A Dynamic Feedforward Control Strategy for Energy-efficient Building System Operation

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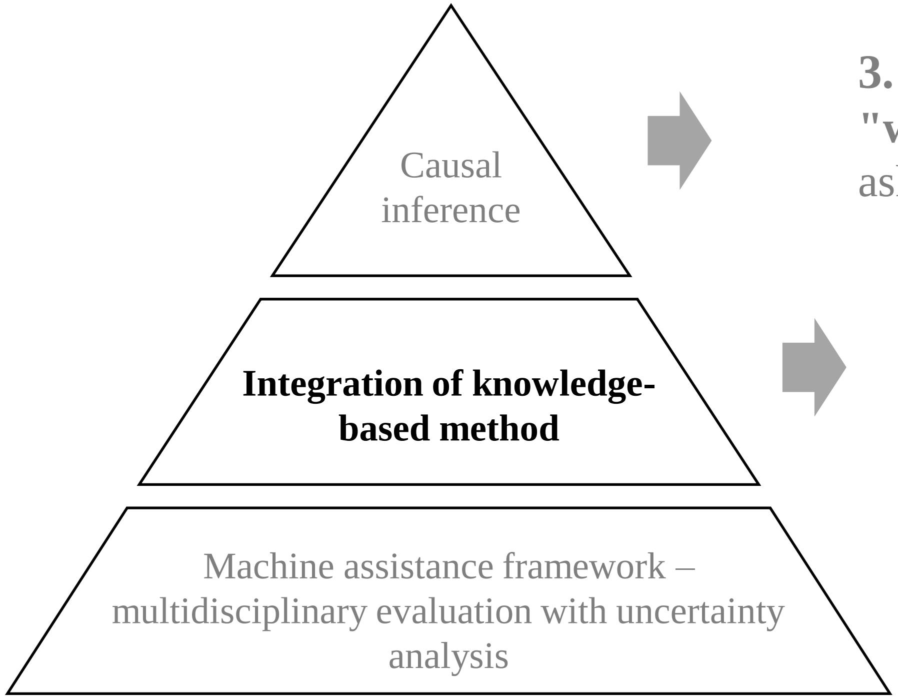
General objective: Keys toward higher intelligence of machine assistance in design



3. Encoding causal modeling process of **reasoning and answering "what-if" questions** which are intuitively generated and commonly asked during the design process

2. Exploring methodologies to identify, analysis, and present information not only relying on empiricism, data-driven methods, but also **embedded with logicism representation of domain principles**

1. A **machine assistance framework** takes a shared set of representations to conduct **multi-disciplinary evaluation** and **uncertainties analysis** with incomplete inputs acceptance that aligned with the design process

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Overview

As the **building sector** consumes up to **30-45% of global energy with the growing trend**, efforts in building **system fine control and management** are recognized to contain **considerable potential in saving energy**.

Current methodologies focus on receiving information from:

- Real-time feedback
- Predictive signals based on modeling
- Agent-based modeling

1. Informational support from the optimal design through simulation or **first-principles models**;
2. System load and energy prediction through **machine learning (ML)**

Research gap:

- Knowledge-based methodologies and data-driven models run in parallel for simulation
- Dynamic building information is not fully utilized in building system control optimization

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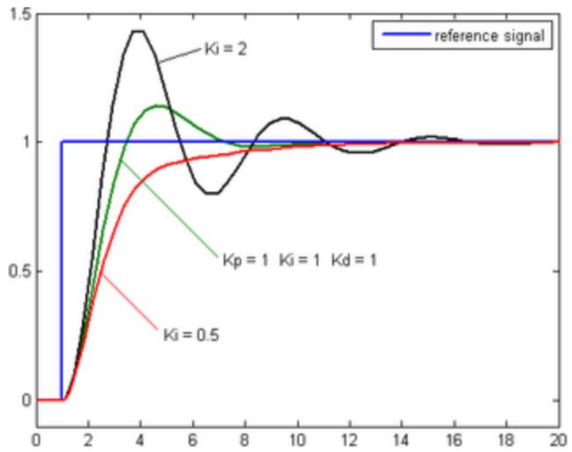
Current methods review



Real-time feedback

- Rule-based Controls (RBC) - “if-then” trigger rules with traditional PID controller
    - *Less flexible to anticipate optimization with changing external conditions*

Predictive signals based on modeling

- Model Predictive Control (MPC) - implicit pattern learning from historical records
    - *Relies solely on historical information embedded in data, dynamic building information is not fully utilized*

Agent-based modeling

- Reinforcement Learning (RL) - maximizing the set reward function under environmental constraints
    - *Modeling process requires reprogramming for different environments, and the model itself is in a black box state*

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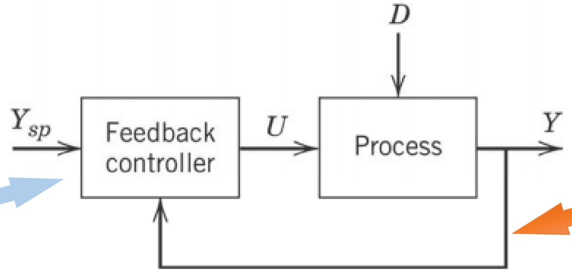
Current methods review: from a cybernetic perspective

Real-time feedback

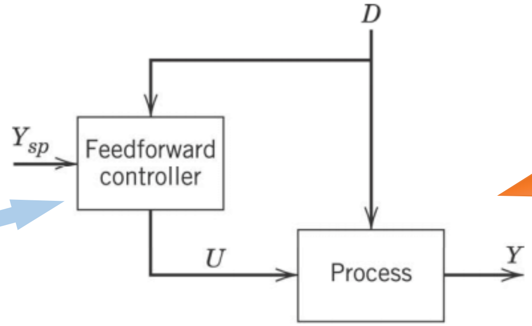
RBC



Time lag exist in feedback loop (building thermal load), causing oscillation in controlling, inefficient.

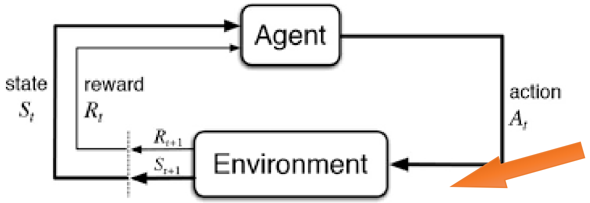
Predictive signals based on modeling

MPC



Lack of feedback, sensitive to modeling errors and process parameter changes

Agent-based modeling



Pure ML hard to learn dynamic from a time-variant environment, model is less engineer-friendly for deployment and interpretation

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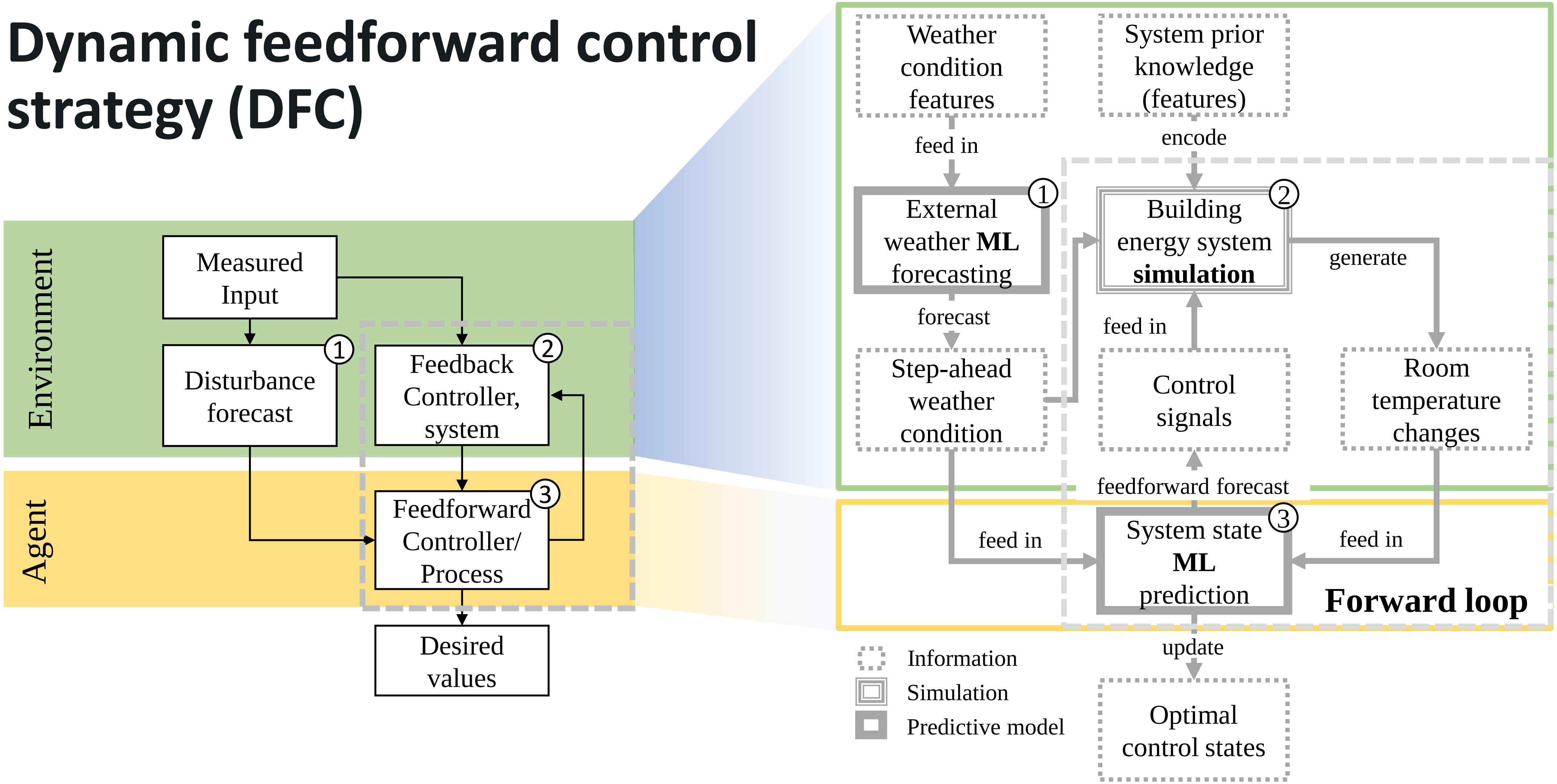
Dynamic feedforward control strategy (DFC)



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Framework of DFC: methodologies

Physical-based simulation: Modelica with AixLib

- Equation-based and object-oriented modelling approaches
- A model library with focus on modeling the dynamic behavior of buildings, HVAC equipment and distribution networks to enable integrated analyses of energy systems on the scales from single building to city district.

ML model: Tree-based gradient boosting algorithm - LightGBM

- Tree-based models and neural networks recognize implicit dynamics in time-series data in the state-of-the-art
- Tree-based models are "off-the-shelf" without extensive preprocessing or tuning required to perform accurately with generalization flexibility

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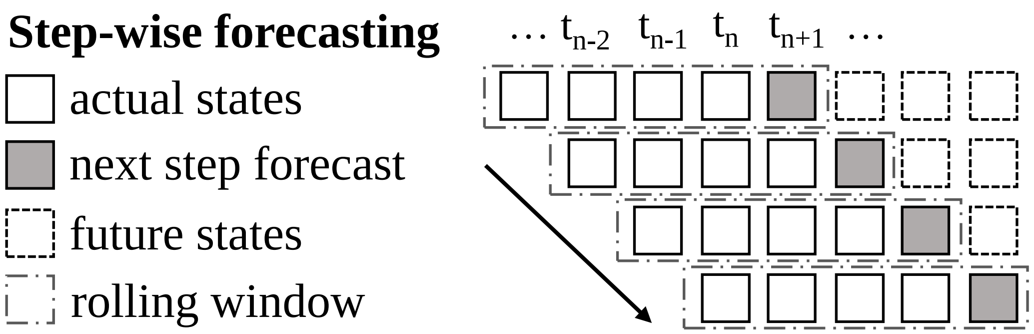
Framework of DFC: Rolling window

Implementation: step-ahead (stepwise) time-series forecasting with a rolling window



$\boldsymbol{t_n}$ stands for the time step. The rolling window means that with the ongoing time, the predive model takes the current state and a certain number of past states as input to forecast the next step. It learns the dynamic relationship in a time-series sequential window.

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Framework of DFC: Dynamic

$t_{n-i} \cdots t_n$

- Weather condition

① External weather ML forecasting

t_{n+1}

Step-ahead weather condition

$t_{n-i} \cdots t_n$

- Weather conditions
- Control signals
- Building features

② Building energy system simulation

$\cdots t_{n+1}$

Room temperature changes

$\cdots t_{n+1}$

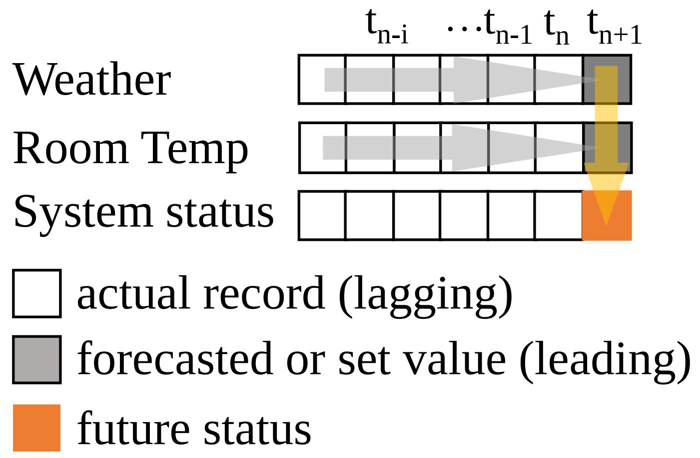
- Room temperature changes
- Weather conditions

③ System state ML prediction

t_{n+1}

Step-ahead control signals

Schematic diagram of data input



Dynamic: The target model is designed to access **feedforward (leading)** and **historical (lagging)** information within a time-rolling window to make each step of the **control strategy optimal** with the consideration of **consistency**.

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Framework of DFC: Knowledge integration

Input: $\{(\boldsymbol{x}_i, \boldsymbol{T}_i)\}_1^n$, in total $\boldsymbol{n}$ sequential set of building information features $\boldsymbol{x}_i$ (building feature, historical load, weather condition, etc.) with forecasted temperature $\boldsymbol{T}_i$, a differentiable loss function $\boldsymbol{L}(\boldsymbol{T}, \boldsymbol{F}(\boldsymbol{x}))$, number of iterations $\boldsymbol{M}$.

Algorithm:

Feedback

For $\boldsymbol{i} = \boldsymbol{1}$ to $\boldsymbol{n}$:

If the forecasted temperature in the next $\boldsymbol{M}$ steps doesn't fulfill the comfort standard, initialize model with a constant value:

$$F_0(x) = arg\min_{\gamma} \sum_{i=1}^{M} L(T_i, \gamma) \qquad (1)$$

Feedforward

For $\boldsymbol{m} = \boldsymbol{1}$ to $\boldsymbol{M}$:

a. Feed $\boldsymbol{F}_{\boldsymbol{m}-\boldsymbol{1}}(\boldsymbol{x})$ into simulation to get the system states output and consequential temperature $(\boldsymbol{S}_{\boldsymbol{m}}(\boldsymbol{x}_i), \boldsymbol{F}_{\boldsymbol{m}}(\boldsymbol{x}_i))$.

b. Compute pseudo-residuals: the difference between temperature standard and intermediate predicted temperature:

$$r_m = -\left[\frac{\partial L(T_i, F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{m-1}(x)} \qquad (2)$$

a. Fit a regression tree to the $\boldsymbol{r}_{\boldsymbol{m}}$ values and create terminal regions $\boldsymbol{R}_{\boldsymbol{j},\boldsymbol{m}}$ for $\mathbf{j} = \mathbf{1}, \dots, \boldsymbol{J}_{\boldsymbol{m}}$

b. Compute multiplier $\boldsymbol{\gamma}_{\boldsymbol{j},\boldsymbol{m}}$ by:

$$\gamma_{j,m} = arg\min_{\gamma} \sum_{x_i \in R_{j,m}} L(T_i, F_{m-1}(x_i) + \gamma) \quad (3)$$

a. Update the model with forecasted temperature:

$$F_m(x) = F_{m-1}(x) + \nu \sum_{j=1}^{J_m} \gamma_{j,m} \qquad (4)$$

Update loop

Output: control state sequential $\{(\boldsymbol{S}_{\boldsymbol{M}}(\boldsymbol{x}_i))\}_{i-1}^n$

- Recognition of encoded building physical information from simulation output data by the ML model.
- **Dynamic pattern learning** from :
  - Lagging & Leading information of external weather conditions, indoor temperature, and system states information.

Thus optimizing system control signal.

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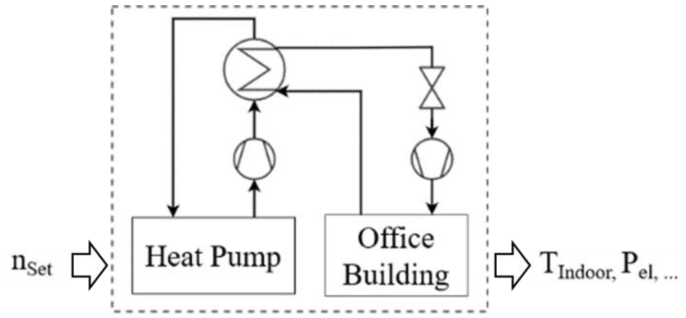
Case study: Overview

Typical **office building** (1675 m2) in Modelica with the standard of the **passive house,** equipped with **space heaters** and a **Viessman heat pump** with nominal power of 18,5 kW in weather condition of **Aachen, Germany**



- n_{set} : relative rotational speed of compressor;
- T_{Indoor}: indoor temperature;
- P_{el}: electrical power;

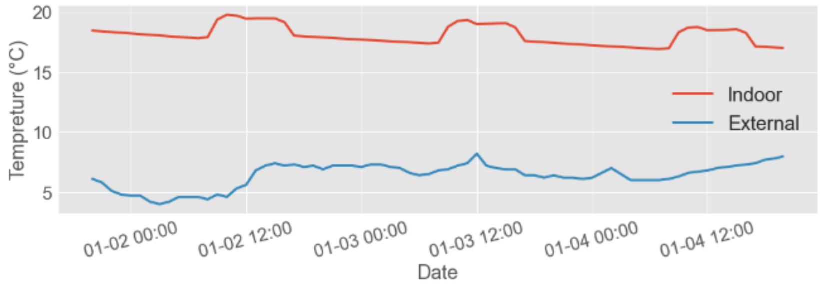
Parameters of the office building simulation with passive house standard

Parameter	Value	Unit
Resistances of exterior walls	$1.41 \cdot 10^{-4}$	K/W
Heat capacities of exterior walls	$4.93 \cdot 10^{8}$	J/K
Resistances of floor plate	$1 \cdot 10^{-3}$	K/W
Resistances of roof	$1 \cdot 10^{-3}$	K/W
Resistances of interior wall	$1.3 \cdot 10^{-4}$	K/W

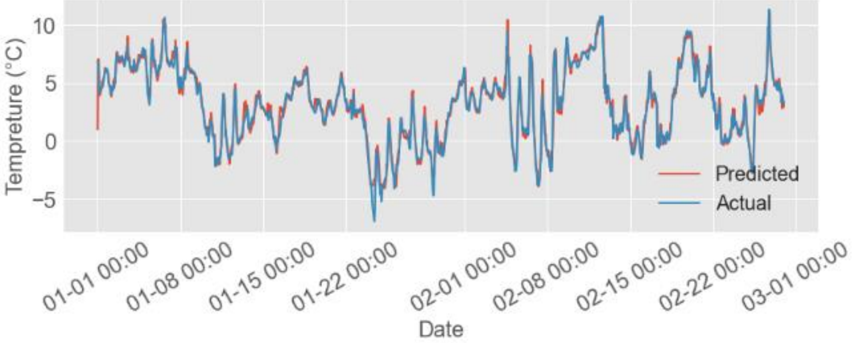
Weather features

Input feature	Description
temp	Air temperature (°C)
dew	Dew point (°C)
hum	Relative humidity (%)
pres	Atmospheric pressure (hPa)
winds	Wind speed (m/s)

Indoor temperature behavior without control



Rolling weather forecasting result (R2: 0.98)



Rules for the **comfort objective** applied in 10-minute time-step granularity :

- *IF day (7 AM – 6 PM), THEN the temperature setpoint is 21°C;*
- *IF night, THEN the temperature setpoint is 19°C.*

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Case study: Methods & Result

Two Reference Control (RC1 and RC2):

- **RC1** is based on a PID controller, employs a responsive correction in **real-time** to **reduce the difference** between the **set indoor temperature** and the **measured value**.
- **RC2** features predictive control, which uses **simulation leading signals** and **cumulative adjusting *nSet*** until the room temperature fulfills the comfort objective.
- **DFC** is dynamic feedforward control strategy.

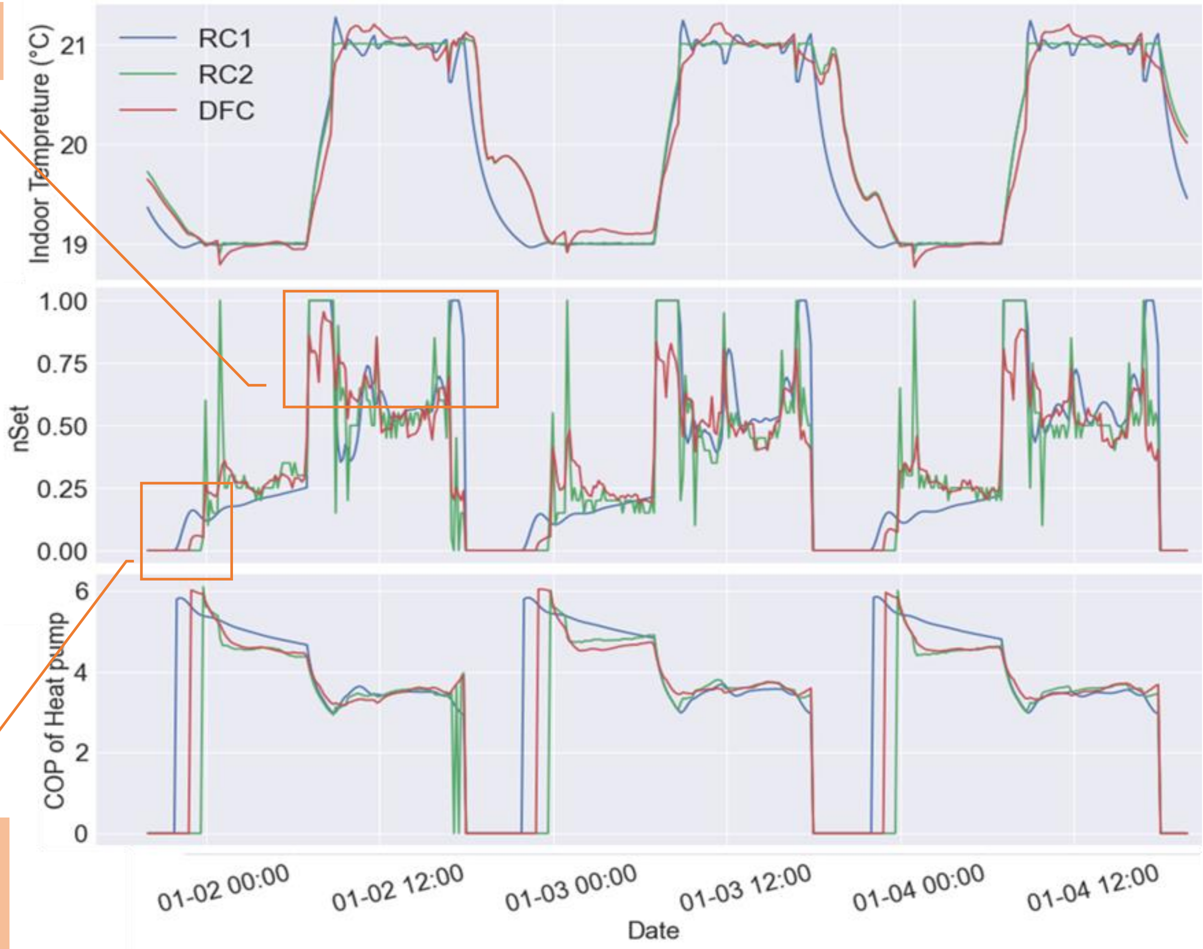
Strategy	Energy consumption
RC1 (PID-based)	0.305 kWh/day per m²
RC2 (predictive)	0.273 kWh/day per m²
DFC	**0.251** kWh/day per m²

Comparison of electrical energy consumption in different strategies

8.1%

17.7%

Peak shaving



Preheating with less oscillation

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Key takeaways

- An engineer-friendly, dynamic feedforward strategy for building system control, which efficiently utilized the building information knowledge and historical data records.
- A cybernetic mindset of combining feedforward & feedback loops to achieve high-efficiency control strategy.
- Feedforward (leading) and historical (lagging) information within a time-rolling window to make each step of the control strategy optimal with the consideration of consistency.
- Prior-knowledge validation is accessible in the loop of the data-driven process.

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Thank you

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Contact & More research insights

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