Massachusetts Institute of Technology

Data-efficient scientific machine learning for urban intelligence and sustainability

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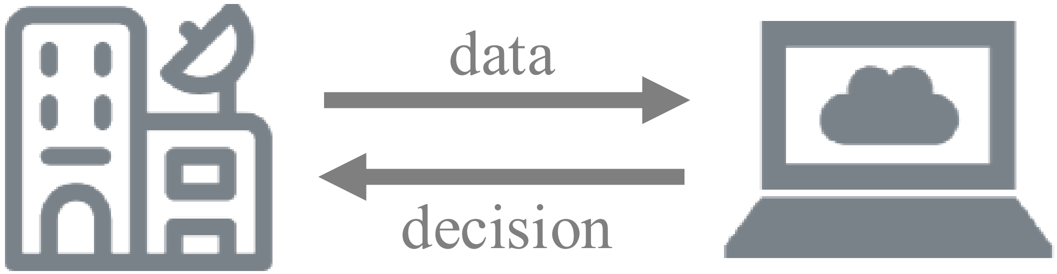
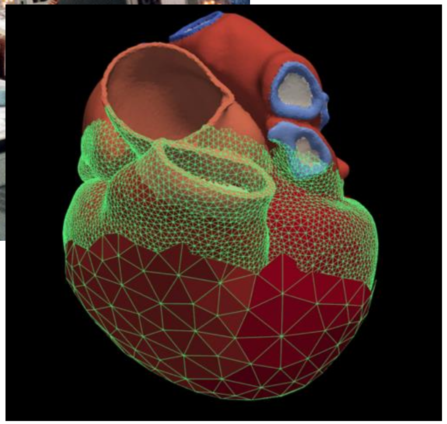
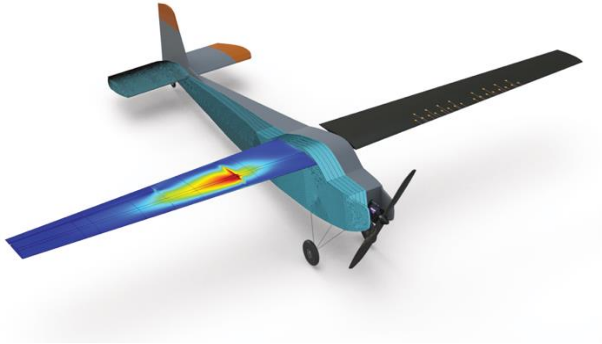
25/11/18

Data-centric scientific machine learning for urban intelligence and sustainability

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







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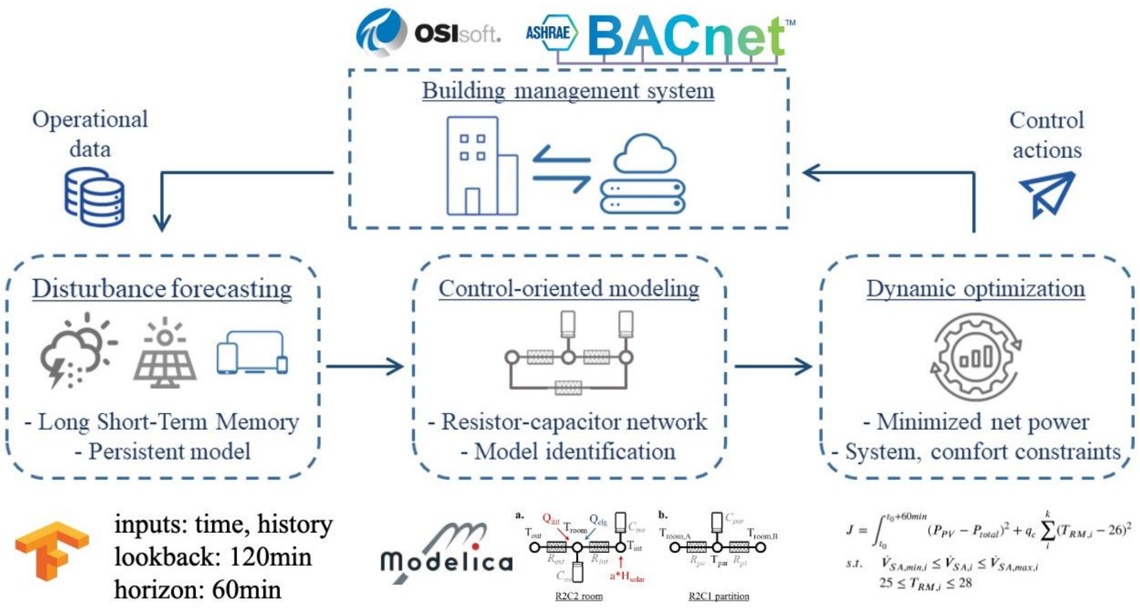
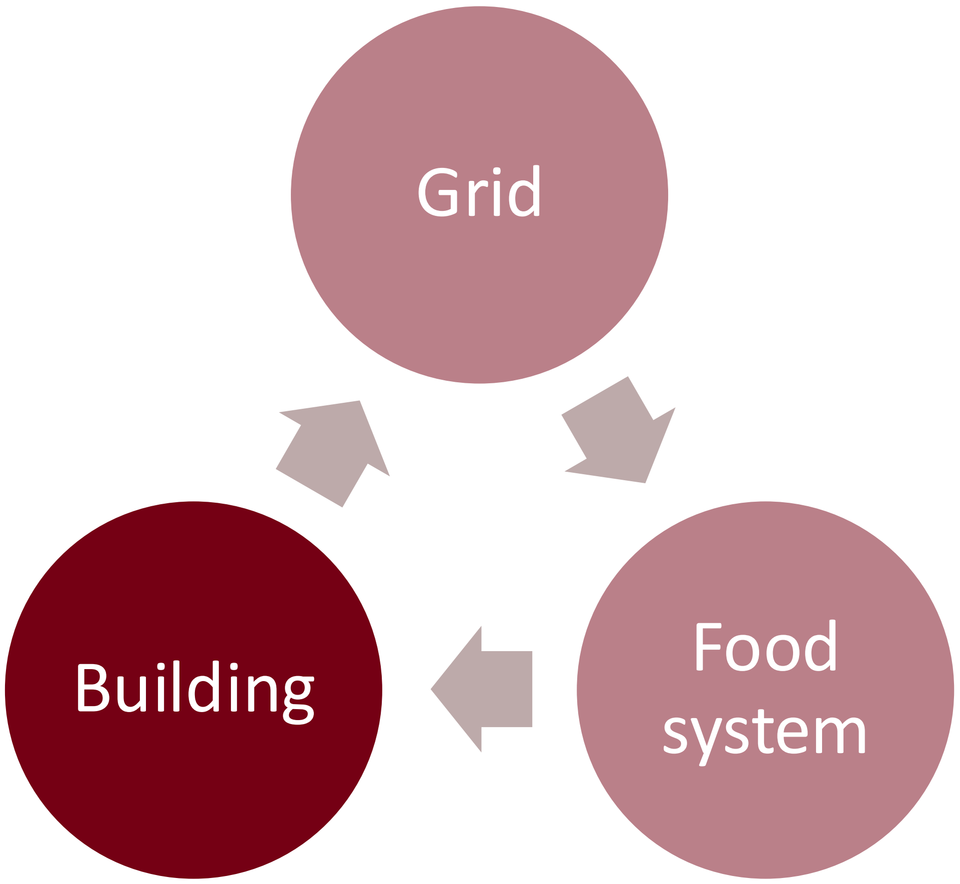


Optimal control implemented at multiple real-world buildings

Thermal comfort, energy conservation, self-sufficiency, etc.



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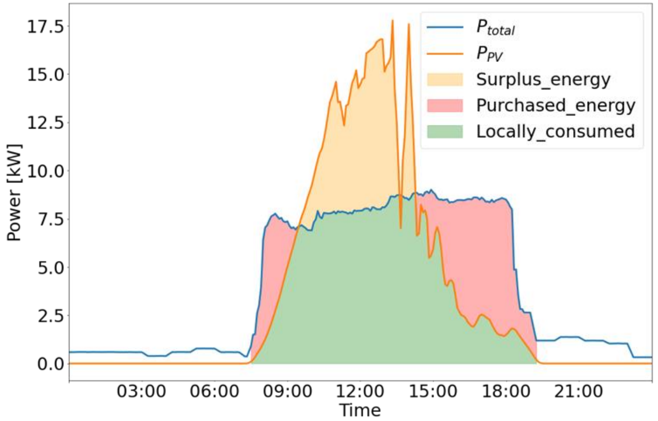
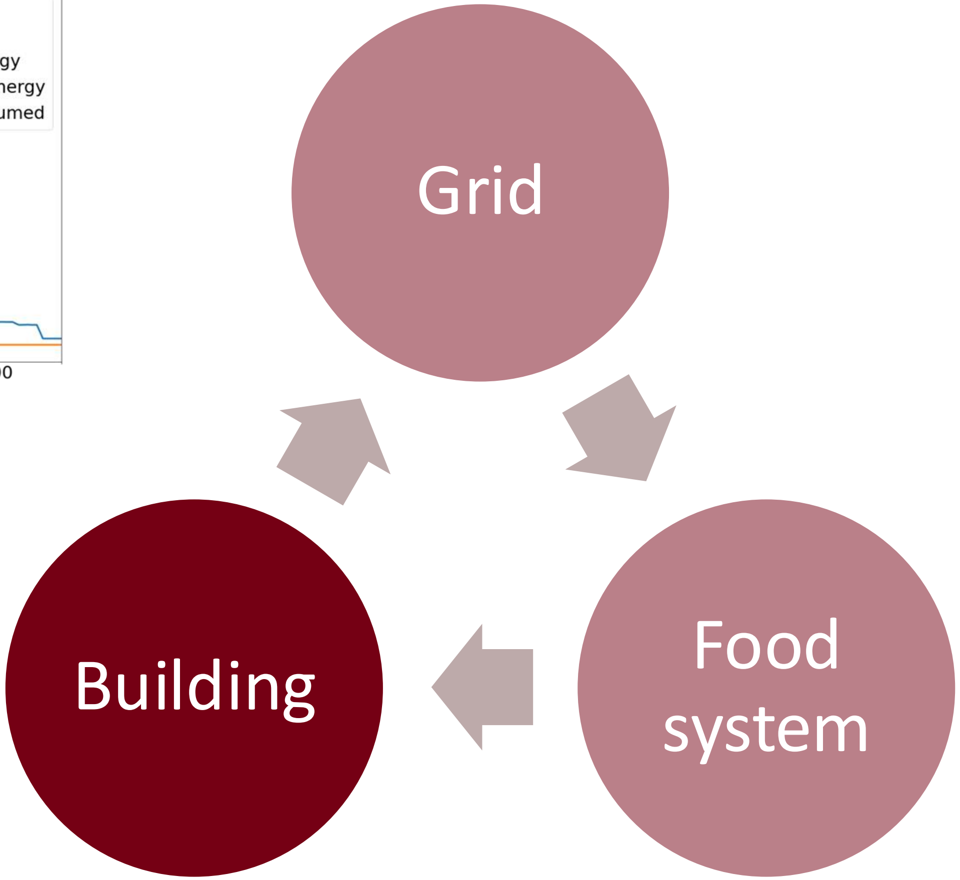


Self-consumption: $$SC = \frac{E_{locally\_consumed}}{E_{PV}}$$

Self-sufficiency: $$SS = \frac{E_{locally\_consumed}}{E_{total}}$$

SC improved by 19.5%, SS improved by 10.6%



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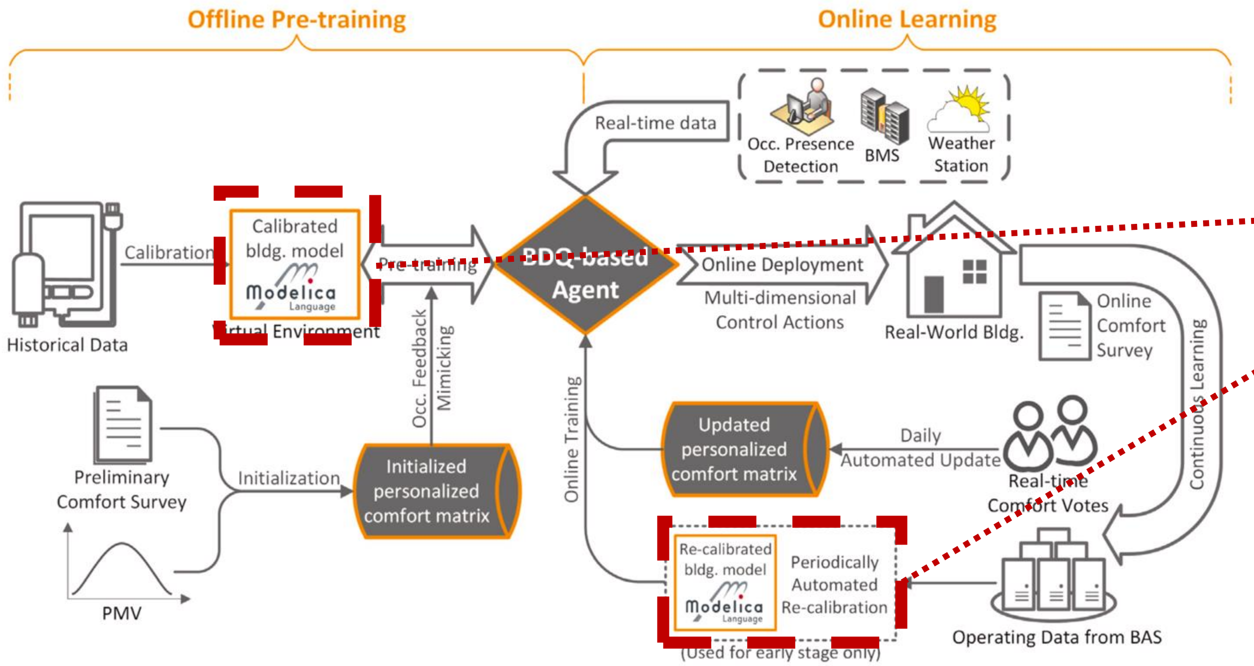
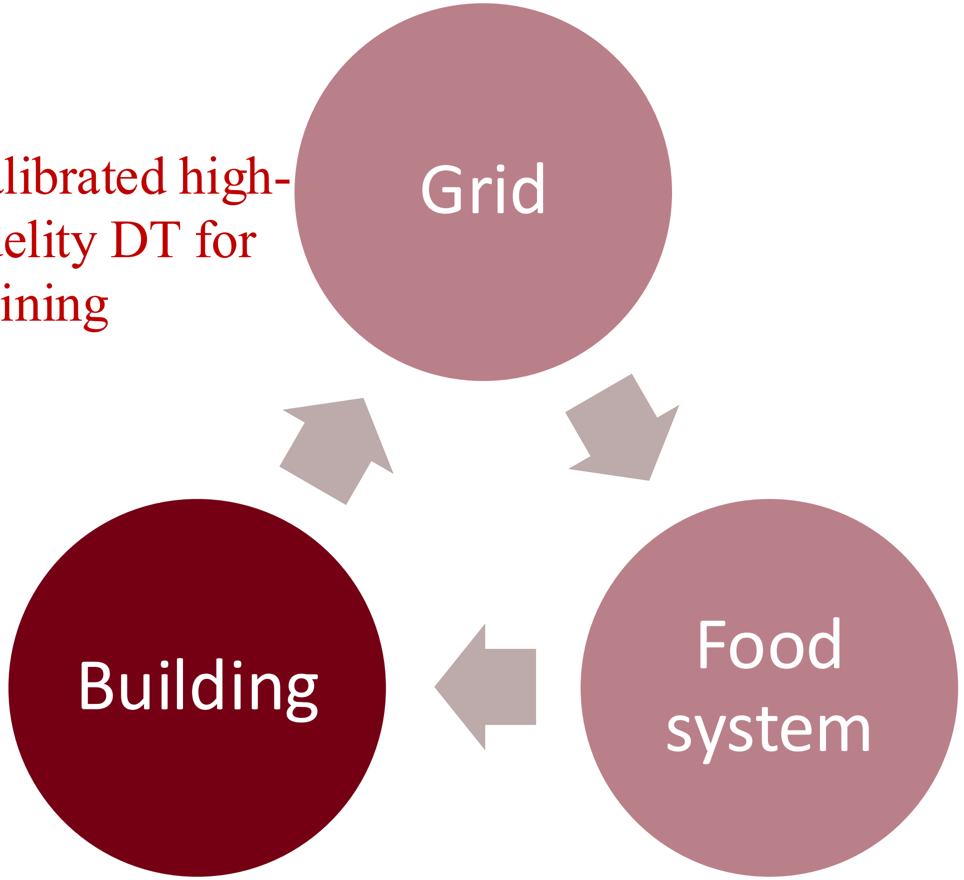


Calibrated high-fidelity DT for training



- Occupant in the loop optimal control of temperature setpoints and fan speeds
- 14% reduction in cooling energy and 11% improvement in total thermal acceptability

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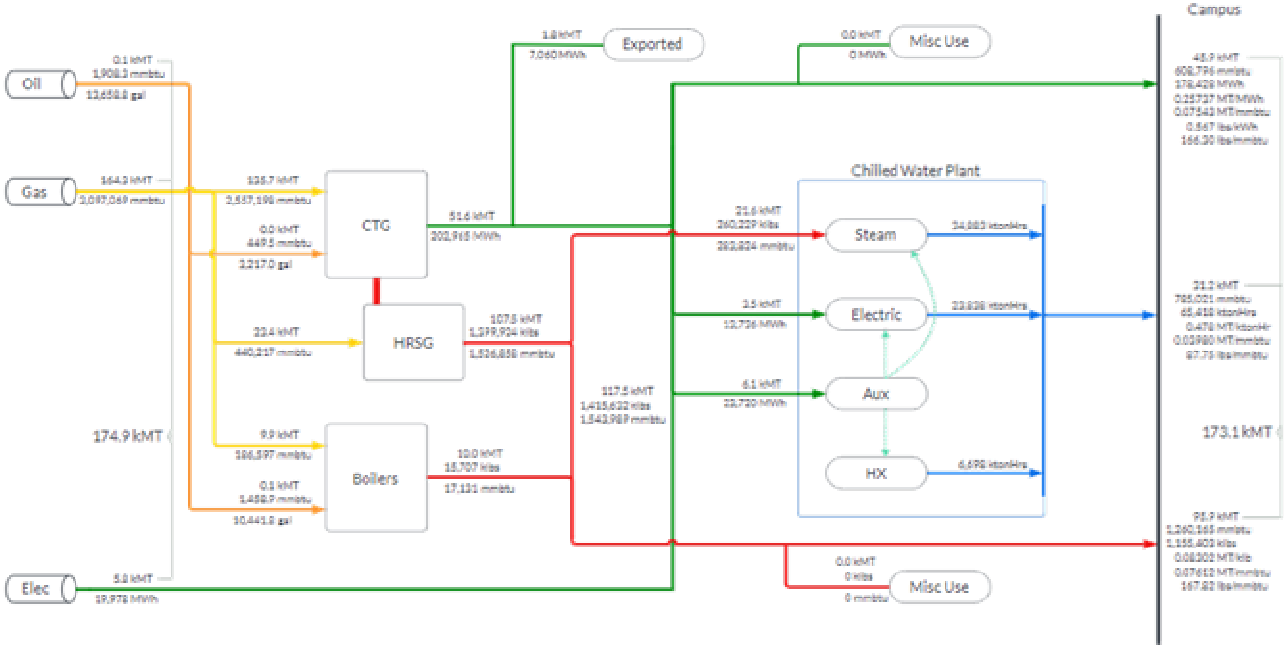

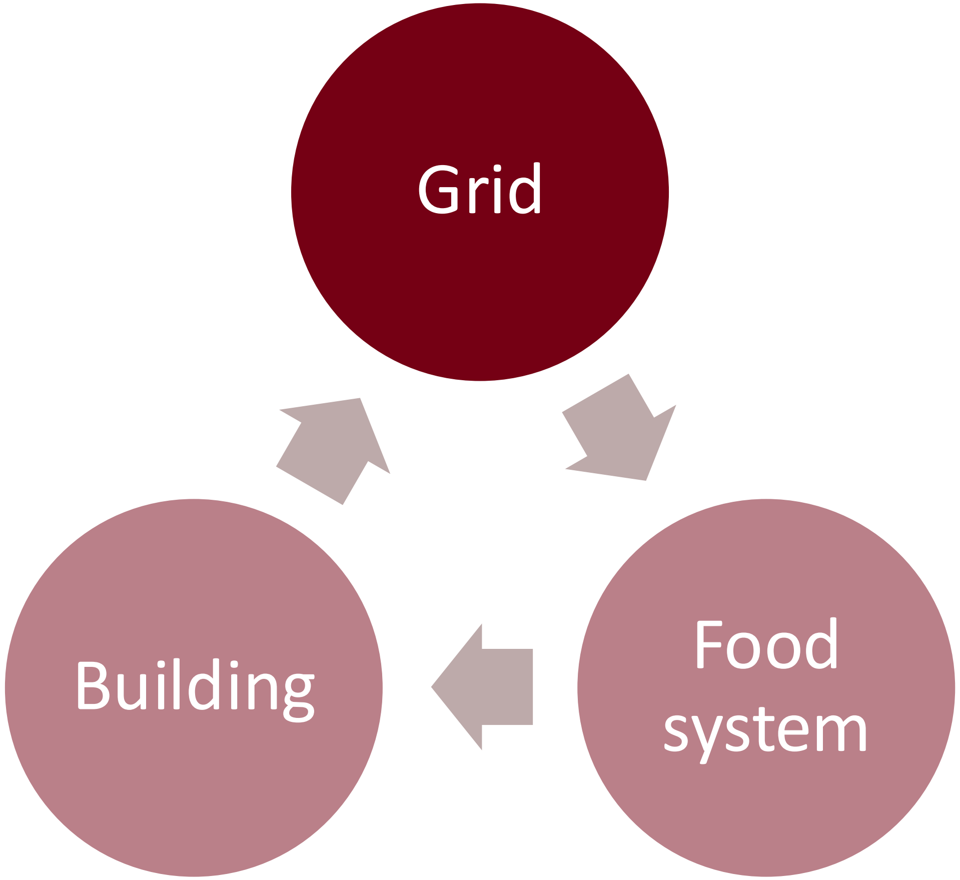

Minimize electricity purchase (total and peak load) from the main grid

Reduce carbon intensity by coordinating electricity, heating, and cooling loads

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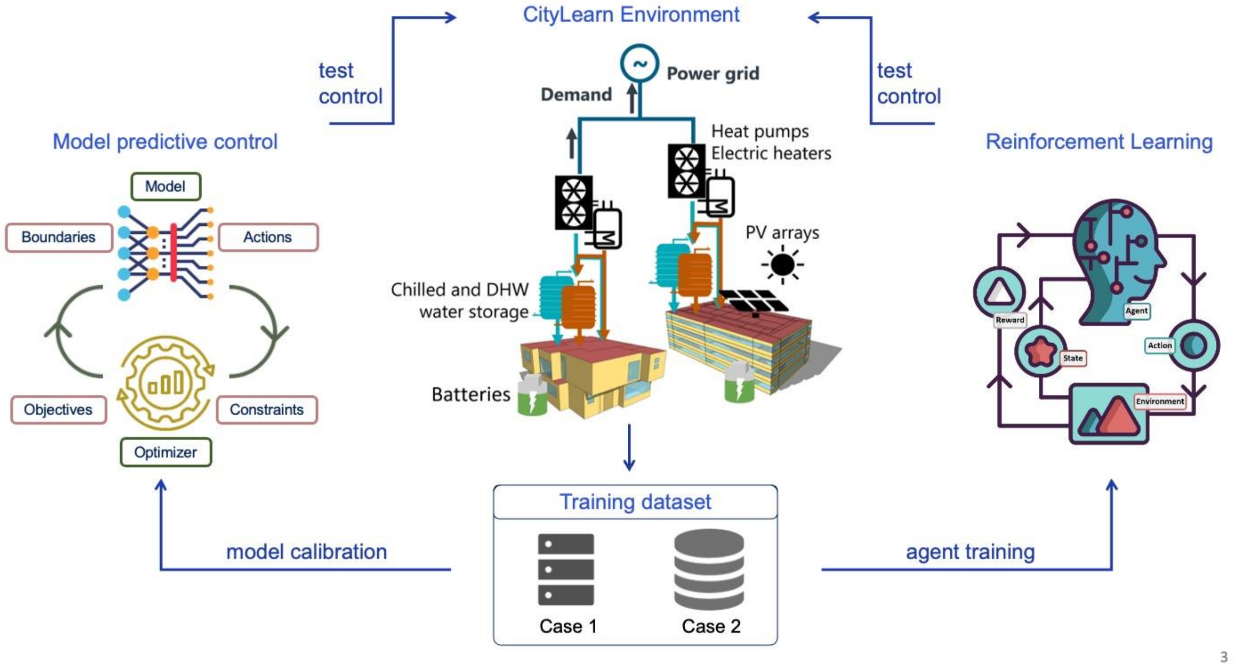

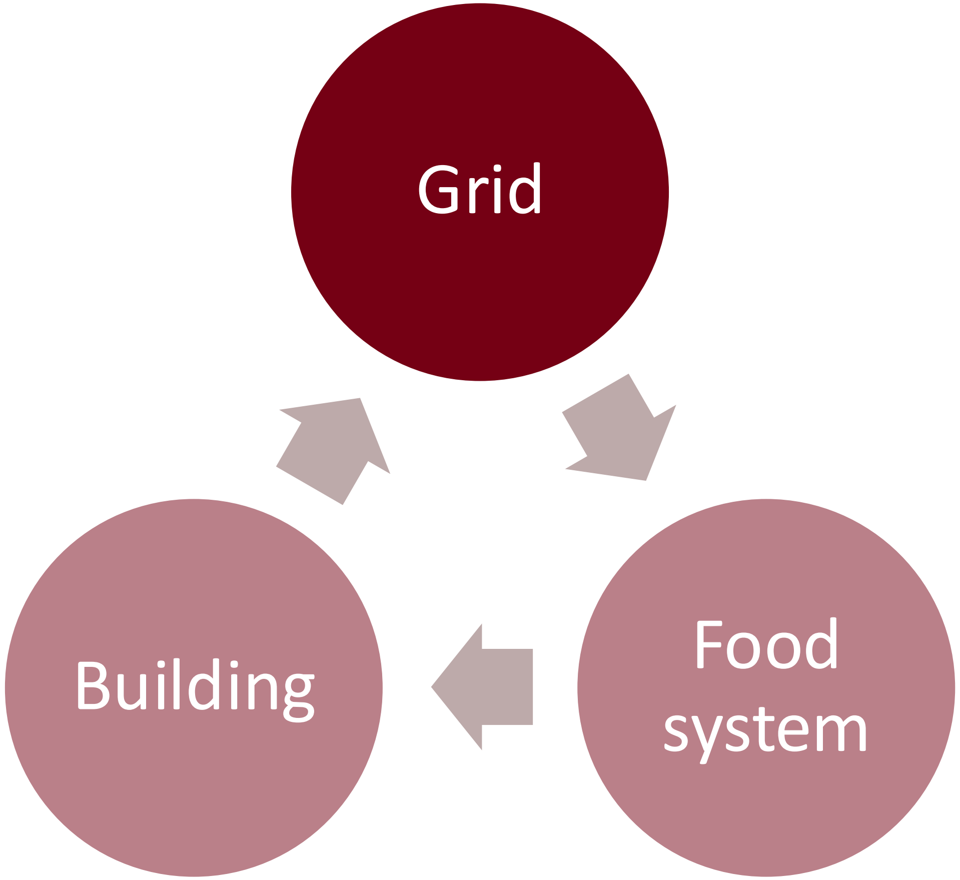

Building-grid interaction, distributed renewable energy, district energy system decarbonization

More scalable solutions required for complex systems and tasks

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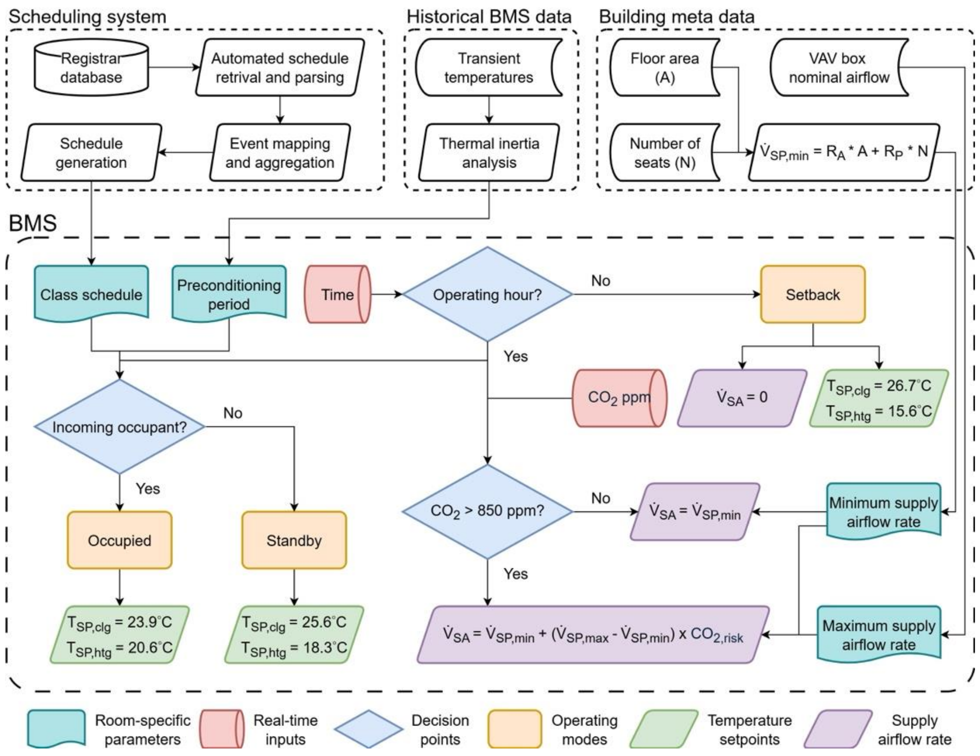
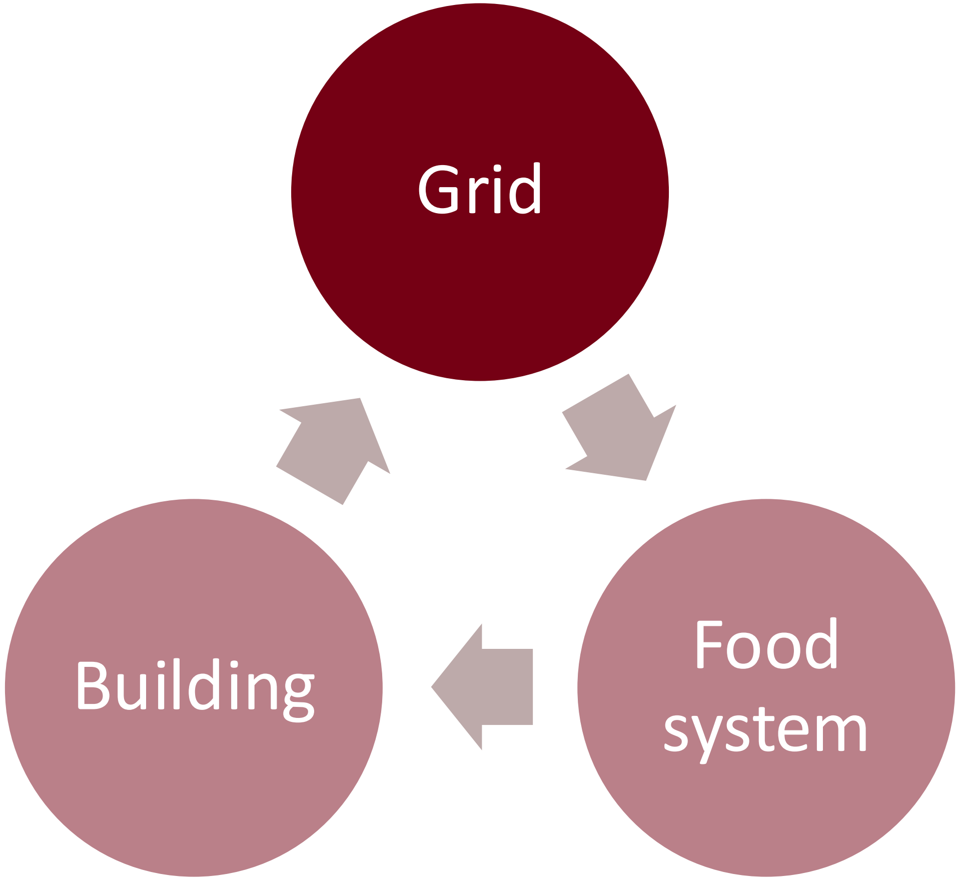


- Rule-based control to obtain near-optimal control actions
- DT for monitoring and measurement & verification
- Over 40% energy saving and ~30% carbon reduction



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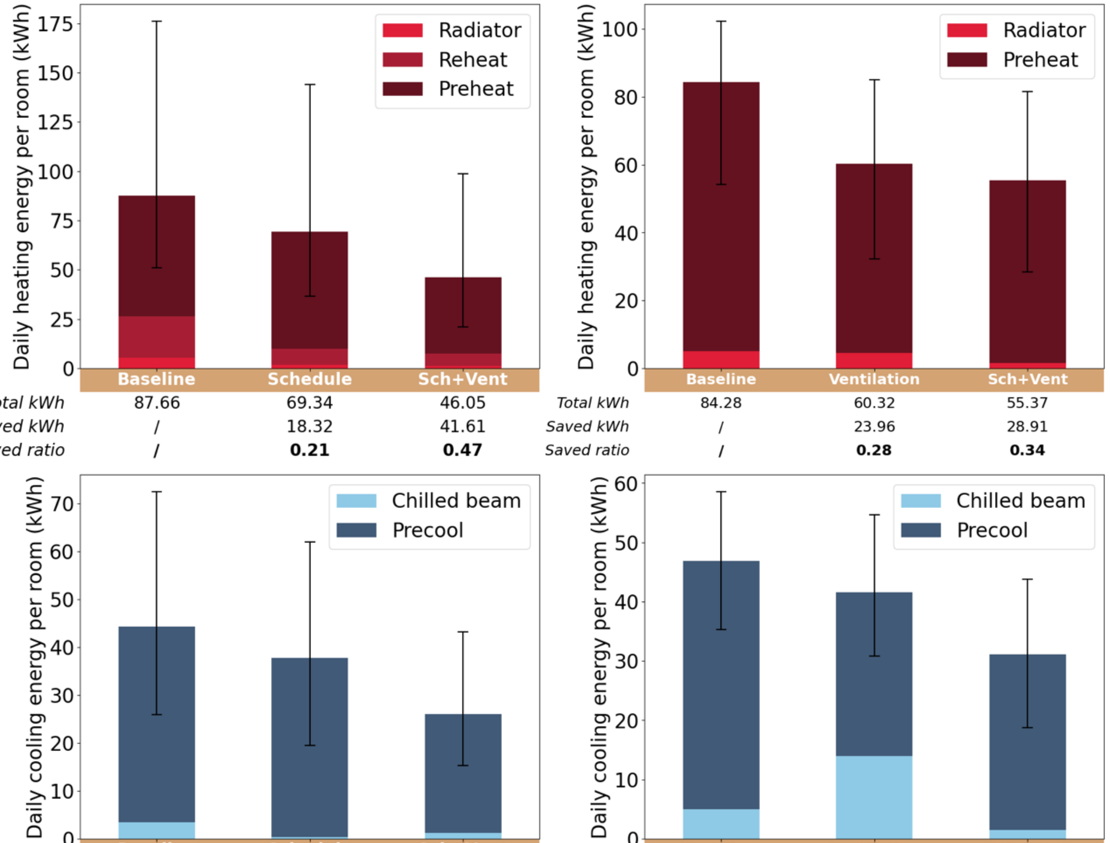
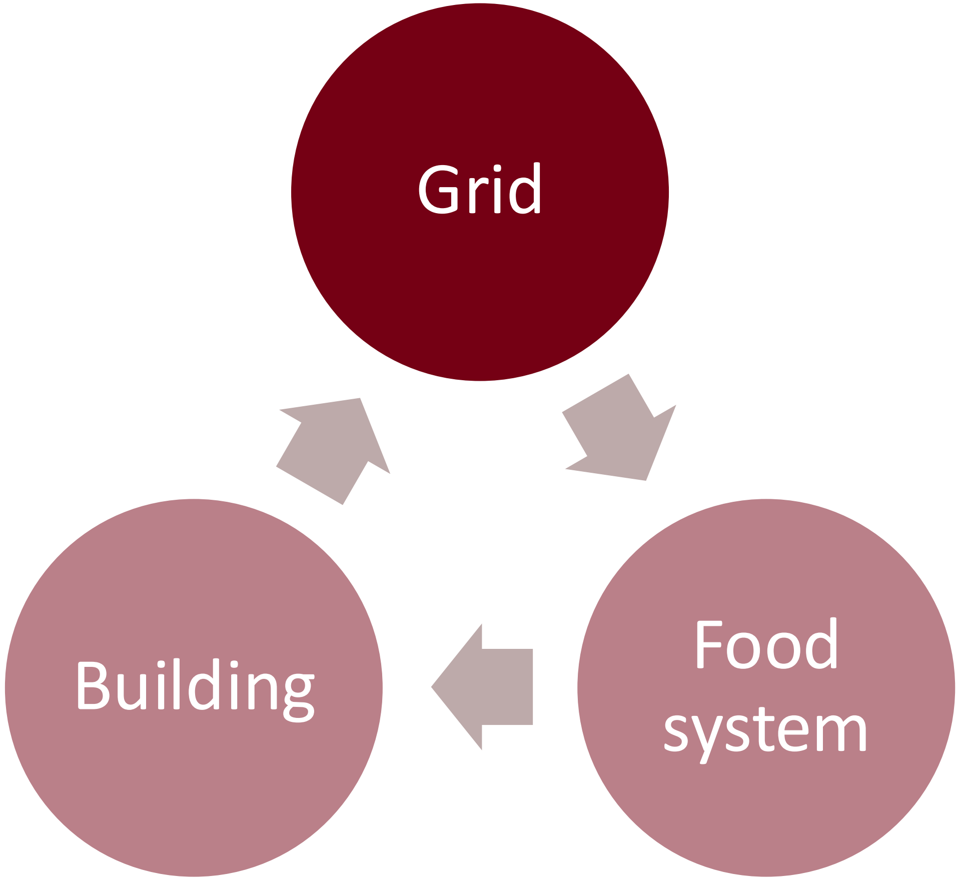


	Baseline	Schedule	Sch+Vent
Total kWh	87.66	69.34	46.05
Saved kWh	/	18.32	41.61
Saved ratio	/	**0.21**	**0.47**

	Baseline	Ventilation	Sch+Vent
Total kWh	84.28	60.32	55.37
Saved kWh	/	23.96	28.91
Saved ratio	/	**0.28**	**0.34**

	Baseline	Schedule	Sch+Vent
Total kWh	44.27	37.75	25.98
Saved kWh	/	6.52	18.29
Saved ratio	/	**0.15**	**0.41**

	Baseline	Ventilation	Sch+Vent
Total kWh	46.87	41.6	31.06
Saved kWh	/	5.27	15.81
Saved ratio	/	**0.11**	**0.34**



- Over 40% energy saving and ~30% carbon reduction

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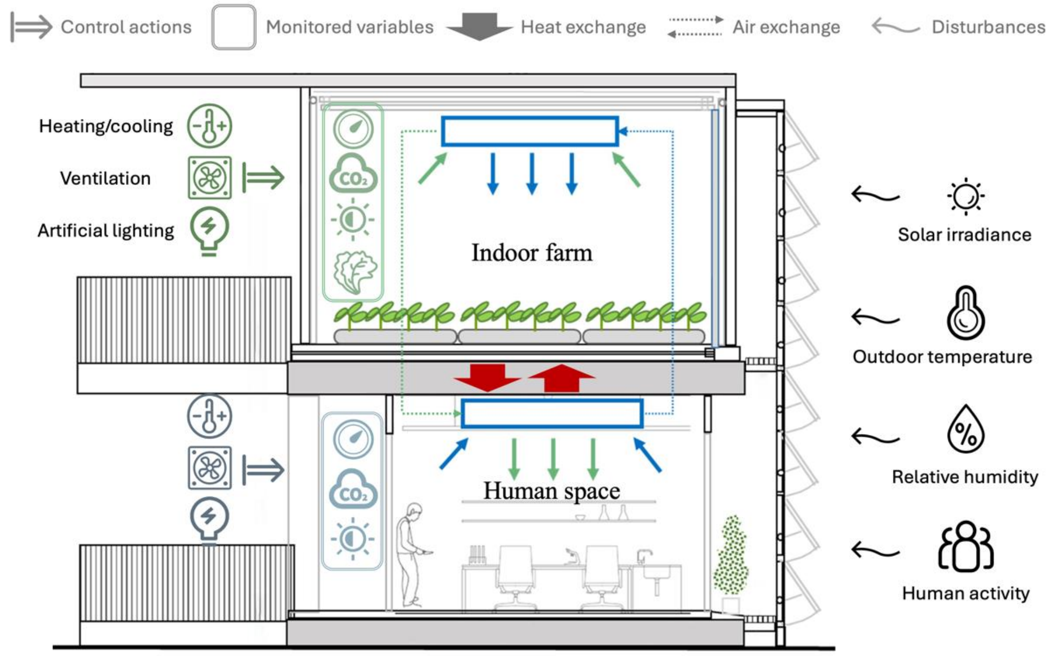
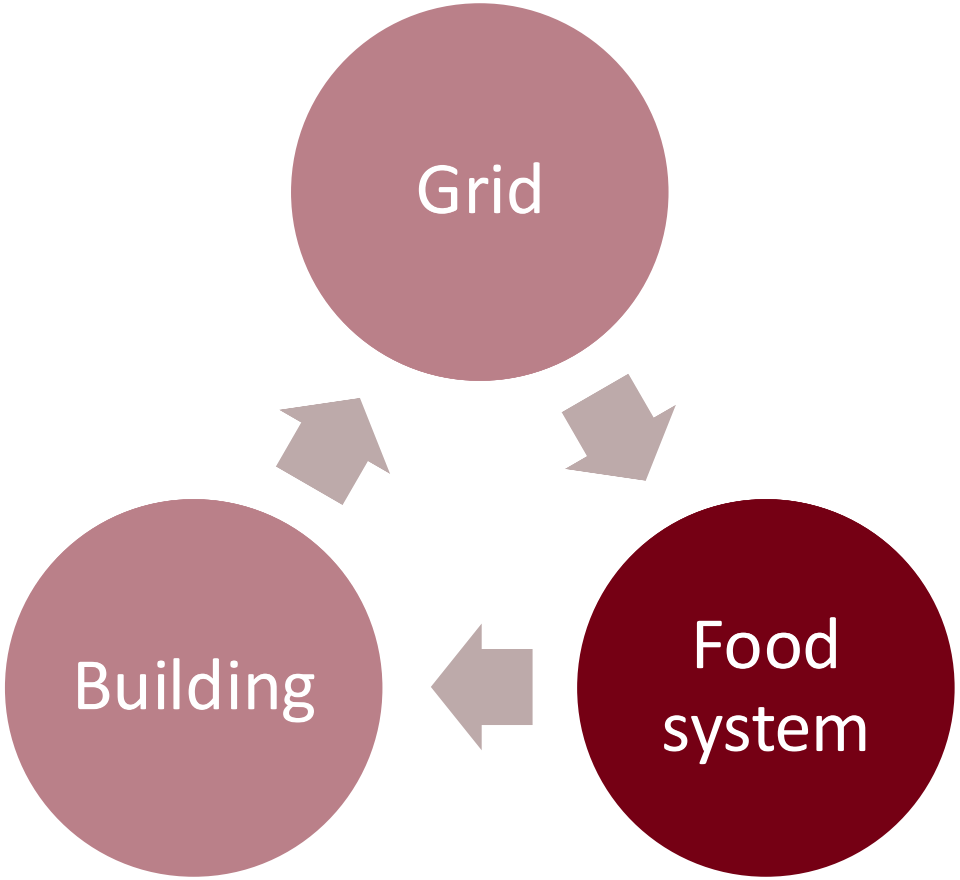


Synergetic urban farming and human environment



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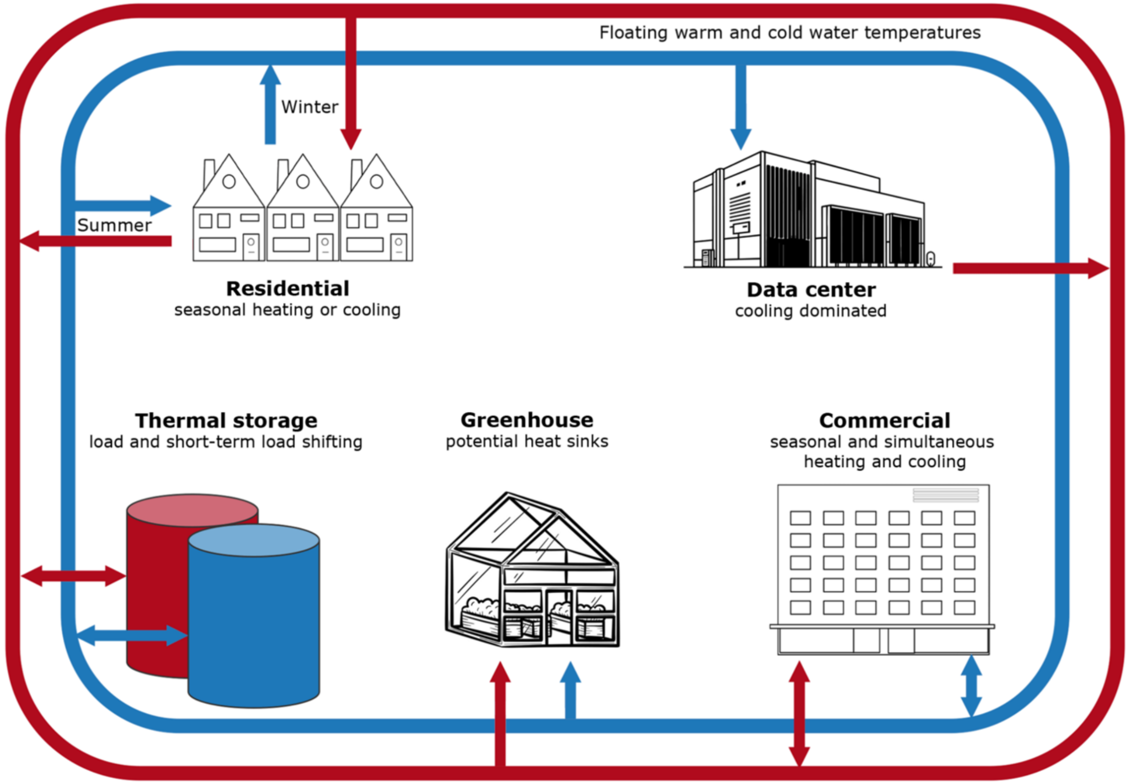
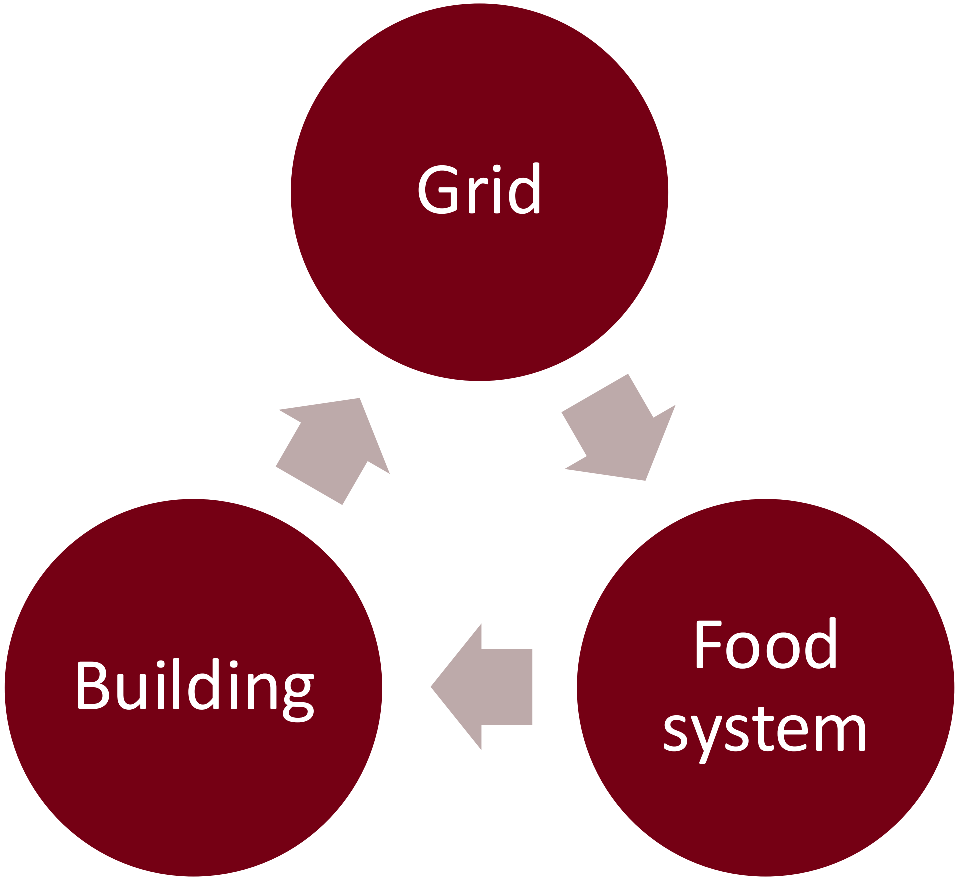


5GDHC, waste heat recovery and building electrification



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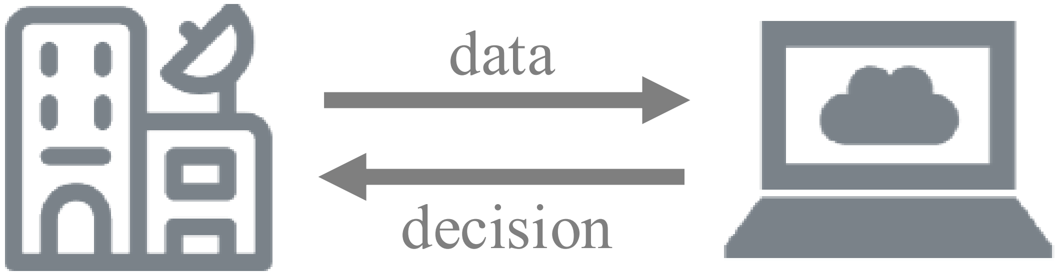

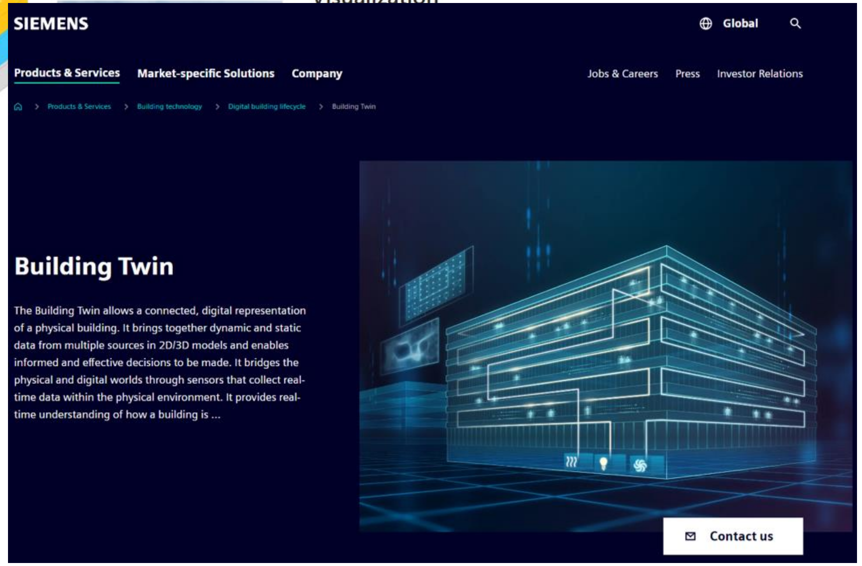

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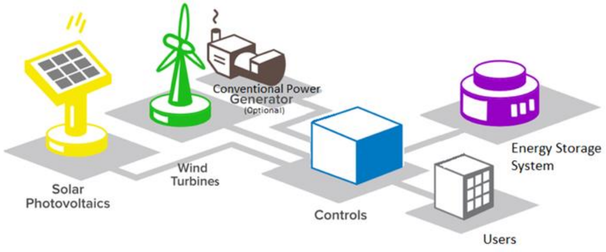
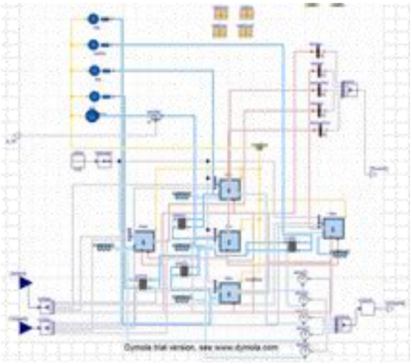
Informed decision-making requires scalable and extrapolatable predictive model

Open complex systems



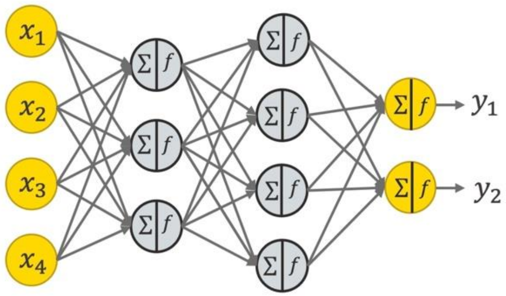
- Heterogeneous dynamics
- Subject to uncertainties
- Under-measured

Physics-based model



- Extrapolatable
- Low fitting capability
- Unscalable

Fully data-driven models



- High accuracy
- Scalable
- Unreliable in unseen scenarios

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Sci-ML via data assimilation:

- Extrapolation enabled by physics-informed constraints
- Expert-agnostics learning mechanism
- Balancing model complexity with data informativeness

Physics-informed models

Extrapolatable physics-informed models through data assimilation

+

Decision-oriented data

Active-learned data acquisition to enable fit-for-purpose modeling

Dynamic digital twins

Dynamically evolving models to support decision-making throughout system life cycles

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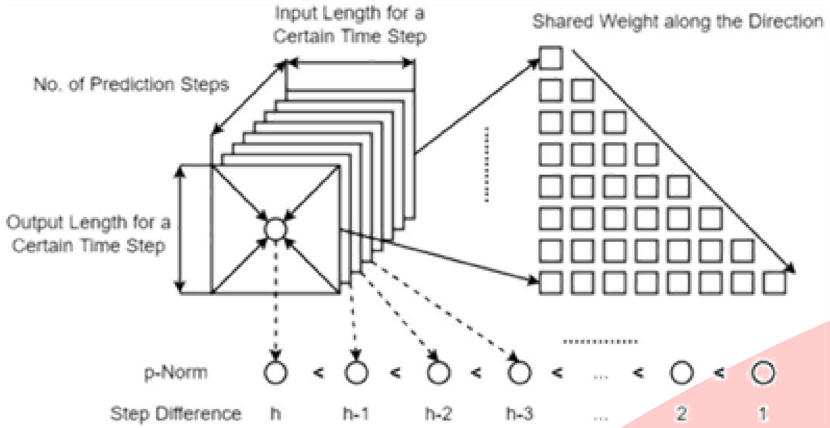


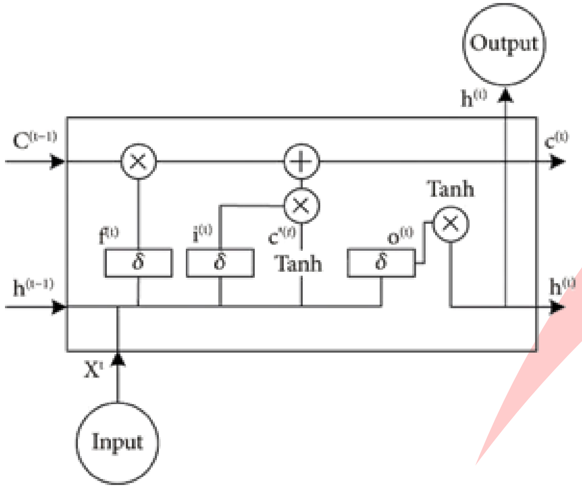
Increasing levels of physics

RC

PCNN

PINN

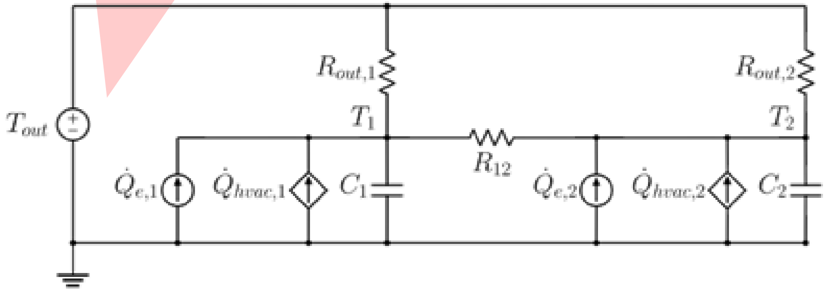
LSTM



$$\mathcal{L}_{PINN} = \mathcal{L}_{MSE} + \lambda \mathcal{L}_{grad},$$

$$\mathcal{L}_{grad} = \frac{1}{l}\sum_{k=0}^{l-1}\left[\frac{1}{m}\sum_{z=1}^{m} g_k^z\right],$$

$$g_k^z = \sum_{y=1}^{m} ReLU\left(-\frac{\partial \hat{T}_l^z}{\partial u_k^y}\right) + ReLU\left(-\frac{\partial \hat{T}_l^z}{\partial T_k^{out}}\right)$$



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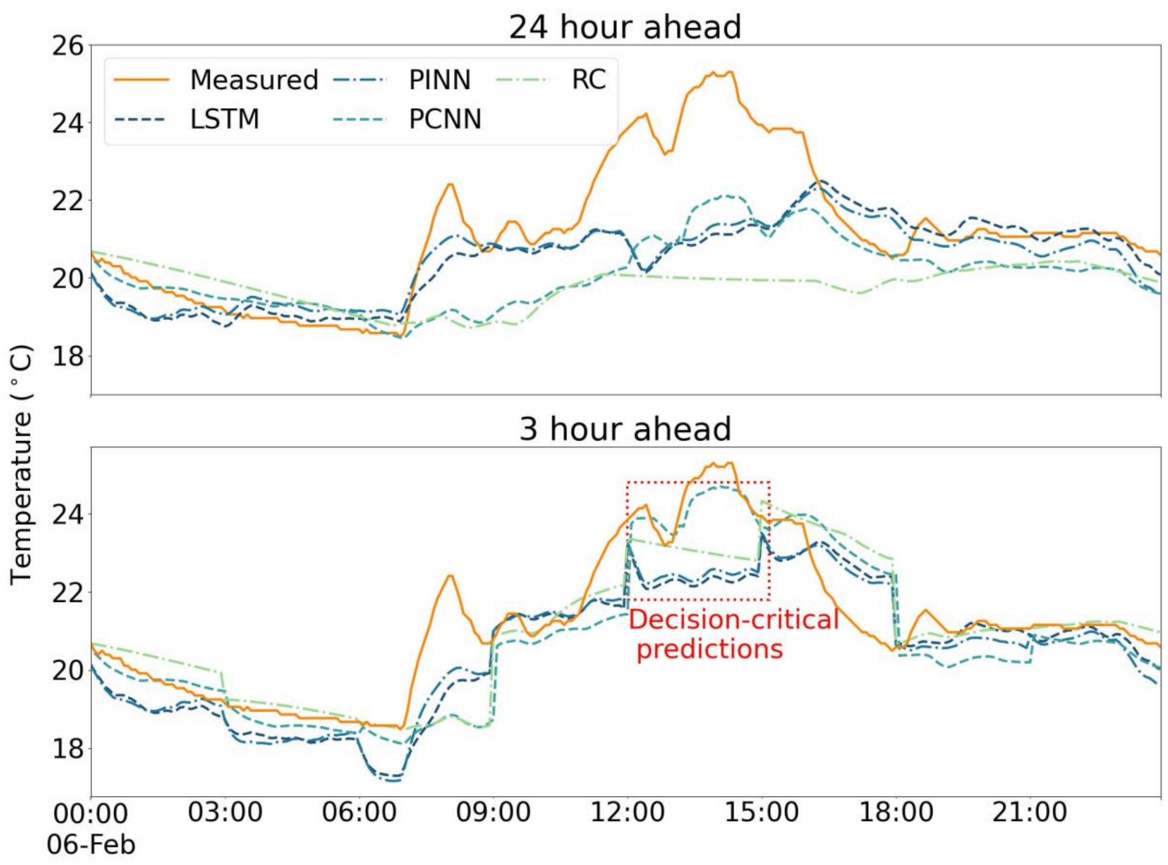
	Traditional test		Extrapolation test	
	std	*avg*	*std*	*avg*
LSTM	0.21	0.89	0.44	1.21
PINN	0.23	0.89	0.51	1.12
PCNN	0.22	0.88	0.27	0.87
RC	0.15	1.39	0.13	1.78



Multi-zone thermal response model
- Essential to balance fitting capability and physics-based constraints
- Physics-consistency more important than predictive accuracy

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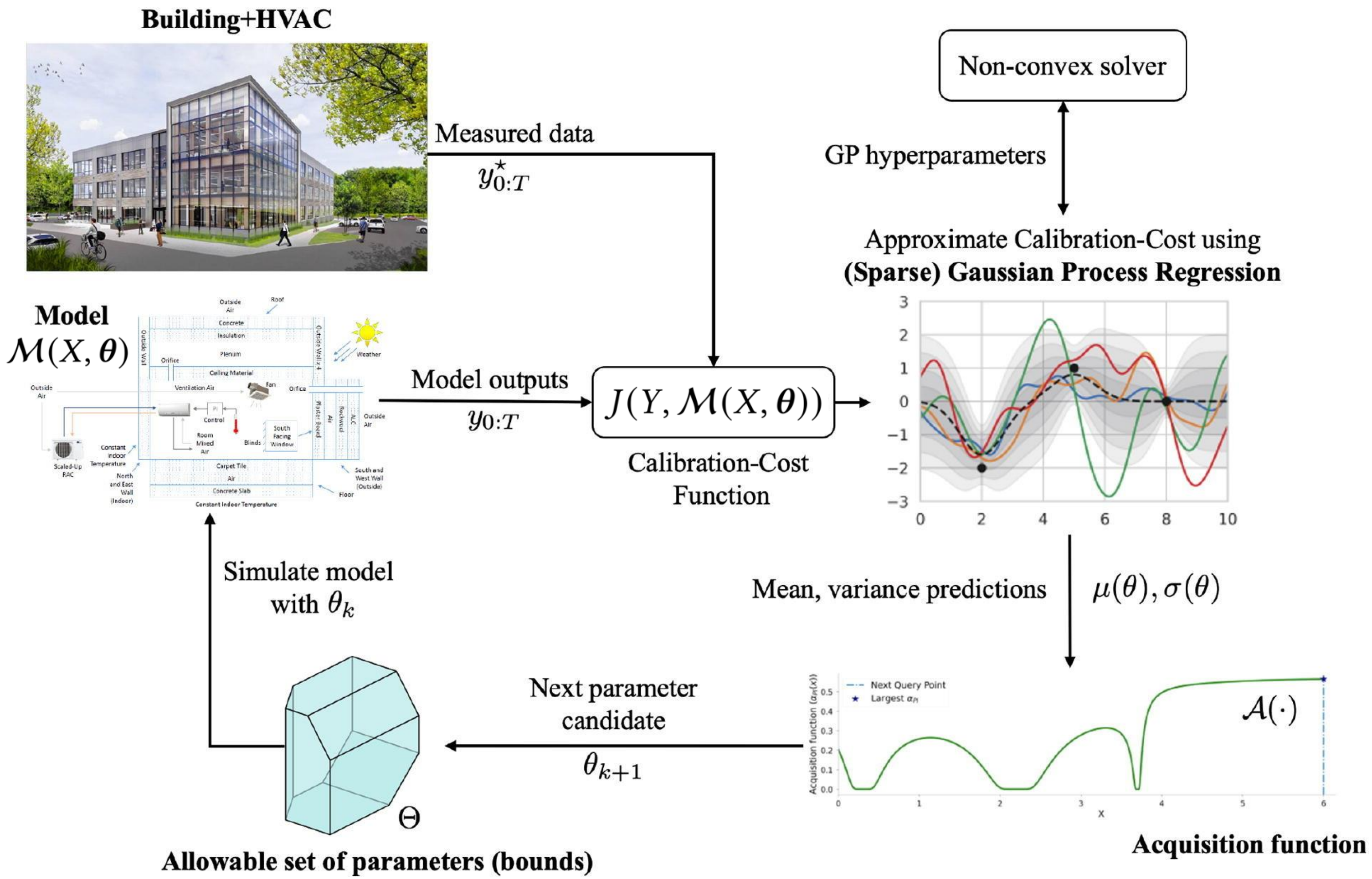

$$\theta^* = arg \min_{\theta \in \Theta} (J(\hat{Y}, Y))$$
$$s.t. \quad \hat{Y} = \mathcal{M}(X, \theta)$$

Define the optimization under limited information

- Develop base model
- Obtain X, Y
- Screen parameter

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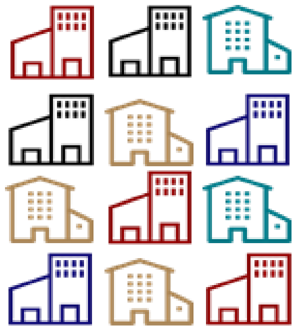
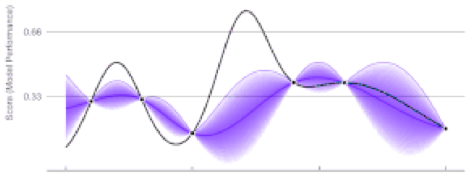
Previous calibration runs:
source tasks





Calibration by Vanilla-Bayesian Optimization with Gaussian Process

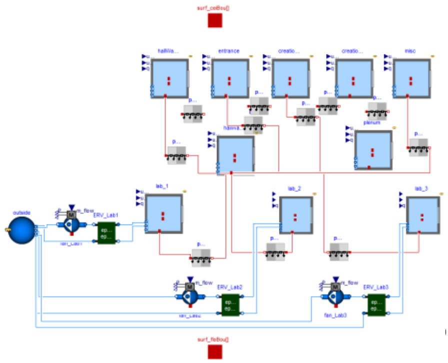
Training data storage

Source task data archived in the cloud: training set

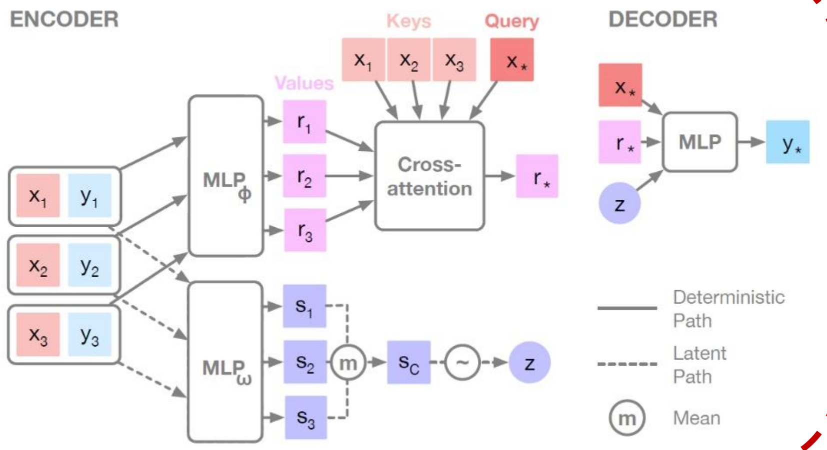
	θ_1	θ_2	...	θ_m	J
1	$\theta_{1,1}$	$\theta_{2,1}$	...	$\theta_{m,1}$	J_1
2	$\theta_{1,2}$	$\theta_{2,2}$	...	$\theta_{m,2}$	J_2
...		...			...
n	$\theta_{1,n}$	$\theta_{2,n}$	...	$\theta_{m,n}$	J_n

Meta-train

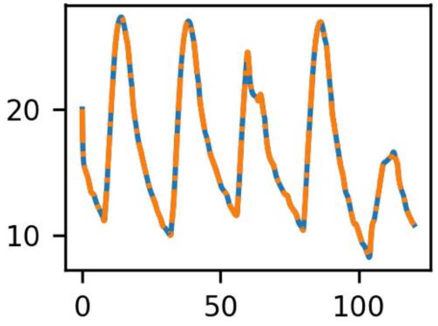
Previously unseen building data and model:
target tasks



Data-driven initialization



Meta-ANP-BO



Data-efficient learning

- Meta-learn the governing equations from a group of similar buildings
- Fastened target task with limited data
- 50% reduction in computational costs

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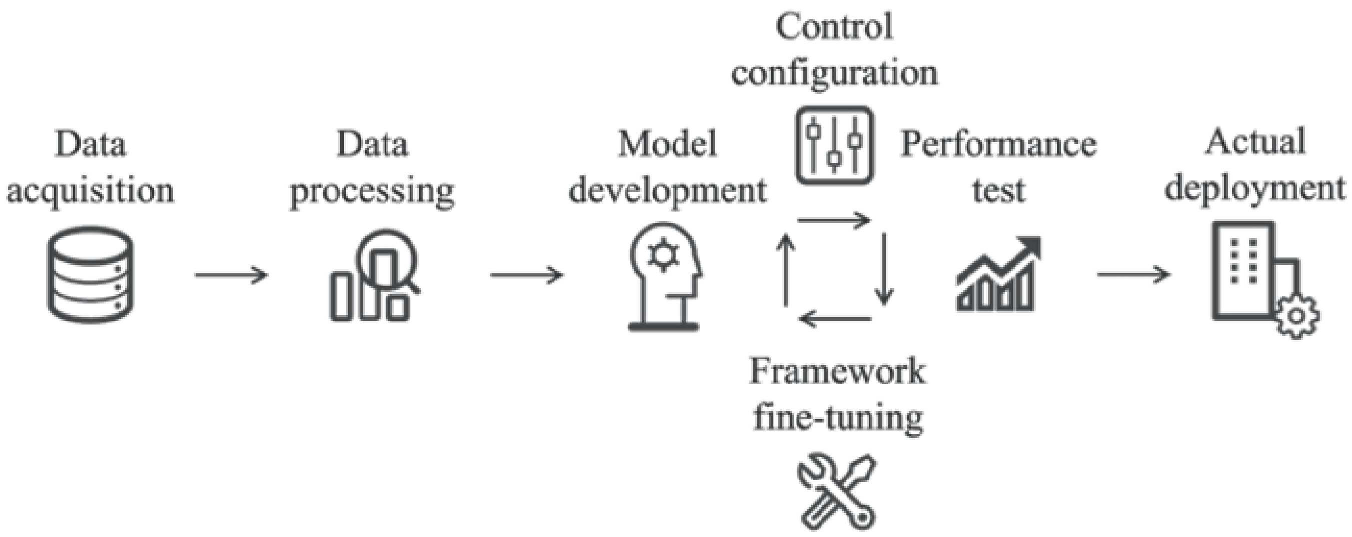

Traditional model-centric approach

- Arbitrary beforehand data acquisition
- Hard to reproduce
- Unknown consequence before deployment
- Low data usage rate

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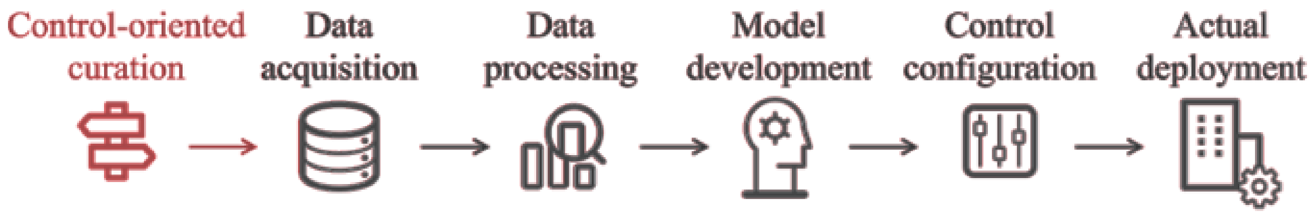
Data is like minerals, everywhere but few are useful . You need to know where to drill.



Data-centric approach

- Active learning guided by downstream applications
- Streamlined model development and implementation
- End-to-end performance estimation

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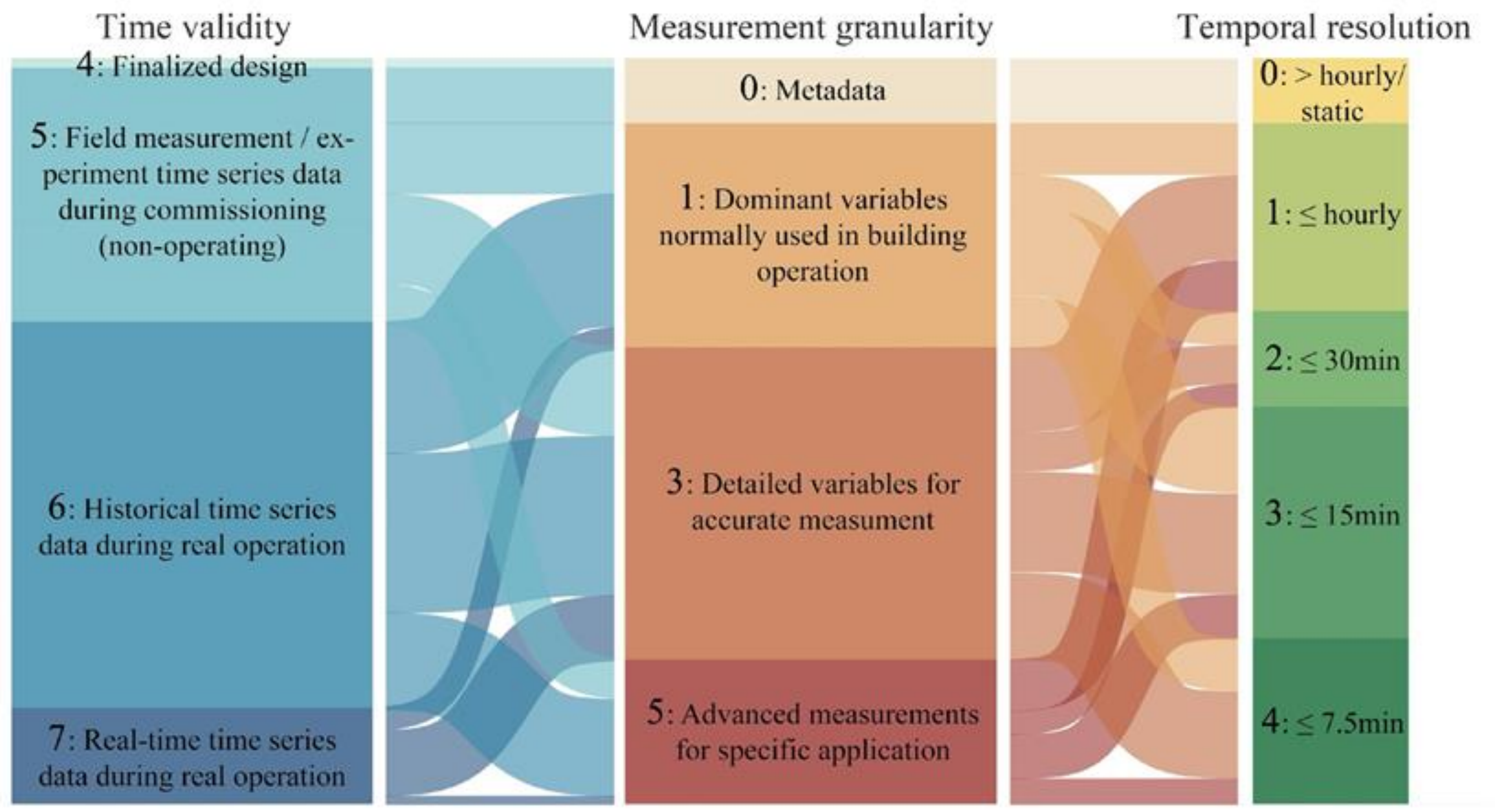


- Inherit from BIM LoD
- Three dimensions to define data availability
- Time validity: how up-to-date is the data
- Temporal resolution: time interval
- Measurement granularity: detailed definition for <u>6 data categories</u>
- Higher LoD corresponds to higher data acquisition cost

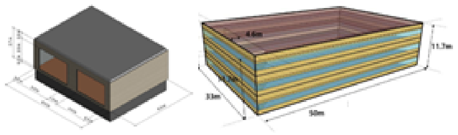
Data-centric scientific machine learning for urban intelligence and sustainability

Level	*0*	*1*	*3*	*5*[a]
Energy consumption	N/A	Total consumption by energy sources	Separated consumption by usage type	Separated consumption by sub-components
Indoor condition	N/A	Indoor air temperature	Variables affecting thermal comfort	Thermal comfort/ sensation feedback
System condition	System specifications	On/off operating mode, thermostat setpoints	Temperature and flow rate variables	Static pressures
Envelop condition	Geometric and thermal properties	N/A	Surface or core temperature	N/A
Internal disturbance	Assumed operating schedules/ profiles	N/A	Estimated operating profile	Additional occupant sensors
External disturbance	N/A	Weather data of the city/region	On-site weather station/sensors	Solar heat gain on different orientations

Data-centric scientific machine learning for urban intelligence and sustainability

Emulator setup

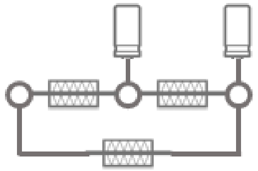
Measured disturbance inputs
- Actual meteorology year
- Occupant and electricity (office and classroom)



High-fidelity models
- BESTEST case600
- DOE medium office prototype

Evaluated against the emulators

Model identification

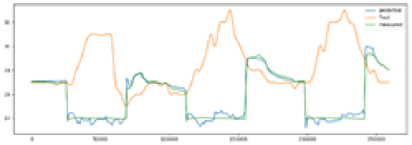


$$\theta = argmin \int_{t0}^{t1} \sum_{i}^{k} (T_{room,i} - \hat{T}_{room,i})^2$$

Control-oriented models
- RC model complexities
- Inputs for internal heat gain
- Open-loop prediction error

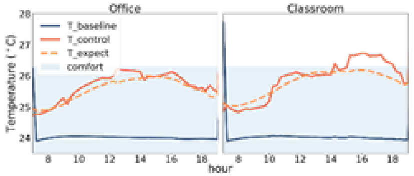
Evaluated against the emulators

Predictive evaluation



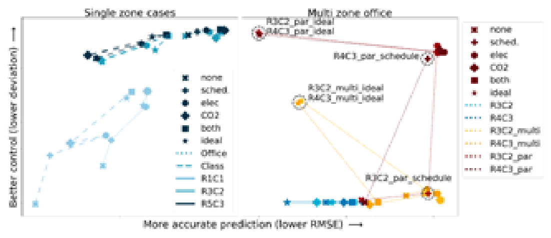
- Root mean square error
- Tested under multiple operating conditions

Control evaluation



- Minimize overall penalty of energy and comfort
- Track multiple setpoints

Post analysis



- Affecting factors of data usefulness
- The interaction between data and model in identification
- Heterogeneous requirements of prediction and control

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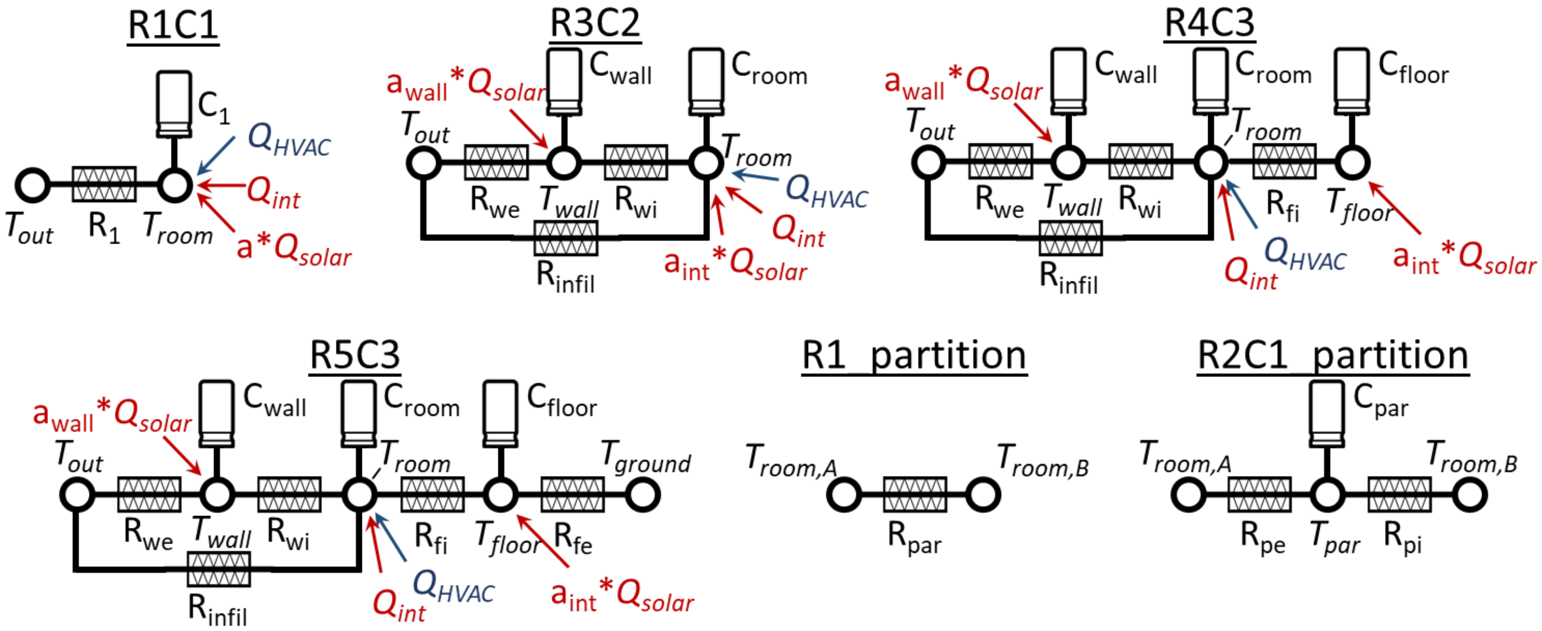

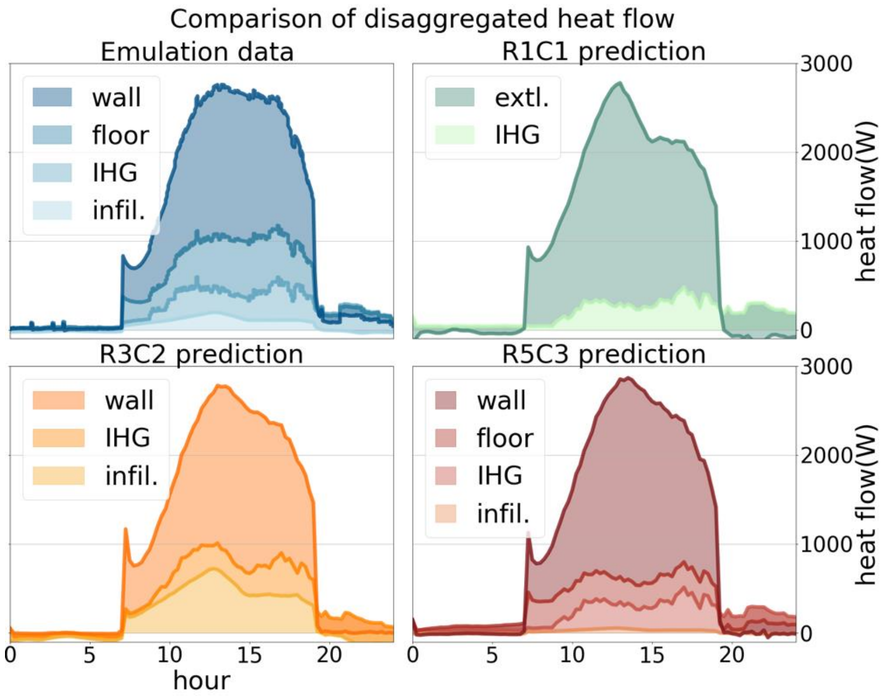

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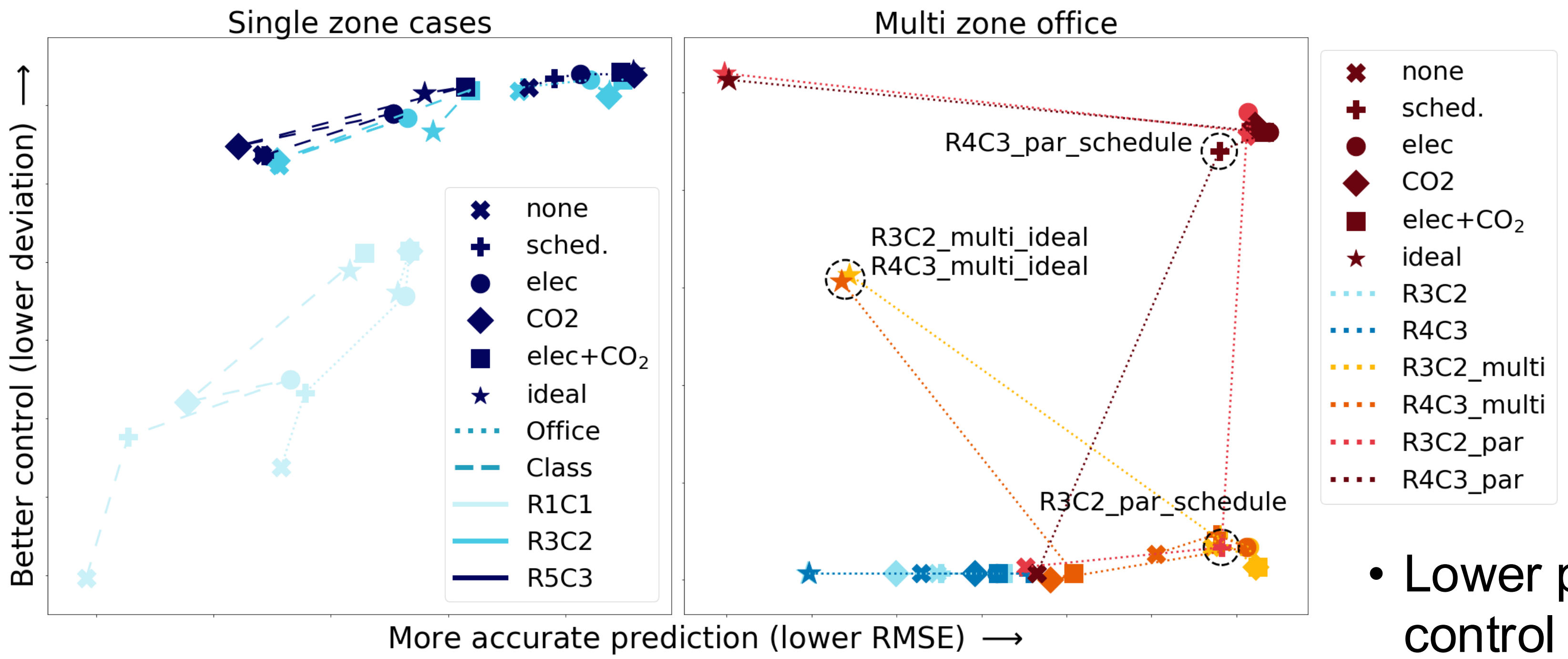

- Lower prediction error means better control for simple dynamics
- For complex buildings, more data only led to lower predictive errors
- Better control requires adequate model
- Critical physical component should be preserved (partition capacitor here)

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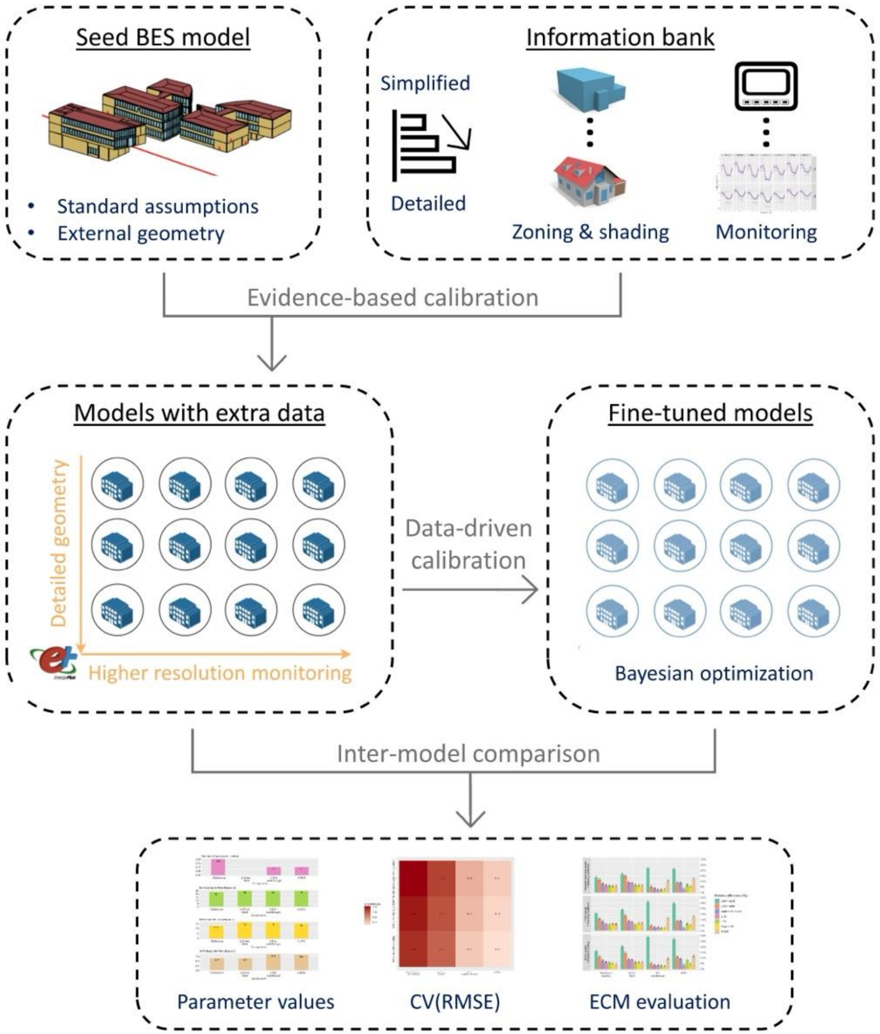

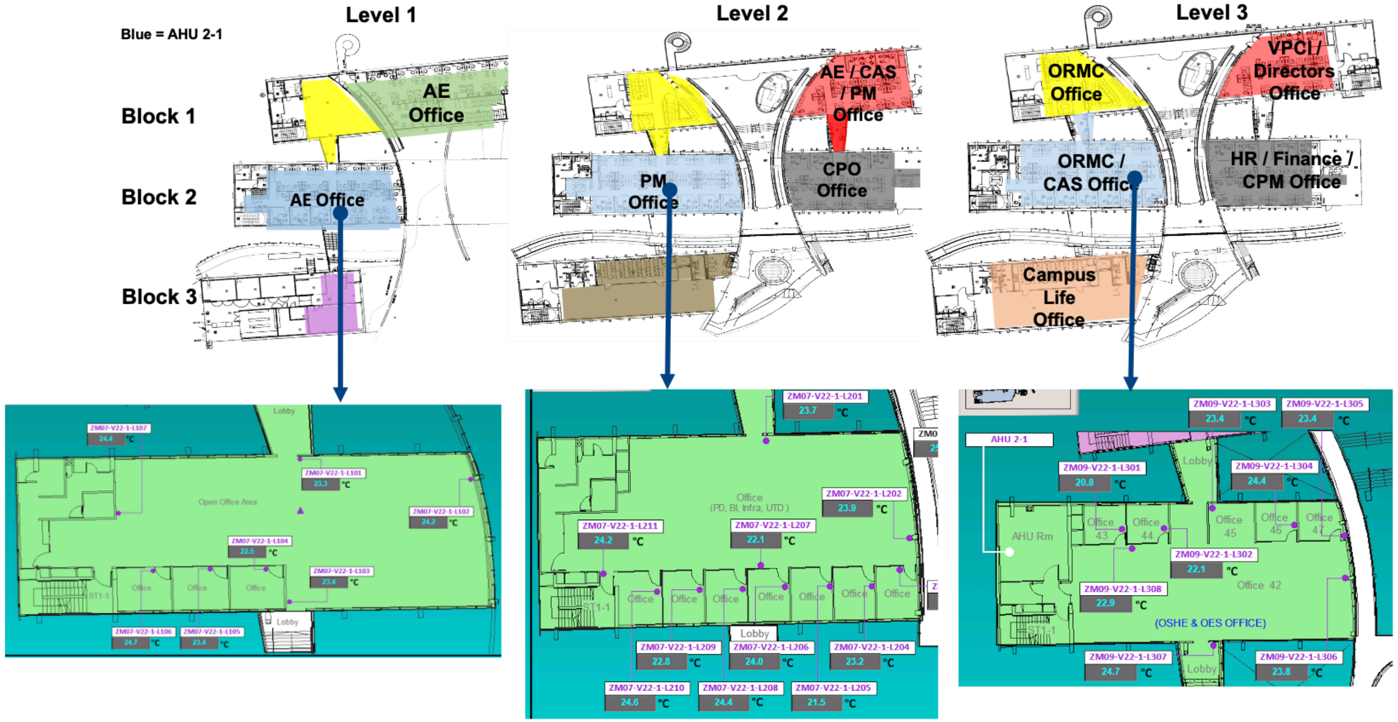

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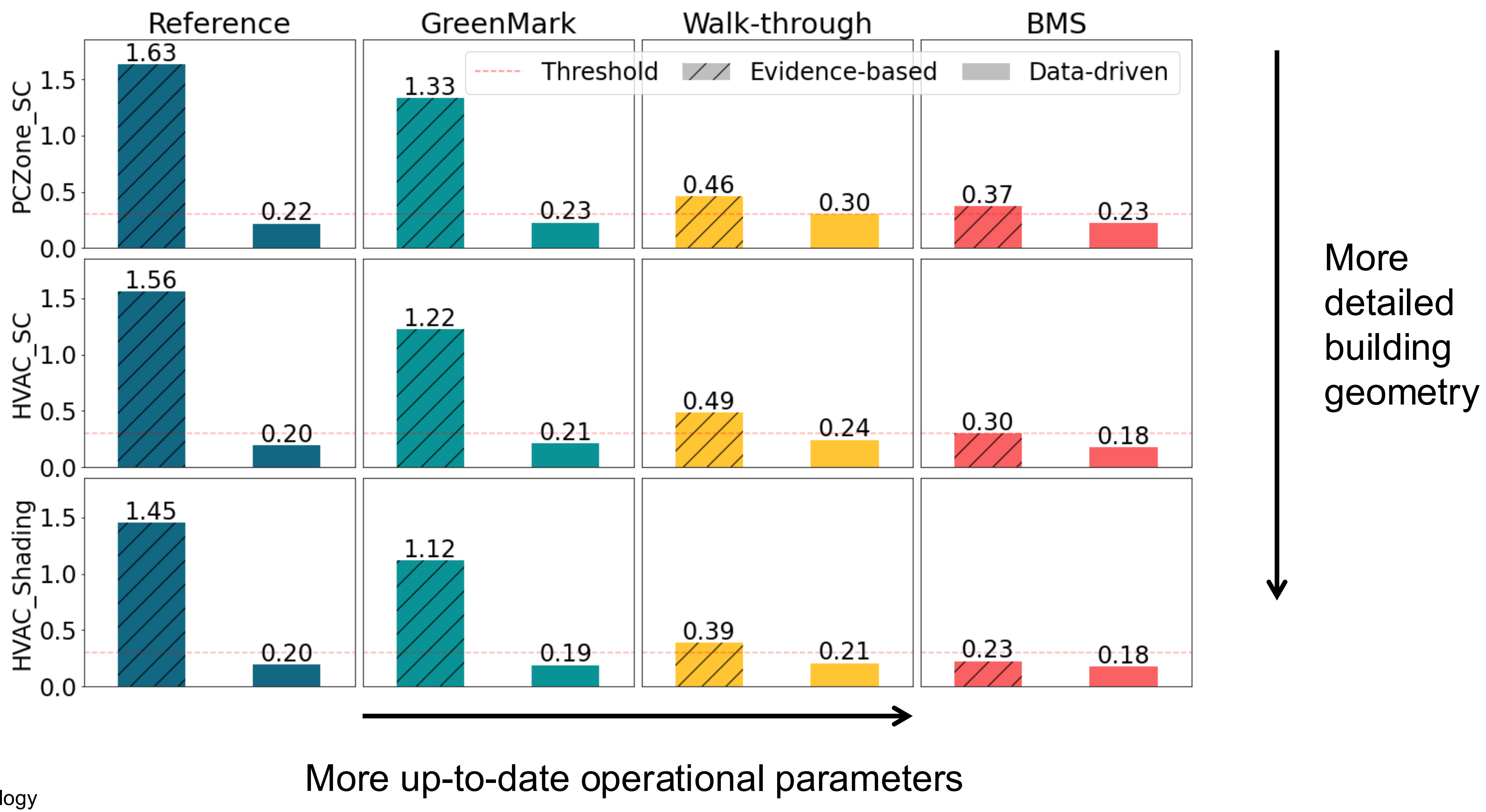

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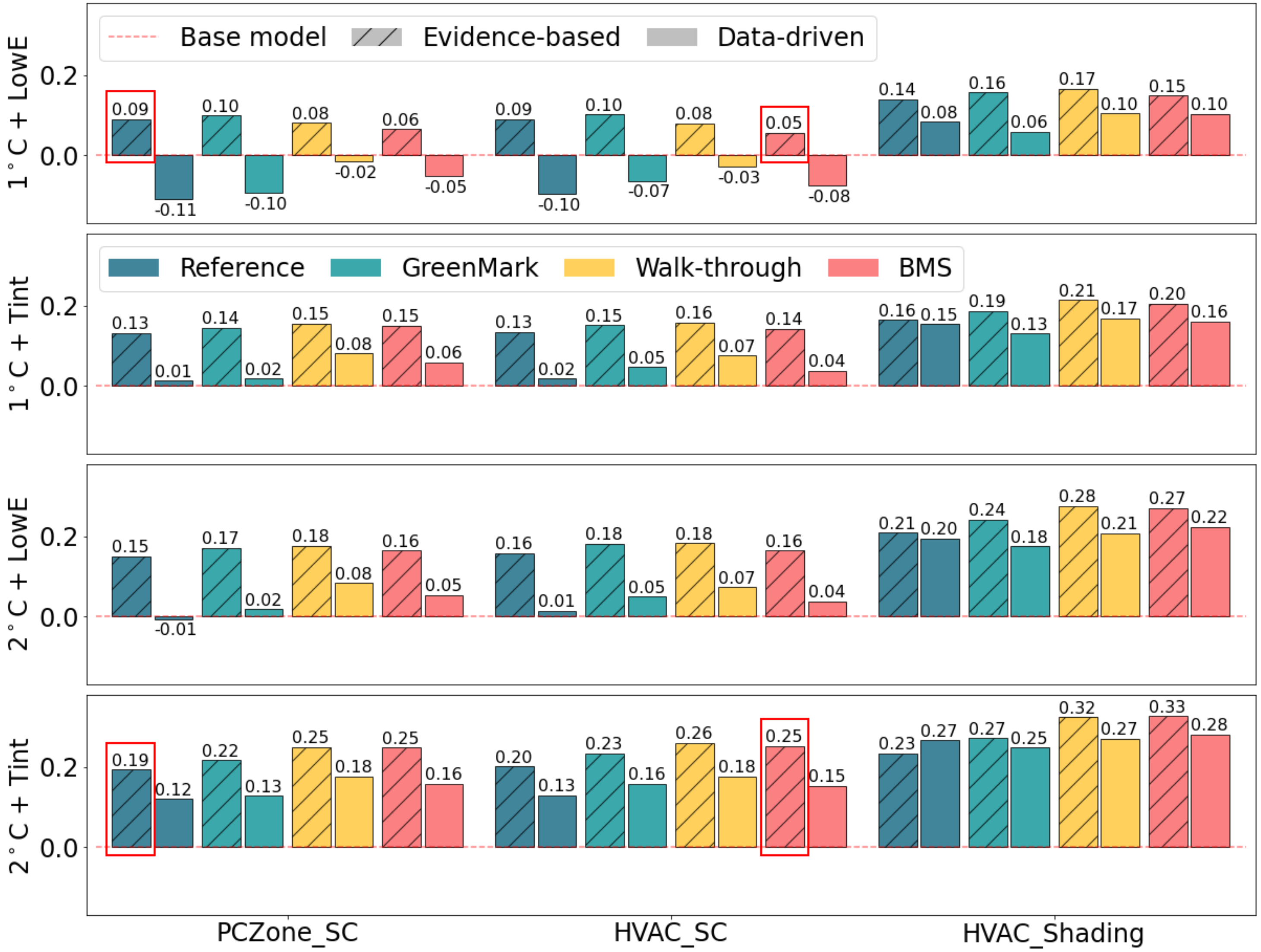


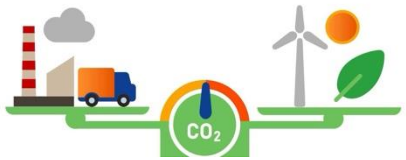
- Models with similar accuracy could have distinct ECM evaluation
- The key to informed decision-making is a good estimate of the relevant parameter

Data-centric scientific machine learning for urban intelligence and sustainability

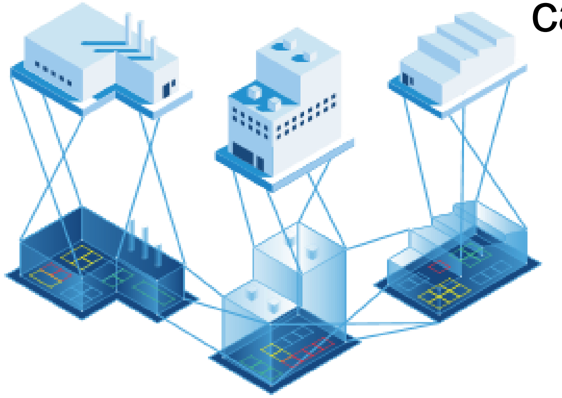
- Be cautious about low predictive errors in digital twin applications
- Scalable DT frameworks should start from data exchange infrastructure
- Model development needs to be fit-for-purpose
- Multi-system and cross-scale applications remain challenging

Thank you!

Human societal activities

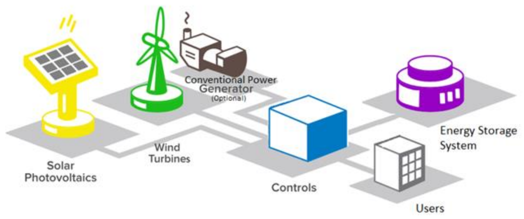


Energy-food-carbon nexus



Cross-scale digital twins for urban sustainability

Carbon-aware system operations



Optimal dispatch of hybrid energy

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