Meta-Learned Bayesian Optimization for Calibrating Building Simulation Models with Multi-Source Data

Sicheng Zhan
Gordon Wichern
Christopher Laughman
Ankush Chakrabarty

achakrabarty@ieee.org
Motivation

- Buildings account for almost 40% of global greenhouse gas emissions\(^1\) and model-based control can reduce energy\(^2\) use up to 28% --- critical role in tackling climate change
  - **Proper calibration of building simulation models** (e.g., in digital twins) is critical for downstream performance optimization\(^3\)

- Classical calibration relies only on data observed from the target building to be calibrated
  - This is usually a limited dataset
  - This wastes all the data collected during calibration of other, similar buildings

We demonstrate that data obtained during calibration of related, non-identical, buildings often contain useful information about general building dynamics that can significantly accelerate the calibration of new buildings.

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\(^1\) UN Environment, 2020

\(^2\) Drgona et al., Annual Reviews in Control, 2020

\(^3\) S. Zhan and A. Chong, Renewable and Sustainable Energy Reviews, 2021

\(^4\) A. Chakrabarty et al., ICML CCAI 2021
Problem: How to assimilate data from (related but not identical) source calibration tasks and exploit it to accelerate a target calibration task?

Potential solution: Meta-learning for few-shot building calibration
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Meta Learning for Building Calibration

**Meta Training**
- Meta-training data storage

**Source Task Data**
- Forms meta-training set

**Inference**
- Via meta + target data

**Previous Calibration Runs:**
- Source tasks

**Previously Unseen Building Data and Model:**
- Target tasks

**Limited Target Dataset for BO**
- BO: Bayesian Optimization

**Uncalibrated Simulation Model**

**Calibrated Simulation Model**

**Attentive Neural Process (ANP)**
- Learn from meta-data and predict target objective by observing a few context points
- Incorporate uncertainty brought by different tasks in the latent path
- Scalable to massive datasets
Experimental Setup

Construct a library with 60 similar (but not identical) houses across the US

Generate meta-training data via Bayesian Optimization with Gaussian Processes (GP-BO)

Target: 3-day room temperature and relative humidity
Parameters: external roof solar emissivity, effective infiltration leakage area, window thermal conductivity

Meta-training set: parameter and calibration cost function values for 48 buildings, 3 parameters, 150 data points/building

Train the Attentive Neural Process

Train the Attentive Neural Process

Calibrate unseen target tasks

Few-shot initialization

ANP-BO

faster convergence rate

GP-BO

slower convergence rate

Comparative study
Effectiveness of Meta-ANP-BO

Convergence to optimum is $3x$ faster

- With 10 initial pts:
  - ANP-BO, 10
  - GP-BO, 10

- With 40 initial pts:
  - ANP-BO, 40
  - GP-BO, 40

Meta-learned Bayesian Optimization

10 context points

- ANP-BO vs GP-BO

40 context points

- ANP-BO vs GP-BO

Meta-learned model is more representative of the true calibration cost

Final calibrated model exhibits excellent predictive performance

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