2023 IEEE PES ISGT-Europe

October 23rd-26th, 2023, Grenoble, France

A C-HIL based data-driven DC-DC power electronics converter model for system-level studies

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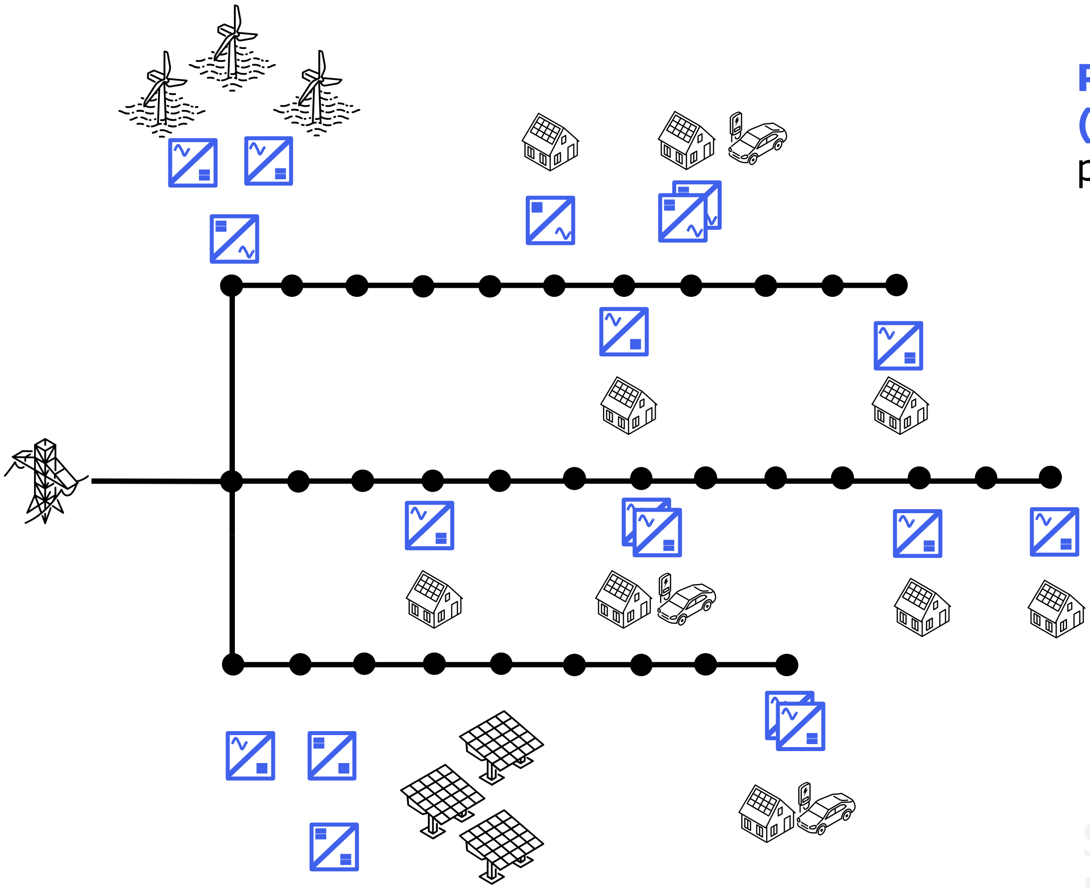
Paper №: A8784BE

Introduction



Power Electronics Converters (PEC) are **ubiquitous** in modern power systems

→ Need for **system-level studies**

Challenges :

- **Modeling,**
  PECs are Non-LTI system
- **Privacy,**
  Manufacturers don't want to disclose their secrets

System identification and black box modeling.

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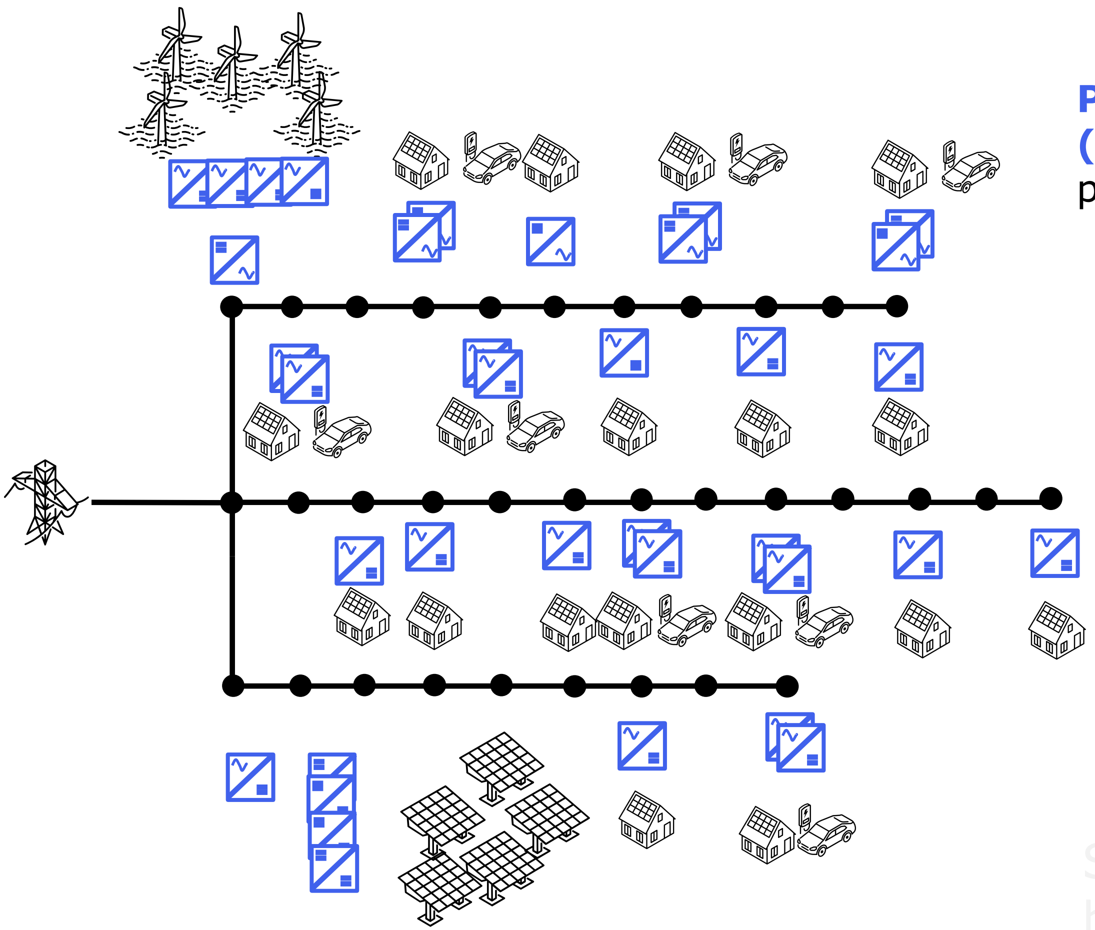

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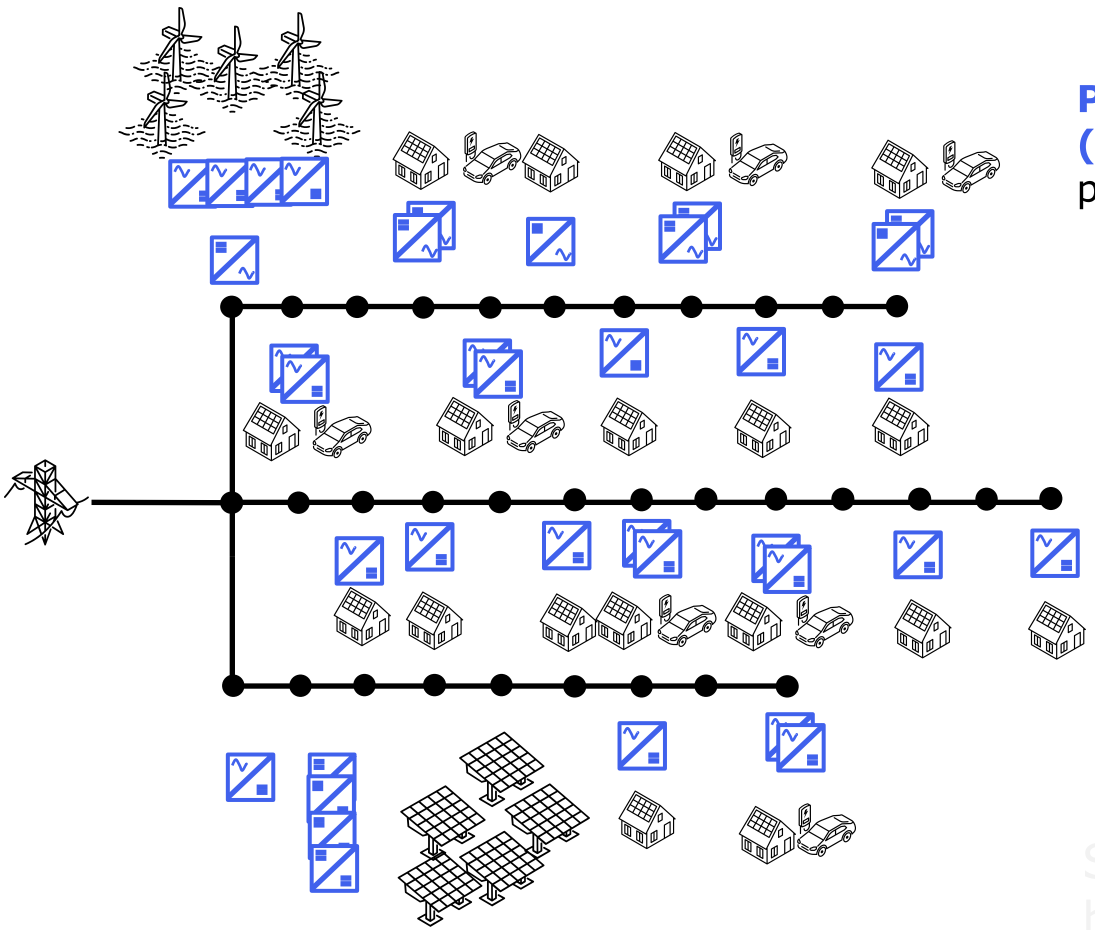

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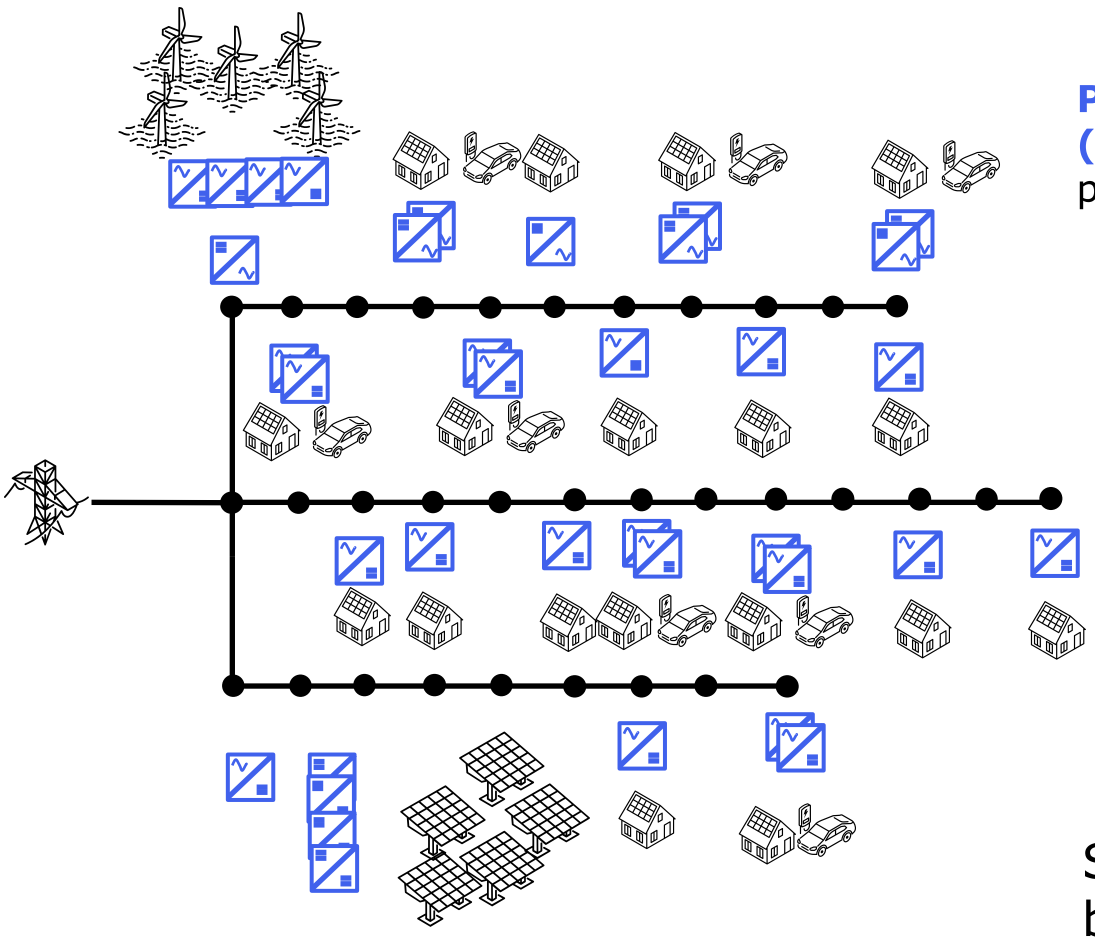

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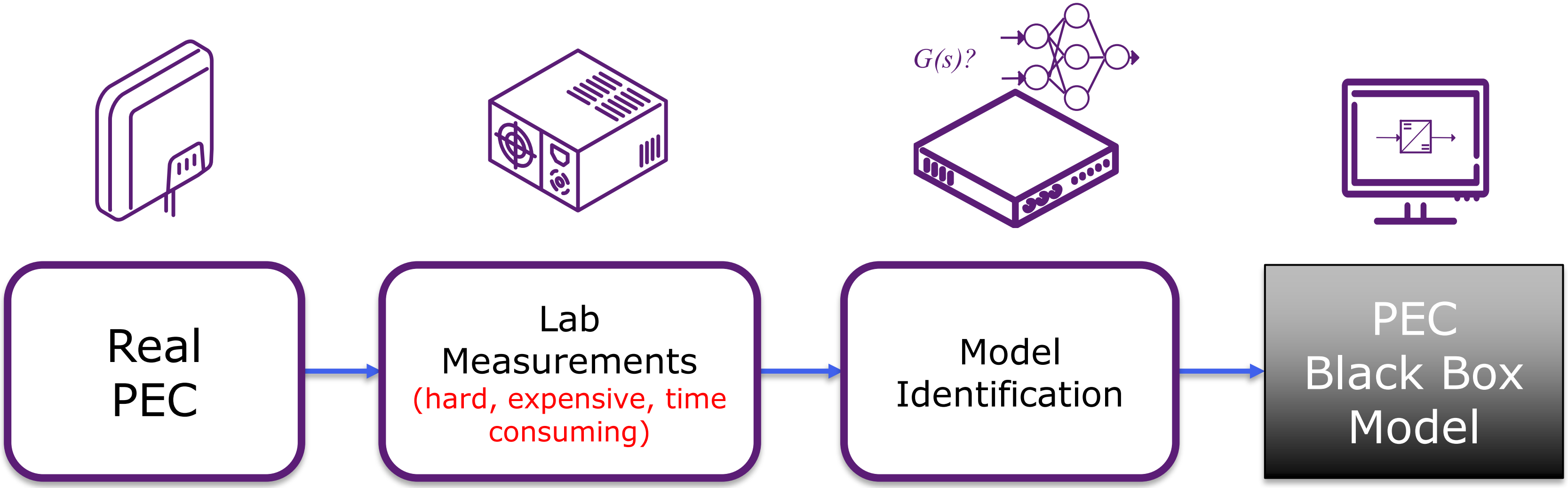
Black Box Model Generation

Real PEC

PEC Black Box Model

Black Box Model Generation



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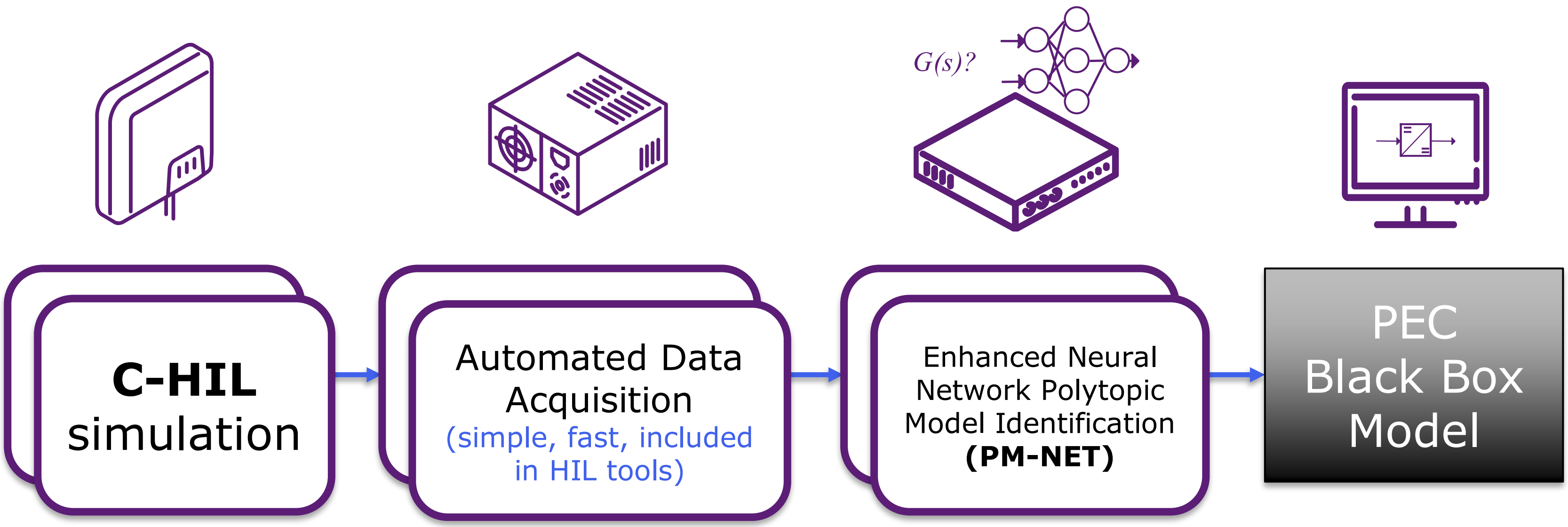

Polytopic models

Combination of N weighted linear models

Procedure :

1) Identify linear models around different operating points : $g_i(x)$

2) Design the input-depent weighting function : $\omega_i(x) \in [0\,;1]$

3) Output of polytopic model : $\hat{y} = \sum_{i=1}^{N} \omega_i(x)\, g_i(x)$

Main challenges : 1) and 2)

Which order and parameters of linear models ?

How to partition the operating space ?

How to design the weighting function ?

Proposed approach : **PM-NET**

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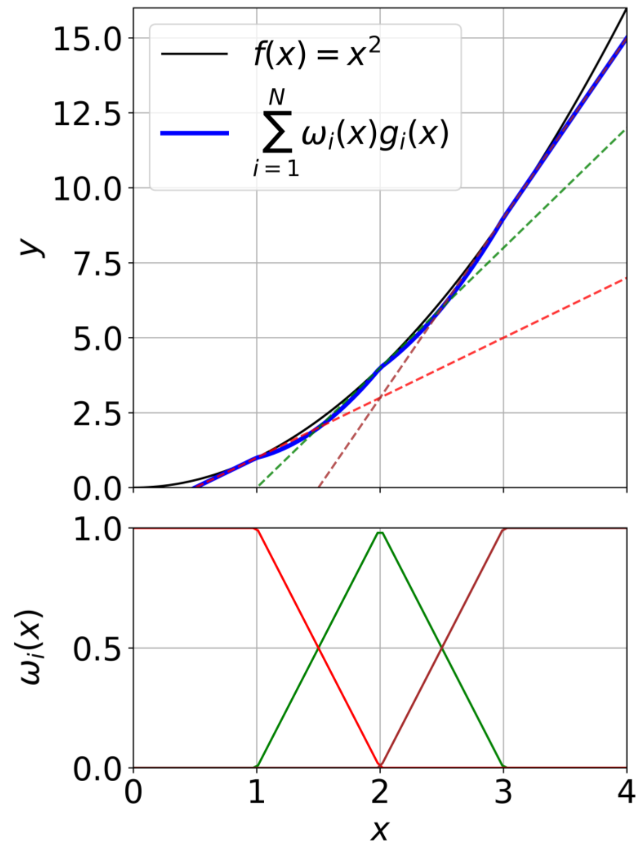

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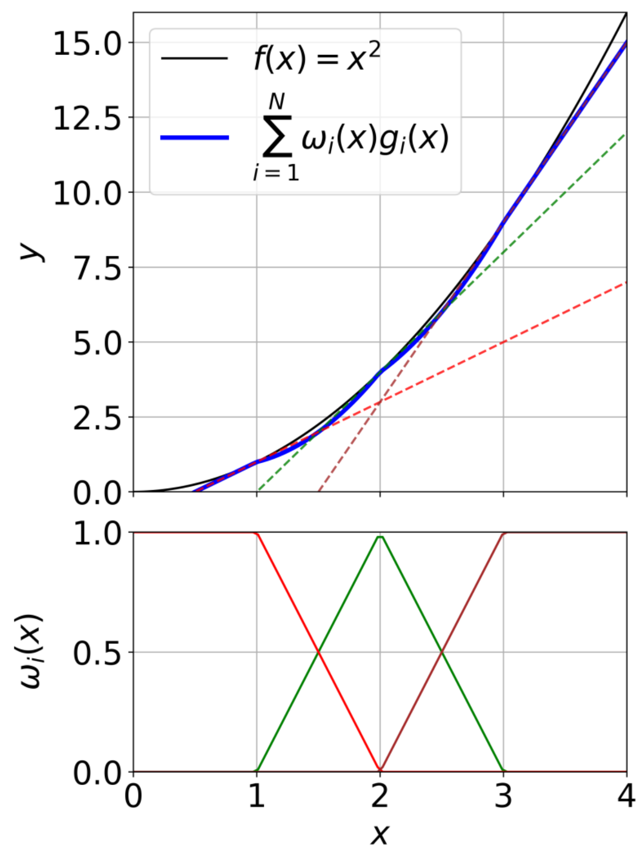

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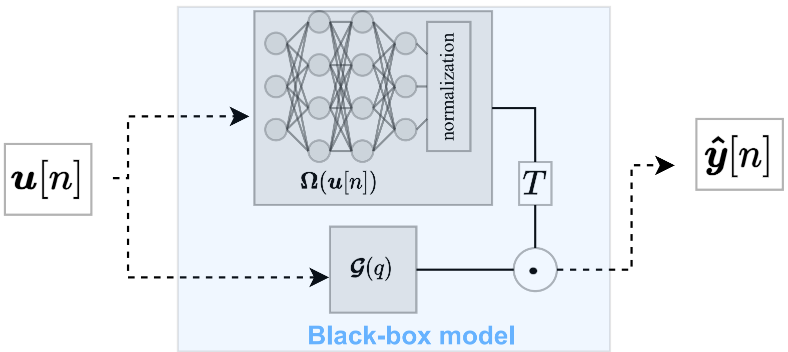
PM-NET Identification



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1) Data harvesting among the entire operating space

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Iterative procedure :

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3) Train MLP that yields the weighting function : $\boldsymbol{\Omega}(\mathbf{u}[\mathrm{n}])$

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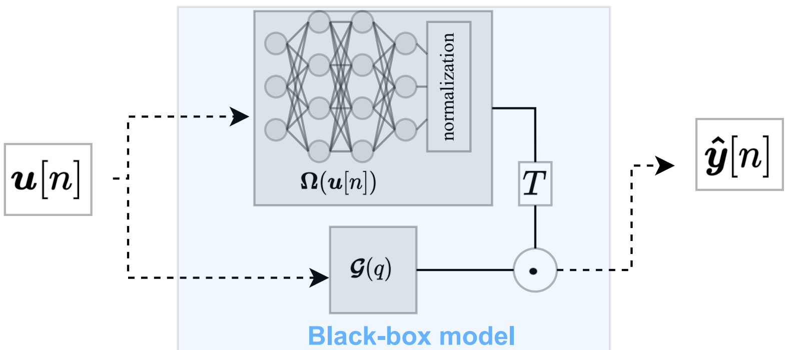

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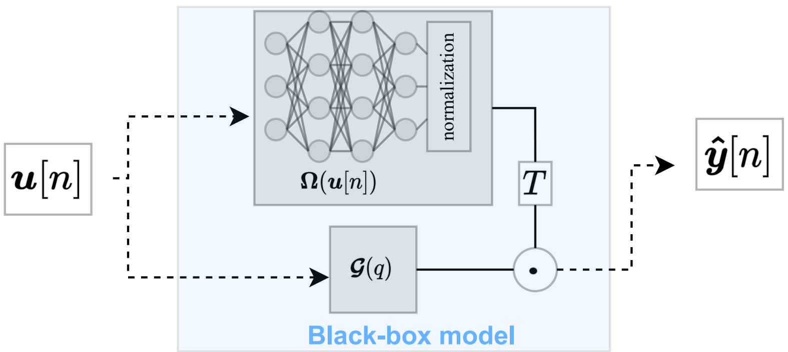

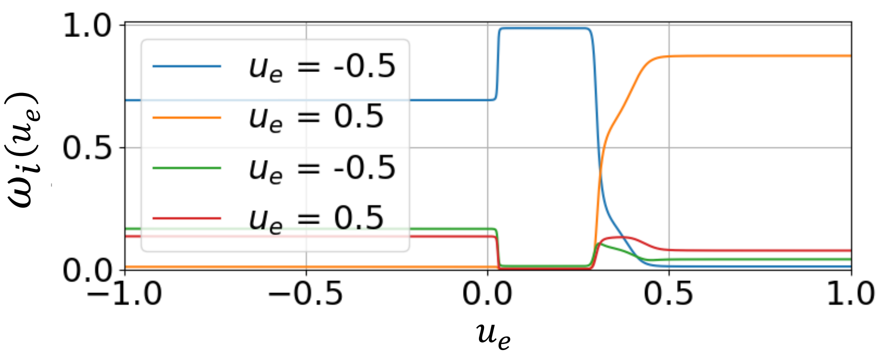

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C-HIL simulation

Why C-HIL data are suitable for black box modeling:

C-HIL …

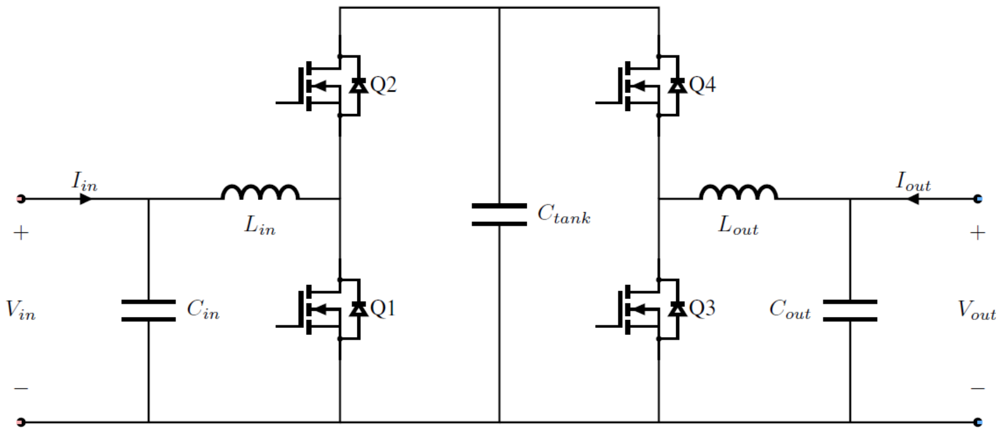
…models PECs with ideal switches and R,L,C components at ~1MHz bandwidth
→ **Accurate model for low frequencies**

…includes the true controller
→ **Closed loop system data**
(steady-state, start up, turn off, ramp…)

… is still partly a simulation
→ No technical constraint on **operating points browsing** and system perturbation

…can script the data acquisition
→ **Ease of use**

PEC under test



Bidirectionnal DC/DC droop controlled converter from an industrial partner

Specify I/O for model identification
(~Inverse hybrid parameters of a voltage amplifier)

Outputs **Inputs**

$$\begin{pmatrix} I_{in}[n] \\ V_{out}[n] \end{pmatrix} = \begin{pmatrix} G_{11}(q) & G_{12}(q) \\ G_{21}(q) & G_{22}(q) \end{pmatrix} \begin{pmatrix} V_{in}[n] \\ I_{out}[n] \end{pmatrix}$$

$$\boldsymbol{y}[n] = \boldsymbol{G}(q)\ \boldsymbol{u}[n]$$

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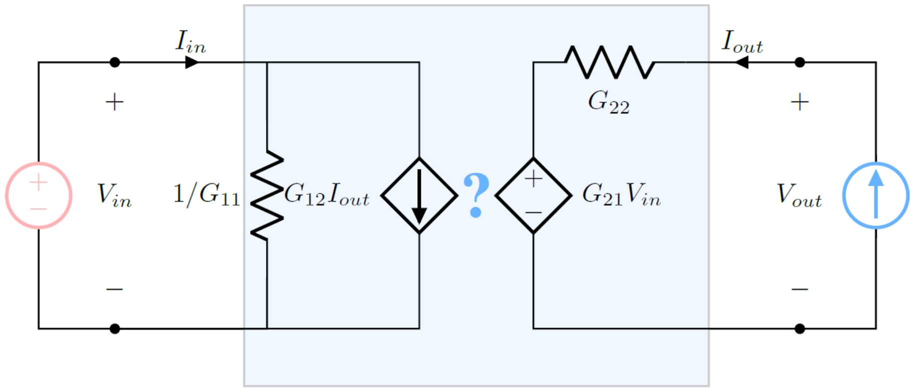

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C-HIL data acquisition

PRBS inputs

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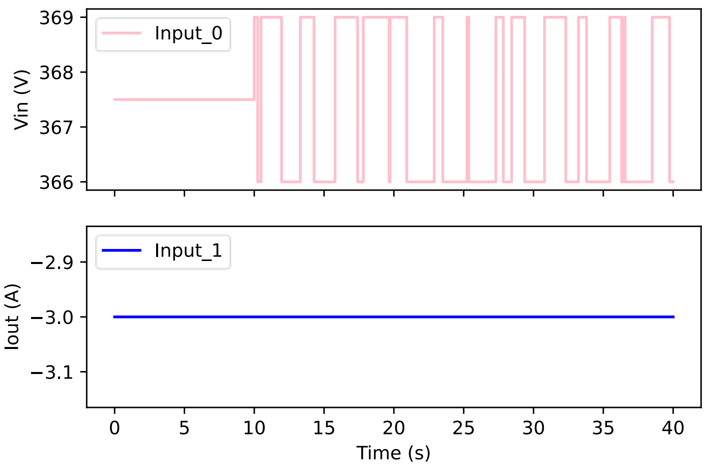
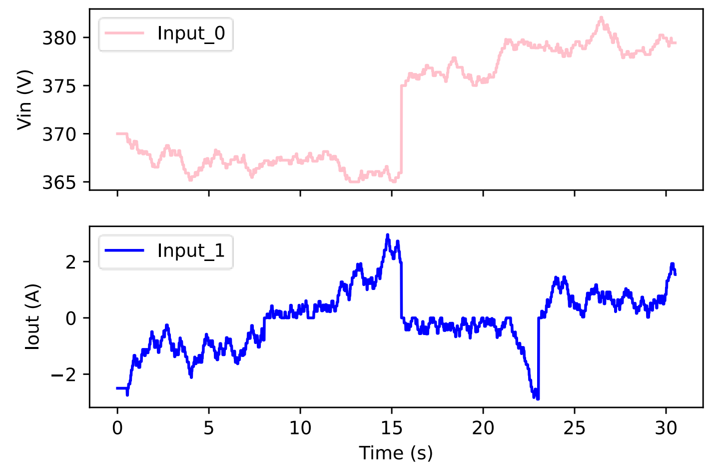
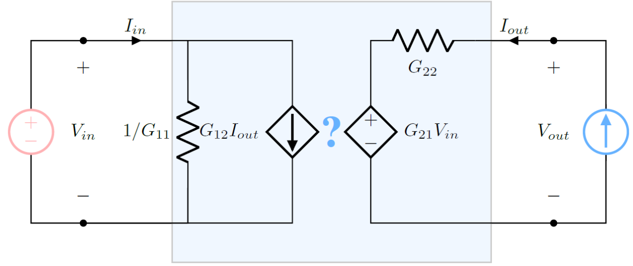


Browsing operating space

weighting function $\boldsymbol{\Omega}(\mathbf{u}[\mathrm{n}])$



→ Fmax of PRBS:
100 Hz



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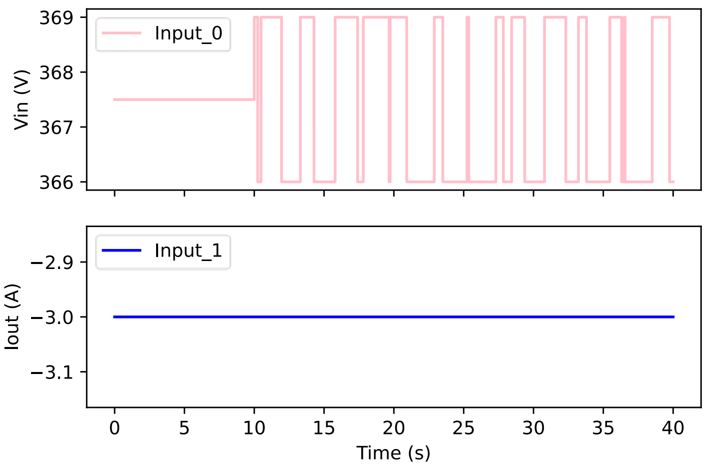

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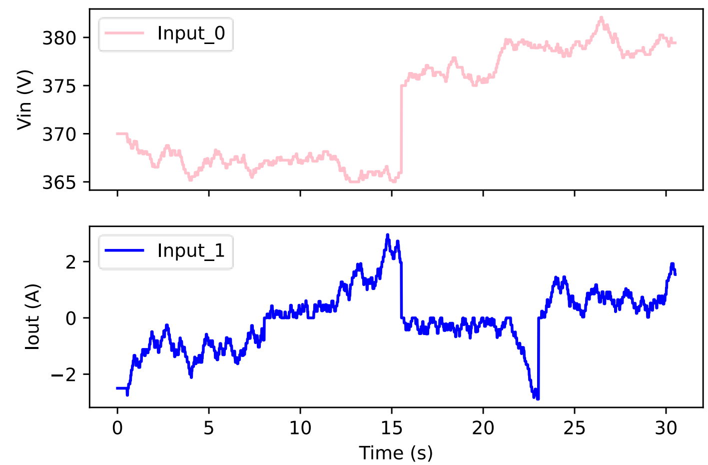

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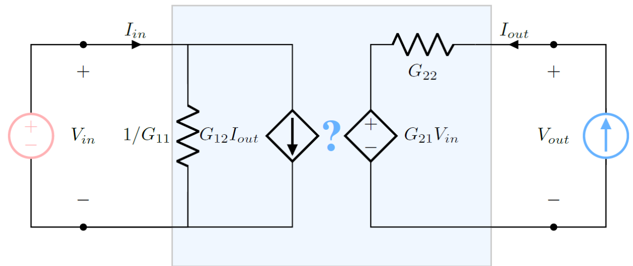
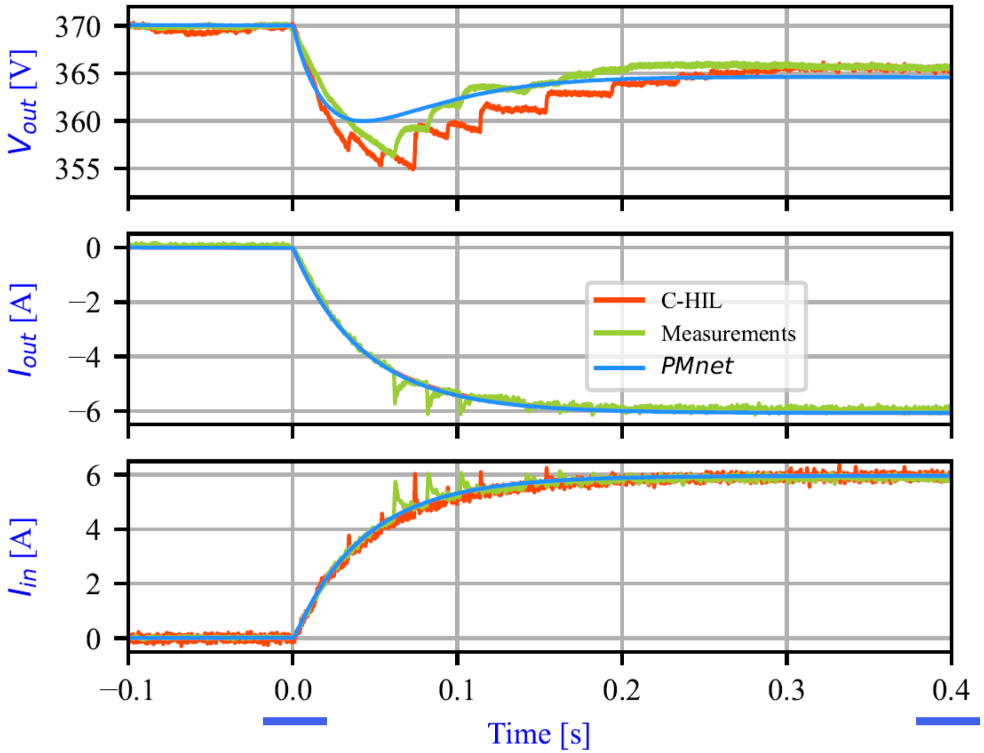


Results analysis : R-L load connection



Black box PM-net model fits well both real measurements and C-HIL simulation data.

- Steady state values v
- Lower voltage drop ~
- Slow dynamics v
- Fast transients x

Results analysis : small DC system

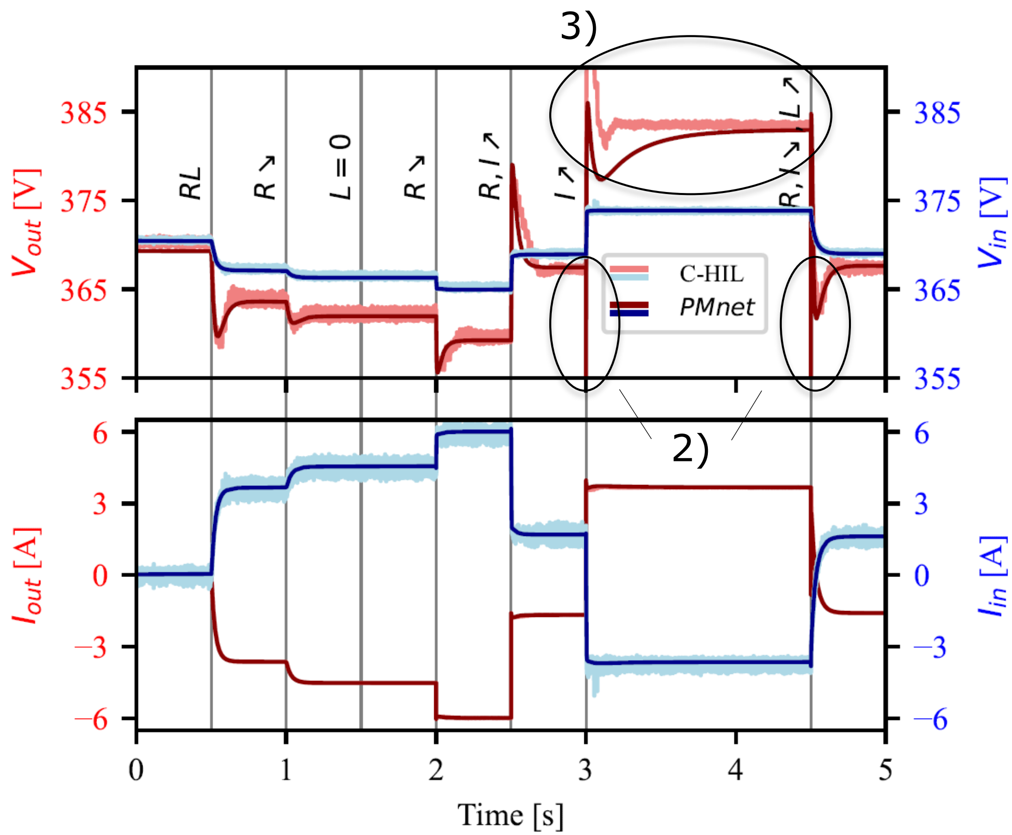
Testing single black box model with a battery and a variable load

Noticeable results :

1) **Model fits well while the battery was not present for the training**

2) An abrupt transition from one $G(q)$ to another can lead to an overshoot

3) Dead-band control operating points can be improved



Conclusion

Advantages of our approach :

- The PM-net black box models accuratly represent slow dynamics of PECs
- C-HIL simulation is viable for model identification

Further work :

- Applying state estimation for non-active LTI systems to prevent transients when sudden change in operating point
- Realize complete system-level studies

PM-NET operating space partion

Analyze if some weights are constantly below a threshold α:

- Remove the associated linear model and train again the neural network. *(pruning)*

- Compute numerically the gradients of the weighting function to identify along which direction to partition the operating space. *(segregation)*