

Building Simulation 2021 Data requirements and performance evaluation for control-oriented models

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Background and research gaps

Methodology

Results and discussion



Background

- The necessity of optimal control in buildings
- The importance of control-oriented models in building optimal control
- The difficulty of obtaining these models hindering actual MPC application
- An attempt to promote the scalability from a modeling perspective



Research gaps

- The data availability varied across buildings, making past results less generalizable. A data quantification framework is required.
- Comparative study is needed to determine which level of data is necessary:
 e.g. none/schedule/plug load/CO2 for internal heat gain
- Most studies evaluated model by prediction error, few have systematically investigate model evaluation in the control context



Methodology

- High-fidelity single-room models built in Modelica Buildings library (lbnl)
- Actual internal disturbance data (collected in Beehub)
- RC models with 3 different complexity
- Model identification and control based on non-linear programming



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| Table 1: | Summarized | design of | experiments. |
|----------|------------|-----------|--------------|
|----------|------------|-----------|--------------|

| Subject | Variations | | |
|---------------|---|--|--|
| Emulator | BESTEST, Insulated (higher | | |
| Emulator | internal load percentage) | | |
| | R1C1 $(R1, C1, a)$, R3C2 $(R_{wi}, $ | | |
| RC model | $R_{we}, R_{infil}, C_{room}, C_{wall}, a_{wall}),$ | | |
| sturcture | R5C3 $(R_{wi}, R_{we}, R_{fi}, R_{fe},$ | | |
| (parameters) | $R_{infil}, C_{room}, C_{wall}, C_{floor},$ | | |
| | $a_{wall}, a_{floor})$ | | |
| Internal heat | No input, Design schedule (Cap) , | | |
| gain input | Plug load (a_{plug}, b) , CO ₂ | | |
| (parameters) | $ppm(a_{CO_2}, b)$, Ideal | | |
| (parameters) | measurement | | |

Results_RMSE



Results RMSE



hour

Results_control

Much worse control results under 26°C



R5C3 perform slightly better than R3C2 under 22 and 24°C

No significant difference among alternative inputs



Discussion #1: towards more an informative metric

- RMSE captured the general trend but not always correspond, making it a necessary but not sufficient indicator
- Short-term RMSE is more promising but still limited
- A more informative indicator is needed.

Instead of telling which one is slightly better, it is more important to detect when it will be bad.



Discussion #2: granularity and complexity

- Higher granularity for internal heat gain has merits, more significant when the prediction horizon is longer
- Better representation of internal heat gain also improves the models by help estimating other heat gains in model identification
- Internal heat gain parameters (capacities and coefficients) could be compromised to better fit the training data (possibly overfit), especially when the model is less expressive
- Design schedule is a good enough estimate for MPC in typical offices

Applies to other types of model

Discussion #3: what makes a good model

- Models don't have to be physically authentic to accurately predict the building thermal response
- Multi-output identification results in more physical models but not more accurate room temperature prediction
- Similar situation when calibrating the high-fidelity model for BEEHUB



