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Multi-Objective Optimization of Building Energy Performance Using Genetic Algorithms Analysis

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Abstract. This study develops a framework for optimizing building energy performance using multi-objective optimization. The EnergyPlus simulation model was validated using the BESTEST methodology under ASHRAE Standard 140. Monte Carlo simulations and sensitivity analyses quantified the effects of key building parameters—such as insulation thickness, window properties, and set points—on cooling energy consumption and thermal comfort. Roof insulation thickness was found to be the most influential parameter for reducing energy consumption. A multi-objective optimization approach was applied to address the trade-off between cooling energy demand and CO_2 emissions, constrained by predicted mean vote (PMV) thresholds. The optimization results showed that prioritizing cooling energy reduction led to higher CO emissions, while reducing carbon emissions increased cooling energy use. This study offers insights for balancing energy efficiency, sustainability, and occupant comfort in building.

Keywords: Multi-Objective Optimization, CO_2 Emissions, Energy Efficiency

1. Introduction

The increasing demand for energy-efficient buildings, driven by global climate goals and occupant comfort requirements, has intensified the need for robust simulation and optimization frameworks in sustainable design [1]. Building energy performance is inherently complex, influenced by dynamic interactions between envelope properties, HVAC systems, and environmental conditions [2]. While energy simulation tools like EnergyPlus are widely used, their reliability depends on rigorous validation against standardized benchmarks—a critical step often inadequately addressed in practice [3]. Furthermore, the inherent uncertainties in building parameters (e.g., insulation variability, occupant behavior) and the conflicting objectives of energy minimization and carbon reduction remain persistent challenges [4].

To address these gaps, this study establishes a three-stage methodology integrating model validation, uncertainty quantification, and multi-objective optimization. First, we validate the EnergyPlus model using the Building Energy Simulation Test (BESTEST) protocol under ASHRAE Standard 140 [5], comparing free-floating (Case 600FF) and HVAC-controlled (Case 600) scenarios. This validation ensures the model's accuracy in replicating temperature dynamics and load profiles, with deviations under 3% from benchmark data. Second, Monte Carlo simulations and sensitivity analyses are employed to quantify the probabilistic impacts of 8 key parameters—including

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insulation thickness, window properties, and setpoints—on cooling energy consumption and thermal comfort. Finally, a genetic algorithm-based multi-objective optimization framework is developed to resolve the trade-off between cooling energy demand and CO_2 emissions, constrained by PMV thresholds.

2. Methodology

2.1. Building energy simulation

2.1.1. Building geometry

This simulation utilizes the BESTEST base model as shown in Figure 1, which is founded on a standardized rectangular configuration. The target building's geographical coordinates are 39.833° N latitude and 104.650° W longitude, at an elevation of 1650 meters. The proportions are 2.7 meters in length, 8 meters in breadth, and 6 meters in height. The southern facade of the building features two windows positioned 0.2 meters above the ground. Both windows have dimensions of 3 meters by 2 meters.

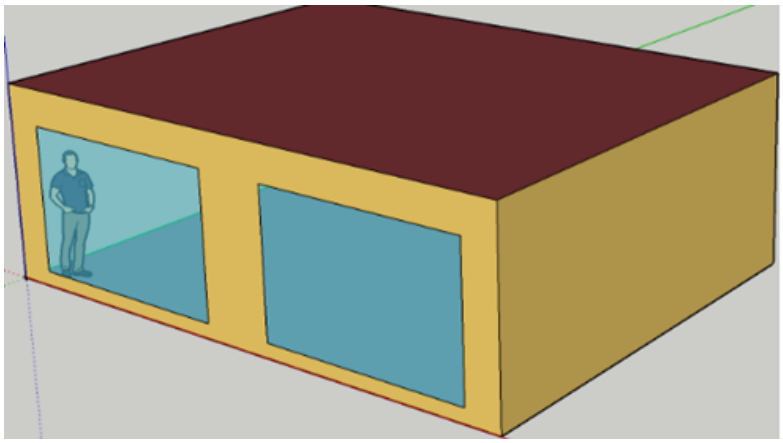

Figure 1. Standard building model

2.1.2. Ventilation data and heating

With Case 600, there is an absence of latent heat, and the internal gain is only derived from the lighting power of 200 W, with an energy distribution of 40% convective energy and 60% radiative energy.The model's ventilation frequency is set at 0.5 air changes per hour.The mechanical system features a ideal air load system regulated by an air temperature thermostat. Cooling initiates when the temperature surpasses 27 degrees Celsius, whereas heating activates when the temperature falls below 20 degrees Celsius.

For Case 600FF, the internal gain from illumination, energy distribution, and the previous factor are uniformly 200 W, with 40% attributed to convection and 60% to radiation. The ventilation setting is also 0.5 ACH; however, unlike Case 600, this model lacks a temperature control device, permitting indoor temperature to vary freely.

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2.2. Uncertainty analysis

Parameters are set in the Monte Carlo simulation based on appropriate probability distributions. The main idea is to calculate the response output by taking random input variables multiple times [6]. For instance, the roof insulation layer's thickness is set to a uniform distribution of 0.08 m to 0.12 m to show its uniform fluctuation within a reasonable physical range. The cooling set point follows a triangular distribution of 19°C to 25°C, with a mode of 23°C in 75% point [7]. A normal distribution with a mean of 0.12 m and a standard deviation of 0.02 is used to model the window gas gap; the number of occupants inside is also normally distributed (mean 3, standard deviation 0.4), and is rounded to an integer value. To accurately represent the distribution of height, weibull distribution with a shape parameter of 2 and a scale parameter of 800 m is used to describe the building elevation(see Figure 2). Furthermore, the Latin Hypercube Sampling (LHS) method is used to produce input samples, and the sample size is set to 180.

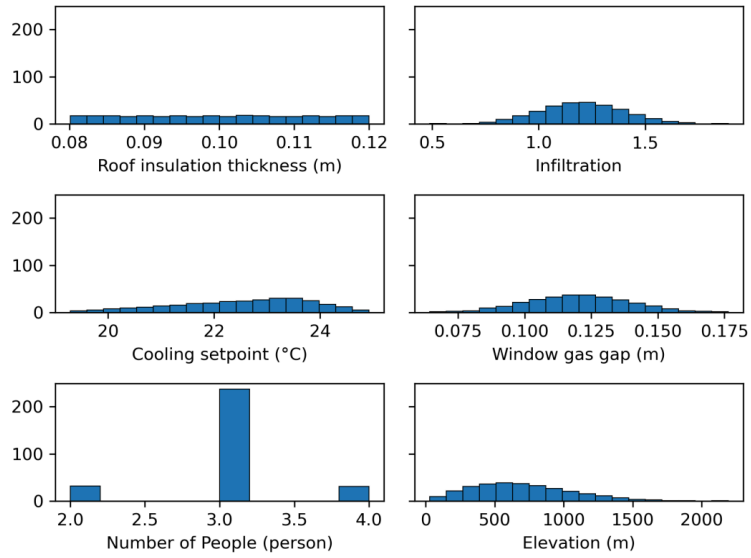

Figure 2. Uncertainty analysis parameters

2.3. Sensitive analysis

Sensitivity analysis (SA) examines the effect of variations in the input parameters of a numerical model on its output findings [8]. This analysis identifies numerous critical characteristics to assess their influence on the building's energy usage and thermal comfort. The insulation thickness of the floor and roofs was uniformly distributed between 1-1.2 m and 0.03-0.17 m, respectively. The cooling and heating set points adhered to a normal distribution with means of 24°C and 17°C, respectively, and a standard deviation of 2°C. The window gas gap was represented by a normal distribution with a mean of 0.02 m and a standard deviation of 0.002 m. Air infiltration was modeled using a normal distribution with a mean of 1 and a standard deviation of 0.4. Wall solar absorption rate was characterized by a triangular distribution ranging from 0.5 to 0.8, with a mode of 0.6(see Figure 3).

The selected parameters directly influence energy consumption and thermal comfort, with insulation, temperature set points, infiltration, and light gain may impact heating and cooling loads as well as indoor thermal balance.

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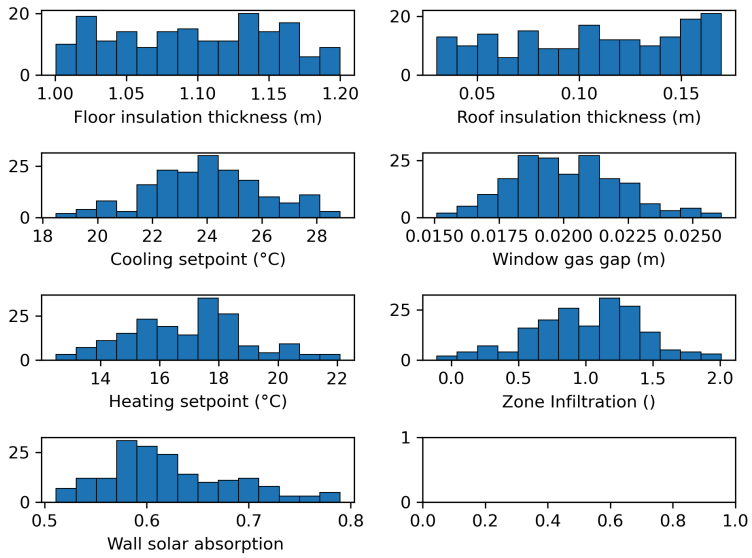

Figure 3. Sensitive analysis parameters setting

2.4. Multi-objective optimization

The selected optimization parameters include the principal aspects influencing energy performance and thermal comfort in buildings.

Infiltration rate is defined as the number of air changes per hour (ACH) within a designated area, ranging from 0.1 to 3 ACH. Ventilation rates are modeled between 0.1 and 3 ACH, representing typical intake ventilation levels to maintain indoor air quality and thermal comfort.

The thickness of the wall insulation is provided as discrete values (0.02, 0.04, 0.06, 0.08, 0.10 m) and includes prevalent insulation materials. This characteristic directly influences heat transport through the building envelope and is essential for energy optimization. The thickness of the window gas layer varies from 0.01 to 0.03 m, and the conductivity of window glazing ranges from 0.5 to 1.5 W/mK, reflecting the enhancement in window insulation.

Cooling and heating set points are defined within the ranges of 22°C–26°C and 17°C–22°C, respectively. The set points substantially influence energy demand throughout cooling and heating seasons while preserving occupant comfort within the usual preference range.

In multi-objective optimization, cooling energy consumption and annual CO2 emissions serve as the primary objectives, while PMV (predicted mean vote) is employed as a constraint. Cooling energy consumption constitutes the primary element of building energy consumption, whereas annual CO_2 emissions encompass electrical emissions associated with cooling and emissions from gas heating. Optimizing these two indicators achieves a balance between energy efficiency and environmental effect, while maintaining an appropriate level of indoor comfort within the PMV restriction.

3. Results and discussion

3.1. Buidling energy simulation results

The graph below shows the temperature fluctuations over time on February 1st.

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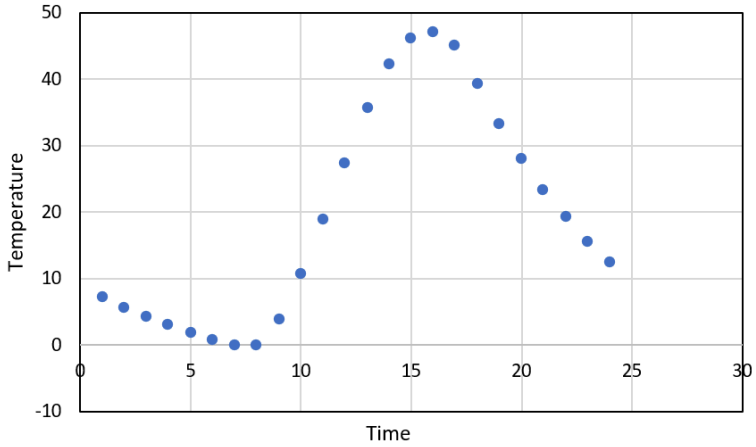

Figure 4. Building temperature on February 1st

Figure 4 shows that the initial temperature on February 1st commenced at 8 °C and progressively fell to almost 0°C Celsius. Following sunrise, the temperature exhibited a notable climb, to a maximum near 50°C in the afternoon. Ultimately, it decreased in the afternoon and settled at 11 °C by day's end. This variation indicates that the temperature typically increases significantly throughout the day, likely due to direct sunshine, and then decreases.

The BESTEST report indicates a temperature of 24.9 °C, however the yearly average temperature is 25.12 °C, resulting in a minimal temperature differential. The peak temperature of the year reached 61.9°C, at 4 PM on October 18, but the maximum temperature recorded at the same time in the report was 63.8°C. The minimum temperature recorded at 7 am on February 9 was -12.6 ° C. The results demonstrate the simulation's reliability, with the simulated outcomes closely aligning with the observed values, exhibiting just minimal variance.

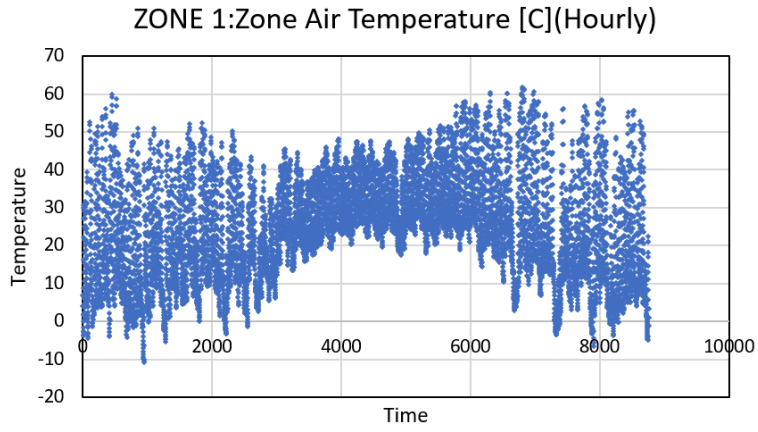

Figure 5. Building temperature of running period

Figure 5 depicts the hourly temperature variations in Zone 1 throughout the course of the year. The temperature exhibits daily and seasonal variations. During the hotter months, temperatures frequently surpass 40°C Celsius and occasionally exceed 60°C. Conversely, during the colder months, temperatures frequently fall below 0°C, perhaps reaching as low as -10°C.

The table presents the annual solar radiation received by various building surfaces and windows, with the windows having a solar transmittance of 1104.1 W (92 W/m^2)(Table 1). The south-facing

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wall and roof of the external envelope experience the greatest solar radiation, measuring 156.423 W/m² and 189.978 W/m² respectively, attributable to direct and diffuse radiation. The heat gain of the east-west walls is moderate, measuring 121.115 W/m² and 110.240 W/m², respectively; however, the north-facing wall registers only 49.980 W/m², indicating it receives the least sunlight.

Table 1. Radiation parameters of the building

Windows Total Transmitted Solar Radiation Rate [W] (Annual)	SURFACE NORTH: Surface Outside Face Solar Radiation Heat Gain Rate per Area [W/m2](Annual)	SURFACE EAST: Surface Outside Face Solar Radiation Heat Gain Rate per Area [W/m2](Annual)
1104.104	49.980	121.115
SURFACE SOUTH: Surface Outside Face Solar Radiation Heat Gain Rate per Area [W/m2](Annual)	SURFACE WEST: Surface Outside Face Solar Radiation Heat Gain Rate per Area [W/m2](Annual)	SURFACE ROOF: Surface Outside Face Solar Radiation Heat Gain Rate per Area [W/m2](Annual)
156.423	110.240	189.978

The maximum heating load is recorded at midnight (00:00) on December 31, reaching 3446.73814 W; moreover, a peak of 3204 W was seen on the same date(see Figure 6). Despite the tiny discrepancy between the two numbers, they remain within an acceptable range. The simulation findings indicate a yearly heating load of 4.49 MWh, although the report presents a value of 4.324 MWh; generally, the two figures are closely comparable.

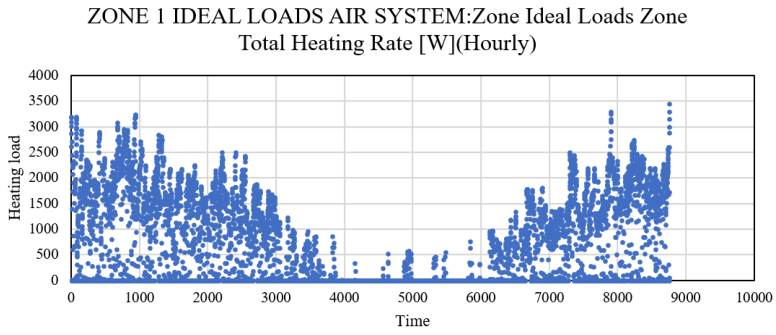

Figure 6. Heating load of the running period

The highest cooling load is 6708 W, recorded at 1:00 p.m. on December 1; this figure is near the reported value of 6352 W, however the peak period in the report is 1:00 p.m. on November 22. Upon arranging the data in descending order by value, it is evident that the simulated cooling load at 1:00 p.m. on November 22 is 6685 W, securing the second position among all outcomes(see Figure 7). The total yearly cooling energy usage was 6.36 MWh, although the reported amount was 6.027 MWh, indicating a minor discrepancy.

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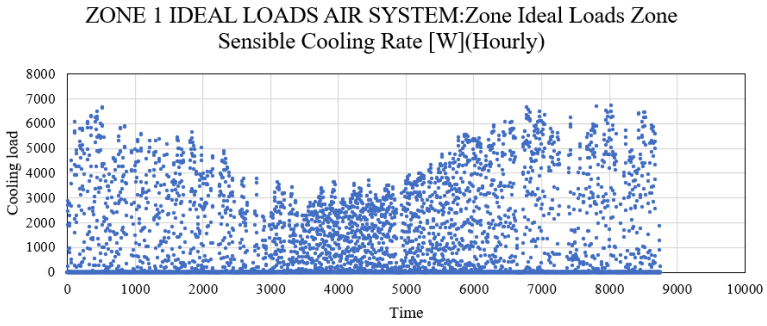

Figure 7. Cooling load of the running period

3.2. Parametric analysis

The simulation's time step was initially set up at four intervals per hour. After changing the time step to 20 occurrences per hour, the total annual heating and cooling loads exhibited substantial alterations: the heating load rose to 4.78 MWh, while the cooling load escalated to 6.44 MWh. Furthermore, the heat balance algorithm initially employed a conduction transfer function [9]; however, upon transitioning to a conduction finite difference, the annual heating and cooling loads were modified, rising to 4.82 MWh and 6.48 MWh, respectively.

3.3. Monte carlo simulation

The histogram(Figure 8) indicates that cooling energy consumption ranges from 580 kWh to 628 kWh. The majority of input parameters, including cooling setpoint, zone infiltration, and window gas gap, which have the same distribution with the output results exhibit, characterized by about symmetrical pattern. The mean is 604.84 kWh, and the standard deviation is 9.27 kWh, indicating variability in the input values. For instance, modifications in the cooling setpoint directly influence the cooling load, whereas insulation thickness impacts the heat transfer mechanism. The 95% confidence interval (585.33–622.94 kWh) delineates the spectrum of cooling energy consumption derived from the parameter distribution(see Table 2).

Table 2. Statistical summary of cooling energy

mean	604.84
standard deviation	9.27
skewness	-0.22
median	605.81
95% CI lower bound	585.33
95% CI upper bound	622.94

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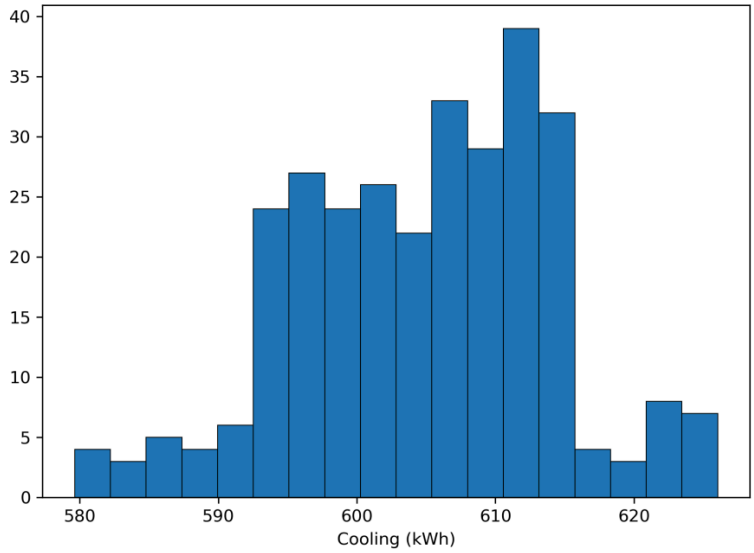

Figure 8. Simulation results of cooling load

3.4. Sensitive analysis

Scatter plots illustrate the correlations between energy usage and each variable, whereas Pearson correlation coefficients measure these correlations(Figure 9). The thickness of floor insulation exhibited the most substantial negative correlation (r=−0.048), suggesting that enhanced floor insulation can not decrease energy demand. The thickness of roof insulation exhibited a moderate negative correlation (r=−0.924), highlighting its significance in diminishing heat loss or gain. The correlation coefficients for cooling set point (r=−0.031), heating set point (r=−0.143), window gas gap (r=−0.03), and infiltration (r=−0.037) were minimal, suggesting they exerted negligible influence under the simulated conditions(Table 3).

It is important to acknowledge that infiltration and window gas gap exert contrary influences on energy usage. In the heating phase, reduced infiltration and larger window gas gap may decrease heat loss to the frigid exterior environment; conversely, in the cooling phase, increased infiltration or smaller windows gas gap can facilitate the dissipation of excess domestic heat.

Table 3. Cooling and heating - Peason's r

floor insulation thickness	-0.04834
Wall solar absorptance	0.19667
Cooling setpoint	0.03164
Window gas gap	-0.03001
Heating setpoint	0.14326
Infiltration	0.03728
Roof insulation thickness	-0.92428

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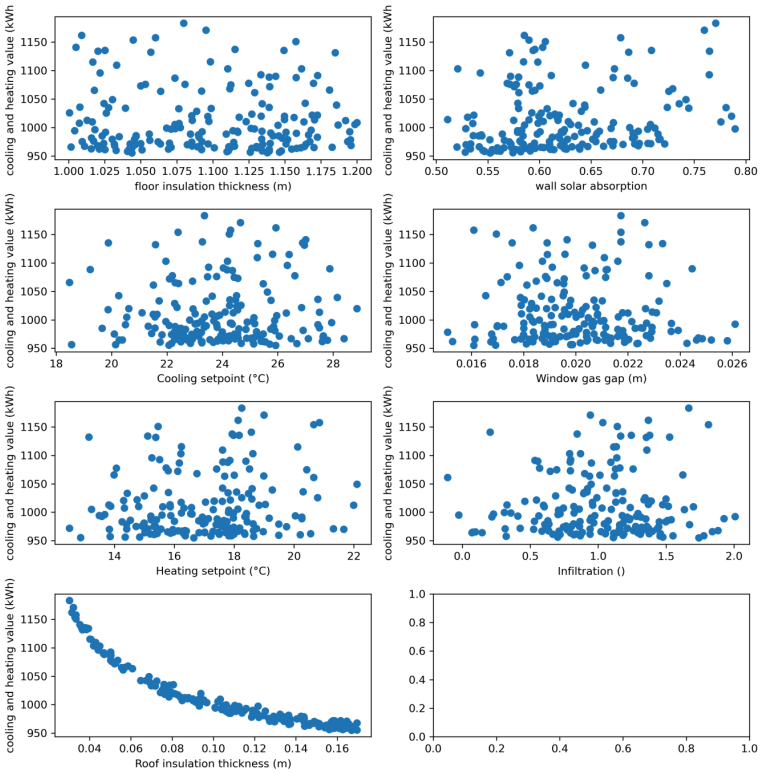

Figure 9. Sensitive analysis of cooling and heating load

PMV serves as the primary metric for assessing thermal comfort, grounded in the concept of human thermal equilibrium, and is presently the most prevalent logical approach [10]. The findings(Table 4) indicate that roof insulation thickness exhibits the most substantial positive correlation with PMV (r=0.948), signifying its crucial role in mitigating heat transfer and enhancing the indoor environment; floor insulation thickness demonstrates a minor positive correlation (r=0.0331), contributing to thermal stability; window gas gap shows a weak positive correlation (r=0.0391), serving to balance advantages against heat loss or gain; conversely, the impacts of cooling and heating set points (r=-0.021, r=-0.132), infiltration (r=-0.045), and wall solar absorptance (r=-0.0378) are minimal. PMV readings between -1.5 and -1.3 signify that the general temperature experience is categorized as "slightly cold" to "cool" under the simulated conditions(Figure 10).

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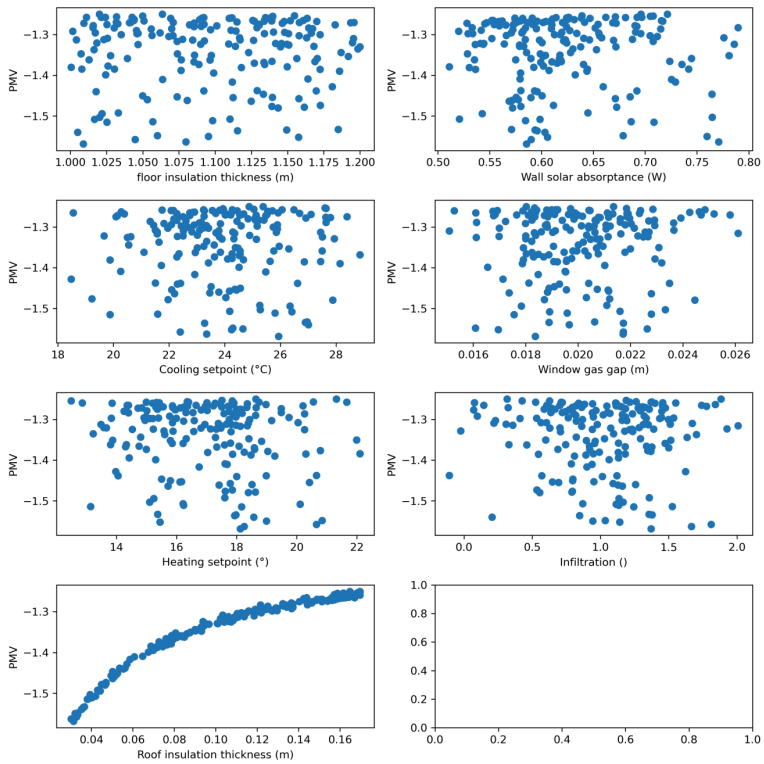

Figure 10. Sensitive analysis of PMV value

Table 4. PMV - Peason's r

Roof insulation thickness	-0.014531
Wall solar absorptance	-0.037873
Cooling setpoint	-0.021454
Window gas gap	0.039184
Heating setpoint	-0.132597
Infiltration	-0.045530
Roof insulation thickness	0.948289

*ental effect, while maintaining an appropriate level of indoor comfort within the PMV restriction.

3.5. Results of multi-objective optimization

The optimization results shown in the scatter plot illustrate the trade-off between cooling energy demand (GJ) and annual CO_2 emissions (kg): the blue markers denote all computed solutions, whilst the red markers emphasize the Pareto optimal solutions that delineate the trade-off boundary(Figure 11). As the requirement for cooling diminishes, CO_2 emissions generally escalate.

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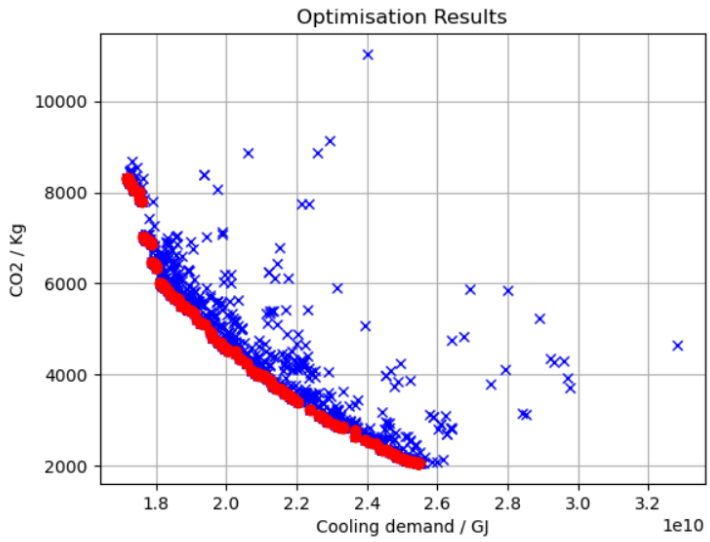

Figure 11. Multi-objective optimization results

The changes in the hypervolume mirror the entire optimization process, starting at about 0.675 and growing fast to about 0.55 during the first 18 generations; thereafter, the growth slows but remains stable between generations 18 and 50. By the 70th generation, the hypervolume stabilizes at approximately 0.875, signifying that the algorithm has converged(Figure 12).

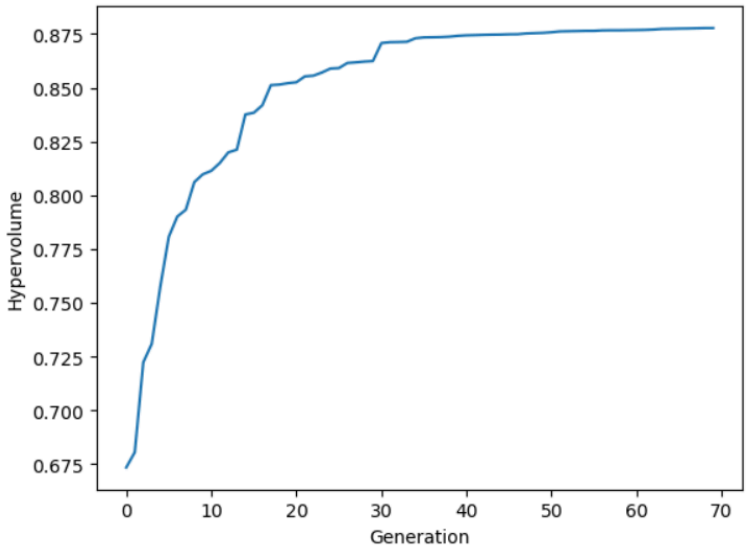

Figure 12. Convergence of multi-objective optimization

If the decision maker prioritizes cooling energy usage, an optimal set of solutions will be derived; conversely, if CO_2 emissions are deemed more significant, an alternative set of solutions may be generated. If the priority of the two objectives are identical, the optimization outcomes will also differ.

Table 5 lists the optimization solutions exhibiting the minimal cooling demand, as identified from the Pareto frontier. The chosen parameters included a infiltration of 2.03 ACH, wall insulation thickness of 0.02 m, window air layer thickness of 0.010 m, ventilation rate of 2.99 ACH, cooling set point of 25.9°C, and heating set point of 17°C. Under these settings, the overall cooling energy

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consumption amounted to 1.72×10^{10} J, CO_2 emissions totaled 8312.4 kg, and the PMV was -1.83, signifying a somewhat chilly interior environment. Increased permeability and ventilation rates correlate with decreased outdoor temperatures, facilitating greater outdoor air influx, which diminishes the inside thermal load and lessens reliance on the cooling system, ultimately lowering overall cooling energy consumption.

Table 5. The result of giving higher weight to cooling energy consumption

Infiltration	Wall insulation thickness (m)	Window glazing conductivity (W/mK)	Window Gas Thickness (m)	Ventilation rate
2.03	0.02	1.23	0.010	2.999
Cool Setpoint (°C)	Heat setpoint (°C)	Total Cooling Energy [J]	CO2 Facility [kg]	PMV
25.9	17.0	1.72E+10	8312.42	-1.83

Table 6 shows the optimization results, prioritizing the reduction of CO_2 emissions. The optimum parameters consist of a permeability of 2.341 ACH, wall insulation thickness of 0.1 m, window air layer thickness of 0.025 m, ventilation rate of 0.1 ACH, cooling set point of 25.9°C, and heating set point of 17°C. Under these circumstances, the overall cooling energy consumption is 2.58×10^{10} J, CO_2 emissions amount to 2054 kg, and the PMV is -1.242, signifying an enhancement in thermal comfort relative to prior measurements.

This method markedly decreases CO_2 emissions (2054 kg vs. 8312 kg) by increasing wall insulation thickness and window gas thickness, hence successfully mitigating carbon emissions during heating and cooling, in contrast to optimization findings focused on decreasing cooling energy usage. Nonetheless, the cooling energy consumption has increased significantly (2.55×10^{10} J compared to 1.72×10^{10} J) due to diminished effectiveness in expelling indoor heat loads via external air.

Table 6. The result of giving higher weight to CO_2 emission

Infiltration	Wall insulation thickness (m)	Window glazing conductivity (W/mK)	Window Gas Thickness (m)	Ventil rate
2.341	0.1	0.5	0.025	0.1
Cool Setpoint (°C)	Heat Setpoint (°C)	Total Cooling Energy [J]	CO2: Facility [kg]	PMV
25.9	17	2.55E+10	2054	-1.242

4. Conclusion

This study presents a comprehensive framework for optimizing building energy performance, integrating model validation, uncertainty analysis, and multi-objective optimization to address the challenges of energy efficiency, environmental sustainability, and occupant comfort. The EnergyPlus simulation model was rigorously validated using the BESTEST methodology under ASHRAE Standard 140, demonstrating high accuracy in predicting temperature dynamics and load profiles, with deviations of less than 3% from benchmark data. Monte Carlo simulations and sensitivity analyses quantified the probabilistic impacts of key parameters, revealing that roof insulation thickness (Pearson's r = -0.924) and ventilation rates significantly influence energy consumption and thermal comfort, while infiltration and window gas gaps exhibit seasonally dependent effects. The

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multi-objective optimization framework, employing genetic algorithms, successfully resolved the trade-off between cooling energy demand (1.72×10^{10} J to 2.55×10^{10} J) and annual CO_2 emissions (2,054–8,312 kg), constrained by PMV thresholds (-1.83 to -1.24).

The key findings of this research are summarized as follows:

1. Validation Accuracy: The EnergyPlus model demonstrated reliable performance under both free-floating (Case 600FF) and HVAC-controlled (Case 600) scenarios, with minimal deviations in temperature, heating, and cooling load predictions.

2. Parameter Sensitivity: Roof insulation thickness emerged as the most influential parameter for reducing energy consumption, while cooling setpoints and infiltration rates showed limited impact under the tested conditions.

3. Optimization Trade-offs: Prioritizing cooling energy minimization led to higher CO_2 emissions (8,312 kg), whereas focusing on carbon reduction increased cooling energy demand (2.55×10^{10} J), highlighting the need for balanced design strategies.

4. Despite these advancements, this study has certain limitations. First, the analysis was conducted under specific climatic and geometric conditions, which may limit the generalizability of the findings. Second, the optimization framework did not account for dynamic occupant behavior or real-time energy pricing, which could further refine the results. Future research should explore the integration of machine learning techniques for predictive modeling and extend the framework to multi-zone buildings with diverse occupancy patterns.

5. In conclusion, this work provides a robust methodology for optimizing building energy performance, offering actionable insights for designers and policymakers to achieve sustainable and comfortable built environments. By bridging simulation validation, uncertainty quantification, and multi-objective optimization, this study lays a foundation for future advancements in energy-efficient building design.

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