AI-POWER

Artificial Intelligence for Next-Generation Power Electronics (AI-Power)

"Application of Statistical Model Checking for Robustness Comparison of Power Electronics Controllers"

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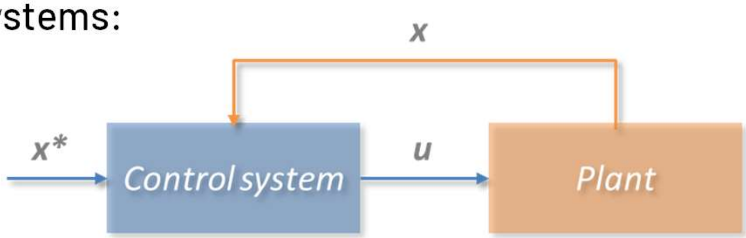
▶ Outline

- Introduction
- Modeling formalism
- Statistical Model Checking (SMC)
- Controller structures (PI controller, FS-MPC controller, NN controller)
- Controller performance validation
- Conclusion

▶ Introduction

- Requirements for control algorithms in power electronics systems:
  - Accurate reference tracking
  - Fast transient response
  - Verified robustness and stability
  - Low computational burden



x(t) – controlled variables
y(t) – output variables
u(t) – input variable

- Control algorithms used in power electronics applications
  - Linear control (P, PI, PR)
  - Direct torque control
  - Model predictive control
  - Fuzzy-logic control
  - Sliding mode control
  - Neural networks
  - ....

How to verify the requirements for all control algorithms?

How to perform it simultaneously for all control algorithms ?

Hypothesis: *Our power electronics system is deterministic*
Is that true?

▶ Introduction

- ❑ Reality:
  - ❑ Power electronics systems **don't operate in deterministic** operating conditions
    - How do we select **which conditions** to compare?
    - **How many iterations** are needed for obtaining performance certainty?
  - ❑ System **components degrade** over time
    - It will influence performance over time – how do we adapt our control?

Problem: Deterministic validation of robustness might miss potential critical scenarios

- ❑ Proposed solution:
  - Model the stochasticity of components
  - Define the confidence level
  - Obtain statistical guarantee of the desired performance

→ Statistical Model Checking (SMC)

▶ Statistical Model Checking (SMC)

- Formal method which uses techniques from mathematics for checking the system behavior
  - Applies statistical instead of exact analysis of the models

Every system that has states and transitions between the states is suitable for SMC application

- Well known technique used in:
  - Aeronautics, embedded automotive systems, sensor networks, communication systems

- UPPAAL toolbox (https://uppaal.org/)
  - integrated tool environment for modeling, validation and verification of real-time systems
  - free for non-commercial applications in academia

▶ Statistical Model Checking (SMC)

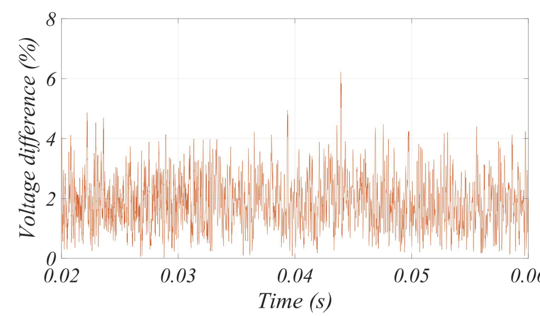
Define a hypothesis about the system

Run multiple simulations and perform Monte-Carlo analysis

Obtain probability of the hypothesis
or estimate the value

Example

$\Delta v = \left(v_{ref} - v_{meas}\right)^2 < 5\%$
or
$\max(\Delta v)$



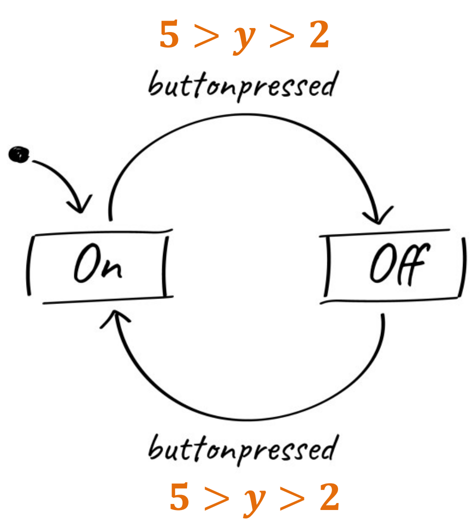
$P(\Delta v < 5\%) = 0.907\ - 1$
$No.runs = 36$
or
$E(max(\Delta v)) = 7.5V$

▶ Modeling formalism

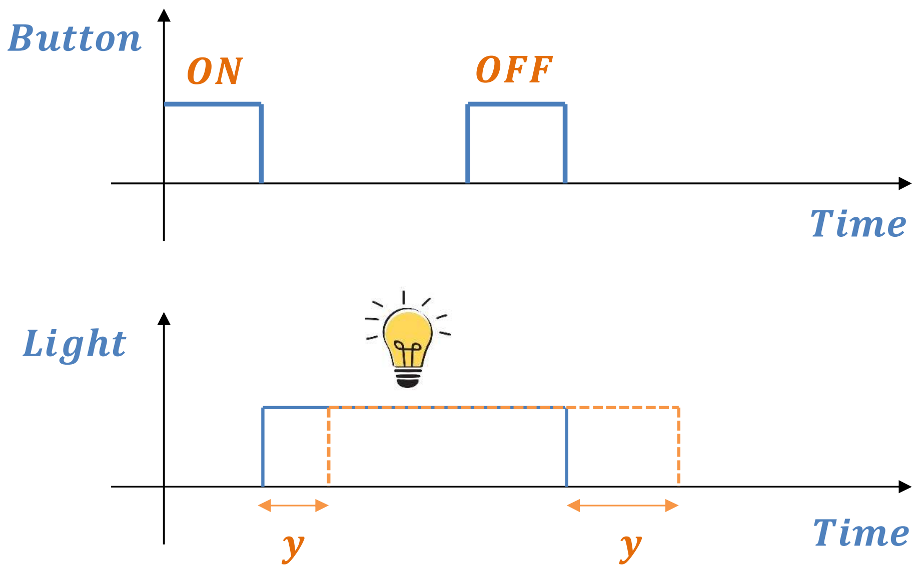
❑ Hybrid timed automata

- Can model deterministic dynamics (e.g., control algorithm, modulator)
- Can model stochastic dynamics (e.g., grid sags, load changes)

Automaton (State machine)



Timed automaton



▶ Modeling formalism

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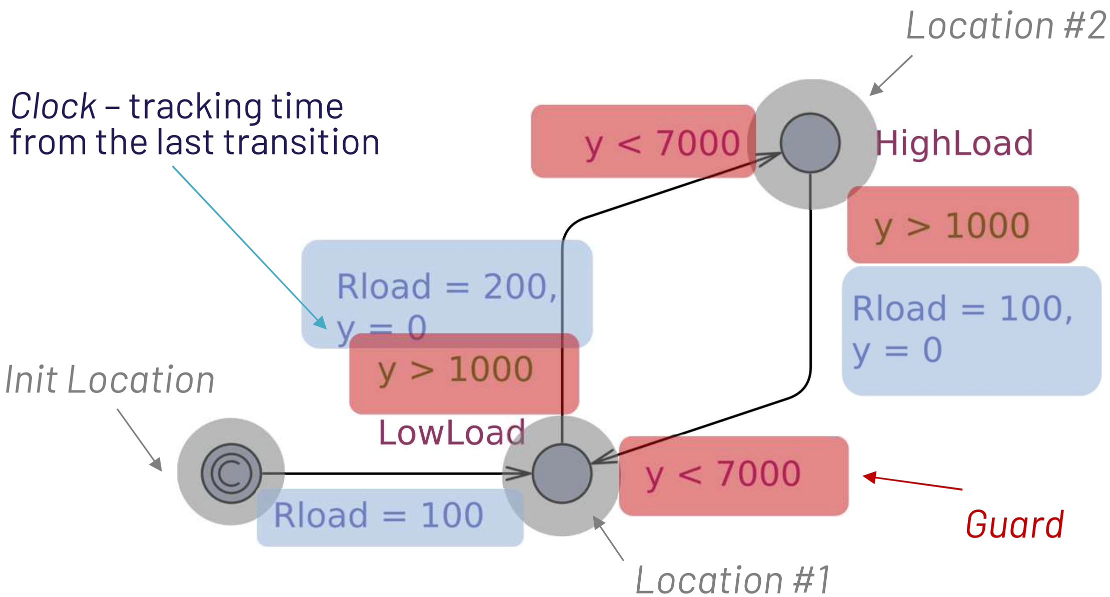
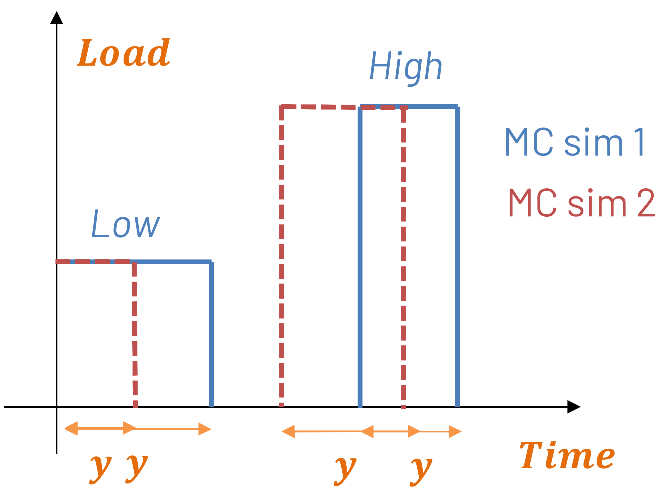
Stochastic load modeled in UPPAAL





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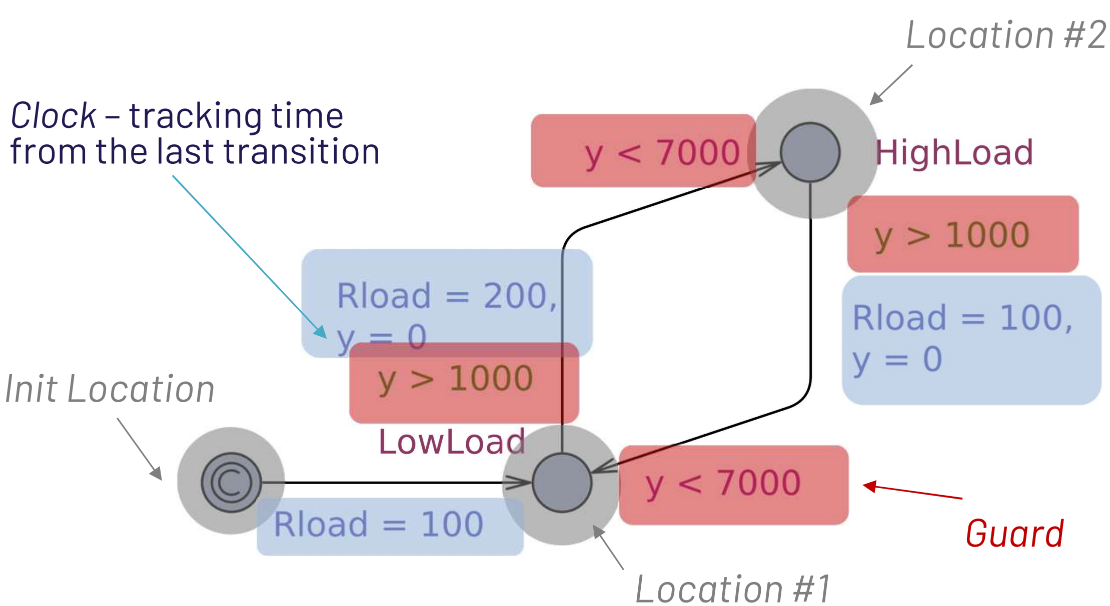
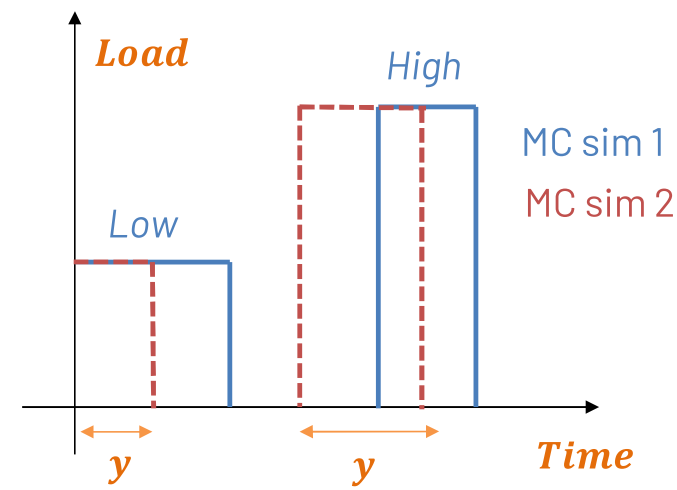
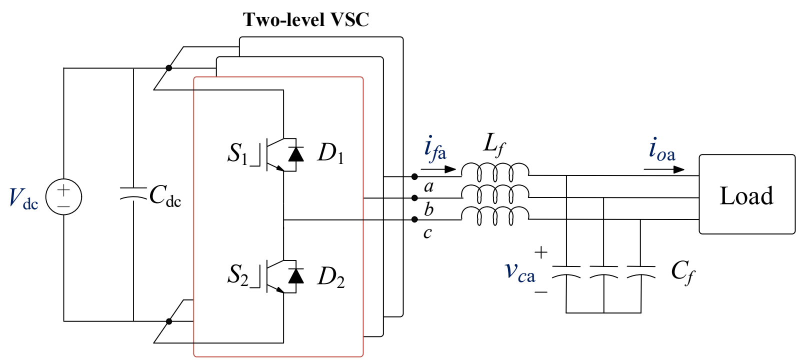




▶ Controller structures (PI controller, FS-MPC controller, NN controller)

- ❑ Two level voltage source converter with output LC filter and passive load



SYSTEM PARAMETERS.

Parameter	Value
DC link voltage (V_{dc})	700 V
Filter inductance (L_f)	2.4 mH
Filter capacitance (C_f)	14 μF
Reference voltage ($V_{c\ rms}^{*}$)	400 V
Reference freq. (f^{*})	50 Hz

- ❑ System controllers

Linear controller

- Slower dynamics (cascade)
- Low model parameter dependency
- Low computation burden
- Fixed switching frequency

Model Predictive controller

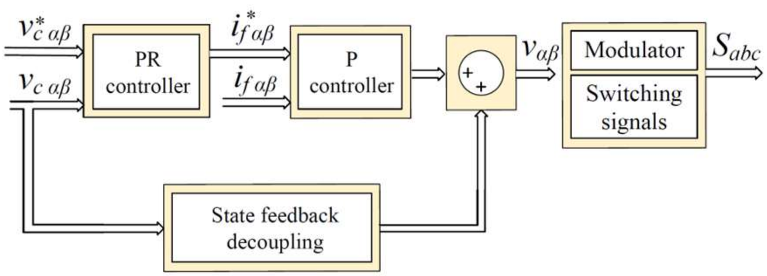
- Fast dynamics
- Model parameter dependency
- Highest computational burden
- Variable switching frequency

NN controller

- Fast dynamics
- Training data quality
- High computational burden
- Variable switching frequency

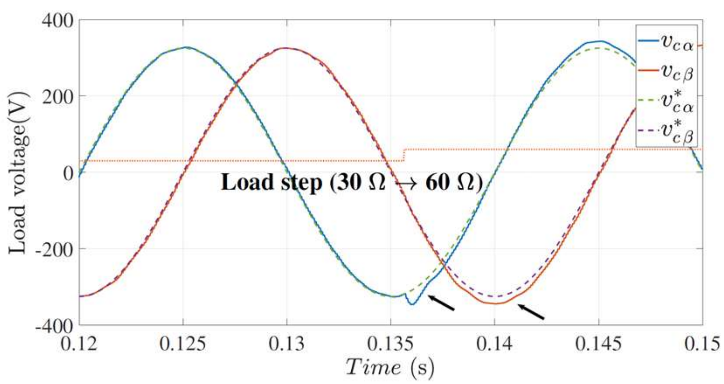
▶ Controller structures (PI controller, FS-MPC controller, NN controller)

❑ Linear controller



- P inner current loop control
- PR outer voltage loop control (5th and 7th harmonics)
- State-feedback decoupling – system delay compensation
- Switching frequency 10 kHz
- Tunning: Nyquist criterion

❑ Load step response



PR voltage controller

$$G_v = k_{pV} + \sum_{h=1,5,7} k_{iV,h} \frac{s\cos(\phi_h) - h\omega_1 \sin(\phi_h)}{s^2 + (h\omega_1)^2}$$

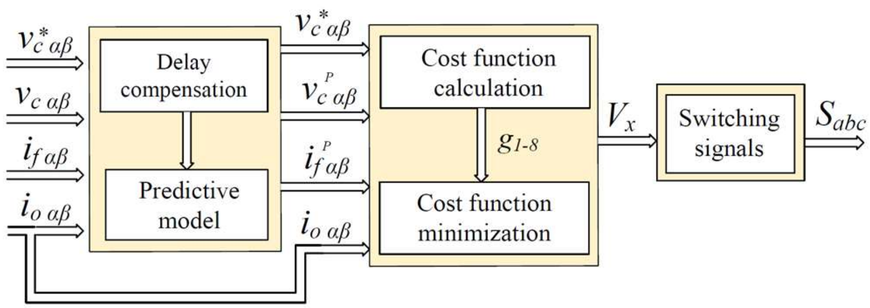
State-feedback decoupling with low pass filter

$$G_{dec} = \frac{1 + \tau_z s}{1 + \tau_p s} \cdot G_{LPF}$$

Reference: F. de Bosio, L. A. de Souza Ribeiro, F. D. Freijedo, M. Pastorelli, and J. M. Guerrero, "Effect of state feedback coupling and system delays on the transient performance of stand-alone VSI with LC output filter," IEEE Trans. Ind. Electron., vol. 63, no. 8, pp. 4909–4918, 2016.

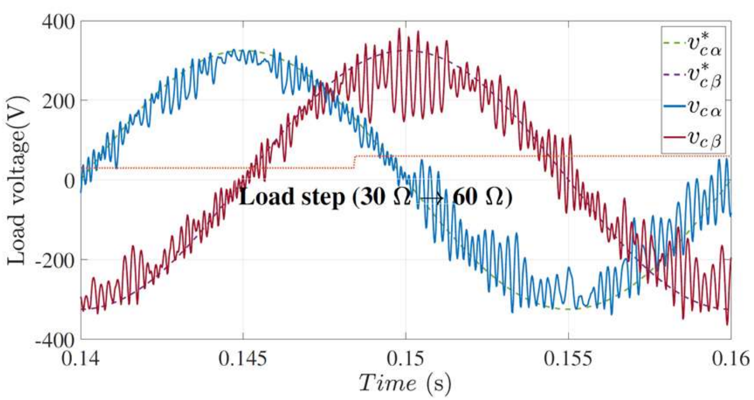
► Controller structures (PI controller, FS-MPC controller, NN controller)

❑ Finite Control Set Model Predictive Controller (FS-MPC)



- Predictive model is used to obtain voltage and current predictions
- Cost function defined for low distortion of voltage
- No modulator (1 voltage vector applied to whole Ts)
- Computational delay compensated with two step prediction

❑ Load step response with 50% error in the model parameters



System model

$$\frac{d}{dt}\begin{bmatrix} i_{f\,\alpha\beta} \\ v_{c\,\alpha\beta} \\ i_{o\,\alpha\beta} \end{bmatrix} = \begin{bmatrix} 0 & -\frac{1}{Lf} & 0 \\ \frac{1}{C_f} & 0 & -\frac{1}{C_f} \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} i_{f\,\alpha\beta} \\ v_{c\,\alpha\beta} \\ i_{o\,\alpha\beta} \end{bmatrix} + \begin{bmatrix} \frac{1}{Lf} \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} v_{i_{\alpha\beta}} \end{bmatrix}$$

Cost function

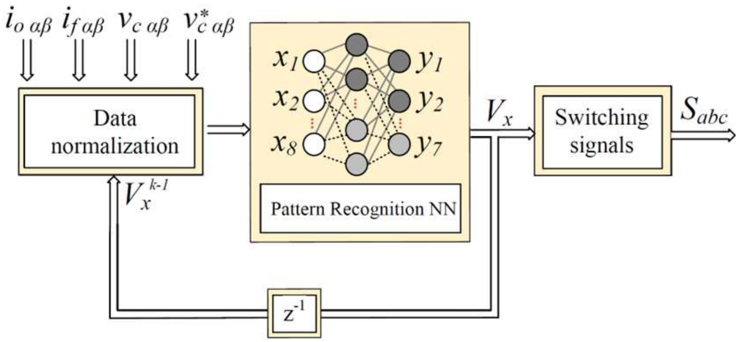
$$g = (v^*_{c\alpha} - v^P_{c\alpha})^2 + \left(v^*_{c\beta} - v^P_{c\beta}\right)^2 + \lambda_d \cdot g_d$$

$$g_d = \left(i^P_{f\alpha} - i^P_{o\alpha} + C_f\omega v^*_{c\beta}\right)^2 + \left(i^P_{f\beta} - i^P_{o\beta} + C_f\omega v^*_{c\alpha}\right)^2$$

Reference: T. Dragicevic, "Model predictive control of power converters for robust and fast operation of ac microgrids," IEEE Trans. Power Electron., vol. 33, no. 7, pp. 6304–6317, 2018.

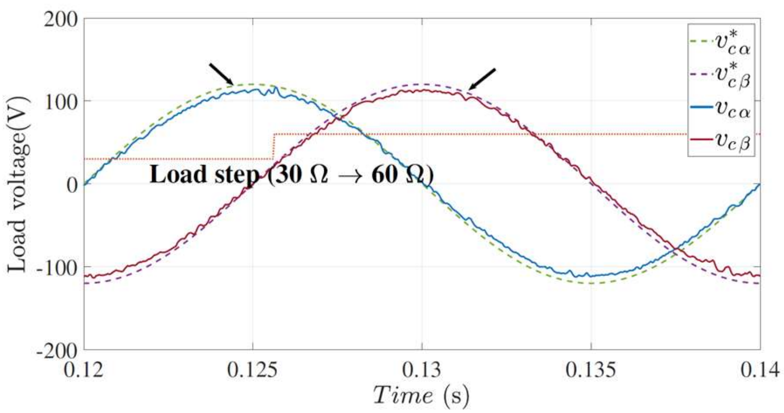
► Controller structures (PI controller, FS-MPC controller, NN controller)

❑ Neural networks controller (trained on FS-MPC data)



- Data from FS-MPC algorithm are used for training the NN
- NN structure: 8 inputs, 15 hidden neurons, 7 outputs
- Adam optimization algorithm used in training
- No modulator (1 voltage vector applied to whole Ts)

❑ Load step response with 50% reduced V_{dc}



Output of the n-th neuron in the hidden layer

$$h_n = f_1(b_{n1} + \sum_{j=1}^{8} w_{nj}^{(1)} \cdot x_n)$$

Output of the y-th neuron in output layer

$$y_m = f_2(b_{n2} + \sum_{k=1}^{15} w_{nk}^{(2)} \cdot h_n)$$

Source: M. Novak and T. Dragicevic, "Supervised imitation learning of finite set model predictive control systems for power electronics," IEEE Trans. Ind. Electron., vol. 68, no. 2, pp. 1717–1723, 2021

▶ Controller performance validation – steady state

- Controllers for 2L-VSC converter supplying a passive load were modeled using timed automata and simulated in UPPAL
- For each simulation run a calculation of root mean square difference of the load voltage is performed

$$RMSD = \sqrt{\frac{\sum_{j=1}^{N}(v_j - v_j^*)}{N}}$$

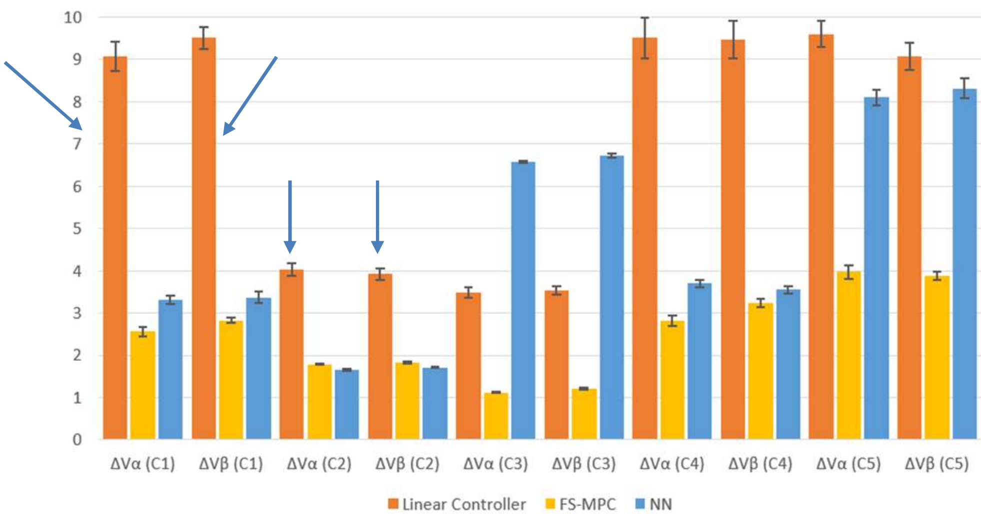
N – number of samples
v_j - measured voltage
v_j^* - reference voltage

- Results for estimation of max RMSD ($\Delta v_{c\alpha}, \Delta v_{c\beta}$) for three controllers with constant load (steady state performance)

Load (Ω)	L error	C error	Vref ampl. (V)	Vdc (V)	Linear Controller	FS-MPC	NN
30	0	0	325	700	$\Delta V_\alpha = 3.57$ $\Delta V_\beta = 3.41$	$\Delta V_\alpha = 2.39$ $\Delta V_\beta = 2.61$	$\Delta V_\alpha = 3.20$ $\Delta V_\beta = 3.20$
60	0	0	325	700	$\Delta V_\alpha = 2.26$ $\Delta V_\beta = 2.21$	$\Delta V_\alpha = 2.28$ $\Delta V_\beta = 2.47$	$\Delta V_\alpha = 3.10$ $\Delta V_\beta = 3.10$

▶ Controller performance validation – dynamics

- Confidence interval for MC simulations is set to 95%
- Results for estimation of max RMSD ($\Delta v_{c\alpha}, \Delta v_{c\beta}$) for three controllers with variable load $30\Omega \rightarrow 60\Omega$



C1: $L_{error} = 0$, $C_{error} = 0$, $V_{ref} = \mathbf{325\ V}$, $V_{dc} = 700$ V

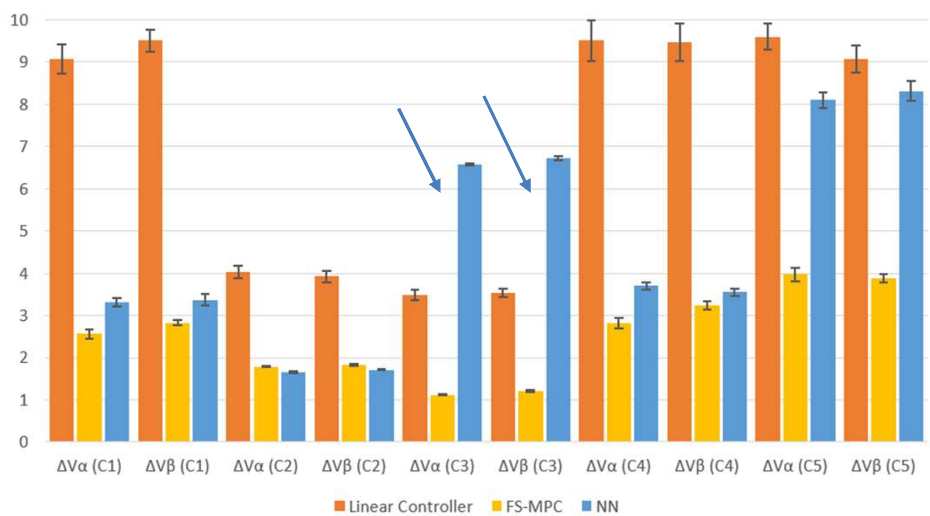
C2: $L_{error} = 0$, $C_{error} = 0$, $V_{ref} = \mathbf{120\ V}$, $V_{dc} = 700$ V

Linear Controller	FS-MPC	NN
ΔV_α = 9.07 +/- 0.34	ΔV_α = 2.56 +/- 0.11	ΔV_α = 3.31 +/- 0.10
ΔV_β = 9.50 +/- 0.26	ΔV_β = 2.83 +/- 0.07	ΔV_β = 3.37 +/- 0.14
ΔV_α = 4.03 +/- 0.15	ΔV_α = 1.79 +/- 0.02	ΔV_α = 1.65 +/- 0.02
ΔV_β = 3.92 +/- 0.14	ΔV_β = 1.83 +/- 0.02	ΔV_β = 1.72 +/- 0.02

- Observations:
  - Load changes have the highest effect on PI controller performance (no effect of parameter mismatch)

▶ Controller performance validation - dynamics

- ❑ Confidence interval for MC simulations is set to 95%
- ❑ Results for estimation of max RMSD ($\Delta v_{c\alpha}, \Delta v_{c\beta}$) for three controllers with variable load $30\Omega \rightarrow 60\Omega$



C3: L_{error} = **+25%,** C_{error} = **+25%,** V_{ref} = 120 V, V_{dc} = **300** V

C4: L_{error} = **+25%,** C_{error} = **+25%,** V_{ref} = 325 V, V_{dc} = 700 V

C5: L_{error} = **-25%,** C_{error} = **-25%,** V_{ref} = 325 V, V_{dc} = 700 V

System parameters are smaller then in the model

- ❑ Observations:
  - Changing the DC-link voltage effected the performance of NN controller (missing training data)
  - Negative parameter mismatch effects the performance of NN controller

▶ Conclusion

- Application of SMC for comparative controller robustness verification
  - can show in **which conditions** controllers are **underperforming and need retuning**
    - e.g., parameter adjustment (PI, FS-MPC), obtain missing training data (NN)
  - is **applicable** for **different power electronics systems applications**
    - e.g., grid-connected systems (voltage dips and harmonic pollution)

- Future development
  - Incorporate stability validation in automated SMC test to find a set of controller parameters that can provide stable response in a system with stochastic elements

► Acknowledgement

"Part of this work was supported by the Innovation Fund Denmark (IFD) through the project of Artificial Intelligence for Next-Generation Power Electronics (AI-Power)"

Thank you for your attention!

Questions?

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