Workshop on power electronics reliability
in outdoor grid-connected systems

June 23, 2022, Berlin, Germany

Condition & Health Monitoring (CHM) of Power Electronic Components and Converters

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Reliability of Power Electronic Converters (ReliaPEC Group)
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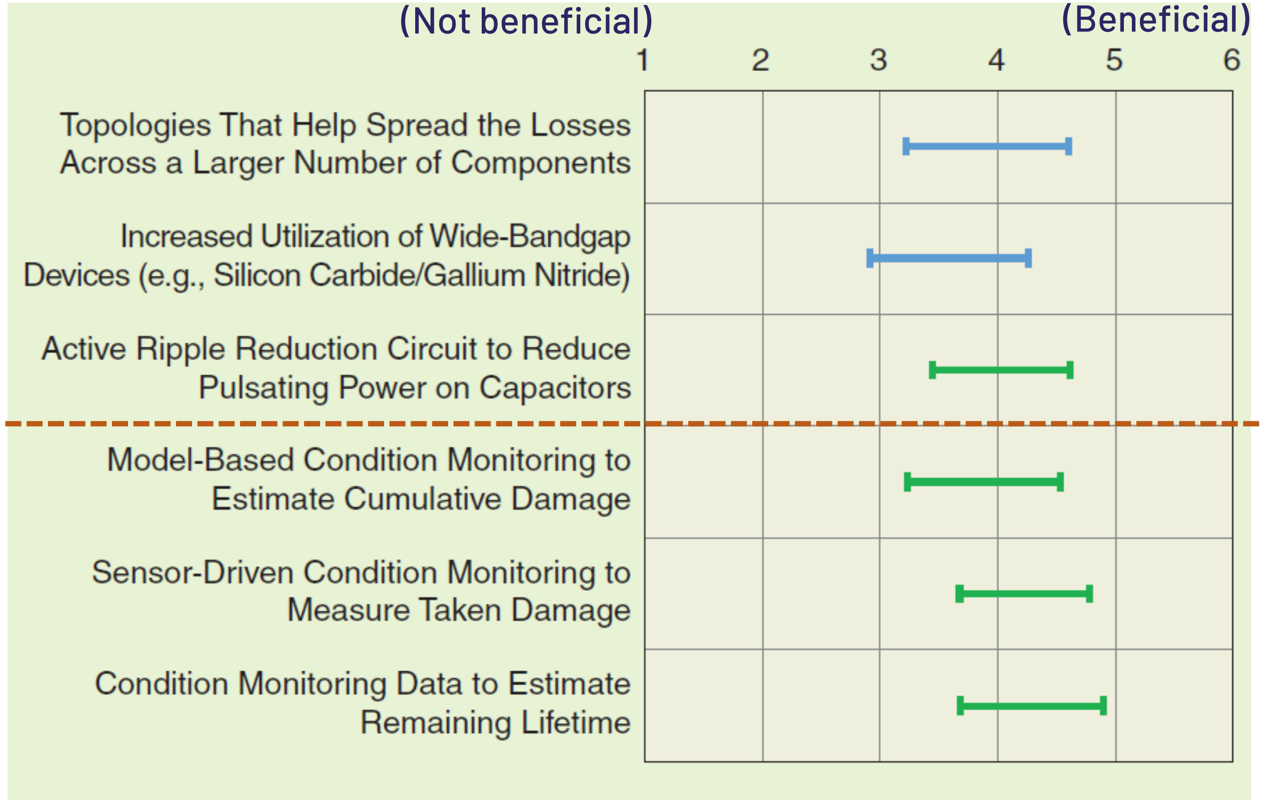
AAU ENERGY   AALBORG UNIVERSITY

▶ Condition monitoring in industry

APPLICATION	RESPONSES
All	83
Wind power	Eight
PV	Nine
Electric vehicles	21
Drive systems	20
Traction	Eight
UPS and power supplies	Seven
Lighting	Two
Air and spacecraft	Five
Energy transmission	Three

UPS: uninterruptible power supply.

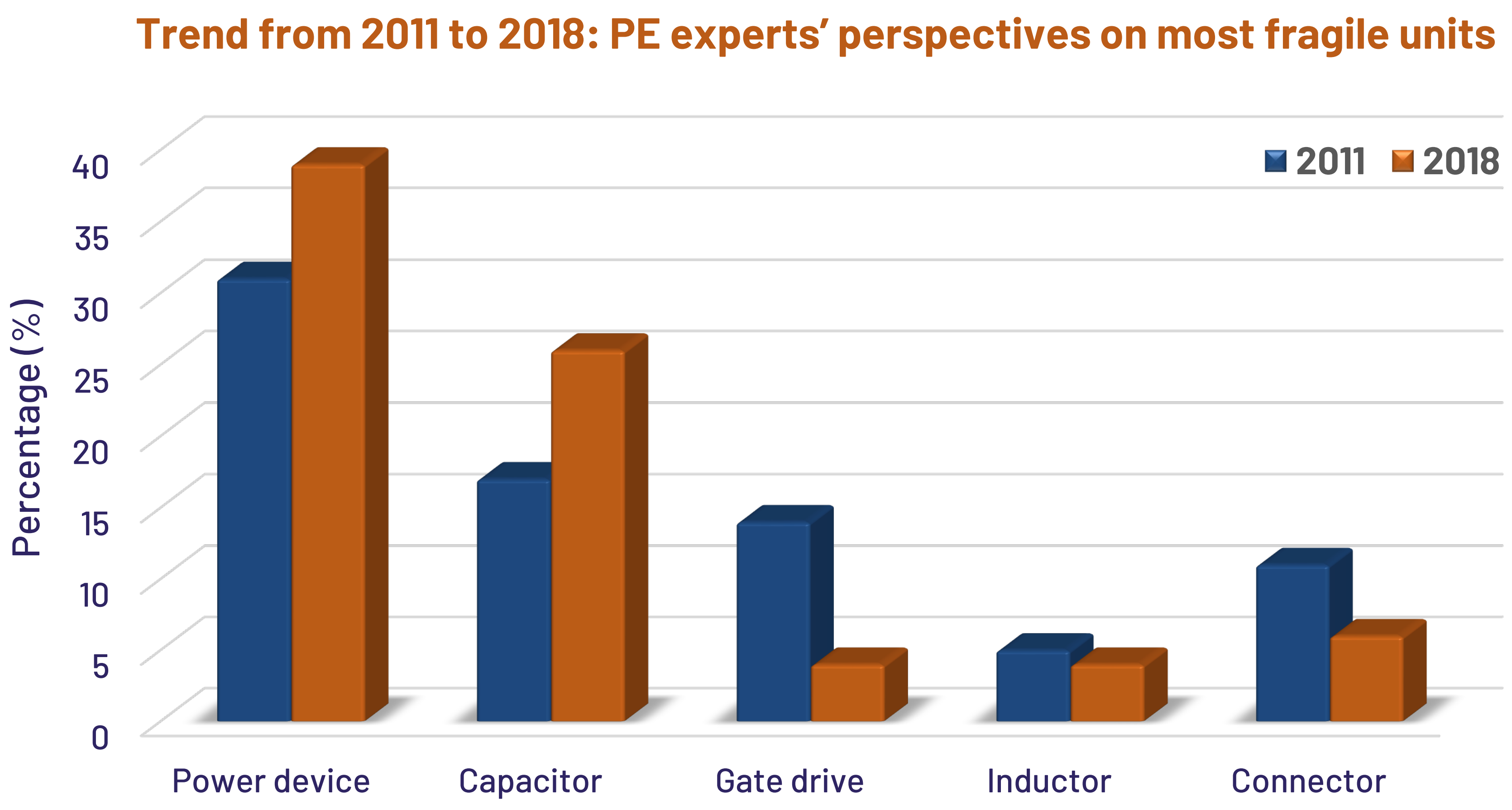


In your opinion, which trends/approaches will improve the system reliability of power electronics converters in the future?

Condition monitoring is very beneficial to system reliability

Source: Falck, Johannes, et al. "Reliability of power electronic systems: An industry perspective." IEEE Industrial Electronics Magazine 12.2 (2018): 24-35.

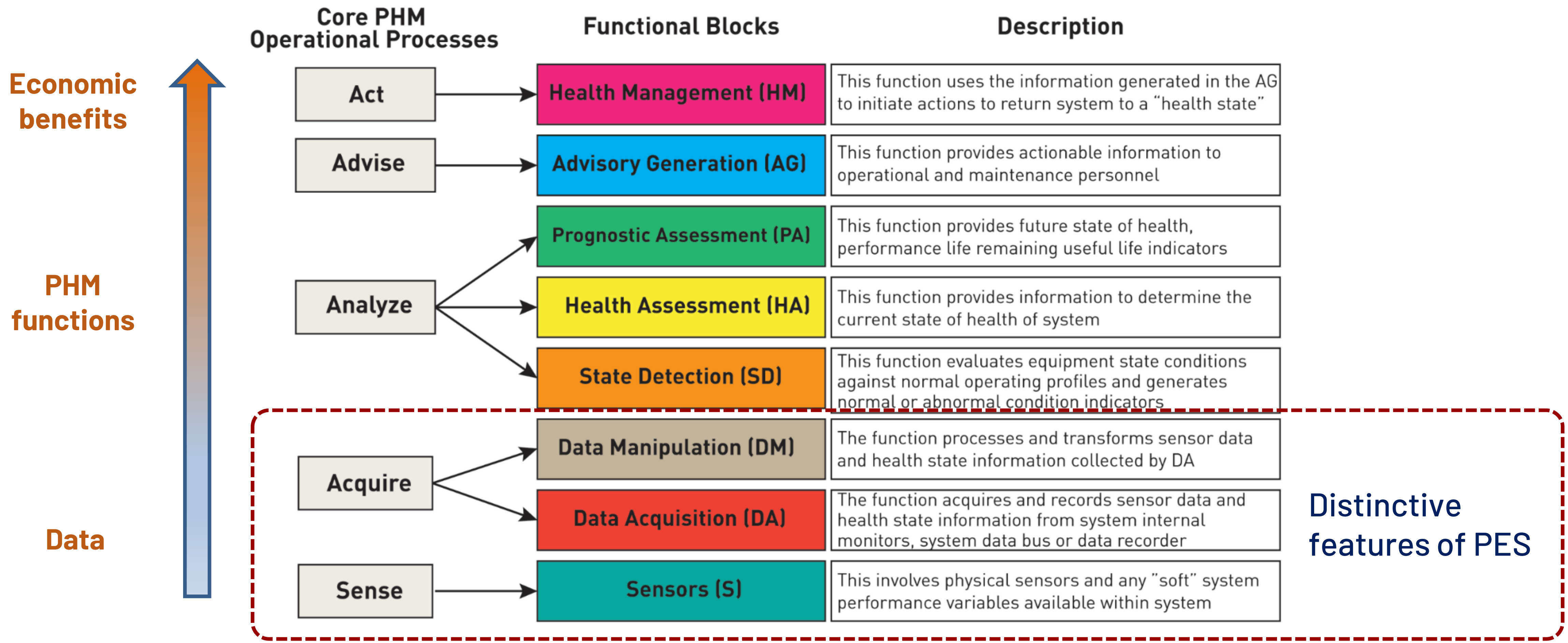
▶ Condition monitoring in industry



Power device and capacitor are two major fields with continuously strong requirement on condition monitoring

Source:
1. Yang, Shaoyong, et al. "An industry-based survey of reliability in power electronic converters." IEEE Transactions on Industry Applications 47.3 (2011): 1441-1451.
2. Falck, Johannes, et al. "Reliability of power electronic systems: An industry perspective." IEEE Industrial Electronics Magazine 12.2 (2018): 24-35.

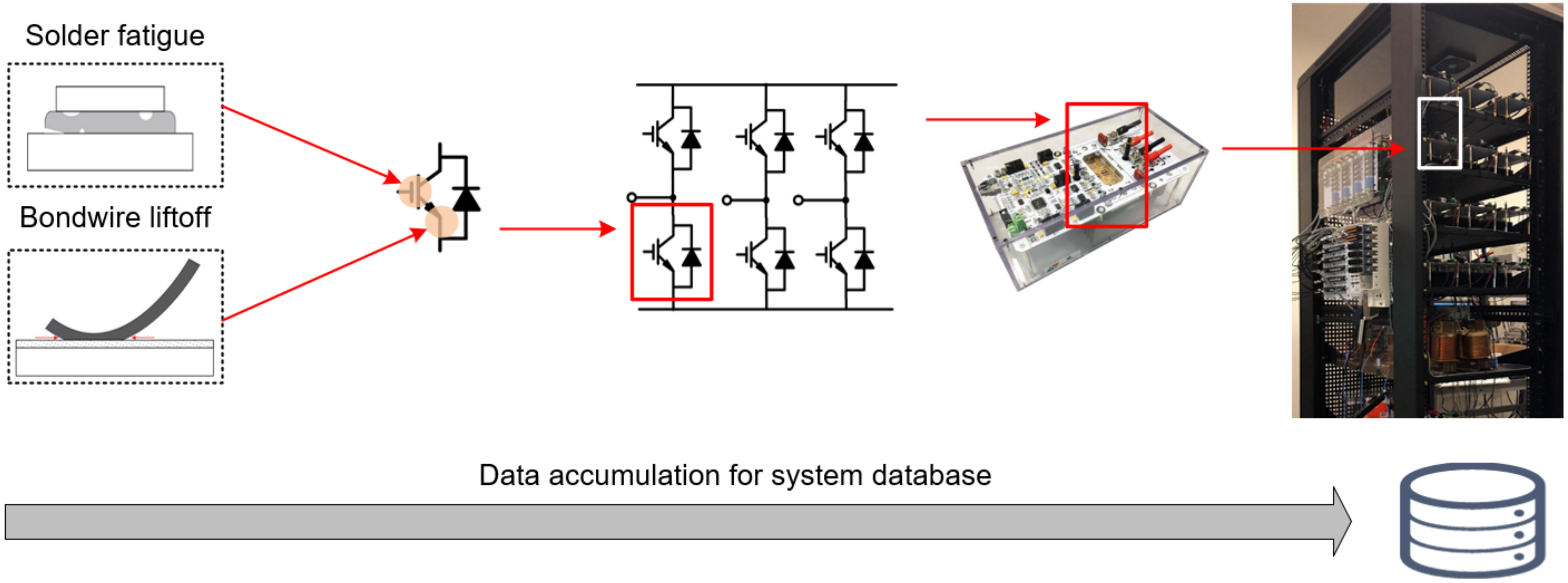
▶ IEEE PHM Standards for Electronic Systems



Source: IEEE Std 1856-2017: IEEE Standard Framework for Prognostics and Health Management of Electronic Systems.

▶ Implementation levels

Sub-component level	Component level	Assembly level	Sub-system level	System level
Film, solder mask, solder, bondwire, etc.	Capacitors, MOSFETs, IGBTs, diode, etc.	Power modules, capacitor banks, etc.	Power converters, inverters, etc.	Power electronic systems



▶ Condition monitoring precursors

■ Selection criteria

	Requirements	Possible solutions
1	Minimal impacts on system normal operation	- Non-invasive methods with less hardware
2	Feasible & economic implementation	- Optimize number of sensors - Cheap & effective
3	Reliable sensory solution with much slower degradation compared to system	- Highly robust sensory system
4	Omni-dimensional monitoring	- Temperature, current, voltage, parasitic parameters, turn-on/off time, volume, weight, humidity, etc.

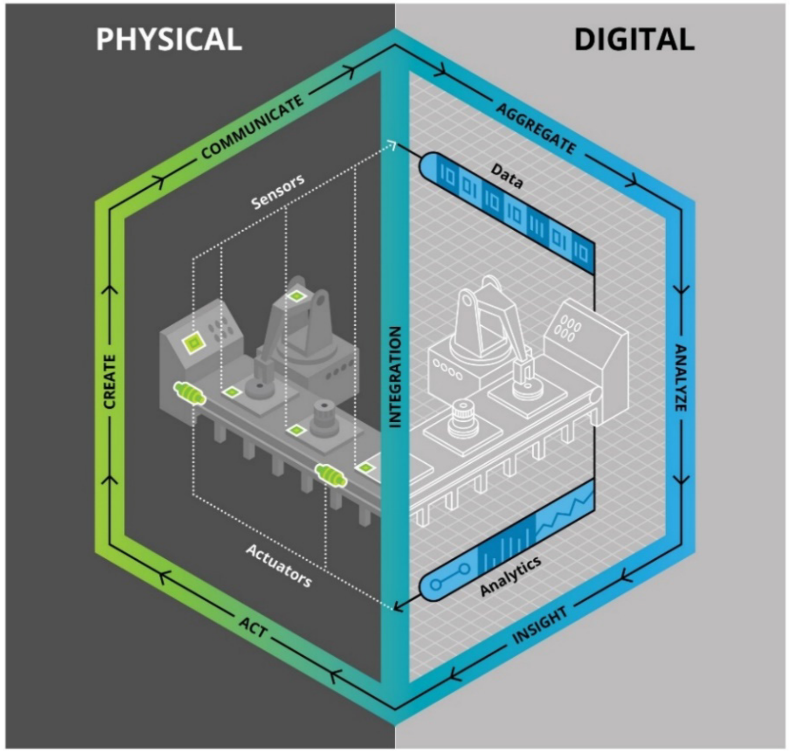
■ Features of condition monitoring system in PE

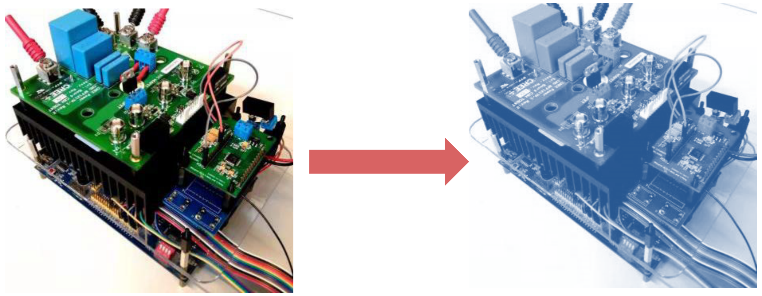
- Multi-failure modes
- Multi-sensory signals
- Multi-affecting factors
- Multi-modal data
- Multi-scale data

▶ Digital-twin for non-invasive condition monitoring

Source: Network world

Source: Deloitte Univ. Press





- Non-invasive condition monitoring
- Virtual sensing
- Highly accurate digital model of converter

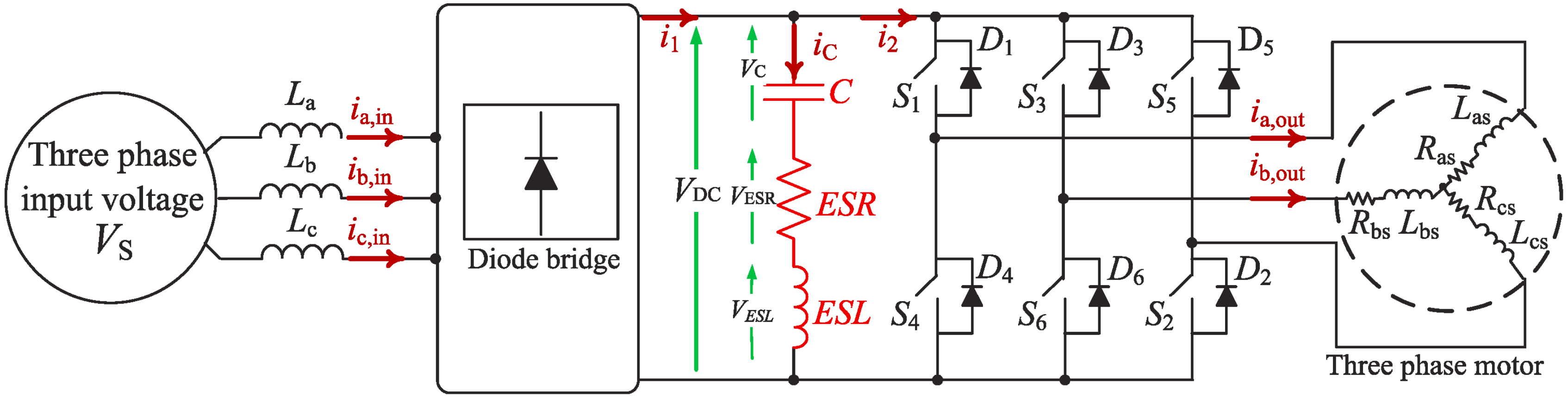
▶ Direction calculation with linearization

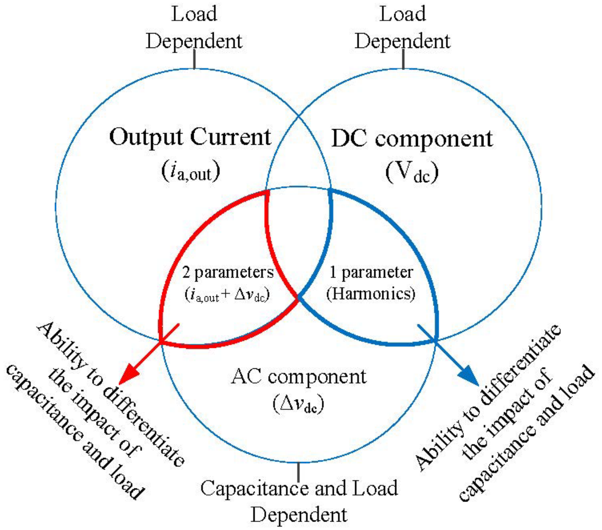
Run #	L	Calculation error of inductance (%)	C	Calculation error of capacitance (%)
1	L	22.8%	0.3C	14.2%
2	L	21.8%	0.5C	7.8%
3	L	21.2%	0.7C	4.0%
4	L	23.4%	0.9C	4.0%
5	L	22.0%	C	4.4%
6	L	21.8%	1.2C	9.1%
7	L	21.5%	1.6C	20.1%
8	L	19.2%	2C	34.0%

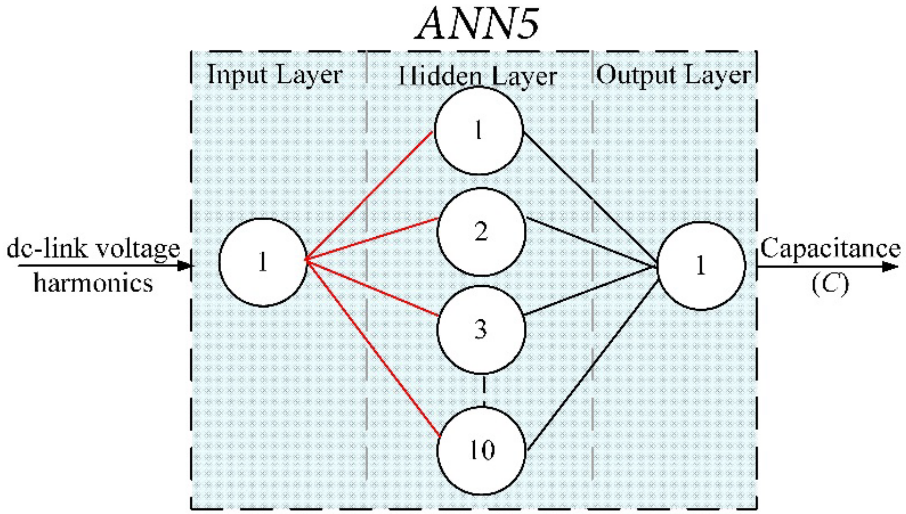
$$L = \frac{\bar{v}_o / D - \bar{v}_o}{\Delta i_L / \Delta t}$$

$$C = \frac{\Delta i_L \cdot T_s}{8 \cdot \Delta v_o}$$

▶ ANN-based condition monitoring

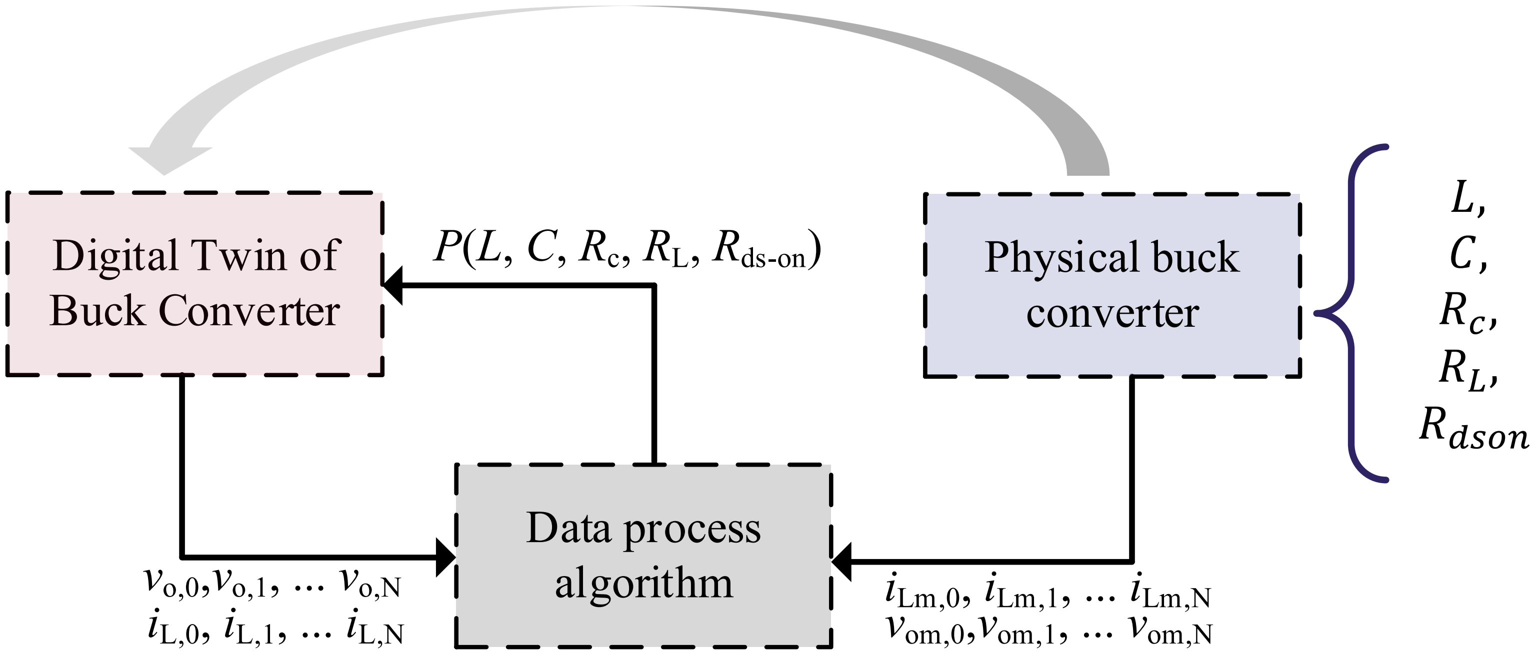






Source: Soliman, Hammam, et al. "Artificial neural network-based DC-link capacitance estimation in a diode-bridge front-end inverter system." 2017 IEEE 3rd International Future Energy Electronics Conference and ECCE Asia (IFEEC 2017-ECCE Asia). IEEE, 2017.

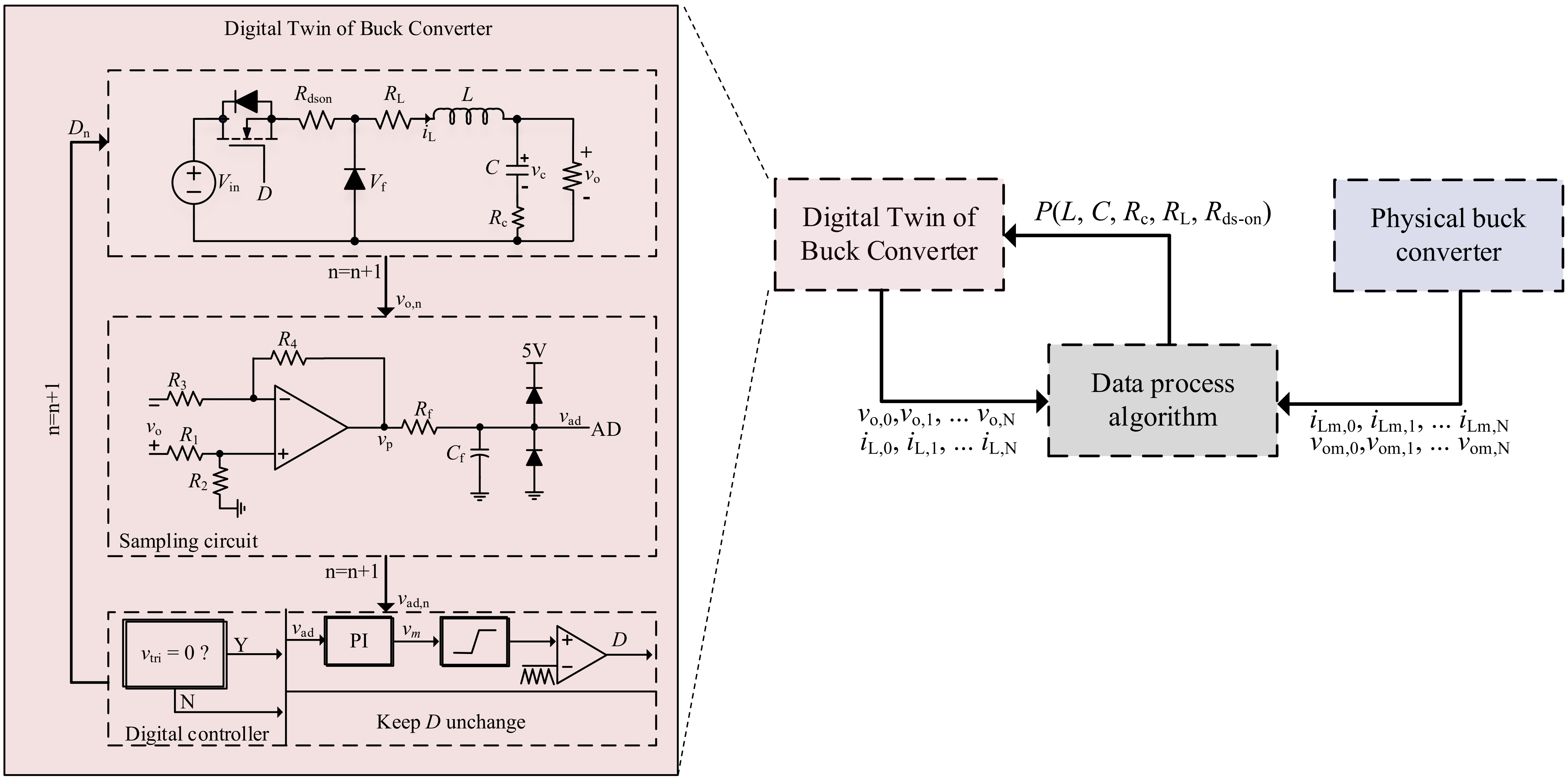
► Digital twin for condition monitoring (Ver. 1)



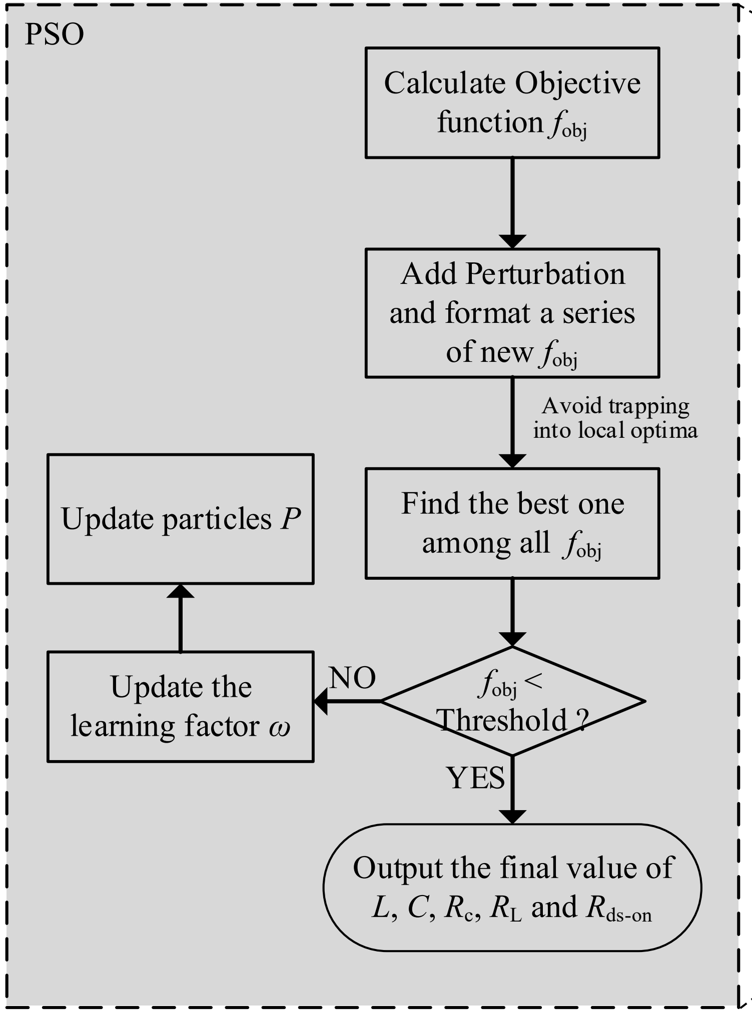
- **Digital twin is the digital replicate of a physical system**
- **They virtually share same operational characteristics**
- **It enables customers to better understand, optimize, predict, and monitor the performance of its installed systems**

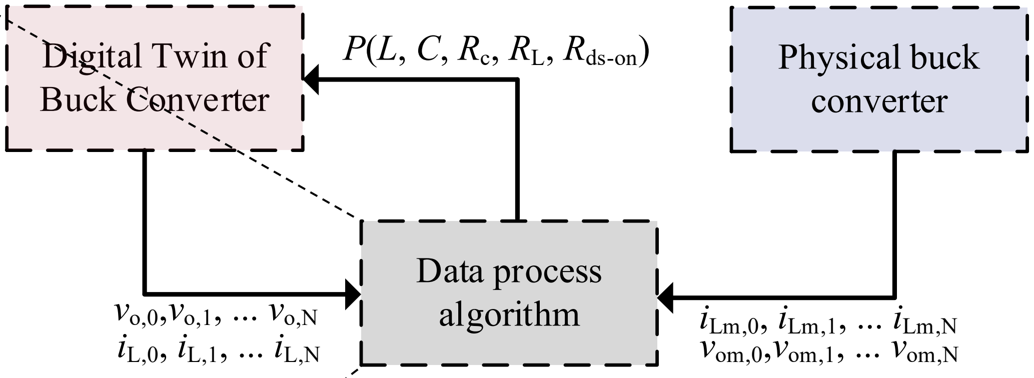
Source: Yingzhou Peng, Shuai Zhao, and Huai Wang, "A digital twin-based estimation method for health indicators of DC-DC converters," IEEE Transactions on Power Electronics, vol. 36, no. 2, pp. 2105 - 2118, Feb. 2021.

► Buck converter modeling



▶ Optimizer: Particle swarm optimization

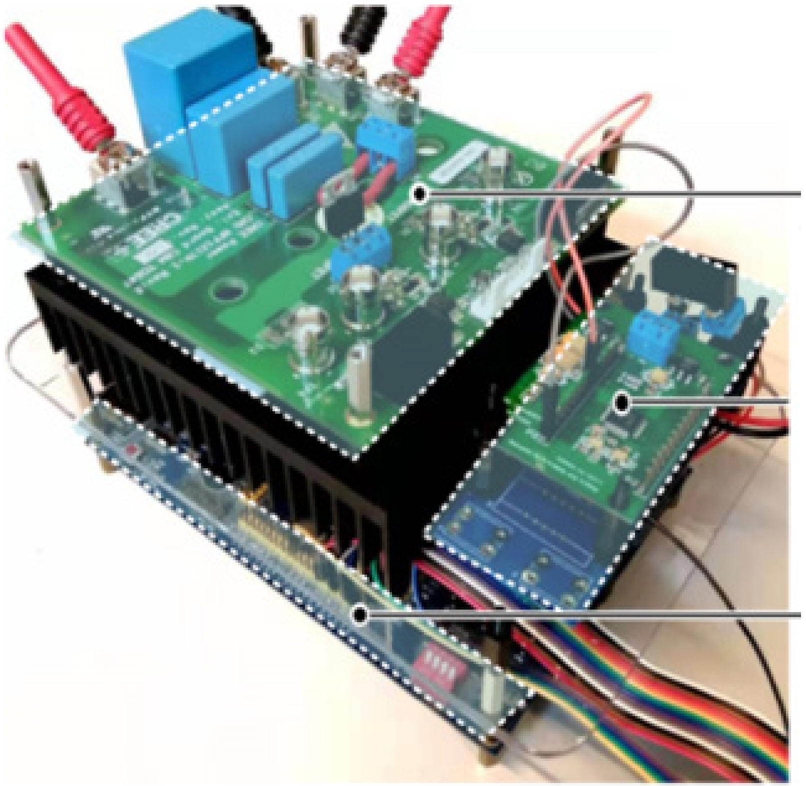




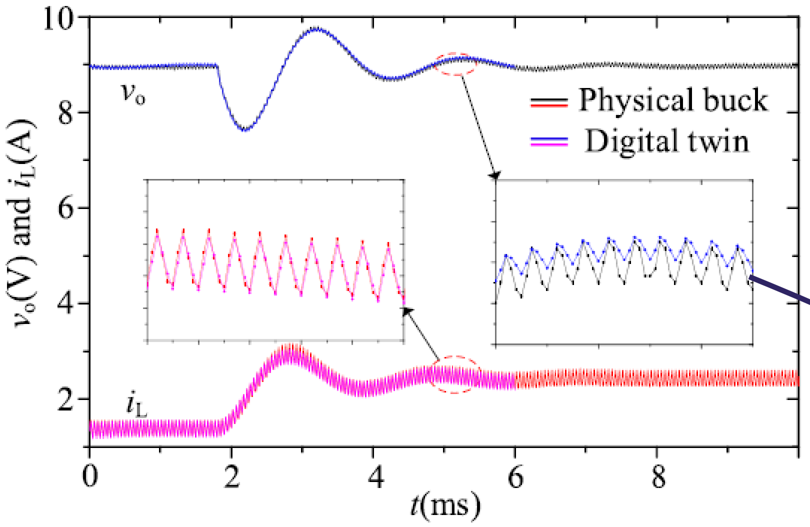
Particle swarm optimization (PSO)

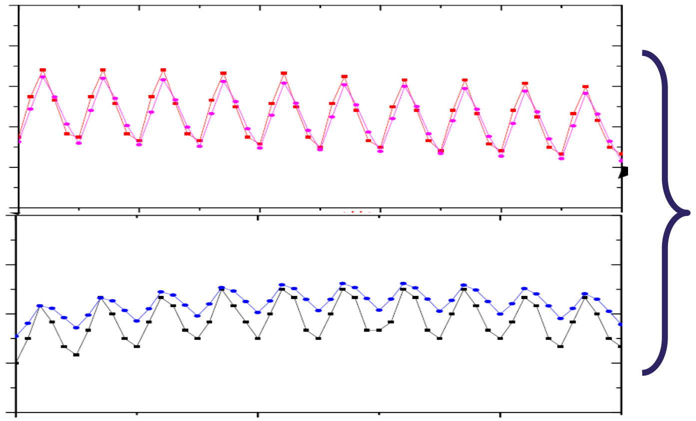
$$f_{obj} = \frac{\sum_{j=1}^{N}\left[\left(i_{L,j} - i_{Lm,j}\right)^2 + \left(v_{o,j} - v_{om,j}\right)^2\right]}{N}$$

▶ Hardware implementation

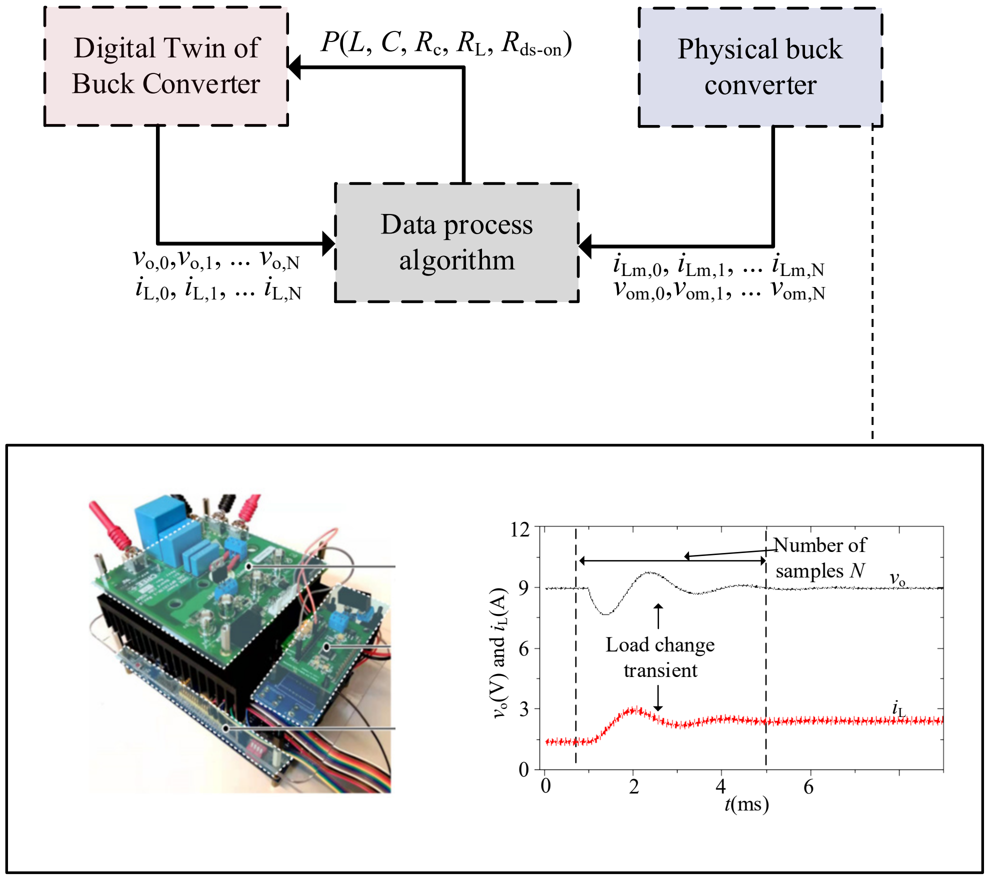


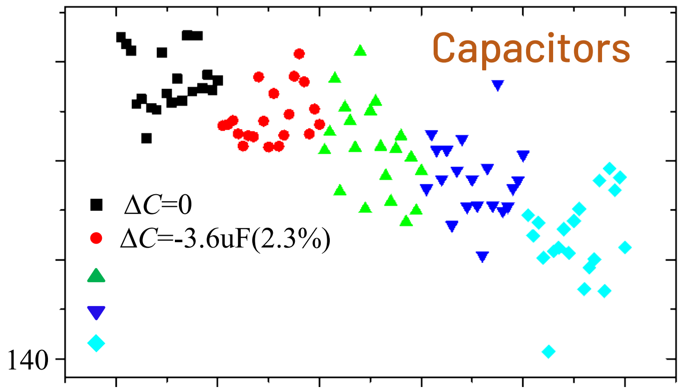
Load change transient waveform

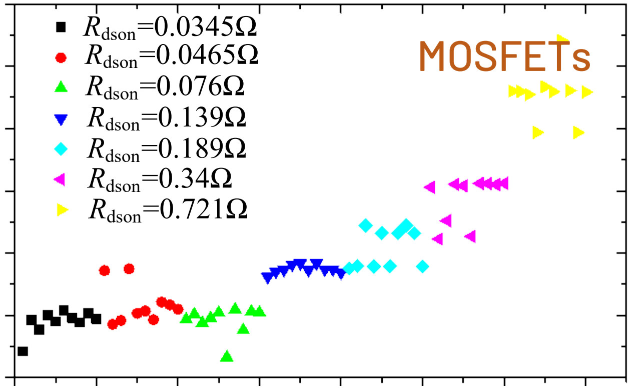




▶ Degradation detection

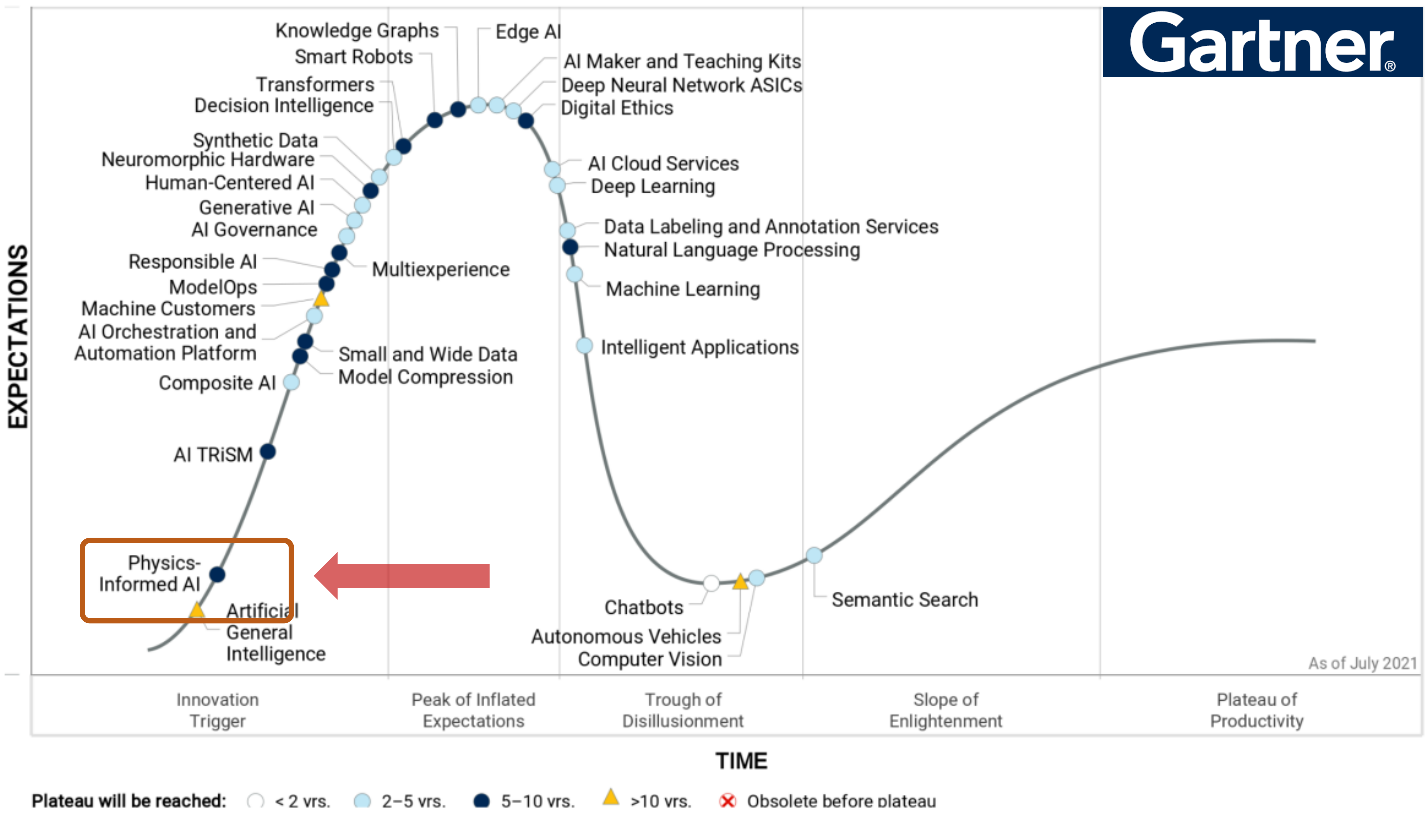






- **No additional hardware**
- **No calibration**
- **Converter-level for multi-components**

▶ Physics-informed AI for digital twin



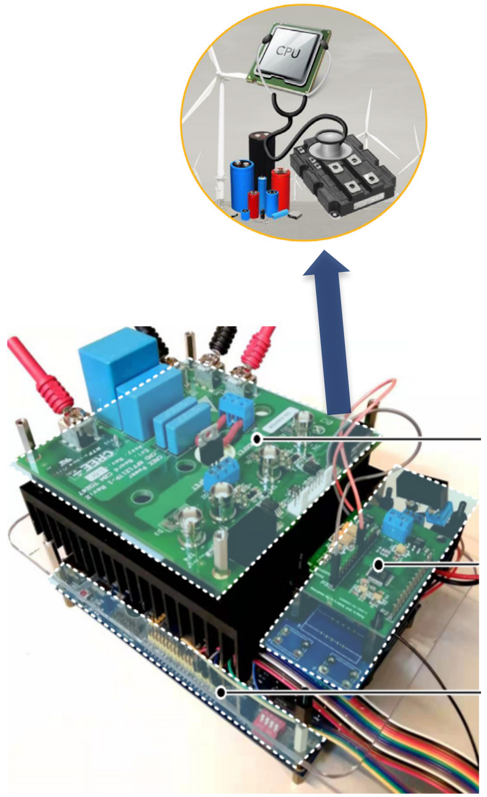
Physics-informed AI
starts riding Gartner Hype Cycle 2021

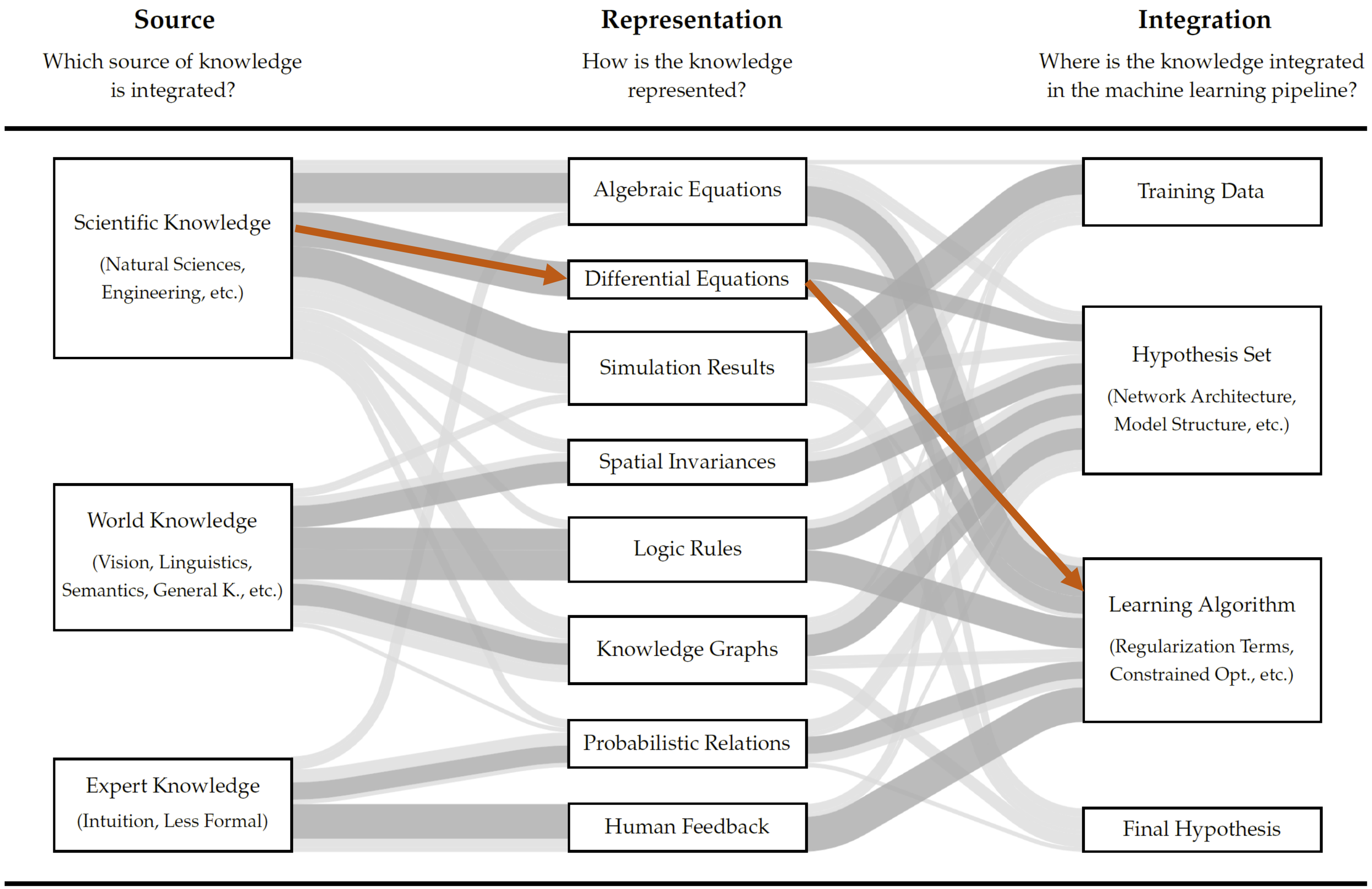
U.S. DoE Report (2019)
Blending physics and deep learning

Source: Hype Cycle for Artificial Intelligence, 2021, Gartner.

▶ Digital twin for condition monitoring (Ver. 2)

Physics-informed machine learning enabled digital twin for condition monitoring

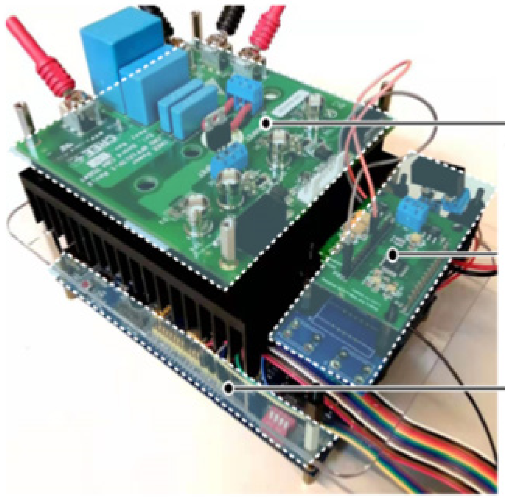


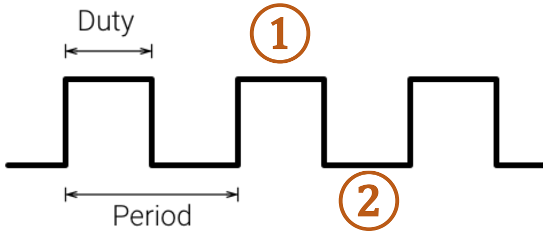


Source: S. Zhao, Y. Peng, Y. Zhang, H. Wang. "Parameter Estimation of Power Electronic Converters with Physics-informed Machine Learning", IEEE Transactions on Power Electronics, doi: 10.1109/TPEL.2022.3176468.

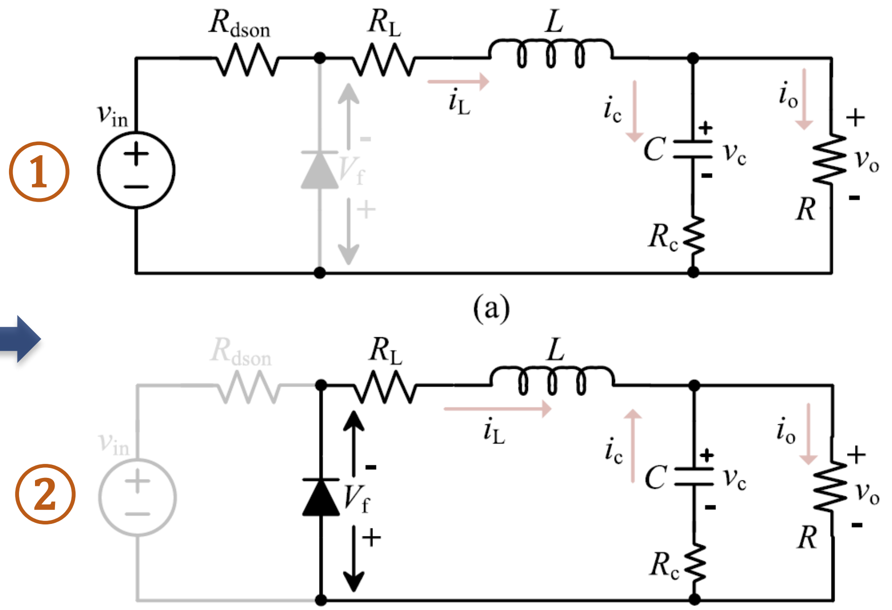
▶ Physical knowledge: converter model

Buck converter with continuous mode operation





PWM control seq.



Data:

- Inductor current i_L
- Output voltage v_o

Physical Parameters:

$$\boldsymbol{\theta} = \{L, R_L, C, R_C, R_{dson}, V_{in}, V_F, R\}$$

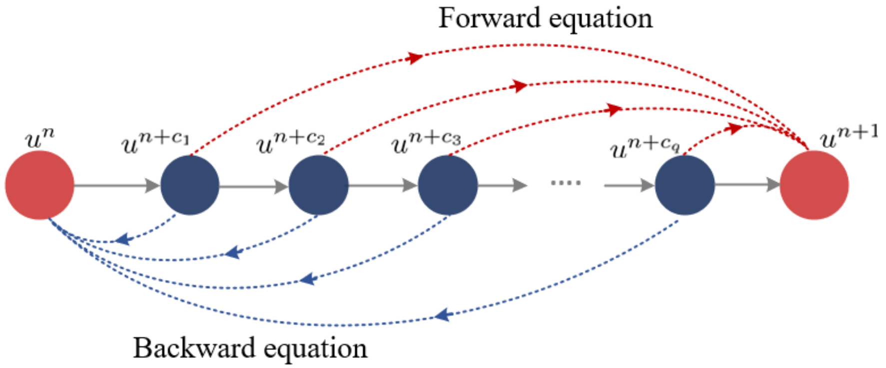
Converter dynamic model

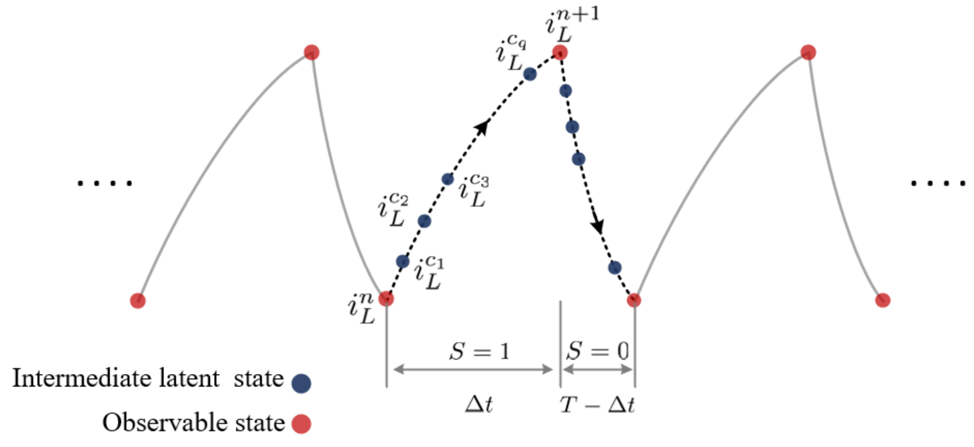
$$\begin{bmatrix} \frac{di_L}{dt} \\ \frac{dv_C}{dt} \\ v_o \end{bmatrix} = \begin{bmatrix} -\frac{A}{L} & -\frac{1}{L}(\frac{R}{R_C+R}) \\ \frac{1}{C}(\frac{R}{R_C+R}) & -\frac{1}{C}(\frac{1}{R_C+R}) \\ \frac{R_C R}{R_C+R} & \frac{R}{R_C+R} \end{bmatrix} \times \begin{bmatrix} i_L \\ v_C \end{bmatrix} + S \begin{bmatrix} \frac{v_{in}}{L} \\ 0 \\ 0 \end{bmatrix} + (1-S) \begin{bmatrix} \frac{-V_F}{L} \\ 0 \\ 0 \end{bmatrix}$$

Source: S. Zhao, Y. Peng, Y. Zhang, H. Wang. "Parameter Estimation of Power Electronic Converters with Physics-informed Machine Learning", IEEE Transactions on Power Electronics, doi: 10.1109/TPEL.2022.3176468.

► How to integrate physics and data

Implicit Runge-Kutta method





A general dynamic system

$$u_t + \mathcal{N}[u;\lambda] = 0, x \in \Omega, t \in [0,T].$$

$$\boxed{f := u_t + \mathcal{N}[u;\lambda]}$$

Backward eq. $$u_i^n = u^{n+c_i} + \Delta t \sum_{j=1}^{q} a_{ij}\mathcal{N}[u^{n+c_j};\lambda],$$

Forward eq. $$u_i^{n+1} = u^{n+c_i} + \Delta t \sum_{j=1}^{q} (a_{ij} - b_j)\mathcal{N}[u^{n+c_j};\lambda].$$

$$\boldsymbol{\theta} = \{L, R_L, C, R_C, R_{dson}, V_{in}, V_F, R\}$$

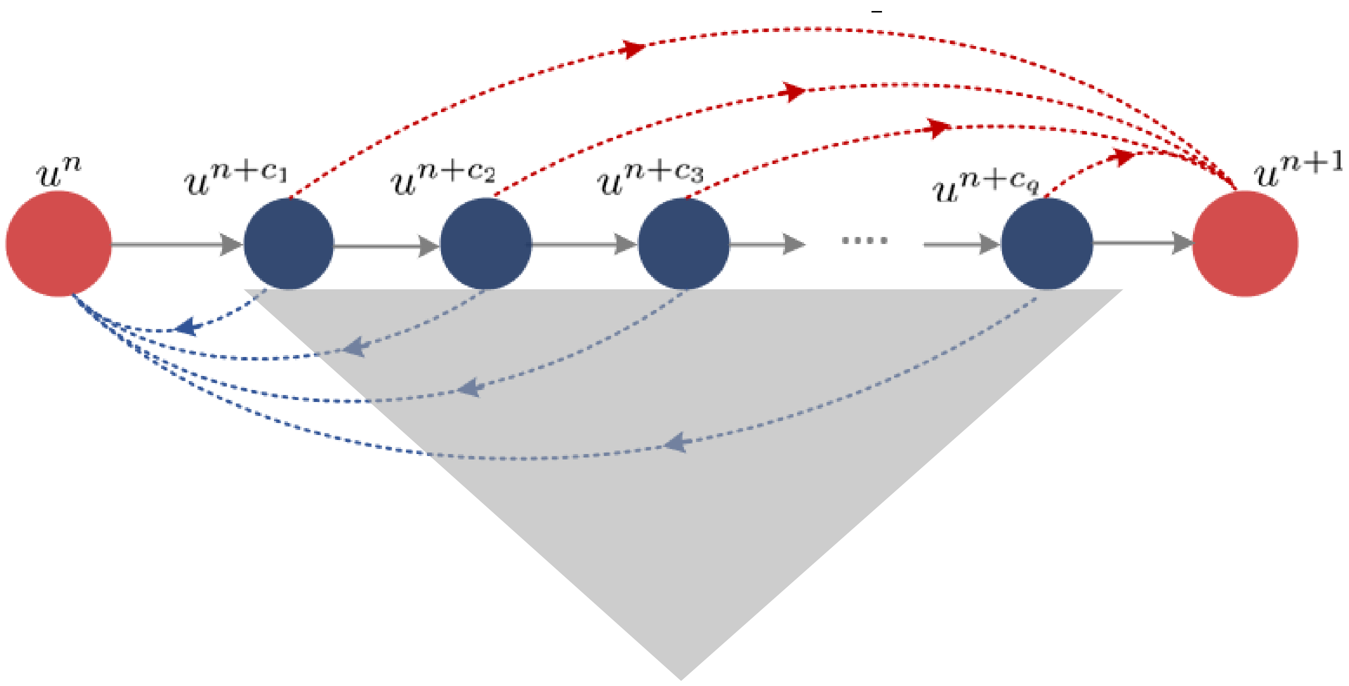
Inductor current

$$\frac{di_L}{dt} + \mathcal{N}[i_L;\boldsymbol{\theta}] = 0, \quad \mathcal{N}[i_L;\boldsymbol{\theta}] = \frac{\begin{bmatrix} (S \cdot R_{dson} + R_L)i_L + v_o \\ -S \cdot V_{in} + (1-S) \cdot V_F \end{bmatrix}}{L}$$

$$\frac{dv_o}{dt} + \mathcal{N}[v_o;\boldsymbol{\theta}] = 0, \quad \mathcal{N}[v_o;\boldsymbol{\theta}] = \frac{v_o + C \cdot R_C \cdot R \cdot \mathcal{N}[i_L] - R \cdot i_L}{C \cdot (R_c + R)}$$

Output voltage

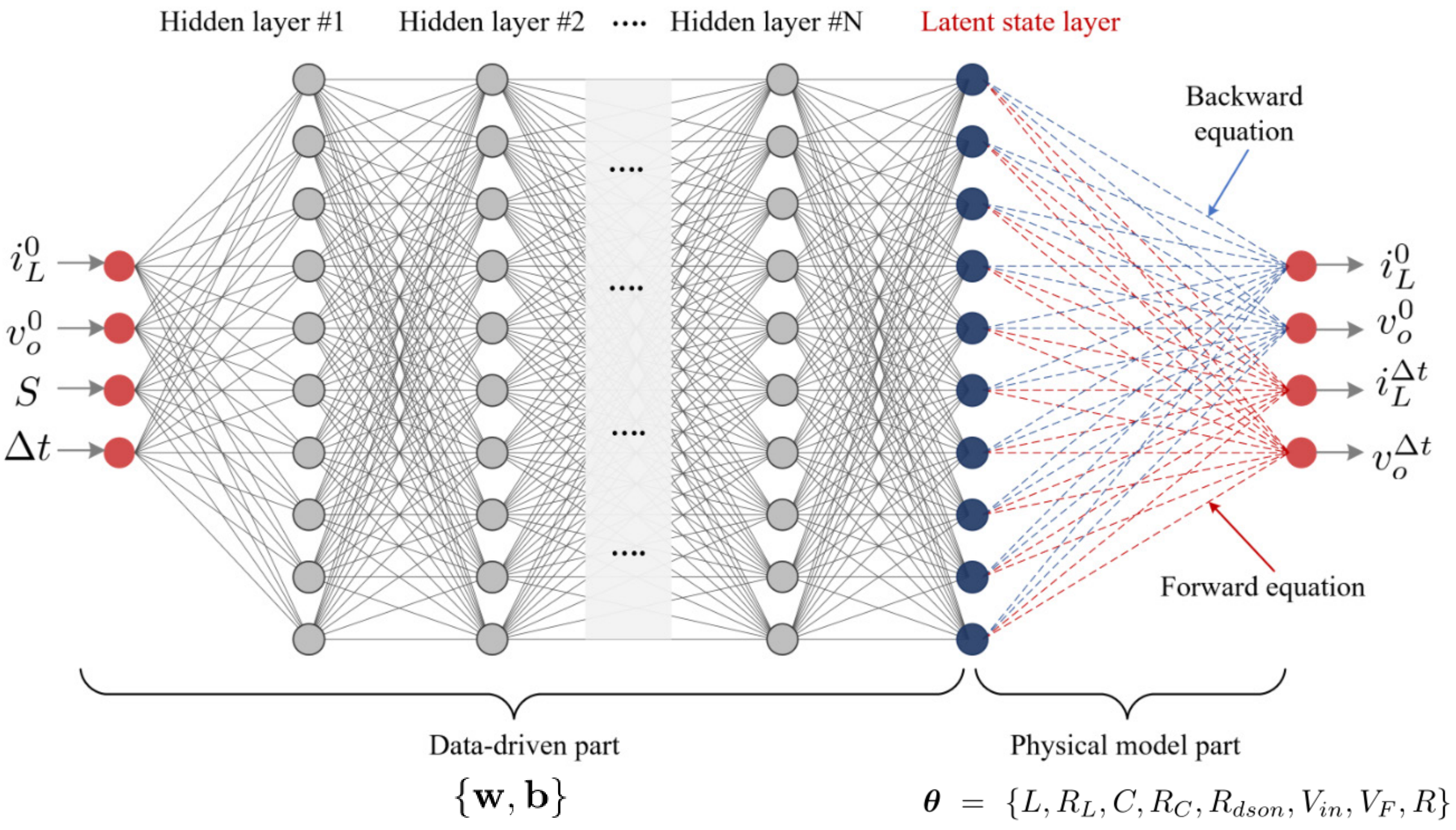
▶ How to integrate physics and data



How can approximate these intermediate hidden states?

Deep neural network: a powerful approximator to nonlinear function with arbitrary accuracy

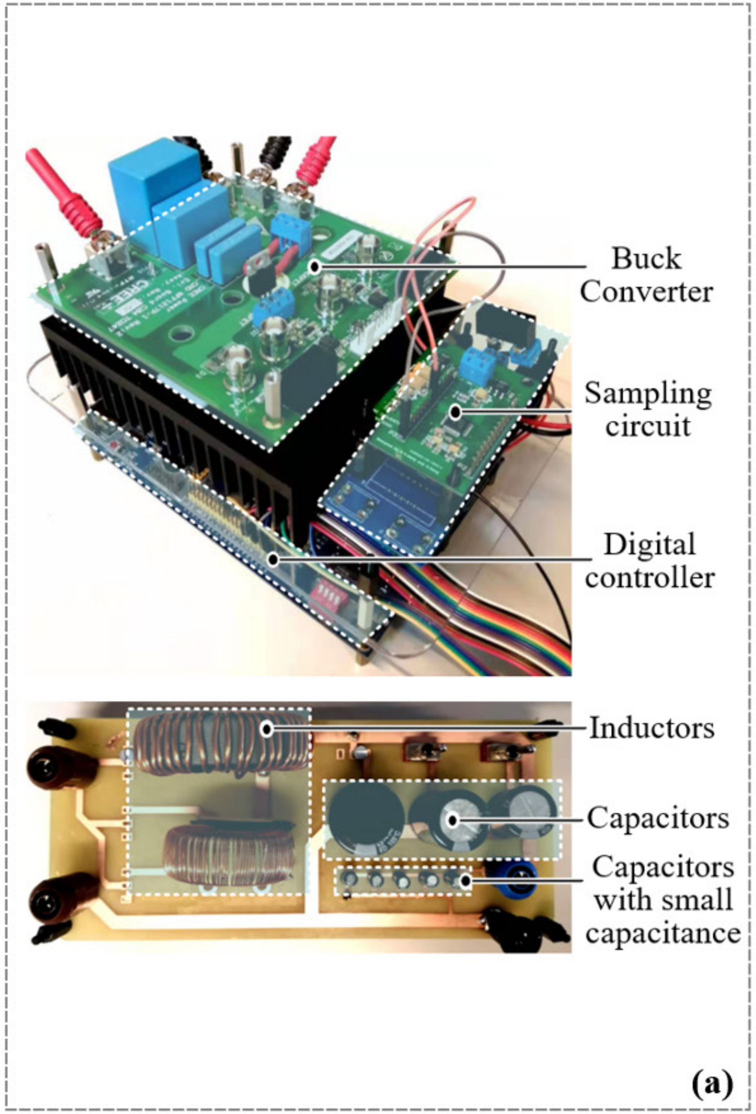
▶ Physics-informed neural network architecture

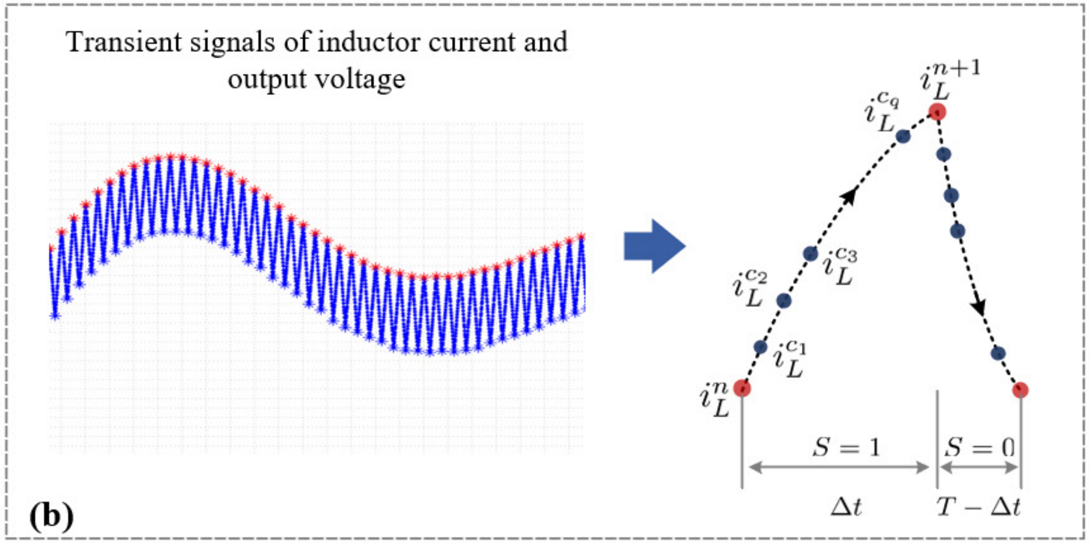


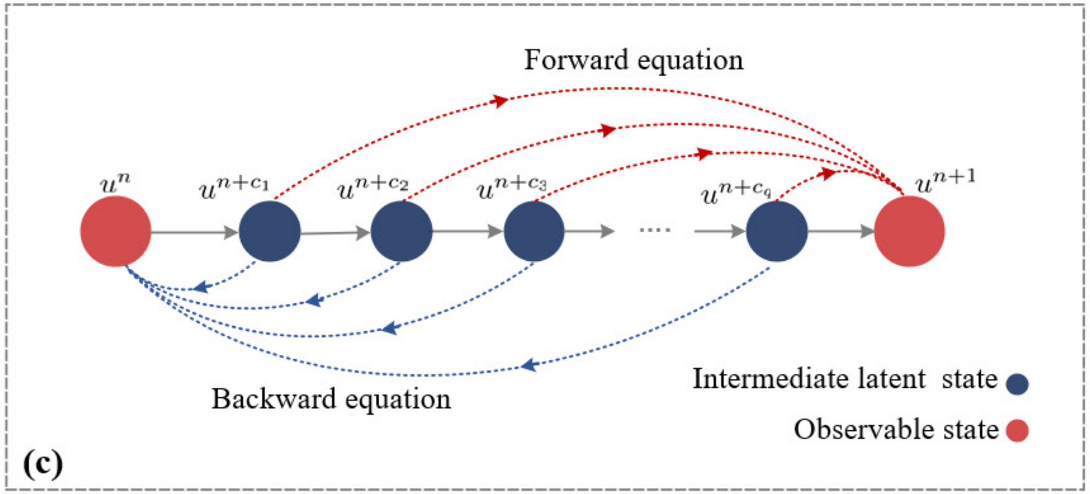
- Differentiable physics for Backprop training
- Data-light by seamlessly integrated data & physics
- Scalable to larger systems
- Robust & accurate

https://github.com/ms140429/PIML_Converter

▶ Hardware and data acquisition





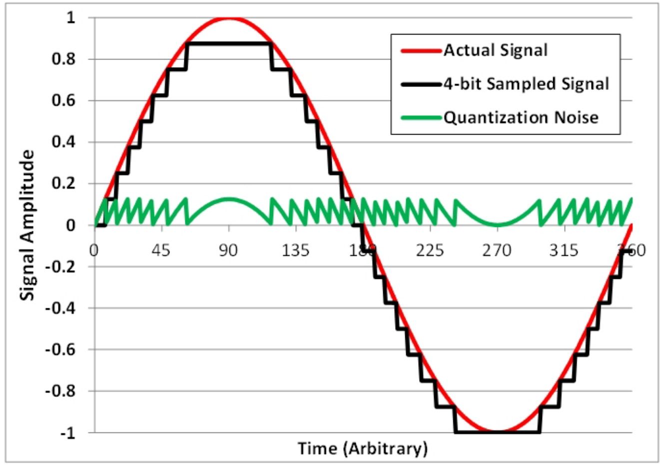


▶ Testing & verification

Loss function

$$E(\boldsymbol{\Theta}) = \sum(i_L^0 - \hat{i}_L^0)^2 + \sum(i_L^{\Delta t} - \hat{i}_L^{\Delta t})^2 + \sum(v_o^0 - \hat{v}_o^0)^2 + \sum(v_o^{\Delta t} - \hat{v}_o^{\Delta t})^2$$

- 360 data samples (data-light)
- 5 layers, 50 neurons in each layer
- ~15 mins (Xeon CPU E5-2620, 2.4 GHz)



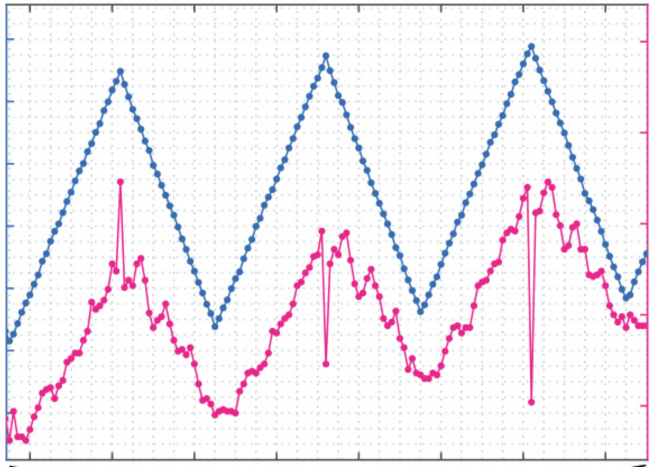
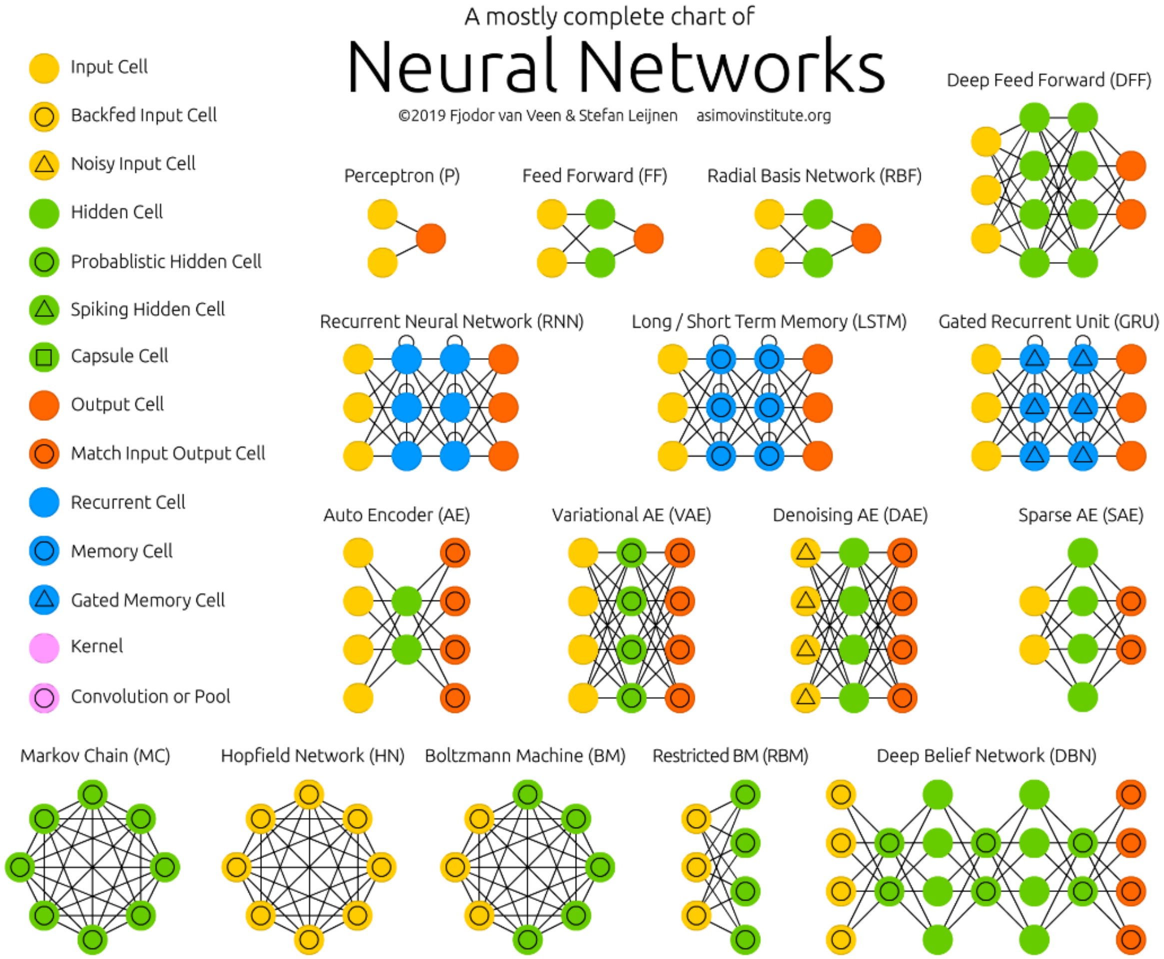


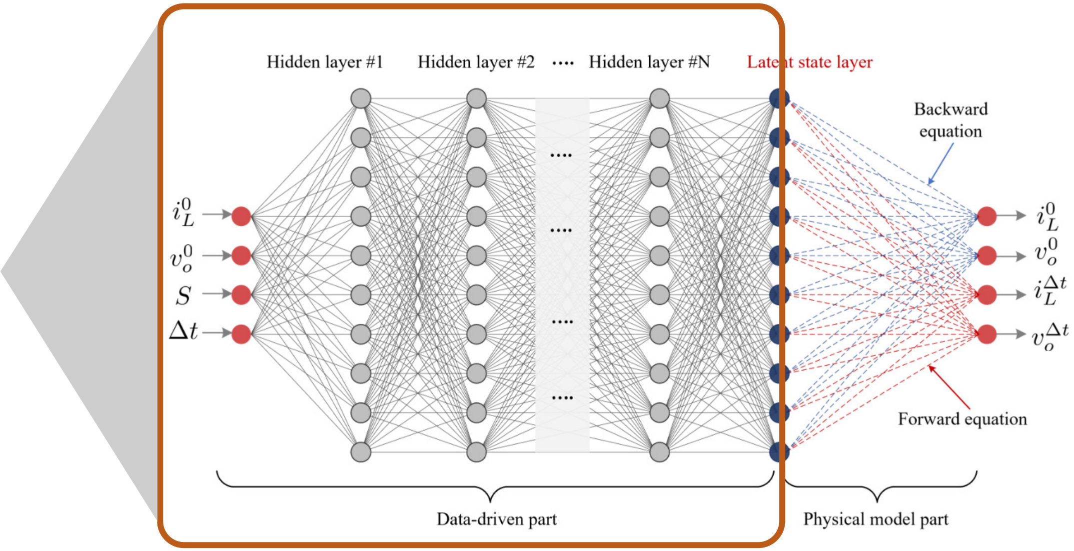
Table II: Percentage error (%) of component parameters in different testing cases (ADC error: ADC quantization error; Sync error: Synchronization error)

Testing (mean) \ Error (%)	L	R_L	C	R_C	R_{dson}	R_D	R_1	R_2	R_3	V_{in}	V_F
Clean data (0.0073)	8.35e-4	0.011	0.003	0.026	0.009	0.003	6.42e-4	3.53e-4	0.001	5.79e-4	0.026
ADC error (0.109)	0.004	0.217	0.040	0.111	0.460	0.063	4.03e-4	0.051	0.009	0.011	0.227
Sync error (1.444)	0.361	0.513	0.018	5.697	0.030	0.289	0.006	0.013	0.007	0.178	8.765
5 noise (0.743)	0.053	0.615	0.139	2.772	0.823	0.021	0.005	0.133	0.092	0.080	3.437
10 noise (1.966)	0.301	1.104	0.661	5.520	0.594	0.402	0.005	0.287	0.180	0.267	12.305
ADC-Sync-5noise (3.350)	0.833	5.915	1.019	5.214	11.007	1.075	0.036	0.035	0.067	0.266	11.389
ADC-Sync-10noise (4.768)	0.950	13.027	1.109	4.369	27.267	3.618	0.102	0.173	0.152	0.124	1.558

► Explore a better network



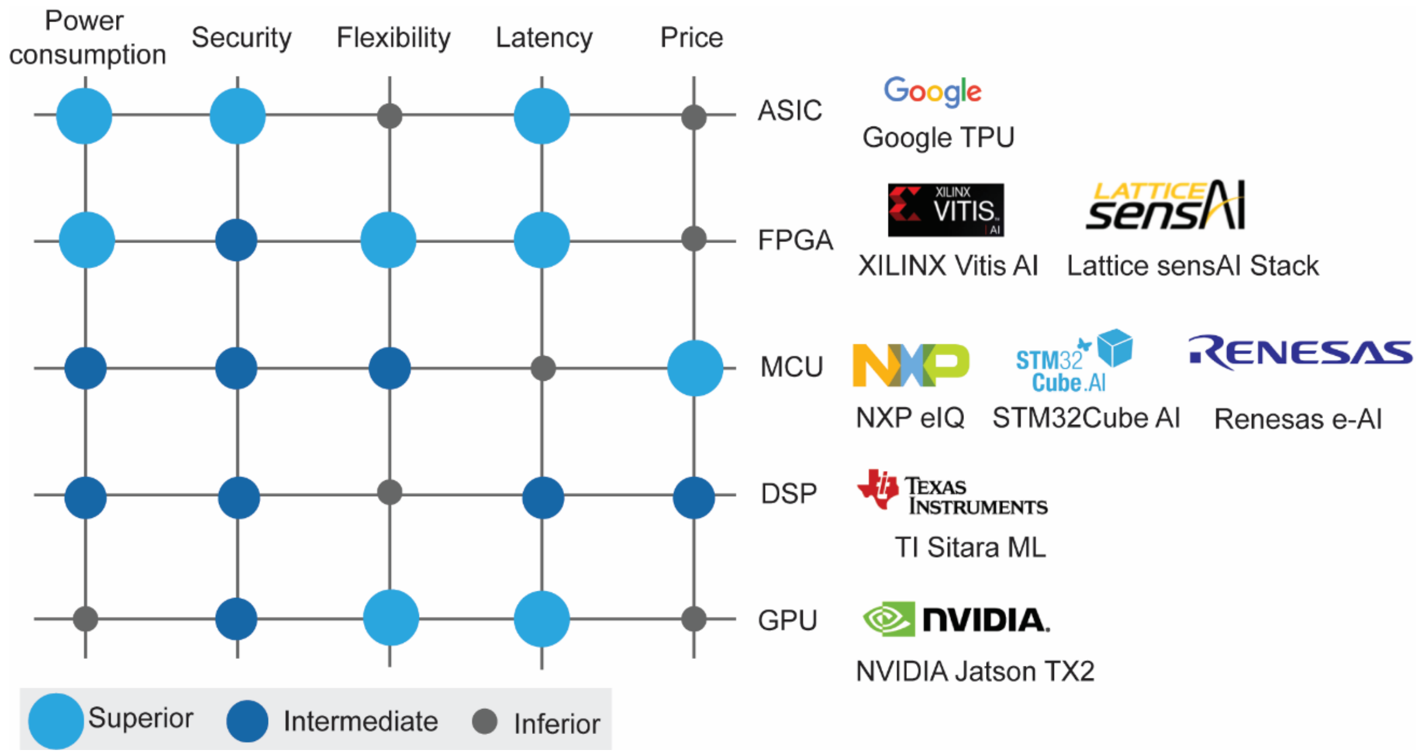
Can we find a more efficient structure from neural network zoo?

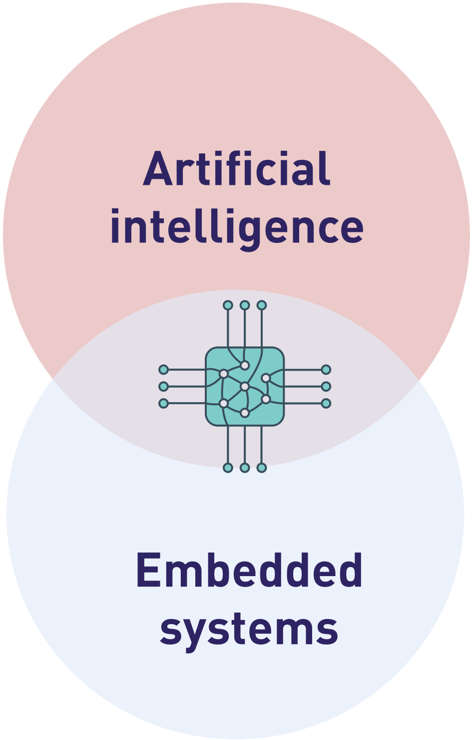


- Number of layers
- Neuron size
- New architecture
- …

Source: X. Wu, B. Yang, D. Zhang, M. Zhang, C. Guo, S. Zhao and H. Wang, AutoPIML: when AutoML meets physics-informed neural network, CIKM 2022.

▶ Smart edge node





NVIDIA

$129

Google

$129

STM32 Cube.AI

$4-8

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Source: S. Zhao, H. Wang, Enabling Data-Driven Condition Monitoring of Power Electronic Systems With Artificial Intelligence: Concepts, Tools, and Developments. IEEE Power Electronics Magazine, 8(1), 18-27, 2021.

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