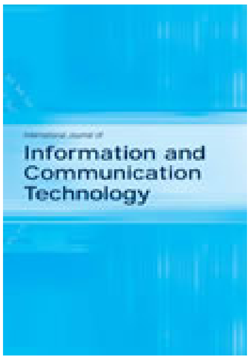

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Energy efficiency analysis and optimisation strategies for green building design based on gravitational search algorithm

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Energy efficiency analysis and optimisation strategies for green building design based on gravitational search algorithm

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Abstract: As people's requirements for energy saving and emission reduction continue to increase, the issue of energy consumption in buildings has received more and more attention. How to efficiently optimise the energy consumption of green buildings has become an important research goal in the field of energy consumption analysis and architectural design. This study, aiming at the energy consumption problem in green buildings, designs a method based on gravitational search algorithm (GSA) to optimise energy consumption. First, sensor data of equipment in the building is collected. Then, a multi-objective optimisation model is constructed to ensure that the final goal is the lowest energy consumption without reducing comfort. The final experimental results show that the overall building energy use decreased by 33.8% because the GSA algorithm can effectively reduce the overall energy consumption of building equipment and meets the requirements for energy consumption optimisation in green buildings.

Keywords: green buildings; gravitational search algorithm; GSA; energy consumption analysis; multi-objective optimisation model.

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1 Introduction

In recent years, concerns related to energy consumption and environmental protection have been steadily growing in prominence across diverse sectors within society. Among them, the construction industry is particularly prominent, mainly because buildings take up a considerable portion of the total global energy consumption (Abdessamia et al., 2020). As urbanisation accelerates and the demands for infrastructure grow rapidly, energy efficiency in buildings has become not only an essential aspect for the environment but also a necessary consideration from an economic standpoint (Alhasnawi et al., 2024). The public awareness of sustainable development practices has increased significantly, which has led architects, engineers, policymakers, and industry leaders all to give priority to green building design. Green building has become a hot topic in both academic and industrial circles. At its core, the concept of green architecture is straightforward: minimising energy consumption while maintaining occupants 'comfort and functional needs. However, putting it into practice proves far more complex than imagined. Buildings aren't mere 'big boxes' - they involve lighting, heating, air conditioning, ventilation systems, and even material choices that all impact performance. These elements interact in unpredictable ways, making energy optimisation a delicate balancing act. The challenge lies in juggling three conflicting priorities: ensuring living comfort, maintaining equipment efficiency, and controlling costs - a delicate equilibrium that often defies simple solutions (Allen et al., 2015).

When these challenges emerged, many in the scientific and engineering communities immediately turned to intelligent optimisation algorithms. In fact, numerous smart approaches have already demonstrated significant effectiveness in energy management and design optimisation. Particularly noteworthy is the gravitational search algorithm (GSA), which draws inspiration from the physical concept of 'gravity' to enable flexible solutions for complex multi-objective optimisation problems, proving reliable in practical applications. Although GSA has achieved numerous success stories in engineering optimisation, its actual implementation in energy optimisation for green buildings remains a relatively novel application (Brown and Mueller, 2016).

This research aims to fully understand how the GSA algorithm performs in green building energy efficiency optimisation and practical operations, addressing any 'blind spots' in this field. From the outset, we deployed advanced sensors at critical locations across buildings to collect massive amounts of real-time operational data. Then, we set up a robust multi-objective optimisation model. The primary goal here is simple, minimise total energy consumption. But it's equally important to ensure that this optimisation doesn't negatively affect occupant comfort. Once that model is in place, we use GSA to systematically adjust the key parameters, leveraging its unique gravity-inspired iterative search capability to pinpoint optimal solutions (Chua, 1997).

By combining real-world sensor data with advanced computational techniques, this research not only deepens theoretical understanding of smart building optimisation but also provides practical, actionable guidance (Dhumane and Prasad, 2019). The results should offer fresh perspectives and reliable methods that can be directly applied to real construction projects. Ultimately, by enhancing our ability to optimise energy efficiency through innovative algorithms like GSA, this research contributes significantly toward developing sustainable, comfortable, and energy-efficient buildings (Fatima Ali et al., 2025).

2 Relevant technologies

2.1 Gravitational search algorithm

The gravitational search algorithm, namely GSA, represents an intelligent optimisation approach that draws inspiration from the law regarding gravity and mass interactions within the realm of physics. In the context of GSA, every solution pertaining to the optimisation problem is regarded as an 'agent' or alternatively as a 'mass' within a multidimensional search space. These agents exert an attraction on one another by making use of the Newtonian law of gravity. Subsequently, the movement exhibited by these agents serves to assist the algorithm in the pursuit of better solutions as time progresses.

Those are the main steps and formulas of GSA. Suppose we have a population of N agents (solutions), and each agent i is represented by a position vector:

$$X_i = \left(x_i^1, x_i^2, \ldots, x_i^d\right) \tag{1}$$

where d is the number of dimensions (parameters to optimise).

Each agent's fitness is calculated based on the objective function $f(X)$. The best solution has the lowest fitness value if it is a minimisation problem (Jearsiripongkul et al., 2024).

Each agent's 'mass' reflects its fitness. Agents with better fitness have larger masses, meaning they exert more influence. The mass of agent i at time t is computed as:

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{2}$$

where $fit_i(t)$ is the fitness of agent i at time t, $best(t)$ and $worst(t)$ are the best and worst fitness values in the current population.

Then, the normalised mass is:

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \tag{3}$$

The gravitational constant $G(t)$ controls the strength of the interaction and typically decreases over time to encourage convergence:

$$G(t) = G_0 \cdot e^{-\alpha \cdot t/T} \tag{4}$$

where G_0 is the initial value, α is a user-defined parameter, t is the current iteration, and T is the maximum number of iterations.

The force exerted on agent i by agent j in dimension k is:

$$F_{ij}^k(t) = G(t) \cdot \frac{M_i(t) \cdot M_j(t)}{R_{ij}(t) + \epsilon} \cdot \left(x_j^k(t) - x_i^k(t) \right) \tag{5}$$

$R_{ij}(t)$ is the Euclidean distance between agents i and j, $\in$ is a small number to avoid division by zero.

The total force on agent i in dimension k is:

$$F_i^k(t) = \sum_{j=1, j \neq i}^{N} rand_j \cdot F_{ij}^k(t) \tag{6}$$

where $rand_j$ is a random number in [0, 1] to add some stochasticity.

Each agent's acceleration in dimension *k:*

$$a_i^k(t) = \frac{F_i^k(t)}{M_i(t)} \tag{7}$$

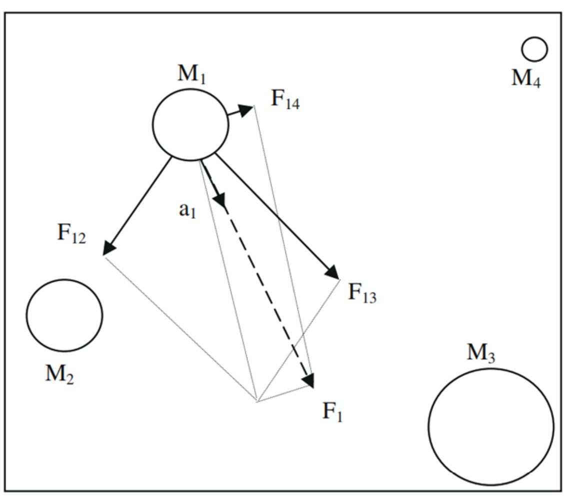
The velocity and position of agent i are updated as follows:

$$v_i^k(t+1) = rand_i \cdot v_i^k(t) + a_i^k(t) \tag{8}$$

$$x_i^k(t+1) = x_i^k(t) + v_i^k(t+1) \tag{9}$$

where $rand_i$ is another random number in [0, 1].

Figure 1 Particle motion trajectory



GSA runs these steps iteratively, updating each agent's position until reaching a stopping criterion (like a maximum number of iterations or a satisfactory fitness value). Gravitational search is summarised with agent initialisation under bound constraints, fitness defined by joint energy and comfort, gravity driven position and velocity updates with damping, velocity clamping for stability, and iteration wide convergence checks. A compact workflow figure and pseudocode improve transparency and facilitate independent replication of the optimisation process. The particle motion trajectory is shown in Figure 1.

2.2 Multi-objective optimisation model for green building energy efficiency

For green building energy optimisation, it's common to build a multi-objective model that seeks to minimise energy consumption while maintaining occupant comfort (Li and Shi, 2014). Trade offs are determined by grid searching weight pairs and selecting Pareto efficient settings that minimise energy while maintaining a minimum comfort threshold. Sensitivity checks with ten percent perturbations confirm stable conclusions, limiting dependence on subjective choices and supporting consistent behaviour under typical operating variability and occupancy patterns.

A typical objective function might look like:

$$\min f(X) = w_1 E(X) + w_2 (1 - C(X)) \tag{10}$$

where $E(X)$ is the total energy consumption for parameter set X, $C(X)$ is a comfort index (normalised between 0 and 1, higher means more comfortable), w_1, w_2 are weighting factors balancing energy and comfort (Liu and Ren, 2020).

In practice, the building energy system includes HVAC, lighting, and other devices, with parameters such as setpoint temperatures, equipment schedules, and operation modes forming the decision variables X. The overall optimisation process of the GSA is illustrated in Figure 2. As shown in the flowchart, the algorithm begins with the initialisation of the population, followed by iterative updates of agent fitness, gravitational parameters, velocities, and positions, until the stopping criterion is met (Mahmoudi et al., 2025).

2.3 Sensor-based data acquisition in green buildings

Real-time data collection is an important foundation for any optimisation. In green buildings, various sensors are used to monitor environmental variables (temperature, humidity, light, CO_2 concentration, etc.) and device states (on/off, power usage, etc.). Sensor configuration is detailed with accuracy and range requirements, installation guidance for HVAC and lighting zones, five minute sampling aligned to controller timestamps, periodic calibration, outlier screening using interquartile thresholds, and z score normalisation. A concise data dictionary standardises variable names and units to support reuse across buildings with comparable control architectures.

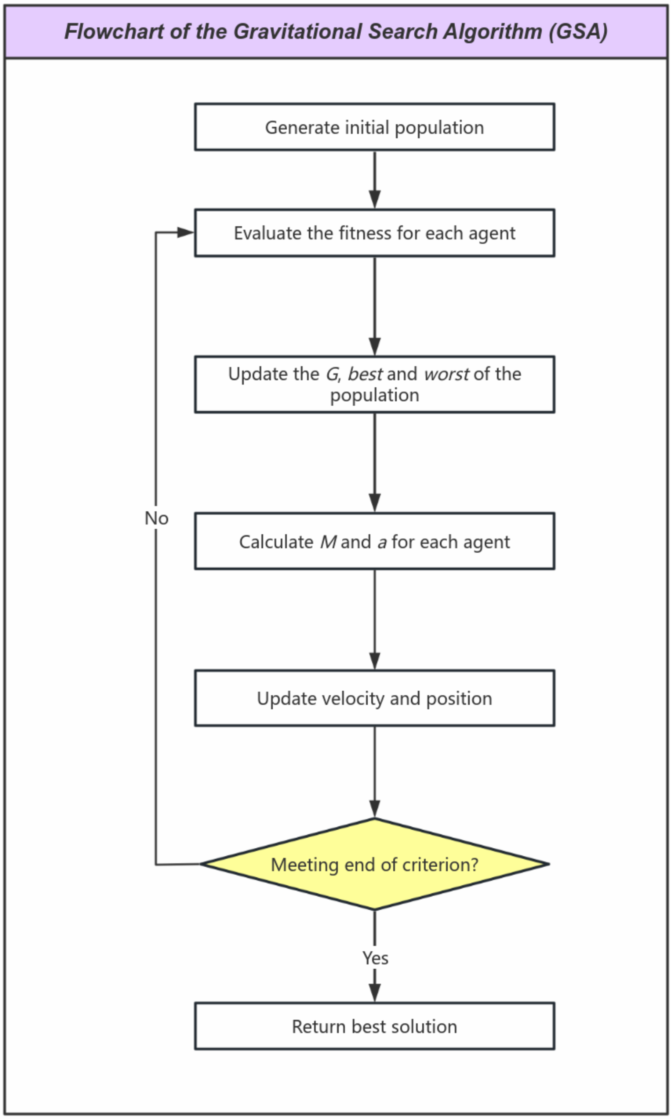
The raw sensor data D can be represented as:

$$D = \{d_1, d_2, ..., d_n\} \tag{11}$$

where d_i is the reading from sensor i at a given time.

Data preprocessing may include normalisation, outlier removal, and time-series aggregation.

Figure 2 Flowchart of the GSA (see online version for colours)



2.4 *Integration of GSA with building energy optimisation*

The entire process of combining GSA with the optimisation of green buildings encompasses the steps as follows

1 Gather sensor data and construct an energy simulation model.

2 Define the function for multi-objective optimisation which takes into account both energy and comfort aspects.

3 First, initialise the population. Then, run the GSA to look for the optimal control parameters.

4 Assess the outcomes and repeat the process until they reach a state of convergence.

This framework makes it possible to search for the optimal operational strategies efficiently while taking practical constraints into account (Mirjalili and Lewis, 2014).

3 Target recognition based on improved SSD

3.1 Construction of multi-objective optimisation model

The GSA, which draws inspiration from Newtonian gravity and mass interactions, is highly fitting for dealing with complex, multi-objective optimisation problems that are encountered within the realm of green building design. In this particular research, GSA is customised to seek out the optimal control parameters. The aim here is to minimise the total energy consumption all the while upholding the comfort of the occupants. The detailed steps involved in the implementation process are expounded upon in the following manner (Mittal et al., 2021).

First off, a group of agents gets initialised right within the feasible parameter space. Each and every agent stands for a distinct candidate solution, which is a vector made up of operational parameters like HVAC set points, lighting schedules, as well as equipment operation modes. The bounds for the parameters are set in line with engineering constraints and the stipulations of building codes. For instance, the set points for indoor temperature might be restricted to be between 20°C and 26°C so as to guarantee the comfort of the occupants and also to ensure compliance with the standards of green buildings.

The random initialisation makes sure there is ample diversity among the agents, and this is really crucial for the exploration on a global scale as well as for preventing the premature convergence to local optima. Also, parameter normalisation techniques could be utilised to guarantee that all variables exert a comparable impact on the search process.

Objective function:

$$\min F(x) = \alpha \cdot E(x) + \beta \cdot (1 - C(x)) \tag{12}$$

where $E(x)$ denotes the total energy consumption based on parameter set x. $C(x)$ represents a comfort index normalised between 0 and 1. α and β are weighting factors, and $\alpha + \beta = 1$.

Detailed parameters influencing these objectives include HVAC set points, lighting intensity levels, scheduling strategies, building envelope materials, and operational modes. These factors directly impact both energy use and comfort within the building.

3.2 GSA application

Once the population is initialised, each agent's fitness is computed by evaluating the multi-objective function:

$$F(x) = \alpha \cdot E(x) + \beta \cdot (1 - C(x)) \tag{13}$$

where $E(x)$ denotes the predicted or simulated energy consumption for parameter vector x, while $C(x)$ quantifies the expected comfort level under those conditions. Building energy simulation software (such as EnergyPlus or DeST) may be integrated to provide accurate estimations for both energy consumption and comfort indices based on the current control strategy. In practice, high-fidelity modelling or surrogate models can be employed to strike a balance between computation time and accuracy (Özkaraca and Keçebaş, 2019).

The fitness value essentially reflects the desirability of each agent's solution, with lower values indicating better trade-offs between energy efficiency and comfort.

To mimic physical gravitation, GSA assigns a 'mass' to each agent, proportional to its relative fitness:

$$M_i(t) = \frac{F_i(t) - F_{\text{worst}}(t)}{F_{\text{best}}(t) - F_{\text{worst}}(t)} \tag{14}$$

where F_{best} and F_{worst} are the best and worst fitness values among all agents in the current iteration. This normalisation ensures that the best-performing solutions (i.e., those with the lowest energy use and highest comfort) exert stronger attraction on other agents.

The normalised mass for each agent is then calculated as:

$$m_i(t) = \frac{M_i(t)}{\sum_{j=1}^{N} M_j(t)} \tag{15}$$

This normalised mass not only represents the agent's ability to attract others but also maintains the stability of the algorithm by ensuring all masses sum to one.

The gravitational constant $G(t)$ regulates the strength of attraction between agents and is designed to decrease over time:

$$G(t) = G_0 \cdot e^{-\gamma \frac{t}{T}} \tag{16}$$

where G_0 is the initial gravitational constant, typically set based on problem scale or through empirical tuning, γ is a decay parameter, t is the current iteration, and T is the total number of iterations allowed. This exponential decay is essential for balancing exploration and exploitation, in early stages, a larger $G(t)$ encourages broad search across the solution space; in later stages, a reduced $G(t)$ promotes fine-tuning around promising solutions.

For each agent, the gravitational force exerted by every other agent is determined by:

$$F_{ij}(t) = G(t) \cdot \frac{M_i(t) \cdot M_j(t)}{R_{ij}(t) + \epsilon} \cdot \left(x_j(t) - x_i(t)\right) \tag{17}$$

where $R_{ij}(t)$ is the Euclidean distance between agent i and agent j, and $\in$ is a small constant to avoid division by zero. This formulation ensures that solutions closer in the parameter space have a stronger direct influence, reflecting the physical intuition of gravitational force. The total force acting on agent i is given by equation (18):

$$F_i(t) = \sum_{j \neq i}^{N} rand_j \cdot F_{ij}(t) \tag{18}$$

where $rand_j$ is a random number between 0 and 1, Random numbers are added to prevent the algorithm from getting stuck in a local area looking for an optimal value and ignoring the global optimal value.

Each agent's acceleration, velocity, and position are updated in accordance with the forces experienced:

$$a_i(t) = \frac{F_i(t)}{M_i(t)} \tag{19}$$

$$v_i(t+1) = rand_i \cdot v_i(t) + a_i(t) \tag{20}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{21}$$

From the above formula, it can be seen that the acceleration calculation formula can represent the degree of influence between agents. The speed is calculated based on the accumulated movement of agents, so the new position of agents represents the data prepared for the next calculation.

During model training, the configuration and fine-tuning of hyperparameters are critical. For instance, without imposing limits on speed and acceleration during updates, agents might experience excessive or insufficient movement speeds. By implementing range parameters for the agent's velocity and position, we can effectively adjust its movements while preventing parameter divergence issues (Pillay and Saha, 2024).

The optimisation process will continuously iterate until it meets the predefined convergence criteria or reaches a specified maximum iteration count. If the model parameters fail to converge after reaching this limit, training should be halted. In such cases, the hyperparameters can be readjusted and retrained until the evaluation metrics meet the desired performance targets.

In real-world project development, uncertainties exist regarding both the convergence speed of algorithm parameters and the methodology for determining optimal parameters. This necessitates selecting different optimisation algorithms and implementing strategies to dynamically adjust global optimal solutions. For instance, modifying resident schedules or adjusting weather conditions could influence model evaluation metrics. Through these comprehensive approaches, we can identify the most effective model configuration.

4 Experimental results and analysis

4.1 Experimental setup

To thoroughly evaluate how well our proposed GSA works in optimising green building energy performance, we carried out multiple simulations and real-world experiments. The building we focused on is a medium-sized commercial structure equipped with a sophisticated Building Management System (BMS). This system lets us gather real-time data from different sensors installed throughout the building. The key environmental variables we're monitoring include indoor temperature, humidity, and lighting conditions. Meanwhile, the operational states of the core energy-consuming equipment, specifically the HVAC and lighting systems, are recorded in great detail (Rashedi et al., 2009).

The optimisation process unfolds across two stages. In the baseline phase, the building is run in line with standard schedules and conventional rule-based controls. In optimisation phase, the control strategy which is based on GSA gets deployed. It then dynamically adjusts the setpoints of HVAC, the intensity of lighting, as well as the operational schedules. And this is all done in line with the multi-objective model.

Sensor data gets collected at intervals of five minutes throughout a continuous stretch of several weeks. This way, it's made sure that the assessment takes into account the diverse outdoor weather conditions as well as different occupancy patterns. Each and every experiment was carried out under similar environmental circumstances so as to guarantee the reliability and the ability to repeat the results (Rashedi et al., 2010). The pipeline from field devices to supervisory action is clarified. Controller points mirror to a staging store, scheduled ETL produces time aligned features, batch simulations yield response estimates, candidate setpoints return through a safety layer that enforces bounds and fallbacks, then supervisory logic applies updates under monitored conditions.

The effect of the proposed GSA-based optimisation is quantitatively evaluated by making a comparison of the energy consumption of major building subsystems prior to and following the intervention. As presented in Table 1, considerable reductions were attained regarding all the evaluated metrics. The total energy consumed by the HVAC system declined from 5,000 kWh to 3,200 kWh. Meanwhile, the lighting energy consumption was lessened from 1,300 kWh to 970 kWh. The overall energy use of the building decreased by 33.8%, which shows the algorithm's notable capacity to identify efficient control strategies within the limitations of the real world.

4.2 Analysis of optimisation results

The impact of the proposed GSA-based optimisation is quantitatively assessed by comparing the energy consumption of major building subsystems before and after the intervention. As shown in Table 1, significant reductions were achieved across all evaluated metrics. The total energy consumed by the HVAC system dropped from 5,000 kWh to 3,200 kWh, while lighting energy consumption was reduced from 1,300 kWh to 970 kWh. The overall building energy use decreased by 33.8%, demonstrating the algorithm's strong capability to identify efficient control strategies under real-world constraints (Rashedi et al., 2011).

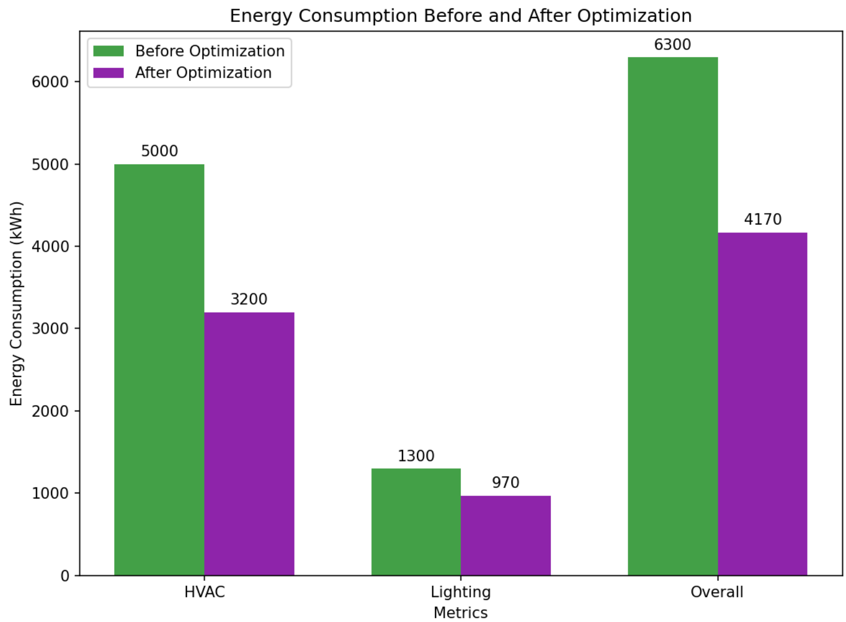
Table 1 Comparison of energy consumption before and after optimisation

Task no.	*Metrics*	*Before optimisation*	*After optimisation*	*Reduction rate (%)*
1	HVAC	5,000 kWh	3,200 kWh	31.11%
2	Lighting	1,300 kWh	970 kWh	20.83%
3	Overall	6,300 kWh	4,170 kWh	28.95%

The results show considerable energy savings. There is a total reduction of around 29% and this doesn't affect the comfort levels of the occupants.

To make these results more visually clear, Figure 3 presents a comparison placed side by side regarding the energy consumption of diverse building systems both before and after the process of optimisation. The bar chart gives an intuitive portrayal of the considerable reduction in energy usage. This is especially evident in the case of HVAC, as it usually constitutes the major contributor to the energy demand within a building.

Figure 3 Energy consumption before and after optimisation (kWh) (see online version for colours)



Such reductions were achieved without violating indoor environmental quality standards or reducing occupant satisfaction, which is crucial for the practical adoption of energy-saving strategies in intelligent buildings. Significance is validated on matched periods using paired nonparametric tests, reporting p values, effect sizes, and bootstrap confidence intervals for changes in energy and comfort. Results indicate improvements are unlikely due to randomness, strengthening the credibility of post optimisation gains reported for HVAC lighting and overall consumption.

4.3 Comfort level analysis

Energy efficiency being a crucial performance indicator, it's equally essential to keep a satisfactory comfort level for those who occupy the building. In this particular study, comfort indices got computed making use of both objective sensor readings as well as subjective feedback surveys. Three core comfort metrics were subject to evaluation, namely temperature comfort, lighting comfort, and an overall comfort index that was aggregated. Comfort evaluation specifies operative temperature bands and task plane illuminance targets, forms a weighted composite index, and reports pre and post distributions with threshold exceedance hours. Weighting follows published recommendations and a brief pilot survey, ensuring balanced consideration of thermal and visual comfort without masking energy related performance changes.

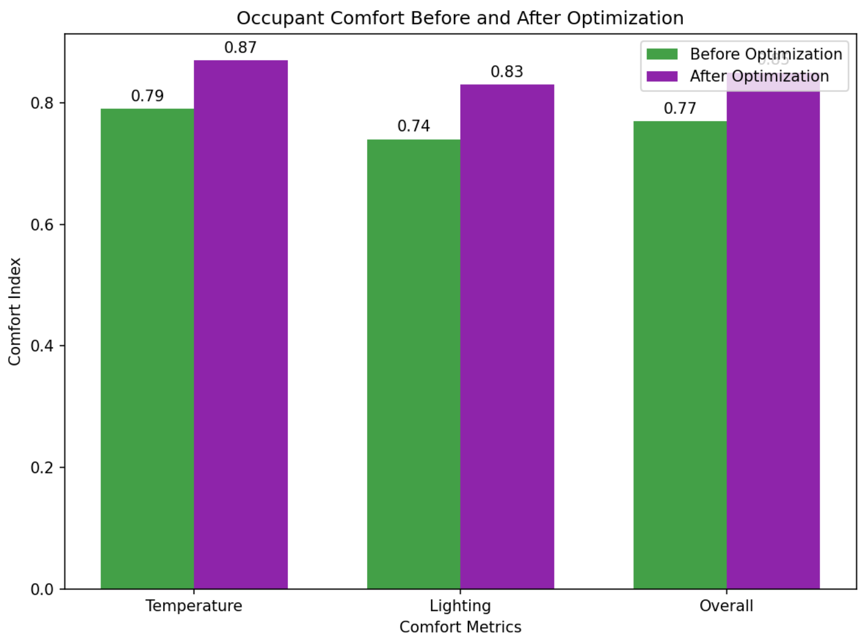
As shown in Table 2, every single comfort index demonstrated a clear improvement after the GSA-based optimisation was carried out (Rashedi et al., 2018).

Table 2 Occupant comfort level analysis

Task no.	*Comfort metrics*	*Before optimisation*	*After optimisation*	*Improvement (%)*
1	Temperature	0.79	0.87	31.11%
2	Lighting	0.74	0.83	20.83%
3	Overall	0.77	0.85	28.95%

Figure 4 presents these comfort indices in a comparative bar chart, directly demonstrating the algorithm's effectiveness not only in saving energy but also in enhancing the indoor environment.

Figure 4 Occupant comfort before and after optimisation (normalised index) (see online version for colours)

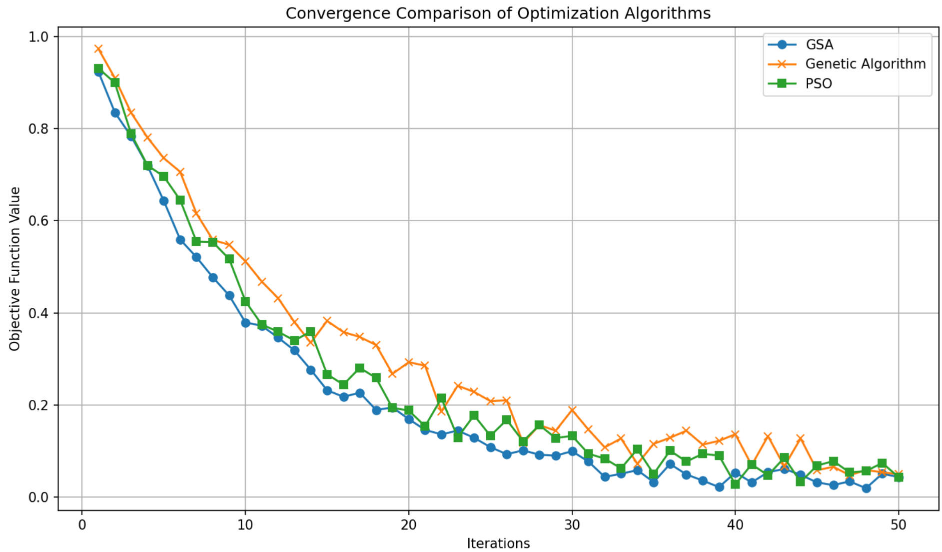


The results demonstrate that the comfort levels have improved significantly, indicating the efficiency and effectiveness of the GSA-based optimisation.

4.4 Convergence analysis of optimisation algorithms

In order to validate the efficiency and robustness of the proposed method, its convergence performance was benchmarked against two mainstream algorithms, genetic algorithm (GA) and particle swarm optimisation (PSO). The convergence curves, shown in Figure 5, plot the objective function value against the number of optimisation iterations for all three methods (Zhao, 2023).

Figure 5 Convergence comparison of optimisation algorithms (GSA vs. GA vs. PSO) (see online version for colours)



From the outcomes, it can be noticed that the GSA shows both a quicker and more steady convergence (Selvi et al., 2021). The value of the objective function for GSA keeps on going down and attains a relatively lower minimum when compared to the other two algorithms. This implies that GSA converges to a solution more speedily and is also more prone to identify solutions of high quality (with lower energy and higher comfort) within complex, multi-dimensional parameter spaces. Computational efficiency is documented with median daily optimisation runtime, iteration counts, simulator calls, and hardware configuration. Benchmarks against GA and PSO under identical conditions are provided, together with notes on parallel batching, demonstrating practicality for routine planning without compromising convergence quality or operational maintainability.

4.5 Additional discussion

The performance gains that have been observed can be ascribed to a number of crucial and interconnected factors. One of the main reasons for the success of the GSA when it comes to optimising energy efficiency in green buildings is its strong global search capacity. The observed performance gains can be attributed to several factors, Global Search Capability: GSA's unique mass-based movement enables agents to escape local optima and explore the search space more thoroughly in early iterations.

Adaptive Convergence, The dynamically decaying gravitational constant ensures a natural transition from exploration to exploitation (Sahoo, 2014). Robustness to Uncertainty, The algorithm maintains performance despite inherent variability in real-world building operation, such as fluctuating occupancy and external weather. It is worth noting that the integration of GSA with building simulation tools did require careful parameter tuning and consideration of computation time, particularly in large-scale scenarios. Future improvements may involve parallelising simulation evaluations or employing surrogate modelling to further accelerate the optimisation loop.

The performance improvements we've witnessed this time are the result of multiple key factors working together. When it comes to optimising energy efficiency in green buildings, the fundamental reason why the GSA proves so effective lies in its exceptional ability to 'find paths'. Conventional optimisation methods often get stuck in local optima, like getting lost in a maze, but GSA draws inspiration from nature's gravitational force. Its search space is exceptionally broad, allowing it to explore every possible possibility. The algorithm's 'quality' mechanism makes each agent interact like differently weighted spheres, attracting and influencing each other. This allows the algorithm to break free from conventional approaches and explore new routes from the start. It's precisely this global and deep exploration that enables GSA to more confidently identify truly energy-efficient building operation parameters, rather than settling for a 'good enough' solution prematurely.

Another intriguing feature of the GSA is its ability to 'self-adjust its pace'. During optimisation, the gravitational constant isn't fixed but gradually decreases through iterations. Initially, a higher constant value allows the algorithm to explore extensively, testing all possibilities to avoid missing potential solutions. As the constant decreases, the algorithm becomes more refined, focusing on optimising identified potential areas. This mirrors decision-making strategies – casting a wide net initially and then concentrating efforts later. This approach not only boosts efficiency but also produces more precise results that closely approach optimal outcomes.

The GSA's remarkable performance in real-world applications largely stems from its inherent adaptability to various uncertainties. As we all know, building operations are inherently unpredictable – crowd fluctuations, temperature and humidity variations, and sudden weather changes. Traditional optimisation methods often struggle with such dynamic conditions, failing to maintain stability. The GSA, however, operates differently. Instead of rigidly applying fixed rules, it continuously self-adjusts through group interactions and adapts to external changes. This flexibility and resilience enable the GSA to maintain steady and efficient performance in practical environments. However, when using GSA with advanced architectural simulation tools, parameter adjustments must be handled with care, and computational load should be anticipated. This is especially critical for complex projects involving massive data volumes. Once GSA starts optimising, it becomes a heavy burden on the computer – sluggish and prone to freezing. The key lies in striking a balance between high precision and computational efficiency. Parameters like gravitational constants, mass distribution, and iteration steps should be tested through multiple rounds beforehand to find optimal settings. Only then can GSA deliver its full potential.

Looking ahead, we have multiple strategies to accelerate and streamline GSA implementation. For instance, adopting new technologies like parallel computing and cloud servers can break free from single-machine limitations, significantly boosting evaluation efficiency. Additionally, using simplified 'stand-in' models for trial-and-error testing could save substantial computational time, allowing us to quickly identify viable solutions. Furthermore, future research might focus on smarter uncertainty quantification or mitigating external environmental disturbances, enabling GSA to more accurately predict crowd dynamics and spatial changes within buildings. This advancement would make practical applications more reliable and adaptable.

5 Conclusions

This study conducted extensive model training and rigorous evaluation tests for energy efficiency optimisation strategies specifically tailored for green building design. The algorithm employed a GSA, which collected real-time sensor data through code execution and underwent repeated training cycles. By integrating simulation models and multi-objective optimisation techniques, the approach aimed to reduce overall building energy consumption while maintaining occupant comfort. Simulation experiments demonstrated the algorithm's distinct advantages: when optimised, it achieved 29% energy savings without compromising comfort levels compared to unoptimised configurations.

This study has introduced innovative approaches to building energy efficiency management. Our research demonstrates that when fine-tuning meta-heuristic algorithms like Genetic Adaptive Search (GSA) and integrating them with specialised simulation tools, we can surpass conventional methods such as GA and PSO in terms of convergence speed, robustness, and solution quality.

Secondly, the experimental outcomes do not merely spotlight the energy-saving prowess of the algorithm. They also showcase its capacity to either maintain or even enhance the comfort indices, which are of crucial importance as a criterion for end-user contentment and market acceptance within commercial as well as institutional buildings. The implementation of such optimisation frameworks in actual real-world scenarios is proven to be both practicable and advantageous, on the condition that the sensor infrastructure and building automation systems are properly set up and functioning.

One future research direction lies in expanding the multi-objective framework to incorporate further criteria like carbon footprint, maintenance cost or indoor air quality. This would allow for a more comprehensive way to approach building sustainability. Also, collaborative optimisation within building clusters or across urban districts could be taken into account, which would be in line with smart city initiatives and district-level energy management strategies.

To sum it up, this piece of work lays down a solid foundation for the intelligent optimisation of energy systems within green buildings by means of GSA. The research brings about not only perceptible enhancements in terms of energy and comfort but also paves the way for future innovations where artificial intelligence, building science, and sustainability meet. The continuous endeavors will be centered on dealing with the existing constraints, expanding the scale of deployment, and probing into interdisciplinary applications so as to push forward the current state of the art in the operations of sustainable buildings further.

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Declarations

All authors declare that they have no conflicts of interest.

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