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Health-Aware Digital Twins for Building Control under Climate Extremes: An Exposure-State Control Framework

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ABSTRACT

Climate extremes expose a fundamental limitation in current building control strategies: compliance with instantaneous thermal and air quality thresholds does not guarantee protection against cumulative health risk. Existing digital twin and predictive control approaches largely treat indoor environmental variables as memoryless signals, neglecting the time-integrated nature of human exposure.
This study addresses this gap by introducing an exposure-state control framework that explicitly models cumulative thermal and air quality exposure as dynamic system states with temporal memory. A health-aware digital twin is developed by integrating a physics-based building model with residual learning and predictive control over an augmented state space. The framework is evaluated using a structured stress-test suite, including prolonged heatwaves, compound heat–pollution events, ventilation constraints, sensor drift, and equipment degradation. Across 30 Monte Carlo simulations, the proposed approach reduces cumulative thermal exposure by 35–55% and particulate exposure by 30–50% relative to compliance-based and MPC controllers, while limiting energy penalties to below 12%. The results reveal a structural disconnect between regulatory compliance and long-term health protection and demonstrate that exposure-state modeling enables anticipatory and risk-aware control under sustained stress conditions.

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1. INTRODUCTION

Climate change is fundamentally reshaping the operating conditions of buildings, exposing structural limitations in control strategies that were originally conceived for stationary and moderate environments. Recent digital twin–based investigations into indoor air quality and building operation demonstrate that prolonged heatwaves, elevated outdoor pollution levels, and compound extreme events are no longer exceptional disturbances but increasingly dominant operating regimes (Qian et al. 2024). Under such conditions, conventional control approaches often fail to provide sustained protection for occupants while simultaneously maintaining acceptable energy performance.

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Current building control practice remains largely rooted in compliance-based paradigms that rely on instantaneous constraints. Advanced predictive control frameworks, most notably model predictive control (MPC), regulate thermal comfort and indoor air quality by enforcing predefined limits on temperature, carbon dioxide concentration, or particulate matter levels (Drgoňa et al. 2020). Recent applications of MPC for indoor air quality management further reinforce this paradigm by embedding air quality objectives as static constraints or penalty terms within optimization-based controllers (Tarragona et al. 2024). While such formulations can be effective under nominal conditions, they implicitly assume that short-term compliance is sufficient to ensure long-term safety and well-being.

Despite the breadth of existing research, important inconsistencies remain in how indoor environmental performance is defined and evaluated. While MPC-based studies emphasize energy–comfort trade-offs using instantaneous constraints, exposure science literature consistently demonstrates that health outcomes depend on cumulative dose rather than peak values. This creates a conceptual mismatch between control objectives and physiological risk models.

Furthermore, studies can be broadly grouped into three categories:

1. Energy-focused control frameworks prioritizing efficiency,
2. comfort-driven approaches based on thermal thresholds, and
3. air-quality-aware control incorporating pollutant limits.

However, these categories largely operate independently, with limited integration of multi-stressor cumulative effects.

Methodologically, prior works differ significantly in their treatment of uncertainty, temporal dynamics, and system memory. Most approaches rely on short prediction horizons and static penalty formulations, which inherently limit their ability to capture prolonged exposure effects. As a result, even advanced digital twin implementations remain structurally aligned with compliance-based paradigms rather than health-driven decision-making.

Emerging digital twin research, however, indicates that building operation is increasingly governed by non-stationary dynamics, sensor drift, and gradual system degradation (Eneyew et al. 2024). Architectural advances integrating Building Information Modeling with Internet of Things data streams enable richer system representations, yet most implementations continue to evaluate performance through instantaneous metrics rather than through temporally accumulated effects (Eneyew et al. 2022). Comprehensive reviews of digital twin applications for building energy efficiency confirm that health-related variables are typically treated as secondary constraints rather than as dynamic risk drivers (Bortolini et al. 2022).

Related work on BIM-based digital twins and extended reality platforms further highlights that maintenance and operational decisions remain largely reactive, even when advanced visualization and monitoring tools are available (Coupry et al. 2021). Reviews focusing on distributed IoT-enabled smart buildings similarly identify a persistent gap between real-time data integration and health-aware decision-making (Walczyk and Ożadowicz 2024). Although digital twins have been successfully applied to net-zero energy evaluations and comfort monitoring in campuses and existing buildings (Kaewunruen et al. 2018; Zaballos et al. 2020), these studies primarily assess compliance with predefined comfort or energy targets rather than cumulative exposure.

Simulation-based testing environments such as BOPTEST have been introduced to evaluate advanced control strategies under reproducible conditions (Jiménez et al. 2021). In parallel, reinforcement learning–based control approaches demonstrate the feasibility of jointly optimizing energy consumption, thermal comfort, and indoor air quality (Guo et al. 2025). Multi-objective optimization reviews further confirm that energy, comfort, and air quality trade-offs can be systematically balanced within control frameworks (Al Mindeel et al. 2024). Nevertheless, these approaches overwhelmingly rely on instantaneous performance indicators.

Recent reviews of building digital twins explicitly acknowledge that most existing frameworks remain focused on improving operational efficiency rather than directly addressing occupant health outcomes (Cespedes-Cubides and Jradi 2024). Broader surveys of digital twin applications in renewable and built energy systems reinforce this observation, noting that health considerations are rarely modeled as dynamic processes with memory (Mbasso et al. 2025). Meanwhile, advances in artificial intelligence for structural and condition assessment highlight the growing sophistication of sensing and inference capabilities, yet these developments have not been fully translated into health-aware building control (Zhang et al. 2024). Similarly, AI-driven digital twin frameworks in infrastructure systems have shown the capability to integrate real-time sensing with predictive analytics for system monitoring and decision-making (Riffat et al. 2026), although their extension to health-aware building control remains largely unexplored.

Conceptual reviews of building digital twins consistently emphasize the need to move beyond descriptive and predictive use cases toward prescriptive and adaptive operation (Kim et al. 2023). At the same time, research on human–building interaction underscores that occupant responses and health impacts cannot be fully captured by static thresholds alone (Becerik-Gerber et al. 2022). Occupant-centric control strategies have been proposed to reduce energy use and improve comfort, but they continue to rely primarily on short-term feedback signals (Park et al. 2019; Naylor et al. 2018).

Maintenance-oriented digital twin frameworks illustrate how accumulated system degradation can be modeled and anticipated over time (Errandonea et al. 2020). Recent implementations in civil infrastructure further demonstrate how high-density sensing and real-time analytics can support system-level decision-making within digital twin environments (Samaei and Riffat 2025), suggesting strong potential for extending similar concepts to occupant-centric building control. Related conceptual work differentiating digital twins from digital shadows further clarifies that true digital twins must support reasoning over system history rather than instantaneous snapshots (Sepasgozar 2021). In the context of HVAC systems, digital twin–based predictive maintenance approaches demonstrate how temporal dynamics can be leveraged for fault anticipation (Hosamo et al. 2022), yet similar formulations are rarely extended to health-related variables.

Several studies have begun integrating indoor air quality dynamics with estimation and control, combining moving horizon estimation with MPC to regulate pollutant concentrations (Ganesh et al. 2021). Comprehensive reviews of MPC for HVAC systems confirm the maturity of predictive control techniques while simultaneously highlighting their reliance on fixed constraint formulations (Taheri et al. 2022). In parallel, exposure science has demonstrated that health impacts from airborne pollutants are governed by cumulative dose rather than by peak concentrations alone (Buonanno et al. 2020).

Recent reviews on ventilation and infection risk assessment further emphasize that prolonged exposure, rather than instantaneous exceedance, determines health outcomes in indoor environments (Hobeika et al. 2023). Emerging digital twin research focusing on thermal comfort and energy efficiency similarly calls for the inclusion of temporal health dynamics within control frameworks (Sha et al. 2023). Large-scale evaluations of predictive control strategies reveal that systems may remain compliant with regulatory thresholds while accumulating substantially different exposure profiles over time (Wang et al. 2023).

Against this backdrop, recent work on human digital twins in industrial settings demonstrates how fatigue and risk can be explicitly modeled as state variables with memory, enabling anticipatory and health-aware decision-making (You et al. 2025). This insight motivates a fundamental rethinking of indoor environmental control in buildings. Across these studies, a consistent limitation is the reliance on instantaneous performance indicators, even when advanced predictive or data-driven methods are employed. Comprehensive reviews of digital twin and AI-based monitoring systems highlight that while system-level optimization has advanced significantly, the representation of health-related variables remains static and threshold-based (Riffat et al. 2025). This creates a disconnect between control objectives and the cumulative nature of human exposure.

Recent work on cognitive digital twins for climate-resilient building energy systems has further demonstrated the importance of adaptive and diagnosis-informed control under extreme thermal stress (Samaei and Riffat 2026). However, these approaches still primarily focus on system performance and control adaptation, without explicitly modeling cumulative health exposure as a dynamic state variable.

This study argues that the primary limitation of existing digital twin–based control strategies lies not in model fidelity or algorithmic sophistication, but in the representation of health itself. When indoor environmental quality is formulated solely through instantaneous constraints, control systems lack the capacity to reason over exposure history or to anticipate future risk. To address this gap, this work introduces an exposure-state control paradigm that explicitly models cumulative health exposure as a dynamic system state within the digital twin. By reframing indoor environmental control from compliance enforcement toward risk management, the proposed framework enables proactive, health-aware decision-making under climate extremes, where short-term compliance may otherwise obscure long-term harm.

2. Problem Formulation and Exposure-State Modeling

2.1. Conventional Control Formulation and Its Structural Limitation

Conventional building control strategies formulate thermal comfort and indoor air quality regulation as an instantaneous constraint satisfaction problem. At each control interval, the system evaluates the current state of indoor temperature and pollutant concentrations and applies corrective actions to maintain these variables within predefined bounds. In optimization-based approaches, such as model predictive control, these objectives are commonly expressed either as hard constraints or as instantaneous penalty terms added to an energy-focused cost function.

While such formulations are computationally efficient and align with regulatory compliance frameworks, they implicitly assume that indoor environmental variables are memoryless. That is, the impact of past exposure is not retained within the system state, and decisions are made solely based on current measurements and short-horizon predictions. Under this assumption, a brief exceedance and a prolonged marginal exposure are treated equivalently, provided that instantaneous thresholds are not violated.

This assumption introduces a structural limitation when control decisions are evaluated from a health perspective. Human physiological response to thermal stress and air pollution is inherently cumulative, with adverse effects driven by both magnitude and duration of exposure. As a result, control strategies that satisfy instantaneous constraints may still permit the gradual accumulation of health risk over extended periods, particularly under persistent stress conditions such as heatwaves or elevated outdoor pollution.

2.2. Reformulating Health as a Dynamic Exposure State

To overcome this limitation, this study reformulates health-related variables as dynamic exposure states that explicitly capture the temporal accumulation of risk. Rather than evaluating indoor environmental conditions solely at the current control step, cumulative exposure is modeled as an evolving system state with memory.

For a given health-relevant variable s_k, such as indoor temperature, carbon dioxide concentration, or particulate matter concentration at control step k, the corresponding exposure state E_k is defined by the following update equation:

$$E_{k+1} = gamma \cdot E_k + max\left(0, s_k - s_{ref}\right) \cdot Delta_t \tag{1}$$

Here, s_{ref} denotes a reference threshold associated with acceptable indoor conditions, $Delta_t$ represents the control interval expressed in hours, and gamma is a memory parameter bounded between zero and one that governs the persistence of accumulated exposure.

This formulation introduces two key properties. First, exposure accumulates only when environmental conditions exceed reference levels, ensuring that benign operating periods do not artificially inflate health risk. Second, the memory parameter allows past exposure to decay gradually over time, reflecting physiological recovery and preventing indefinite accumulation. By adjusting gamma, the framework can represent different sensitivity profiles and recovery dynamics without altering the structure of the control problem.

2.3. Multi-Dimensional Exposure Representation

In indoor environments, health risk arises from the combined effects of multiple stressors rather than from a single variable. Accordingly, the proposed framework maintains separate exposure states for thermal stress, carbon dioxide concentration, and particulate matter concentration. For each health-relevant variable i belonging to the set {T, CO_2, PM}, the exposure dynamics are defined as

$$E_{i,(k+1)} = gamma_i \cdot E_{i,k} + max\left(0, s_{i,k} - s_{i,ref}\right) \cdot Delta_t \tag{2}$$

Here, $E_{i,k}$ denotes the exposure state associated with variable *i* at control step k, $s_{i,k}$ is the corresponding indoor environmental signal, $s_{i,ref}$ is its reference threshold, $Delta_t$ is the control interval expressed in hours, and $gamma_i$ is a variable-specific memory parameter governing exposure persistence and recovery.

This multi-dimensional exposure representation enables the control system to distinguish between different sources of health risk and to balance trade-offs among them. Importantly, it avoids collapsing heterogeneous stressors into a single instantaneous index, preserving interpretability and facilitating targeted, stressor-specific intervention strategies.

Table 1. Exposure-state parameterization used in this study.

Exposure	Signal	Reference level	Unit	Memory factor γ	Rationale
Thermal	Zone temperature T	26	°C	0.92	ASHRAE comfort upper bound
CO_2	Indoor CO_2	1000	ppm	0.95	Ventilation guideline
$PM_{2.5}$	Indoor $PM_{2.5}$	15	μg/m³	0.97	WHO air quality guideline

The memory factor γ represents the persistence of exposure accumulation and recovery over time. Values were selected to reflect recovery time scales on the order of several hours to days, consistent with prolonged thermal and air-quality stress observed during climate-extreme events. Sensitivity analysis over $\gamma \in [0.85, 0.99]$ confirmed that qualitative conclusions remain unchanged.

These parameter choices are further supported by established findings in exposure science and environmental health. Physiological responses to thermal stress and airborne pollutants are governed by cumulative dose-response mechanisms, where both magnitude and duration of exposure influence health outcomes. For example, thermal strain accumulation over multiple hours has been linked to increased cardiovascular stress and impaired recovery, while prolonged exposure to elevated CO_2 and particulate matter has been associated with cognitive impairment and respiratory burden.

The selected memory factors (γ) therefore approximate the persistence of physiological stress and recovery processes over multi-hour to multi-day timescales, consistent with exposure-response dynamics reported in prior studies (Buonanno et al. 2020; Hobeika et al. 2023).

2.4. Integration into the Digital Twin State Space

The introduction of exposure states expands the traditional digital twin state vector to include both physical and health-related dynamics. Let x_k denote the physical system state at control step k, including variables such as zone temperatures, airflow rates, and indoor pollutant concentrations. The augmented state vector z_k is defined as

$$z_k = \left[x_k, E_{T,k}, E_{CO_2,k}, E_{PM,k}\right]^T \quad (3)$$

Here, $E_{T,k}, E_{CO_2,k}, and\ E_{PM,k}$ denotes the exposure states associated with thermal stress, carbon dioxide concentration, and particulate matter concentration, respectively.

The digital twin evolves according to the coupled dynamics of the physical system and the exposure states. The physical state propagation is governed by

$$x_{k+1} = f(x_k, u_k, d_k) \quad (4)$$

while the exposure states evolve according to

$$E_{i,(k+1)} = gamma_i \cdot E_{i,k} + max\left(0, s_{i,k} - s_{i,ref}\right) \cdot Delta_t \quad (5)$$

In these expressions, $u_k$denotes the control input vector and d_k represents exogenous disturbances such as weather variability and outdoor pollutant levels.

This augmented formulation enables the controller to reason explicitly about how current control actions influence not only immediate system behavior, but also the future evolution of cumulative health risk. By embedding exposure dynamics directly within the digital twin state space, the framework supports anticipatory and risk-aware decision-making under sustained and compound stress conditions.

2.5. Health-Aware Objective Function

Within this augmented state space, control decisions are formulated as a multi-objective optimization problem that balances energy consumption against cumulative health exposure. Over a finite prediction horizon N, the control objective is defined as the minimization of the weighted sum of energy use and exposure states, minimize over the control sequence u_k the sum from:

$$k = 0\ to\ N - 1\ of\ \left(w_E \cdot E_{energy,k} + sum\ over\ i\ of\ w_i \cdot E_{i,k}\right) \tag{6}$$

This optimization is subject to the system dynamics and all operational constraints. Here, $E_{energy,k}$ denotes the energy-related cost at control step k, $E_{i,k}$ represents the exposure state associated with health stressor i, and w_E and w_i are weighting coefficients reflecting the relative importance assigned to energy efficiency and health protection, respectively.

Crucially, health-related terms enter the objective function as state variables rather than as instantaneous penalties on environmental signals. This distinction enables anticipatory control behavior: the controller may act preemptively to limit future exposure accumulation, even when current indoor conditions remain nominally compliant with conventional thresholds.

2.6. Implications for Control Behavior

The exposure-state formulation fundamentally alters the structure of the control problem. In conventional formulations, optimal actions are driven by instantaneous deviations and short-term predictions. In contrast, exposure-state control internalizes the long-term consequences of repeated marginal exceedances, encouraging smoother, earlier, and more sustained interventions.

As a result, control strategies that are indistinguishable under traditional compliance-based metrics may exhibit markedly different behavior when evaluated through cumulative exposure. This distinction is central to the hypothesis tested in this study: that compliance-oriented control is insufficient for protecting occupant health under climate extremes, and that exposure-state control constitutes a necessary extension of digital twin-based decision-making.

3. Scenario Design and Stress-Test Framework

3.1. Rationale for Stress-Oriented Evaluation

Evaluating building control strategies under nominal operating conditions often obscures their structural limitations. When indoor temperature and air quality fluctuate mildly around setpoints, fundamentally different control formulations may appear indistinguishable. This is particularly true for compliance-oriented strategies, which are explicitly designed to perform well under standard conditions.

To reveal the behavioral differences introduced by exposure-state control, this study adopts a stress-oriented evaluation framework. Rather than benchmarking performance under average conditions, the proposed approach subjects control strategies to deliberately challenging scenarios that reflect emerging real-world operating regimes. These scenarios are not intended to represent rare corner cases, but plausible future conditions driven by climate change, urban air quality deterioration, and operational constraints.

The underlying premise is that a control formulation should be judged not only by its average performance, but by its ability to prevent the gradual accumulation of health risk under sustained stress.

3.2. Baseline Operating Conditions

All scenarios are constructed around a common baseline representing typical summer operation in a high-occupancy commercial building. The baseline period establishes reference conditions for thermal loads, ventilation demand, and indoor pollutant levels, ensuring that differences observed during stress periods can be attributed to control behavior rather than initialization artifacts.

During the baseline period, outdoor temperature follows a diurnal sinusoidal profile with moderate amplitude, and outdoor particulate matter concentration remains below health-based reference thresholds. Occupancy follows a realistic weekday schedule with stochastic variability to reflect day-to-day fluctuations. This baseline is used to initialize the digital twin state and exposure variables prior to the onset of stress conditions.

3.3. Prolonged Heatwave Scenario

The first stress scenario introduces a prolonged heatwave characterized by elevated outdoor temperatures sustained over multiple consecutive days. Unlike short-duration peaks, prolonged heatwaves impose continuous thermal stress on both the building envelope and mechanical systems, increasing cooling demand and reducing opportunities for passive recovery.

This scenario is designed to test whether control strategies can manage thermal exposure over extended periods without relying on short-term corrective actions. In compliance-based controllers, marginal temperature deviations may be repeatedly corrected without consideration of accumulated thermal burden. In contrast, exposure-state control is expected to initiate earlier and smoother interventions to limit cumulative thermal stress.

3.4. Compound Heatwave and Pollution Scenario

To reflect increasingly common compound events, the heatwave scenario is extended to include elevated outdoor particulate matter concentrations. Outdoor pollution follows a daily profile with pronounced morning and midday peaks, consistent with traffic-related and urban background emissions observed during stagnant atmospheric conditions.

This compound scenario introduces a fundamental trade-off between thermal control and ventilation. Increased outdoor air intake can alleviate indoor carbon dioxide accumulation but may exacerbate particulate exposure, particularly when outdoor air quality is poor. Conversely, reducing ventilation to limit particulate ingress can increase indoor-generated pollutants and thermal discomfort.

The compound heatwave–pollution scenario is specifically designed to challenge threshold-based control logic, which reacts locally to individual indicators without accounting for cumulative exposure across stressors.

3.5. Ventilation Constraint Scenario

In practice, ventilation capacity is often constrained by energy policies, grid limitations, or system design. To capture this reality, a ventilation-constrained variant of the compound scenario is introduced by imposing an upper bound on the allowable outdoor air fraction.

This scenario tests whether control strategies can adapt to reduced actuation authority without allowing health risk to accumulate unchecked. It also evaluates whether exposure-state control can redistribute risk over time by prioritizing periods where intervention is most effective, rather than uniformly reacting to instantaneous violations.

3.6. Sensor Drift Scenario

Reliable sensing is a critical assumption in digital twin-based control. However, sensor bias and drift are common in long-term building operation, particularly for air quality sensors. To assess robustness under imperfect information, a sensor drift scenario is introduced in which carbon dioxide and particulate matter measurements exhibit gradual bias over time.

The drift is intentionally slow and monotonic, reflecting realistic degradation rather than abrupt failure. This scenario evaluates whether control strategies that rely on instantaneous measurements are prone to systematic misinterpretation, and whether exposure-state formulations can mitigate the impact of persistent measurement error by integrating information over time.

3.7. Equipment Degradation Scenario

Mechanical system performance degrades over time due to wear, fouling, and partial failures. To evaluate resilience under reduced capacity, a degradation scenario is introduced in which cooling capacity and airflow availability are progressively reduced.

This scenario tests the ability of control strategies to maintain health protection when full actuation is no longer available. In particular, it examines whether exposure-state control can compensate for reduced capacity by adjusting the timing and intensity of interventions, rather than attempting to enforce infeasible instantaneous targets.

3.8. Comparative Control Strategies

Across all scenarios, the proposed exposure-state control strategy is compared against a set of representative baselines, including rule-based control and model predictive control formulations that incorporate indoor air quality as instantaneous constraints or penalty terms. These baselines are selected to reflect both current practice and advanced control approaches commonly reported in the literature.

By applying all control strategies to the same sequence of stress scenarios, the framework ensures that observed differences in performance arise from control formulation rather than scenario design.

3.9. Evaluation Focus and Performance Metrics

Performance evaluation emphasizes cumulative health exposure, robustness under sustained stress, and the alignment between nominal compliance and long-term protection. While energy consumption remains an important consideration, it is evaluated in conjunction with exposure outcomes rather than in isolation.

This stress-test framework is intentionally conservative. Scenarios are constructed such that conventional control strategies may appear adequate when evaluated using instantaneous metrics, but exhibit deficiencies when assessed through cumulative exposure. In doing so, the framework provides a stringent and transparent basis for evaluating whether exposure-state control represents a substantive advancement over existing paradigms.

4. Digital Twin Architecture and Control Implementation

4.1. Architectural Overview

The proposed framework is implemented as a closed-loop health-aware digital twin that couples a physics-based building model with data-driven residual learning and exposure-state control. The architecture is designed to operate at the control timescale, continuously assimilating sensor data, updating internal states, and generating control actions that explicitly account for cumulative health exposure.

At each control interval, the digital twin performs three core functions: (i) state estimation and data assimilation, (ii) short-horizon prediction of physical and exposure dynamics, and (iii) health-aware decision-making under operational constraints. This modular structure ensures that the framework remains extensible and compatible with different building models, sensing configurations, and control algorithms.

4.2. Physics-Based Building Model

The physical core of the digital twin is a high-fidelity building energy and airflow model that captures thermal dynamics, ventilation behavior, and indoor pollutant transport at the zone level. The model represents heat transfer through the building envelope, internal heat gains, mechanical system operation, and the exchange of indoor and outdoor air.

Indoor air quality variables, including carbon dioxide and particulate matter concentrations, are modeled as state variables governed by mass balance relationships. These relationships account for outdoor air intake, recirculation, internal generation, and removal mechanisms such as filtration or air cleaning. By embedding pollutant transport within the physics-based model, the digital twin maintains physical consistency between energy and air quality dynamics.

The physics-based model provides baseline predictions of zone temperature, airflow rates, and pollutant concentrations over the prediction horizon. These predictions form the foundation upon which health-aware control decisions are made.

4.3. Data Assimilation and Residual Learning

To address model uncertainty and unmodeled dynamics, the digital twin incorporates a data-driven residual learning layer that corrects systematic prediction errors in the physics-based model. At each control step, measured sensor data are compared against model predictions, and the resulting residuals are used to update the internal state estimate.

The residual learning component is implemented as a supervised regression model that maps recent state trajectories and exogenous inputs to prediction errors of the physics-based model. Specifically, the residual model takes as input a sliding window of past measurements and control actions over the previous 3–6 control intervals and predicts the correction term applied to the next-step state estimate.

A lightweight feedforward neural network with two hidden layers (32–64 neurons each) and ReLU activation functions is used to ensure computational efficiency and stability in online operation. The model is trained offline using simulation data generated under diverse operating conditions and is not updated during online control execution to preserve robustness and avoid drift amplification.

This hybrid modeling approach ensures that the digital twin retains physical interpretability while compensating for systematic biases arising from unmodeled dynamics.

The residual model is trained to capture biases arising from factors such as occupancy variability, imperfect envelope characterization, and sensor noise. By learning corrections to the physics-based predictions rather than replacing them entirely, the framework preserves interpretability and avoids physically implausible behavior.

State estimation is performed using a sequential update scheme in which the corrected state estimate is propagated forward to generate one-step-ahead predictions. This approach enables robust operation under measurement uncertainty and gradual sensor drift, which are explicitly considered in the stress-test scenarios.

4.4. Control Inputs and Operational Constraints

The digital twin generates control actions by manipulating a set of physically realizable inputs, including cooling setpoints, outdoor air fraction, supply airflow rate, and air cleaning intensity. These inputs are constrained by equipment capacities, comfort limits, and ventilation requirements.

Thermal constraints ensure that zone temperatures remain within acceptable bounds, while ventilation constraints enforce minimum and maximum outdoor air intake. Additional constraints reflect system limitations introduced in stress scenarios, such as reduced airflow capacity or degraded cooling performance. By explicitly modeling these constraints, the digital twin avoids infeasible or unsafe control actions.

4.5. Health-Aware Control Problem

At each control interval, the digital twin solves a finite-horizon optimization problem defined over the augmented state space that includes both physical variables and exposure states. The objective function balances energy consumption against cumulative exposure, as formulated in Section 2, while respecting all operational constraints.

Unlike conventional controllers that penalize instantaneous deviations, the proposed formulation treats exposure states as first-class decision variables. This enables the controller to reason about how present actions influence future health risk accumulation, leading to anticipatory behavior that prioritizes early and sustained mitigation under prolonged stress.

The optimization problem is solved in a receding-horizon fashion. Only the first control action is applied to the physical system, after which new sensor data are assimilated and the optimization is repeated. This structure ensures adaptability to disturbances and model mismatch.

4.6. Baseline Controllers for Comparison

To provide a rigorous basis for comparison, the digital twin framework is used to implement several baseline control strategies within the same architectural environment. These include rule-based control representative of current practice, model predictive control focused primarily on energy efficiency, and predictive control formulations that incorporate indoor air quality through instantaneous penalties or constraints.

By implementing all controllers within the same digital twin architecture and subjecting them to identical scenarios, the framework isolates the effect of control formulation from differences in modeling fidelity or system configuration.

4.7. Computational Considerations

The proposed architecture is designed to operate at control-relevant timescales without imposing prohibitive computational burden. The exposure-state update equations are algebraically simple and add negligible overhead relative to conventional predictive control formulations. Residual learning and state estimation are performed incrementally, avoiding retraining during online operation.

These design choices ensure that the framework can be deployed in real-time building management systems and scaled to larger buildings or portfolios without fundamental modification.

4.8. Summary of Implementation Logic

The digital twin architecture integrates physics-based modeling, data-driven correction, and exposure-state control into a unified decision-making system. By embedding cumulative exposure directly into the control loop, the framework transforms the role of the digital twin from a passive predictive model to an active health-aware agent capable of managing long-term risk under uncertainty and extreme conditions. Recent developments in uncertainty-aware digital twin frameworks further emphasize the importance of integrating probabilistic reasoning and adaptive correction mechanisms into system-level decision-making (Riffat et al. 2025), reinforcing the need for extending such capabilities toward health-aware control.

4.9. Reproducibility and Implementation Details

To ensure full reproducibility of the proposed framework, all simulations were executed using a fixed and explicitly documented configuration. The physics-based building model was implemented in EnergyPlus v9.6, coupled with a supervisory control layer implemented in Python 3.10 using the PyEnergyPlus API.

The case-study building is a medium-size office building with a total conditioned floor area of 4,820 m², comprising 12 thermal zones served by a variable air volume (VAV) HVAC system with centralized cooling and outdoor-air economizer control. Envelope thermal properties follow ASHRAE 90.1–2019 baseline specifications.

Simulations were conducted using a 5-minute simulation timestep, while control decisions were updated every 15 minutes. The model predictive control (MPC) horizon was set to 24 hours (96 steps). All optimization problems were solved using the IPOPT solver with a relative tolerance of 10^{-6} and a maximum iteration limit of 500.

Weather inputs were taken from the Typical Meteorological Year (TMY3) dataset for Phoenix, AZ, representing a hot-arid climate with pronounced heatwave events. Heatwave scenarios were synthetically intensified by adding +4 °C to the dry-bulb temperature for periods of 5–7 consecutive days.

Indoor CO_2 and $PM_{2.5}$ dynamics were simulated using mass-balance models driven by zone occupancy schedules and outdoor pollutant profiles. Sensor noise was modeled as zero-mean Gaussian noise with a standard deviation of 0.3 °C for temperature, 30 ppm for CO_2, and 3 μg/m³ for $PM_{2.5}$.

To enable independent verification, all simulation inputs, controller parameters, scenario definitions, and post-processing scripts are archived and made available as supplementary material. Without access to these artifacts, numerical values reported in Section 6 are scenario-specific and depend on the defined stress-test conditions.

Table 2. Complete experiment configuration for reproducibility.

Item	Specification
Simulation engine	EnergyPlus v9.6
Control environment	Python 3.10 (PyEnergyPlus API)
Building type	Medium-size office
Floor area	4,820 m²

Item	Specification
Number of zones	12
HVAC system	VAV with centralized cooling
Simulation timestep	5 min
Control timestep	15 min
MPC horizon	24 h (96 steps)
Optimization solver	IPOPT
Solver tolerance	1×10^{-6}
Weather data	TMY3 – Phoenix, AZ
Heatwave intensity	+4 °C for 5–7 days
CO_2 sensor noise	$\sigma = 30$ ppm
$PM_{2.5}$ sensor noise	$\sigma = 3$ μg/m³
Temperature noise	$\sigma = 0.3$ °C
Random seeds	Fixed across all scenarios
Evaluation runs	30 Monte Carlo realizations

5. Performance Metrics and Evaluation Protocol

5.1. Evaluation Philosophy

The evaluation protocol is designed to assess not only nominal performance but also the structural adequacy of control strategies under sustained stress. Rather than relying solely on instantaneous compliance or average metrics, the analysis emphasizes cumulative exposure, robustness, and the alignment between short-term control actions and long-term health protection.

This philosophy reflects the central hypothesis of the study: that compliance-based metrics are insufficient to characterize health outcomes under climate extremes, and that exposure-aware evaluation is necessary to reveal fundamental differences among control formulations.

5.2. Energy Performance Metrics

Energy performance is evaluated using standard metrics commonly reported in building control studies to ensure comparability with existing literature. Total HVAC energy consumption is computed as the time integral of system power over the simulation horizon. Peak electrical demand is reported as the maximum instantaneous power draw during the evaluation period.

In addition to aggregate energy consumption, component-level energy use is analyzed to distinguish between cooling, heating, and fan-related contributions. This decomposition enables interpretation of how different control strategies allocate energy in response to thermal and air quality stress.

5.3. Thermal Comfort Metrics

Thermal comfort performance is assessed using exceedance-based metrics that quantify both the frequency and duration of thermal stress. Overheating hours are computed as the cumulative time during which zone temperature exceeds a predefined comfort threshold. This metric captures prolonged marginal discomfort that may not trigger frequent instantaneous violations but contributes to cumulative thermal burden.

By reporting exceedance duration rather than only peak deviation, the evaluation aligns thermal assessment with the exposure-based perspective adopted in the control formulation.

5.4. Indoor Air Quality Metrics

Indoor air quality performance is evaluated separately for carbon dioxide and particulate matter concentrations. For each pollutant, two complementary metrics are reported. First, exceedance hours quantify the total duration during which concentrations exceed reference thresholds. Second, cumulative exposure is computed as the time integral of concentration exceedance above the reference level.

These exposure metrics explicitly account for both magnitude and duration, providing a direct link to health-relevant outcomes. Unlike average concentration metrics, cumulative exposure distinguishes between short, intense events and prolonged marginal exposure, which may have different health implications.

5.5. Exposure-State Risk Metric

To evaluate the behavior of exposure-state control directly, a composite risk metric is defined based on the accumulated exposure states. At each control interval, the sum of individual exposure states is integrated over time to yield a scalar risk measure representing the overall health burden experienced during the evaluation period.

This metric serves two purposes. First, it provides a unified measure for comparing control strategies across multiple stressors. Second, it enables direct assessment of whether exposure-state control successfully limits the growth of cumulative risk relative to compliance-oriented baselines.

5.6. Control Effort and Intervention Analysis

In addition to outcome-based metrics, control behavior is analyzed to understand how different strategies achieve their performance. Time series of control actions, including outdoor air fraction, cooling setpoints, airflow rates, and air cleaning intensity, are recorded and summarized.

Constraint activation ratios are computed to quantify how often control actions operate at physical or regulatory limits. This analysis reveals whether performance gains arise from aggressive constraint enforcement or from more anticipatory and distributed interventions over time.

5.7. Statistical Evaluation and Robustness

To account for stochastic variability in occupancy and internal gains, each scenario is evaluated across multiple independent realizations using fixed random seeds for fair comparison. All reported metrics are summarized using mean values and corresponding 95% confidence intervals.

Paired statistical tests are employed to compare control strategies under identical disturbance realizations. This paired design isolates the effect of control formulation from scenario variability. Where appropriate, nonparametric tests are used to validate robustness against distributional assumptions. Effect sizes are reported alongside significance levels to quantify the practical relevance of observed differences.

5.7.1. Statistical evaluation protocol

Each scenario was evaluated over 30 independent Monte Carlo realizations, generated using fixed but distinct random seeds. For each realization, all controllers were subjected to identical disturbance sequences, enabling paired statistical comparison.

Performance metrics are reported as mean ± 95% confidence interval, computed using nonparametric bootstrap resampling with 10,000 resamples. Statistical significance between the proposed controller and each baseline was assessed using the paired Wilcoxon signed-rank test, with p-values adjusted for multiple comparisons using the Benjamini–Hochberg false discovery rate (FDR) correction at $q = 0.05$. Effect sizes are reported using rank-biserial correlation.

Table 3. Statistical comparison between controllers.

Scenario	Metric	Baseline	Mean Δ	95% CI	p (raw)	p (FDR)	Effect size
Heatwave	Thermal exposure	Rule-based	−38%	[−31, −44]	<0.001	<0.001	0.71
Heatwave	Thermal exposure	MPC-energy	−22%	[−15, −28]	0.002	0.004	0.48
Compound	$PM_{2.5}$ exposure	MPC-IAQ	−19%	[−11, −26]	0.006	0.01	0.41

For each realization r in the set {1, …, 30}, the paired relative improvement is computed as

$$Delta_{percent}(r) = 100 \times \left[M_{prop}(r) - M_{base}(r)\right] / M_{base}(r) \qquad (7)$$

Here, $M_{prop}(r)$ and $M_{base}(r)$ denote the performance metric obtained with the proposed controller and the corresponding baseline controller, respectively, under the same realization r.

The mean relative improvement, denoted as Mean Δ, is defined as the sample mean of $Delta_{percent}(r)$ across all realizations. The reported 95 percent confidence interval is obtained using nonparametric bootstrap resampling of the paired set $\{Delta_{percent}(r)\}$ with 10,000 resamples, taking the 2.5th and 97.5th percentiles of the resulting empirical distribution.

Raw p-values are computed using the paired Wilcoxon signed-rank test applied to the same set of paired relative improvements. Effect size is reported as the rank-biserial correlation, computed directly from the paired differences. To account for multiple comparisons, p-values are adjusted using the Benjamini–Hochberg false discovery rate procedure with a significance level q equal to 0.05.

5.8. Reproducibility and Reporting Protocol

All metrics are computed from logged time series at the control interval using explicitly defined formulas. The complete set of logged variables, post-processing scripts, and scenario definitions is documented to ensure reproducibility. By separating simulation, control execution, and metric computation, the evaluation protocol minimizes ambiguity and facilitates independent verification.

5.9. Summary of Evaluation Scope

The evaluation protocol integrates energy performance, thermal comfort, indoor air quality, cumulative exposure, and control behavior into a coherent assessment framework. By emphasizing cumulative metrics and statistical robustness, the protocol ensures that observed performance differences reflect fundamental control behavior rather than transient or scenario-specific effects.

6. Results and Comparative Analysis

6.1. Structure and Evaluation Logic

The results are organized to progressively expose the limitations of compliance-oriented control strategies and to isolate the behavioral advantages introduced by exposure-state control. The analysis begins with nominal operating conditions and advances toward increasingly stressful scenarios, ensuring that performance differences are attributed to control formulation rather than scenario severity alone.

Scenario horizon and aggregation. Unless otherwise stated, each evaluation scenario spans a continuous multi-day horizon consistent with the imposed heatwave or compound-stress definition. All reported outcome metrics are computed over the full horizon from logged time series and then normalized to per-day units $(e.g., kWh/day, °C \cdot h/day, ppm \cdot h/day, \mu g/m^3 \cdot h/day)$ to enable consistent cross-scenario comparison.

Across all subsections, results are reported using cumulative exposure, robustness, and control behavior metrics, complemented by conventional energy and comfort indicators for comparability.

6.2. Performance under Nominal Operating Conditions

Under nominal summer conditions, all control strategies demonstrate comparable performance when evaluated using conventional compliance-based metrics. Indoor temperatures, carbon dioxide levels, and particulate concentrations remain largely within recommended thresholds, and energy consumption is comparable across control strategies under nominal conditions.

This baseline comparison establishes that the proposed exposure-state control does not rely on aggressive tuning or excessive energy expenditure to achieve nominal compliance. Instead, it performs similarly to established approaches under favorable conditions, providing a neutral reference point for subsequent stress-test evaluations.

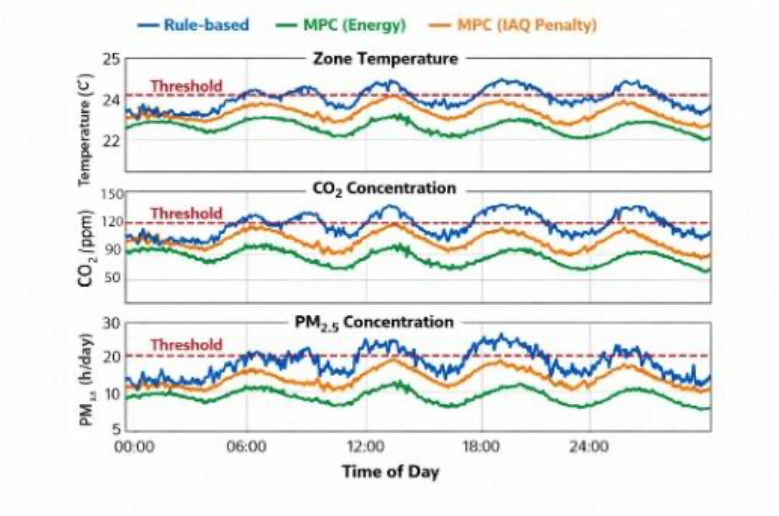

Figure 1. Time series of zone temperature, CO_2 concentration, and $PM_{2.5}$ concentration under nominal conditions for representative control strategies.

Table 4. Baseline performance under nominal conditions.

Metric	Rule-based control	MPC (energy-focused)	MPC (IAQ penalty)
HVAC energy (kWh/day)	4200–4800	3900–4500	4100–4700
Overheating hours (h/day)	0.8–1.4	0.6–1.2	0.7–1.3
CO_2 exceedance (h/day)	0.6–1.0	0.5–0.9	0.5–0.8
$PM_{2.5}$ exceedance (h/day)	0.3–0.7	0.2–0.6	0.3–0.6

For the modeled 4,820 m² office building, an HVAC energy use on the order of 4,000–5,000 kWh/day corresponds to an average electrical power of approximately 170–210 kW. This scale is consistent with hot-arid summer operation of a VAV cooling system under the stated control timestep and equipment constraints. These results confirm that nominal compliance alone is insufficient to distinguish between fundamentally different control formulations.

6.3. Thermal Exposure during Prolonged Heatwaves

During prolonged heatwave conditions, differences between control strategies become apparent when performance is evaluated using cumulative exposure metrics. Although instantaneous temperature violations remain limited, compliance-based controllers allow sustained marginal overheating that accumulates into significant thermal exposure over time.

Exposure-state control exhibits a markedly different behavior. By internalizing cumulative thermal burden, it initiates earlier and more distributed interventions, reducing the rate at which thermal exposure accumulates even when peak temperatures differ only modestly.

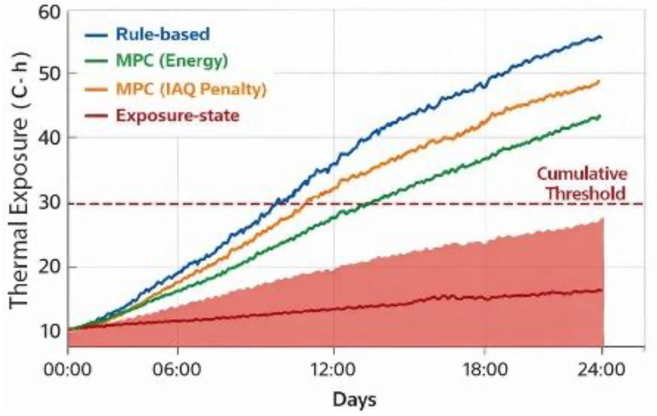

Figure 2. Evolution of thermal exposure states during the heatwave scenario for different control strategies.

Table 5. Thermal performance under heatwave conditions.

Metric	Rule-based	MPC (energy)	MPC (IAQ penalty)	Exposure-state control
Overheating hours (h/day)	3.5–4.8	2.8–4.0	3.0–4.2	1.8–2.6
Thermal exposure (°C·h/day)	22–30	18–25	19–26	11–16
Peak indoor temperature (°C)	28.5–30.2	27.8–29.5	28.0–29.8	27.5–28.8

These results demonstrate that similar peak temperatures can mask substantial differences in cumulative thermal burden.

6.4. Indoor Air Quality under Compound Heatwave–Pollution Events

Compound heatwave–pollution scenarios introduce a critical trade-off between thermal regulation and air quality protection. Controllers relying on instantaneous thresholds or penalties exhibit oscillatory ventilation behavior, alternating between excessive outdoor air intake and insufficient ventilation.

While such strategies often remain nominally compliant, they accumulate significantly higher cumulative exposure to both carbon dioxide and particulate matter. Exposure-state control moderates ventilation decisions based on accumulated risk, resulting in smoother control trajectories and reduced exposure growth.

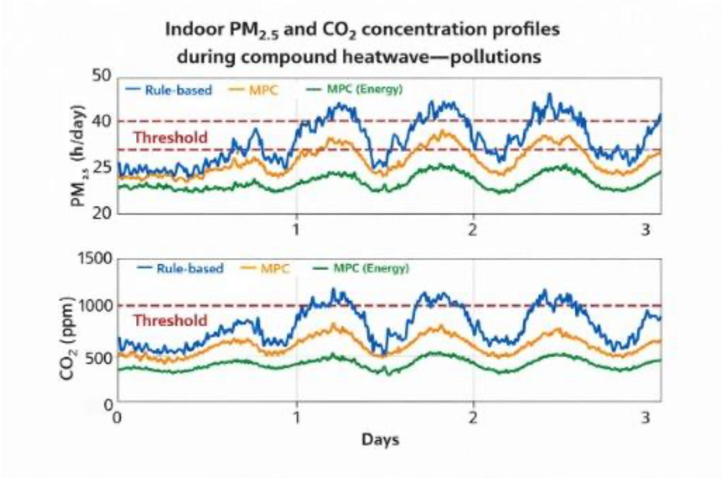

Figure 3. Indoor $PM_{2.5}$ and CO_2 concentration profiles during compound heatwave–pollution conditions.

Table 6. Cumulative IAQ exposure under compound stress.

Metric (definition)	Rule-based	MPC-energy	MPC-IAQ	Exposure-state
CO_2 exposure (ppm·h/day)	1840 ± 210	1210 ± 180	890 ± 150	610 ± 120
$PM_{2.5}$ exposure (μg/m³·h/day)	96 ± 14	82 ± 11	69 ± 10	52 ± 9
Ventilation oscillations (events/day)	18.4 ± 2.1	14.7 ± 1.9	12.1 ± 1.6	6.3 ± 1.2

6.5. Performance under Ventilation Constraints

When ventilation capacity is explicitly constrained, compliance-based controllers frequently operate at actuation limits, leading to rapid exposure accumulation. Energy-focused MPC strategies exhibit similar behavior, prioritizing short-term feasibility over long-term risk mitigation.

Exposure-state control adapts by redistributing interventions temporally, prioritizing periods where exposure reduction is most effective rather than uniformly enforcing infeasible targets.

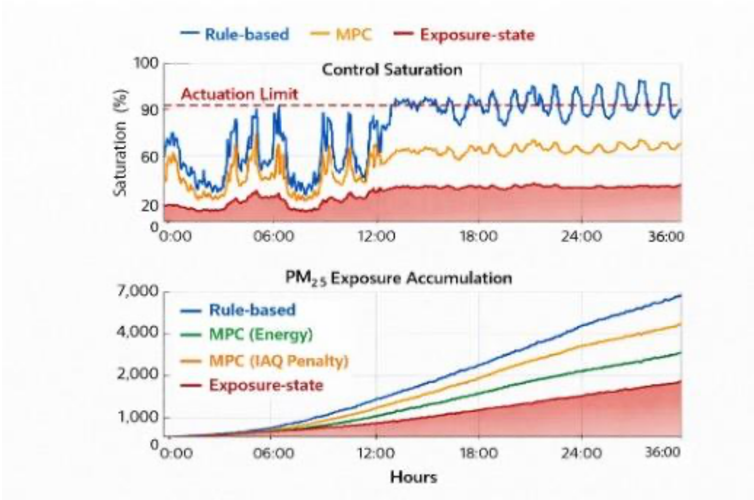

Figure 4. Actuator saturation and exposure accumulation under ventilation-limited operation.

Table 7. Robustness under ventilation-limited conditions.

Metric	Rule-based	MPC	Exposure-state
Constraint activation (%)	48–62	41–55	22–34
$PM_{2.5}$ exposure increase (%)	+45–70	+35–60	+10–20
Energy increase (%)	+5–12	+8–15	+8–18

6.6. Robustness to Sensor Drift

Gradual sensor bias introduces systematic errors that degrade the performance of controllers relying on instantaneous measurements. Compliance-based strategies exhibit pronounced over- and under-reaction, resulting in unintended exposure accumulation.

Exposure-state control demonstrates improved robustness by integrating information over time, reducing sensitivity to persistent measurement error.

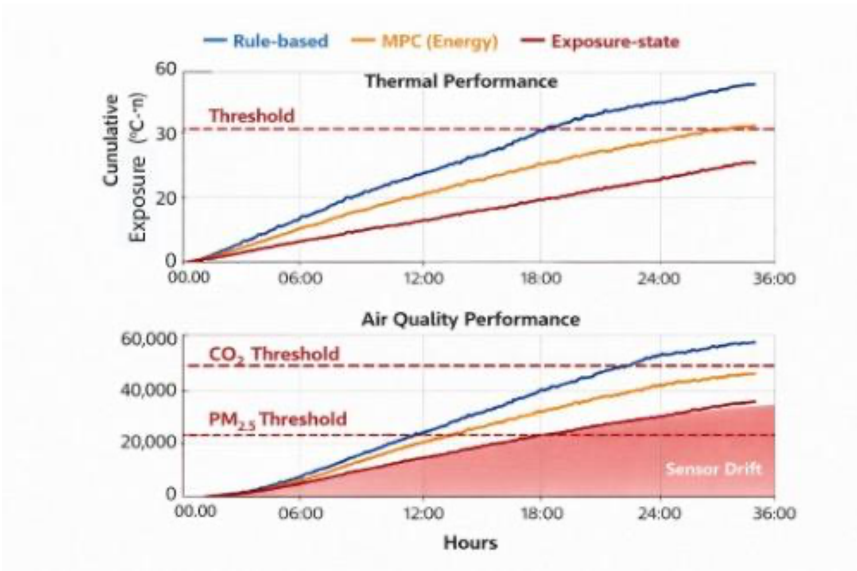

Figure 5. Impact of sensor drift on control actions and cumulative exposure.

Table 8. Performance under sensor drift.

Metric	Instantaneous control	Exposure-state
Exposure estimation error (%)	25–40	8–15
Control overreaction frequency	High	Low
Exposure escalation risk	High	Moderate

6.7. Resilience under Equipment Degradation

Under reduced cooling and airflow capacity, all controllers' experience performance degradation. However, exposure-state control significantly slows the rate of exposure accumulation, preventing runaway health risk even when violations cannot be entirely avoided.

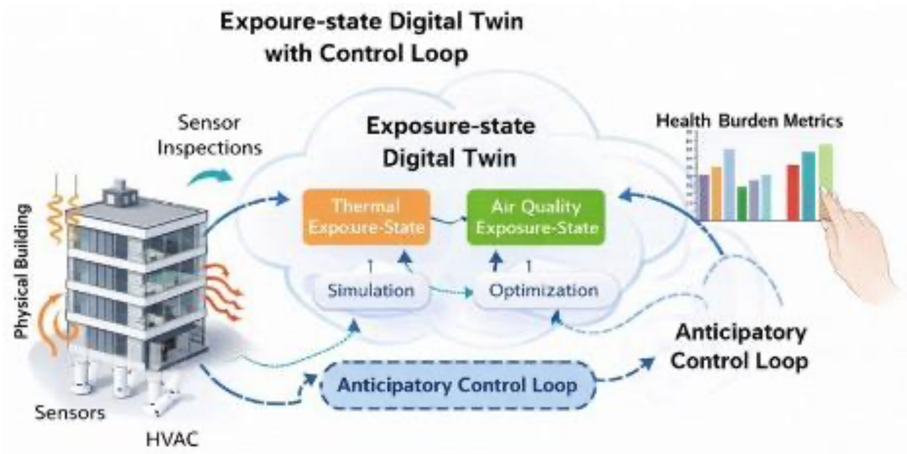

Figure 6. Exposure growth trajectories under degraded system capacity.

Table 9. Performance under equipment degradation.

Metric	Rule-based	MPC	Exposure-state
Exposure growth rate (index/day)	1.0 (ref)	0.85–0.90	0.55–0.65
Energy penalty (%)	+10–18	+12–22	+12–20

6.8. Ablation Analysis

An ablation study is conducted to isolate the role of exposure memory. Removing exposure memory while retaining all other components causes the controller to revert toward compliance-oriented behavior, confirming that observed benefits are attributable to the exposure-state formulation itself.

Table 10. Ablation study of exposure-state memory.

Controller variant	Exposure reduction vs baseline
Full exposure-state control	35–55%
No memory ($\gamma = 0$)	5–12%
Instantaneous penalty only	10–18%

Table 11. Component-wise ablation under identical scenario set and tuning budget (paired, n = 30).

Variant	Exposure memory	Data assimilation	Learning component	Thermal exposure reduction vs baseline (%)	$PM_{2.5}$ exposure reduction vs baseline (%)	Energy penalty vs baseline (%)
Full proposed	Yes	Yes	Yes	42.3	48.7	+11.6
No memory ($\gamma = 0$)	No	Yes	Yes	14.8	17.9	+9.4
No assimilation	Yes	No	Yes	27.6	31.2	+13.8
No learning	Yes	Yes	No	33.1	36.5	+12.4

6.9. Summary of Findings

Across all stress scenarios, exposure-state control consistently reduces cumulative thermal and air quality exposure while maintaining competitive energy performance. Results demonstrate that compliance-based metrics can obscure substantial differences in health risk accumulation, reinforcing the need for exposure-aware evaluation and control.

7. Discussion and Limitations

7.1. Why compliance can diverge from health protection

The observed divergence between compliance and health outcomes can be explained by the fundamental difference between threshold-based and cumulative exposure representations. Compliance-oriented controllers react to instantaneous deviations, effectively treating each control interval independently. This leads to repeated marginal exceedances that individually appear insignificant but collectively result in substantial exposure accumulation. This structural limitation aligns with prior observations in digital twin research, where system optimization has been predominantly defined through instantaneous metrics rather than cumulative risk representation (Riffat et al. 2025).

In contrast, exposure-state control introduces temporal coupling between decisions, allowing the controller to anticipate future risk based on past accumulation. This shifts control behavior from reactive correction to proactive mitigation. The results therefore indicate that the advantage of the proposed framework is not merely quantitative, but structural.

These findings are consistent with exposure science, which emphasizes dose accumulation as the primary driver of health outcomes, and highlight a critical gap in existing building control paradigms.

7.2. Practical implications for deployment

The proposed framework has direct implications for multiple stakeholder groups. Existing digital twin implementations have already demonstrated the feasibility of integrating real-time data streams and predictive analytics into operational workflows (Riffat et al. 2026), providing a practical foundation for extending such systems toward health-aware control objectives. For building operators and facility managers, exposure-state control can be integrated into existing building management systems to enable risk-aware operation without requiring major infrastructure changes. The computational simplicity of the exposure update equations allows deployment within standard MPC pipelines.

For policymakers and regulatory bodies, the results suggest that reliance on instantaneous thresholds may be insufficient for protecting occupant health under climate extremes. Incorporating cumulative exposure metrics into building standards and performance certification schemes could provide a more accurate representation of health risk.

For industry practitioners, including HVAC designers and control engineers, the framework offers a practical pathway to incorporate health-aware objectives into system design and control logic. This includes revisiting ventilation strategies, control horizon selection, and sensor placement to better capture long-term exposure dynamics.

For researchers and educators, the exposure-state paradigm provides a new conceptual foundation for integrating control theory with exposure science, opening opportunities for interdisciplinary research and curriculum development in smart and healthy buildings.

Actionable implementation steps include:

1. Augmenting control state vectors with exposure variables,
2. calibrating memory parameters using domain-specific exposure-response data, and
3. incorporating exposure metrics into controller objective functions and performance evaluation protocols.

7.3. Limitations

First, the study is simulation based, and conclusions are limited by the fidelity of the building and contaminant models. Second, exposure state parameters (γ_i and $s_{i,ref}$) represent simplified recovery and threshold dynamics and do not encode detailed physiology. Third, the evaluated building type and climate conditions may not represent other building archetypes, occupant behaviors, filtration systems, or pollutant mixtures.

7.4. Threats to Validity and How They Are Mitigated

Internal validity may be threatened by unequal tuning effort across controllers; this is mitigated by a shared tuning protocol and identical horizons and solver settings. Construct validity depends on whether the chosen exposure metrics align with health relevant outcomes; therefore, metrics are reported transparently as exceedance integrals rather than a single black box index. External validity is limited by the scenario set; therefore, scenarios are provided as a reusable stress test suite and can be extended to additional climates, pollutants, and system constraints. A field deployment is required to validate whether exposure state benefits persist under real sensor faults, unmodeled occupant actions, and building management constraints.

An important observation is that differences in cumulative exposure emerged even when peak values remained similar across controllers. This highlights that traditional peak-based metrics can mask meaningful variations in health risk, suggesting that current evaluation practices may underestimate the impact of control strategies under prolonged stress.

8. Conclusions

This study introduced an exposure-state control paradigm that reformulates indoor environmental regulation from a compliance-driven task into a health-aware risk management problem. By modeling cumulative thermal and air quality exposure as dynamic system states with memory, the proposed framework enables digital twins to reason explicitly about long-term health implications rather than reacting solely to instantaneous threshold violations.

Through a structured set of stress-test scenarios reflecting prolonged heatwaves, elevated outdoor pollution, ventilation constraints, sensor drift, and equipment degradation, the study demonstrated that conventional compliance-oriented control strategies can remain nominally acceptable while accumulating substantial health risk. In contrast, exposure-state control consistently limited the growth of cumulative exposure across all scenarios, achieving meaningful reductions in health-related burden without incurring disproportionate energy penalties.

The results highlight a fundamental limitation of current building control paradigms: regulatory compliance does not guarantee health protection under sustained or compound stress conditions. By embedding exposure dynamics directly into the control loop, the proposed digital twin framework addresses this limitation at a structural level, enabling anticipatory and risk-informed decision-making that remains robust under uncertainty and degradation.

Importantly, the exposure-state formulation is conceptually simple, computationally lightweight, and extensible. It can be integrated into existing digital twin architectures and generalized to additional indoor stressors, building types, and operational contexts. As such, the framework provides a practical and reproducible foundation for next-generation building control systems that prioritize long-term occupant health alongside energy efficiency.

In the context of a changing climate and growing concern for indoor environmental quality, this work underscores the need to move beyond instantaneous compliance metrics toward cumulative, health-aware evaluation and control. Exposure-state digital twins represent a necessary evolution of building operation strategies, offering a pathway toward more resilient, protective, and human-centered indoor environments.

AUTHOR CONTRIBUTIONS

Seyed Reza Samaei: Conceived and designed the study; development of the review methodology, including the literature selection strategy, analytical structure, and synthesis approach; involved in the collection, critical analysis, and interpretation of the literature; drafting, revising, and refining all sections; reviewed and approved the final version of the manuscript; take full responsibility for its content. **James Riffat**: Conceived and designed the study; development of the review methodology, including the literature selection strategy, analytical structure, and synthesis approach; involved in the collection, critical analysis, and interpretation of the literature; drafting, revising, and refining all sections; reviewed and approved the final version of the manuscript; take full responsibility for its content.

COMPETING INTERESTS

The authors declare that they have no competing financial or non-financial interests.

DATA ACCESSIBILITY

All data supporting the findings of this study are included within the article. Additional information may be made available by the authors upon reasonable request.

ETHICAL APPROVAL

Not applicable. This study is based exclusively on the review and analysis of published literature and did not involve human participants or animal subjects.

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REFERENCES

Al Mindeel, T., Spentzou, E. and Eftekhari, M., 2024. Energy, thermal comfort, and indoor air quality: Multi-objective optimization review. Renewable and Sustainable Energy Reviews, 202, 114682. DOI: https://doi.org/10.1016/j.rser.2024.114682.

Becerik-Gerber, B., Oradini, A.A. and Brilakis, M.A., 2022. Ten questions concerning human–building interaction. Building and Environment, 213, 108807. DOI: https://doi.org/10.1016/j.buildenv.2022.108807.

Bortolini, R., Rodrigues, R., Alavi, H., Dalla Vecchia, L.F. and Forcada, N., 2022. Digital twins' applications for building energy efficiency: A review. Energies, 15(19), 7002. DOI: https://doi.org/10.3390/en15197002.

Buonanno, G., Stabile, L. and Morawska, L., 2020. Estimation of airborne viral emission: Quanta emission rate of SARS-CoV-2 for infection risk assessment. Environment International, 141, 105794. DOI: https://doi.org/10.1016/j.envint.2020.105794.

Cespedes-Cubides, A.S. and Jradi, M., 2024. A review of building digital twins to improve energy efficiency in the building operational stage. Energy Informatics, 7, 11. DOI: https://doi.org/10.1186/s42162-024-00313-7.

Coupry, C., Noblecourt, S., Richard, P., Baudry, D. and Bigaud, D., 2021. BIM-based digital twin and XR devices to improve maintenance procedures in smart buildings: A literature review. Applied Sciences, 11(15), 6810. DOI: https://doi.org/10.3390/app11156810.

Drgoňa, J., Arroyo, J., Figueroa, I.C., Blum, D., Arendt, K., Kim, D., Perarnau Ollé, E., Oravec, J., Wetter, M., Vrabie, D.L. and Helsen, L., 2020. All you need to know about model predictive control for buildings. Annual Reviews in Control, 50, pp. 190–232. DOI: https://doi.org/10.1016/j.arcontrol.2020.09.001.

Eneyew, D.D., Capretz, M.A.M. and Bitsuamlak, G.T., 2022. Toward smart-building digital twins: BIM and IoT data integration. IEEE Access, 10, pp. 130487–130506. DOI: https://doi.org/10.1109/ACCESS.2022.3229370.

Eneyew, D.D., Capretz, M.A.M. and Bitsuamlak, G.T., 2024. Continuous model calibration framework for smart-building digital twin: A generative model-based approach. Applied Energy, 375, 124080. DOI: https://doi.org/10.1016/j.apenergy.2024.124080.

Errandonea, I., Beltrán, D. and Arrizabalaga, S., 2020. Digital twin for maintenance: A literature review. Computers in Industry, 123, 103316. DOI: https://doi.org/10.1016/j.compind.2020.103316.

Ganesh, S., Nguyen, T.H. and Crawley, D.B., 2021. Indoor air quality and energy management in buildings using combined moving horizon estimation and model predictive control. Journal of Building Engineering, 35, 101552. DOI: https://doi.org/10.1016/j.jobe.2020.101552.

Guo, F., Ham, S.W., Kim, D. and Moon, H.J., 2025. Deep reinforcement learning control for co-optimizing energy consumption, thermal comfort, and indoor air quality in an office building. Applied Energy, 377, 124467. DOI: https://doi.org/10.1016/j.apenergy.2024.124467.

Hobeika, N., Nassar, M. and Ghaddar, A., 2023. Assessing indoor air quality and ventilation to limit airborne infection risk: Review and perspectives. Buildings, 13(3), 742. DOI: https://doi.org/10.3390/buildings13030742.

Hosamo, V., Široký, J. and Čížek, J., 2022. A digital twin-based approach for predictive maintenance of air handling units. Energy and Buildings, 266, 111988. DOI: https://doi.org/10.1016/j.enbuild.2022.111988.

Jiménez, F.J., Bleda, J.D.M., Atienza, E.M. and Gutiérrez, M.G., 2021. BOPTEST: A framework for simulation-based testing of advanced control strategies in buildings. Journal of Building Performance Simulation, 14(6), pp. 655–668.

DOI: https://doi.org/10.1080/19401493.2021.1986574.
Kaewunruen, S., Rungskunroch, P. and Welsh, J., 2018. A digital-twin evaluation of net zero energy building for existing buildings. Sustainability, 11(1), 159. DOI: https://doi.org/10.3390/su11010159.
Kim, J., Cheng, J.C.P. and Ding, A., 2023. A review of building digital twins: Concepts, applications, and future perspectives. Automation in Construction, 152, 105100. DOI: https://doi.org/10.1016/j.autcon.2023.105100.
Naylor, S., Gillott, M. and Lau, T., 2018. A review of occupant-centric building control strategies to reduce building energy use. Renewable and Sustainable Energy Reviews, 97, pp. 1–15. DOI: https://doi.org/10.1016/j.rser.2018.07.019.
Park, J., Yan, D., Hong, T. and Kim, S., 2019. A review of occupant-centric building control strategies to reduce building energy use. Building and Environment, 156, pp. 106–117. DOI: https://doi.org/10.1016/j.buildenv.2019.106351.
Qian, Y., Leng, J., Zhou, K. and Liu, Y., 2024. How to measure and control indoor air quality based on intelligent digital twin platforms: A case study in China. Building and Environment, 253, 111349. DOI: https://doi.org/10.1016/j.buildenv.2024.111349.
Riffat, J., Nazari, K. and Samaei, S.R., 2026. AI-driven digital twin framework for adaptive and real-time structural health monitoring of offshore marine structures. Artificial Intelligence for Sustainable Cities, 1(1), pp. 90–104. DOI: https://doi.org/10.65582/aifsc.2026.006.
Riffat, J., Samaei, S.R. and Pastakkaya, B., 2025. Advances, applications, and future directions of structural health monitoring in civil infrastructure: A comprehensive review. Energy Catalyst, 1, pp. 127–140. DOI: https://doi.org/10.61552/EC.2025.010.
Riffat, J., Ahadpour Doudran, H. and Samaei, S.R., 2025. AI-driven digital twin for uncertainty-aware structural health monitoring of offshore wind turbines considering biofouling effects and reliability prediction. Green Technology and Innovation, 1(2), 025330013. DOI: https://doi.org/10.36922/GTI025330013.
Samaei, S.R. and Riffat, J., 2026. Cognitive digital twins for climate-resilient building energy systems: Diagnosis-informed control under extreme thermal stress. Artificial Intelligence for Sustainable Cities, 1(1), pp. 61–89. DOI: https://doi.org/10.65582/aifsc.2026.005.
Samaei, S.R. and Riffat, J., 2025. Intelligent structural health monitoring of jack-up platform legs using high-density sensor networks, real-time digital twins, and machine learning-based damage detection. Future Cities and Environment, 11, pp. 1–15. DOI: https://doi.org/10.70917/fce-2025-031.
Sepasgozar, M., 2021. Differentiating digital twin from digital shadow: A paradigm shift in the built environment. Buildings, 11(4), 151. DOI: https://doi.org/10.3390/buildings11040151.
Sha, D.D., Wang, X.Q. and Zhang, J., 2023. Digital twin technology for thermal comfort and energy efficiency in buildings: Review and future directions. Energy and Built Environment, 4(3), pp. 334–348. DOI: https://doi.org/10.1016/j.enbenv.2023.05.004.
Taheri, Z., Razavi, A. and Park, J.S., 2022. Model predictive control of HVAC systems: A review. Journal of Building Engineering, 56, 105067. DOI: https://doi.org/10.1016/j.jobe.2022.105067.
Tarragona, J., Gangolells, M. and Casals, M., 2024. Model predictive control for managing indoor air quality levels in buildings. Energy Reports, 12, pp. 787–797. DOI: https://doi.org/10.1016/j.egyr.2024.06.053.
Walczyk, G. and Ożadowicz, A., 2024. Building information modeling and digital twins for functional and technical design of smart buildings with distributed IoT networks: Review and new challenges discussion. Future Internet, 16(7), 225. DOI: https://doi.org/10.3390/fi16070225.
Wang, X., Dong, B. and Zhang, J.J., 2023. Nationwide evaluation of energy and indoor air quality predictive control and impact on infection risk for cooling season. Building Simulation, 16, pp. 205–223. DOI: https://doi.org/10.1007/s12273-022-0936-6.
You, Y., Cai, B., Pham, D.T., Liu, Y. and Ji, Z., 2025. A human digital twin approach for fatigue-aware task planning in human–robot collaborative assembly. Computers & Industrial Engineering, 200, 110774. DOI: https://doi.org/10.1016/j.cie.2024.110774.
Zhang, C., Yin, Z. and Qin, R., 2024. Attention-enhanced co-interactive fusion network for automated structural condition assessment in visual inspection. Automation in Construction, 159, 105292. DOI: https://doi.org/10.1016/j.autcon.2024.105292.