

Hierarchical Model Predictive Control for Energy-Efficient Building
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Hierarchical Model Predictive Control for Energy-Efficient Building Climate Management: A Simulation-Based Evaluation

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Abstract

Heating, ventilation and air-conditioning (HVAC) systems must hold the indoor temperature within prescribed limits, and doing so with less energy is a central problem in building energy management. This paper develops a two-layer hierarchical model predictive control (HMPC) scheme and evaluates it in simulation for a representative 100 m² administrative office zone in Az Zawiyah, Libya. The upper-layer MPC, with a 1-h sampling interval and an 8-h horizon, optimizes the indoor temperature reference by weighing reference tracking against HVAC power and setpoint smoothness. Beneath it, a lower-layer MPC with a 5-min sampling interval and a 1-h horizon regulates the zone temperature and is coordinated with the upper layer through a supervisory power target. Both layers share a control-oriented second-order resistance-capacitance (2R2C) thermal model; its zero-order-hold discretization reproduces a high-resolution continuous-time reference simulation with an RMSE of 0.107 °C and $R^2 = 0.9998$. We compare the HMPC with single-layer MPC and a conventional PID baseline in four 24-h scenarios: mild spring, winter heating, severe summer cooling and an autumn transition with variable internal gains. Both predictive controllers keep the indoor

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temperature inside the 20–24 °C band 100% of the time, whereas PID averages 76.30%. Single-layer MPC tracks the 22 °C reference most closely (mean RMSE 0.017 °C versus 0.345 °C for HMPC), but HMPC, by letting the temperature float within the permitted band, uses 2.6% less simulated HVAC energy on average (2.0–3.9% across scenarios). Mean quadratic-programming solution times of about 1.8 ms (upper layer) and 1.2 ms (lower layer) point to a low computational burden. The results quantify a trade-off between tracking precision and energy use; experimental validation with measured building data is left for future work.

Keywords: Building energy management, Energy efficiency, Hierarchical model predictive control, HVAC systems, Temperature-band compliance.

التحكم التنبؤي الهرمي القائم على النموذج لإدارة مناخ المباني بكفاءة

طاقية: تقييم قائم على المحاكاة

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الملخص

يُعدّ خفض استهلاك الطاقة في أنظمة التدفئة والتهوية وتكييف الهواء (HVAC) مع الحفاظ على درجة الحرارة الداخلية ضمن الحدود المقررة من المسائل المحورية في إدارة طاقة المباني. تطوّر هذه الورقة مخططاً ثنائي الطبقة للتحكم التنبؤي بالنموذج الهرمي (HMPC) وتقيّمه بالمحاكاة لمنطقة مكتبية إدارية نموذجية مساحتها 100 م² في مدينة الزاوية بليبيا. تعمل الطبقة العليا بفترة اعتيان مدتها ساعة واحدة وأفق تنبؤ مدته 8 ساعات، وتحدّد المسار الأمثل لدرجة الحرارة المرجعية بالموازنة بين تتبّع المرجع وقدرة نظام التكييف ونعومة تغير نقطة الضبط، في حين تعمل الطبقة السفلى بفترة اعتيان مدتها 5 دقائق وأفق تنبؤ مدته ساعة واحدة لتنظيم درجة حرارة المنطقة والتنسيق مع هدف القدرة الإشرافي. وتعتمد الطبقتان على نموذج حراري موجه للتحكم من الدرجة الثانية قائم على

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شبكة المقاومة والسعة (2R2C)، وقد طابق النموذج المتقطع الناتج بطريقة المسك من الرتبة الصفرية (ZOH) محاكاة مرجعية مستمرة عالية الدقة بجذر متوسط مربع خطأ (RMSE) بلغ 0.107°C ومعامل تحديد $R^2 = 0.9998$. قورن المتحكم الهرمي بالتحكم التنبؤي أحادي الطبقة وبمتحكم PID تقليدي ضمن أربعة سيناريوهات مدة كل منها 24 ساعة: ربيع معتدل، وتدفئة شتوية، وتبريد صيفي شديد، وفترة انتقالية خريفية بأحمال داخلية متغيرة. حافظ كلا المتحكمين التنبؤيين على درجة الحرارة الداخلية ضمن النطاق $20-24^{\circ}\text{C}$ طوال زمن المحاكاة (100%)، مقابل متوسط امتثال بلغ 76.30% لمتحكم PID. وحقق التحكم التنبؤي أحادي الطبقة أدق تتبع للمرجع 22°C (متوسط RMSE بلغ 0.017°C مقابل 0.345°C للمتحكم الهرمي)، بينما خفض المتحكم الهرمي استهلاك الطاقة المحاكى بنسبة 2.6% في المتوسط (2.0-3.9% بحسب السيناريو) بالسماح لدرجة الحرارة بالتغير داخل النطاق المسموح. كما تشير أزمنة الحل المتوسطة لمسائل البرمجة التريبيعية، البالغة نحو 1.8 مللي ثانية للطبقة العليا و1.2 مللي ثانية للطبقة السفلى، إلى عبء حسابي منخفض. تُبين النتائج وجود مفاضلة كمية بين دقة التتبع واستهلاك الطاقة، ويبقى التحقق التجريبي باستخدام بيانات مقاسة من مبنى فعلي ضمن الأعمال المستقبلية.

الكلمات الدالة: إدارة طاقة المباني، الامتثال لنطاق درجة الحرارة، التحكم التنبؤي الهرمي، أنظمة التدفئة والتهوية وتكييف الهواء، كفاءة الطاقة.

1. Introduction

Buildings account for a large share of global final energy consumption and greenhouse-gas emissions, and within buildings HVAC systems are among the largest contributors to energy demand [1–3]. Pressure to improve energy efficiency, cut operating costs and raise indoor environmental quality has pushed building energy management towards more advanced strategies. In practice, rule-based and proportional–integral–derivative (PID) controllers remain the industrial standard, chiefly because they are simple and reliable. Their weakness is that they respond only to current measurements and predefined rules. This leaves them poorly placed

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to anticipate disturbances, exploit weather forecasts or minimize energy use while keeping indoor conditions acceptable.

Model predictive control (MPC) tackles these limitations directly. It uses a mathematical model of the building's thermal dynamics to predict future behavior and computes control actions that optimize an objective over a finite horizon, subject to explicit comfort and actuator constraints [4,5]. Weather, occupancy and operational limits therefore enter the control problem directly, and many studies report better temperature regulation and lower HVAC energy consumption with MPC [6,7]. Technical and economic comparisons of PID and linear MPC in process-control applications point the same way on performance, while also documenting the implementation trade-offs that model-based predictive formulations bring [8]. The price is computation: the effort grows with model order, prediction horizon, number of decision variables and update frequency, and this can stand in the way of practical deployment [7]. A common way to keep the prediction model tractable is to use reduced-order thermal models built from resistance–capacitance (RC) networks [9–11]. With only a handful of lumped parameters, an RC model captures the dominant mechanisms of heat transfer and storage, striking a balance between physical interpretability and computational cost. The second-order 2R2C model, which describes how the indoor air interacts with the thermal mass of the envelope, is well suited to repeated prediction and optimization. How useful it proves in practice, however, depends on sensible parameter selection and on whether the control framework can cope with changing operating conditions [10, 11].

Most building MPC studies adopt a single-layer architecture, solving energy optimization and temperature regulation within one optimization problem. Regulation can be accurate, but a single sampling rate then has to serve two very different dynamics: the slow envelope, which calls for long horizons, and the fast indoor air, which calls for frequent updates [11,12]. Hierarchical MPC resolves this conflict by assigning supervisory and fast regulatory tasks to coordinated layers that operate at different time scales [13,14]. Yet few studies have systematically evaluated hierarchical building

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controllers built on reduced-order thermal models under contrasting weather and internal-load conditions [11, 12,14].

Our case study is a 100 m² administrative office zone in Az Zawiyah, Libya. Complementing regional energy demand-side studies [15–17], this work focuses on predictive HVAC control.

Thermal comfort is represented here by a prescribed indoor air-temperature band of 20–24 °C, and we report the percentage of time the indoor temperature stays within it as *temperature-band compliance*. This criterion is simpler than a full comfort assessment based on the predicted mean vote and predicted percentage of dissatisfied (PMV/PPD), which would also account for metabolic rate, clothing insulation, air velocity and mean radiant temperature [18, 19], and it is not meant to replace one.

2. Building Thermal Model

2.1. RC thermal network

A control-oriented building model has to be detailed enough to represent the dominant thermal dynamics, yet simple enough to evaluate repeatedly inside an optimization loop. High-order models describe heat-transfer mechanisms in detail but raise the computational cost of MPC; overly simplified ones may miss the very dynamics that matter for control. Reduced-order RC networks offer a practical compromise [11]. They rest on the thermal–electrical analogy of Table 1, in which temperature plays the role of voltage, heat flow that of current, and thermal resistance and capacitance those of their electrical counterparts. Their appeal lies in physical interpretability, numerical robustness and low computational cost [9].

Table 1: Thermal–electrical analogy underlying the 2R2C model.

Thermal quantity	Symbol	Unit	Electrical analogue	Symbol	Unit
Temperature	T	°C	Voltage	V	V
Heat flow	q	W	Current	I	A
Thermal resistance	R	K/W	Electrical resistance	R	Ω
Thermal capacitance	C	J/K	Electrical capacitance	C	F

We represent the single thermal zone with a 2R2C network (Fig. 1). One state captures the relatively fast response of the indoor air, the

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other the slower thermal inertia of the building envelope. Compared with higher-order structures such as 2R3C models, the 2R2C configuration needs fewer states and parameters yet retains the dynamics the hierarchical controller relies on [10, 20, 21].

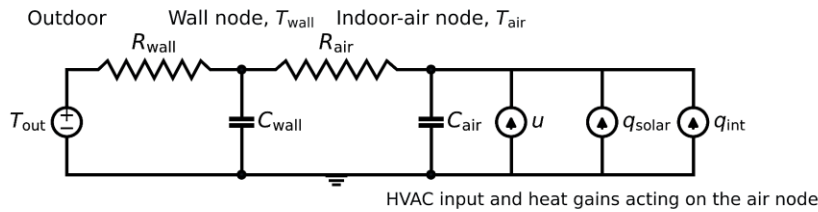


Figure 1: Adopted 2R2C thermal network of the single-zone office.

The HVAC power and the solar and internal heat gains act on the indoor-air node, while the wall node exchanges heat with the outdoor environment.

Heat flows between the indoor-air node and the envelope through R_{air} , and the HVAC power u is delivered to the air node. The wall node, in turn, exchanges heat with the outdoor air through R_{wall} . The capacitances C_{air} and C_{wall} represent the heat-storage capacities of the two nodes. Three quantities are treated as exogenous disturbances: the outdoor temperature T_{out} , the solar heat gain q_{solar} and the internal heat gain q_f .

2.2. Governing equations

An energy balance on each of the two lumped nodes [10, 20, 21] gives, for the indoor air,

$$C_{air} \frac{dT_{air}(t)}{dt} = \frac{T_{wall}(t) - T_{air}(t)}{R_{air}} + u(t) + q_{solar}(t) + q_f(t) \quad (1)$$

and, for the building envelope,

$$C_{wall} \frac{dT_{wall}(t)}{dt} = \frac{T_{out}(t) - T_{wall}(t)}{R_{wall}} + \frac{T_{air}(t) - T_{wall}(t)}{R_{air}} \quad (2)$$

where $u(t) > 0$ corresponds to heating and $u(t) < 0$ to cooling. The two terms on the right-hand side of Eq. (2) are the heat exchanged with the outdoor environment and with the indoor air, respectively.

2.3. State-space representation and discretization

Defining the state and disturbance vectors as

$$(t) = \begin{bmatrix} T_{\text{air}}(t) \\ T_{\text{wall}}(t) \end{bmatrix}, \quad d(t) = \begin{bmatrix} T_{\text{out}}(t) \\ q_{\text{solar}}(t) \\ q_{\text{int}}(t) \end{bmatrix} \quad (3)$$

Eqs. (1)–(2) then take the continuous-time state-space form

$$\dot{x}(t) = A x(t) + B u(t) + E d(t) \quad (4)$$

with

$$A = \begin{bmatrix} -\frac{1}{R_{\text{air}}C_{\text{air}}} & \frac{1}{R_{\text{air}}C_{\text{air}}} \\ \frac{1}{R_{\text{air}}C_{\text{wall}}} & -\left(\frac{1}{R_{\text{air}}C_{\text{wall}}} + \frac{1}{R_{\text{wall}}C_{\text{wall}}}\right) \end{bmatrix} \quad (5)$$

$$B = \begin{bmatrix} \frac{1}{C_{\text{air}}} \\ 0 \end{bmatrix}, \quad E = \begin{bmatrix} 0 & \frac{1}{C_{\text{air}}} & \frac{1}{C_{\text{air}}} \\ \frac{1}{R_{\text{wall}}C_{\text{wall}}} & 0 & 0 \end{bmatrix} \quad (6)$$

Here A describes the thermal coupling between the air and wall states, B maps the HVAC power into the states, and E does the same for the disturbances, which are assumed to be measurable or forecastable.

For digital implementation we discretize the model with a zero-order hold (ZOH), holding u and d constant over each sampling interval T_s [22]:

$$A_d = e^{AT_s}, \quad B_d = \int_0^{T_s} e^{A\sigma} d\sigma B, \quad E_d = \int_0^{T_s} e^{A\sigma} d\sigma E \quad (7)$$

which yields the discrete-time prediction model

$$x_{k+1} = A_d x_k + B_d u_k + E_d d_k \quad (8)$$

The lower control layer uses $T_s = 300$ s; with the parameters of Section 2.4, the discrete-time matrices are

$$A_d = \begin{bmatrix} 0.63883569 & 0.35527205 \\ 0.08881801 & 0.88308523 \end{bmatrix}, \quad B_d = \begin{bmatrix} 9.61833349 \times 10^{-4} \\ 5.89225722 \times 10^{-5} \end{bmatrix}$$

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$$E_d = \begin{bmatrix} 5.892257 \times 10^{-3} & 9.618334 \times 10^{-4} & 9.618334 \times 10^{-4} \\ 2.809676 \times 10^{-2} & 5.892257 \times 10^{-5} & 5.892257 \times 10^{-5} \end{bmatrix}$$

The eigenvalues of A , $\lambda_1 = -2.021 \times 10^{-3} \text{ s}^{-1}$ and $\lambda_2 = -7.918 \times 10^{-5} \text{ s}^{-1}$, give two thermal time constants,

$$\tau_i = -\frac{1}{\lambda_i}: \quad \tau_1 \approx 495 \text{ s (8.2 min)}, \quad \tau_2 \approx 12\,630 \text{ s (3.5 h)} \quad (9)$$

The fast mode belongs mainly to the indoor air and plays out over a few 5-min intervals ($T_s \approx 0.6 \tau_1$). The slow mode, dominated by the envelope, unfolds over several hours and is spanned by the 8-h supervisory horizon ($\approx 2.3 \tau_2$). This clear separation of time scales gives the two-rate hierarchical structure of Section 3 its physical rationale.

2.4. Model parameters

The 2R2C parameters were chosen a priori to represent the dominant heat-transfer and heat-storage behavior of a representative 100 m² office zone. Their selection followed the building thermal-modeling principles of ISO 13790 and the ASHRAE Handbook—Fundamentals [20, 21], together with established practice in lumped RC modeling [10]. They are equivalent, network-level quantities, not properties of particular construction materials. The thermal conductivity of envelope and insulation materials varies with composition and microstructure, as work on kaolinite-filled polymer nanocomposites illustrates [23].

Table 2 gives the adopted values. Expressed as effective conductances, they amount to $1/R_{air}=400 \text{ W/K}$ and $1/R_{wall}=100 \text{ W/K}$, and their RC products, $R_{air}C_{air}=625 \text{ s}$ and $R_{wall}C_{wall}=10000 \text{ s}$, produce the distinct fast and slow response scales quantified in Eq. (9). One parameter set serves all scenarios, so the controllers are compared on a consistent basis.

Table 2: Thermal parameters of the 2R2C model.

Parameter	Description	Value
R_{air}	Indoor air–wall equivalent thermal resistance	0.0025 K/W
R_{wall}	Wall–outdoor equivalent thermal resistance	0.0100 K/W
C_{air}	Indoor-air thermal capacitance	$2.5 \times 10^5 \text{ J/K}$
C_{wall}	Wall thermal capacitance	$1.0 \times 10^6 \text{ J/K}$

The building is hypothetical, and the parameters were therefore neither identified nor calibrated from measurements of an existing building.

2.5. Numerical verification

Figure 2 outlines how the discrete-time model was verified against a continuous-time reference simulation. The reference integrates Eqs. (1) – (2) directly with SciPy's `solve_ivp` integrator [24, 25] and reports outputs at 1-s intervals, whereas the prediction model applies the ZOH formulation of Eq. (8) with $T_s=300$ s. The two implementations share the same parameters, initial conditions and input trajectories (T_{out} , q_{solar} , q_f and u), and the reference trajectory is sampled at the instants of the discrete model, so any difference between them can be attributed to time discretization. Because the study is purely numerical, this procedure verifies the discrete-time implementation; it is not an experimental validation of the parameters against a real building.

Agreement is quantified by three metrics: the root-mean-square error (RMSE), the mean absolute error (MAE) and the coefficient of determination (R^2):

$$RMSE = \sqrt{\frac{1}{N} \sum_{k=1}^N (T_{air}^{ref}(k) - T_{air}^{model}(k))^2} \quad (10)$$

$$MAE = \frac{1}{N} \sum_{k=1}^N |T_{air}^{ref}(k) - T_{air}^{model}(k)| \quad (11)$$

$$R^2 = 1 - \frac{\sum_{k=1}^N (T_{air}^{ref}(k) - T_{air}^{model}(k))^2}{\sum_{k=1}^N (T_{air}^{ref}(k) - \bar{T}_{air}^{ref})^2} \quad (12)$$

where N is the number of samples and $\bar{T}_{air}^{ref}$ the mean reference temperature. Table 3 and Figs. 3–4 report the results.

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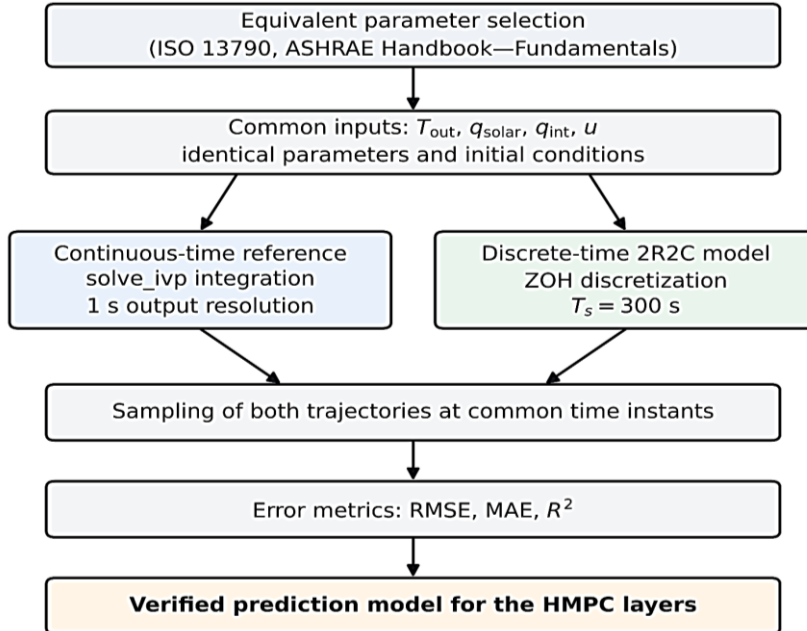


Figure 2: Workflow of the reference simulation and numerical verification procedure.

Table 3: Numerical verification of the discrete-time 2R2C model against the continuous-time reference.

Metric	Value	Interpretation
RMSE	0.107 °C	Low numerical discrepancy
MAE	0.091 °C	Small average deviation
R^2	0.9998	Very strong agreement

The discrete-time model follows the reference closely (RMSE = 0.107 °C, MAE = 0.091 °C, $R^2 = 0.9998$). ZOH discretization is exact when the inputs stay constant over each sampling interval, so the residual discrepancy is due mainly to input variations within the 300-s intervals. The largest instantaneous deviation, about -0.45 °C near $t = 18$ h (Fig. 4), is short-lived and consistent with a step change in the inputs falling between two sampling instants. The discretization thus preserves the dominant thermal behavior of the continuous-time model, and the discrete-time model serves as the prediction model in all the MPC simulations that follow.

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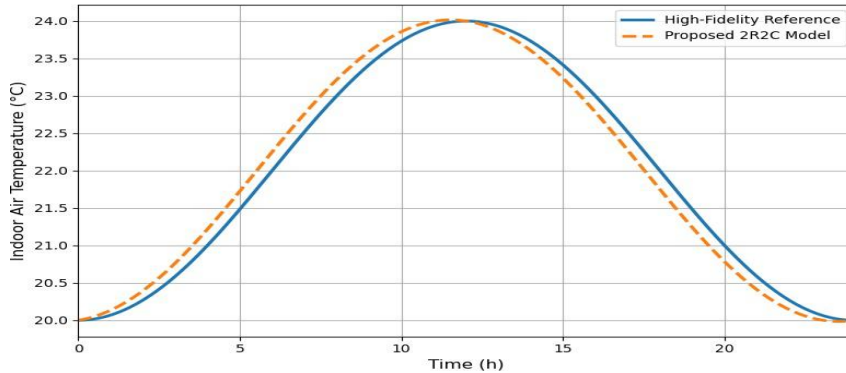


Figure 3: Indoor-air temperature predicted by the discrete-time 2R2C model and by the continuous-time reference simulation under identical operating conditions.

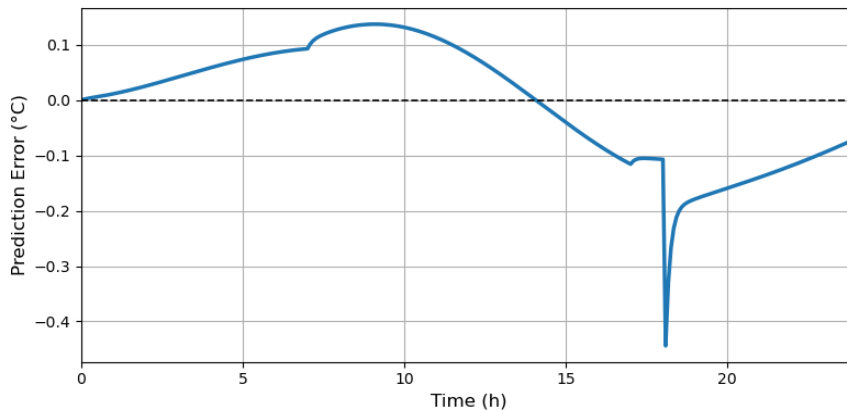


Figure 4: Prediction error between the discrete-time 2R2C model and the continuous-time reference over the verification period.

3. Hierarchical Model Predictive Control Framework

3.1. Architecture

The proposed controller, HMPC-2E (hierarchical MPC with energy-oriented coordination; HMPC for short in the rest of the paper), consists of two coordinated MPC layers that run at different time scales (Fig. 5). Both layers rely on the 2R2C model of Section 2, but they divide the work: one handles supervisory energy optimization, the other short-term temperature regulation.

The *upper layer* runs every hour over an 8-h horizon. From forecasts of outdoor temperature, solar radiation, occupancy and internal heat

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gains, it computes an indoor temperature reference trajectory T_{set}^U and an associated supervisory HVAC power trajectory P^U , chosen to balance reference tracking, HVAC power and setpoint smoothness. The *lower layer* runs every 5 min over a 1-h horizon. It takes the current state, updated disturbance information and the supervisory trajectories mapped onto its finer time grid, and computes the HVAC power applied to the zone; in doing so it supplies fast feedback against short-term disturbances and prediction errors.

Splitting the problem across two rates lets each layer's horizon and sampling interval match the time scale of the dynamics it deals with (Eq. (9)). Each optimization problem stays small, without any sacrifice of short-term responsiveness. Because the structure is modular, it can also be extended to multi-zone control, adaptive parameter estimation, demand response or renewable-energy integration.

3.2. Upper-layer MPC: supervisory energy optimization

3.2.1. Prediction model and horizon

The upper layer uses the 2R2C model of Section 2.3, discretized by ZOH at the supervisory sampling interval $\Delta t_U = 1$ h. At each supervisory instant k , it predicts the state trajectory from the current state and the forecast disturbance sequence,

$$x(k+i+1|k) = A_d^U x(k+i|k) + B_d^U P^U(k+i) + E_d^U \hat{d}(k+i) \quad (13)$$

for $i=0, \dots, N_U-1$, where the superscript U marks matrices discretized with Δt_U and $\hat{d}$ is the disturbance forecast. The envelope responds slowly, so an hourly update is enough to follow changes in weather, occupancy and internal gains, and it keeps computation down. The prediction horizon is $N_U=8$, i.e., 8 h. Operation follows the receding-horizon principle: each update repeats the optimization with the latest state and forecasts and passes the resulting supervisory trajectories to the lower layer (Section 3.4).

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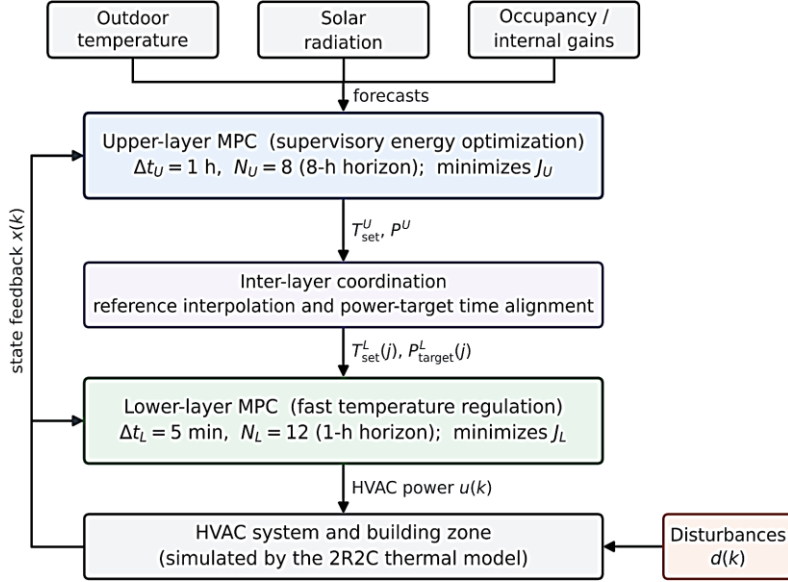


Figure 5: Architecture of the proposed hierarchical model predictive control (HMPC) framework for building climate management.

3.2.2. Objective function

The supervisory reference follows from minimizing the quadratic cost

$$J_U = \sum_{i=0}^{N_U-1} [Q_U (T_{set}^U(k+i) - T_{ref}(k+i))^2 + R_U (P^U(k+i))^2 + S_U (\Delta T_{set}^U(k+i))^2] \quad (14)$$

with the setpoint increment

$$\Delta T_{set}^U(k+i) = T_{set}^U(k+i) - T_{set}^U(k+i-1) \quad (15)$$

where $T_{set}^U(k-1)$ is the previously applied setpoint. The first term penalizes deviation of the setpoint from the desired reference T_{ref} , the second penalizes HVAC power, and the third penalizes abrupt setpoint changes; the weights Q_U , R_U and S_U set their relative

importance. It is the power term that gives the formulation its energy orientation. The smoothness term, for its part, yields references that the lower layer can follow without aggressive control action.

3.2.3. Constraints

The optimization is subject to

$T_{\min} \leq T_{\text{set}}^U(k+i) \leq T_{\max}, \quad i = 0, \dots, N_U - 1$	(16)
$ T_{\text{set}}^U(k+i) - T_{\text{set}}^U(k+i-1) \leq \Delta T_{\max}, \quad i = 0, \dots, N_U - 1$	(17)
$-P_{\max} \leq P^U(k+i) \leq P_{\max}, \quad i = 0, \dots, N_U - 1$	(18)

with $T_{\min} = 20$ °C, $T_{\max} = 24$ °C and $P_{\max} = 8000$ W, where positive power denotes heating and negative power cooling. Eq. (16) keeps the supervisory reference within the prescribed band, Eq. (17) limits its rate of change, and Eq. (18) keeps the supervisory power consistent with the actuator limits enforced by the lower layer.

3.3. Lower-layer MPC: fast temperature regulation

The lower layer operates with a sampling interval $\Delta t_L = 5$ min and a prediction horizon $N_L = 12$ (1 h), using the discrete-time model of Eq. (8) with $T_s = \Delta t_L = 300$ s. At each lower-layer instant k it minimizes

$$J_L = \sum_{j=0}^{N_L-1} [Q_L (T_{\text{air}}(k+j|k) - T_{\text{set}}^L(k+j))^2 + R_L u(k+j)^2 + R_{\text{rate}} \Delta u(k+j)^2 + R_{\text{power}} (u(k+j) - P_{\text{target}}^L)] \quad (19)$$

subject to

$$\begin{aligned} x(k+j+1|k) &= A_d x(k+j|k) + B_d u(k+j) + E_d \hat{d}(k) \\ -P_{\max} &\leq u(k+j) \leq P_{\max}, \\ u(k+j) &= u(k+N_C-1), \quad j \geq N_C, \end{aligned} \quad (20)$$

where $\Delta u(k+j) = u(k+j) - u(k+j-1)$. The four terms of Eq. (19) penalize, in turn, deviation from the interpolated reference, control effort, abrupt input changes and deviation from the supervisory power target. The control horizon is shorter than the prediction horizon ($N_C < N_L$), and the input is held constant beyond it, which reduces the number of decision variables. Only the first optimized

input, $u(k)$, is applied; the problem is then solved again at the next 5-min instant, as the receding-horizon principle requires.

3.4. Coordination between the layers

The upper layer refreshes its trajectories every hour, but the lower layer acts every 5 min, so the supervisory information has to be mapped onto the finer time grid. The number of lower-layer intervals in one supervisory interval is

$$M = \frac{\Delta t_U}{\Delta t_L} = \frac{3600 \text{ s}}{300 \text{ s}} = 12 \quad (21)$$

Intermediate temperature references come from linear interpolation between consecutive supervisory values,

$$T_{set}^L(j) = T_{set}^U(i) + \frac{j}{M} (T_{set}^U(i+1) - T_{set}^U(i)), j=0, \dots, M-1 \quad (22)$$

so that the reference moves gradually from one supervisory value to the next. The supervisory power trajectory, by contrast, is mapped by zero-order time alignment,

$$P_{target}^L(j) = P^U \left(\left\lfloor \frac{j}{M} \right\rfloor \right) \quad (23)$$

where j now counts intervals along the lower-layer prediction grid and the floor operator $\lfloor \cdot \rfloor$ assigns each lower-layer interval to the supervisory interval that contains it. Closed-loop regulation in the lower layer therefore draws on both the interpolated temperature reference and the time-aligned power target. The energy-oriented decisions of the upper layer are preserved, yet the HVAC input can still adapt quickly to current conditions. Figure 6 illustrates the resulting timing and information exchange.

3.5. Benchmark controllers

The HMPC is compared against two benchmarks. The first, a *single-layer MPC*, computes the HVAC power directly from one optimization problem that tracks the constant reference $T_{ref} = 22$ °C; it uses the same 2R2C prediction model, temperature band and

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HVAC power limits as the HMPC. The second is a conventional *PID controller*,

$$u(t) = \text{sat}_{\pm P_{\max}} \left[K_p e(t) + K_i \int_0^t e(\sigma) d\sigma + K_d \frac{de(t)}{dt} \right] \quad (24)$$

where $e(t) = T_{\text{ref}} - T_{\text{air}}(t)$ and $\text{sat}_{\pm P_{\max}}$ limits the output to $\pm P_{\max}$.

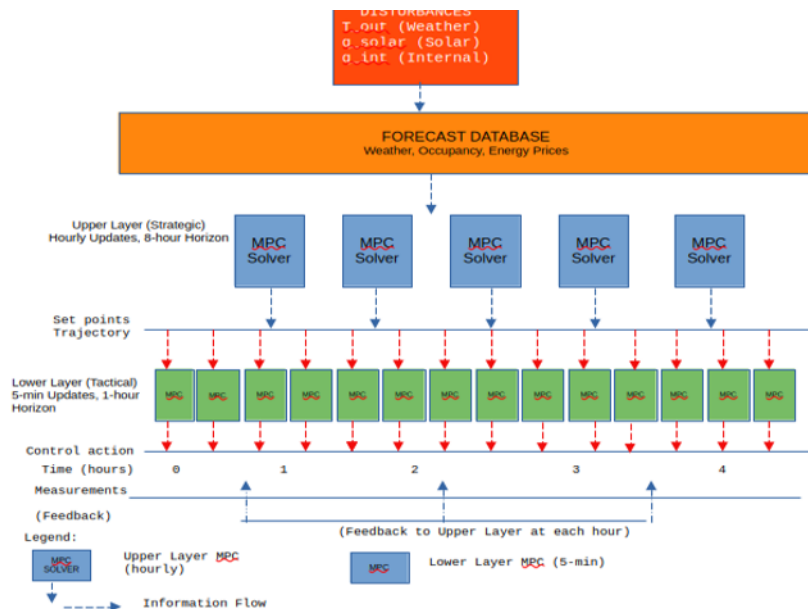


Figure 6: Coordination between the layers: (a) solver executions of the hourly upper layer and the 5-min lower layer; (b) linear interpolation of the supervisory temperature reference onto the 5-min grid; (c) zero-order alignment of the supervisory power target. Values in (b) and (c) are illustrative.

Following established PID–MPC comparison procedures [8], the gains are fixed at $K_p = 500$, $K_i = 0.01$ and $K_d = 0$, which amounts to proportional–integral action. The integral term is bounded, anti-windup is applied during actuator saturation, and the saturation limit ($P_{\max} = 8000$ W) is the same as for the predictive controllers. The gains were left unchanged across all scenarios, with no scenario-specific retuning.

3.6. Controller parameters

Table 4 lists the MPC weights, which set the relative importance of reference tracking, HVAC power, reference smoothness, supervisory power coordination and lower-layer control effort. Two of them are easily confused. The supervisory power-tracking weight R_{power} acts in the lower layer, whereas R_U penalizes HVAC power in the upper layer. The penalty weights ρ_U and ρ_L are large weights on the constraint-violation terms of the upper- and lower-layer problems, respectively. All parameters were kept identical across the four scenarios.

Table 4: MPC parameters used in all simulations.

Layer	Parameter	Value	Description
Upper layer	Q_U	0.005	Temperature-reference tracking weight
	R_U	1.0	HVAC power penalty weight
	S_U	0.05	Reference smoothness weight
	ρ_U	10^5	Constraint-violation penalty weight
	$\Delta t_U, N_U$	1 h, 8	Sampling interval, prediction horizon
Lower layer	Q_L	10.0	Temperature-reference tracking weight
	R_L	0.2	HVAC control-effort weight
	R_{rate}	0.01	Control-input rate weight
	R_{power}	20.0	Supervisory power-target tracking weight
	ρ_L	10^5	Constraint-violation penalty weight
	$\Delta t_L, N_L$	5 min, 12	Sampling interval, prediction horizon

4. Simulation Setup

4.1. Operating scenarios

Table 5 summarizes the four 24-h scenarios, which differ markedly in thermal load. They were designed to represent the climatic conditions of Az Zawiyah, and representative environmental and building conditions were selected with reference to building-characteristics and climate data sources [26 –31]. The hourly disturbance profiles themselves were generated within the simulation framework and are not direct observations from these

sources. Every scenario uses the desired reference $T_{ref} = 22\text{ }^{\circ}\text{C}$, the $20\text{--}24\text{ }^{\circ}\text{C}$ temperature band and an HVAC power limit of $\pm 8\text{ kW}$.

Table 5: Simulation scenarios.

Scenario	Representative condition	Outdoor temperature	Main characteristic
S1	Mild spring	Moderate	Low thermal load (reference case)
S2	Winter	$8.0\text{--}17.2\text{ }^{\circ}\text{C}$	Heating-dominated operation
S3	Hot summer (stress test)	$26\text{--}45\text{ }^{\circ}\text{C}$	Severe cooling load
S4	Autumn transition	Time-varying	Variable outdoor temperature and internal heat gains

4.2. Performance metrics

Tracking accuracy is assessed from the tracking error $e(k) = T_{air}(k) - T_{ref}$ using the RMSE and MAE (computed as in Eqs. (10)–(11), with T_{ref} in place of the reference trajectory) and the maximum absolute error $e_{max} = \max_k |e(k)|$. Temperature-band compliance is the share of samples that fall within the band,

$$CR = \frac{100}{N} \sum_{k=1}^N 1 [T_{min} \leq T_{air}(k) \leq T_{max}] (\%) \quad (25)$$

where the indicator $1[\cdot]$ is one when its argument holds and zero otherwise. The simulated HVAC energy is the time integral of the absolute HVAC thermal power over the 24-h period,

$$E_{HVAC} = \frac{1}{3.6 \times 10^6} \sum_{k=1}^N |u(k)| \Delta t (\text{kWh}) \quad (26)$$

so heating and cooling count equally. A controller can lower E_{HVAC} simply by applying less corrective action, so energy figures are read together with tracking accuracy and compliance, never on their own.

4.3. Computational environment

All simulations were run under identical conditions on an Intel Xeon E5-2665 CPU at 2.40 GHz (16 logical CPUs) with 15 GiB of memory under Ubuntu 26.04 LTS. The controllers were implemented in Python, and CVXOPT [32] solved the quadratic

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programs (QPs) of both layers: 24 QPs in the upper layer and 288 in the lower layer over each 24-h simulation. QP solution times were measured around the solver calls, the total wall-clock time covers the complete simulation, and peak memory is the maximum resident memory during execution.

5. Results and Discussion

We first compare PID, single-layer MPC and HMPC scenario by scenario, on tracking accuracy, temperature-band compliance and simulated HVAC energy, before turning to the overall trade-off, the computational burden and the sensitivity to model parameters. In Tables 6–9, bold marks the lowest value in each column.

5.1. Scenario S1: mild spring

Table 6: Performance of PID, MPC and HMPC in scenario S1 (mild spring).

Controller	RMSE (°C)	MAE (°C)	Max. error (°C)	Compliance (%)	Energy (kWh)
PID	0.7173	0.5788	1.3652	100	13.7093
MPC	0.0322	0.0290	0.1521	100	14.9408
HMPC	0.1786	0.1614	0.2719	100	14.6357

The thermal load in S1 is low, and all three controllers held the indoor temperature within the band for the whole day (Fig. 7, Table 6). Single-layer MPC tracked most tightly (RMSE 0.032 °C, MAE 0.029 °C, maximum error 0.152 °C), ahead of HMPC (0.179, 0.161 and 0.272 °C) and PID (0.717, 0.579 and 1.365 °C). With compliance identical at 100%, HMPC consumed 14.64 kWh, 2.04% less than MPC (14.94 kWh). PID used the least energy of the three (13.71 kWh, 6.3% less than HMPC); in a scenario this mild, even its larger deviations, which reached down to about 20.6 °C, stayed inside the band.

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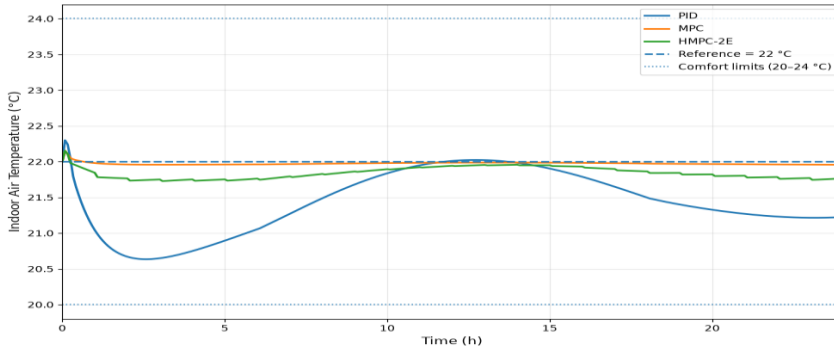


Figure 7: Indoor-air temperature under PID, MPC and HMPC in scenario S1 (mild spring).

5.2. Scenario S2: winter heating

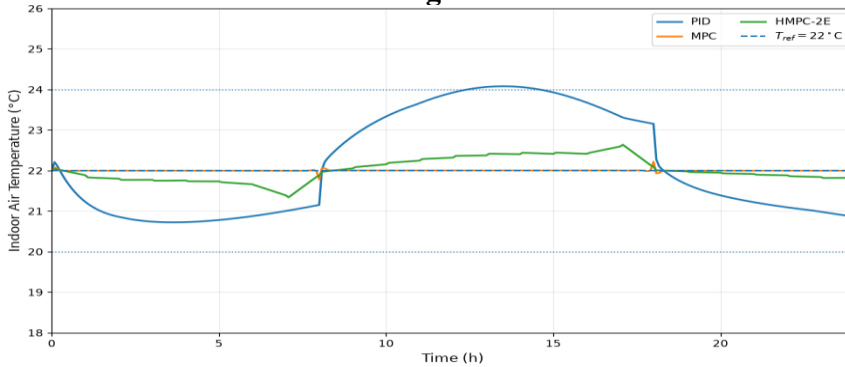


Figure 8: Indoor-air temperature under PID, MPC and HMPC in scenario S2 (winter heating).

Table 7: Performance of PID, MPC and HMPC in scenario S2 (winter heating).

Controller	RMSE (°C)	MAE (°C)	Max. error (°C)	Compliance (%)	Energy (kWh)
PID	1.2804	1.1692	2.0796	90.97	14.7439
MPC	0.0205	0.0055	0.2175	100	17.9696
HMPC	0.2933	0.2454	0.6596	100	17.2706

Outdoor temperatures in S2 range from 8.0 to 17.2 °C (Fig. 8, Table 7). Once again, MPC produced the lowest tracking errors (RMSE 0.0205 °C, MAE 0.0055 °C, maximum error 0.2175 °C). HMPC also kept full compliance, with an RMSE of 0.2933 °C, an MAE of 0.2454 °C and a maximum error of 0.6596 °C. PID deviated further,

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rising above the upper band limit around midday, and its compliance dropped to 90.97%. On energy, HMPC needed 17.27 kWh against 17.97 kWh for MPC, a 3.89% reduction and the largest relative saving of the four scenarios.

5.3. Scenario S3: hot-summer stress test

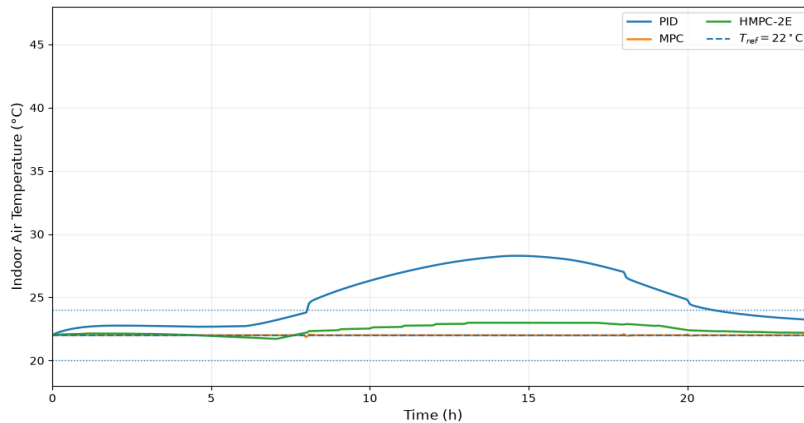


Figure 9: Indoor-air temperature under PID, MPC and HMPC in scenario S3 (hot-summer stress test).

Table 8: Performance of PID, MPC and HMPC in scenario S3 (hot-summer stress test).

Controller	RMSE (°C)	MAE (°C)	Max. error (°C)	Compliance (%)	Energy (kWh)
PID	3.7065	3.0304	6.2866	46.88	37.4977
MPC	0.0128	0.0044	0.1522	100	43.6289
HMPC	0.5940	0.4780	0.9947	100	42.7349

S3 is the most demanding case, with outdoor temperatures between 26 and 45 °C (Fig. 9, Table 8). MPC tracked the reference with an RMSE of 0.0128 °C, an MAE of 0.0044 °C and a maximum error of 0.1522 °C. HMPC again stayed fully compliant (RMSE 0.5940 °C, MAE 0.4780 °C, maximum error 0.9947 °C) and consumed 42.73 kWh, 2.05% less than MPC (43.63 kWh). The fixed-gain PID controller, by contrast, could not reject the high cooling load. The indoor temperature climbed above 28 °C in the afternoon, the maximum error reached 6.29 °C, and compliance fell to 46.88%. PID's lower energy use (37.50 kWh) is therefore a consequence of insufficient cooling, not of efficient operation.

5.4. Scenario S4: autumn transition

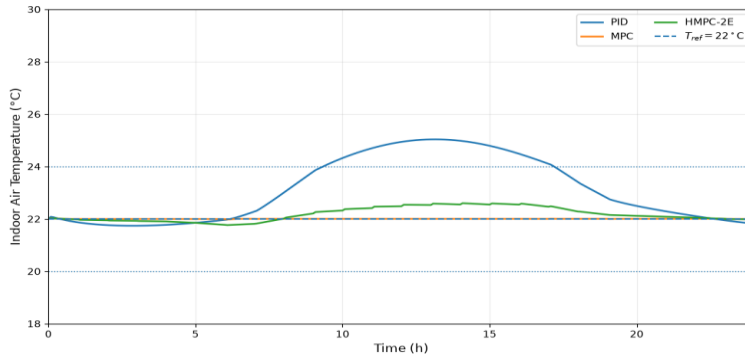


Figure 10: Indoor-air temperature under PID, MPC and HMPC in scenario S4 (autumn transition with variable internal heat gains).

Table 9: Performance of PID, MPC and HMPC in scenario S4 (autumn transition).

Controller	RMSE (°C)	MAE (°C)	Max. error (°C)	Compliance (%)	Energy (kWh)
PID	1.6490	1.1957	3.0356	67.36	15.0821
MPC	0.0040	0.0030	0.0260	100	17.4123
HMPC	0.3150	0.2425	0.5990	100	16.8913

In S4, time-varying outdoor conditions coincide with variable internal heat gains (Fig. 10, Table 9). MPC again achieved the lowest errors (RMSE 0.0040 °C, MAE 0.0030 °C, maximum error 0.0260 °C), while HMPC remained fully compliant with an RMSE of 0.3150 °C, an MAE of 0.2425 °C and a maximum error of 0.5990 °C. PID rose above the upper band limit around midday and in the early afternoon; its maximum error reached 3.04 °C and its compliance 67.36%. HMPC used 16.89 kWh, 2.99% less than MPC (17.41 kWh).

5.5. Overall comparison and the tracking–energy trade-off

Averaged over the four scenarios (Table 10, Fig. 11), single-layer MPC has the lowest tracking errors: an RMSE of 0.017 °C, an MAE of 0.010 °C and a maximum error of 0.137 °C, against 0.345, 0.282 and 0.631 °C for HMPC and 1.838, 1.494 and 3.192 °C for PID.

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Both predictive controllers achieved 100% compliance in every scenario. PID averaged 76.30% and fell furthest short under the severe cooling load of S3.

Table 10: Average performance of PID, MPC and HMPC across scenarios S1–S4.

Controller	RMSE (°C)	MAE (°C)	Max. error (°C)	Compliance (%)	Energy (kWh)
PID	1.838	1.494	3.192	76.30	20.258
MPC	0.017	0.010	0.137	100	23.488
HMPC	0.345	0.282	0.631	100	22.883

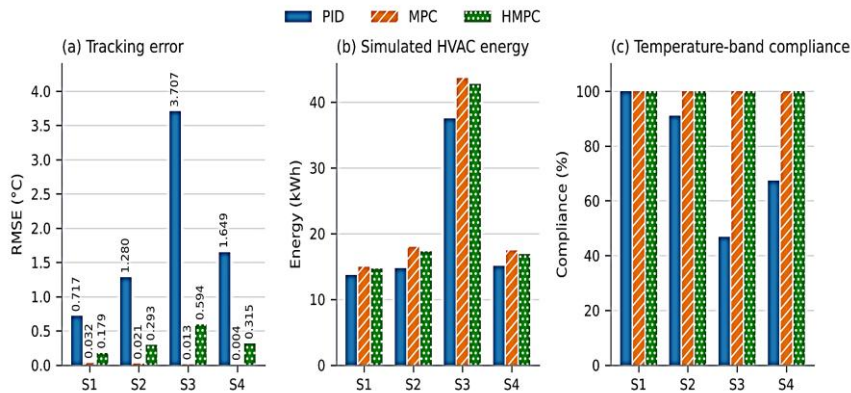


Figure 11: Comparison of PID, MPC and HMPC across scenarios S1–S4: (a) tracking RMSE, (b) simulated HVAC energy and (c) temperature-band compliance.

In every scenario HMPC consumed less energy than single-layer MPC, with reductions between 2.04% and 3.89% and an average of 2.58% (Table 11). PID used the least energy on average (20.258 kWh, about 11% less than HMPC). Outside the mild scenario S1, however, that saving came with large temperature deviations and reduced compliance. It reflects less corrective action rather than more efficient regulation, and it shows why energy has to be read together with tracking accuracy and compliance. Because the PID gains were not retuned for each scenario, these results describe a fixed-gain baseline, not the best performance a PID controller could achieve.

Table 11: Simulated HVAC energy of single-layer MPC and HMPC and the relative reduction achieved by HMPC.

Scenario	MPC (kWh)	HMPC (kWh)	Reduction (kWh)	Reduction (%)
S1	14.9408	14.6357	0.3051	2.04
S2	17.9696	17.2706	0.6990	3.89
S3	43.6289	42.7349	0.8940	2.05
S4	17.4123	16.8913	0.5210	2.99
Mean	23.488	22.883	0.605	2.58

The temperature trajectories in Figs. 7–10 show where the saving comes from. Single-layer MPC holds the indoor temperature at 22 °C. HMPC instead lets it float within the band in whichever direction reduces HVAC effort: slightly below the reference during heating-dominated periods (most of S1 and the night hours of S2), and above it when internal or solar gains create cooling demand (the daytime hours of S2–S4, most clearly in S3). The upper-layer weighting drives this behavior by favoring reduced HVAC power over strict adherence to T_{ref} , while the band constraint of Eq. (16) keeps the supervisory reference between 20 and 24 °C. Small steps in the HMPC trajectories mark the hourly supervisory updates. The higher RMSE of HMPC is therefore a measure of deviation from the 22 °C target, not a loss of temperature-band compliance, and the size of the energy saving depends on the width of the band and on the balance between Q_U and R_U . With the objectives and parameters used here, MPC is preferable when precise reference tracking is required; HMPC gives up some of that precision in exchange for a modest energy reduction at the same compliance.

5.6. Computational performance

Table 12 collects the computational measurements for the HMPC. Across S1–S4, the mean QP solution times were 1.77 ms in the upper layer and 1.15 ms in the lower layer, with average peaks of 10.77 ms and 2.06 ms. The lower layer solves twelve times as many QPs, yet its individual solution times remained low. The upper-layer peak of 26.83 ms occurred only in S1, while in S2–S4 the peak lay between 5.02 and 5.84 ms, so the S1 value is an isolated case rather than the typical burden. Total wall-clock times (4.62–5.63 s) and peak memory (176.82–192.32 MiB) varied little from one scenario to the next.

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Even the longest measured solution time is several orders of magnitude shorter than the corresponding sampling interval: 26.8 ms against 3600 s in the upper layer and 3.0 ms against 300 s in the lower layer, i.e., below 0.01% in both cases. These figures characterize the simulation implementation on the stated platform. They are not hardware-independent real-time limits, and they are no substitute for hardware-in-the-loop or field testing on building automation hardware.

Table 12: Computational performance of the HMPC across the simulation scenarios.

Scenario	Upper mean (ms)	Lower mean (ms)	Upper peak (ms)	Lower peak (ms)	Wall-clock (s)	Peak memory (MiB)
S1 – Mild spring	2.4233	1.1360	26.8251	3.0142	5.63	191.33
S2 – Winter	1.5964	1.0957	5.8379	1.5688	4.87	192.32
S3 – Hot summer	1.4645	1.0733	5.0245	1.7015	4.62	176.90
S4 – Autumn transition	1.5948	1.3033	5.3748	1.9412	4.75	176.82
Average	1.7698	1.1521	10.7656	2.0564	4.9675	184.34

5.7. Sensitivity to model parameters

The 2R2C model is a reduced-order approximation, so we also examined how sensitive HMPC is to parameter uncertainty. R_{air} , R_{wall} , C_{air} and C_{wall} were perturbed simultaneously by -20% , -10% , $+10\%$ and $+20\%$ relative to their nominal values, with the controller settings and operating conditions left unchanged. This analysis uses its own 24-h operating condition, distinct from S1–S4, which is why its nominal values (Table 13) differ from the scenario averages of Table 10, themselves arithmetic means of four scenario-level results.

With nominal parameters, HMPC achieved an RMSE of $0.430\text{ }^{\circ}\text{C}$, a maximum error of $1.200\text{ }^{\circ}\text{C}$, an energy use of 19.80 kWh and a compliance of 94.40% . A $\pm 10\%$ perturbation raised the RMSE to $0.463\text{ }^{\circ}\text{C}$, and a $\pm 20\%$ perturbation raised it to $0.523\text{ }^{\circ}\text{C}$, about 21.6% above the nominal case, with the maximum error growing to $1.823\text{ }^{\circ}\text{C}$. Compliance stayed above 92% at all perturbation levels,

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and energy use varied monotonically from 18.50 to 21.30 kWh across the tested range. Within the $\pm 20\%$ parameter mismatch investigated, HMPC performance therefore degrades gradually rather than abruptly. The receding-horizon feedback of both layers, the explicit temperature and power constraints, and the penalties on reference and input variations are expected to contribute to this behavior.

Table 13: Sensitivity of HMPC performance to simultaneous perturbations of the 2R2C parameters.

Perturbation	RMSE (°C)	Max. error (°C)	Energy (kWh)	Compliance (%)
-20%	0.523	1.823	18.50	92.10
-10%	0.463	1.489	19.40	93.80
Nominal	0.430	1.200	19.80	94.40
+10%	0.463	1.489	20.40	93.80
+20%	0.523	1.823	21.30	92.10

5.8. Limitations

These findings should be read within the scope of the study. All results are numerical. The 2R2C parameters were selected a priori for a hypothetical zone rather than identified from measurements, and the reference simulation verifies the discretization, not the model's fidelity to a real building. The evaluation covers a single zone over four 24-h scenarios, so seasonal energy savings cannot be extrapolated from it directly. Comfort is represented by an air-temperature band rather than PMV/PPD indices [18, 19], and energy is computed from HVAC thermal power without modeling equipment efficiency. Finally, robustness was assessed only for the simulated disturbance profiles and parameter perturbations considered here; measurement noise, forecast errors, actuator dynamics, unmodeled disturbances and actual building operation all require dedicated experimental or hardware-based evaluation.

6. Conclusions and Future Work

This paper formulated a two-layer hierarchical MPC (HMPC-2E) for building climate management on the basis of a numerically verified 2R2C thermal model, and compared it with single-layer

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MPC and a fixed-gain PID baseline in four simulated 24-h scenarios. The main conclusions are these:

1. The ZOH-discretized 2R2C model closely reproduced the continuous-time reference (RMSE 0.107 °C, MAE 0.091 °C, $R^2 = 0.9998$), and its fast (≈ 8 min) and slow (≈ 3.5 h) time constants support the two-rate hierarchical design.
2. Both predictive controllers maintained 100% temperature-band compliance in all scenarios. PID averaged 76.30%, and its compliance fell to 46.88% under the severe cooling load.
3. Single-layer MPC tracked the reference most precisely (mean RMSE 0.017 °C). HMPC, by exploiting the permitted temperature band, reduced simulated HVAC energy by 2.6% on average (2.0–3.9% per scenario; 22.883 versus 23.488 kWh), at the cost of a higher mean RMSE of 0.345 °C.
4. PID's lower energy use (20.258 kWh) came with substantially poorer tracking and compliance, and so does not indicate better overall regulation.
5. On the stated platform, the HMPC required mean QP solution times of about 1–2 ms in each layer, 4.6–5.6 s for a complete 24-h simulation and at most 192.3 MiB of memory. Its compliance remained above 92% under simultaneous $\pm 20\%$ perturbations of the thermal parameters.

Under the conditions investigated, the hierarchical formulation is an energy-oriented alternative to single-layer MPC: it achieves a modest energy reduction while keeping full temperature-band compliance. Where precise reference tracking is the priority, single-layer MPC remains preferable. Future work will (i) validate the framework experimentally or through hardware-in-the-loop testing to assess measurement noise, actuator limitations, equipment dynamics and model mismatch; (ii) consider uncertainty in weather forecasts, occupancy and internal heat gains, longer simulation periods and a wider range of operating conditions; (iii) investigate alternative weightings and coordination mechanisms to characterize the tracking–energy trade-off more fully; and (iv) extend the approach to multi-zone buildings and building energy management systems with adaptive or uncertainty-aware prediction.

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