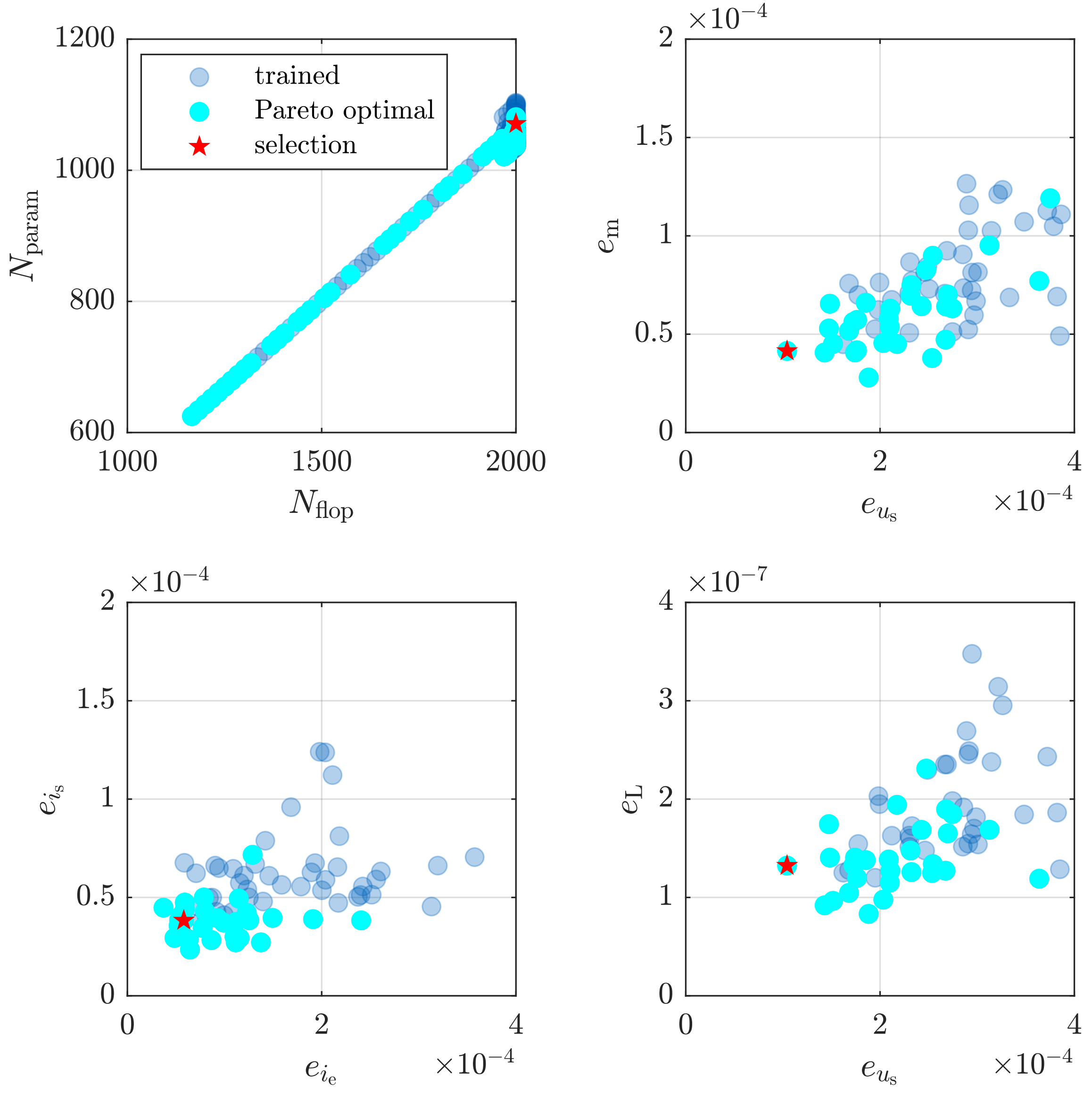
$$e_{i_s} = \frac{1}{K}\sum_{k=1}^{K} \max\left(0, \left\|i_s^{dq}[k]\right\| - i_{s,\max}[k]\right)^2$$

$$e_{i_e} = \frac{1}{K}\sum_{k=1}^{K} \max\left(0, |i_e[k]| - i_{e,\max}[k]\right)^2$$

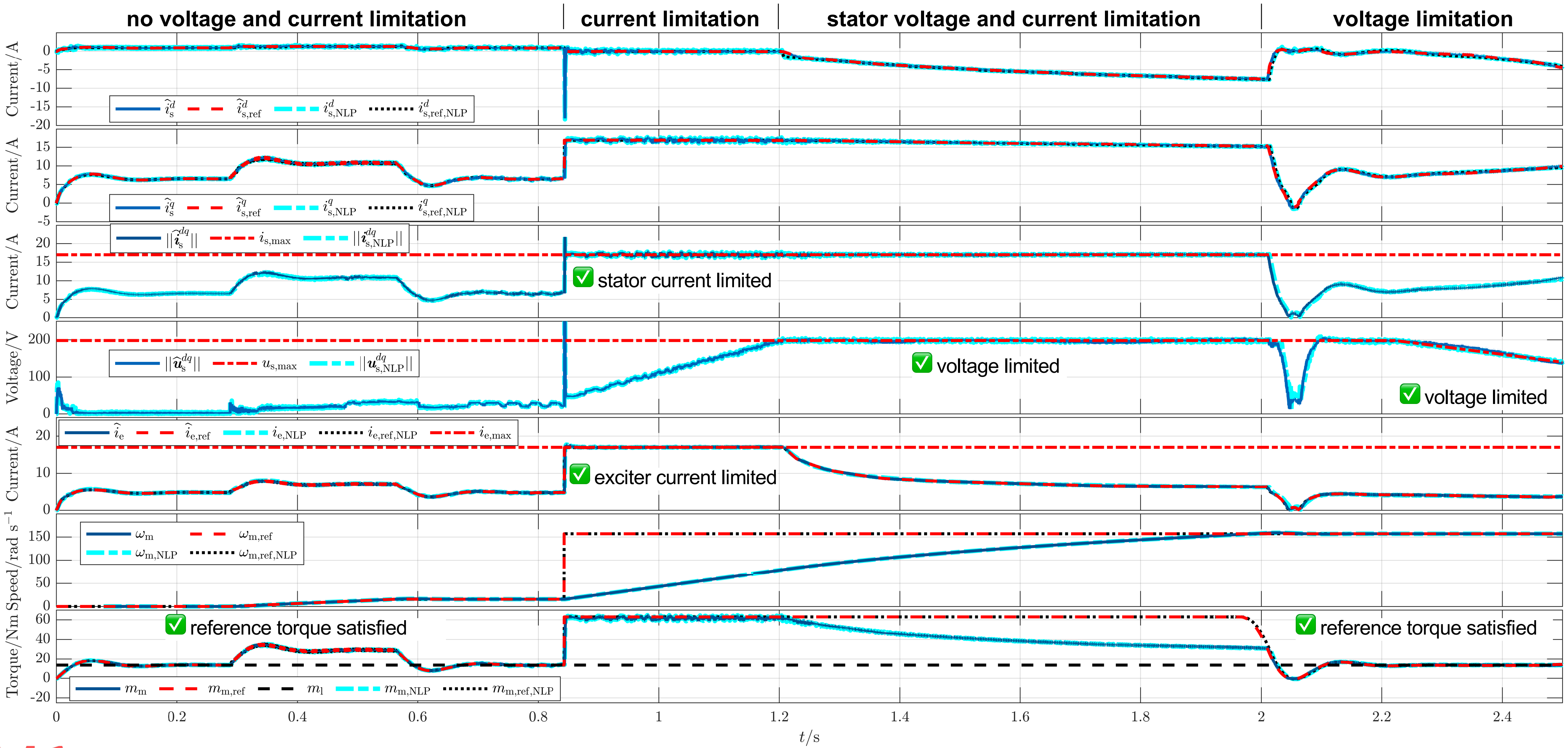
$$e_m = \frac{1}{K}\sum_{k=1}^{K} \left(\hat{m}_m[k] - \operatorname*{sat}_{m_{m,\max}} m_{m,\mathrm{ref}}[k]\right)^2$$

$$e_L = \frac{1}{K}\sum_{k=1}^{K} \left(\hat{p}_L[k] - p_L[k]\right)^2$$

Number of parameters: N_{param}
Number of floating-point-operations: N_{flop}



ANN-based OFTC of EESM
Simulation results



Conclusion & Outlook

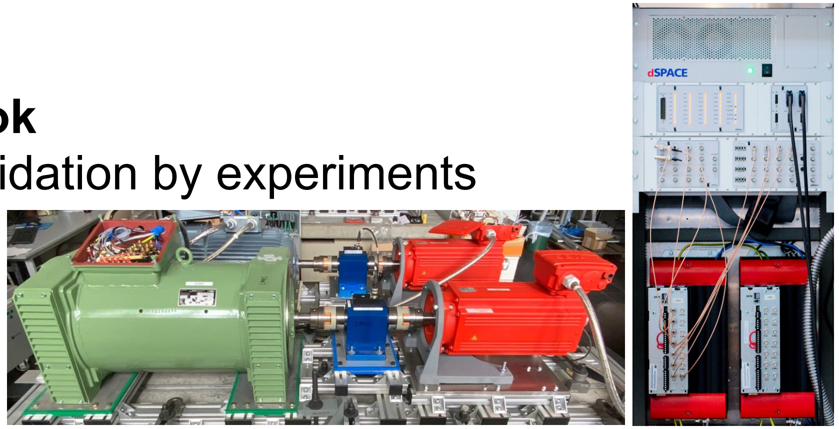
Conclusion

- ANN-based OFTC for EESM feasible, considering
  - machine nonlinearities, Iron and copper losses
  - stator and exciter voltage and current limits
  - real-time capable implementation

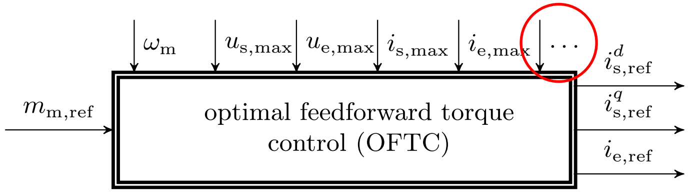
- Complete framework to design ANN-based OFTC by supervised learning
  - dataset creation based on the nonlinear machine model
  - training (and validation) of suitable ANN topologies
  - Optimal ANN design and choice as result of trade-off between the OFTC goals

Outlook

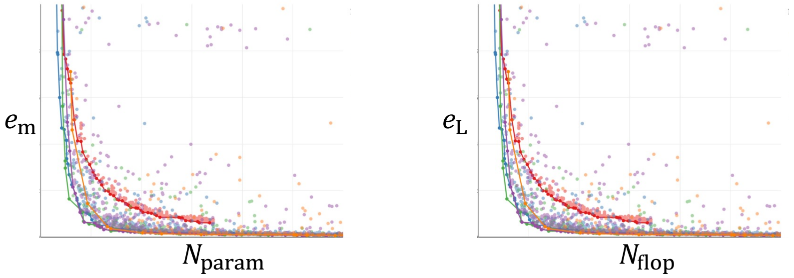
- Validation by experiments



- Considering further inputs e.g. temperatures



- Multi-objective optimization of ANN



- Considering dynamic effects

Hochschule
München
University of
Applied Sciences

Faculty of Electrical
Engineering and Information
Technology (FK04)

Institute for Sustainable
Energy Systems (ISES)

Artificial neural network based optimal feedforward torque control of electrically excited synchronous machines

Niklas Monzen, M.Sc. and Prof. Dr.-Ing. habil. Christoph M. Hackl

IEEE 32nd International Symposium on Industrial Electronics (ISIE)
Aalto University, Helsinki-Espoo, Finland
June 19th – June 21st, 2023

Niklas Monzen, 2023/06/19