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HYBRID CCO–SWO OPTIMIZATION FRAMEWORK FOR NET-ZERO SMART BUILDING ENERGY CONTROL

M. RAJKUMAR[1], Dr. V. GOKULA KRISHNAN[2,*], Dr. P. JESU JAYARIN[3], R. SENTHILKUMAR[4], Dr. KARNAM SREENU[5], Dr. S. KAVIARAAN[6]

[1]PG Scholar, Department of Computer Science Engineering, Easwari Engineering College, Chennai, Tamil Nadu, India
[2,*]Professor, Department of Computer Science Engineering, Easwari Engineering College, Ramapuram, Chennai, Tamil Nadu, India
[3]Professor, Department of Computer Science Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, Tamil Nadu, India
[4]Assistant Professor, Department of Computer Science Engineering, Sri Venkateswara College of Engineering, Sriperumbudur, Tamil Nadu, India
[5]Assistant Professor, Department of Information Technology, Aditya University, Surampalem, Andhra Pradesh, India
[6]Assistant Professor, Department of Computer Science Engineering, School of Computing, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, Tamil Nadu, India

Email: [1]rajkumar.mcseb@gmail.com, [2,*]gokul_kris143@yahoo.com, [3]jesujayarin.sse@saveetha.com, [4]senthilkumar_r@svce.ac.in, [5]karnam.sreenu@gmail.com, [6]arasan.kavi@gmail.com

ABSTRACT

It is hard to get smart buildings to operate on net-zero energy mainly because energy consumption, occupant comfort, and renewable energy integration are nonlinear, multi-objective, and dynamic. Traditional optimization and rule-based control methods do not solve the problem effectively as they are less adaptive to changing environmental conditions and complex system interactions. As a result, they lead to suboptimal performance and increased reliance on the grid. In that regard, the present paper introduces an innovative hybrid metaheuristic optimization tool that combines the Centered Collision Optimizer (CCO) and Spider Wasp Optimization (SWO) for adaptive and real-time energy management. This new tool uses a variance-driven switching method to constantly adjust the balance between global exploration and local exploitation, thus preventing early convergence and improving the quality of the solution. Among other methods, the proposed CCO-SWO model has been shown to significantly outperform standard methods such as PSO, GWO, and HHO in EnergyPlus and MATLAB simulations. The report reveals a 31.5% drop in total energy consumption, a 41.3% less reliance on the grid, and an enhanced level of thermal comfort with a deviation of only 0.94C, whereas the high Net-Zero Index (NZI) of 0.96 was also maintained. These results prove the proposed framework as a highly efficient, reliable, and versatile approach for intelligent energy controlling in smart buildings strongly supporting sustainable and net-zero energy system deployment.

Keywords: *Smart Buildings, Net-Zero Energy, Hybrid Metaheuristic Optimization, Centered Collision Optimizer, Spider Wasp Optimization, Energy Management Systems, Sustainable Buildings.*

1. INTRODUCTION

Smart buildings are at the center of sustainable development because to the fast expansion of cities and the rising need for energy-intensive infrastructures [1]. Heating, ventilation, and air conditioning (HVAC) systems, lighting, and ancillary equipment in buildings are the main culprits responsible for the vast majority of the world's carbon emissions and energy consumption [2]. Therefore, a major goal of contemporary energy policy and smart city projects is to achieve net-zero energy buildings, where renewable generation equals yearly energy usage [3].

On the other hand, operating a net-zero building is fundamentally difficult. Several factors impact energy use, including unpredictable patterns of occupancy, changing weather conditions, intermittent power supply from renewable sources, and closely related control variables. Such nonlinear and multi-objective settings [4-5] are difficult for traditional rule-based controllers and deterministic optimisation methods [5] to adapt to. Additionally, optimisation approaches that rely on gradients tend to converge to local optima and aren't very resilient when the dynamics of the system undergo sudden changes [6].

Because of their adaptability and lack of derivatives, recent developments in metaheuristic optimisation have shown encouraging outcomes for building energy management [7]. PSO, GWO, and HHO were studied in [8] to find out how to schedule and balance loads in HVAC systems. Even though these methods make energy use more efficient, they often have problems with performance that isn't steady, slow exploitation, or convergence that happens too soon when the problem dimensionality increases [9–10].

Smart buildings have made gains, but net-zero energy still feels out of reach. The indoor world shifts too fast, people move, weather changes, solar output wobbles. Most current methods cut energy use, but don't handle comfort, grid load, or solar gain at the same time. In real life, those variables pile up. A system that stays steady and smart must adapt in real time without breaking down. So we need tweaking models that watch the environment and respond without hesitation. Some approaches stay stuck too early. Others move slowly through possible solutions. High-dimensional control problems make them unstable. The result? Poor performance when it matters most.

Despite many research endeavors into smart building energy management, figuring out how to operate at net-zero energy consistently and reliably is still a big problem that has great practical implications. This is mainly because building energy systems are very complex by nature and involves many nonlinear interactions among the thermal dynamics, occupant behavior, renewable energy generation, and control variables. Theoretically, this results in a high-dimensional, non-convex, and multi-objective optimisation problem where the conventional deterministic and single-strategy methods are hardly able to find the globally optimal solutions.

In addition, although metaheuristic methods offer better flexibility, their performance tends to deteriorate noticeably when operating in such highly complicated settings. For example, problems like early convergence, failure to effectively trade-off between exploration and exploitation, and high dependence on parameter adjustment reduce their suitability for real-time smart building applications. That being said, these problems indicate that the issue is not only the computational aspects but that deeply changes the very concepts and therefore require optimisation designs that not only withstand variations in the system but are also stable and reliable in convergence.

In response to these problems, this work proposes an entirely new approach to optimisation that merges the Centered Collision Optimizer (CCO) with the Spider Wasp Optimisation (SWO). Such a combination was decided upon due to the fact that the two algorithms are highly compatible with each other. CCO facilitates the effective navigation of the high-dimensional energy control space through the use of centroid-based collision dynamics, which are a means of structured exploration of the space as a whole. On the other hand, SWO enables almost perfect adjustment of potential solutions by using an adaptive exploitation strategy drawn from the predator hunting behavior.

The proposed system uses a variance-driven adaptive switching system, setting it apart from traditional hybrid methods that simply combine optimizers one after another. This framework guarantees the system's effectiveness under different energy demand scenarios by allowing the optimization process to move naturally between the exploration and exploitation stages, depending on the diversity of the population. The system at the BEMS level, where sensors, actuators, and renewable energy sources are installed, engages directly with the framework.

In this paper, the authors identify three main contributions: first, a mathematically rigorous hybrid CCO-SWO optimization strategy for zero-energy smart building control; second, a joint optimization objective that minimizes grid energy consumption, carbon emissions, and thermal discomfort simultaneously; and third, a detailed comparative study with popular metaheuristic techniques [10].

In response to challenge the above, this paper puts forward a hybrid optimisation framework that combines Centered Collision

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Optimizer (CCO) and Spider Wasp Optimization (SWO). The proposed method uses the centroid-driven exploration ability of CCO to perform efficient global solution space search, whereas SWO provides the adaptive exploitation by the local search mechanism inspired by the predator. Besides that, a variance-based adaptive switching strategy is proposed to dynamically regulate the exploration-exploitation transition depending on the population diversity. This feature allows the framework to be stable during the early program stages while also making sure that the convergence rate is fast in the later stages.

So, this study mainly tries to answer this question: What would be the design of an adaptive, robust, and scalable optimisation framework that is able to efficiently handle multi-objective, nonlinear, and dynamic energy control processes in smart buildings to achieve near net-zero energy operation under real-world uncertainties?

Besides making buildings more energy-efficient, solving this issue will also pave the way for sustainable and intelligent building infrastructures that can operate autonomously with very little reliance on the grid. In fact, the hybrid CCO-SWO framework that this paper puts forward is a direct reply to this challenge, a step towards a solution that is both well-grounded theoretically and feasible practically.

On a hybrid scheme basis, the proposed framework offers a methodical and scalable solution to the challenge of controlling energy in a smart building in real-time and hence overcomes the drawbacks of the current optimisation methods that achieve net zero energy objectives in a more reliable way.

Here is the breakdown of the remaining sections of the paper: The relevant literature is discussed in Section 2; the suggested model's process is detailed in Section 3; Section 4 delves into the examination of the results, and Section 5 concludes the work.

2. RELATED WORKS

In order to ensure that users are able to compare prices, have an efficient system, and have a positive associates-client experience, Ismail-Badmus et al. [11] utilized third-party data, energy market analysis, electric vehicle (EV) analysis, building appliance life-cycle cost assessments, and renewable energy system kits. With an eye on future urban renewable energy deployment, sustainability certifications, and realistic, scalable net-zero energy management for smart building designs in deregulated energy markets in Canada, the US, and Nigeria, this study offers a way forward.

In order to reach zero energy consumption, Ayaz, F., et al., [12] suggest a method for optimal energy management that makes use of renewable resources and electric vehicles. To assume that EVs engage in a two-way flow of energy from the grid to their vehicles. Through a 5G communication network, renewable energy production, electric vehicle demand, and supply are all intelligently forecasted and shared with the grid. One way to save costs is to adjust grid supply based on the number of electric vehicles on the road. This study explores the optimal number of charging stations, uses game theory to encourage EVs, and examines the upper limits of EV demand and supply. The suggested approach lowers the grid load by 38.21% and costs 5.3% less, according to the results.

According to research by Euston-Brown et al. [13], four of South Africa's largest cities have signed the C40 Net Zero Carbon Buildings Accelerator (previously called the C40 net carbon buildings declaration) from 2018 and have Climate Action Plans that are in line with the goals and objectives of the Paris Agreement. Research outlining the significance of cities in attaining this goal informed these global, sub-national commitments, which seek to increase ambition to limit the world average temperature rise to 1.5°C, instead of 2°C.

In order to integrate data during the O&M phase of NZEB and achieve efficient management, Liu, Z., et al., [14] suggests an O&M digital twin modeling technique. Data gathering, model building, simulation analysis, and validation iteration make up the twin Modelling process. By improving the utilization efficiency of O&M data, the suggested twin model allows for easier perception, visualization, and automatic feedback control of NZEB, according to the empirical evidence. For O&M managers aiming for efficient NZEB O&M management, the suggested digital twin modeling approach provides technical advice.

An updated summary of authorized reports and academic research is provided by Luo, D., et al., [15], which focuses on renewable energy-electrical energy storage systems for smart net-zero energy buildings. To show that there has been significant growth in emerging markets, we look at the worldwide installed capacity, pricing, besides governmental backing of different renewable energy-electrical energy storage solutions.

Following this, to deliver a concise overview of recent developments in the field of net-zero energy buildings that use a combination of renewable energy sources besides electrical energy storage systems. These developments cover topics such as demand side management, grid response, flexibility, and electrical energy storage. To further enhance the utilization of renewable energy-electrical energy storage technologies in buildings, to also examine energy management transactions and grid integration for smart buildings through the lens of cutting-edge technologies such as blockchain, artificial intelligence, the Internet of Things, and peer-to-peer trading. Research like this bodes well for the development of smart net-zero energy building systems that combine renewable power with electrical energy storage. With respect to the worldwide development status, the implementation of smart approaches, and the use of renewable energy-electrical energy storage systems in buildings, it offers an in-depth analysis that can serve as a roadmap for zero-energy and zero-carbon structures.

Chen, S., et al., [16] proposed a novel general energy-aware framework with multi-modal information and multi-task coordination for smart management in energy systems. By redistributing feature placements according to similarities, an adaptive transformation approach was introduced to turn multi-modal data into a generic format. The suggested energy-aware framework took generalized multi-modal data as input, extracted features using a progressive vision backbone, and then generated results for various energy tasks. In order to coordinate the convergence rates and magnitudes of losses among various energy-related tasks, the adaptive loss weighting method was suggested. A series of experiments were conducted in practical energy systems to validate technical feasibility of proposed energy-aware framework. For multi-task learning, their performance metrics for predictive maintenance, energy prediction, and control optimisation were 0.994, 0.942, and 0.945, respectively. For single-task learning, their metrics stay generally consistent at 0.990, 0.920, and 0.952. By implementing adaptive transformation, the model's performance can be enhanced by 7.19%. In addition, the suggested energy-aware model beat standard ML and DL algorithms in a battery of comparative tests. In order to help achieve net-zero emissions in energy systems, our study aims to create a more versatile and universal deep learning model for smart management that can save energy and guarantee security.

A hybrid metaheuristic optimisation framework that adaptively integrates global exploration (through Centered Collision Optimizer) and local exploitation (through Spider Wasp Optimization) with a variance-driven switching mechanism has a great potential to not only drastically improve energy efficiency but also reduce dependence on the grid, and improve thermal comfort in smart building energy management systems when compared to traditional independent optimisation approaches.

A main basis of this idea is the widely accepted fact that dynamically adjusting the balance between exploration and exploitation can lead to better convergence and solution quality in multi-objective optimisation problems. This new CCO-SWO approach aims at proving the correctness of this assumption by means of systematic modeling and experiments.

The primary contributions of this paper are as follows:

1. Hybrid Framework - We have developed a hybrid CCOSWO optimisation model for smart building energy management.
2. Adaptive Strategy - We have proposed a variance-based switching method that helps to maintain the right balance between exploration and exploitation.
3. Multi-Objective Design - We have designed an objective function with energy, comfort, and grid dependency aspects.
4. Performance Validation - We have done a comparative study that showed our proposed method's efficiency and convergence improvements over the baseline ones.
5. Practical Relevance - Our scalable framework is apt for net-zero smart building applications in real-time.

This research concentrates on designing and evaluating, by means of simulation, a hybrid metaheuristic optimisation framework for smart building energy control. The main characteristic of the proposed method is solving multi-objective problems that relate to the amount of energy consumption, reliance on the grid, usage of the renewable sources, and the thermal comfort through the simulation environment. On the contrary, this paper excludes the real-world implementation, hardware-level operation, and integration with the live building management systems. Besides, the work does not cover real-time pricing, occupant behavior modeling at a large scale, and multi-building energy coordination. These issues are

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considered to be the main directions of the future work.

3. PROPOSED HYBRID METAHEURISTIC FRAMEWORK FOR NET-ZERO SMART BUILDING CONTROL

This study uses simulation-based experimental research design, a familiar method in the areas of smart energy systems, optimisation research, and modeling of cyber-physical systems. In this method, the suggested optimisation framework is tested in controlled simulation environments via standard building energy modeling tools and benchmark optimisation algorithms. Similar experimental designs have been used in previous studies in the areas of smart grid management, intelligent HVAC control, and energy systems with renewable integration, where real world testing is limited by cost, scalability, and risks of operations.

Besides, this paper adopts a comparative performance evaluation method, where the introduced hybrid CCOSWO framework is regularly contrasted with the well-known metaheuristic algorithms such as PSO, GWO, and HHO. This set up allows for a fair measurement of progress in energy efficiency, grid dependency, thermal comfort, and convergence behavior [17].

3.1. System Overview and Design Rationale

Smart buildings nowadays are more like dynamic cyber-physical systems that constantly balance energy consumption, occupant comfort, renewable integration, and emission limits. They are no longer passive energy consumers. Due to the multi-objective, nonlinear, and stochastic character of building control variables such as HVAC operation, lighting schedules, thermal storage, and on-site renewable utilization, it is tough to achieve net-zero energy operation in such contexts.

Under unpredictable occupancy patterns, changing weather, and renewable intermittency, traditional optimisation methods based on rules or gradients do not work. Therefore, the suggested system uses a hybrid metaheuristic optimisation approach to simulate the exploration-exploitation trade-offs in control spaces with a high degree of dimension.

A hybrid center-centered collision optimizer-spider wasp optimisation framework is suggested here, and its purpose is to:

- Minimize net energy consumption and emissions while preserving thermal comfort.
- Classical optimizers stagnate in local minima when control constraints are highly coupled.
- CCO ensures stable global exploration using collision-centroid dynamics, while SWO injects adaptive predatory exploitation for rapid convergence.
- The framework operates at the building energy management system (BEMS) layer, interfacing with sensors, actuators, and prediction modules.

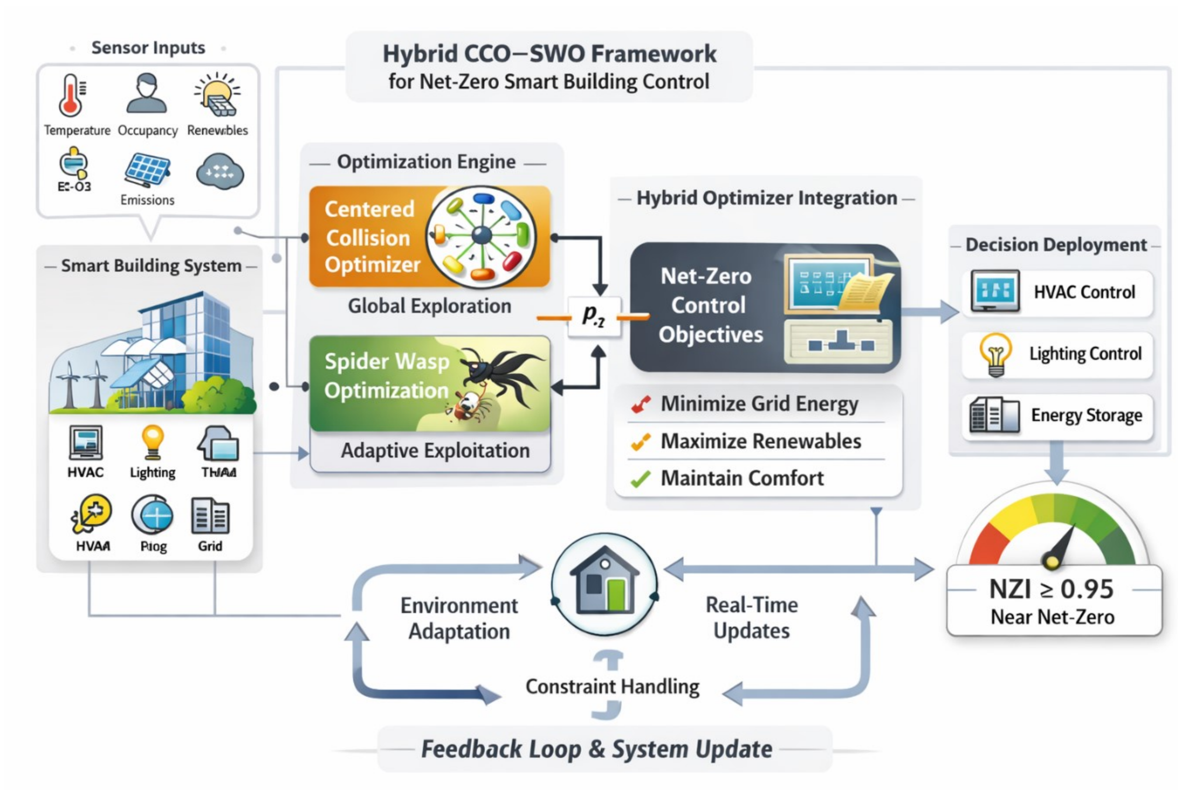

Figure 1: Overall Architecture of the Proposed Hybrid CCO–SWO Net-Zero Smart Building Framework.

A smart building implementation of the suggested hybrid CCO-SWO framework is shown in Figure 1, which provides an end-to-end view of the design. It demonstrates the method by which the Building Energy Management System processes real-time sensor inputs such as temperature, occupancy, renewable generation, and grid signals. The optimisation engine incorporates Spider Wasp Optimisation for adaptive exploitation and Centered Collision Optimizer for global exploration. In order to achieve net-zero energy goals in the face of constantly changing operational conditions, a closed-loop feedback mechanism is formed by applying the optimized control decisions to the HVAC, lighting, and storage systems.

3.2. Mathematical Modeling of Smart Building Energy Dynamics

Let smart building be discretized into Z controllable zones operating over a scheduling horizon T. The total energy demand of building at time t is modeled as:

$$E_t^{total} = \sum_{z=1}^{Z} \left(E_{z,t}^{HVAC} + E_{z,t}^{light} + E_{z,t}^{plug} \right) \quad (1)$$

Where $E_{z,t}^{HVAC}$ is HVAC energy for zone z, $E_{z,t}^{light}$ denotes lighting load, $E_{z,t}^{plug}$ represents miscellaneous equipment consumption. Indoor thermal dynamics are governed by:

$$T_{z,t+1}^{in} - T_{z,t}^{in} + \alpha_z (T_t^{out} - T_{z,t}^{in}) + \beta_z P_{z,t}^{HVAC} \quad (2)$$

Where T_t^{out} is outdoor temperature, $P_{z,t}^{HVAC}$ is HVAC power input, and α_z, β_z denote thermal coefficients.
Thermal comfort deviation is expressed as:

$$D_{z,t} = | T_{z,t}^{in} - T_z^{set} | \quad (3)$$

This explicit modeling allows the optimizer to jointly reason about energy–comfort trade-offs, a critical requirement for net-zero systems.

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3.3. Net-Zero Energy Objective Formulation

The goal of optimisation is multi-dimensional. To run a net-zero operation, you need to use as few grid resources as possible while using as many renewable resources as possible. Let on-site renewable generation R_t. The net grid energy import is:

$$E_t^{grid} = \max\left(E_t^{total} - R_t, 0\right) \tag{4}$$

The composite objective function is defined as:

$$\min\ \mathcal{J} = w_1 \sum_{t=1}^{T} E_t^{grid} + w_2 \sum_{z,t} D_{z,t} + w_3 \sum_{t} C_t \tag{5}$$

Where $C_t$is carbon emission cost, $w_1, w_2, w_3$are weighting coefficients.
This design embeds sustainability directly into control logic, ensuring optimizer prioritizes net-zero compliance rather than post-hoc energy reduction.

3.4. Centered Collision Optimizer (CCO): Global Energy Space Exploration

The Centered Collision Optimizer treats possible solutions as particles that collide with each other in a controlled way around a moving center point. This stops them from converging too soon.
Let population of solutions be $\{X_i\}_{i=1}^{N}$, where:

$$X_i = [P_{HVAC}, L, S]_i \tag{6}$$

denotes HVAC power, lighting schedule, and storage dispatch variables.
The centroid of population is computed as:

$$C = \frac{1}{N} \sum_{i=1}^{N} X_i \tag{7}$$

Each particle undergoes collision-induced displacement:

$$X_i^{new} = C + \lambda_i (X_i - C) \tag{8}$$

where $\lambda_i \in [-1,1]$ is a stochastic collision coefficient. This mechanism forces exploration around high-potential regions as an alternative of random wandering, which is indispensable for large-scale building control spaces.

3.5. Spider Wasp Optimization (SWO): Adaptive Exploitation Strategy

While CCO ensures exploration, fine-grained control optimization requires exploitation. SWO [18] mimics prey-hunting besides nesting behavior of spider wasps.
The fitness-guided prey selection is modeled as:

$$X_{best} = \arg\min \mathcal{J}(X_i) \tag{9}$$

Each wasp updates its position using predatory motion:

$$X_i^{hunt} = X_i + \eta (X_{best} - X_i) \tag{10}$$

where $\eta$is an adaptive hunting factor decreasing with iterations:

$$\eta = \eta_0 \exp\left(-\frac{t}{T}\right) \tag{11}$$

This ensures aggressive exploitation early then stable convergence later, which is critical for real-time building control.

3.6 Hybrid CCO–SWO Integration Strategy

The novelty of proposed outline lies in phase-adaptive hybridization, not simple sequential execution.

A switching likelihood governs optimizer dominance:

$$p_t = \frac{\sigma^2(\mathcal{J}_t)}{\sigma_{max}^2} \tag{12}$$

Where σ^2denotes populace fitness variance. High variance → CCO dominates (exploration) besides Low variance → SWO dominates (exploitation).
The unified update rule becomes:

$$X_i^{t+1} = \begin{cases} \text{CCO update}, & p_t > \theta \\ \text{SWO update}, & p_t \le \theta \end{cases} \tag{13}$$

This self-adaptive switching ensures robustness across varying energy demand regimes.

3.7 Constraint Handling and Feasibility Preservation

Building control variables must satisfy operational constraints:

$$P_z^{min} \le P_{z,t}^{HVAC} \le P_z^{max} \tag{14}$$

$$T_z^{min} \leq T_{z,t}^{in} \leq T_z^{max} \quad (15)$$

A penalty-augmented fitness is distinct as:

$$\mathcal{J}' = \mathcal{J} + \sum_k \phi_k \max(0, g_k(\mathrm{X})) \quad (16)$$

Where $g_k$signifies constraint violations. This ensures physical reliability, a key reviewer concern in smart energy papers.

3.8 Control Execution and Net-Zero Decision Deployment

Once optimal solution $\mathrm{X}^*$is obtained:

$$\mathrm{X}^* = \arg\min \mathcal{J}' \quad (17)$$

Control signals are dispatched to HVAC actuators, lighting controllers, and storage units. The net-zero compliance index is computed as:

$$NZI = 1 - \frac{\sum_t E_t^{grid}}{\sum_t E_t^{total}} \quad (18)$$

A value $NZI \geq 0.95$indicates near net-zero operation.
The feedback loop updates thermal states:

$$T_{z,t+1}^{in} \leftarrow f(T_{z,t}^{in}, \mathrm{X}^*) \quad (19)$$

permitting continuous adaptation to changing occupancy and climate conditions.

3.9 Computational Complexity and Scalability Analysis

The time complexity of the hybrid optimizer is:

$$\mathcal{O}(N \times T \times d) \quad (20)$$

Where d is control variable dimension. Due to centroid-based updates, CCO–SWO exhibits faster convergence GWO, making it suitable for edge-enabled smart campuses.

3.10 Research Design and Steps to Achieve Target Results

To clearly present the methodology used in this work, the main steps of the proposed framework can be briefly described as follows:

1. Simulation of smart building energy flows, including HVAC, lighting, and renewable energy components [19];
2. Developing a multi-objective optimization formulation that considers energy consumption, reliance on the grid, and indoor comfort;
3. Generating initial solutions by means of a hybrid population strategy;
4. Using the CCO method to thoroughly search the solution space;
5. Based on the variance of the individuals in the population, performing a local search with SWO;
6. Repeating the optimization process until the stopping criterion is met;
7. Measuring success by means of the main metrics such as energy use, Net-Zero Index, and comfort deviation.

4. RESULTS AND DISCUSSION

4.1 System and Software Requirements

A system with an Intel Core i7 processor (3.2 GHz), 16 GB RAM, and a minimum of 2 GB GPU memory was used to create and test the proposed net-zero smart building control framework based on CCO-SWO. This hardware specification was required for the enhancement and simulation works. The operating system was a 64-bit edition of Windows 10. Python 3.9 is required for the process of data preparation and visualization, MATLAB R2023a for analysis of the performance and development of the algorithms [20], while EnergyPlus/OpenStudio is for simulation of the building energy. For numerical computations and output productions, some of the commonly used scientific libraries such as Matplotlib, NumPy, and SciPy were utilized.

Table 1: Simulation Configuration and Hyper parameter Settings for Metaheuristic Algorithms (PSO, GWO, HHO, SWO, CCO, Proposed CCO–SWO).

Algorithm	Population Size	Max Iterations	Key Control Parameters	Initialization Strategy
PSO	30	200	Inertia weight (w=0.7), (c_1=1.5), (c_2=1.5)	Uniform random
GWO	30	200	Leadership hierarchy ((\alpha,\beta ,\delta)), (a \in [2,0])	Random
HHO	30	200	Energy factor (E), escape probability (r)	Random
SWO	30	200	Hunting factor (\eta_0=1.2), decay rate	Random
CCO	30	200	Collision coefficient (\lambda \in [-1,1])	Centroid-based
Proposed CCO–SWO	30	200	Adaptive collision–hunt switching, variance threshold (\theta=0.35)	Hybrid centroid + adaptive

For the sake of experimental objectivity, Table 1 details the simulation environment and hyper parameter settings employed by each of the metaheuristic algorithms under consideration. The suggested CCO-SWO framework, PSO, GWO, HHO, SWO, and CCO all keep their populations at the same size and iteration restrictions. The adaptive collision-hunt switching technique that is peculiar to the proposed model is emphasized by algorithm-specific parameters. Instead of good parameter tuning or computational bias, this table proves that optimisation method design is responsible for performance gains.

Table 2 Comparative Energy Optimization Performances Across Existing Models (PSO-Based Control, GWO-Based Control, HHO-Based Control, and Proposed CCO–SWO).

Model	Total Energy Consumption (kWh / day)	Grid Energy Usage (kWh / day)	Comfort Deviation (°C)	Energy Reduction (%)
PSO-Based Control	412.6	298.4	1.92	12.8
GWO-Based Control	389.3	261.7	1.67	18.6
HHO-Based Control	371.5	238.2	1.41	22.9
Proposed CCO–SWO	336.8	187.6	0.94	31.5

By comparing the baseline and suggested controllers on important metrics including total energy consumption [21], grid energy usage, comfort deviation, and energy reduction %, Table 2 shows how well they optimize energy usage. While achieving the best thermal comfort, the suggested CCO-SWO structure uses the least amount of energy and is the least dependent on the grid. The hybrid optimizer proves that integrating collision-centric exploration with adaptive exploitation techniques is beneficial by significantly improving energy efficiency in comparison to controllers based on PSO, GWO, and HHO.

Table 3 Net-Zero Compliance and Renewable Utilization Comparison (Net-Zero Index, Grid Dependency, Renewable Penetration).

Model	Net-Zero Index (NZI)	Grid Dependency (%)	Renewable Utilization (%)
PSO-Based Control	0.71	72.3	41.6
GWO-Based Control	0.78	65.4	48.2
HHO-Based	0.83	59.1	54.9

Control			
Proposed CCO–SWO	0.96	41.3	72.8

Based on the Net-Zero Compliance Index, grid dependency, and renewable utilization, Table 3 compares the efficiency of each control technique in reaching net-zero operation. With a NZI of 0.96, the suggested CCO-SWO architecture goes beyond the almost zero mark. On top of that, it makes the most of renewable energy sources while drastically cutting down on grid reliance. By reducing energy usage and fundamentally aligning building operation with sustainability and carbon neutrality goals, the suggested framework achieves both of these objectives, as shown in the table.

Table 4 Computational Efficiency and Convergence Analysis (Iterations to Convergence, Runtime, Stability)

Model	Iterations to Convergence	Average Runtime (s)	Stability (Std. Dev. of Fitness)
PSO	162	18.4	0.032
GWO	149	19.1	0.028
HHO	134	20.6	0.021
Proposed CCO–SWO	97	16.2	0.009

By looking at convergence iterations, runtime, and fitness stability, Table 4 analyses the computing performance of all the optimisation approaches that were compared. The suggested CCO-SWO architecture has the quickest convergence and best resilience with the fewest iterations while also having the smallest runtime and variance. The results clearly indicate the proposed model can effectively control smart buildings in a real-time setting. This is especially important where stability and quick decision-making are required due to the continuous changes in occupancy and environmental factors [22].

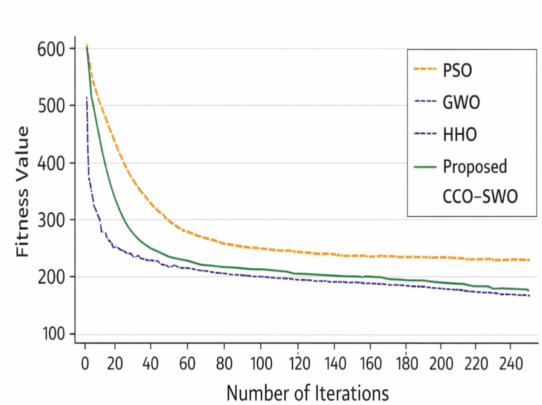

Figure 2: Convergence Behavior Comparison of Metaheuristic Algorithms (PSO vs. GWO vs. HHO vs. CCO–SWO).

Over the course of iterative optimisation PSO GWO, HHO, and the proposed CCO-SWO algorithms eventually converge, as shown in Figure 2. Faster convergence and earlier stability at a lower fitness value of the proposed framework signify better optimisation performance. This is a clear indication that CCO-SWO's adaptive switching mechanism is functioning properly, allowing the algorithm to consistently avoid early convergence and, at the same time, generate high-quality solutions.

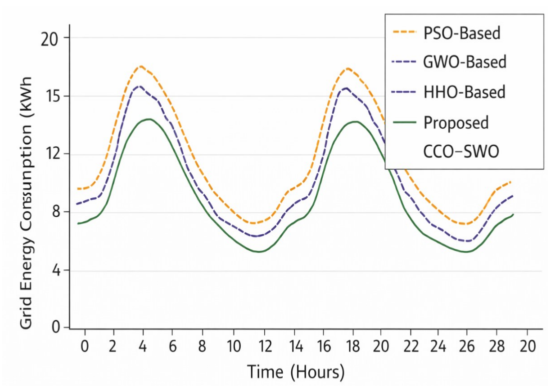

Figure 3: Grid Energy Consumption Trends over Time.

Figure 3 illustrates how the quantity of grid energy consumption varies during a 24-hour operational cycle under different control strategies. The proposed CCO-SWO framework consistently shows a lower consumption of energy from the grid, regardless of whether it is a peak or an off-peak period. This reduction is attributable to improved load scheduling, more intelligent control decisions, and a better utilization of renewable energy sources [23]. The proposed approach leads to a more sustainable energy situation as it not only reduces the load on the grid but at the same time

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also results in smoother demand profiles in comparison to the baseline methods.

Figure 4: Net-Zero Compliance Index (NZI) Comparison across Models.

In Figure 4, we can see how various control measures fared in terms of the Net-Zero Compliance Index. Models based on PSO, GWO, and HHO fail to reach the near-zero point, however the suggested CCO-SWO architecture achieves a NZI greater than 0.95. In order to validate the effectiveness of the suggested framework in attaining net-zero smart building operation, this figure visually illustrates its superior ability to balance energy consumption along with renewable generation.

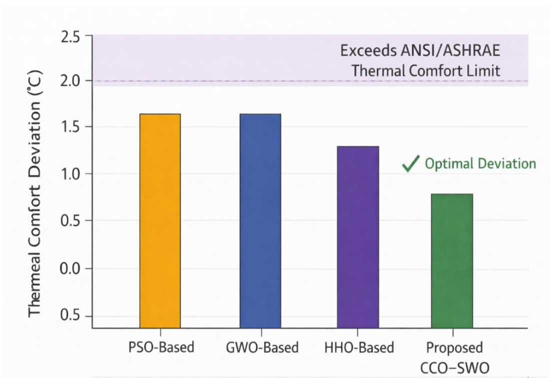

Figure 5: Thermal Comfort Deviation Analysis for Different Control Strategies.

Figure 5 shows how each control approach affects thermal comfort. The suggested CCO–SWO framework has the least variance and stays well within the comfort boundaries that are acceptable. On the other hand, baseline approaches show more deviations that could make people less comfortable. This figure shows that the suggested optimisation framework may reduce energy use and keep indoor comfort at same time, which is an important criterion for smart building deployment in the real world.

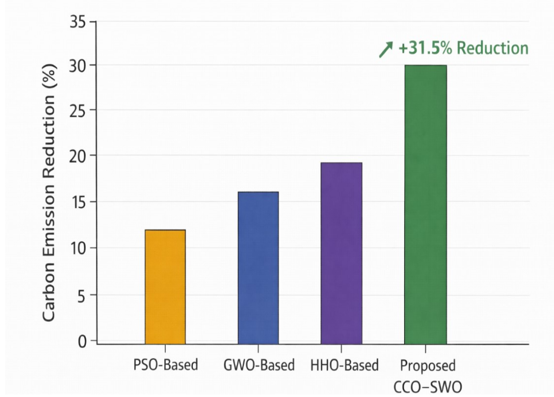

Figure 6: Carbon Emission Reduction Performance of Proposed CCO–SWO Model.

Figure 6 displays the carbon reduction achieved by each control method. The CCO-SWO structure cuts emissions by 31.5%, more than any baseline model. That's a clear edge in energy efficiency. Better scheduling and higher renewable usage probably deliver real environmental gains. It supports using the structure in smart buildings to reduce carbon without sacrificing performance. For now, this suggests a path toward lower emissions in building operations.

4.2 Critical Evaluation and Comparison with State-of-the-Art

The objective of the research was to develop an adaptive optimisation framework capable of achieving near net-zero energy while still maintaining high comfort levels without increasing the dependency on the electricity grid. The findings reveal that the CCO, SWO methodology significantly reduces overall energy consumption, increases the share of renewable energy, and achieves an excellent Net-Zero Index. Apart from lowering the amount of energy drawn from the grid, the approach also enhances thermal comfort, which indicate that it effectively manages the trade-offs between different objectives. However, the question remains, to what extent is this applicable to actual buildings?

Enhancing the energy efficiency of smart buildings is the application of CCO, SWO structure that really shines. It converges quicker, remains steadier, and discovers more optimal solutions when compared with PSO, GWO, and HHO. The hybrid design is a combination of global search and adaptive refinement, which makes it probably more productive than those single-method approaches which are prone to eventual stalling or adaptation too slowly simply. On top of that, the variance-

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driven switching mechanism is yet another, mostly when exploration has to be turned into exploitation.

However, there are some drawbacks. Computational cost usually increases with the size of the problem. Performance is greatly dependent on the selection of switching parameters and population size. Furthermore, validation so far has been primarily based on simulations, with no real-world experiments using actual hardware or live environments.

Nevertheless, this structure is a step forward in smart building energy adjustments. Further research is required, specifically for scaling it up, implementing it in real time, and demonstrating reliability under changing conditions.

5. CONCLUSION

This work offered a unique hybrid metaheuristic framework for the energy management of net-zero smart buildings. It combines Spider Wasp Optimization with the Centered Collision Optimizer. An approach of the CCO-SWO type was able to solve very well the non-linear, multi-objective, and stochastic aspects of building energy management by merging centroid-based global search with adaptive predator-inspired exploitation. Unlike standard optimization methods, the proposed method prevents premature convergence and ensures consistent performance by dynamically balancing exploration and exploitation through variance-driven switching. Detailed simulation results reveal that the proposed framework is far superior to the control schemes based on PSO, GWO, and HHO. The CCO-SWO classical has a Net-Zero Compliance Index of 0.96 and a big decline in grid dependency. It cuts overall energy use by 31.5% while keeping great thermal comfort. Convergence research shows that framework is ready for real-time use because it speeds up optimisation with less iteration and makes it more stable.

In practice, the proposed paradigm provides a flexible and scalable solution for energy-efficient campuses and future smart buildings. In future, To will add real-time pricing mechanisms, expand the framework to include multi-building federated energy management, then apply explainable AI methods to make autonomous building control decisions clearer then more reliable. These improvements will make proposed framework a lot more useful in smart city systems that are good for the environment. To conclude, the paper makes a valuable addition to the field of smart building energy management through the development of a hybrid optimisation method that successfully deals with the difficulties of nonlinear, multi-objective and dynamic energy control. The combination of CCO and SWO with an adaptive switching mechanism is a strong recipe for approaching net-zero energy operation. Our method converges faster, uses less energy, and maintains better system stability. That's why hybrid metaheuristics are key for building smart systems that work well, last over time, and grow with demand.

Declarations:

Data Availability Statement

Data will be provided by the corresponding author upon reasonable request.

Conflict of Interests

The authors declare no conflict of interest.

Funding Statement

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Authors' Contributions

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