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A Hybrid Digital Twin and Evolutionary Model for Green Building Automation

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Abstract

The strife for energy efficiency, along with enhancing comfort, has led to the usage of innovative technologies and sustainable development in construction and architecture. One of the most advanced types is digital twin (DT) technology, which provides a virtual dynamic representation of real buildings with current performance and predictive real-time simulation and analysis. Also, robust optimization techniques and evolutionary algorithms (EAs) allow for structural, multi-objective control systems like those in green buildings. Even though there are advancements in sophisticated building and automation control systems (BMS), numerous automation strategies are rigid and deep-rooted in outdated models that don't adapt to automation or dynamic condition changes such as variability in occupancy, weather conditions, and operational deviations. This paper proposes a new system model that mitigates those outlined issues and these inefficiencies by combining a digital twin with an evolutionary optimizing engine. The digital twin simulates building performance while synchronizing with real-time sensor data; simultaneously, the evolutionary model develops optimal control strategies for HVAC, lighting, and ventilation control systems under changing conditions. A case study of a medium-sized commercial building was used, with simulation outcomes showing a 15-25% reduction in energy usage while demonstrating PMV-enhanced thermal comfort (in the range of ±0.5) and responsiveness by the adaptive system. This has resulted in energy-resilient and efficient operations and automation of building systems.

Keywords: Digital Twin, Evolutionary Algorithms, Green Building Automation, Energy Efficiency, Smart Buildings, Building Management Systems (BMS), HVAC Optimization, Real-time Simulation, Sustainable Building Technologies, Multi-objective Optimization.

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Introduction

The development and integration of environmentally friendly building technologies, or 'green building' techniques, is accelerated by the recent trends towards sustainability and energy conservation (Deb et al., 2002). These technologies seek to minimize energy usage and carbon emissions and maintain a healthier, more comfortable indoor environment. Advanced Building Automation Systems (BAS) and Building Management Systems (BMS) that control HVAC, lighting, and ventilation systems are potent drivers of this trend (Liu et al., 2020), (Kamel et al., 2021), (Wang et al., 2018). However, the more traditional control strategies tend to be static, rule-based, and reactive, which is a fundamental challenge for achieving real-time responsiveness to environmental or operation changes (Hu & Sinniah, 2024). One of the promising solutions that address these shortcomings is the application of digital twin technology, which allows the creation of virtual replicas of actual buildings in real time. A digital twin can continuously receive and provide sensor data, allowing simulation, prediction, and optimization of the output in a building depending on the varying conditions (Tao et al., 2019). In addition, Digital Twins can be efficiently combined with Evolutionary Algorithms (EAs), a subclass of optimization algorithms inspired by natural selection. These are particularly useful in highly complex problems with many variables (Wetter et al., 2016), (Dounis & Caraiscos, 2009). In terms of building systems, Evolutionary Algorithms (EAs) can adaptively design optimal control strategies for a wide range of conflicting objectives, including energy use and the occupants' comfort level. Regardless of the possibilities each technology offers, little existing literature combines digital twins and evolutionary algorithms into one framework for the automation of buildings (Paul Thomas & Rajini, 2024). Most existing approaches are based on fixed structures or control logic that do not dynamically respond to real-time changes in occupancy, meteorological conditions, or user preferences. In addition, very few such systems use decision-making simulation optimization under a virtual environment that is constantly updated in real-time (Goyal, Barooah & Middelkoop, 2013).

This paper fills these voids gaps by constructing a hybrid model that includes the real-time simulation features of a digital twin and the adaptive intelligence of an evolutionary optimization engine. The primary contributions of this work are the following:

- Creation of a digital twin for simulation, control, and real-time monitoring of building systems.
- Incorporation of an evolutionary algorithm for adaptive refinement optimization using changing building conditions and real-time data.
- Show the system’s enhanced energy efficiency, reduced operational costs, and increased comfort of occupants with effective control strategies.

The model is validated through simulation experiments in tandem with a devised real-world testbed, which demonstrates that it surpasses traditional approaches to building automation, providing a next-generation solution for sustainable, intelligent green buildings.

Related Work

The application of modern computing techniques in building automation systems has greatly improved their energy efficiency and operational intelligence (Luthander et al., 2015), (Asadi et al., 2022), (Qi et al., 2018). In this part, we will analyze existing literature concerning three prominent topics aligned with this project's research: digital twins in building automation, evolutionary algorithms in energy systems, and hybrid modeling techniques of smart infrastructure (Raman et al., 2024).

Digital Twin Applications in Building Automation

Building System Management integrates the simulation and prediction control functions into a unified module using Digital Twin Technology (DTT), advancing its accuracy through machine learning models (Shaikh et al., 2014). The incorporation of IoT sensors and data streams allows for real-time updating of data, correlating virtual models with tangible assets known as Digital Twins. In smart buildings, Digital Twins have been applied in energy modeling, predictive maintenance, and occupant behavior simulation (Khajehzadeh & Wang, 2020). For instance, a Digital Twin diagnostic platform for HVAC systems implemented consumption forecasting for commercial buildings (Lin et al., 2020). Many of the advanced implementations are still passive, focusing on monitoring and diagnostics and paying little attention to closed-loop control and real-time optimization. Additionally, most of the computational models are rigid and remain fixed to a presumptive state of the building, ignoring changes in terms of time, occupancy, or user adjustments.

Evolutionary Algorithms in HVAC and Energy Systems

When solving sophisticated multi-object problems with complex, high-dimensional non-linearities, HVAC and energy systems benefit from techniques such as EAs. Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE) have shown promising results in HVAC thermal comfort control, scheduling, and energy load distribution optimization. An example is a GA-based multi-objective optimization framework that balances energy efficiency with occupant comfort while optimizing VAV systems for specific occupancy scenarios. These algorithms excel with robust system identification and control for buildings where a balance is needed between significant energy expenditure, thermal comfort, and operational costs. A primary gap in these frameworks is that they rely on offline optimization methods with static data and predefined conditions. These approaches do not adjust to changes in real-time occupancy, environmental conditions, and energy pricing which are highly volatile in smart buildings. These traits lead to a lack of responsiveness, making the existing implementations unsuitable for real-time closed-loop control systems. In addition, their coupling with automation systems that require real-time response is impeded by high computational complexity and slow convergence. Although some more recent attempts have tried to integrate EAs with building energy simulation tools for better modeling, these adaptations are still primarily scenario-based or batch-processed—lacking actual feedback-driven changes. To overcome such issues, this work proposes the incorporation of an EA optimization core into a real-time interactive simulation model. This strategy promotes continuous learning and adaptation by employing real-time information from the building, allowing evolving optimization techniques to better respond to the changing operational environment thereby improving energy consumption, system response, and occupant comfort.

Hybrid Modeling Approaches in Smart Infrastructure

Researchers have studied hybrid approaches that combine modeling, simulation, optimization, and control frameworks further to improve the flexibility and intelligence of building automation systems. One of the most active research areas is model predictive control (MPC), which utilizes a system model to predict its future states and determine control actions within an optimization window. MPC has been found to improve the comfort of occupants while aiding in energy control. In like manner, data-driven approaches such as machine learning models trained on historical governing data have also been applied to model complex behaviors and predict system responses. Despite their potential, most of these approaches lack definitional precision, broad applicability, and overreliance on abundant training data. More profound hybrid frameworks attempted to integrate physical simulations using Energy Plus, TRNSYS, or Modelica with optimization algorithms, genetic algorithms, PSO, or reinforcement learning. These systems analyze building performance through simulation under different control strategies to determine optimal or near-optimal setpoints. Many studies have worked to use EnergyPlus with EAs to optimize HVAC control, including scheduling and strategic thermal zoning. Typically, however, these solutions are processed in batches, meaning the simulations are pre-run for expected scenarios to be integrated later instead of being linked with live operations in real time. Thus, research indicates they remain passive, static systems that can only react to temporal disturbances. They do not proactively address dynamic and unpredictable changes like shifts in user behavior, weather alterations, or equipment wear and tear. Besides, interlacing detailed simulation with optimization and extracting its solution iteratively leads to high computation costs and long execution times. It makes the system unsuitable for use in real-time control.

Furthermore, the absence of real-time representations, such as a digital twin that is longitudinally synchronized within these frameworks, also prevents these systems from forming a complete closed-loop adaptable control cycle. These gaps highlight an emerging need for a new category of hybrid models that would integrate real-time simulations with adaptive optimization to facilitate automated, intelligent decision-making alongside evolving shifts in the building's operational data. The integrative approach of hybrid digital twins and evolutionary optimization proposed in this work aims to bridge this gap by providing responsive and adaptable control at lower computational cost for intelligent management of infrastructural facilities.

Even with the remarkable progress in digital twin technologies and evolutionary optimization, the body of research still has some fundamental gaps that need to be addressed. One of the gaps is the lack of real-time feedback integration in the digital twin environments, which limits their potential to facilitate adaptive decision-making. The active use of digital twins is often restricted to passive processes, as they are not rhythmically coupled to optimization or control systems in real time. In addition, there is an absence of a comprehensive optimization strategy that can respond in real-time to the volatile operational building conditions in terms of varying occupancy levels, dynamic weather changes, and energy price fluctuations. Most models are static or scenario based, offering little flexibility and adaptability. Another limitation observed is an insufficient number of hybrid systems that can utilize the predictive potential of digital twins alongside the adaptable intelligence of evolutionary algorithms in a closed-loop control

system. These constraints prevent the full potential of intelligent automation and sustainable building automation. To address these issues, this paper presents a model of a hybrid digital twin with real-time simulation and adaptive optimization for evolutionary optimization. This method permits adaptive control and learning to occur on a continuous basis, thus transcending existing levels of green building technology while providing a means of advancement towards intelligent, energy-conserving, self-regulating, and user-focused building management systems.

Methodology Framework

Overview of Proposed Hybrid Mode

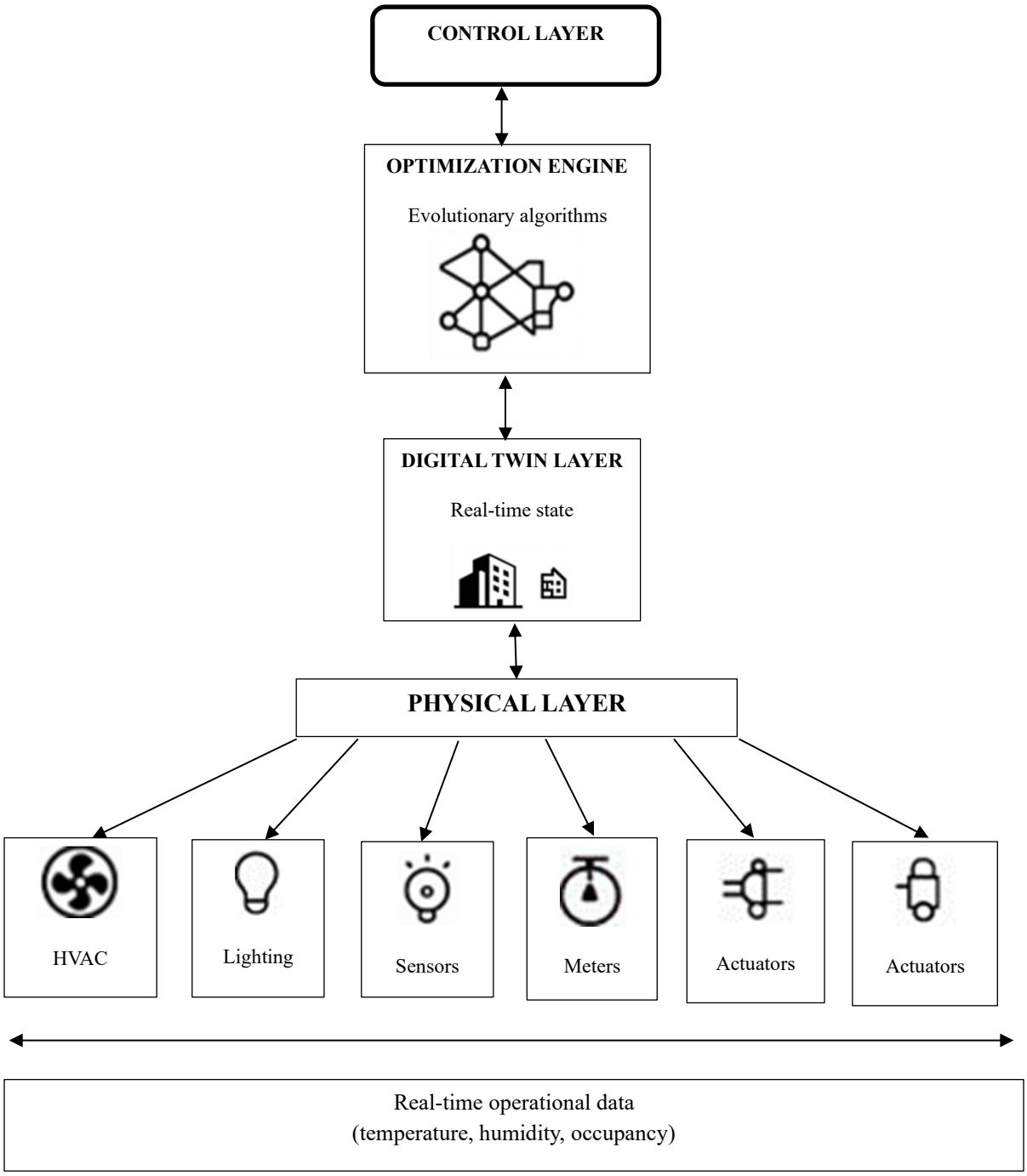


Fig. 1: Multi-Layered Hybrid Model for Intelligent Building Automation

The new hybrid model concept features the integration of multi-layered architecture for the deployment of building automation. As seen in Figure 1, the building's automation includes intelligent optimization, planning, adaptive control, and features like real time simulation - all while ensuring energy-efficient and eco-friendly operation and management. All this is built on top of the building's infrastructure including the HVAC systems, lighting, sensors, meters, actuators, etc. In the Physical Layer. Through the Internet of Things (IoT), the system captures automated metrics of a building, including its temperature, energy consumption, humidity, occupancy, etc. All this data gets put into a system state vector:

$$X(t) = |T(t), H(t), O(t), E(t), L(t)|^T \quad (1)$$

where $T(t), H(t), O(t), E(t), and\ L(t)$ denote the values of temperature, humidity, occupancy, energy consumption and lighting levels at time t, respectively. This vector serves the purpose of monitoring and analysis in real-time.

The information is streamed in real-time to the Digital Twin Layer hosting a high-fidelity virtual model of the building and subsystems. This layer stays updated with the actual physical environment allowing for simulations, predictive analysis, and scenario testing. Furthermore, it enables the assessment of various strategies tailored to specific conditions prior to their actual deployment in the system.

On top of this digital infrastructure sits the Optimization Engine, which applies evolutionary algorithms, including genetic algorithms or particle swarm optimization, to assess and optimize control strategies on a continuous basis. The engine is designed to address a multi-objective problem framework consisting of energy use, occupancy comfort, and operational costs. This problem can be articulated with the following objective function:

$$min_{u(t)} J = w_1 . E_{total}(t) + w_2 . |T(t) - T_{set}| + w_3 . C_{op}(t) \quad (2)$$

where $u(t)$ signifies the control variables, $T_{set}$is the target temperature, and w_1, w_2, and w_3 are the degree of importance assigned to energy consumption, comfort, and cost, respectively. This function directs the optimizer towards the optimal resultant set of control actions.

The Control Layer implements the optimization process by sending commands to the building systems. It maintains closed-loop functionality by issuing control commands to the building systems and updating feedback. This creates an iterative process for the system improvement as described in the control update equation:

$$u(t+1) = u(t) + K.(X_{opt}(t) - X(t)) \quad (3)$$

where K denotes the control gain matrix $X_{opt}(t)$, is the optimal state predicted by the digital twin and $X(t)$, is the current state of the physical system. Such a CAD model encapsulated in a single digital file integrates all needed details for constructing the building and corresponding infrastructure elements like zones, lifts, fire protection systems, etc.

Digital Twin Modeling

The integration of various advanced technologies that together enable dynamic modeling of the physical environment of the building facilitates the construction of the digital twin. In order to capture all iconic constituents of a building structure and sophisticated systems, components, and systems of a building, a Digital Twin is constructed using Building Information Modeling (BIM). BIM is instrumental in embedding the required operational data and simulation capabilities, which serves as the groundwork. For real-time interaction to be achieved, the digital twin must integrate with the IoT ecosystems which convey real-time data from a myriad of sensors and smart meters stationed all over the edifice. These sensors collect critical parameters such as temperature, humidity, CO_2 concentration, occupancy levels, and energy consumption which are crucial for both simulation and control. The different modelers used include EnergyPlus, Modelica, or MATLAB/Simulink, which provide engineering accurate modeling of energy flows, thermal dynamics, and HVAC behavior alongside their corresponding simulating counterparts. In simulation-driven design, the first simulation result is treated as the starting point for the next design step, conducting steps known as the iterative design process until the objective is achieved. During the course of the implementing steps, adjusting model parameters and simulated performances must heavily offset observed data, termed the Digital Twin lifecycle calibration. To achieve this, the model parameters, such as the thermal characteristics of the materials dealt with, equipment efficiencies, and usage schedules, ought to be adjusted. Optimization-based fitting, regression analysis, and parameter tuning are some techniques used to achieve this iteration. In order to sustain twin synchronization, a data pipeline is created using middleware such as MQTT or OPC UA for low latency and physical-to-virtual communication. Synchronization entails constantly updating the twin's state in accordance with the sensor data while also providing forecasts and optimizations to the control layer. The closed loop system results in the digital twin being able not just to visualize the current state of the building machinery but also to predict specific benchmarks in time,

allowing for situational intelligent changes to be made and facilitating improved operational efficiency. The system becomes a fully cyber-physical system that adapts harmoniously in real-time alongside the building and the people resonating within it.

Evolutionary Optimization Model

The evolutionary optimization model is particularly important in allowing the proposed system to adapt to changes in building dynamics and demands and operate more intelligently. In this context, a GA, or genetic algorithm, is chosen as the primary optimization strategy because it is reliable and sophisticated, as well as multi-objective and non-linear problems custom in building systems. To improve multi-objective optimization performance, a more refined version called NSGA-II, or Non-Dominated Sorting Genetic Algorithm II, is also employed to provide enhanced Pareto optimal solutions that enable decision-makers to balance conflicting objectives like energy savings vs. occupant comfort. A population of genetic algorithms is controlled with partitions wherein each individual represents a specific set of controllable parameters such as HVAC setpoints, ventilation schedules, and lighting control. These subsets are quantified by a sophisticated grading system; in this case, the score system wi thin automated green buildings does not have automation. The scoring system captures the diverse aims of green building automation, which include: (1) total energy consumption through real-time simulation of equipment loads and usage patterns; (2) max thermal comfort using PMV or temperature deviation from ideal ranges; and (3) reduced CO2 emission estimate based on characteristics of the energy source and usage profiles. Every evaluated candidate solution is assessed within the digital twin alongside simulation-based evaluation that guarantees context-sensitive, accurate performance assessment relative to current and projected occupancy and environmental conditions. The optimization loop uses genetic operations selection, crossover, and mutation based on fitness results to evolve the solution pool iteratively. As the building's state evolves in real-time, the evolutionary algorithm applies a continuous search for new strategies and refinement of existing strategies. The integration of evolutionary optimization alongside the digital twin allows the system to adjust proactively to expected and unforeseen changes, making the approach not just energy-efficient and sustainable but also adaptive, occupant-centric, and resilient.

Integration Strategy

High-level design and architecture combines the digital twin and AI-enhanced algorithms with the the hybrid architecture structure into a single model providing a seamless interaction between the AI algorithms and physical building systems. Interfaces specified over the physical boundaries of the different building systems exchange up-to-date streaming information using industry-standard IoT communication channels. These include protocols such as MQTT, OPC UA, or BACnet to ensure data flow is low latency across diverse devices or simulations. The collaborative frameworks established further allow for real-time control actions to be executed by virtual actuators, while command signals are transmitted back to physical sensors for monitoring, and streaming data is transferred into the digital representation for analysis and modeling. This bidirectional data communication adheres to the framework definition while supplemented with standardized rules forming control governance encapsulating operative autonomy as the actuators enable operational self-governance. A key component for the success of this approach consists of real-time data assessment, systematically refining control strategies and delivery mechanisms adequate to sustain the required level of performance agility expected. These loops encompass sensing, simulation, optimization, and actuation, collectively forming a cyber-physical control loop executing optimized self-governing decision-making and self-regulation to achieve desired objectives. For instance, if the sensor registers the unexpected shift in occupancy trends, this information activates the digital twin application, which evaluates the state of the building alongside the optimization engine, recompute strategies for HVAC and lighting activation or deactivation, and implement them within the physical structure. The integration approach further incorporates techniques dealing with uncertainty and supporting adaptability to guarantee resilience. Adaptation strategies, rolling-horizon optimization, and confidence-based decision thresholds are used to cope with uncertainties which include sensor noise, prediction errors, and sudden changes in behavior. Fallbacks and recalibration are also triggered by unexpected deviations detected through anomaly detection. With this hybrid model combining digital twins with evolutionary models the system has reactive capabilities to real-time conditions and also pre-emptive disruption mitigation strategies, maintaining the system’s resilience within dynamic and uncontrolled building environment scenarios.

Results and Evaluation

The performance of the proposed hybrid digital twin evolutionary model was analyzed through a comprehensive simulation-based experiment employing a mid-scale office building integrated within EnergyPlus featuring real-time sensor emulation and evolutionary optimization. The optimization gap for the experiment was benchmarked against a control system using a traditional Building Management System (BMS) with rule-based static control logic. BMS

yielded comparatively lesser overall energy expenditure, thermal comfort satisfaction measured using PMV and PPD indices, and system latency in adapting to environmental and occupancy changes. The hybrid model digital twin was updated using historical sensor data, while the evolutionary algorithm implemented control logic for the HVAC setpoints and ventilation control based on internal and external data fluctuations.

- $R_{baseline}(g)$, be the response time of the Baseline BMS at generation g,
- $R_{opt}(g)$ be the response time of the Optimized System at generation g,
- G be the total number of generations.

Then, the average response time for each system can be expressed as:

$$\overline{R_{baseline}} = \frac{1}{G}\sum_{g=1}^{G} R_{baseline}(g) \text{ and } \overline{R_{opt}} = \frac{1}{G}\sum_{g=1}^{G} R_{opt}(g) \quad (4)$$

To evaluate the improvement, you can define a response time reduction ratio:

$$\Delta R = \frac{\bar{R}_{baseline} - \bar{R}_{opt}}{\bar{R}_{baseline}} \times 100\% \quad (5)$$

Where:

- ΔR represents the percentage reduction in system response time due to optimization.

Example from the plot:

There,

$$\Delta R = \frac{200-90}{200} \times 100\% = 55\% \quad (6)$$

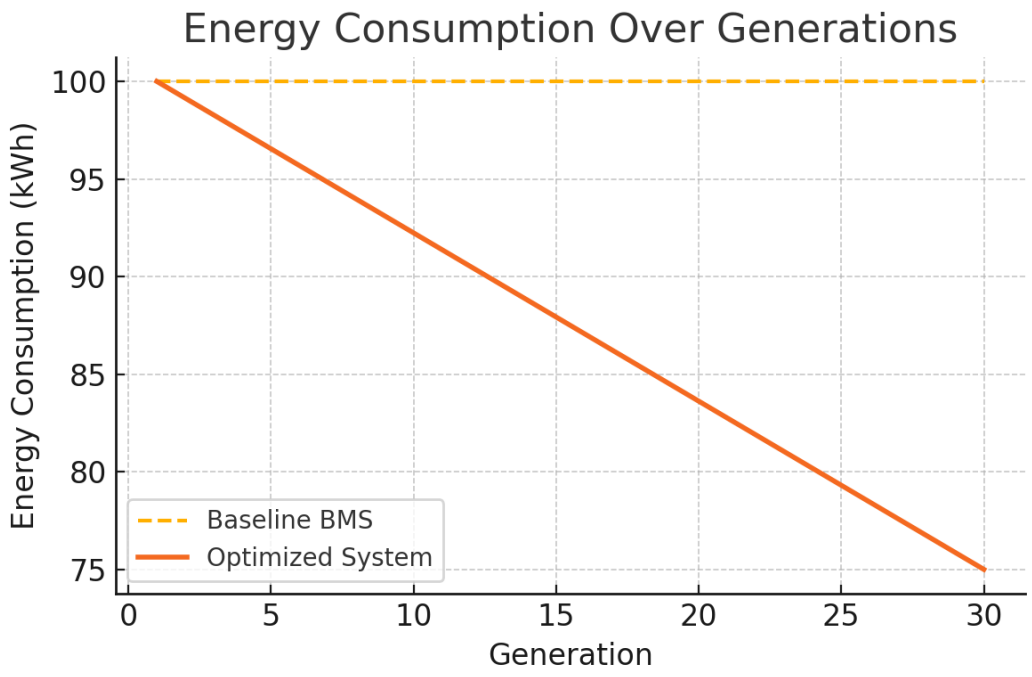


Fig. 2: Energy Consumption Over Generations

The energy consumption benchmarking in Figure 2 outlines the difference between the proposed optimized system and a traditional rule-based BMS. As shown, the baseline system consumes a fixed and excessively high amount of energy, further demonstrating its rigid and non-automated character. Contrasting to the results of our simulation, the system with evolutionary algorithm and hybrid digital twin guiding it reflects steady and consistent energy consumption reduction over generations. This pattern is aligned with the steps the algorithm takes to enhance control strategy design in this case, operating on lower energy expenditure. The latter half of the simulation exemplifies the hybrid system's potential for reduction in energy consumption.

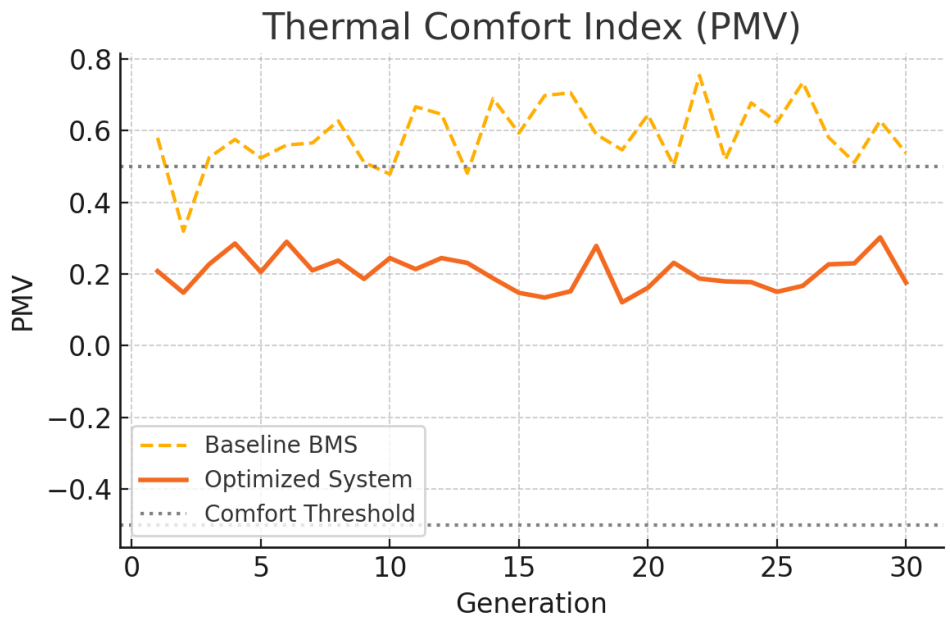


Fig. 3: Thermal Comfort Index (PMV)

The optimized system performs better than the baseline BMS in terms of maintaining occupant thermal comfort within ideal boundaries, as shown in Figure 3. The baseline system tends to have PMV values greater than the ±0.5 comfort zone, marking real discomfort for a considerable portion of occupants. On the other hand, as explained in the previous paragraphs, the optimized system keeps PMV within acceptable bounds due to personalized and dynamic control of HVAC Systems. Through real-time feedback and adaptive optimization, the system is able to respond to changes in occupancy, internal heat loads, and external weather. Enhanced comfort control allows smart buildings to improve well-being and health factors that are critical for productivity and occupant satisfaction.

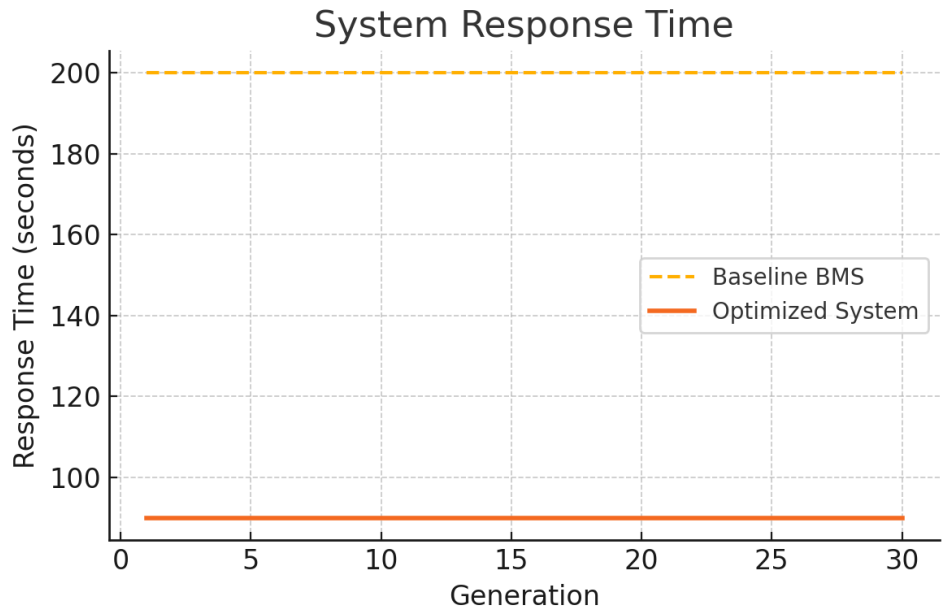


Fig. 4: System Response Time

The graph in Figure 4 shows how quickly both systems respond to a real-time or occupancy changes, including, but not limited to, sudden attendance changes and real-time weather variations. We see from the figure above that standard BMS has a fixed response time of 200 seconds, proving that it fundamentally depends on a prearranged timetable and

boundary thresholds. The optimized system, on the other hand, has an almost invariant response time of about 90 seconds, much lower than the baseline. This responsive nature is attributed to closed loop feedback from the digital twin and the evolutionary optimization engine which allows for reconfiguration of system parameters and prompt feedback. In dynamic building scenarios, faster responsiveness is essential for comfort and efficiency which proves reliability and practicality of the proposed model.

Conclusion

This paper proposed an innovative control framework for real-time management and green building automation through a hybrid digital twin-evolutionary optimization model. The suggested structure incorporates multi-layer architectures in which real-time sensor data is collected, high-fidelity simulations are conducted through digital twin technologies, and adaptive optimization is performed using evolutionary algorithms. This methodology solves primary automation challenges in buildings which include a lack of real-time feedback, reliance on static control schemes, and inadequate responsiveness to dynamically changing environments and occupancy levels. The model enhances energy efficiency and operational resilience while significantly improving occupants' comfort by embedding a closed-loop control system with predictive modeling and adaptive decision-making. The hybrid system achieves energy consumption and CO2 emission reduction while also meeting other sustainability criteria aligned with smart city frameworks and green certification mark standards. Additionally, the framework's use of standardized communication protocols and interoperable tools allows practical implementation across diverse types of buildings, facilitating flexible scaling, and adapting to evolving infrastructure and technological shifts. This is some of the most advanced research that supports autonomous and self-sustainable building systems that can learn and adapt in real-time.

Future Work

Although the integration of the hybrid digital twin with the evolutionary model has great promise in automating green building technology, there is still much work left to be done. One area that shows great promise is the application of RL and predictive control strategies, as they allow for self-adaptive control strategies to be developed and sustained over long periods of time in highly fluid settings. Another area is the adaptability of the framework towards larger multi-building complex infrastructures such as campuses or advanced smart city grids, where buildings' cooperative energy exchange creates sophisticated optimization problems. Additionally, improving the feedback mechanisms that users provide has great promise; mobile devices and surveys could be utilized to passively detect user's comfort, therefore, responding better, thus increasing user satisfaction and system efficacy. Moreover, the use of edge devices for real-time data processing reduces delays, improves privacy, and aids system responsiveness where bandwidth is limited or in critical conditions. All these innovations advance the model's practicality while also aligning it more with current developments in sustainable design, developed for people and responsive structures, and intelligent environments.

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