

Application-oriented performance evaluation of digital twins for buildings

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OpenBlue Digital Twin | Overview | Spotlight: OpenBlue Digital Twin | Spotlight: OpenBlue Bridge | [Contact Us](#)

OpenBlue Digital Twin

Locations, Events, Assets and People come together with Johnson Control's Digital Twin as the AI-infused foundation to intelligent buildings.

Digital twins help organize and enrich multiple data silos to provide centralized context for your enterprise while maximizing value.

AI infusion across the data context and sources help to enable predictive outcomes in real time.

Using an API-driven approach, OpenBlue Digital Twin is developed on the building blocks of an open architecture. The brick standard is core to our interfaces and data structure.



3D BIM

Digital Twin Visualization

Digital Twinning is integrated into the 3D BIM for contextual visualization, enabling an immersive analysis of your

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Building Twin

The Building Twin allows a connected, digital representation of a physical building. It brings together dynamic and static data from multiple sources in 2D/3D models and enables informed and effective decisions to be made. It bridges the physical and digital worlds through sensors that collect real-time data within the physical environment. It provides real-time understanding of how a building is ...

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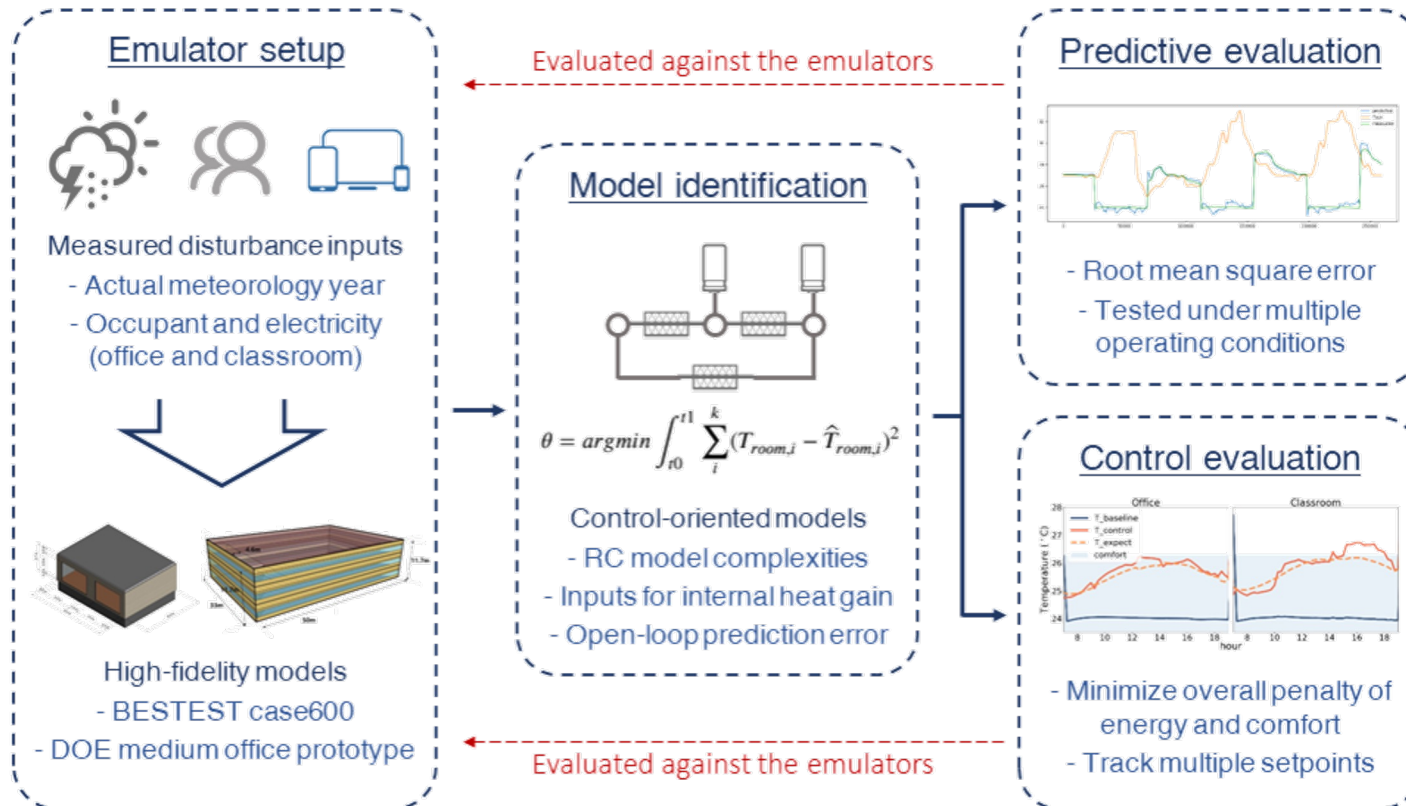
Existing digital twin solutions

- 3D BIM model
- Data acquisition
- Data visualization
- Energy prediction & evaluation

Digital twins: Computational models that replicate the behaviour of real-world systems, conducting virtual experiments in **unseen scenarios** and supporting **decision-making**



Resistor-capacitor model for control



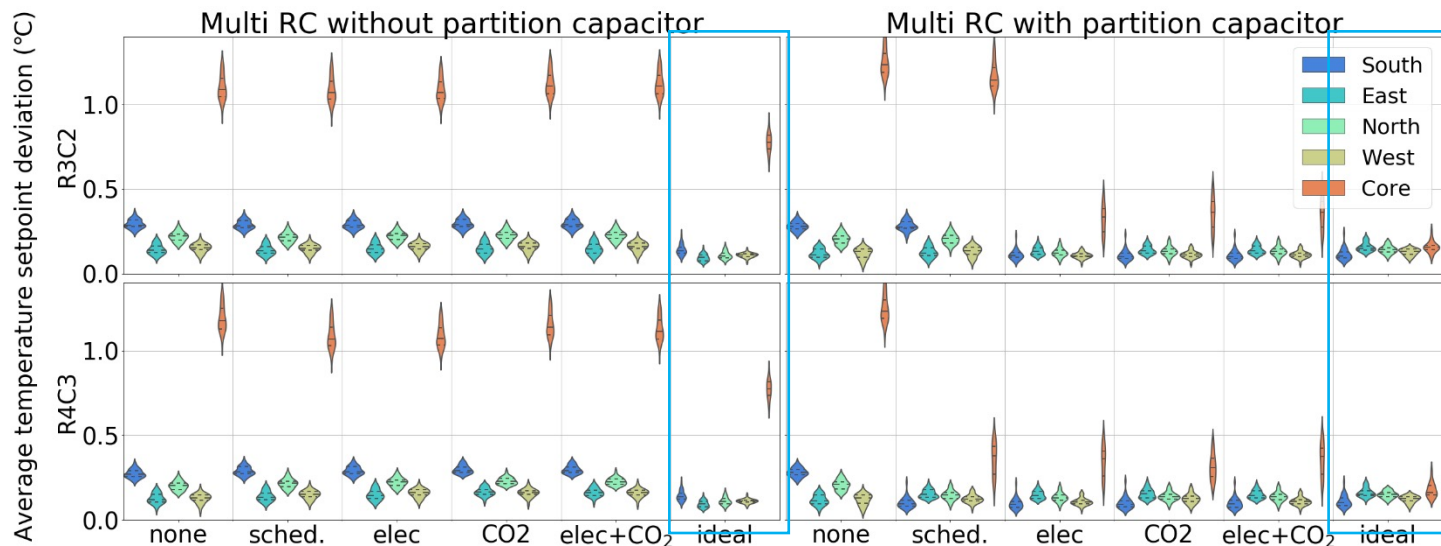
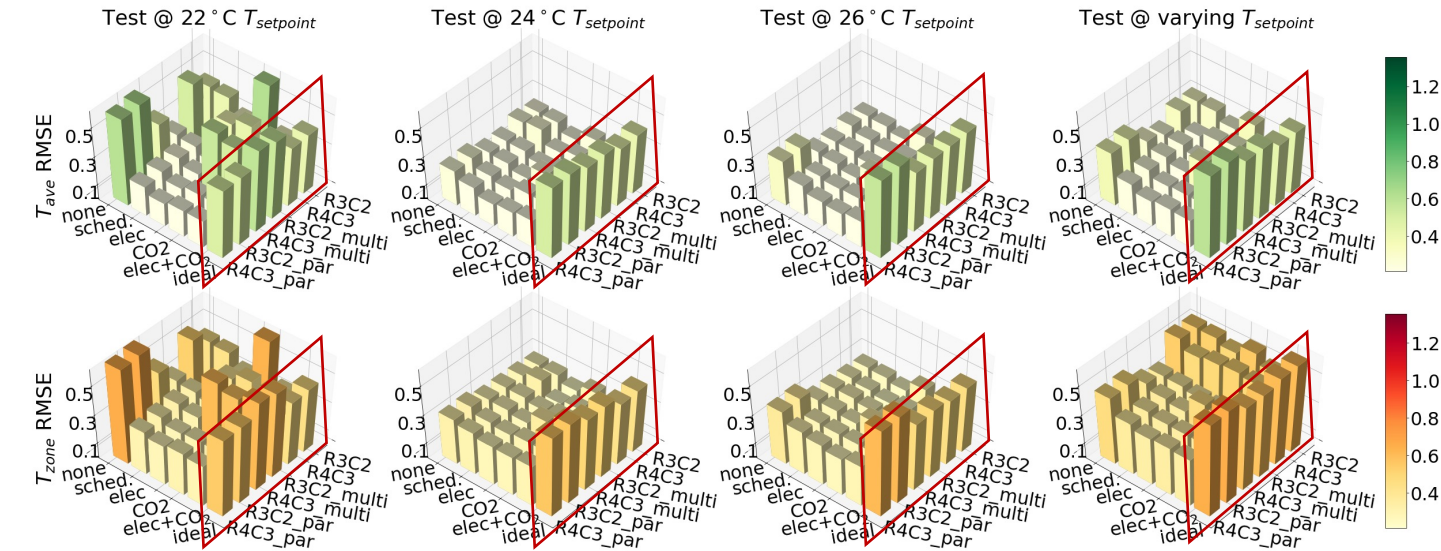
- Increasing RC model complexity
- Identified with the same dataset through non-linear programming

$$\theta = \operatorname{argmin} \int_{t_0}^{t_1} \sum_i^k (T_{room,i} - \hat{T}_{room,i})^2 dt$$

$$s.t. \quad \hat{T}_{room} = f(x, u, d, \theta)$$

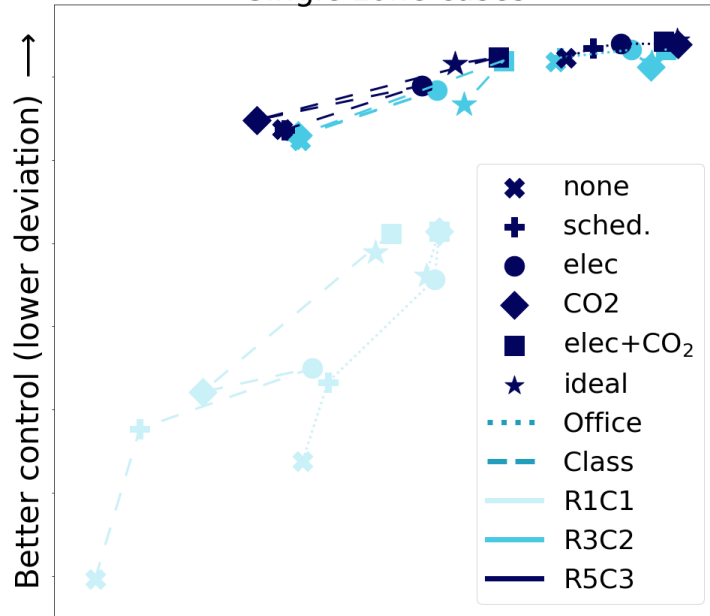
$$\theta^{lb} \leq \theta \leq \theta^{ub}$$

- Prediction under different conditions (extrapolation capability)
- Virtual control experiments on high fidelity models

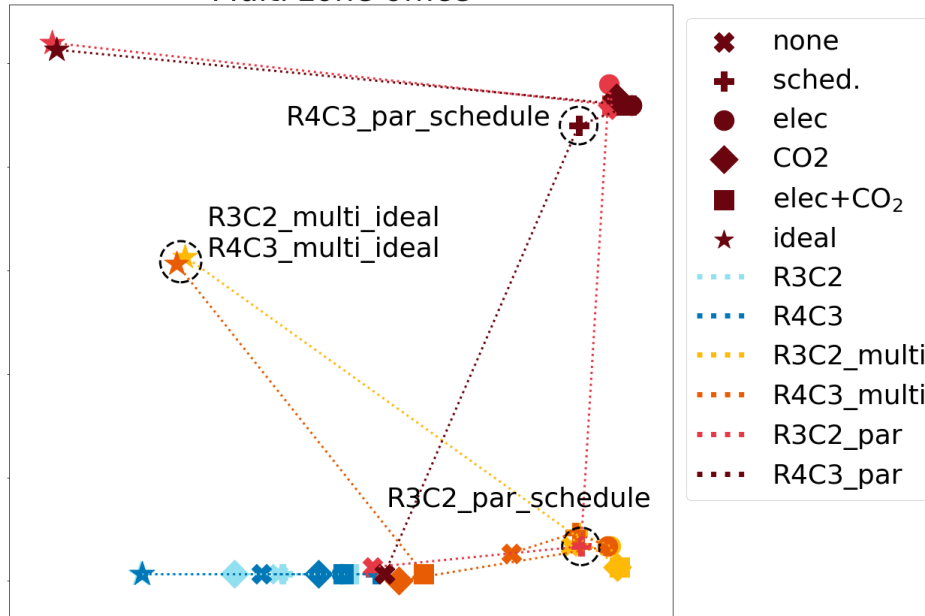


- The identification underestimate partition capacitor for lower RMSE
 - NOT detected by prediction tests
 - Yielded control deviations
- More representative input resulted in larger prediction error but better control

Single zone cases

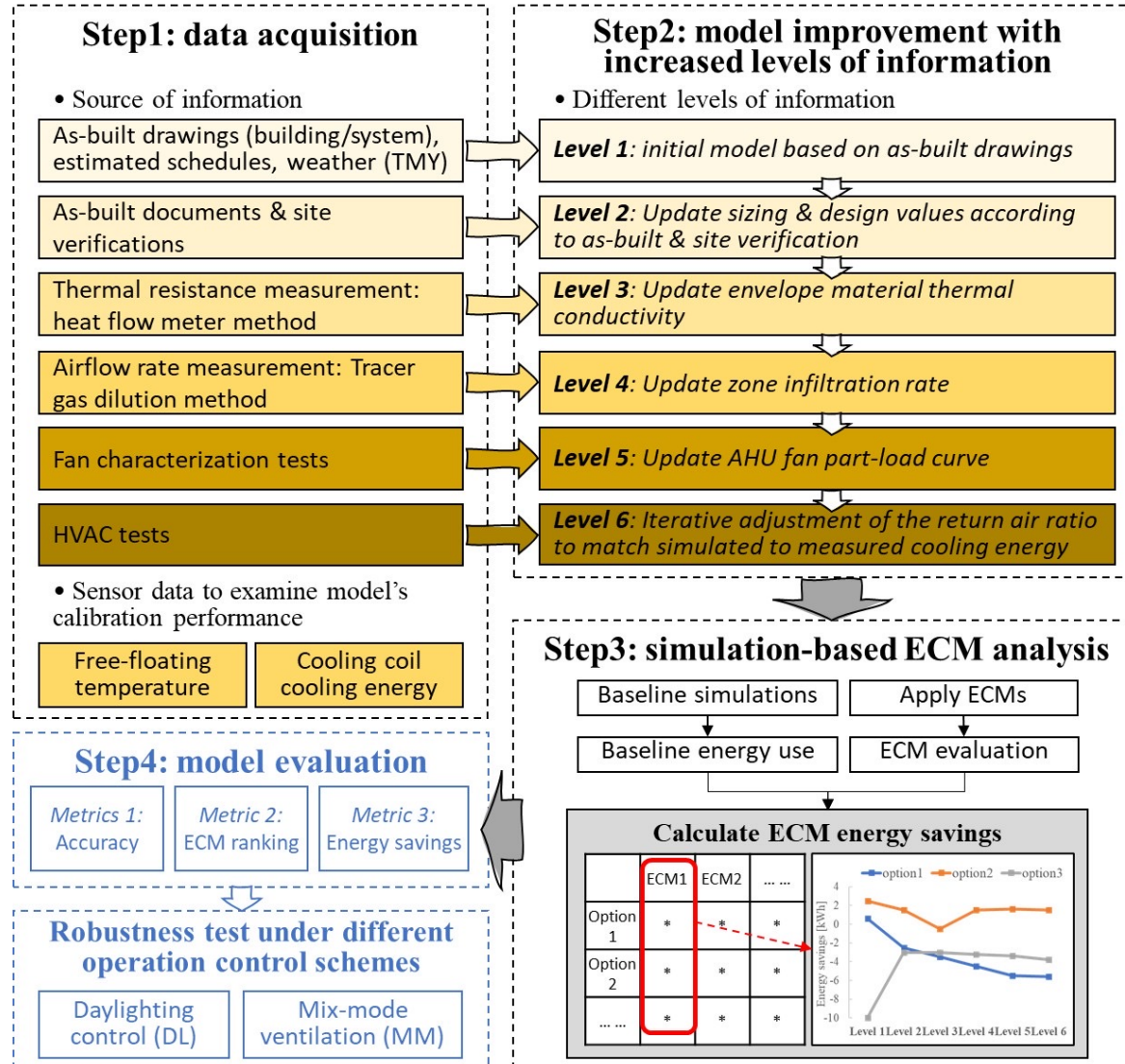


Multi zone office



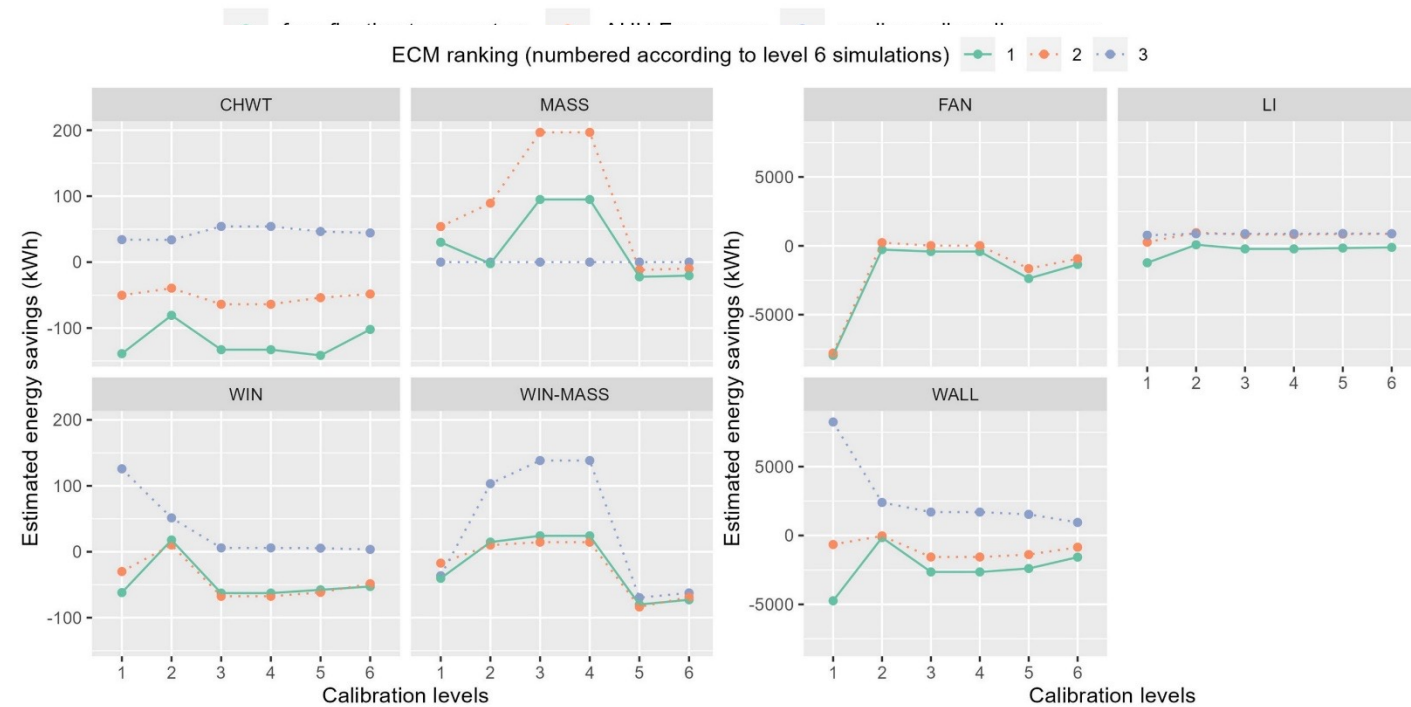
- Lower prediction error means better control for simple dynamics
- For complex buildings, only led to better control with **adequate model**
- **Critical physical component** should be preserved (partition capacitor here)

Energyplus for retrofit analysis



- An actual case study of evidence-based calibration
- the impact of different levels of information
- Robust evaluation in ECM analysis

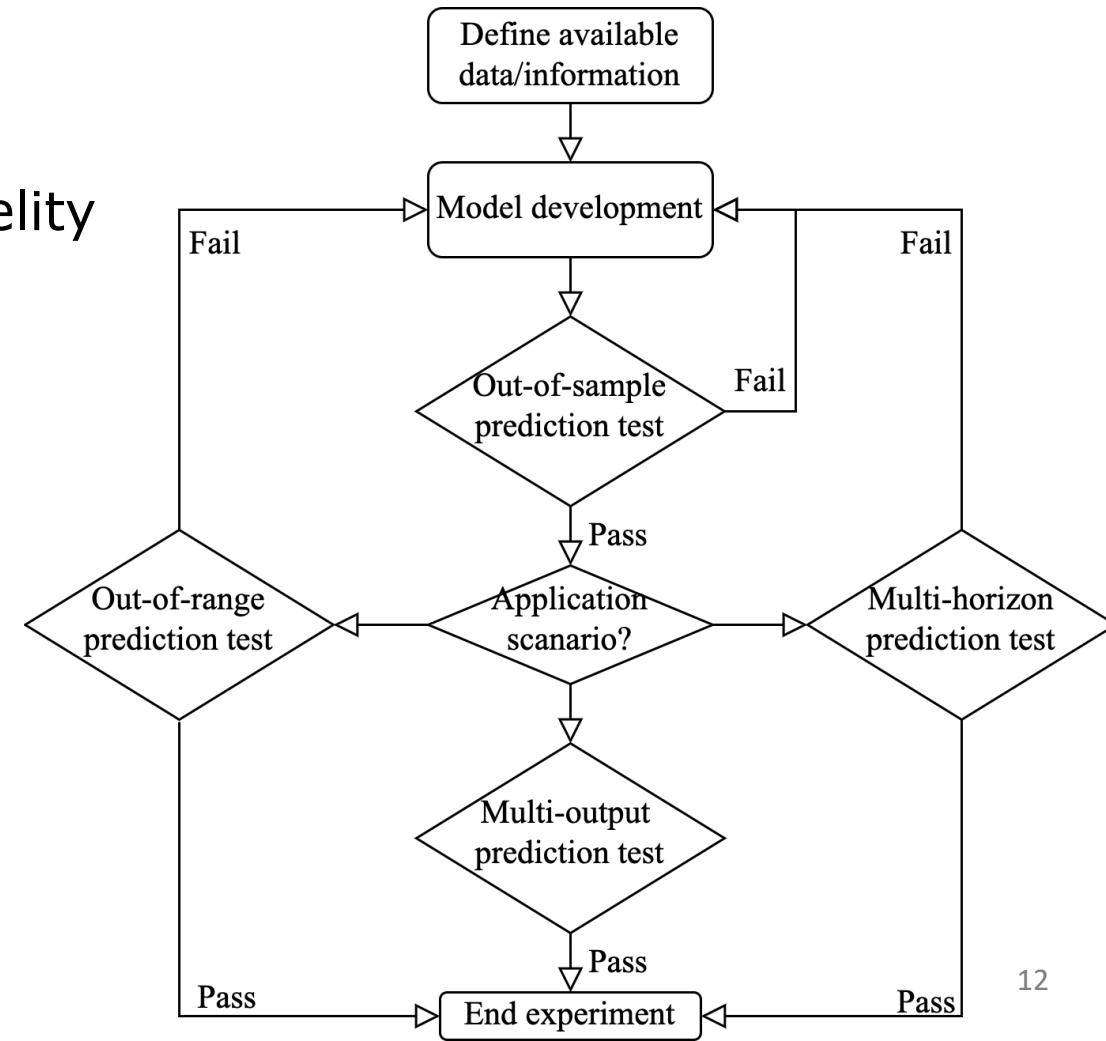
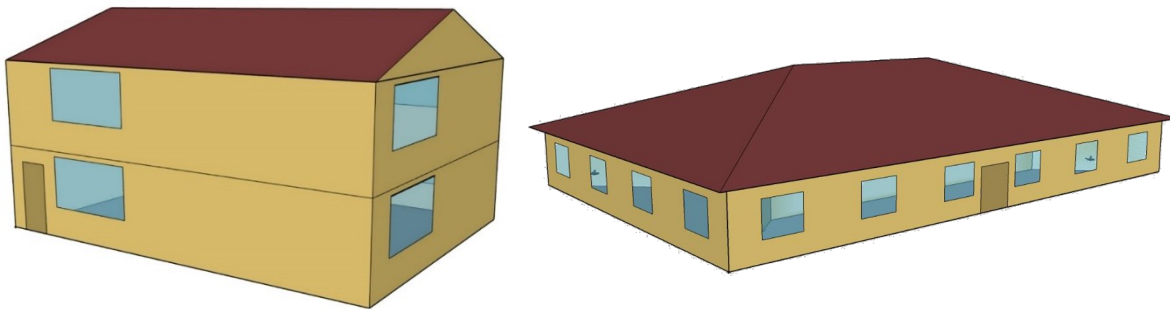
- More information gradually lowered CVRMSE
- Only matters for some design decisions
- Accurate estimation of energy saving requires information corresponding to the ECM



Co-simulation for every building is impractical

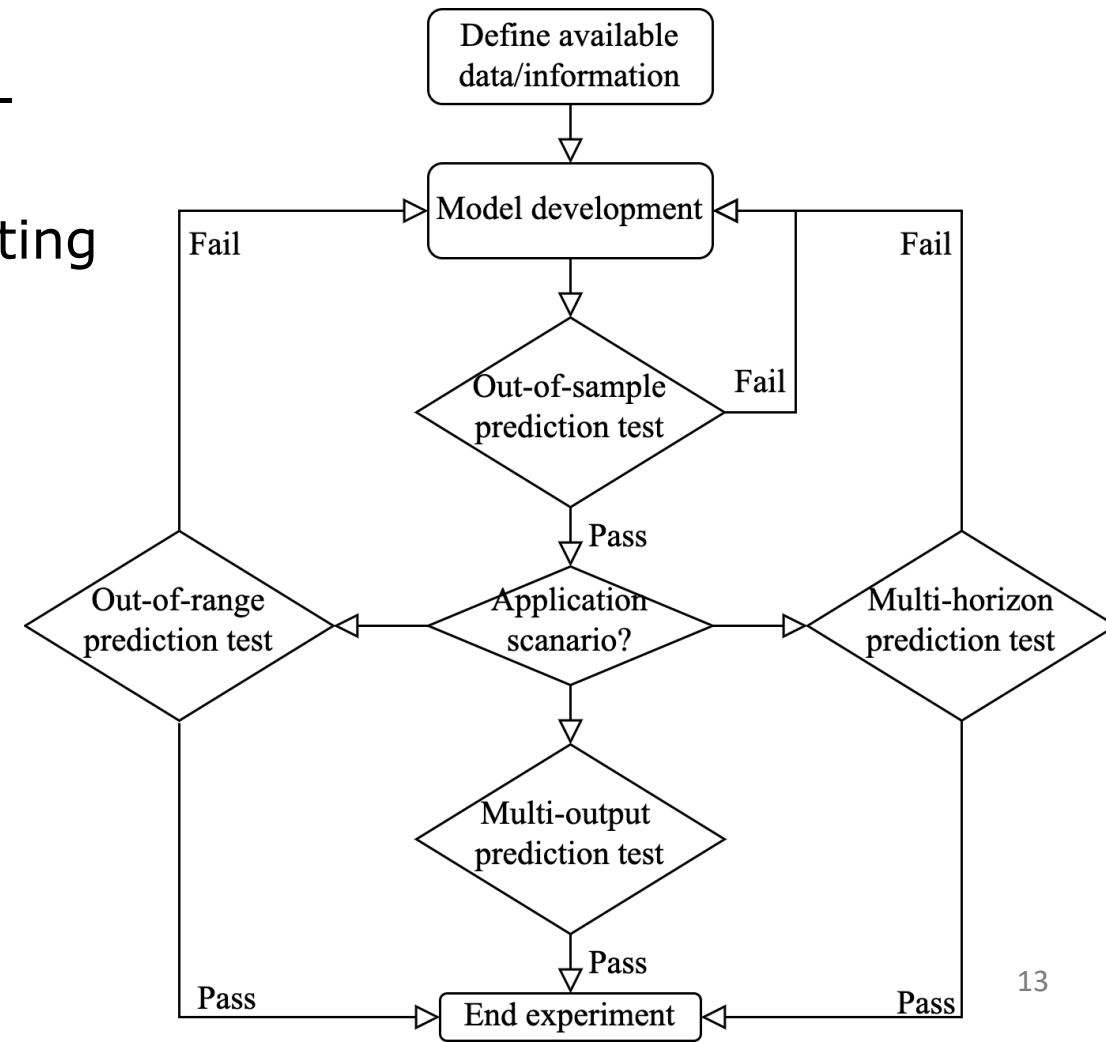
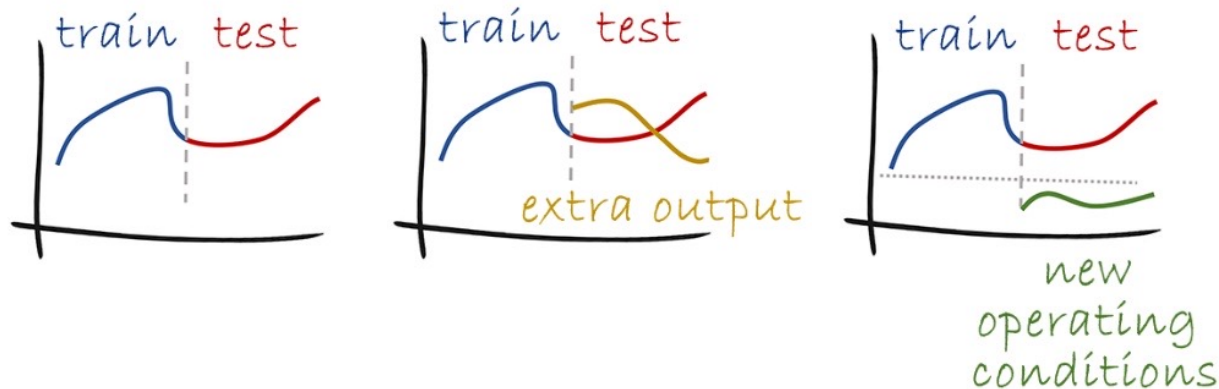
Prediction/extrapolation capability is the key

- A testing framework for digital twins
 - Based on a virtual testbed
 - Emulator as the actual building, higher-fidelity than its twins
 - Reproducibility
 - Single-family house/small office
 - Different climate zone (IECC envelope)



Prediction/extrapolation capability is the key

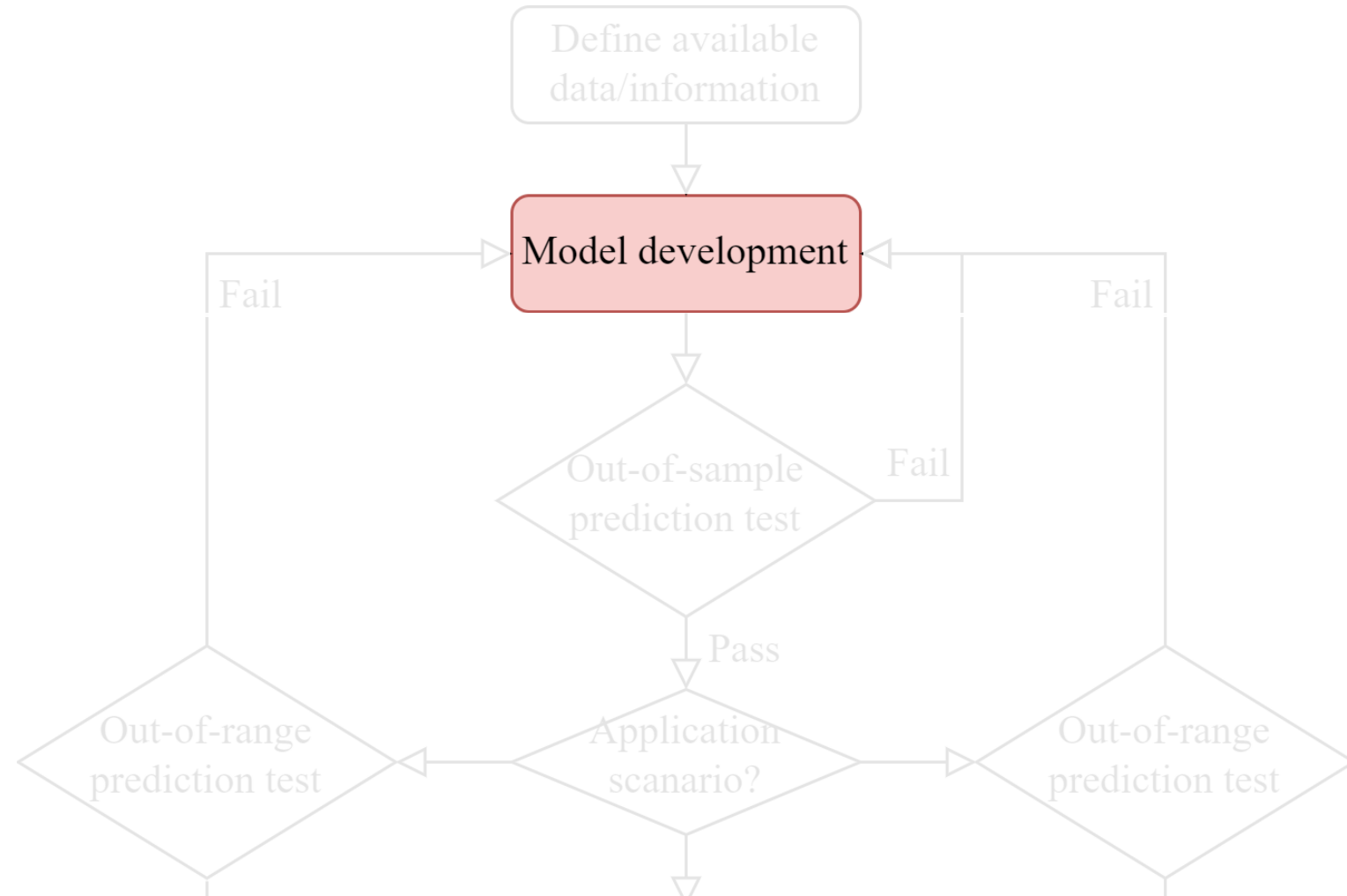
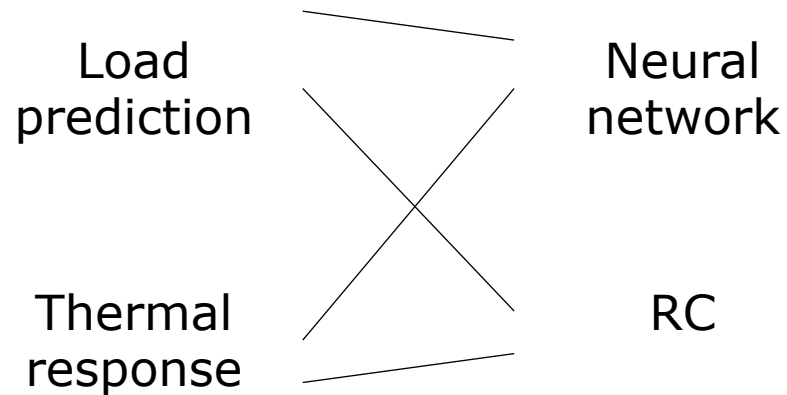
- Out of sample as a must
- Optional more demanding tests, e.g. multi-horizon/resolution
- Ability to generate application-oriented testing data (python script)



How “physical” does the model need to be?

White/grey/black box

An example of pre-cooling



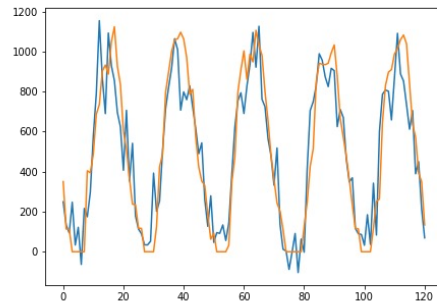
Load prediction

Out of sample test

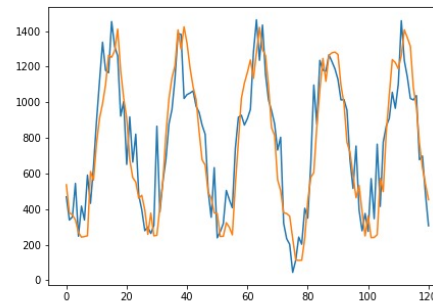
Out of range test

Physical test

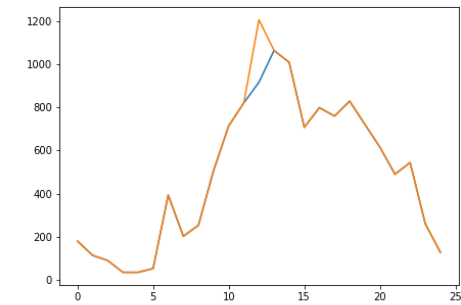
Neural network



30.6%

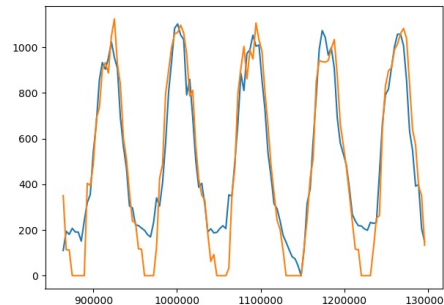


23.5%

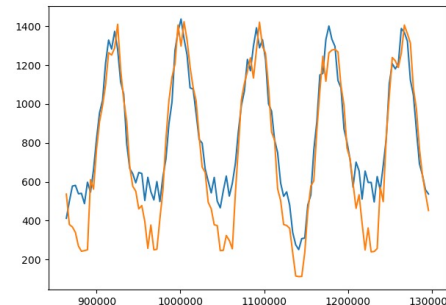


Failed

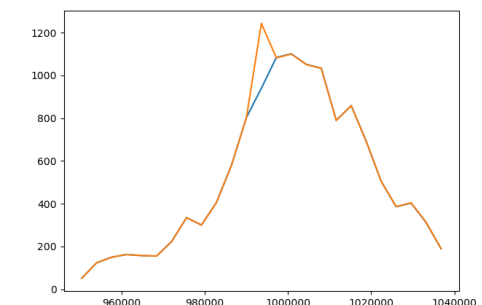
RC



23.9%



20.2%



Failed

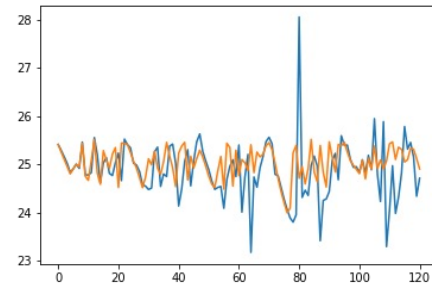
Thermal response

Out of sample test

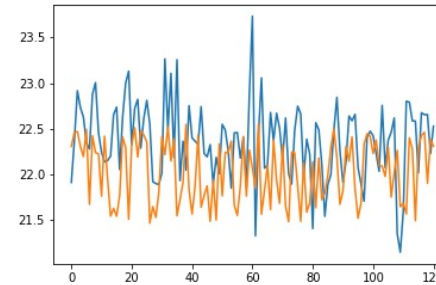
Out of range test

Physical test

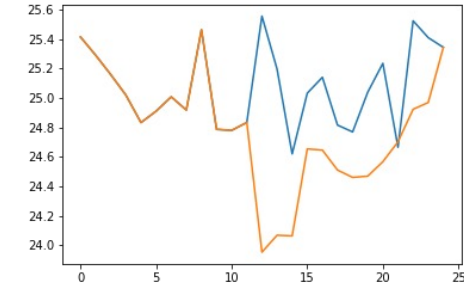
Neural network



2.57%

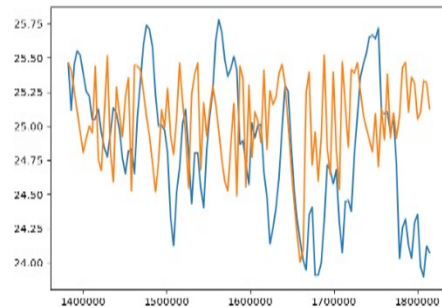


2.81%

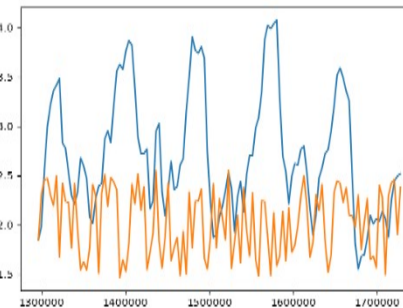


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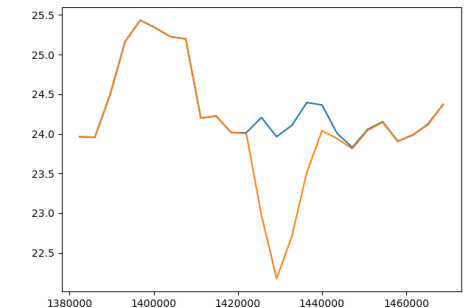
RC



2.55%



4.47%



Passed

- Traditional error-based evaluation could be misleading
- Models need to be developed concerning the predictive scenarios
- More open questions to answer

Thank you!

<https://jamescheng21.github.io/>