Disclaimer: No data shown in the presentation reflects true performance of Mitsubishi equipment

Deep Generative Networks and Fine-Tuning for Net-Zero Energy Buildings

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Mitsubishi Electric

- Main businesses:

Air Conditioning Systems

Automotive Equipment

Building Systems

Energy Systems

Factory Automation Systems

Home Products

Information & Comm. Systems

Public Systems

Semiconductors & Devices

Space Systems

Transportation Systems

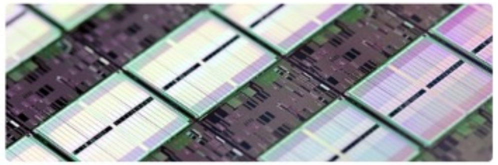
Visual Information Systems

- Many applications require seeking solutions to **open research problems**!

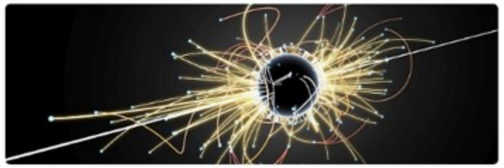
Intern/Postdoc/Visiting Positions In Multiple Areas

For more information:
www.merl.com/internship-openings
www.merl.com/employment/postdoctoral-research

Electric Systems
Modeling & optimization of power systems and electromagnetic machines.



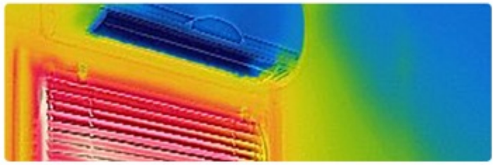
Electronic and Photonic Devices
Pursuing theoretical and experimental research for next generation devices.



Applied Physics
From first-principles modeling to device designs.

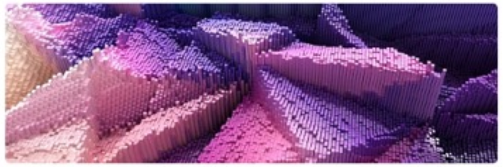
Artificial Intelligence
Making machines smarter for improved safety, efficiency and comfort.

Machine Learning
Data-driven approaches to design intelligent algorithms.



Multi-Physical Modeling
Optimal design & robust control through multi-physical modeling.

Communications
Wireless and optical communications.



Computational Sensing
Utilizing computation to improve sensing capabilities.

Optimization
Efficient solutions to large-scale problems.

Robotics
Where hardware, software and machine intelligence come together.

Computer Vision
Extracting meaning and building representations of visual objects and events in the world.

Control
If it moves, we control it.

Signal Processing
Acquisition and processing of information.

Speech & Audio
Audio source separation, recognition, and understanding.

Data Analytics
Learning from data for optimal decisions.

Dynamical Systems
Exploiting nonlinearity and shaping dynamics in creative and deeply mathematical ways.

Mitsubishi Electric SUSTIE Building

NZEB = net zero-energy buildings
HVAC = heating, ventilation, & air-conditioning

NZEBs operate with negligible net energy consumption on a prescribed length of time (usually, annual)

- while maintaining comfortable indoor environment
- through energy saving technologies in the building
  - highly efficient insulation
  - solar shading and LED lighting
  - renewable energy sources
  - **high-performance HVAC equipment**

Elevator, Lighting, HVAC, & Power Distribution Systems

Mitsubishi Electric SUSTIE Building

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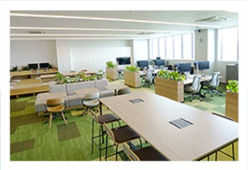
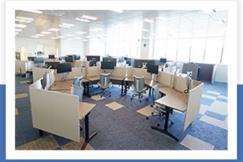
3rd Floor — Relax Zone

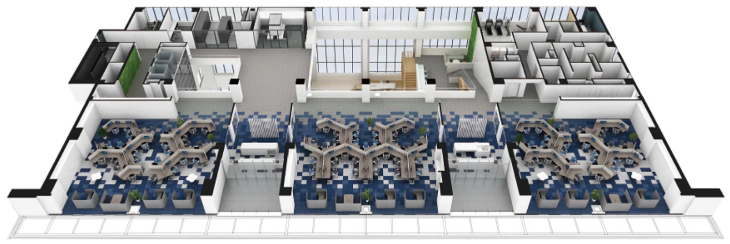


- Experimental Rooms (offices) (LEAF 1—3)

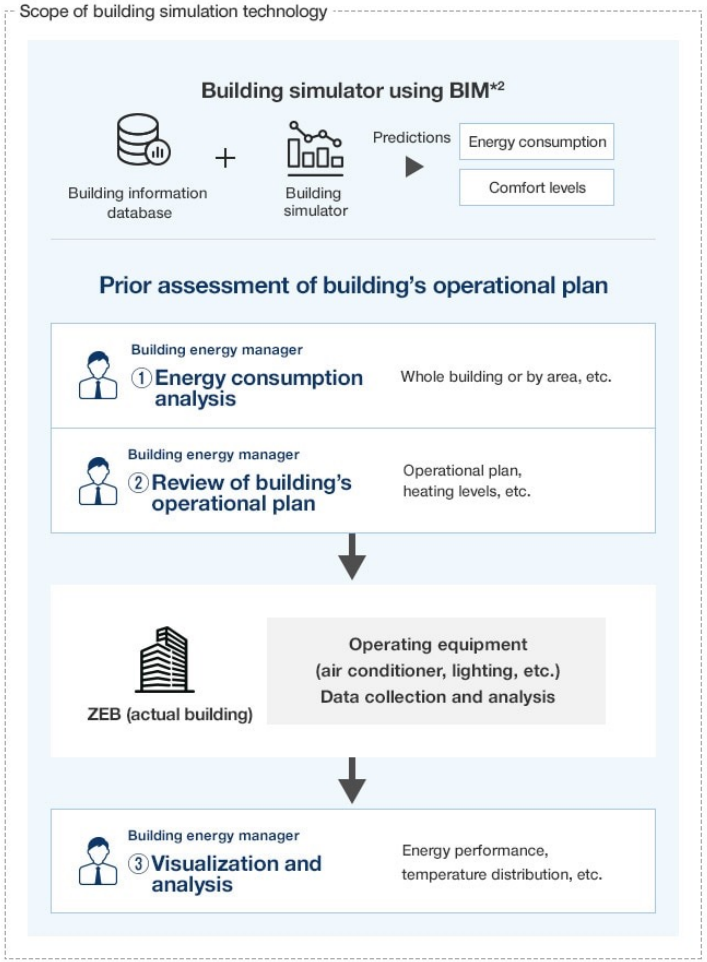
4th Floor — Focus Zone



- Experimental Rooms (offices) (SKY 1—3)
- DC Distribution Control Room
- Operation Center

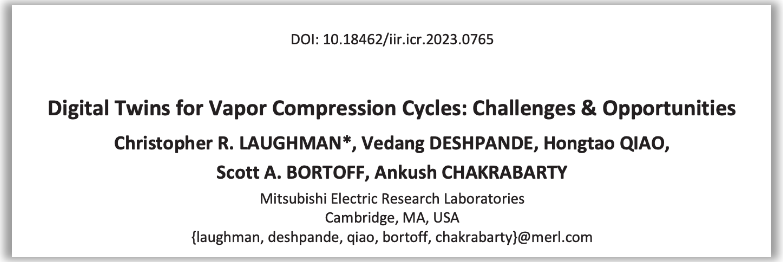


Core Technology: Digital Twin



Business Relevance of Digital Twins

- (Sounds cool, but what does it mean?)
  - Computational models with modules **capable of adapting** to operational data
  - **maintain high prediction accuracy** over product lifetime
  - supports decision-making


DOI: 10.18462/iir.icr.2023.0765

Digital Twins for Vapor Compression Cycles: Challenges & Opportunities

Christopher R. LAUGHMAN*, Vedang DESHPANDE, Hongtao QIAO,
Scott A. BORTOFF, Ankush CHAKRABARTY
Mitsubishi Electric Research Laboratories
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- Provides a **rapid**, **scalable**, **safe**, and **repeatable** alternative to field experiments

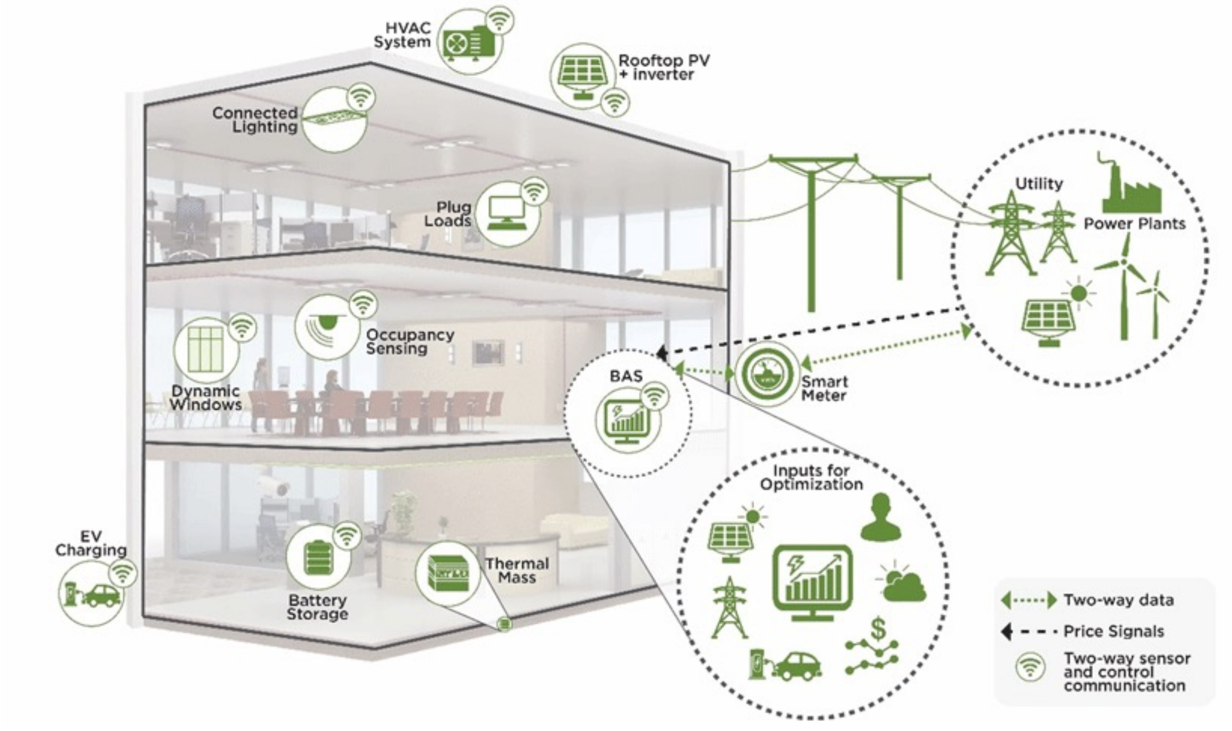
- **Upgrading product lines for existing customers:**
  - Construct libraries of simulation models for controller validation
  - Enable customer-specific design
- **Performance contracting:**
  - Accurate models enable MELCO to validate performance "from design to operation"
  - NZEB regulations are performance-oriented
- **Sustainability and decarbonization:**
  - Carbon use and emissions can be monitored and managed with predictive models and downstream estimation/control

Data, Data, Everywhere…

GEB = grid-interactive efficient buildings, NZEB = net zero-energy buildings
HVAC = heating, ventilation, & air-conditioning

- SUSTIE is an example of a smart building (GEBs, NZEBs) that is a tightly integrated system-of-systems
  - Heavily equipped with sensors = data…
  - …that communicate with cloud storage = more data!!! 🤩 🤩 🤩
    - (all right, let's throw the newest deep net we can afford at it, and all go home…)

Mandatory picture to include when mentioning GEB so that one is taken seriously



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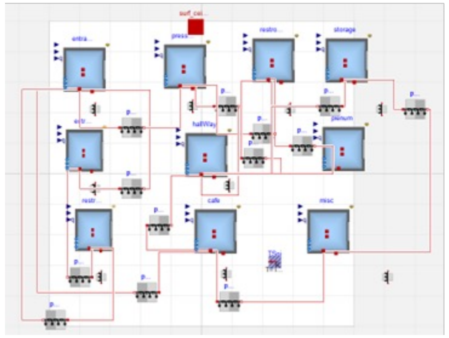
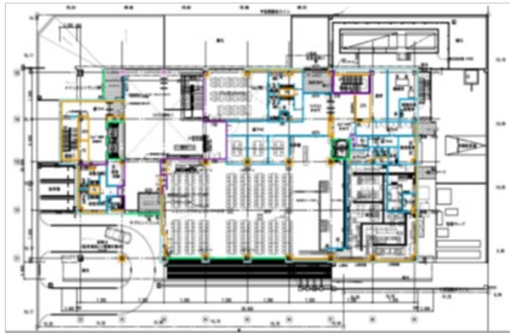
- Customers could be unwilling to share multi-month data
- Data often contain pieces that are not useful for decision-making
  - e.g., some indoor environment variables are close to steady-state, if your HVAC was designed properly

- Instead of relying solely on data, we use **physics-based building simulators** to design and test controllers prior to experiments





- **Real/operating data** can:
  - **inject customer-specificity** into design pipeline
  - **optimize fleets of product** with varying dynamics due to manufacturing, ageing/use, …

- Real/operating data can:
  - **inject customer-specificity** into design pipeline
    - ✓ (Mainly) Generative networks with building simulation informs customer-specific design
  - **optimize fleets of product** with varying dynamics
    - ✓ (If we have time) Meta-learning for rapid adaptation to new operating conditions maintains efficient operation

Mitsubishi Electric
Changes for the Better

Generative Models + Building simulation yield powerful insights for design

Motivation

- Physics-based building simulation tools are often used to size equipment during design and to monitor performance
  - Example: To predict annual energy consumption or carbon footprint

- Sophisticated building simulation models allow joint simulation of building envelopes + integrated HVAC systems
  - Cheap and fast alternative to experiments

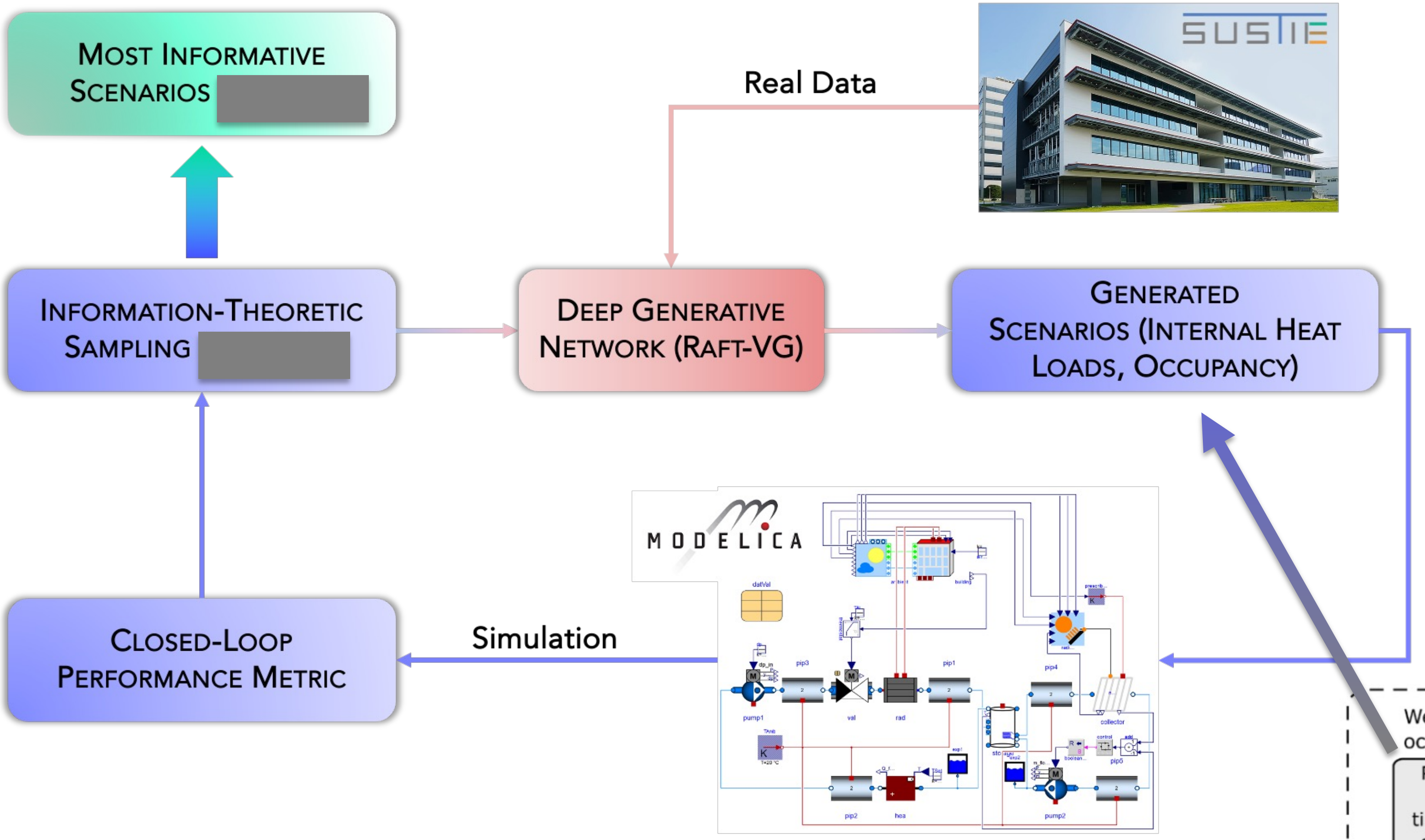
- Energy and mass transfer through walls and windows can be accurately simulated, together with the thermo-fluid physics of modern HVAC systems ⇒ this is **only a fraction** of the heating and cooling load

- Building occupants also produce and absorb latent, sensible and radiative heat
  - Occupant behavior can strongly affect the performance (energy consumption, human comfort, indoor air quality, …)
  - Difficult to explain from first-principles

- Typical building simulators must *assume* scenarios (e.g., occupancy, activity level and schedule, environmental conditions)
  - or distributional forms

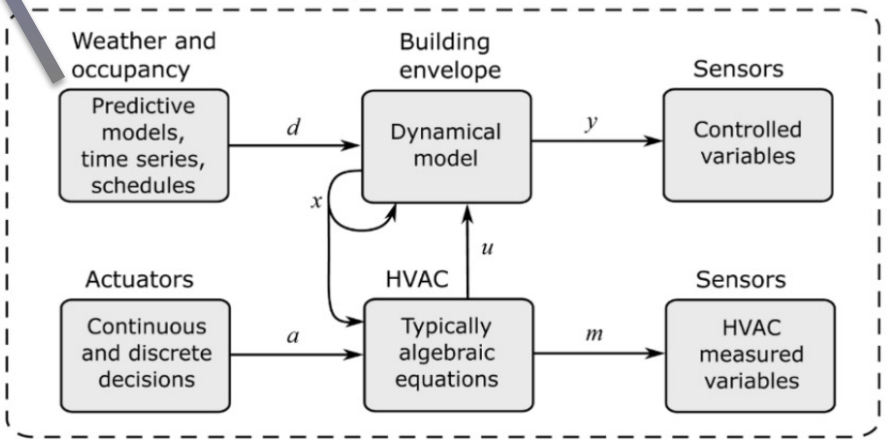
- Deep generative models can *synthesize* informative scenarios to inform design and validation by learning general distributions
  - Construct **limiting scenarios**
  - Construct **representative scenarios**

MERL's Proposed Algorithm Overview



*This is from your class notes: pretend you've seen it before if you haven't.

Building model structure



From Time-Use Surveys to Generative AI

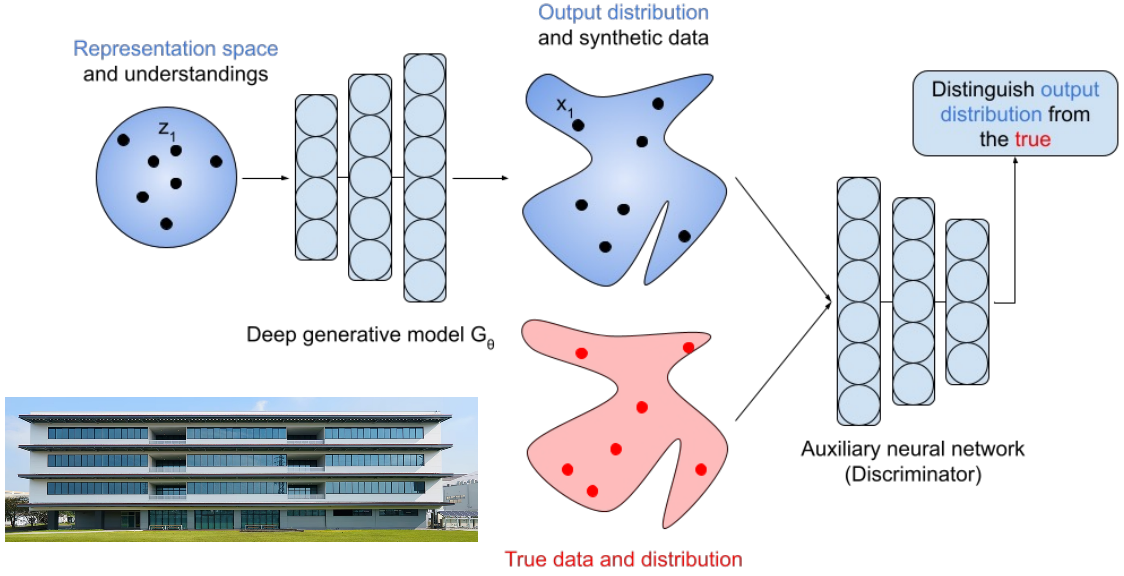
- **Time-use surveys** are a starting point for classical building operation time-series generation
- Expensive and unreliable data collection – at mercy of participants, who ~~may~~ will be grumpy from collecting data
  - – Computationally intensive to extract information from heterogeneously formatted data
- Requires extensive domain knowledge for modeling
- Challenging to revise with evolving socio-economic conditions, more manual effort to scale

- **Generative deep learning** offer a convenient automated alternative to this manual process
- Data collected directly from sensors, no subjectivity
  - – Automatically parse and mine data, everyone less grumpy
- Limited domain knowledge is sufficient for design
- Facilitates the generation of arbitrarily large artificial datasets
- Revision and scaling to large datasets: less manual effort

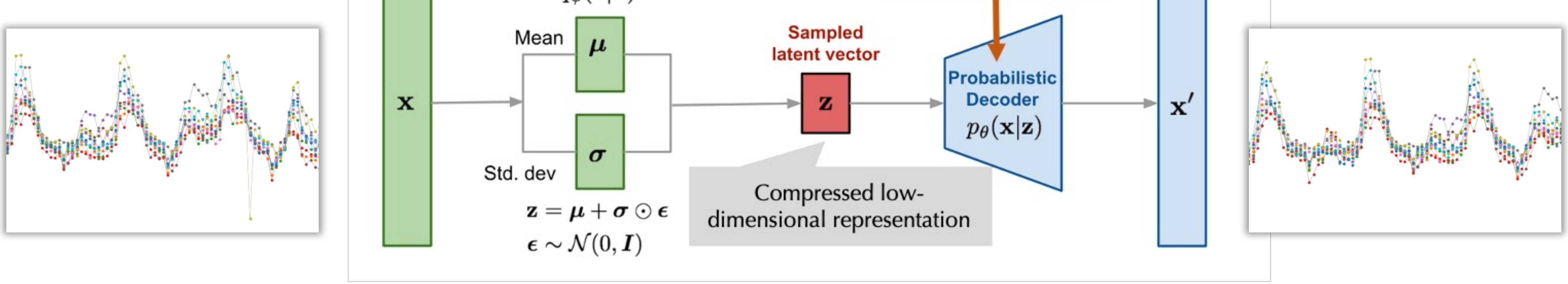
Time Use (FISCT) survey

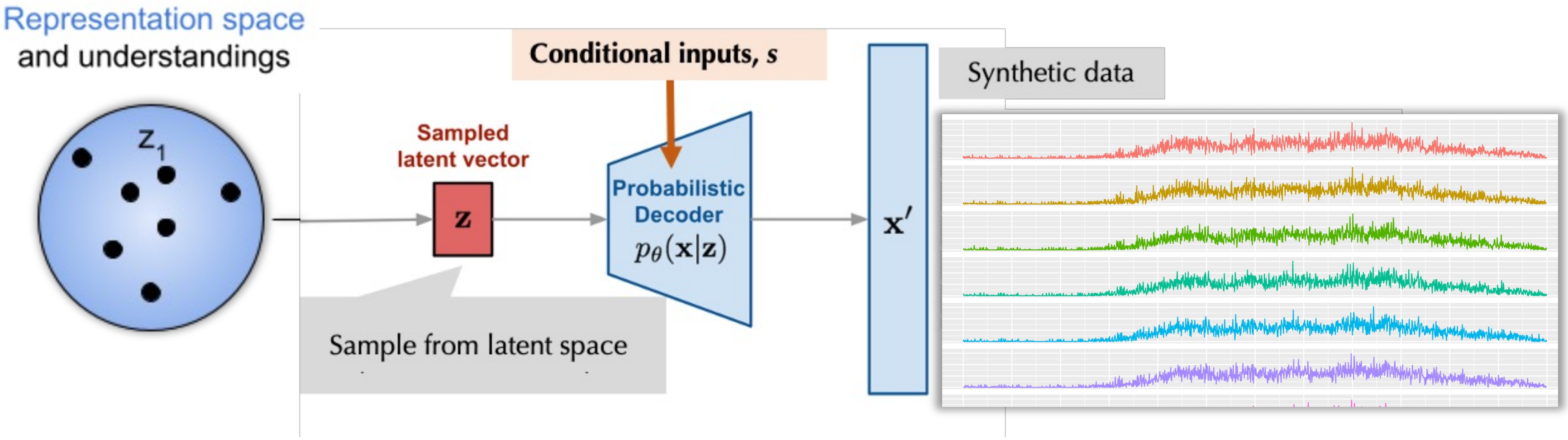
Secondary activity	Episodes with secondary activities, as a percentage of all episodes: ATUS	Episodes with secondary activities, as a percentage of all episodes: FISCT	Minutes per day
Total	2.0731	44.5004	
Sleep	.0140	.0884	
Grooming and not elsewhere classified	[1].0119	.4013	
Travel	[2].0170	.0521	
Work	[1].0528	.3077	
Childcare	[1].0756	.1471	
Adult care	.0178	.0195	
Education	[2].0057	.0715	
Leisure and sports	[1].571	35.1	
Organizational activities	.0233	.0678	
Purchasing goods and services	[1].0250	.275	
Television	[1].586	4.61	
Household work	[1].228	1.22	
Eating and drinking	[1].445	2.14	

Weekday				
00:00	01:00	Washing	Bathroom	General lighting, hot water
01:00	06:30	Sleeping, dressing	Master bedroom	General lighting, night lighting
06:30	07:30	Washing	Bathroom	General lighting, hot water
07:30	10:00	Eating, sitting, cooking	Living room, kitchen	Gas stove, general lighting
10:00	12:00	Travel		
12:00	13:30	Sitting relaxed	Living room	Mobile phone
13:30	17:30	Travel		
17:30	18:45	Eating	Dining room	General lighting
18:45	19:15	Sleeping	Master bedroom	General lighting
19:15	20:30	Washing	Bathroom	General lighting, hot water
20:30	22:45	Eating, sitting	Living room	General lighting
22:45	01:00	Sitting relaxed	Living room	General lighting
Friday				
00:00	01:00	Watching television	Living room	Television
01:00	07:45	Sleeping, dressing	Master bedroom	General lighting, night lighting
07:45	08:15	Washing	Bathroom	General lighting, hot water
08:15	10:00	Eating, sitting, cooking	Living room, kitchen	Gas stove, general lighting
10:00	12:00	Sleeping	Master bedroom	
12:00	13:30	Sitting relaxed	Living room	Mobile phone
13:30	17:30	Travel		
17:30	18:00	Eating	Dining room	General lighting
21:00	22:00	Watching television	Living room	Television, general lighting
22:00	23:00	Washing	Bathroom	General lighting, hot water
23:00	00:00	Sleeping	Bedroom	Night lighting
Weekend				

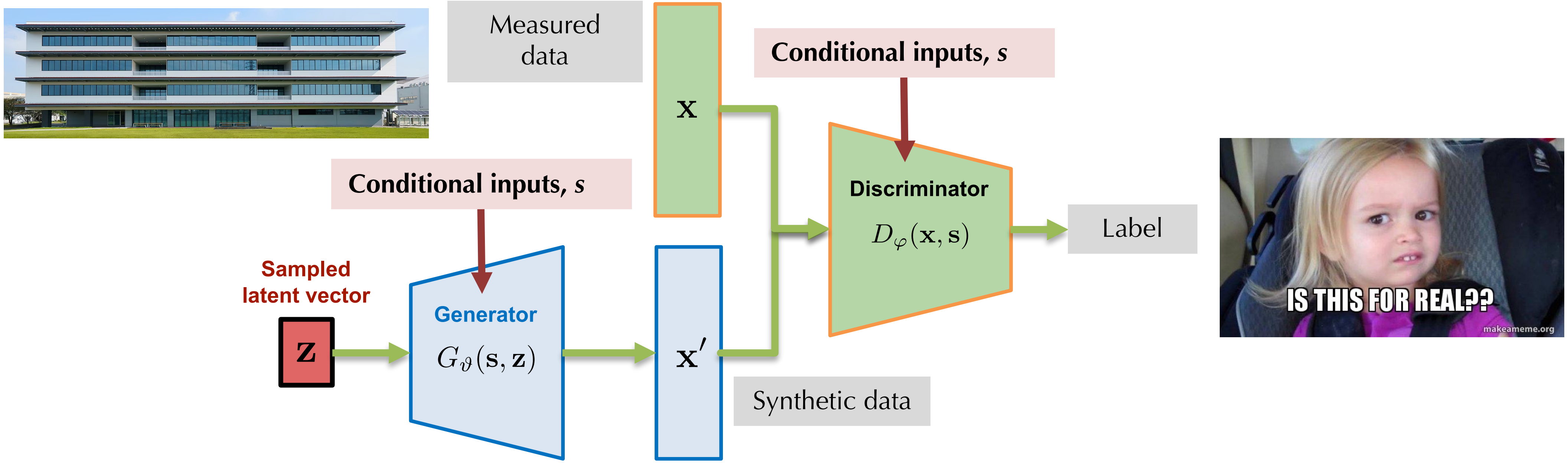


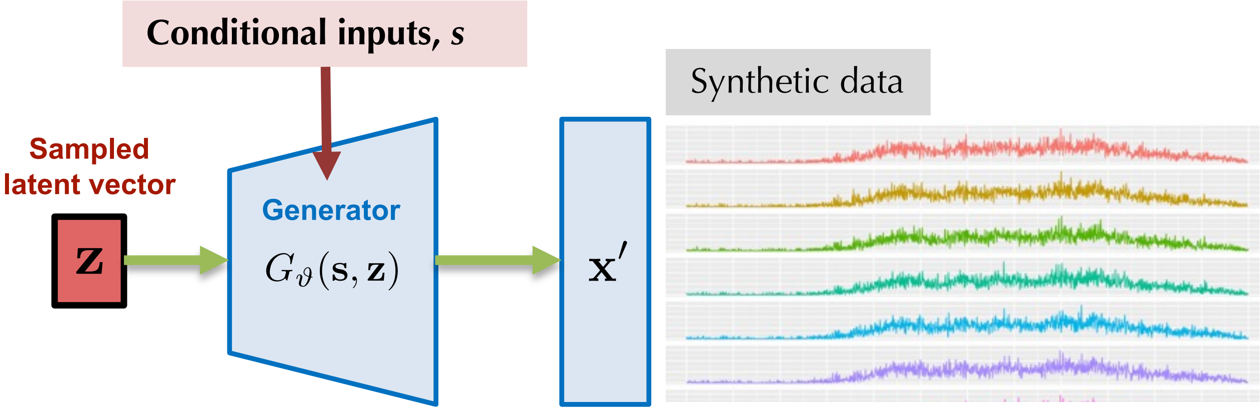
Preliminaries: Conditional VAEs





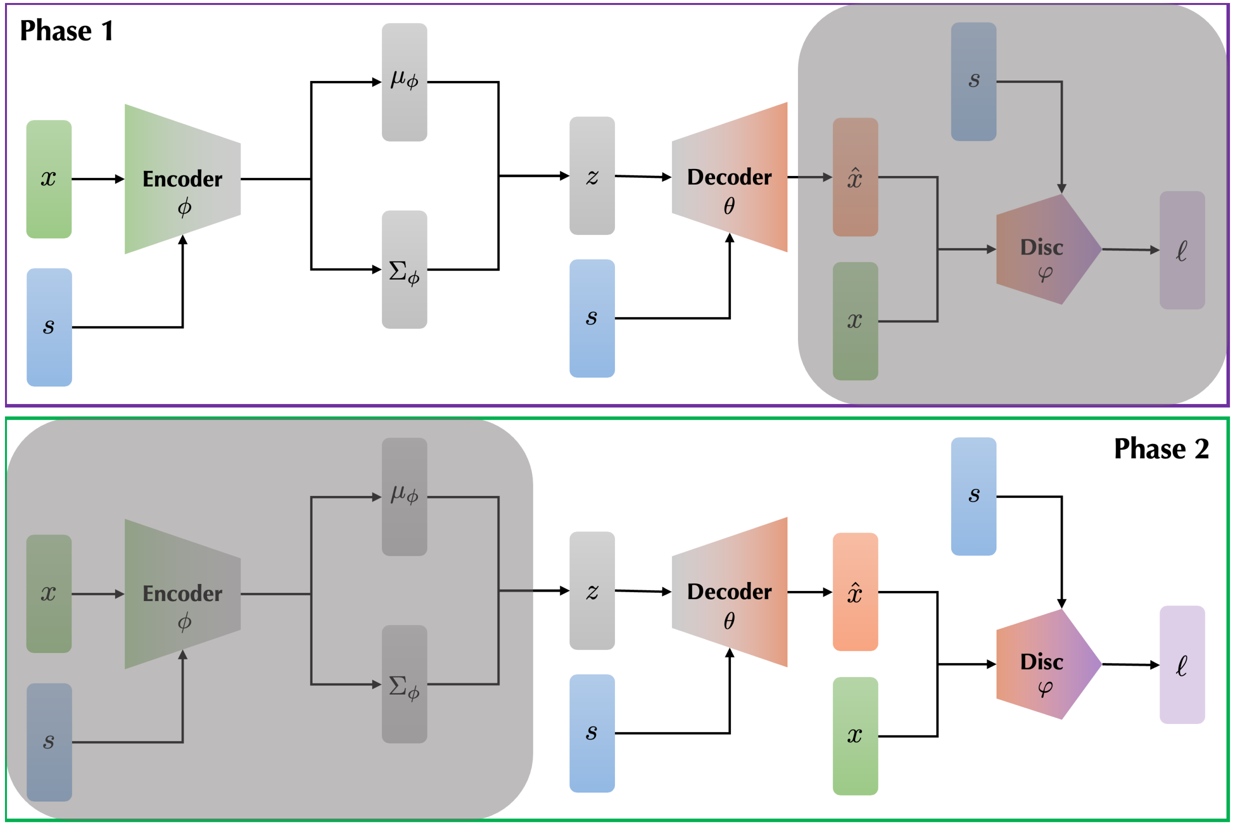
Preliminaries: Conditional GANs





MERL Proposed RAFT-VG

- Deep generative model fine-tuning procedure to synthesize **arbitrarily large, multivariate** building operation time-series profiles;
  - e.g., 24h profile of internal heat loads in a room
- Provides a **stable training procedure** and allows realistic approximations of the true data distribution
- **Outperforms the competing models** in terms of accurately identifying the ground-truth distribution and training stability



adversarial fine-tuning regularizing

$$\min_{\theta} \max_{\varphi} \mathrm{E}\left[D_\varphi(x, s) - D_\varphi(\hat{x}_\theta(z, s), s)\right] + \lambda \|\theta - \theta_\star\|_2^2$$

RAFT Loss Function

Synthesizing Building Operation Data with Generative Models: VAEs, GANs, or Something In Between?

Authors: Alessandro Salatiello, Ye Wang, Gordon Wichern, Toshiaki Koike-Akino, Yoshihiro Ohta, Yosuke Kaneko, Christopher Laughman, Ankush Chakrabarty Authors Info & Claims

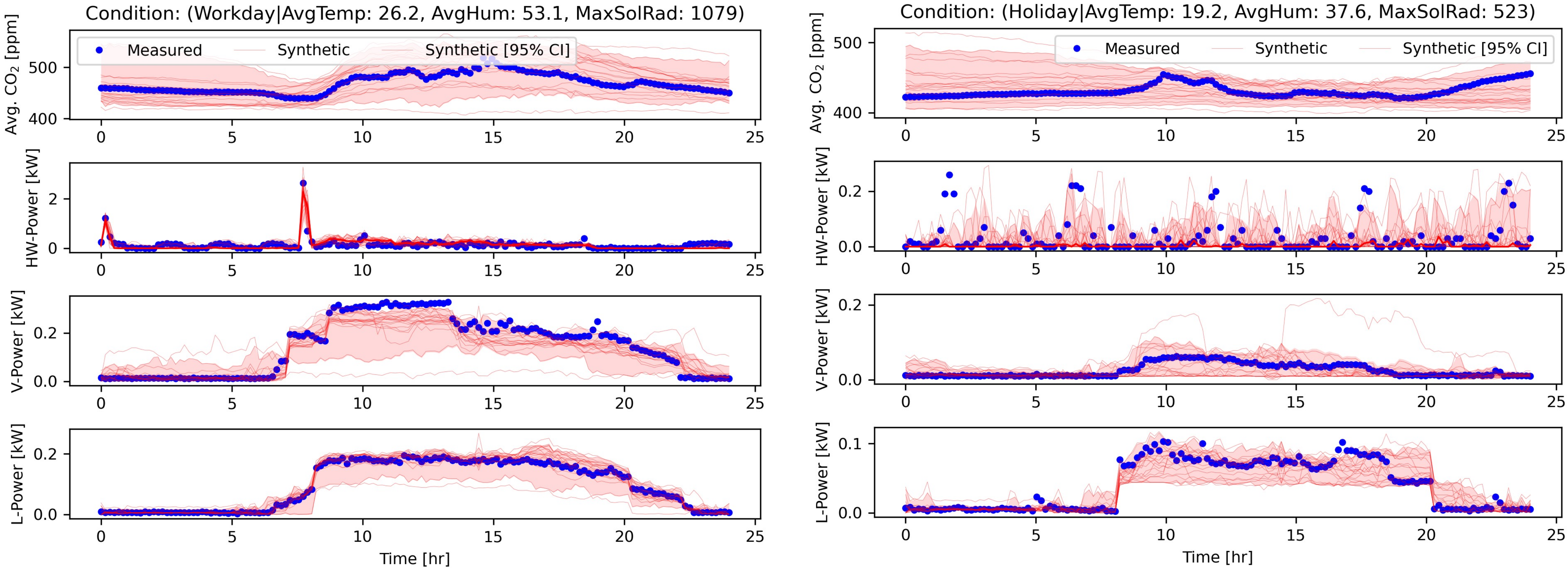
e-Energy '23 Companion: Companion Proceedings of the 14th ACM International Conference on Future Energy Systems • June 2023 • Pages 125–133 • https://doi.org/10.1145/3599733.3600260

SUSTIE Dataset

- SUSTIE has 9 rooms, a total floor area of >6400m^2
  - The electrical energy is measured for each type of equipment (air-conditioning, ventilation, lighting, hot water supply and elevators) and for each room
  - Outdoor temperature and humidity, wind speed and direction, rainfall, and solar radiation
  - 330 sensors for indoor air quality and emissions
  - Occupancy in each room

- The data is collected 24 hours a day, with a sampling rate of 1 minute by the building management system
- Total dataset selected: **585 days x 144 samples/day x 4 signals**
  - CO_2, Power: hot water, ventilation, air-conditioner
- Conditional inputs:
  - Workday/holiday flag
  - Median outdoor dry-bulb temperature and RH over 24hr
  - Max solar radiation over 24hr

Conditionally Generated Examples using RAFT-VG

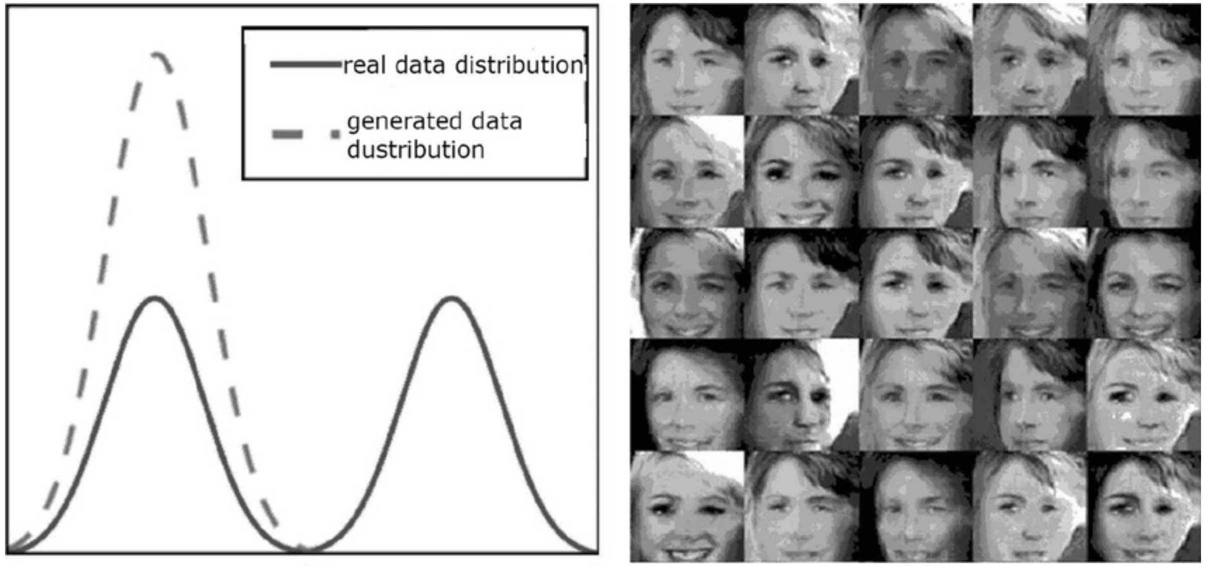


Comparison with Popular Generative Models

- Performance indices:
  - Normalized root mean squared error (mean accuracy)
  - Fréchet distance (**mode collapse**)
  - KL divergence (quality of the learned distribution)

$$\boxed{\mathrm{FD}(\mathbf{x},\hat{\mathbf{x}}) \triangleq \|\mu_{\mathbf{x}} - \mu_{\hat{\mathbf{x}}}\|^2 + \|\sigma_{\mathbf{x}} - \sigma_{\hat{\mathbf{x}}}\|^2}$$

$$\boxed{\mathrm{KLD}(\mathbf{x},\hat{\mathbf{x}}) \triangleq \log\frac{\sigma_{\mathbf{x}}}{\sigma_{\hat{\mathbf{x}}}} + \frac{\sigma_{\hat{\mathbf{x}}}^2 + (\mu_{\mathbf{x}} - \mu_{\hat{\mathbf{x}}})^2}{2\sigma_{\mathbf{x}}^2} - \frac{1}{2}.}$$



(a) (b)

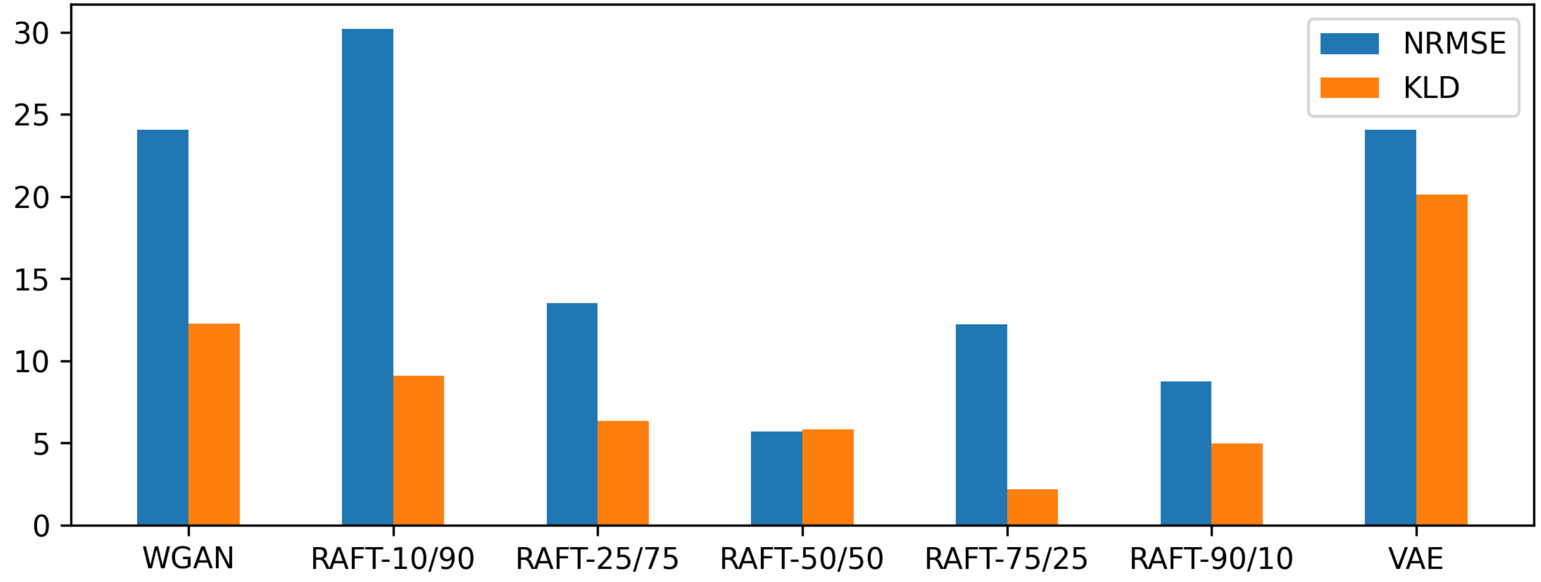
- RAFT-VG outperforms some competitor algorithms

Customary table one uses to justify buying a GPU

Network	NRMSE	FD	KLD
VAE	2.77e-01	1.47e+03	2.29e+01
GAN	9.88e+00	1.01e+06	2.33e+04
W-GAN	1.97e-01	2.22e+03	2.15e+01
VAE-GAN	8.10e-01	1.19e+05	5.58e+01
RAFT-VG (ours)	**7.07e-02**	**1.83e+02**	**2.06e+00**

Effect of Fine-Tuning

- Q: Does fine-tuning improve generation performance?



- Clear benefit to letting the VAE component train well, then fine-tune
  - Best performance exhibited RAFT-75/25 = VAE 75% training iterations, fine-tuning 25% training iterations

- No fine-tuning = VAE/WGAN leads to poor generalization

META-LEARNING FOR FINE-TUNING/ADAPTATION IS CRITICAL FOR MAINTAINING ENERGY EFFICIENCY

Motivation

- Despite your best initial design, things will change from simulation to reality ("sim2real")
  - Unfortunately, also true from verification (in factories) to deployment (in customer environment)
  - Example: fleets of product from manufacturing lines, effect of time, wear, tear, on NZEBs…
- **Data-efficient online adaptation** is critical for maintaining good **performance throughout product lifetime**!

With adaptation

Without

Motivation

- Despite your best initial design, things will change from simulation to reality (“sim2real”)
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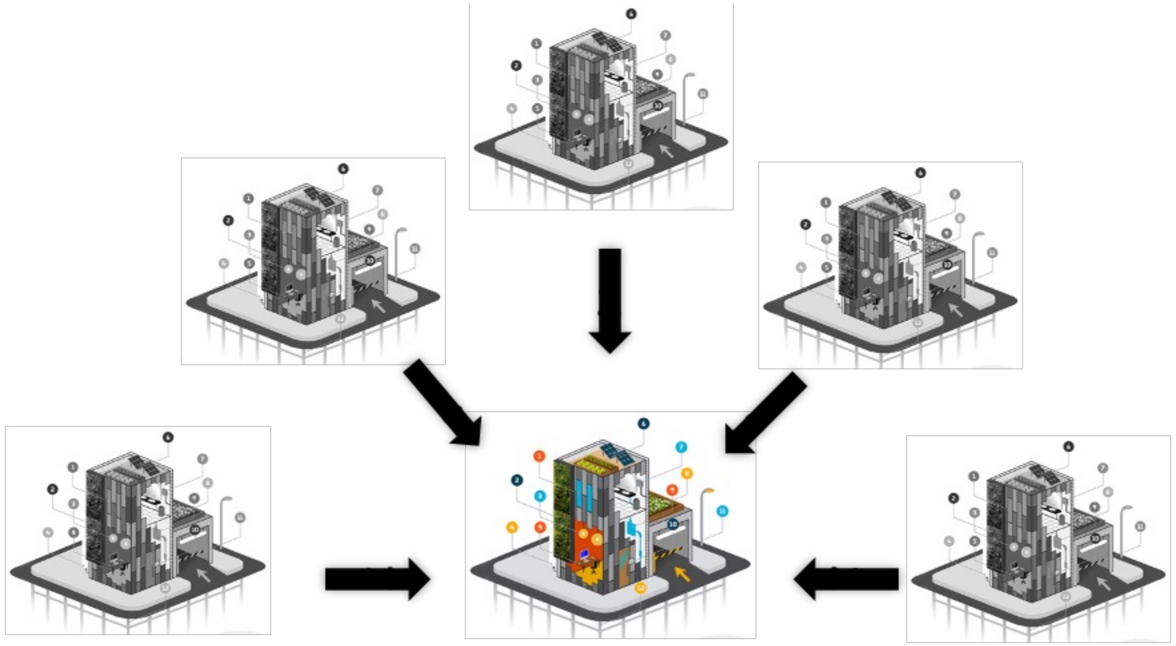
Meta-learning reduces data requirements for each target building/HVAC system
by learning how to **adapt** rapidly using data from **multiple** similar systems



Meta-Learning for Digital Twins

- Key technology for implementation: simulation, machine learning, estimation, control, …
- For deployment, **data-efficient online adaptation** is critical!
- Meta-learning curtails data requirements from each customer by adapting quickly using data from multiple customers

- (… ok, so what is meta-learning anyway?)

Meta-Learning: Intuition

- Key technology for implementation: simulation, machine learning, estimation, control, …
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- Intuition:
  - *Supervised learning*:
    - (1 month) read Math, History, and Chemistry (training)
    - write Math, Hist, Chem exams (inference)
  - *Transfer learning:*
    - (1 month) read Math, History, and Chemistry (pre-training)
    - (next week, unplanned) read physics exploiting critical M, H, C concepts (fine-tuning)
    - write a physics exam (inference on new task)

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    - write a physics exam (inference on new task)
  - *Meta-learning:*
    - (1 month) learn and improve how to manage time, take notes, … (meta-training/**task-independent**)
    - (same month, 1 week/topic) use task-independent skills to read M, H, C (meta-training/**task-specific**)
    - (next week) use task-independent skills to read physics (meta-inference/task-specific)
    - write a physics exam (inference on new task)

Gradient-Based Meta-Learning

- Key technology for implementation: simulation, machine learning, estimation, control, …
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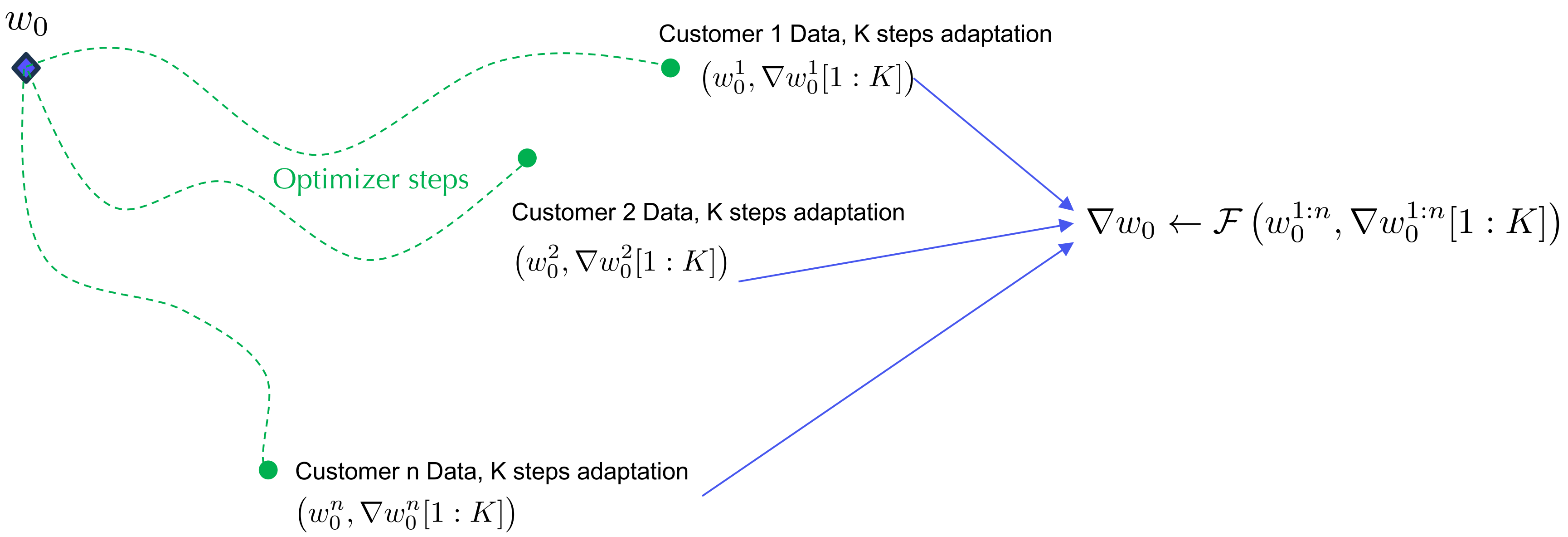
- Classical gradient-based meta-learners[1,2] rely on a bilevel training procedure i.e., 2 training loops:
  - A feature re-use loop for learning task independent weights
  - A rapid adaptation loop for learning task-specific weights (given an adaptation budget)

[1] C. Finn, P. Abbeel, S. Levine, *Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks*, ICML 2017.
Terminology from: [2] A. Raghu, M. Raghu, S. Bengio, and O. Vinyals. *Rapid learning or feature reuse? Towards understanding the effectiveness of MAML*, ICLR 2019.



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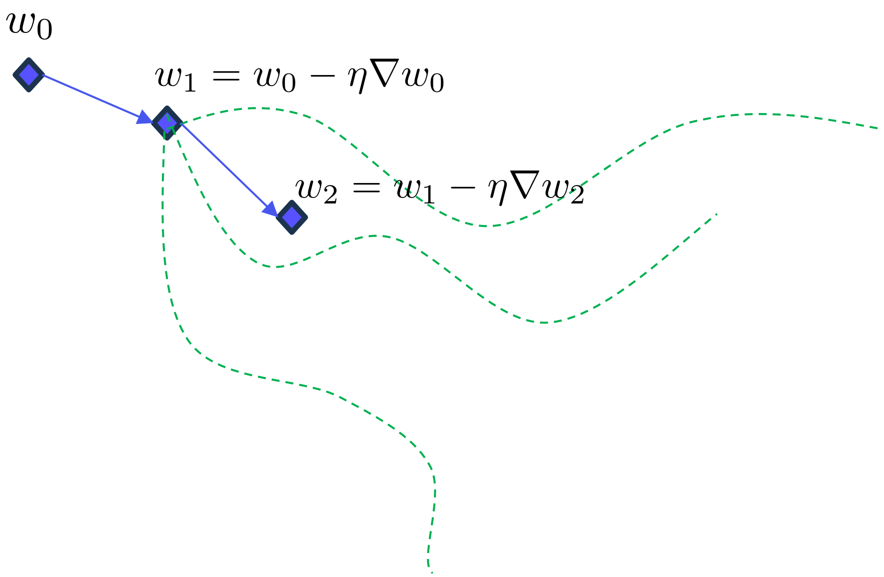

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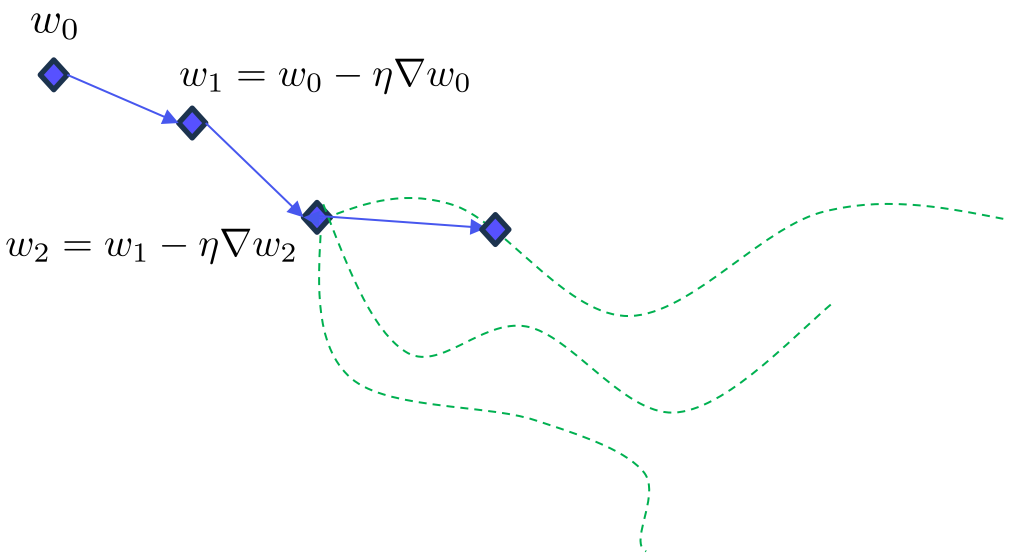

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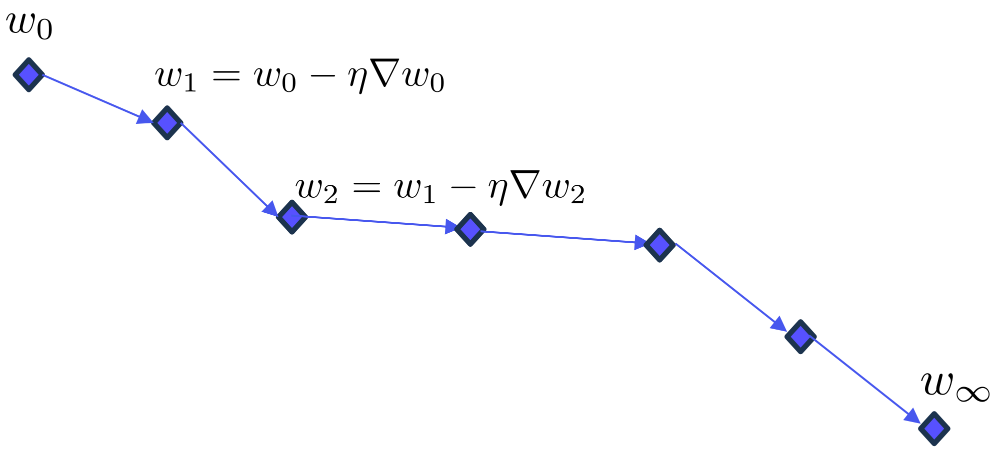


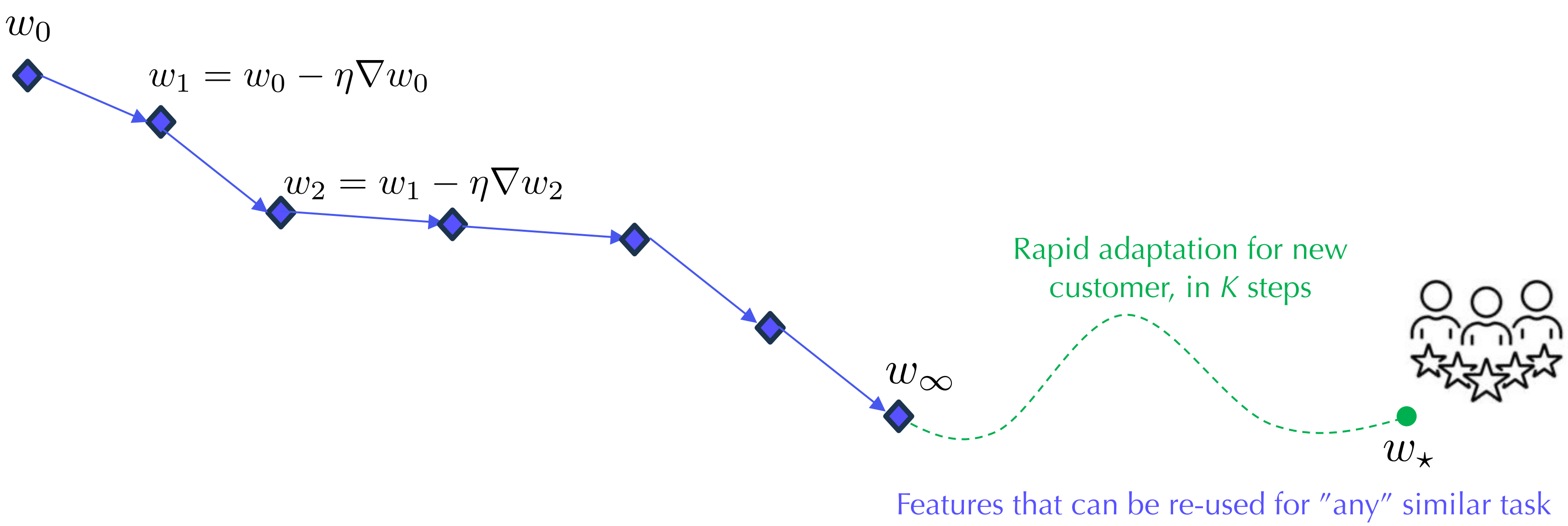
Features that can be re-used for "any" similar task

Gradient-Based Meta-Learning

- Key technology for implementation: simulation, machine learning, estimation, control, …
- For deployment, **data-efficient online adaptation** is critical!
- Meta-learning curtails data requirements from each customer by adapting quickly using data from multiple customers

- Classical gradient-based meta-learners rely on a bilevel training procedure i.e., 2 training loops:
  – A feature re-use loop for learning task independent weights
  – A rapid adaptation loop for learning task-specific weights

  – The **adaptation is "baked in"** to the training procedure: this will be exploited at inference



Gradient-Based Meta-Learning: Use-Cases in Energy Systems

- Meta-L is a general framework for fine-tuning neural weights using customer-specific data
  - The "base learner" is a deep neural network, which is expressive and **can incorporate physical constraints for predictions**

- We have found use-cases in:

Predictive modeling

IEEE CSS — IEEE CONTROL SYSTEMS LETTERS, VOL. 7, 2023 — 3483

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Model calibration

ELSEVIER — Energy and Buildings — Volume 270, 1 September 2022, 112278

Calibrating building simulation models using multi-source datasets and meta-learned Bayesian optimization

Sicheng Zhan [a,1], Gordon Wichern [b], Christopher Laughman [b], Adrian Chong [a], Ankush Chakrabarty [b]

Controller adaptation

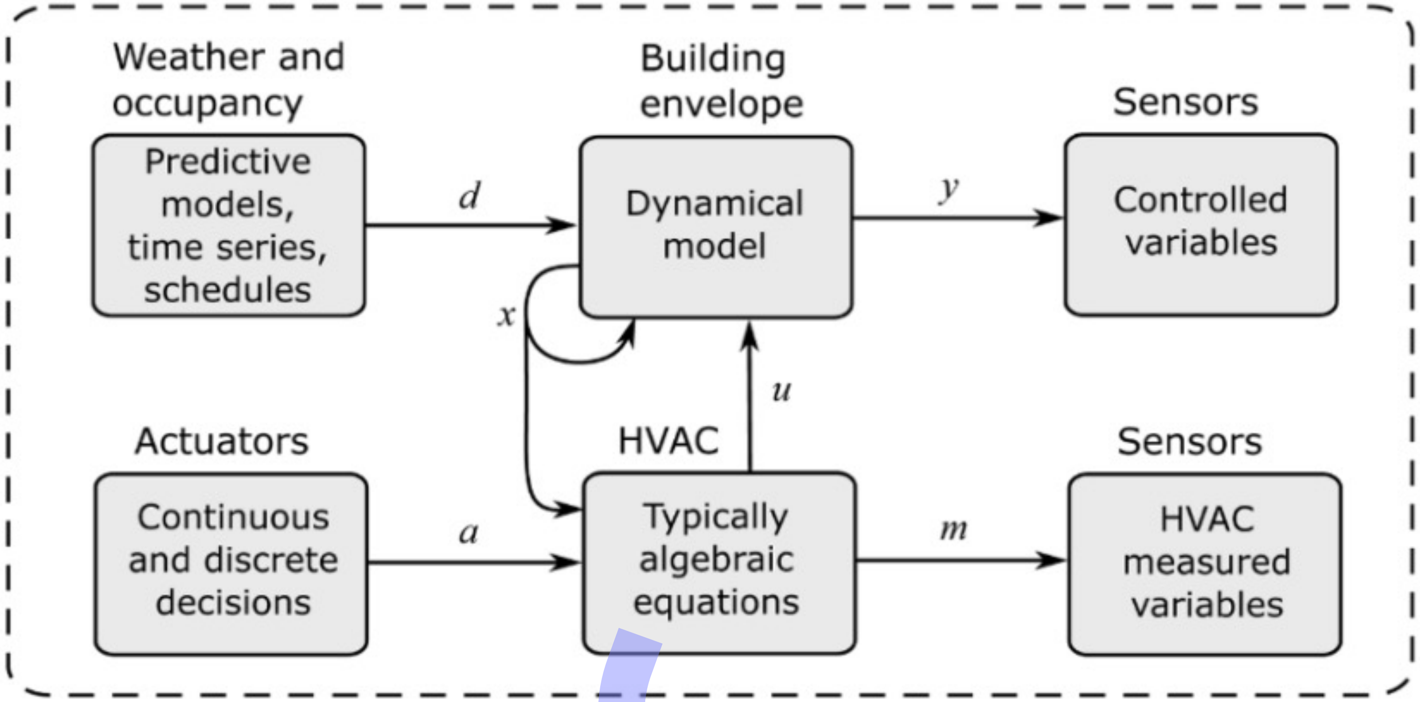
2022 IEEE 61st Conference on Decision and Control (CDC)
December 6-9, 2022. Cancún, Mexico

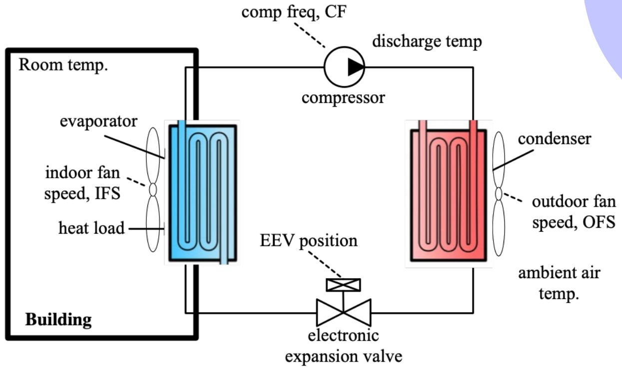
Optimizing Closed-Loop Performance with Data from Similar Systems: A Bayesian Meta-Learning Approach

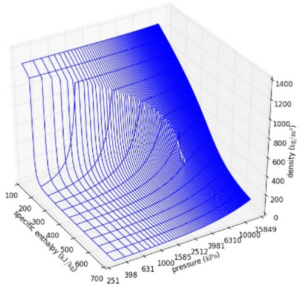
Ankush Chakrabarty[†]

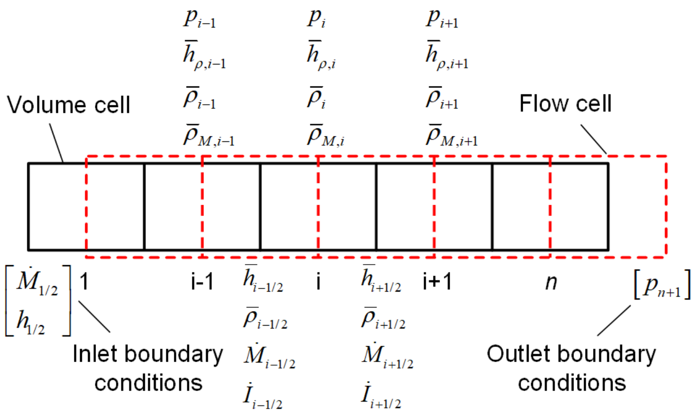
Gradient-Based Meta-Learning: Predictive Modeling for HVAC Dynamics

Building model structure









Actually, HVAC dynamics are so complex, most people (over)simplify these dynamics as algebraic equations

But since our job is to control HVAC systems, we need simpler representations of these dynamics than **this** horrible thing:

Mass balance:

$$\frac{\partial(\rho A)}{\partial t} + \frac{\partial(\rho A v)}{\partial x} = 0$$

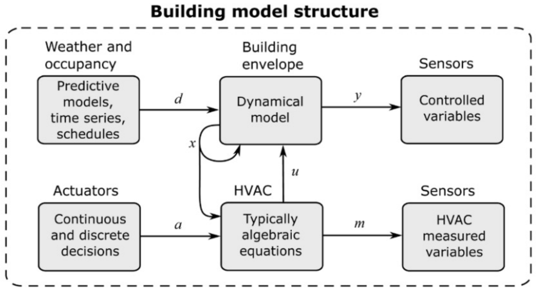
Momentum balance:

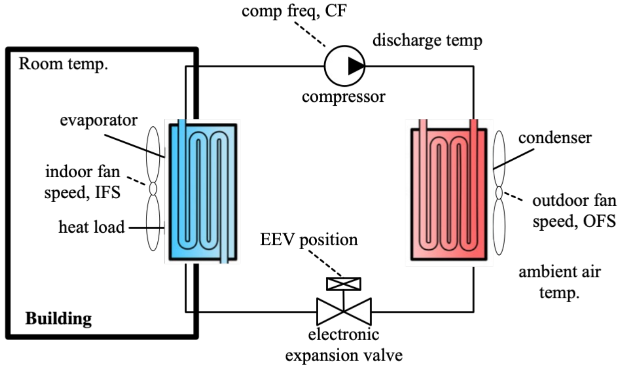
$$\frac{\partial(\rho v A)}{\partial t} + \frac{\partial(\rho v^2 A)}{\partial x} = -A\frac{\partial p}{\partial x} - F_f$$

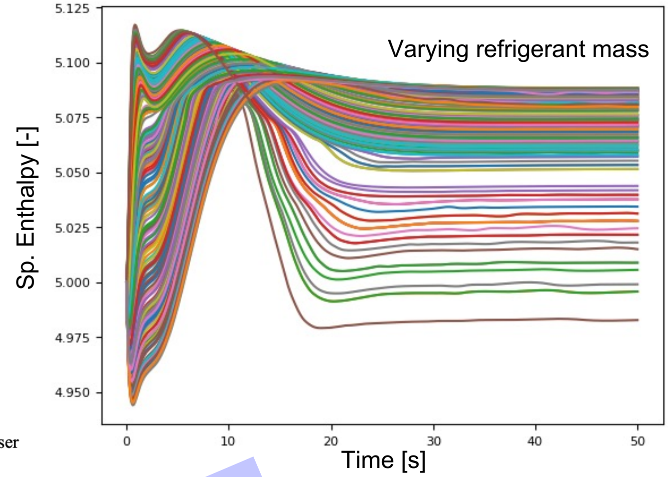
Energy balance:

$$\frac{\partial(\rho u A)}{\partial t} + \frac{\partial(\rho v h A)}{\partial x} = vA\frac{\partial p}{\partial x} + vF_f + \frac{\partial Q}{\partial x}$$

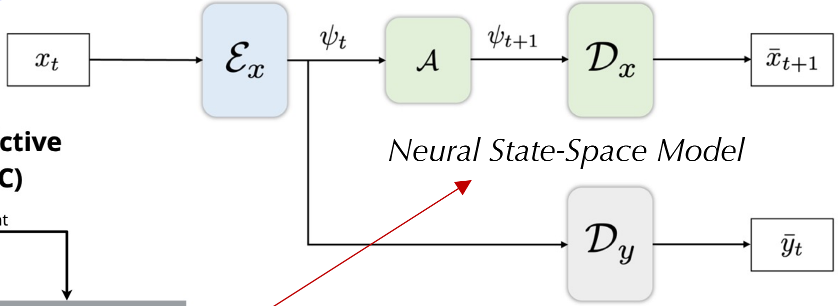
Gradient-Based Meta-Learning: Predictive Modeling

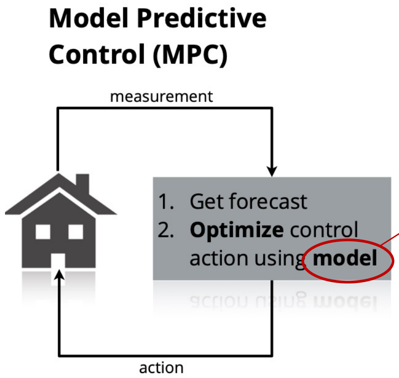






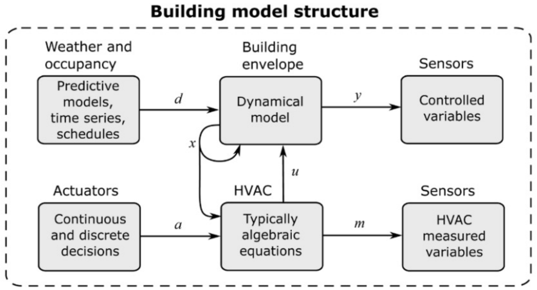
Meta-learning: quickly identify control-oriented neural predictive models for MPC, state estimation, …

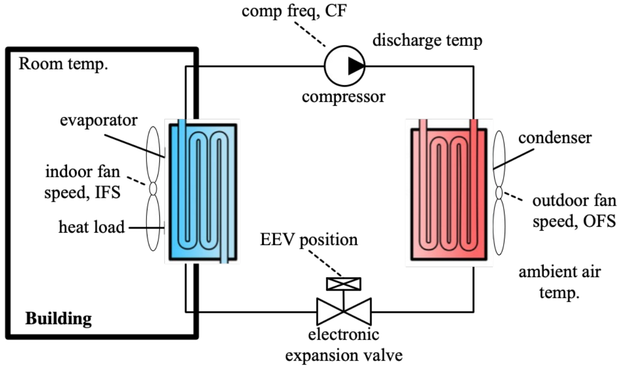


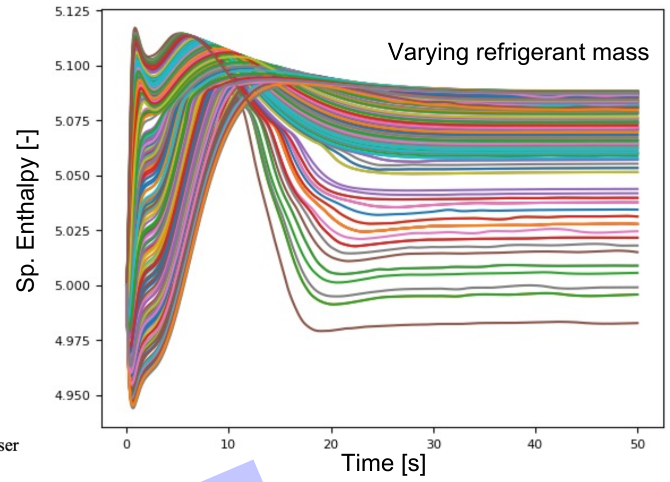


HVAC systems often contain difficult-to-estimate parameters that change over time (e.g. refrigerant mass, heat transfer coefficients, manufacturing)

Gradient-Based Meta-Learning: Predictive Modeling







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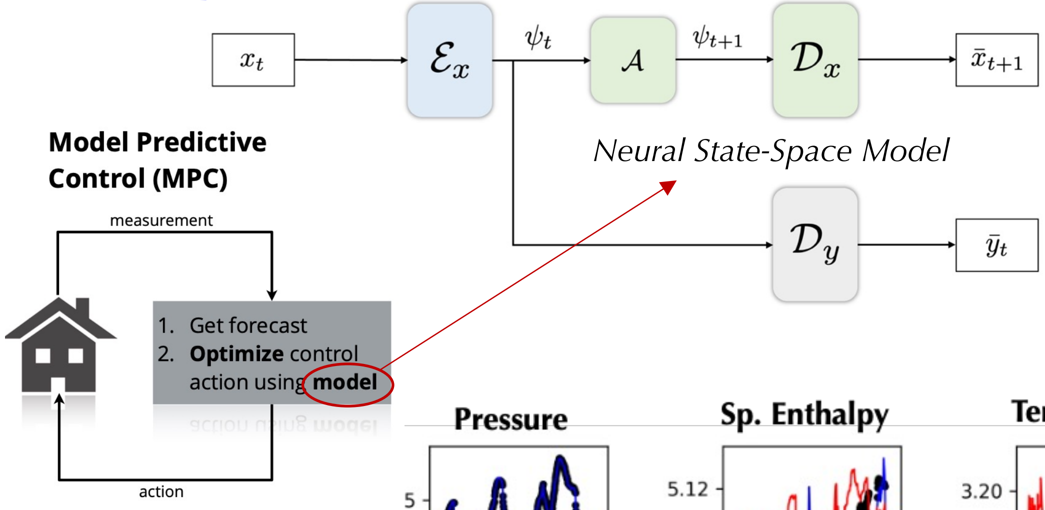
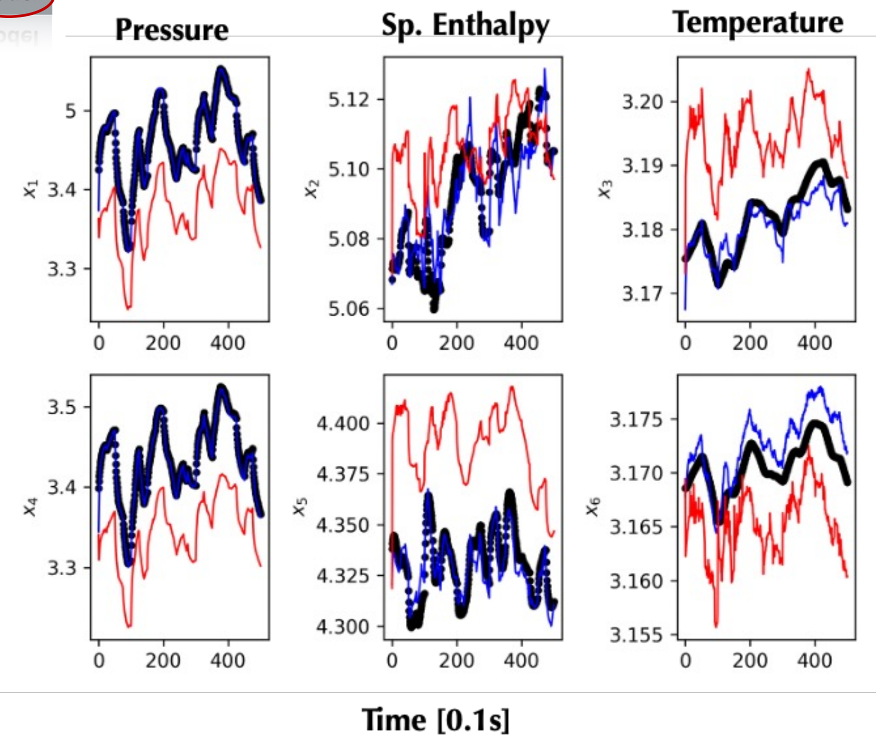
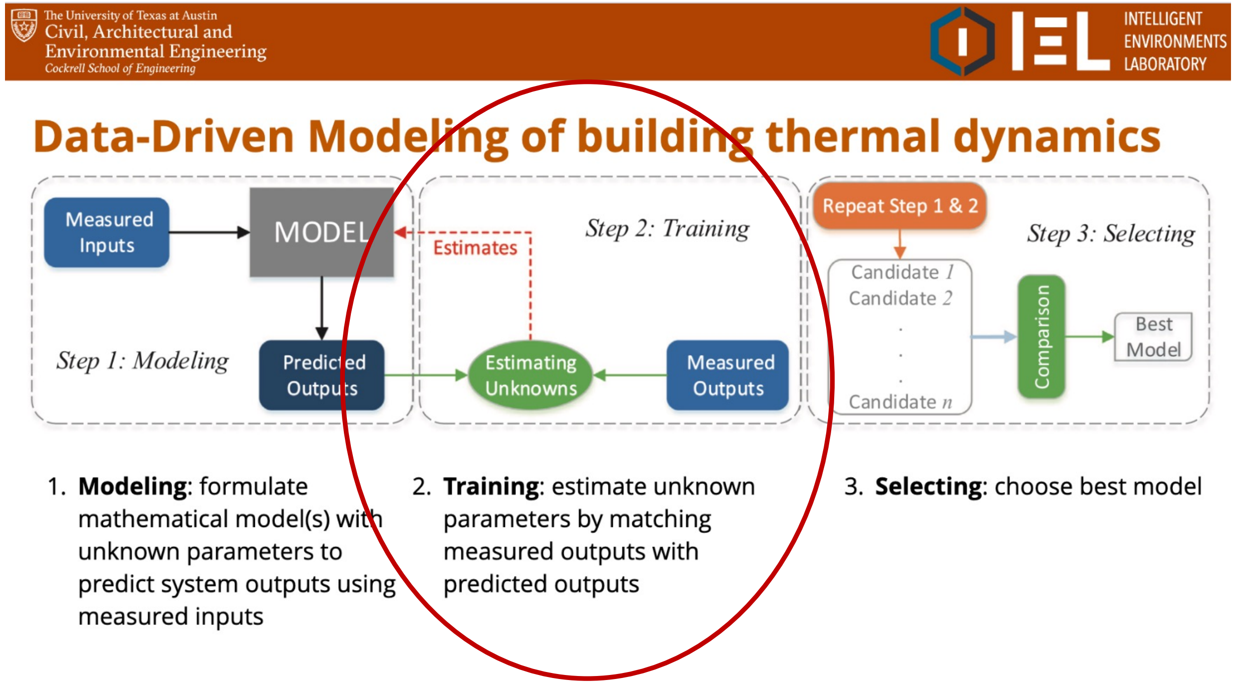




HVAC systems often contain difficult-to-estimate parameters that change over time (e.g. refrigerant mass, heat transfer coefficients, manufacturing)

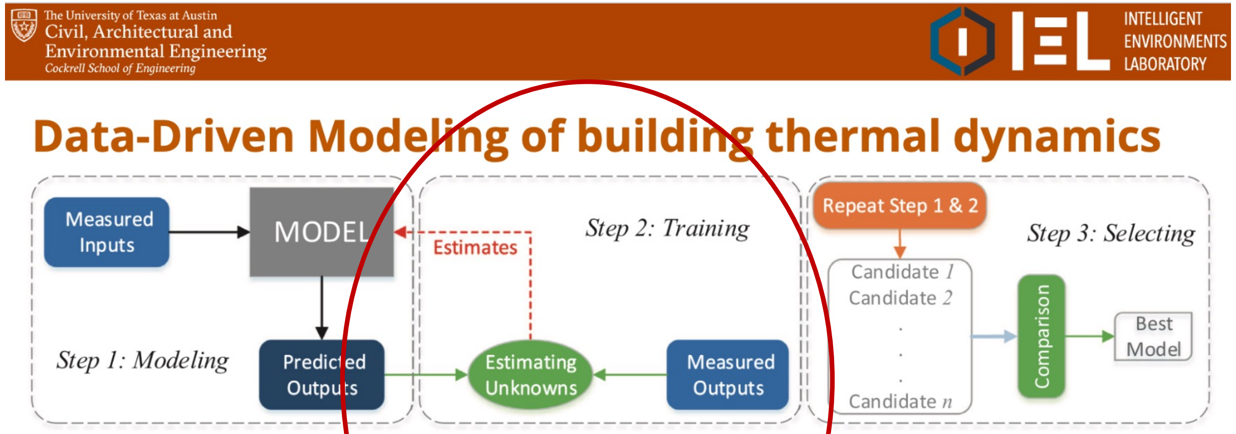
Black = high-fidelity model
Blue = meta learning
Red = classical supervised learning

Gradient-Based Meta-Learning: Model Calibration and Controller Tuning



Model (and controller) parameters need to be estimated (= calibrated, tuned)
usually by solving an optimization problem
e.g. minimize predictive error or some likelihood function

Gradient-Based Meta-Learning: Model Calibration and Controller Tuning



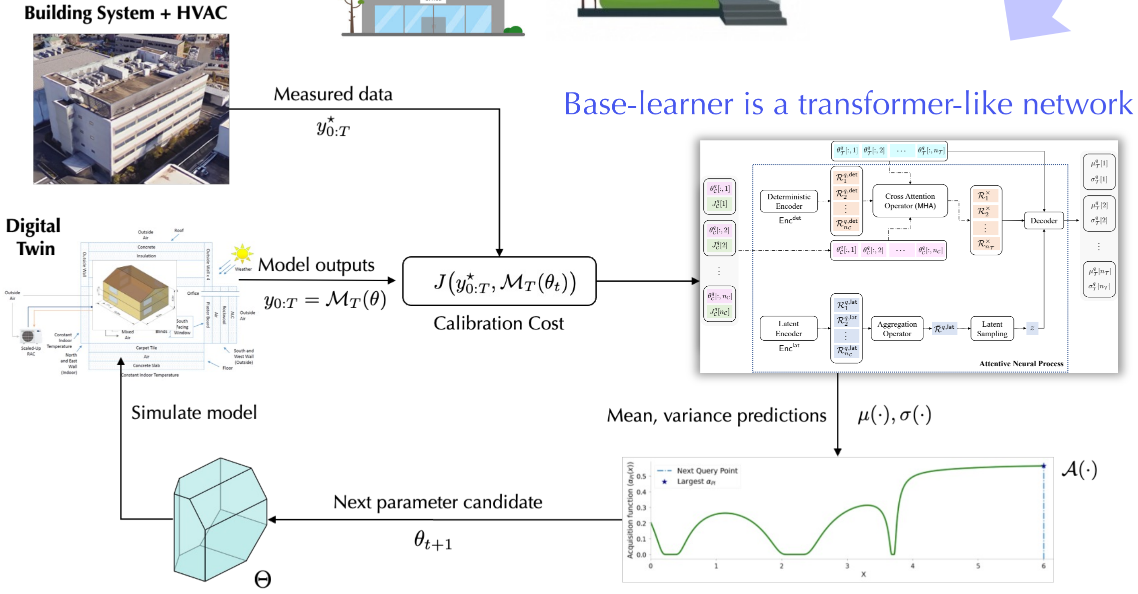
1. **Modeling**: formulate mathematical model(s) with unknown parameters to predict system outputs using measured inputs
2. **Training**: estimate unknown parameters by matching measured outputs with predicted outputs
3. **Selecting**: choose best model

Meta-learning learns commonalities among objective functions in similar optimization problems, so we can start from a good guess of the parameters (called a `*warm-start*'), leads to faster convergence i.e., we can get to energy-efficiency faster

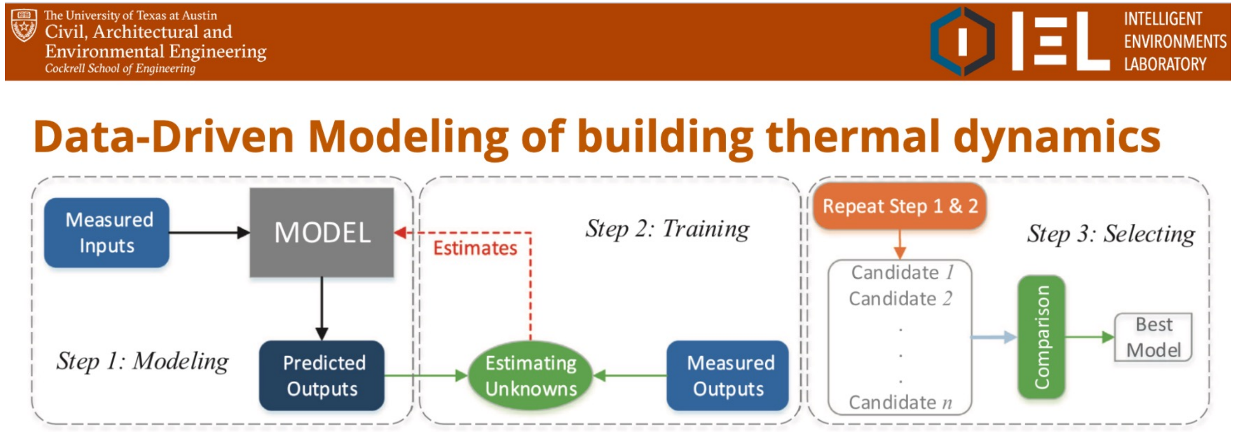
multiple data sources

Model (and controller) parameters need to be estimated (= calibrated, tuned) usually by solving an optimization problem
e.g. minimize predictive error or some likelihood function

Base-learner is a transformer-like network



Gradient-Based Meta-Learning: Model Calibration and Controller Tuning



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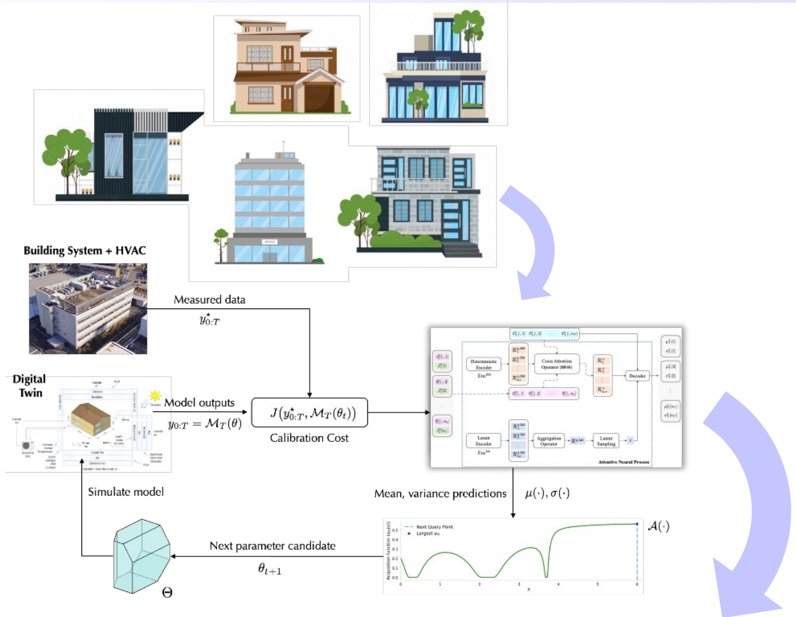

Model (and controller) parameters need to be estimated (= calibrated, tuned) usually by solving an optimization problem
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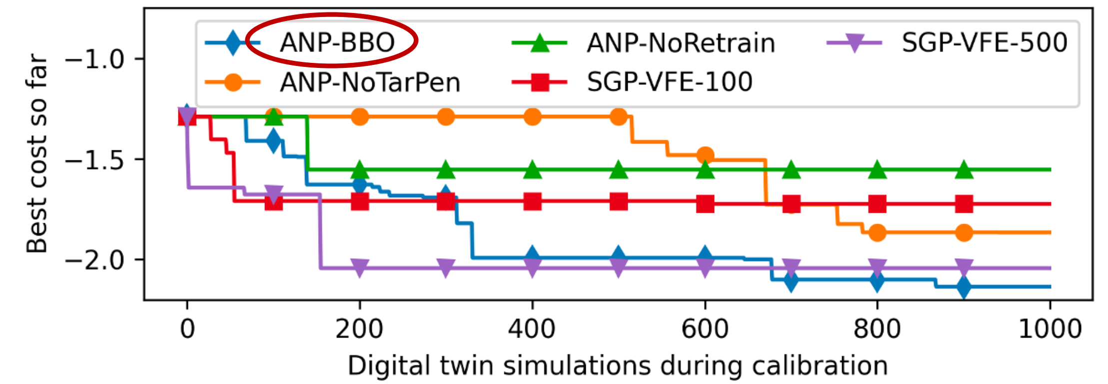
Example. Calibrating 12 parameters of Building Simulation Model



Lessons Learned and Open Opportunities

- In practical engineering systems (esp. energy systems), big data is available, but big <u>useful</u> data is rare
- Generative networks can be used as a powerful way to construct synthetic scenarios to understand when we are operating at ‘net-zero’ energy
  - Especially in conjunction with good physics-oriented/real-world calibrated simulation models!
- Fine-tuning via meta-learning can ensure consistently high operating performance
  - Design *achieves* net-zero, adaptation helps *preserve* it (which is equally important)

Lessons Learned and Open Opportunities

- Design of generative learning frameworks at scale with additional real-world concerns such as privacy
- Transference of knowledge across building types e.g. residential to commercial, across climate zones, …
- Interfacing organically with decision-makers such as RL or control algorithms
- Incorporation of large language models for maintenance of efficient operations via human-AI interaction

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Meta-Learning of Neural State-Space Models Using Data From Similar Systems

Ankush Chakrabarty *, Gordon Wichern *, Christopher R. Laughman *

Synthesizing Building Operation Data with Generative Models: VAEs, GANs, or Something In Between?

Authors: Alessandro Salatiello, Ye Wang, Gordon Wichern, Toshiaki Koike-Akino, Yoshihiro Ohta, Yosuke Kaneko, Christopher Laughman, Ankush Chakrabarty Authors Info & Claims

e-Energy '23 Companion: Companion Proceedings of the 14th ACM International Conference on Future Energy Systems • June 2023 • Pages 125–133 • https://doi.org/10.1145/3599733.3600260

IEEE Control Systems Letters paper presented at
2023 American Control Conference (ACC)
San Diego, CA, USA. May 31 - June 2, 2023

Physics-Informed Machine Learning for Modeling and Control of Dynamical Systems

Truong X. Nghiem[1], Ján Drgoňa[2], Colin Jones[3], Zoltan Nagy[4], Roland Schwan[3], Biswadip Dey[5], Ankush Chakrabarty[6], Stefano Di Cairano[6], Joel A. Paulson[7], Andrea Carron[8], Melanie N. Zeilinger[8] Wenceslao Shaw Cortez[2], and Draguna L. Vrabie[2]

A Virtual Testbed for Robust and Reproducible Calibration of Building Energy Simulation Models

Sicheng Zhan[1], Ankush Chakrabarty[2], Christopher Laughman[2], Adrian Chong[1]
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Learning Residual Dynamics via Physics-Augmented Neural Networks: Application to Vapor Compression Cycles

Raphael Chinchilla[1], Vedang M. Deshpande[2,†], Ankush Chakrabarty[2], and Christopher R. Laughman[2]

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