



Energy-Efficient Design and Control of HVAC Systems for Smart Buildings

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Abstract

Heating, ventilation and air-conditioning (HVAC) systems are a dominant controllable load in smart buildings, and their efficiency depends on both equipment design and supervisory control. This methodology paper develops an integrated framework that combines high-efficiency variable-speed HVAC equipment, Internet-of-Things sensing, occupancy information, weather forecasts, a reduced-order thermal model and model predictive control (MPC). The proposed method is evaluated through a reproducible seven-day summer simulation of a representative single-zone smart office. Three cases are compared: a conventional fixed-setpoint proportional controller with coefficient of performance (COP) 3.0, a higher-efficiency variable-speed HVAC system with COP 3.6 under the same control logic, and the efficient system supervised by an eight-hour receding-horizon predictive controller. The simulated framework maintains occupied-zone temperature within 23–25 °C while minimizing electricity use and actuator effort. The high-efficiency equipment case reduces electricity use from 477.5 to 397.9 kWh (16.7%), while predictive control further reduces it to 348.3 kWh, corresponding to a 27.1% reduction relative to the conventional case. Peak electrical demand falls by approximately 14.5% in the integrated design-control case. The results support a practical research methodology in which sensing, control-oriented modeling and equipment efficiency are co-designed rather than optimized independently.

Introduction

Building energy performance is strongly affected by HVAC operation because heating, cooling, ventilation, fans and pumps must continuously respond to weather, occupancy and internal gains. In a smart building, the control problem is therefore not limited to maintaining a temperature setpoint; it also involves coordinating sensing, forecasting, equipment efficiency and occupant comfort. Earlier work on optimized building control showed that advanced supervisory strategies can exploit building thermal mass and dynamic information more effectively than static schedules or purely

reactive control [5]. Reviews of HVAC control similarly identify MPC as a particularly suitable framework because it uses a model to anticipate disturbances and explicitly handles energy-comfort trade-offs [4].

The development of smart sensors, building management systems and Internet-of-Things (IoT) communication has made predictive control more practical. An IoT architecture can connect zone temperature, relative humidity, carbon-dioxide concentration, occupancy estimates, weather data and actuator commands in a closed feedback loop [8]. At the same time,

the practical MPC literature emphasizes that controller performance is determined by model quality, data availability, forecast reliability, optimization formulation and commissioning effort [9]. Consequently, energy-efficient HVAC research should treat equipment design and control design as a coupled problem rather than as separate tasks.

This paper proposes a step-by-step methodology for such an integrated investigation. The method combines (i) selection of efficient variable-speed HVAC equipment, (ii) sensor and data acquisition design, (iii) reduced-order building thermal modeling, (iv) occupancy- and weather-aware MPC, and (v) comparative simulation against conventional control. The study is intentionally bounded by literature published up to 2021, in accordance with the requested reference cutoff. The main research objective is to quantify how much additional benefit is obtained when efficient equipment and predictive control are implemented together while preserving thermal comfort.

Literature Review

Early building MPC studies established the feasibility of using thermal models and weather forecasts to reduce heating energy. Prívará et al. demonstrated real-building predictive heating control and emphasized the importance of reliable building identification [2], while Široký et al. reported a two-month experimental analysis of MPC for an energy-efficient building heating system [1]. Oldewurtel et al. extended this line of work by incorporating weather forecasts and stochastic constraints, showing how predictive building climate control can manage uncertain disturbances while respecting comfort limits [3].

Afram and Janabi-Sharifi reviewed conventional and advanced HVAC control methods and summarized the theoretical basis, modeling

requirements and practical advantages of MPC [4]. Shaikh et al. broadened the scope to smart sustainable buildings and showed that optimized control must coordinate energy consumption and occupant comfort across building systems [5]. These reviews established that prediction, dynamic optimization and comfort constraints are central features of high-performance HVAC control.

More recent literature focused on implementation, scalability and smart-building connectivity. Serale et al. formulated building and HVAC MPC as an energy-efficiency problem and reviewed application opportunities, including thermal storage and demand-responsive operation [6]. Carli et al. proposed an IoT-based MPC architecture for smart-building HVAC, linking sensing, communication, optimization and actuation in a real-time framework [8]. Gholamzadehmir et al. reviewed adaptive-predictive strategies and argued that successful smart-building controllers should respond to changes in weather, occupants, system behavior and energy signals [7].

The 2020–2021 literature also highlighted deployment challenges. Drgoňa et al. provided a unified treatment of building MPC, covering modeling paradigms, optimization choices and real-world implementation requirements [9]. Kathirgamanathan et al. reviewed data-driven predictive control as a route to scalable building energy flexibility, particularly when building data and IoT infrastructures are available [10]. Yao and Shekhar summarized state-of-the-art HVAC MPC applications and confirmed the importance of model selection, prediction horizon, control variables, disturbance forecasts and optimization algorithms [11]. These studies motivate the present methodology: an efficient HVAC plant is paired with a control architecture that can use data predictively rather than reactively.

Table 1. Selected literature underpinning the methodology

Reference	Focus	Methodological contribution	Year
Široký et al. [1]	Building heating	Experimental MPC with weather prediction	2011
Oldewurtel et al. [3]	Climate control	Stochastic MPC and forecast uncertainty	2012
Afram & Janabi-Sharifi [4]	HVAC control	MPC theory and HVAC application review	2014
Serale et al. [6]	Building/HVAC efficiency	MPC formulation and application opportunities	2018
Carli et al. [8]	Smart buildings	IoT architecture for MPC implementation	2020
Drgoňa et al. [9]	Building MPC	Unified framework for real-world deployment	2020
Yao & Shekhar [11]	HVAC MPC	State-of-the-art modeling and optimization review	2021

Methodology

The methodology is organized as a sequence of design and control steps so that equipment efficiency, data quality and supervisory optimization can be assessed on the same basis. The framework follows the practical MPC principles synthesized by Serale et al. [6], Dragoña et al. [9] and Yao and Shekhar [11], with IoT connectivity patterned after Carli et al. [8].

Step 1: Define Building, Comfort and Energy Requirements

A representative single-zone smart office is considered for the comparative study. Occupancy is scheduled from 08:00 to 18:00, and the occupied comfort band is set to 23–25 °C. The outdoor temperature follows a seven-day summer profile varying approximately from 28 to 38 °C. Internal sensible gains are represented by a 4-kW occupied load plus a 0.5 kW background load, while a daytime solar gain is

superimposed. These boundary conditions are not intended to reproduce a particular building; they create a transparent test environment in which alternative HVAC designs and control strategies can be compared under identical disturbances.

Step 2: Select Energy-Efficient HVAC Equipment

The baseline plant is represented by a conventional cooling system with COP = 3.0. The efficient design uses variable-speed equipment with COP = 3.6, reflecting the benefit of improved compressor, heat-exchanger and part-load performance. Variable-speed fans and pumps are assumed to be available to the supervisory controller, so cooling capacity can be modulated rather than switched only between fully on and fully off. This design choice allows the control layer to translate predictive decisions into lower electrical consumption and smoother operation.

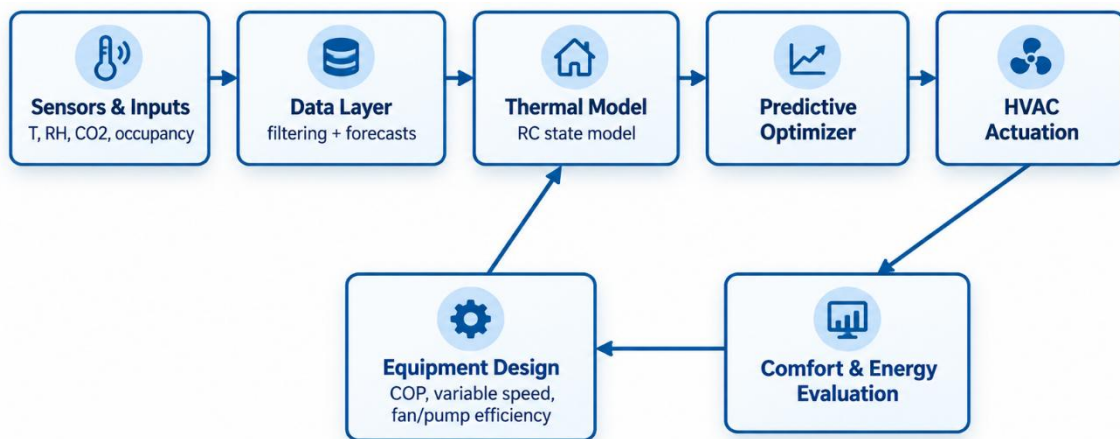


Figure 1. Integrated methodology for energy-efficient smart HVAC design and control.

Step 3: Establish the Smart Sensing and Data Layer

The proposed architecture collects zone temperature, relative humidity, CO₂ concentration, occupancy state, outdoor temperature and short-term weather forecasts. In a physical deployment, the building automation gateway would timestamp, filter and synchronize these data before passing them to the predictive controller. Occupancy may be obtained from passive infrared sensors, badge systems, people counters or fused sensor estimates. The IoT layer should also expose actuator states and electrical power measurements so that model calibration and fault detection can be performed. This sensing-to-control loop is consistent with the implementation logic described by Carli et al. [8].

Step 4: Develop a Control-Oriented Thermal Model

A first-order resistance-capacitance model is used because it is simple enough for repeated online optimization while retaining the dominant zone thermal dynamics. The hourly zone temperature is calculated from the heat balance: $T(k+1) = T(k) + (\Delta t/C)[UA(T_{out}(k) - T(k)) + Q_{int}(k) + Q_{solar}(k) - Q_{cool}(k)]$. Here $C = 10$ kWh/K is the effective thermal capacitance, $UA = 0.55$ kW/K is the envelope conductance, Q_{int} is the internal sensible gain, Q_{solar} is the solar gain and Q_{cool} is the HVAC cooling rate. Reduced-order models of this type are widely used in building predictive control because they provide a practical compromise between physical interpretability and computational tractability [4], [9].

Step 5: Formulate the Predictive Control Problem

At each hour, the predictive controller solves an eight-hour receding-horizon optimization. The decision variable is cooling capacity Q_{cool} , constrained between 0 and 18 kW. The objective combines electrical energy use, occupied-zone comfort penalties and a small quadratic actuator penalty. The occupied temperature target is 24 °C, with hard-like penalty bounds of 23–24.9 °C in the numerical solver. During unoccupied hours, the allowable range is relaxed to 21–29 °C, enabling load shedding and use of the building thermal mass. The optimizer uses the known disturbance trajectories in the simulation as perfect short-term forecasts; in real implementation, these inputs would be replaced by weather and occupancy predictions as recommended in earlier MPC studies [3], [7], [9].

For each candidate control sequence, the thermal model predicts future indoor temperatures. The first optimized cooling command is applied, the state is updated, and the optimization is repeated one hour later. This receding-horizon process allows the controller to pre-cool before occupancy, when necessary, reduce cooling during unoccupied periods, and avoid excessive temperature excursions. The formulation directly reflects the MPC structure described in the pre-2021 literature [4], [6], [11].

Step 6: Define Comparative Cases and Performance Indicators

Three cases are simulated under identical weather, solar and occupancy disturbances. Case A is the conventional system (COP 3.0) controlled by a fixed 22.5 °C proportional setpoint chosen to keep occupied temperature within the 23–25 °C

evaluation band. Case B retains the same controller and thermal behavior but increases plant COP to 3.6, isolating the effect of equipment efficiency. Case C combines COP 3.6 with predictive supervisory control. The principal indicators are seven-day HVAC electricity consumption (kWh), peak electrical demand (kW), average occupied temperature and percentage of occupied hours within the 23–25 °C comfort band.

Step 7: Validate and Interpret the Simulation

The numerical results are checked for energy balance; control bounds and comfort compliance. Because the purpose is methodological, the reported values are model-based simulation results rather than measured field data. The interpretation therefore focuses on relative differences between cases, which are more robust than absolute energy values. This approach also avoids attributing the simulated savings to any specific building while still demonstrating how the proposed co-design framework can be evaluated reproducibly.

Results

The seven-day simulation shows a clear separation between equipment-only efficiency gains and the additional benefit of predictive control. The conventional case consumes 477.5 kWh. Increasing COP from 3.0 to 3.6 while leaving the control law unchanged reduces consumption to 397.9 kWh, a 16.7% saving. When the efficient plant is combined with the occupancy- and weather-aware predictive controller, electricity uses falls to 348.3 kWh, corresponding to a 27.1% reduction from the conventional case. Peak electrical demand also falls from 5.00 to 4.27 kW (14.5% reduction).

Table 2. Simulated performance of the three HVAC configurations

Case	7-day energy (kWh)	Energy saving	Peak demand (kW)	Comfort compliance
A. Conventional HVAC	477.5	Reference	5.00	100%
B. Efficient equipment	397.9	16.7%	4.17	100%
C. Efficient + predictive	348.3	27.1%	4.27	100%

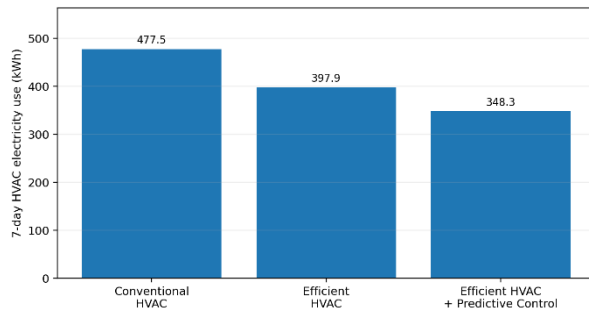


Figure 2. Simulated seven-day HVAC electricity use for the three cases.

Conclusion and Discussion

The results demonstrate the central methodological point of this paper: equipment efficiency and intelligent control provide complementary savings. Improving COP alone reduces electricity use by 16.7%, but combining the efficient plant with predictive supervisory control increases the total simulated saving to 27.1% while maintaining full occupied-hour compliance with the 23–25 °C comfort band. The predictive case also lowers peak electrical demand, showing that smart control can contribute to both building efficiency and demand-side flexibility. The pattern is consistent with the pre-2021 literature, which repeatedly reports that predictive building control can reduce unnecessary heating or cooling by anticipating weather, occupancy and thermal-storage effects [1], [3], [6], [9]. The present values should not be interpreted as universal field savings because they arise from a simplified single-zone model, assumed COP values and ideal short-term forecasts. In a real building, sensor errors, equipment cycling, humidity control, ventilation requirements, forecast uncertainty, commissioning quality and occupant behavior would affect performance. Data-driven model adaptation, emphasized by Kathirgamanathan et al. [10], may be useful when first-principles calibration is difficult. For future experimental work, the same methodology can be implemented in EnergyPlus, Modelica or a building automation testbed, with measured power, indoor environmental quality and occupancy data used for validation. Field studies should compare equivalent comfort conditions and should report tuning and implementation effort as well as energy savings. Within these limitations, the proposed workflow provides a concise, reproducible basis for investigating energy-efficient HVAC design and control in smart buildings using literature available up to 2021 [7], [11]. A practical implication is that HVAC energy efficiency should be evaluated at

both the component and supervisory levels. A high-COP chiller or heat pump can reduce electricity per unit of delivered cooling, but poor schedules, simultaneous heating and cooling, excessive ventilation, aggressive setpoints or unnecessary after-hours operation can still dominate whole-building consumption. Conversely, advanced control cannot fully compensate for inefficient equipment. The co-design approach therefore begins with appropriate equipment sizing, high part-load efficiency, variable-speed capability and low-pressure-drop air and water distribution, and then adds predictive supervisory control. This interpretation is consistent with the broader smart-building control perspective summarized by Shaikh et al. [5] and the application-oriented MPC formulation reviewed by Serale et al. [6]. The sensing and data layer is equally important. Predictive algorithms depend on accurate zone temperatures, trustworthy occupancy estimates, stable actuator feedback and sufficiently reliable disturbance forecasts. Sensor bias can cause systematic overcooling or undercooling, while missing occupancy data can eliminate much of the scheduling advantage of the predictive controller. In real deployment, automated data-quality checks should therefore be included before optimization, and the thermal model should be recalibrated when the building envelope, space use or HVAC configuration changes. The implementation studies and reviews by Carli et al. [8], Dragoña et al. [9] and Kathirgamanathan et al. [10] support treating data management and model maintenance as part of the control system rather than as one-time commissioning activities. A further extension is to formulate a multi-objective controller that jointly considers temperature, humidity, indoor air quality, electricity price and peak demand. The present simulation uses temperature as the primary comfort variable to keep the methodology transparent, but a field-ready smart-building controller should preserve ventilation and humidity constraints while responding to occupancy. Time-varying electricity tariffs or demand-response signals can also be added directly to the MPC objective, allowing thermal mass to shift cooling loads without sacrificing comfort. The adaptive-predictive and HVAC MPC reviews available by 2021 identify these multi-variable and uncertainty-aware formulations as important directions for robust smart-building operation [7], [11].

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