A Scenario-based Predictive Control Approach to Building HVAC Management Systems

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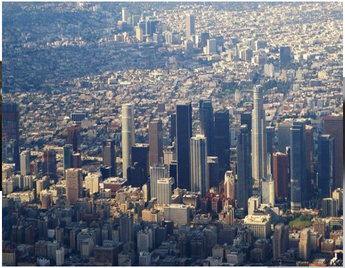
Thanks to...

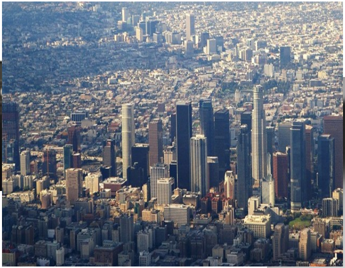
  

Motivations



Motivations

diminish energy requirements



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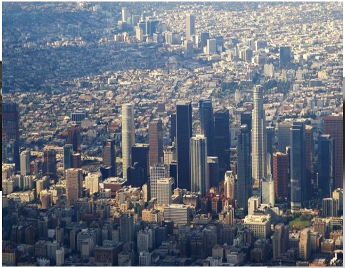

maintain comfort levels

Methodology (big vision)

How to, for HVAC systems?

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☞ **exploit buildings thermal capacity** ☜

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use accurate models

use forecasts

Methodology (big vision)

How to, for HVAC systems?

☞ **exploit buildings thermal capacity** ☜

use accurate models

use forecasts

use Model Predictive Control (MPC)

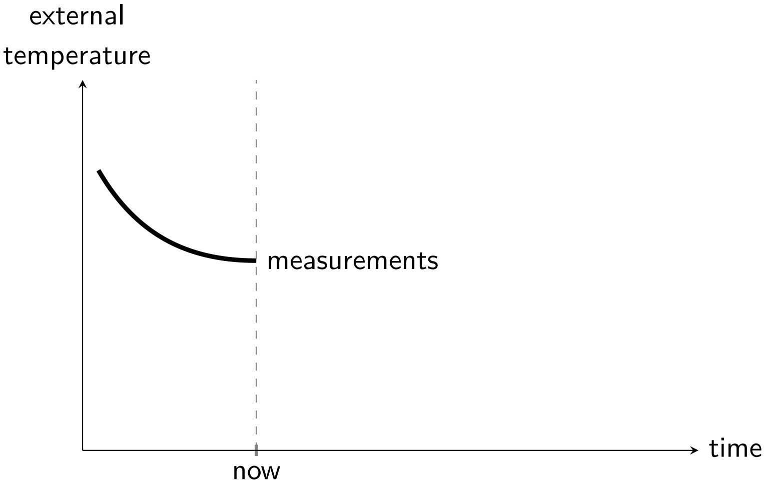
Literature review

- Ma (2012)
  Fast stochastic MPC with optimal risk allocation applied to building control systems
  Conference on Decision and Control
- Oldewurtel (2012)
  Use of model predictive control and weather forecasts for energy efficient building climate control
  Energy and Buildings
- Salsbury (2012)
  Predictive control methods to improve energy efficiency and reduce demand in buildings
  Computers and Chemical Engineering
- Mady (2011)
  Stochastic model predictive controller for the integration of building use and temperature regulation
  Conference on Artificial Intelligence

Our contributions

- address uncertainties in the forecasts ($\rightarrow$ stochastic MPC)
- consider a peculiar description of these uncertainties

Example in words



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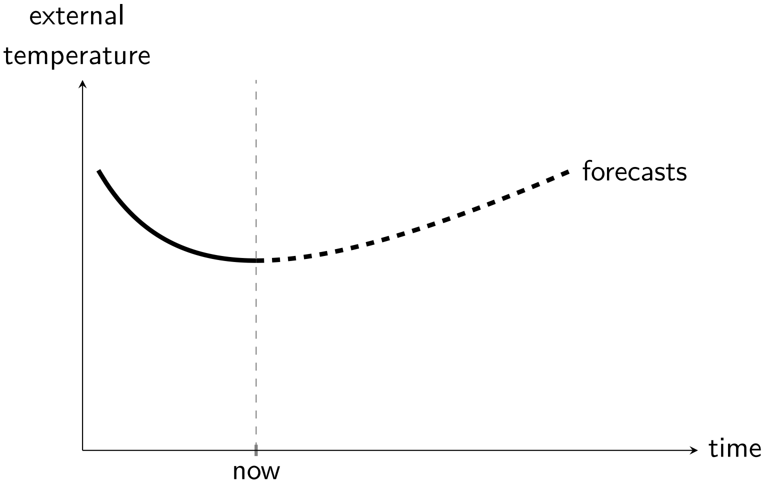

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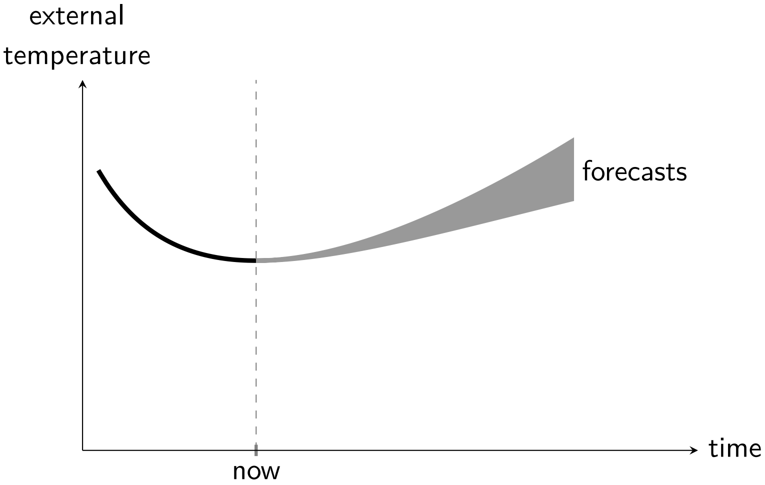

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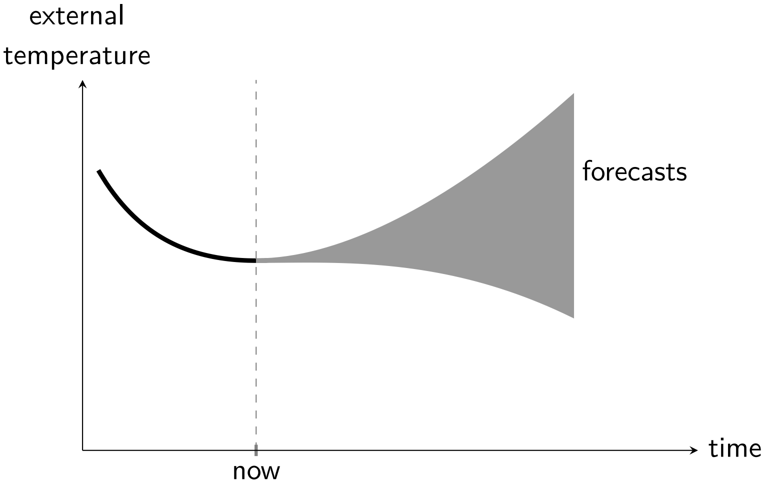
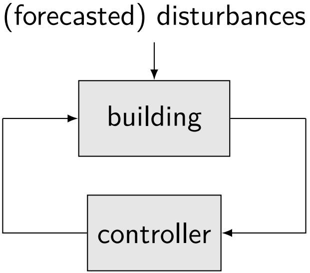


Example in pseudo-formulas

$$
\begin{aligned}
\text{minimize} \quad & \text{(energy usage over the forecast horizon)} \\
\text{subject to:} \quad & \mathbb{P}\left[\text{dynamics will lead to comfort violations}\right] \leq \varepsilon \\
& \text{actuation is constrained}
\end{aligned}
$$



Problems

"subject to $\mathbb{P}$ [dynamics will lead to comfort violations] $\leq \varepsilon$"

may be a formidably complicated constraint

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plausible solution: **simplify it**

caveat: **do not oversimplify it**

Aim

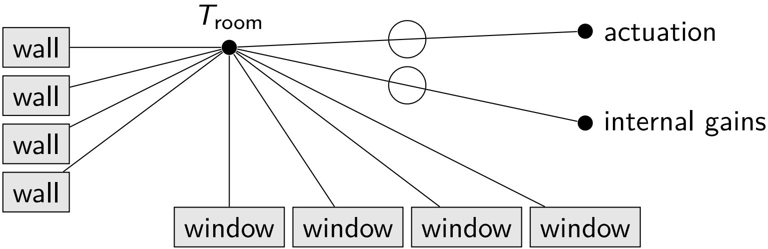
find controllers
accounting for forecasts uncertainties
and handling the associated computational problems

Methodology (for the current problem)

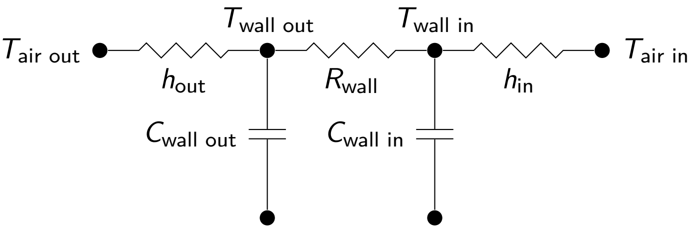
- perform realistic simulations
- describe forecasts uncertainties opportunely
- approximate $\mathbb{P}\left[\text{comfort violations}\right] \leq \varepsilon$ using scenarios

Necessity: model should be accurate and computationally tractable

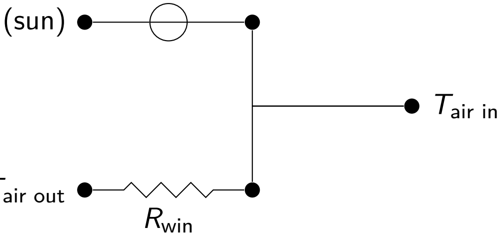
Our choice: RC-network (R $\leftrightarrow$ thermal resistance, C $\leftrightarrow$ thermal capacitance)



Wall model

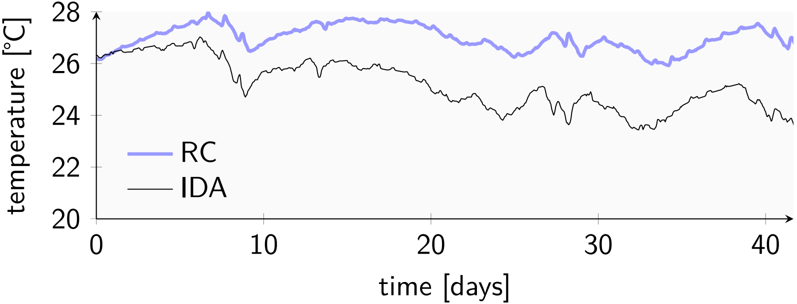


Window model



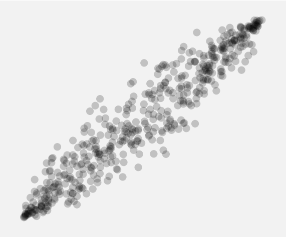
Building model

Validation against IDA-ICE



- simpler than commercial SW exploiting more complex libraries
- captures the most important buildings dynamics' characteristics

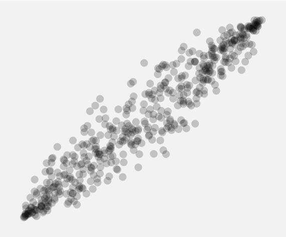
Gaussian



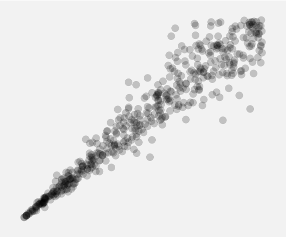
Describing uncertainties through Copulas

Motivations

Gaussian



Clayton



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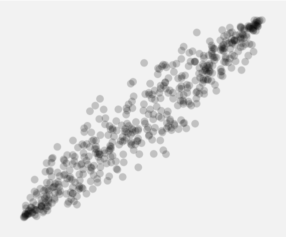

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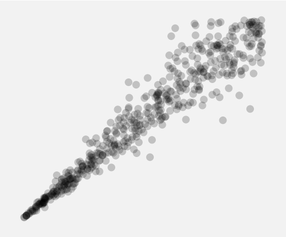

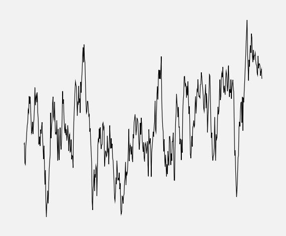

Describing uncertainties through Copulas

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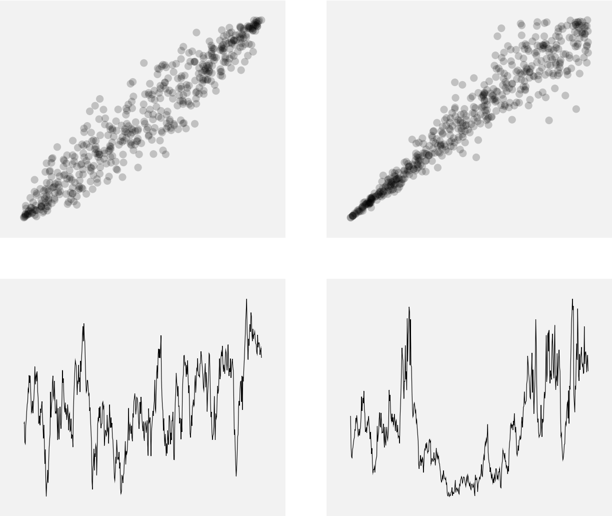
Gaussian | Clayton



Describing uncertainties through Copulas

Formalism

$$\mathbb{F}_{\boldsymbol{w}}(a_1, \ldots, a_K) = \mathbb{C}\left(\mathbb{F}_{w_1}(a_1), \ldots, \mathbb{F}_{w_K}(a_K)\right) \qquad \mathbb{C} : [0,1]^K \mapsto [0,1]$$

In words, Joint distribution = Copula + Marginal distributions

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Pros

- completely generic
- separated modeling / learning of marginals / dependencies

Describing uncertainties through Copulas

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Pros

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Cons

- generating *scenarios* is computationally more expensive

Scenario-based MPC

A cascade of two controllers

Thanks to the physics

IAQ control problem → CO_2 control problem

IAQ control problem → thermal control problem

Scenario-based MPC

A cascade of two controllers

Thanks to the physics

$$\text{IAQ control problem} \begin{cases} CO_2 \text{ control problem} \\ \text{thermal control problem} \end{cases}$$

Thanks to the linear models

$$\begin{aligned} \min_{\boldsymbol{U}} \quad & \boldsymbol{E}\boldsymbol{P}_{\text{room}}^{T}\boldsymbol{U} \\ \text{s.t.} \quad & \mathbb{P}\left[\boldsymbol{G}_u\boldsymbol{U} + \boldsymbol{G}_w\boldsymbol{W} - \boldsymbol{g} \leq 0\right] \geq 1 - \alpha \\ & \boldsymbol{F}\boldsymbol{U} \leq \boldsymbol{f} \end{aligned}$$

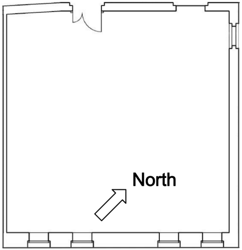
Replace $\mathbb{P}$ with empirical $\mathbb{P}$:

$$
\begin{aligned}
\min_{\boldsymbol{U},\tau} \quad & \boldsymbol{E}\boldsymbol{P}_{\text{room}}^{T}\boldsymbol{U} \\
\text{s.t.} \quad & \boldsymbol{F}\boldsymbol{U} \leq \boldsymbol{f} \\
& \tau + \alpha^{-1} \sum_{i=1}^{N_s} N_s^{-1} z_i \leq 0 \\
& \boldsymbol{G}_u^j \boldsymbol{U} + \boldsymbol{G}_w^j \boldsymbol{W}_i - \boldsymbol{g}^j - \tau - y_i^j \leq 0 \\
& z_i \geq y_i^j \qquad y_i^j \geq 0 \qquad z_i \geq 0
\end{aligned}
$$

- ***scenarios*** := independent extractions of the disturbances ***from their joint distributions*** (i.e., copulas!!)
- N_s := number of i.i.d. scenarios extracted (the more, the better)

Numerical results

Room (`hvac.ee.kth.se`):

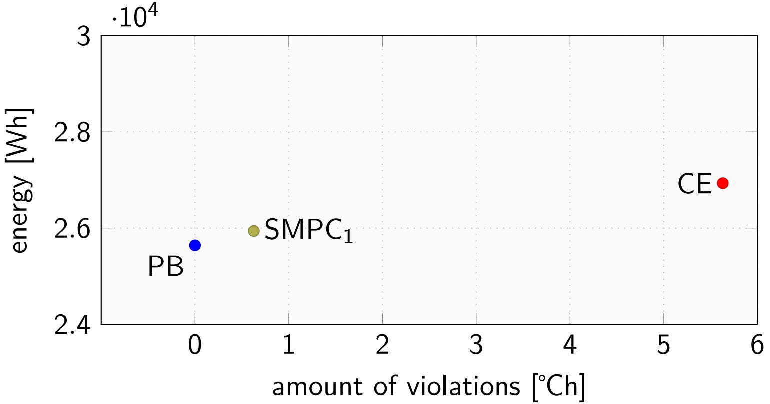


Controllers:

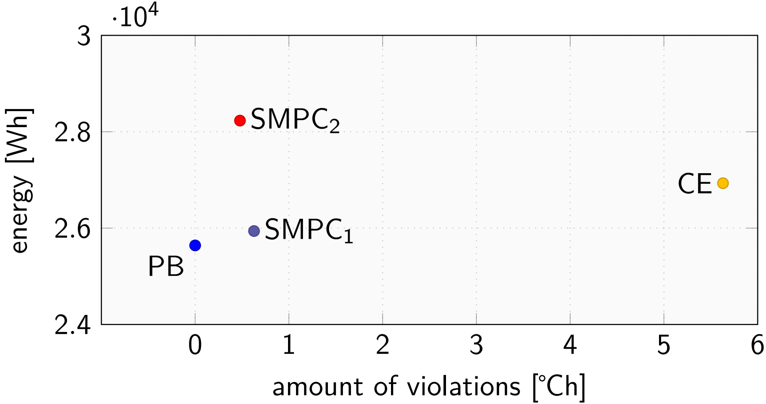
- Performance Bound (PB): has perfect forecasts
- Certainty Equivalence (CE): neglects forecasts uncertainties
- SMPC: our approach

Numerical results

Assessment of performance



- SMPC_1: $\alpha = 0.09$, 60 scenarios



- SMPC_1: $\alpha = 0.09$, 60 scenarios
- SMPC_2: $\alpha = 0.06$, 120 scenarios

Summary

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aim: include forecasts' uncertainties

use scenario-based MPC

generate scenarios using copulas

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Future extensions

- real tests (in progress right now)
- extend to buildings
- learn copulas cooperatively

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