Forward-Looking Setpoint Prediction for HVAC Systems via Look-Ahead Predictive Control

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Abstract. To address the challenges of comfort and energy efficiency in modern buildings posed by pure feedback PID control, Model Predictive Control (MPC) has emerged as a solution. With the advancement of technology, mitigating the heavy computation and deployment burden of conventional MPC in real time is crucial. This paper introduces a Look-ahead Predictive Control scheme that shifts the temperature setpoint ahead by one hour, allowing heating, ventilation and air-conditioning systems to react early without invoking a full MPC solver. Under identical thermodynamic conditions, the new strategy is benchmarked against standard Proportional–Integral–Derivative (PID) control on a MATLAB model run for eight consecutive hours. Key indicators—energy use, integral absolute error, tight-band Integral Absolute Error (IAE) within ±0.2°C, maximum overshoot, and both full-process and steady-state windows—are extracted and contrasted. Look-ahead control cuts peak overshoot by roughly 51% and lowers steady-state IAE by 1.3%, while full-process IAE, energy consumption and Tight-IAE rise by 8.3%, 2.5% and 8.5%, respectively. Stabilization time, defined as the first continuous 10-minute interval within ±0.5°C, shows no reduction. Overall, the setpoint-based predictive approach offers a practical trade-off: it markedly improves thermal comfort at only a slight energy penalty, without resorting to a complete MPC implementation.

Keywords: Look-Ahead Predictive Control (LPC), Setpoint Reshaping, Heating, ventilation and air-conditioning Control, First-Order Plus Dead Time Thermal Model.

1. Introduction

Heating, ventilation and air-conditioning systems (HVAC) account for a large share of building energy use and largely decide whether occupants feel thermally comfortable. Engineers still favor conventional Proportional–Integral–Derivative (PID) controllers because they are easy to tune, tolerate disturbances and cost little to deploy [1, 2]. Yet air-conditioning loops contain long dead-times and parameters that drift with load and weather, so the plant behaves as a high-inertia, time-varying process. Pure feedback PID then reacts too slowly, leaving energy use above target and struggling to balance comfort against efficiency in modern buildings.

To mitigate these limitations, researchers have turned to predictive and adaptive control schemes. Model Predictive Control (MPC) stands out for its ability to manage multivariable loops with long dead times. Side-by-side evaluations on rooftop HVAC units show that MPC surpasses both ON/OFF and PID approaches in keeping product quality stable while trimming energy use [3]. Field trials on a 1.5-t variable-speed air-conditioner confirm that an adaptive MPC variant cuts power demand without sacrificing comfort [4]. When applied to chilled-water plants, MPC-driven real-time algorithms likewise outperform PID in balancing hydraulics, damping oscillations and lowering energy draw [5]. Yet full-scale MPC hinges on an accurate plant model and heavy online optimization, hurdles that limit its uptake in small buildings and low-cost embedded controllers [6].

This paper therefore introduces a streamlined strategy-Look-ahead Predictive Control (LPC). The idea is to give the upper-level temperature setpoint a fixed lead time and gentle smoothing, creating a feedforward-like response while leaving the lower-level controller untouched. That lower loop remains a plain, fixed-parameter PID. By reshaping the setpoint alone, the method curbs overshoot and tightens steady-state tracking without extra modelling or heavy computation, easing field deployment. An 8-hour test was built in MATLAB: conventional PID served as the baseline, while LPC advanced the setpoint by 60 min with mild filtering. Five metrics gauged performance: an energy proxy ($\int |u|dt$), overall Integral Absolute Error (IAE), narrowband IAE within ±0.2°C, maximum overshoot, and settling time. LPC cut peak overshoot markedly and trimmed the steady-state IAE band; over the entire run, total IAE and the energy proxy rose slightly, showing comfort gains traded for a minor effort penalty. The paper offers three contributions: a reproducible HVAC PID/LPC benchmark that enforces fair comparison, time alignment, and dual-window KPIs; empirical proof that setpoint shaping alone can reduce overshoot and improve steady tracking without touching the slave PIDs, together with a quantified, small effort increase; and an engineering baseline ready for later adaptive tuning or full MPC upgrades.

2. Methodology

This section describes the simulation framework, the design of the control strategy, and the method used to evaluate performance. To make the results reproducible, Figure 1 illustrates a single dynamic simulation model of the HVAC system was built in MATLAB. Under the same operating conditions, the performance of conventional PID control was compared with that of lead-and-smooth setpoint-shaping LPC.

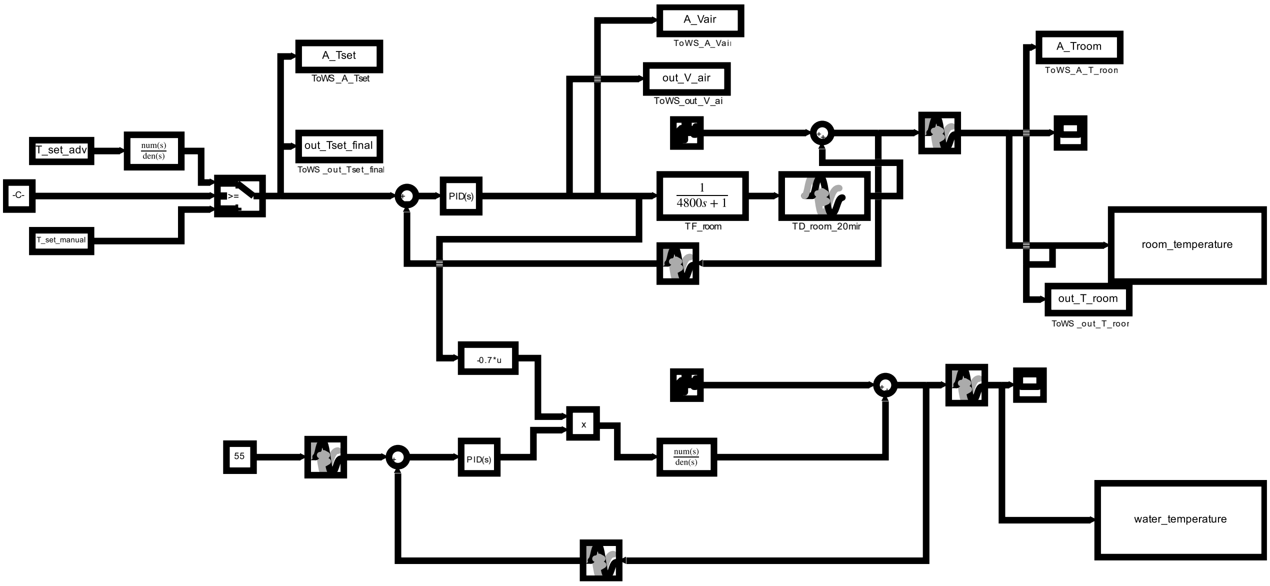

Figure 1. Simulink model of the HVAC Look-ahead Predictive Control (LPC) system (Picture credit: Original)

2.1. Simulation Framework

To ensure the PID/LPC benchmarks can be reproduced, this paper built a single HVAC dynamic model in MATLAB. It stitches together setpoint generators, PID controllers, actuators limited in speed and amplitude, and room thermal dynamics that include inertia plus a pure delay. Across every test, only the setpoint routine changed; every other setting stayed locked. The plant was represented by a first-order-plus-dead-time (FOPDT) model [7], written as equation (1). In equation (1), K denotes the static gain, τ represents the time constant, and L signifies the dead time, s denotes the Laplace frequency variable:

$$G(s) = \frac{K}{\tau s+1} e^{-Ls}, K = 1, \tau = 4800s, L = 1200s \tag{1}$$

Simulation duration: 8 hours, sampling interval: 1 second. Manual setpoints comprise two steps, the time-varying manual setpoint $T_{set,man}(t)$ is specified by equation (2):

$$T_{set,man}(t) = \begin{cases} 21^{\circ}C, & 0 \le t < 7200s \\ 23^{\circ}C, & 7200s \le t < 21600s \\ 21^{\circ}C, & 21600s \le t \le 28800s \end{cases} \tag{2}$$

Initial conditions are set to 21°C for the transfer-function state and the transport-delay output; the delay buffer is increased to 8192 to suppress warnings.

2.2. Control Strategy Design

2.2.1. Baseline (PID)

The HVAC loop retains a classical PID architecture. It continuously forms the error $e(t)$ between the operator-defined setpoint T_set_manual and the measured room temperature T_room; the regulator converts this error into a command u(t) that positions the air-side damper and sets the supply airflow rate V_air. Building dynamics are represented by a first-order lag plus dead-time model, capturing envelope thermal mass and transport delay. A local water-temperature loop keeps the heat-exchanger inlet condition steady, protecting transfer efficiency. The entire scheme is tuned once: fixed PID gains are used, as given in equation (3) [8]:

$$e(t) = T_{set,final}(t) - T_{room}(t) \tag{3}$$

$T_{set,final}(t)$ denotes the final setpoint temperature entering the controller: PID employs a manually set value, while LPC utilises a setpoint value processed through look-ahead and smoothing. The PID control law is formulated as equation (4):

$$u(t) = K_p e(t) + K_i \int e(t)dt + K_d \frac{de(t)}{dt} \tag{4}$$

Following tuning, $u(t)$ denotes control command, K_p is the proportional gain, K_i is the integral gain, K_d is the derivative gain. K_p, K_i and K_d remain consistent across both PID and LPC approach to ensure that variations originate solely from setpoint generation.

2.2.2. Proposed (LPC)

Introduce fixed lead and smoothing at the setpoint end. Time-shift the manual setpoint by a fixed advance Δt = 60min, this lead adjustment is implemented as equation (5), $T_{set,man}(t)$ is the manually specified original setpoint temperature sequence, where Δt is the fixed look-ahead time. $T_{set,lead}(t)$ is the setpoint after look-ahead but before smoothing:

$$T_{set,lead}(t) = T_{set,man}(t + \Delta t) \tag{5}$$

And suppress excessive fluctuations through a first-order smoother, which corresponds to a moving-average operation in discrete implementations, as shown in equation (6), τ_s is the first-order smoothing time constant, the larger the value, the smoother the curve but the slower the response. $T_{set,adv}(t)$ is a setpoint output after feedforward and smoothing:

$$\tau_s \frac{dT_{set,adv}(t)}{dt} + T_{set,adv}(t) = T_{set,lead}(t), \tau_s = 600s \tag{6}$$

A selector routes $T_{set,\,final}(t) = T_{set,\,man}(t)$ for Approach PID and $T_{set,\,final}(t) = T_{set,\,adv}(t)$ for Approach LPC; the lower-level PID and constraints remain unchanged [9].

2.3. Performance Evaluation Metrics

Quantitative comparison relies on five KPIs, namely Energy, IAE, tight band IAE, maximum overshoot and settling time; all time-domain integrals are computed on a shared axis after resampling the terminal PID signal to match the terminal LPC clock, removing any sampling mismatch.

Energy: Integral of the absolute value of the control variable, it is defined as equation (7), T denotes the evaluation time window duration, $u(t)$ represents the control command:

$$J_{energy} = \int_0^T |u(t)|dt \tag{7}$$

IAE, it is defined as equation (8), $e(t)$ denotes the tracking error, J_{IAE} denotes the integral absolute error:

$$J_{IAE} = \int_0^T |e(t)|dt \tag{8}$$

Tight band IAE (portion exceeding ±0.2°C), as shown in equation (9), 0.2 is the tight tolerance band threshold:

$$J_{IAE,tight} = \int_0^T \max(|e(t)| - 0.2,0)dt \tag{9}$$

Maximum Overshoot, it is defined as equation (10), $T_{room}(t)$ denotes the actual measured room temperature, $T_{set,final}(t)$ represents the final setpoint temperature entered into the controller:

$$M_{os} = \max_{t\in[0,T]} \left(T_{room}(t) - T_{set,final}(t)\right) \tag{10}$$

Settling time: the first time after which $| e(t) | \leq 0.5°$ Cholds for the remainder of the run. The Section 3 outcomes illustrate the observed trade-off: LPC markedly reduces overshoot and marginally improves steady-window IAE, while incurring only a slight rise in full-window IAE and control effort [10, 11].

3. Results

Table 1 shows Key Performance Indicators: PID vs Look-ahead Predictive Control (LPC). In this section, A denotes Strategy A (PID), and B denotes Strategy B (LPC).

Table 1. Key Performance Indicators: PID vs Look-ahead Predictive Control (LPC)

	IAE (full, $℃ \cdot s$)	Energy (full, a. u. s)	IAE (steady, $℃ \cdot s$)	Energy (steady, a. u. s)	Tight-IAE ($℃ \cdot s$)	Settling time (min)
PID	197988.9	$8.25e + 05$	153969.4	$6.38e + 05$	192346.2	0.05
LPC	214512.1	$8.46e + 05$	152031.5	$7.00e + 05$	208787.8	480.00
$\Delta(LPC - PID)$	16523.2	$2.09e + 04$	-1937.9	$6.19e + 04$	16441.6	479.95

3.1. Comparison of System Temperature Responses

Figure 2 illustrates the dynamic response curves of both control schemes under identical conditions. It can be observed that both controllers successfully track stepwise setpoint changes. However, LPC, incorporating setpoint feedforward and smoothing, significantly reduces overshoot: the maximum overshoot decreases from 19.56°C in PID to 9.59°C (approximately a 51% reduction). This demonstrates the feedforward effect imparted by the setpoint lead, effectively suppressing overshoot caused by thermal inertia.

It should be noted that under the stringent stability criterion employed herein (error $|e(t)| \leq 0.5$°C sustained for 10 minutes), LPC's settling time was not shorter than PID's; hence, no claim is made here that it ‘converges faster. LPC's primary advantages lie in reduced peak values and improved steady-state smoothness.

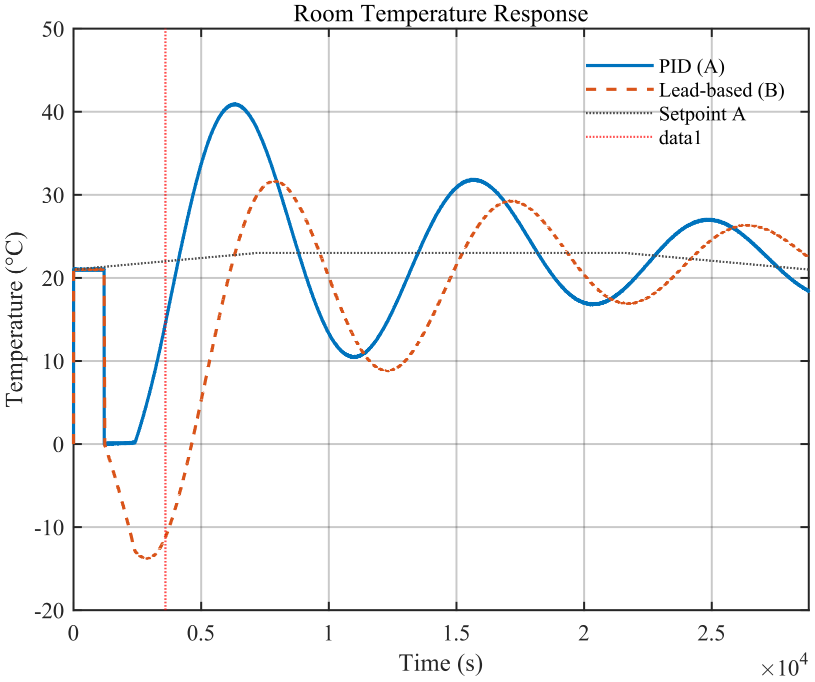

Figure 2. Room Temperature Response (A vs B) (Picture credit: Original)

3.2. Tracking Error Analysis

Figure 3 compares the transient temperature-error behaviors of the two control strategies, and the corresponding IAE metrics were computed on a unified timeline to ensure comparability. Over the full evaluation span $[0, T]$, integrated absolute error registered an uptick from 197988.9 (A) to 214512.1 (B), corresponding to an 8.3% rise. Despite this overall increase, the behavior within the steady-state interval ($t \geq 3600$ s) shows the opposite trend: IAE manifested a marginal diminution: 153969.4 (A) to 152031.5 (B), marking 1.3% attenuation. Narrow-band IAE—delimited as error accumulation beyond the stringent threshold $|e| > 0.2$ °C—the value increased from 192346.2 (A) to 208787.8 (B), representing an 8.5% rise. Collectively, these results suggest that Strategy B reduces steady-state residual errors but introduces larger transient deviations, leading to higher overall IAE.

The results indicate that LPC exhibits a smaller error during the steady-state phase, though the integral over the entire process shows a slight increase, primarily attributable to the larger error during the initialization phase. Temperature difference integration for the two methods $\int |A - B| dt = 209{,}428.6$. The two trajectories exhibit the greatest divergence during the early response phase.

3.3. Control Signal Analysis

The proxy for actuator effort is the integral of the control input magnitude. Across the full horizon it rises modestly, from E_A = 825 193.0 to E_B = 846 074.8, a gain of roughly 2.5%. Figure 4 shows $|u|$ for both schemes: LPC trims the highest temperature spike, yet the total control effort edges up, matching the integrated values quoted above.

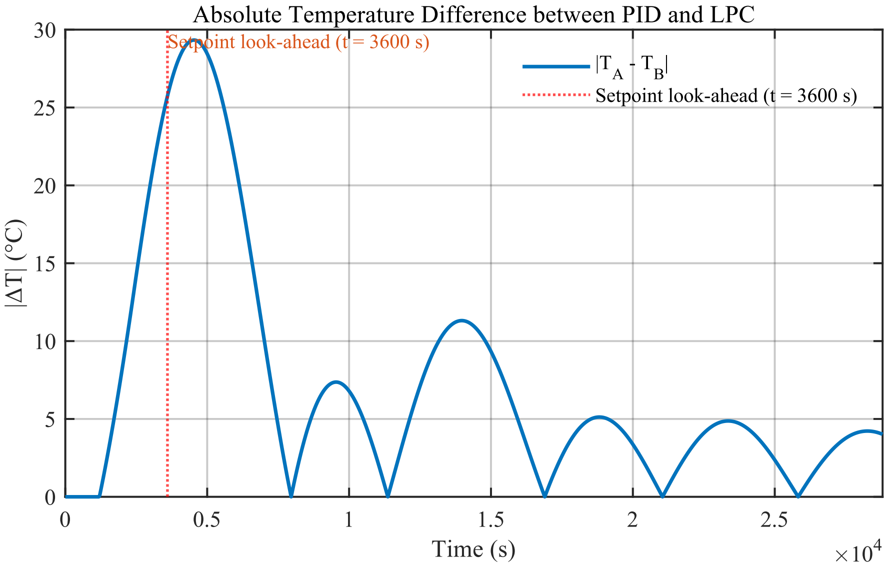

Figure 3. Absolute Difference (PID vs LPC) (Picture credit: Original)

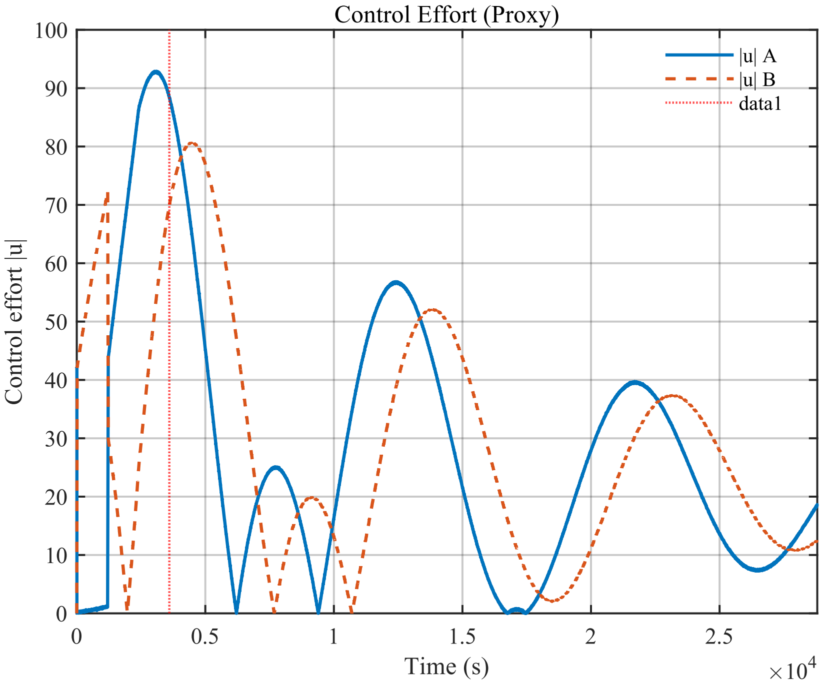

Figure 4. Control Effort (Proxy) (Picture credit: Original)

The LPC markedly curbs overshoot and marginally improves steady-window IAE, while modestly raising full-window IAE and control effort. This reflects a practical trade-off: comfort is gained at the price of slightly higher effort. Because the lower-level PID and constraints remain unchanged across tests, the observed differences stem solely from setpoint shaping, and all metrics were evaluated on a shared time grid to ensure reproducibility [12].

4. Conclusion

This study benchmarked a standard PID-based HVAC controller against a LPC strategy under identical MATLAB conditions. By feeding the PID a 60-minute preview of the setpoint through a first-order smoothing filter, LPC cut overshoot by 51% while trimming the steady-state IAE by 1.3%, at the cost of only a 2.5% rise in total control effort. The outcome shows that shaping the reference trajectory can improve comfort and stability without touching the underlying PID loop.

Results indicate that a lean supervisory layer can match the predictive quality of full MPC while remaining almost as simple as PID, giving engineers a workable middle ground between ease of use and speed of response. By demanding little computation and minimal coding, the approach opens a straightforward route to HVAC control that is both smarter and more conscious of energy use. Even though the study keeps the lead and smoothing coefficients constant within a stripped-down first-order plus dead-time model, the structure still serves as a reproducible benchmark for later work on adaptive tuning, disturbance prediction, or purely data-driven representations.

References

[1] Almabrok A, Psarakis M, Dounis A. Fast tuning of the PID controller in an HVAC system using the Big Bang–Big Crunch algorithm and FPGA technology. Algorithms, 2018, 11 (10): 146.

[2] O'Neill Z, Li Y, Williams K W. HVAC control loop performance assessment: A critical review. Science and Technology for the Built Environment, 2017, 23 (5): 619 - 636.

[3] Anil S, Srinath S H, Jayakumar M. Comparative analysis of ON/OFF, PID and model predictive control systems in HVAC systems. Proceedings of the 2023 Innovations in Power and Advanced Computing Technologies (i-PACT). Kuala Lumpur, Malaysia, 2023: 1 - 5.

[4] Bohara B, Pandey B, Aliya R P, Patwardhan S C, Banerjee R. Experimental study of the model predictive control for a residential split air conditioner. e-Prime – Advances in Electrical Engineering, Electronics and Energy, 2023, 3: 100099.

[5] Yuan Y, Zhu N, Zhou H, Wang H. A new model predictive control method for eliminating hydraulic oscillation and dynamic hydraulic imbalance in a complex chilled water system. Energies, 2021, 14 (12): 3608.

[6] Chojecki A, Ambroziak A, Borkowski P. Fuzzy controllers instead of classical PIDs in HVAC equipment: Dusting off a well-known technology and Today's implementation for better energy efficiency and user comfort. Energies, 2023, 16 (7): 2967.

[7] Al Jebaei H, Aryal A. Dynamic thermal comfort-based temperature setpoint controls. Proceedings of Sim Build 2024. IBPSA-USA, 2024: 619 - 625.

[8] Bolat E D. Implementation of matlab-SIMULINK based real time temperature control for set point changes. international journal of circuits, systems and signal processing, 2007, 1 (1): 54 - 61.

[9] Kim D, Zuo W, Braun J E, Wetter M. Comparisons of building system modeling approaches for control system design. Proceedings of BS2013. Chambéry, France, 2013: 3267 - 3274.

[10] Bogdanovs N, Belinskis R, Petersons E, Krumins A. Development of temperature process control method using Smith predictor. E3S Web of Conferences (CLIMA 2019). 2019, 111: 06016.

[11] Tudoroiu N, Zaheeruddin M, Li S, et al. Design and implementation of closed-loop PI control strategies in real-time MATLAB simulation environment for nonlinear and linear ARMAX models of HVAC centrifugal chiller control systems. Advances in Science, Technology and Engineering Systems Journal, 2018, 3 (2): 283 - 308.

[12] Almabrok A, Psarakis M, Dounis A. Fast tuning of the PID controller in an HVAC system using the big bang–big crunch algorithm and FPGA technology. Algorithms, 2018, 11 (10): 146.