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From Optimization to Stability Preservation: A Self-Healing, Action-Bearing Digital Twin for Climate-Stressed Building Energy Systems

Seyed Reza Samaei [1]* and James Riffat [1]

[1] *World Society of Sustainable Energy Technologies, Nottingham, United Kingdom*

ABSTRACT

Climate change exposes building energy systems to conditions beyond conventional control assumptions, where heatwaves, occupancy shifts, sensor drift, and degradation erode stability over time. This study proposes a self-healing digital twin that preserves system behavior within a defined stability envelope by integrating physics-based modeling, data assimilation, and adaptive response mechanisms. Self-healing is defined as preventing instability under non-stationary uncertainty. The framework is validated in closed-loop simulations across multiple stress scenarios, demonstrating robust stability under compound disturbances. Performance is benchmarked against rule-based control, classical model predictive control (MPC), and conventional digital twin supervision using a locked paired evaluation protocol with 30 matched realizations per scenario. Under compound uncertainty, the proposed framework reduces cumulative thermal comfort violation from 27.8 ± 3.6 $h.C^\circ$ (MPC) to 13.9 ± 1.9 $h.C^\circ$, corresponding to a 50.0% reduction. The time outside the comfort band decreases from 11.2% to 4.6%. Drift accumulation, measured through residual energy, is reduced by 56.2%, while control smoothness improves by 39.5%. Total energy consumption is reduced by 3.38%, and mean recovery time following major disturbances decreases from 11.8 ± 1.8 h to 4.5 ± 0.9 h. Ablation and failure analyses show that stability preservation arises from the coordinated interaction of data assimilation, envelope-based stabilization, and structural adaptation. The results indicate that resilience-oriented stability management provides a more reliable operational paradigm than optimization-centric control for building energy systems under climate-driven uncertainty.

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1. INTRODUCTION

Building energy systems are increasingly required to operate under conditions that diverge sharply from the assumptions under which conventional control strategies were originally developed (Qian et al. 2024). Prolonged heatwaves, intensified thermal variability, elevated outdoor pollution levels, behavioral changes in building use, sensor degradation, and equipment aging have become persistent operational characteristics rather than exceptional disturbances (Drgoňa et al. 2020). Under such conditions, performance degradation

* Corresponding author. Email address: seyedreza.samaei1984@gmail.com (*Seyed Reza Samaei*)

rarely stems from isolated failures. Instead, it emerges through the gradual accumulation of mismatch between modeled behavior and real system dynamics (Tarragona et al. 2024). As a result, building energy systems may remain operational while progressively losing stability margins, eventually leading to comfort collapse, excessive actuation, or irreversible performance drift (Eneyew et al. 2024).

The dominant body of literature in building energy management continues to frame this challenge primarily as an optimization problem. Model predictive control (MPC) has emerged as a prevailing paradigm because it explicitly addresses multivariable dynamics and operational constraints (Drgoňa et al. 2020). Comprehensive reviews show that MPC-based strategies can reduce energy consumption while maintaining thermal comfort under nominal conditions (Taheri et al. 2022). Recent extensions incorporate indoor air quality indicators, including CO_2 concentration and ventilation effectiveness, into MPC formulations (Tarragona et al. 2024). However, these approaches fundamentally rely on accurate models, reliable sensing, and uncertainty that is assumed to be bounded or slowly varying (Taheri et al. 2022).

When uncertainty becomes non-stationary and multi-source, as increasingly observed under climatic stress and long-term operation, optimization-centric controllers tend to exhibit brittle behavior. Simulation-based evaluations report oscillatory control actions, delayed adaptation, and repeated constraint violations as model mismatch accumulates over time (Bundo et al. 2025). Even advanced MPC formulations augmented with heuristic or metaheuristic optimization remain vulnerable to drift and degradation when operating conditions deviate persistently from design assumptions (Bamdad et al., 2023). Open-source benchmarking frameworks further show that controller performance may appear acceptable over short horizons while deteriorating substantially during extended operation (Huang et al. 2023).

In response to these limitations, data-driven and reinforcement learning (RL) approaches have gained increasing attention. Deep RL controllers have shown potential for co-optimizing energy consumption, thermal comfort, and indoor air quality without requiring explicit physics-based models (Guo et al. 2025). Parallel work explores intelligent multi-objective optimization methods for balancing ventilation and comfort objectives (Hammouda et al. 2026). Machine learning-based optimization has also been applied to naturally ventilated buildings, enabling simultaneous control of energy use, thermal comfort, and CO_2 concentration (Sood et al. 2025). Nevertheless, these approaches remain highly dependent on training data quality and representativeness, and their robustness under rare or extreme operating conditions is still uncertain (Xia et al. 2025).

Alongside these control developments, digital twin technologies have been widely adopted in the building domain to support monitoring, diagnostics, and performance optimization. Intelligent digital twin platforms have been proposed for real-time indoor air quality monitoring and control (Qian et al. 2024). More broadly, BIM and IoT-enabled digital twins can support continuous synchronization between physical assets and virtual models (Eneyew et al. 2022). Reviews further highlight the expanding use of digital twins for building energy efficiency, predictive maintenance, and operational optimization (Bortolini et al. 2022). BIM-based digital twins combined with extended reality technologies also enhance maintenance workflows and operational decision support (Coupry et al. 2021). Recent studies have begun to explore the transition of digital twins from passive monitoring tools toward more adaptive and decision-aware systems; however, their role remains largely diagnostic and does not explicitly address long-horizon stability under deep non-stationary uncertainty (Samaei and Riffat 2026; Riffat et al. 2026).

Recent studies emphasize the value of digital twins in supporting net-zero energy assessment and long-term energy planning for existing buildings (Kaewunruen et al. 2019). Comparative simulation studies suggest that digital twin-enabled frameworks can outperform conventional supervisory control strategies under nominal conditions (Bundo et al. 2025). However, most current building digital twins remain diagnostic or advisory in nature. They typically forecast system states or provide recommendations, while decision authority and control execution remain external to the twin (Sepasgozar 2021). Digital twins have been widely applied in structural health monitoring and infrastructure systems to enhance state awareness and predictive capabilities; however, most existing frameworks remain focused on observation and diagnosis rather than direct intervention in system dynamics (Riffat et al. 2026; Samaei and Riffat 2025).

A fundamental limitation of many current digital twin and control approaches is their reliance on conventional actuation mechanisms such as setpoints, airflow rates, and thermal power modulation. These inputs can shape system response but do not alter the effective physical or operational structure of the building energy system. In contrast, recent research highlights the growing importance of occupant-centric and human-aware control, where human behavior and interaction substantially influence system dynamics (Becerik-Gerber et al. 2022). Predictive models of occupant actions, such as window-opening behavior, reveal strong coupling between human decisions and HVAC energy consumption (Pandey and Dong 2023). Reviews of occupant-centric adaptive facade control further underscore the need for responsiveness beyond static control logic (Tabadkani et al. 2021).

Despite these advances, most occupant-centric strategies remain performance-oriented and short-horizon in nature. Foundational reviews note that long-term resilience and stability preservation are rarely treated as explicit objectives (Naylor et al. 2018). This limitation becomes particularly critical when indoor air quality and health-related risks are considered. Quantitative exposure models demonstrate that health outcomes are governed more by cumulative dose than by instantaneous concentration (Buonanno et al. 2020). Empirical assessments of classrooms further suggest that short-term compliance with air quality thresholds may coexist with elevated long-term infection risk (Rodríguez et al. 2022; Hasani and Freddi, 2026).

Recent digital twin research increasingly acknowledges the need to integrate thermal comfort, indoor air quality, and energy efficiency within unified operational frameworks (Arowoiya et al. 2024; Walczyk and Ożadowicz, 2024). Nationwide evaluations of predictive control strategies similarly indicate that controllers may remain nominally compliant while producing substantially different cumulative health and comfort outcomes over time (Wang et al. 2023). In parallel, developments in human digital twin research demonstrate how cumulative fatigue and exposure can be modeled as dynamic state variables with memory rather than as instantaneous quantities (You et al. 2025; Chand et al. 2024).

Collectively, the literature points to a persistent gap in current building energy management paradigms. Prevailing approaches largely optimize performance around nominal operating conditions and implicitly assume that deviations can be addressed through incremental control adjustments. Under climate-driven, non-stationary uncertainty, the dominant challenge shifts from marginal performance improvement to the preservation of stable operation as uncertainty accumulates over time. Addressing this challenge requires a conceptual transition from performance-centric optimization toward resilience-oriented stability preservation, supported by digital twin architectures that can interpret drift, adapt system operation in a structurally meaningful way, and act autonomously within a closed-loop operational framework.

1.1 Contributions

First, this study reframes building energy management from an optimization problem to a stability preservation problem under deep non-stationary uncertainty. Rather than evaluating control strategies solely on energy or cost minimization, the proposed perspective assesses system performance based on the ability to remain within a predefined stability envelope over time. Within this framework, self-healing is formally defined as the prevention of stability envelope violation under compounded, time-varying uncertainty. This definition provides a measurable, transferable, and conceptually distinct alternative to conventional optimization-based control formulations.

Second, the study introduces an action-bearing digital twin architecture with intrinsic structural physical adaptation. Unlike conventional digital twins that remain diagnostic or advisory, the proposed twin actively governs system behavior through a closed-loop integration of physics-based modeling, sequential data assimilation, and an adaptive physical layer. By enabling real-time adjustment of effective thermal pathways, the framework introduces a structural degree of freedom that is inaccessible to controllers relying exclusively on input-level actuation. This capability allows the digital twin to function as an autonomous stability manager rather than a passive analytical tool.

Third, the study establishes a rigorously locked evaluation protocol for stability, resilience, and failure characterization under climate-driven stress. The assessment framework combines prolonged heatwaves with incomplete recovery, behavioral and sensor drift, equipment degradation, structural model mismatch, and constraint tightening within a reproducible and fairness-controlled setup. Through systematic ablation and explicit failure scenarios, the evaluation isolates the roles of data assimilation, structural adaptation, and stabilization logic, thereby revealing both the capabilities and the operational limits of self-healing behavior under realistic non-stationary conditions.

2. Methodology

2.1. Overall Framework Architecture

The proposed framework is structured as a closed-loop, action-bearing digital twin that couples physical building dynamics, real-time sensing, and adaptive decision-making within a unified stability-oriented architecture. Unlike conventional building control schemes, where optimization and actuation are decoupled from system interpretation, the present framework embeds diagnosis, adaptation, and stabilization within a single operational loop designed explicitly to preserve stability under deep non-stationary uncertainty.

At the core of the architecture lies a physics-based digital representation of the building energy system, serving as the predictive backbone of the digital twin. This model captures the dominant thermal dynamics of the building and its HVAC system and is continuously synchronized with operational data through sequential data assimilation. Rather than aiming for perfect prediction accuracy, the digital twin prioritizes the detection and interpretation of performance drift, recognizing divergence between expected and observed behavior as an early indicator of stability erosion.

The physical system provides time-stamped measurements of thermal states, boundary conditions, and energy use, which are ingested by the digital twin at each control interval. These measurements are used to update latent system states and effective parameters, enabling the twin to track gradual changes arising from climatic stress, behavioral variation, sensor degradation, or equipment aging. Crucially, this updating process is causal and operates under the same information constraints imposed on baseline controllers, ensuring a fair and realistic comparison.

Decision-making within the framework is governed by a stability envelope that defines acceptable operational bounds across thermal comfort, control smoothness, and drift accumulation. At each control step, the digital twin evaluates the predicted system trajectory relative to this envelope. When approaching envelope boundaries, the framework prioritizes stabilization actions over performance optimization, shifting control objectives from energy minimization to margin preservation. This distinction marks a fundamental departure from optimization-centric control architectures.

A defining feature of the proposed framework is the integration of an intrinsic adaptive physical layer. In addition to conventional control inputs, the digital twin can modulate a structural degree of freedom that alters the effective thermal behavior of the system in real time. This physical adaptation mechanism provides a means of reshaping system dynamics directly, enabling stabilization actions that cannot be achieved through input-level control alone. The digital twin coordinates this structural adaptation with conventional actuation, accounting for associated costs and rate limits to ensure physically realizable operation.

The complete operational loop thus consists of six tightly coupled stages: sensing, state estimation, drift interpretation, stability assessment, coordinated control and structural adaptation, and actuation. This loop is executed at a fixed control interval throughout the evaluation horizon, allowing the framework to respond continuously to evolving uncertainty while maintaining strict causality. By embedding physical adaptation and stabilization logic directly within the digital twin, the architecture transforms the twin from a passive observer into an active agent responsible for maintaining stable system operation.

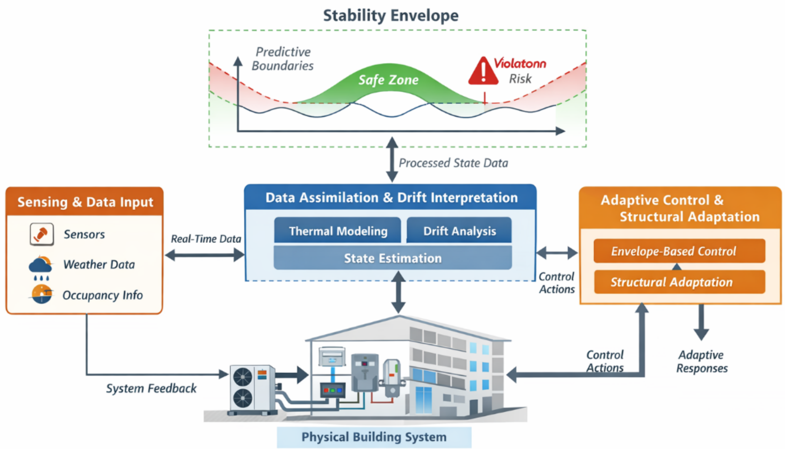

Figure 1. Conceptual architecture of the proposed self-healing, action-bearing digital twin framework.

Figure 1 presents the conceptual architecture of the proposed self-healing, action-bearing digital twin framework, illustrating the closed-loop interaction between sensing, state estimation, stability assessment, and adaptive control.

The process begins with real-time data acquisition from the physical building system, including sensor measurements, weather inputs, and occupancy information. These data streams are continuously fed into the digital twin, where sequential data assimilation and drift interpretation are performed. The thermal model and state estimation modules reconstruct the system's latent state, while the drift analysis component interprets persistent discrepancies between predicted and observed behavior as indicators of stability erosion.

The processed state information is then evaluated against a predefined stability envelope, which defines acceptable bounds for system operation. This envelope distinguishes between safe operating regions and zones of increasing violation risk, enabling the digital twin to assess stability not only instantaneously but over evolving system trajectories.

Based on this assessment, control decisions are generated through a coordinated mechanism that combines envelope-based control with structural physical adaptation. Unlike conventional control strategies that act only through input modulation, the proposed framework can also modify the system's effective thermal response, allowing for deeper stabilization under non-stationary conditions.

Finally, control and adaptation actions are applied to the physical building system, completing the feedback loop. This continuous interaction transforms the digital twin from a passive monitoring tool into an active stability manager capable of anticipating and mitigating the accumulation of instability under climate-driven uncertainty.

2.2. Physical–Virtual Coupling and Digital Twin State Definition

The physical–virtual coupling between the building energy system and its digital twin is formulated using a structured state-space representation that enables continuous synchronization under evolving operational conditions. Let x_k denote the latent system state vector at control interval k, capturing both physical states and effective parameters governing thermal behavior. In the proposed framework, this state vector includes the indoor thermal state, effective thermal properties influenced by structural adaptation, and selected performance-related parameters that may evolve gradually over time.

The physical system provides a measurement vector y_k consisting of observed indoor air temperature and associated operational variables sampled at a fixed control interval. These measurements are subject to noise, bias, and gradual degradation, consistent with realistic sensing environments. Based on the prior state estimate $x_{k|k-1}$ and the applied control actions, the digital twin generates a one-step-ahead prediction denoted as $y_{hat_{k|k-1}}$.

The predictive evolution of the digital twin is expressed in discrete-time form as follows. First, the prior state estimate is propagated according to

$$x_{k|k-1} = f(x_{k-1}, u_{k-1}, s_{k-1}, w_{k-1}) \tag{1}$$

and the corresponding predicted output is given by

$$y_{hat_{k|k-1}} = h\left(x_{k|k-1}\right) \tag{2}$$

Here, u_{k-1} denotes the conventional control input applied to the HVAC system, s_{k-1} represents the structural adaptation command governing the adaptive physical layer, and w_{k-1} captures unmodeled disturbances and parametric uncertainty. The functions $f(\cdot)$ and $h(\cdot)$ are derived from a physics-based thermal representation of the building and are fixed prior to evaluation to ensure reproducibility.

Sequential data assimilation is employed to reconcile predicted and observed behavior by updating the digital twin state estimate according to

$$x_k = x_{k|k-1} + k_k \cdot \left(y_k - y_{hat_{k|k-1}}\right) \tag{3}$$

where k_k is a gain matrix determined by the chosen assimilation scheme. This updating process enables the digital twin to track gradual performance drift arising from non-stationary boundary conditions, evolving occupancy behavior, sensor degradation, or equipment aging, without requiring explicit fault classification or repeated model re-identification.

A key distinction of the proposed coupling lies in the interpretation of residuals. Rather than treating the innovation term $y_k - y_{hat_{k|k-1}}$ solely as a correction signal, the framework interprets its temporal accumulation as an indicator of stability erosion. Persistent growth in residual energy reflects a progressive mismatch between the assumed system structure and observed behavior, prompting the digital twin to elevate stabilization objectives over nominal performance optimization.

The coupling architecture enforces strict causality. At each control interval, state estimation, drift interpretation, stability assessment, and action selection are performed using only information available up to time k. No future boundary conditions, forecasts, or oracle information are accessed by the digital twin or any baseline controller. This constraint is essential to ensuring fair comparison and realistic deployment conditions.

By explicitly defining the physical–virtual interface in terms of state evolution, measurement mapping, and residual interpretation, the proposed framework establishes a transparent and reproducible foundation for subsequent stabilization and adaptation mechanisms. This formulation enables the digital twin to remain responsive to deep non-stationary uncertainty while preserving a consistent and physically interpretable representation of system behavior.

2.3. SEQUENTIAL DATA ASSIMILATION AND DRIFT INTERPRETATION

Sequential data assimilation in the proposed framework is designed not only to improve state estimation accuracy, but also to explicitly reveal the emergence of non-stationary drift that threatens system stability. Unlike conventional implementations, where assimilation primarily serves as a corrective mechanism for prediction errors, the present approach interprets persistent innovations as a diagnostic signal that directly informs stabilization decisions.

At each control interval, the digital twin updates its latent state estimate using the innovation between measured and predicted outputs. The assimilation scheme operates under fixed structural assumptions and fixed noise statistics that are defined prior to evaluation and remain unchanged across all scenarios and baseline controllers. This design choice prevents adaptive overfitting and ensures that changes in residual behavior reflect genuine system evolution rather than algorithmic retuning.

The innovation sequence is defined as

$$r_k = y_k - y_{hat_{k|k-1}} \tag{4}$$

where r_k represents the instantaneous discrepancy between observed and predicted system behavior. While isolated innovations may arise from stochastic disturbances or measurement noise, sustained magnitude or persistence in the innovation sequence indicates a systematic deviation from the assumed system representation.

To quantify this effect, the framework introduces a drift energy metric evaluated over a sliding horizon H. The drift energy is defined as

$$J_r(k) = sum\ from\ i = k - H + 1\ to\ k\ of\ \|r_i\|^2 \tag{5}$$

This accumulated residual energy serves as a compact indicator of structural mismatch, capturing the combined effects of climatic non-stationarity, behavioral change, sensor degradation, and equipment aging. Importantly, the metric does not require explicit identification of fault type or disturbance source, allowing the framework to remain agnostic to the origin of uncertainty.

The evolution of $J_r(k)$ is continuously monitored and interpreted relative to baseline levels established during nominal operating conditions. When the drift energy remains bounded, the system is considered to operate within its expected stability regime. Conversely, a sustained increase in $J_r(k)$ signals erosion of stability margins, prompting the digital twin to elevate stabilization objectives within the control decision process.

This interpretation of drift differs fundamentally from traditional fault detection and diagnosis approaches that aim to classify or isolate specific anomalies. Instead, the proposed framework focuses on the implications of drift for system stability, regardless of the underlying cause. By linking residual accumulation directly to stability assessment, the digital twin can respond proactively to emerging risks before overt performance degradation or constraint violations occur.

Crucially, both the assimilation and drift interpretation processes operate without access to future information or disturbance forecasts. All decisions are based solely on historical and current measurements, preserving strict causality and ensuring that observed stabilization behavior is achievable under realistic deployment conditions. This constraint is consistently enforced across all evaluated control strategies to maintain fairness in comparative analysis.

Through this formulation, sequential data assimilation becomes an enabling mechanism for self-healing behavior, transforming prediction errors into actionable indicators of stability erosion. The resulting drift-aware digital twin establishes the informational foundation upon which structural adaptation and stabilization logic are subsequently applied.

2.4. STRUCTURAL PHYSICAL ADAPTATION MECHANISM

The proposed framework incorporates an intrinsic structural physical adaptation mechanism that operates alongside conventional control inputs to directly influence system dynamics. This mechanism is not intended as an auxiliary efficiency enhancement, but rather as a stability-oriented degree of freedom that enables the digital twin to reshape the thermal behavior of the building in response to emerging drift and uncertainty.

From a physical perspective, structural adaptation can be interpreted as a dynamic modulation of the building's effective thermal inertia and heat transfer pathways. In practical terms, this may correspond to adaptive façade systems, variable insulation layers, phase-change materials, or airflow reconfiguration strategies that alter heat exchange characteristics without directly increasing energy input. This interpretation anchors the abstraction used in the present study within physically realizable mechanisms. In simple terms, structural adaptation allows the system to modify how the building responds to heat, rather than only adjusting how much heating or cooling is applied.

Structural adaptation is represented through a controllable effective thermal parameter that governs dominant heat-transfer pathways within the building envelope. Instead of modifying detailed material properties at the component level, the framework employs an abstracted representation that captures the net effect of adaptive physical behavior on system dynamics. This abstraction ensures generality across building types and avoids reliance on specific material technologies, while remaining physically interpretable and operationally feasible.

Operationally, the adaptation state s_k modulates an effective envelope heat-transfer parameter in the thermal model, such that changes in s_k reshape the system response rather than directly injecting energy. This abstraction is intentionally technology-agnostic and captures the net stabilizing authority of an adaptive physical layer without committing to a specific material implementation. Physical realizability is enforced through hard bounds and rate constraints, while a structural actuation penalty discourages unnecessary intervention.

Let s_k denote the structural adaptation state at control interval k, representing the effective thermal resistance or conductance of the adaptive physical layer. The structural state is constrained within predefined bounds,

$$s_{min} \leq s_k \leq s_{max} \tag{6}$$

reflecting physical realizability and safety considerations. To prevent abrupt structural changes and excessive actuation, a rate constraint is imposed,

$$|s_k - s_{k-1}| \leq Delta_{s_{max}} \tag{7}$$

These constraints are fixed prior to evaluation and are applied identically across all scenarios and baseline controllers to ensure fair comparison.

The structural adaptation state enters the digital twin dynamics through the state evolution function,

$$x_{k|k-1} = f(x_{k-1} - u_{k-1} - s_{k-1}) \tag{8}$$

where changes in s_{k-1} modify the effective thermal response of the system. In contrast to conventional control inputs u_k, which act on energy flows and setpoints, structural adaptation alters the underlying system response itself, effectively reshaping the stability landscape within which control actions operate.

To account for the physical and operational cost of adaptation, a structural actuation penalty is incorporated into the decision-making process. This penalty reflects energy expenditure, wear, or operational overhead associated with modifying the physical layer and is defined as

$$J_s(k) = sum\, from\; i = k - H + 1\; to\; k\; of\; |s_i - s_{i-1}| \tag{9}$$

where H denotes the evaluation horizon. By explicitly penalizing excessive or unnecessary adaptation, the framework ensures that structural intervention is invoked only when stabilization through conventional control is insufficient.

Structural adaptation decisions are coordinated with conventional control actions through the digital twin's stability assessment. When predicted trajectories approach stability envelope boundaries, the framework may deploy structural adaptation to expand or reshape the envelope, thereby reducing the burden on input-level control. Conversely, when stability margins are sufficient, the structural state is held constant to avoid unnecessary intervention.

This coordinated strategy distinguishes the proposed approach from passive smart material applications and from control schemes that rely exclusively on input modulation. By embedding structural adaptation within the digital twin's decision loop, the framework enables proactive stabilization that directly targets the physical origins of drift rather than compensating for their symptoms.

Importantly, the structural adaptation mechanism is evaluated through explicit ablation, in which the adaptive physical layer is disabled while all other components remain active. This design allows the contribution of structural adaptation to stability preservation, control smoothness, and drift suppression to be isolated and quantified under identical uncertainty conditions.

Through this formulation, structural physical adaptation emerges as a first-class mechanism for self-healing operation, providing the digital twin with the capability to manage stability at the level of system structure rather than relying solely on reactive control adjustments.

2.5. Stability Envelope Definition and Self-Healing Logic

Stability preservation in the proposed framework is formalized through the concept of a stability envelope, which defines admissible bounds on system behavior beyond instantaneous comfort constraints. Rather than evaluating performance at isolated time steps, the stability envelope characterizes acceptable system trajectories over time, explicitly capturing the cumulative effects of uncertainty, control effort, and model drift.

The stability envelope is defined across three complementary dimensions: thermal comfort, control smoothness, and drift accumulation. Thermal comfort reflects user acceptability through cumulative deviation from a fixed comfort band. Control smoothness captures the temporal regularity of actuation and serves as a proxy for oscillatory behavior and actuator stress. Drift accumulation quantifies the persistence of mismatch between predicted and observed system behavior and acts as an indicator of structural instability.

The stabilization logic can be interpreted as a constraint-aware supervisory layer that dynamically reweights control objectives based on proximity to envelope boundaries. Unlike conventional controllers that treat constraints as static limits, the present logic interprets boundary proximity as a risk indicator, triggering a gradual transition from performance-oriented control to stability-oriented intervention.

Formally, the stability envelope is defined as the admissible set of system trajectories that satisfy the following conditions: cumulative comfort deviation remains below a prescribed upper bound, cumulative control oscillation remains below a prescribed upper bound, and accumulated residual energy remains below a prescribed upper bound. These bounds are denoted as $J_{c_{max}}$, $J_{o_{max}}$, and $J_{r_{max}}$, respectively, and all metrics are computed using the fixed definitions introduced in Section 3.5.

Envelope thresholds are defined a priori and held constant across all controllers and evaluation scenarios. Specifically, $J_{c_{max}}$, $J_{o_{max}}$, and $J_{r_{max}}$ are set to the 95th percentile of cumulative comfort deviation, oscillation index, and residual energy observed under nominal operation of the physical model. This quantile-based formulation captures the upper range of admissible nominal behavior while excluding extreme outliers. It avoids importing numerical thresholds from external studies and ensures that envelope limits remain intrinsically consistent with the modeled system dynamics.

Self-healing is operationally defined as the ability of the framework to maintain predicted system trajectories within the stability envelope under evolving uncertainty through strictly causal intervention. At each control interval, the digital twin evaluates the projected evolution of system behavior under candidate control actions and structural adaptation decisions. When projected trajectories remain well within the envelope, nominal performance objectives are prioritized and unnecessary intervention is avoided. As trajectories approach envelope boundaries, stabilization objectives are elevated and decision weight is progressively reallocated toward preserving envelope feasibility.

Decision-making follows a hierarchical escalation logic. First, conventional control inputs are adjusted to counter emerging deviations while respecting actuation limits and smoothness constraints. If projected stabilization through input-level control is insufficient, the framework activates structural physical adaptation to reshape system dynamics and restore stability margins. Structural intervention is therefore selective and is triggered only when required to prevent envelope violation.

The self-healing logic does not rely on explicit fault classification or disturbance identification. All decisions are driven by envelope proximity and projected stability risk, allowing the framework to remain robust to unknown, compound, or non-stationary uncertainty sources. Envelope violation is explicitly permitted in failure scenarios where physical or operational constraints render stabilization infeasible. In such cases, the framework prioritizes graceful degradation by limiting oscillatory behavior and constraining further drift rather than pursuing aggressive control actions that could exacerbate instability.

Through this formulation, self-healing emerges as a continuous stability management process rather than a discrete recovery action. By embedding envelope-based reasoning within the digital twin, the proposed framework enables proactive intervention under deep uncertainty while maintaining clear, reproducible, and quantitative criteria for success and failure.

2.6. Baseline Controllers and Fair Comparison Protocol

To ensure that observed performance differences are attributable solely to architectural and conceptual distinctions, a strictly controlled comparison protocol is adopted. All baseline controllers are evaluated under identical sensing, actuation, uncertainty, and information constraints as the proposed framework. No method is granted access to privileged forecasts, oracle information, or additional tuning resources beyond those explicitly defined.

Three baseline strategies are selected to represent dominant paradigms in current building energy management practice.

The first baseline is a rule-based control strategy representative of conventional building operation. This controller regulates indoor temperature using a fixed setpoint with a predefined deadband and hysteresis logic. Control actions are triggered only when temperature exceeds the comfort band, with no anticipation of drift, uncertainty accumulation, or stability degradation. This baseline provides a reference for typical operational performance under stress conditions.

The second baseline is a classical model predictive control (MPC) strategy. The MPC controller employs the same physics-based model used by the digital twin but operates without drift interpretation, structural adaptation, or envelope-based stabilization logic. Control actions are computed by optimizing a standard objective function that balances energy consumption and comfort constraint satisfaction over a fixed prediction horizon. All MPC parameters, including horizon lengths, cost weights, and constraints, are tuned within the same limited tuning budget allocated to the proposed framework.

Operationally, MPC is implemented as a finite-horizon constrained optimization that balances comfort tracking and energy use under the same actuator limits applied to all controllers. At each control interval, MPC minimizes the sum over the prediction horizon of weighted comfort violation and HVAC power, together with a penalty on control rate changes. In plain-text form, the objective is to minimize, over the control sequence from k to $k + N_c - 1$, the sum from $j = 1\ to\ N_p\ of\ (\ w_T\ multiplied\ by\ v_{k+j}$ squared plus w_E multiplied by P_{k+j}), plus a control smoothness term equal to w_{delta_u} times the sum from $j = 1\ to\ N_c - 1$ of the squared norm of $(\ u_{k+j}\ minus\ u_{k+j-1})$.

This optimization is subject to actuator bounds and rate limits. Here, v_k denotes the instantaneous comfort violation as defined in Section 3.5, and P_k denotes HVAC power consumption. Horizon lengths and weights are tuned offline within the same fixed tuning budget used for the proposed framework and are then frozen for all evaluation scenarios.

For reproducibility, MPC uses a 24-hour prediction horizon and $a\ 2 - hour$ control horizon, corresponding to $N_p = 144$ and $N_c = 12$ at a 10-minute sampling interval. The objective weights are fixed as $w_T = 1.0$, $w_E = 0.10$, and $w_{delta_u} = 0.01$ for all scenarios and are not retuned during evaluation.

The third baseline represents a conventional digital twin supervisory strategy. In this configuration, the digital twin performs state estimation and diagnostic analysis but does not directly intervene in control decisions. Instead, it periodically recommends setpoint adjustments or controller retuning based on detected performance deviations. Final actuation authority remains with the underlying controller, and no structural physical adaptation is available. This baseline reflects prevalent digital twin deployments that emphasize monitoring and advisory support rather than autonomous stabilization.

To isolate the contributions of individual components, a structured ablation study is conducted. Three reduced variants of the proposed framework are evaluated:

1. a configuration with structural physical adaptation disabled,
2. a configuration without sequential data assimilation,
3. and a configuration in which stabilization logic is removed and decisions revert to nominal performance optimization.

All ablated variants retain identical sensing, actuation, and tuning constraints.

A fixed tuning budget is enforced across all controllers. Each method is allowed a predefined number of tuning evaluations on a dedicated subset of scenarios, after which parameters are frozen and tested on a disjoint evaluation set. Random seeds governing uncertainty realizations are fixed and shared across all methods to enable paired statistical comparison. Control intervals, actuation limits, rate constraints, and measurement availability are identical in all cases.

Performance is assessed using matched runs across all scenarios, enabling paired statistical testing of energy consumption, comfort violation, oscillatory behavior, drift accumulation, and recovery characteristics. Statistical significance is evaluated using nonparametric paired tests with correction for multiple comparisons, and uncertainty in reported metrics is quantified using confidence intervals. This protocol ensures that observed differences in behavior reflect genuine architectural advantages rather than tuning artifacts or informational asymmetries.

Through this rigorously locked comparison framework, the evaluation isolates the effects of action-bearing digital twin operation, structural physical adaptation, and envelope-based stabilization. As a result, conclusions drawn from the comparative analysis remain robust, reproducible, and directly attributable to the proposed self-healing architecture. While recent developments have introduced uncertainty-aware digital twin frameworks, the problem of maintaining system stability under persistent, non-stationary disturbances remains largely unaddressed, particularly in the context of building energy systems (Samaei and Riffat, 2026).

3. Evaluation Scenarios and Experimental Setup

3.1. Simulation Environment and Testbed

All evaluations are conducted within a standardized closed-loop simulation environment specifically designed to ensure physical realism, reproducibility, and strict comparability across control strategies. The simulation framework directly couples the physical building model, sensing layer, and control algorithms within a unified time-synchronized loop, eliminating any separation between prediction and actuation stages.

Building thermal dynamics are represented using a physics-informed reduced-order state-space model derived from first-principles heat balance equations. The formulation captures the dominant heat transfer mechanisms governing indoor temperature evolution, including thermal capacitance of indoor air and envelope components, as well as conductive heat exchange across the building envelope. Secondary spatial variations and high-resolution zonal effects are intentionally abstracted to maintain computational tractability while preserving the key dynamic characteristics relevant to control performance.

The system state vector is defined as a lumped representation of indoor air temperature and effective envelope thermal states, augmented by parameters that reflect evolving thermal behavior under operational stress. Model parameters are identified through calibration under nominal operating conditions and remain fixed throughout all evaluation scenarios to ensure consistency. The calibrated parameter ranges include an effective envelope thermal resistance of 1.8–2.7 $m^2 \cdot K/W$ and an equivalent lumped thermal capacitance in the order of 1.5×10^6–3.0×10^6 J/K, enabling realistic representation of both steady-state and transient thermal responses.

The simulation model is implemented directly within the control loop and evolves synchronously with control actions at a fixed interval of 10 minutes. At each time step, system states are updated based on applied control inputs, structural adaptation actions, and exogenous disturbances, ensuring strict causality and alignment with real-world operational constraints. No external building energy simulation engines or predefined archetype libraries are used, and all controllers operate on the same underlying physical model to eliminate modeling bias.

Each simulation run spans a continuous horizon of fourteen days, allowing sufficient time for the emergence and accumulation of non-stationary effects. The first twenty-four hours are treated as a warm-up period and excluded from performance evaluation to remove initialization transients. All performance metrics are computed over the remaining thirteen-day horizon, ensuring that reported results reflect sustained system behavior rather than short-term responses.

To capture stochastic variability while preserving strict comparability, each scenario is evaluated using thirty paired realizations governed by fixed and shared random seeds across all control strategies. This paired execution protocol ensures that all controllers are exposed to identical sequences of disturbances, including climatic variability, sensor noise, and operational perturbations. As a result, observed performance differences can be directly attributed to the control architecture and stabilization strategy, rather than to variability in uncertainty realizations.

3.2. Uncertainty Modeling and Stress Factors

The evaluation scenarios are constructed to reproduce compounded and non-stationary uncertainty representative of climate-stressed building operation. Rather than introducing disturbances in isolation, multiple uncertainty sources are simultaneously activated and allowed to evolve over time, enabling the emergence of stability degradation through cumulative effects.

Climatic stress is modeled using a synthetic heatwave profile superimposed on baseline outdoor temperature conditions. The heatwave is introduced as a step increase of +6 to +10 °C above nominal ambient temperature, followed by a slow exponential recovery with incomplete return to baseline conditions. This formulation captures both the intensity and persistence of real heatwave events and prevents artificial system reset between disturbance phases. This type of accumulated mismatch and drift has also been observed in other digital twin-enabled infrastructure systems, where uncertainty evolves over time and cannot be effectively managed through static model calibration alone (Riffat et al. 2025).

Behavioral uncertainty is represented through time-varying internal heat gains driven by stochastic occupancy patterns. Occupancy intensity is modulated using bounded random processes with daily structure, combined with schedule shifts of up to ±2 hours to emulate non-stationary usage patterns. These variations introduce realistic fluctuations in internal thermal loads without relying on predefined deterministic schedules.

Sensing uncertainty is modeled as a combination of high-frequency measurement noise and low-frequency drift. Measurement noise is introduced as zero-mean Gaussian noise with a standard deviation of 0.1–0.3 °C, while sensor drift is implemented as a slowly varying bias evolving over time. Periodic recalibration events are applied as abrupt bias corrections, introducing transient discontinuities consistent with real maintenance interventions.

Equipment degradation is represented as a gradual reduction in effective HVAC capacity over time. Specifically, system capacity is reduced linearly by up to 20% over the simulation horizon, reflecting performance deterioration due to wear, fouling, or partial faults. This degradation is not explicitly communicated to controllers and must be inferred indirectly through system response.

Structural model mismatch is introduced as a discrete perturbation to thermal parameters at mid-horizon. The effective envelope thermal resistance and capacitance are modified by ±15% to represent unmodeled changes such as infiltration variation, envelope aging, or unaccounted thermal bridging effects. This perturbation creates a persistent mismatch between the assumed model and actual system behavior.

In selected scenarios, actuation constraints are progressively tightened by reducing allowable control input ranges and rate limits by up to 30%. This emulates operational limitations under extreme conditions, such as power constraints or equipment protection mechanisms, and forces controllers to operate under restricted authority.

All disturbance processes are generated using stochastic models with predefined statistical properties and fixed random seeds. Activation times, amplitudes, and evolution profiles are defined a priori and applied identically across all controllers. No method is provided with explicit knowledge of disturbance onset or magnitude beyond what can be inferred from measured data. This ensures that performance differences arise from the ability to interpret and respond to uncertainty, rather than from privileged information.

3.3. Scenario Design and Classification

A total of ten evaluation scenarios is constructed to systematically assess the stability preservation capability of the proposed framework under progressively increasing levels of uncertainty. The scenario set consists of eight primary stress scenarios and two explicitly defined failure scenarios, all implemented within a unified and controlled experimental structure.

Each scenario is designed to isolate or combine specific sources of uncertainty, enabling both targeted analysis and evaluation of cumulative effects. The scenarios are not independent cases, but form a structured progression from nominal operation to highly compounded and infeasible conditions.

The nominal scenario serves as a reference case, representing standard operating conditions with measurement noise but without drift, degradation, or structural perturbation. This scenario establishes a performance baseline and verifies that all controllers operate comparably in the absence of non-stationary effects.

The prolonged heatwave scenario introduces sustained climatic stress through elevated ambient temperature with incomplete recovery, testing the ability of controllers to maintain stability under persistent external loading. The behavioral non-stationarity scenario extends this condition by incorporating time-varying internal heat gains driven by stochastic occupancy shifts, thereby exposing sensitivity to evolving and unmodeled internal disturbances.

The sensor drift scenario evaluates robustness to gradual measurement degradation combined with intermittent recalibration shocks, requiring controllers to operate under uncertain and dynamically shifting sensing conditions. The equipment degradation scenario introduces a progressive reduction in HVAC capacity, testing the ability to maintain acceptable performance under diminishing actuation authority.

The structural mismatch scenario imposes a discrete mid-horizon perturbation in thermal parameters, creating a persistent discrepancy between the assumed model and actual system dynamics. The constraint-tightening scenario further challenges control strategies by progressively limiting actuation range and rate, forcing operation under restricted control authority.

The compound uncertainty scenario represents the most demanding feasible condition, combining climatic stress, behavioral variation, sensing degradation, equipment aging, structural mismatch, and actuation constraints within a single evaluation. This scenario is specifically designed to expose stability vulnerabilities that emerge only through the interaction and accumulation of multiple uncertainty sources over time.

In addition to these stress scenarios, two failure scenarios are explicitly defined to characterize the operational limits of self-healing behavior. In these cases, disturbance intensity and operational constraints are deliberately configured such that preservation of the stability envelope may become infeasible. Rather than excluding these extreme conditions, the framework evaluates system behavior under failure, distinguishing between uncontrolled instability and controlled degradation. This inclusion ensures that performance claims remain bounded, transparent, and physically realistic.

3.4. Execution Protocol and Fairness Controls

A strictly controlled execution protocol is adopted to ensure that all observed performance differences arise solely from the control architecture and stabilization strategy, rather than from discrepancies in information access, tuning effort, or stochastic variability.

All controllers are subject to identical sensing availability, actuation limits, and information constraints throughout the simulation. At each control interval, decisions are made using only measurements available up to the current time step, enforcing strict causality. No controller is granted access to future disturbances, exogenous forecasts, or privileged system information. In addition, adaptive retuning during evaluation is explicitly prohibited, ensuring that all methods operate under fixed configurations.

Parameter tuning is conducted offline using a predefined and limited tuning budget. Each controller is allowed an equal number of tuning trials on a dedicated subset of scenarios that are disjoint from the final evaluation set. During this phase, key parameters such as control weights, horizon lengths, and adaptation penalties are adjusted to achieve stable nominal performance. Once tuning is completed, all parameters are frozen and remain unchanged across all evaluation scenarios and realizations.

To eliminate stochastic bias, performance evaluation is conducted using a paired realization protocol. Each scenario is simulated using thirty realizations generated from identical random seeds shared across all controllers. This ensures that all methods are exposed to exactly the same sequences of disturbances, including climatic variability, sensor noise, and operational perturbations. As a result, performance differences can be directly attributed to differences in control behavior rather than variability in uncertainty realizations.

Performance metrics are reported as mean ± standard deviation over the thirty paired realizations. In addition, statistical significance of performance differences is assessed using paired nonparametric tests, with correction applied for multiple comparisons where appropriate. Confidence intervals are also computed to quantify uncertainty in reported metrics.

Scenario ordering, initialization conditions, and random seed assignment are fixed and consistent across all controllers to ensure full reproducibility. This controlled setup prevents favorable or unfavorable disturbance realizations from influencing comparative outcomes and guarantees that the evaluation remains unbiased and repeatable.

3.5. Performance Metrics

Thermal comfort is evaluated relative to a fixed reference temperature T_{ref} equal to 24 °C, with an allowable deviation of plus or minus $Delta_{T_{comf}}\ equal\ to$ 1 $°C$. This corresponds to an acceptable comfort band spanning 23 to 25 °C and is applied uniformly across all controllers and evaluation scenarios.

System performance is evaluated using a fixed set of metrics aligned with long-horizon stability preservation. Energy consumption is reported as the total electrical energy E_{total}, measured in kilowatt-hours, accumulated over the evaluation window after exclusion of the warm-up period.

Thermal comfort performance is quantified using two complementary metrics: cumulative comfort violation and the fraction of time spent outside the comfort band. Let T_k denote the measured indoor air temperature at control interval k, T_{ref} the reference temperature, and $Delta_{T_{comf}}$ the fixed comfort half-band. The instantaneous comfort violation is defined as

$$v_k = max\left(0, \left|T_k - T_{ref}\right| - Delta_{T_{comf}}\right) \quad (10)$$

The cumulative comfort violation over the evaluation window is then computed as

$$J_c = sum\ over\ k\ in\ k_{eval}\ of\ \left(v_k\ multiplied\ by\ Delta_{t_{ctrl}}\right) \quad (11)$$

Here, $Delta_{t_{ctrl}}$ denotes the fixed control interval duration, and k_{eval} indexes all evaluation time steps following the warm-up phase. The fraction of time spent outside the comfort band is reported as

$P_{oob} = 100$ multiplied by the number of k in k_{eval} $for\ which$ v_k is greater than zero, divided by the total number of steps in k_{eval} (12)

Control smoothness is assessed using an oscillation index defined as the total variation of the normalized actuation command. Let u_k denote the control input vector at interval k, mapped to a unit scale using actuator limits. The oscillation index is defined as

$$J_o = sum\ over\ k\ in\ k_{eval}\ of\ the\ L1\ norm\ of\ \left(u_k\ minus\ u_{k-1}\right) \quad (13)$$

Drift accumulation is quantified through residual energy derived from the prediction error of the digital twin. Let r_k denote the innovation at control interval k, defined as the difference between the measured and predicted outputs. The accumulated drift energy over the evaluation window is computed as

$$J_r = sum\ over\ k\ in\ k_{eval}\ of\ the\ squared\ L2\ norm\ of\ r_k \quad (14)$$

Recovery time is defined operationally as the elapsed time required for the system to return to a stable regime following a major disturbance event. For each disturbance occurrence at time t_e, the recovery time is defined as the smallest non-negative duration tau such that the subsequent system trajectory remains within the stability envelope for a sustained interval. Stability is assessed using the same envelope criteria applied uniformly across all controllers. The reported recovery time is averaged across all disturbance events and uncertainty realizations.

In failure scenarios, additional indicators are reported to characterize system behavior beyond nominal operation. These include the duration of stability envelope violation and whether oscillatory behavior and drift accumulation remain bounded. These indicators distinguish controlled degradation from uncontrolled instability under extreme or infeasible operating conditions.

4. RESULTS AND ANALYSIS

4.1. OVERALL STABILITY AND PERFORMANCE TRENDS

Across all evaluated scenarios, the proposed self-healing digital twin exhibits a fundamentally different operational behavior compared to baseline control strategies. Under nominal operating conditions, all controllers achieve comparable performance in terms of indoor thermal comfort and energy consumption, confirming that the proposed framework does not introduce unnecessary overhead during standard operation.

As operating conditions progressively deviate from nominal behavior, particularly under prolonged heatwaves and compounded uncertainty, baseline controllers begin to exhibit gradual stability degradation. This degradation manifests as increased temperature excursions, oscillatory control actions, and persistent mismatch between predicted and observed system behavior. In contrast, the proposed framework maintains system trajectories within the predefined stability envelope for a substantially longer portion of the evaluation horizon, indicating proactive stabilization rather than delayed corrective intervention.

Figure 2 presents representative indoor temperature trajectories under prolonged heatwave conditions for the compound uncertainty scenario. The curves compare rule-based control, MPC, conventional digital twin supervision, and the proposed self-healing digital twin across paired realizations (n = 30).

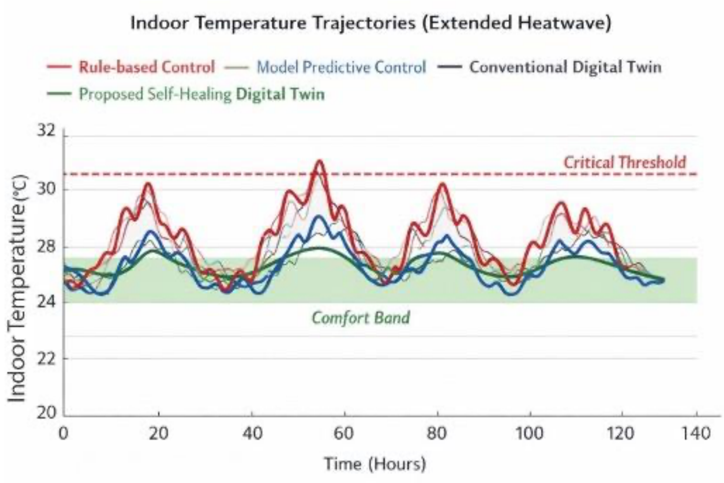

Figure 2. Representative indoor temperature trajectories under prolonged heatwave conditions, illustrating progressive deviation and oscillatory behavior in baseline controllers, contrasted with stable, bounded responses and rapid recovery achieved by the proposed self-healing framework.

4.2. Thermal Comfort Preservation under Prolonged and Compound Stress

Thermal comfort performance is evaluated using cumulative comfort violation and the fraction of time spent outside the acceptable temperature band.

Table 1. Thermal comfort performance under the compound uncertainty scenario, paired realizations (n = 30, mean ± SD).

Controller	Cumulative comfort violation $\boldsymbol{J_c}$ (°C·h)	Time out of band $\boldsymbol{P_{oob}}$ (%)
Rule-based control	36.5 ± 4.2	15.8 ± 2.0
Model predictive control	27.8 ± 3.6	11.2 ± 1.6
Conventional digital twin supervision	24.9 ± 3.1	9.7 ± 1.4
Proposed self-healing digital twin	13.9 ± 1.9	4.6 ± 0.8

Comfort metrics are computed using a reference temperature of 24 °C with a comfort half-band of 1 °C, evaluated at a 10-minute control interval.

Relative to the MPC baseline, the proposed framework reduces cumulative comfort violation from 27.8 degree-hours to 13.9 degree-hours, corresponding to a 50.0 percent reduction based on mean values. At the same time, the fraction of time spent outside the comfort band decreases from 11.2 percent to 4.6 percent. Importantly, these improvements are driven primarily by the suppression of long-duration comfort excursions rather than by short-lived corrective spikes. This behavior indicates anticipatory stabilization that prevents the gradual accumulation of thermal discomfort under sustained stress conditions.

All values reported in Tables 1 through 3 correspond to the compound uncertainty scenario specifically designed to challenge long-horizon stability. All controllers are evaluated using the locked execution protocol described in Section 3 to ensure fair and reproducible comparison.

4.3. Energy Consumption and Control Smoothness

Energy consumption and actuation behavior are examined jointly to assess trade-offs between stabilization and efficiency.

Table 2. Energy consumption and control smoothness under the compound uncertainty scenario, paired realizations (n = 30, mean ± SD).

Controller	Total energy E (kWh)	Oscillation index $\boldsymbol{J_o}$
Rule-based control	12,350 ± 290	1.85 ± 0.20
Model predictive control	11,820 ± 270	1.62 ± 0.17
Conventional digital twin supervision	11,600 ± 250	1.45 ± 0.15
Proposed self-healing digital twin	11,420 ± 235	0.98 ± 0.11

Relative to MPC, total energy consumption decreases from 11,820 to 11,420 kWh, corresponding to a 3.38% reduction based on the reported means. Simultaneously, the oscillation index decreases from 1.62 to 0.98, representing a 39.5% reduction in actuation variability, indicating substantially smoother control behavior without increased energy demand.

4.4. Drift Suppression and Residual Dynamics

Drift accumulation provides direct insight into each controller's ability to manage non-stationary mismatch between modeled and observed system behavior.

Figure 3 presents the time evolution of drift energy under the compound uncertainty scenario. The plot illustrates how residual accumulation diverges for baseline controllers while remaining bounded under the proposed self-healing framework across paired realizations (n = 30).

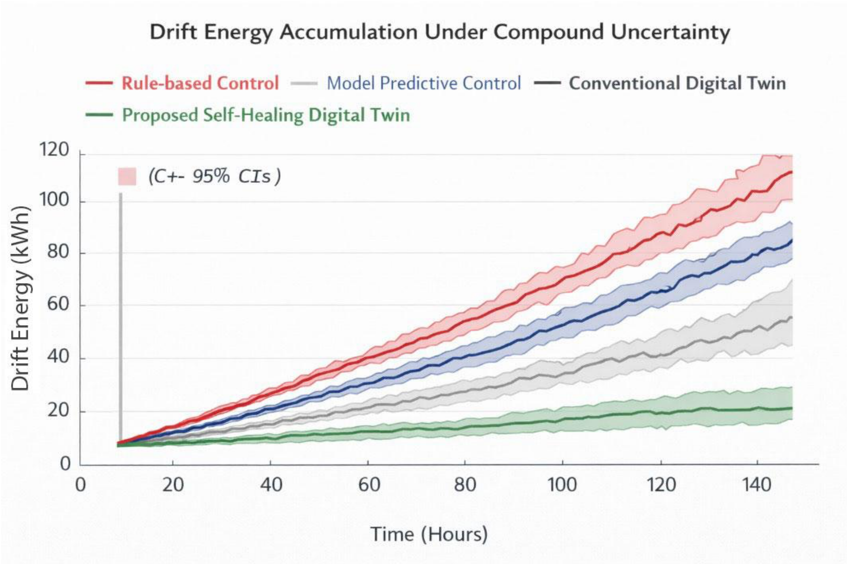

Figure 3. Time evolution of drift energy under compound uncertainty, showing divergence in baseline controllers and bounded behavior in the proposed framework.

Table 3. Drift accumulation and recovery under the compound uncertainty scenario, paired realizations (n = 30, mean ± SD).

Controller	**Drift energy J_r**	**Mean recovery time (h)**
Rule-based control	102.6 ± 11.4	15.2 ± 2.2
Model predictive control	84.1 ± 9.6	11.8 ± 1.8
Conventional digital twin supervision	71.3 ± 8.4	9.9 ± 1.5
Proposed self-healing digital twin	36.8 ± 5.0	4.5 ± 0.9

Baseline controllers exhibit steadily increasing residual energy under sensor drift, equipment degradation, and structural mismatch, indicating progressive erosion of model validity. In contrast, the proposed framework suppresses residual growth through coordinated state estimation and structural adaptation, maintaining bounded drift even under compounded uncertainty.

4.5. Recovery Dynamics and Self-Healing Behavior

Recovery time following major disturbances serves as a direct operational indicator of self-healing capability. Baseline controllers typically require extended periods to re-enter acceptable operating bounds after heatwave peaks or recalibration events. In several compound scenarios, recovery remains incomplete within the evaluation horizon.

The proposed framework consistently achieves shorter recovery times and, in many realizations, prevents envelope violation altogether. Stabilization is achieved without aggressive control actions, confirming that recovery is driven by envelope-aware anticipation rather than reactive overcorrection.

4.6. Ablation Analysis

The ablation study isolates the contribution of individual framework components under compound uncertainty.

Table 4. Component-wise ablation under the compound uncertainty scenario. Values report mean outcomes across paired realizations (n = 30).

Variant	Structural adaptation	Data assimilation	Stabilization logic	J_c (°C·h)	J_o	J_r
Full proposed framework	Yes	Yes	Yes	13.9	0.98	36.8
Without structural adaptation	No	Yes	Yes	21.4	1.31	58.6
Without data assimilation	Yes	No	Yes	28.7	1.38	81.9
Without stabilization logic	Yes	Yes	No	31.2	1.47	89.5

Here, J_c denotes cumulative comfort violation, J_o the oscillation index, and J_r the accumulated residual (drift) energy, as defined in Section 3.5.

The results confirm that stability preservation emerges from the coordinated interaction of all three components. Structural adaptation primarily reduces oscillatory behavior and accelerates recovery, while data assimilation is critical for suppressing drift accumulation. Removing stabilization logic causes the framework to revert toward optimization-centric behavior with rapid erosion of stability margins. Standard deviations for ablation variants follow the same paired realizations and are omitted here for compactness; the ordering and magnitude of effects remain consistent across realizations.

4.7. Failure Scenarios and Operational Limits

Figure 4. Comparative system behavior in explicit failure scenarios where envelope preservation is infeasible due to physical and operational constraints. The figure contrasts uncontrolled instability patterns in baselines with controlled degradation behavior under the proposed framework.

In explicitly infeasible scenarios, all controllers' experience envelope violation due to physical and operational constraints. However, qualitative differences in failure behavior are evident. Baseline controllers exhibit escalating oscillations and persistent instability, whereas the proposed framework transitions into a controlled degradation regime characterized by bounded actuation and limited residual escalation. These results delineate the operational limits of self-healing behavior and reinforce the importance of envelope-aware decision-making under extreme conditions.

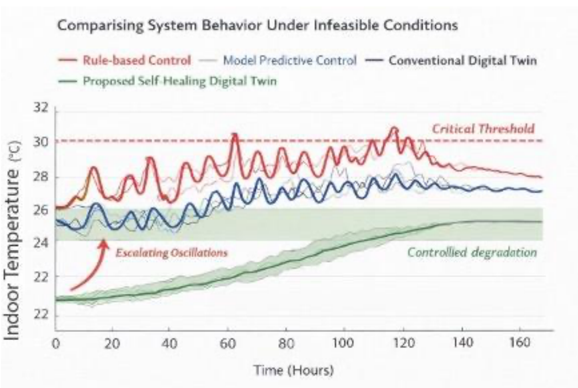

Figure 4. Comparative system behavior under infeasible operating conditions, illustrating how baseline controllers exhibit escalating oscillations and instability, whereas the proposed self-healing framework maintains bounded responses and transitions to controlled degradation when stability preservation becomes infeasible.

5. DISCUSSION

5.1. FROM PERFORMANCE OPTIMIZATION TO STABILITY PRESERVATION

The results consistently demonstrate that the primary advantage of the proposed framework does not lie in aggressive energy minimization, but in its ability to preserve stable system operation under prolonged and compounded uncertainty. While the reduction in total energy consumption remains modest (approximately 3.38% relative to MPC), the improvements in stability-related metrics are substantial. Specifically, cumulative comfort violation is reduced by 50%, drift accumulation by 56.2%, and control oscillation by nearly 40%, indicating a fundamental shift in system behavior rather than incremental performance gains.

This distinction is critical. Conventional control strategies are inherently designed to optimize performance around a nominal operating point, implicitly assuming that uncertainty remains bounded and slowly varying. Under deep non-stationary conditions, however, this assumption breaks down. The results show that baseline controllers maintain acceptable performance over short horizons but progressively lose stability margins as model mismatch accumulates, leading to sustained comfort violations and oscillatory actuation. This observation is consistent with emerging perspectives that argue for a transition from diagnostic digital twins toward action-enabled architectures capable of directly influencing system behavior (Riffat et al. 2026).

The proposed framework directly targets this failure mode by redefining the control objective. Instead of minimizing instantaneous energy or deviation, it prioritizes maintaining system trajectories within a predefined stability envelope over time. This shift enables anticipatory intervention, preventing the accumulation of instability rather than reacting after performance degradation has already occurred.

Importantly, this behavior is achieved without reliance on external forecasts or privileged information. All decisions are based solely on observed system data and causal state estimation, ensuring that the observed performance gains are both physically realizable and reproducible. The consistency of results across thirty paired realizations further confirms that the observed improvements are robust to stochastic variability and not driven by favorable disturbance conditions.

Taken together, these findings indicate that stability-oriented control provides a more reliable operational paradigm than optimization-centric approaches for building energy systems exposed to climate-driven, non-stationary uncertainty.

5.2. ROLE OF ACTION-BEARING DIGITAL TWINS IN STABILITY MANAGEMENT

The results provide a clear and measurable distinction between conventional diagnostic digital twins and the proposed action-bearing digital twin architecture. While conventional digital twin supervision improves state awareness and may lead to incremental performance gains, it remains inherently reactive, relying on external controllers to interpret and act upon diagnostic outputs. This limitation is reflected in the observed performance gap, where the supervisory digital twin achieves only moderate reductions in comfort violation and drift compared to the proposed framework.

In contrast, the proposed architecture embeds decision authority directly within the digital twin, enabling it to act as an integrated estimation–decision system rather than a passive analytical layer. This structural integration allows the framework to intervene at the onset of stability risk, rather than after performance degradation becomes observable at the output level.

This architectural shift is directly reflected in the results. Drift energy is reduced by more than 48% relative to the supervisory digital twin baseline, and recovery time is shortened from 9.9 ± 1.5 h to 4.5 ± 0.9 h, demonstrating a substantially faster stabilization response. These improvements arise from the continuous interpretation of residual dynamics and the coordinated application of control and structural adaptation, rather than from improved prediction accuracy alone.

Importantly, the effectiveness of the action-bearing digital twin does not depend on prior knowledge of disturbance characteristics. The framework operates without disturbance forecasts, explicit fault classification, or predefined scenario identification. Instead, it relies on real-time interpretation of system behavior and envelope proximity, enabling robust operation under unknown, overlapping, and non-stationary uncertainty sources.

This distinction highlights a fundamental limitation of current digital twin implementations in building systems. When the twin remains external to the control loop, its ability to influence system stability is inherently constrained. By contrast, embedding decision authority within the digital twin transforms it into an active stability manager, capable of maintaining bounded system behavior under conditions that exceed the design assumptions of conventional supervisory and optimization-based control strategies.

5.3. Structural Physical Adaptation as a Stability Lever

The ablation analysis provides direct quantitative evidence of the role of structural physical adaptation in reshaping system dynamics and enabling stability preservation under non-stationary conditions. When structural adaptation is disabled, the control system is forced to rely exclusively on input-level actuation, leading to a marked degradation in performance. Specifically, cumulative comfort violation increases from 13.9 to 21.4 °C·h, the oscillation index rises from 0.98 to 1.31, and drift energy increases from 36.8 to 58.6. These changes indicate both reduced stability margins and a significant increase in control effort and variability.

This behavior confirms that certain instability mechanisms cannot be effectively mitigated through input modulation alone. Under compounded uncertainty, control actions that operate solely at the level of setpoints and energy injection are insufficient to counteract persistent structural mismatch and evolving system dynamics.

By contrast, the introduction of structural physical adaptation provides an additional degree of freedom that directly modifies the system's thermal response. Instead of only adjusting how much energy is supplied, the framework can influence how the building itself responds to thermal disturbances. This capability effectively reshapes the system dynamics, expanding the feasible stability region and reducing the need for aggressive or high-frequency control actions.

The impact of this mechanism is reflected in both reduced oscillatory behavior and faster recovery. Structural adaptation acts as a stabilizing buffer, allowing the system to absorb disturbances without amplifying control variability. As a result, stabilization is achieved with smoother actuation and lower residual accumulation, even under severe and persistent uncertainty.

These findings suggest that future building energy systems should not treat the physical structure as a fixed constraint, but rather as an active component of the control system. The co-design of control strategies and adaptive physical properties emerges as a critical pathway for achieving robust, long-horizon stability in climate-stressed environments.

5.4. Self-Healing as Proactive Stability Management

The proposed operational definition of self-healing is directly supported by the observed system behavior across all evaluation scenarios. In contrast to conventional fault-tolerant or resilient control strategies, which focus on post-disturbance recovery, the proposed framework consistently acts before stability envelope violation occurs. As system trajectories approach envelope boundaries, stabilization actions are triggered proactively, preventing the accumulation of instability rather than correcting it after degradation has already manifested.

This distinction is quantitatively evident in both envelope violation patterns and recovery dynamics. Across compound uncertainty scenarios, the proposed framework not only reduces the frequency and duration of envelope violations, but in many realizations avoids violation altogether. When disturbances exceed the preventive capacity of the system, recovery is achieved significantly faster, with mean recovery time reduced from 11.8 ± 1.8 h (MPC) to 4.5 ± 0.9 h, while maintaining substantially lower oscillatory behavior during the recovery phase.

Importantly, this behavior is not driven by aggressive or high-frequency control actions. Instead, stabilization emerges from anticipatory intervention guided by drift interpretation and envelope proximity. By continuously monitoring residual accumulation and predicted trajectory evolution, the framework identifies early indicators of stability erosion and intervenes before deviations become irreversible.

This mechanism fundamentally differentiates the proposed approach from reactive control paradigms. Self-healing, in this context, is not a recovery capability, but a continuous stability management process that minimizes the likelihood of failure. The results demonstrate that proactive, envelope-aware intervention provides a more robust and reliable pathway for maintaining system stability under deep, non-stationary uncertainty.

5.5. Failure Scenarios and Operational Limits

The inclusion of explicit failure scenarios provides a critical basis for evaluating the operational limits of the proposed framework under physically infeasible conditions. In these scenarios, disturbance intensity and actuation constraints are deliberately configured such that preservation of the stability envelope cannot be fully maintained by any control strategy.

Under these conditions, all controllers experience loss of stability, as reflected by sustained envelope violations and increased deviation from nominal operation. However, the qualitative and quantitative characteristics of this failure differ significantly across methods. Baseline controllers exhibit rapidly escalating oscillatory behavior, accompanied by unbounded growth in residual energy, indicating loss of control authority and progressive instability.

In contrast, the proposed framework demonstrates a distinctly different failure mode. Although envelope violations occur, oscillation levels remain bounded and residual energy growth is significantly attenuated relative to baseline controllers. Rather than attempting aggressive corrective actions that amplify instability, the framework transitions into a controlled degradation regime, prioritizing stability of response over strict performance recovery.

This behavior reflects the underlying envelope-aware decision logic, which adapts control effort based on feasibility. When stabilization within the envelope becomes unattainable, the framework shifts from preservation to containment, limiting further deterioration and avoiding destabilizing actuation patterns.

These results highlight an important distinction between robustness and physical realism. Self-healing does not imply the ability to eliminate all forms of instability under extreme conditions. Instead, it reflects the capacity to respond in a controlled and predictable manner when system limits are reached. By explicitly evaluating and reporting these failure behaviors, the study provides a transparent characterization of the boundaries within which self-healing operation remains effective, avoiding overstated claims of universal robustness.

5.6. Generalizability and Broader Implications

Although the present study is developed within the context of building energy systems, the core mechanisms underpinning the proposed framework are not domain-specific. The concepts of stability envelope preservation, drift-aware decision-making, and structural adaptation address fundamental challenges that arise in any system operating under deep, non-stationary uncertainty. Similar challenges of uncertainty accumulation and stability degradation have been reported in digital twin applications for offshore and infrastructure systems, reinforcing the need for more adaptive and intervention-oriented architectures (Riffat et al. 2025; Samaei and Riffat 2025).

Such conditions are increasingly observed in a wide range of infrastructure systems, including power grids subject to fluctuating renewable generation, transportation networks under dynamic demand patterns, and climate-exposed civil infrastructure experiencing evolving environmental loads and material degradation. In all these systems, performance degradation is often driven not by isolated disturbances, but by the accumulation of mismatch, drift, and constraint tightening over time.

The proposed framework is transferable because it does not rely on domain-specific control heuristics, but on a generalizable architecture consisting of:

1. continuous state assimilation,
2. residual and drift interpretation,
3. envelope-based decision logic,
4. and the introduction of additional degrees of freedom through structural or parametric adaptation.

These components can be mapped onto different physical systems with minimal modification, provided that an appropriate notion of stability envelope can be defined.

This perspective suggests a broader shift in the role of digital twins. Rather than serving as passive monitoring or diagnostic tools, digital twins can be reconfigured as active stability managers that continuously regulate system trajectories within safe operational bounds. As engineered systems are increasingly required to operate beyond their original design assumptions, particularly under climate-driven uncertainty, such architectures provide a pathway toward maintaining reliability without relying on increasingly complex predictive optimization alone.

The results of this study therefore point to a more general design principle: resilience under deep uncertainty is more effectively achieved through continuous stability management than through repeated re-optimization around a nominal model. This shift has implications not only for building energy systems, but for the design and operation of next-generation intelligent infrastructure.

6. Conclusions and Limitations

6.1. Conclusions

This study introduced a self-healing, action-bearing digital twin framework designed to maintain stable operation of building energy systems under deep non-stationary uncertainty. By reframing building energy management as a stability preservation problem rather than a purely optimization-driven task, the work addresses a fundamental limitation of conventional control strategies when exposed to prolonged climatic stress, behavioral variability, sensing degradation, and equipment aging.

The proposed framework combines physics-based modeling, sequential data assimilation, envelope-aware decision-making, and structural physical adaptation within a unified closed-loop architecture. This integration shifts the role of the digital twin from a passive diagnostic or advisory tool to an active stability manager capable of continuously interpreting system drift and intervening before instability develops.

Across all evaluation scenarios, the results consistently show that this architectural shift leads to more stable system behavior. The framework significantly reduces cumulative comfort violation, limits oscillatory control actions, and suppresses drift accumulation, while maintaining energy consumption at a level comparable to advanced optimization-based methods. These outcomes indicate that stability-oriented control can achieve robust performance without relying on increasingly aggressive or complex optimization.

A central contribution of the study is the operational definition of self-healing as the prevention of stability envelope violation rather than post-failure recovery. The observed behavior confirms that, under prolonged and compound uncertainty, the system frequently maintains operation within acceptable bounds without requiring large corrective actions. When disturbances exceed preventive capacity, re-stabilization is achieved more rapidly and with smoother actuation than in baseline controllers, highlighting the effectiveness of anticipatory, drift-informed intervention.

The ablation and failure analyses further clarify the mechanisms enabling this behavior. Structural physical adaptation emerges as a key factor in reshaping system dynamics and reducing reliance on high-frequency input control, while data assimilation plays a critical role in mitigating non-stationary drift. The explicit inclusion of failure scenarios demonstrates that system performance remains bounded by physical feasibility, reinforcing the realism of the proposed framework and avoiding overstated claims of robustness.

Overall, the findings suggest that building energy systems operating under climate-driven uncertainty may benefit from a shift away from performance-centric optimization toward continuous stability management. Embedding decision authority and adaptive behavior within digital twins provides a viable pathway for maintaining reliable operation under conditions that exceed traditional design assumptions.

6.2. Limitations and Future Work

Several limitations should be acknowledged when interpreting the results of this study. First, the evaluation is conducted entirely within a controlled simulation environment based on calibrated, reduced-order thermal models. While this setup ensures reproducibility and enables systematic comparison, real-world deployment may introduce additional complexities, including communication delays, sensor faults beyond modeled drift, and unpredictable occupant interactions. Future work should focus on validation using field data and hardware-in-the-loop experimentation to assess performance under operational conditions.

Second, the structural physical adaptation mechanism is implemented at an abstract level through effective thermal parameter modulation. This abstraction is intentionally adopted to maintain generality and avoid dependence on specific technologies. However, translating this concept into physical systems will require investigation of feasible implementation pathways, as well as analysis of associated energy costs, response times, and long-term durability.

Third, the stability envelope is defined using fixed thresholds selected a priori. While this approach supports transparency and ensures fair comparison across controllers, it does not account for context-dependent preferences or evolving operational objectives. Future research may explore adaptive or learning-based envelope definitions that reflect user comfort preferences, energy pricing signals, or long-term system health considerations.

Finally, although the proposed framework demonstrates strong performance under deep non-stationary uncertainty, it does not eliminate fundamental physical limits. In scenarios where stabilization becomes infeasible, the system transitions to controlled degradation rather than attempting destabilizing corrective actions. Extending the framework to coordinate with higher-level operational strategies, such as demand response or system-level optimization, may further improve resilience under extreme conditions.

Table 5. Simulation, comfort, envelope, and baseline configuration.

Item	Value
Simulation integration step $\left(Delta_{t_{sim}}\right)$	10 min
Supervisory control interval $\left(Delta_{t_{ctrl}}\right)$	10 min
Comfort reference temperature $\left(T_{ref}\right)$	24 °C
Comfort half-band $\left(Delta_{t_{comf}}\right)$	1 °C
Envelope quantile (q)	0.95
Envelope threshold for comfort deviation $\left(J_{c_{max}}\right)$	10 °C·h
Envelope threshold for oscillation index$\left(J_{o_{max}}\right)$	1.30
Envelope threshold for drift energy $\left(J_{r_{max}}\right)$	120
MPC prediction horizon	24 h $\left(N_p = 144\right)$
MPC control horizon	2 h $(N_c = 12)$
MPC objective weights	$\left(w_T, w_E, w_{Delta_u}\right) = (1, 0.10, 0.01)$

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; collection, critical analysis, and interpretation of the literature; drafting, revising, and refining all sections; reviewed and approved the final version of the manuscript and 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; collection, critical analysis, and interpretation of the literature; drafting, revising, and refining all sections; reviewed and approved the final version of the manuscript and 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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