2025 5th International Conference on Artificial Intelligence and Industrial Technology Applications (AIITA)

Advancing Building Energy Simulation: A Comprehensive Approach to Performance Evaluation and Optimization

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***Abstract*-This study presents a systematic approach to assess and optimize building energy efficiency. An EnergyPlus model was developed and validated based on the Building Energy Simulation Test (BESTEST). Subsequently, uncertainty and sensitivity analyses were performed to identify parameters with varying degrees of correlation with building performance, focusing on those with significant impact. Finally, the three objectives of the model were optimized by tuning these key parameters to improve efficiency and performance boundaries. The study highlights areas for further improvement, including the incorporation of more comprehensive model setups such as thermal bridges and advanced HVAC systems, the consideration of additional parameters in the sensitivity analysis to refine the optimization, and the use of hyper-volume metrics for higher dimensional objectives to better evaluate multi-objective optimization results. The framework provides a robust approach for advancing building energy efficiency modeling and achieving superior performance results.**

Keywords-bestest, energyplus, multi-objective optimization, energy efficiency, hyper-volume metrics

I. INTRODUCTION

Improving building energy performance is a critical objective in addressing global challenges such as climate change and resource conservation. Buildings account for a significant proportion of global energy consumption and greenhouse gas emissions, making their energy optimization a key area for achieving sustainability goals. This research aims to address these challenges by constructing a building system model using the Building Energy Simulation Test (BESTEST), a standardized method for evaluating and diagnosing the capabilities of building energy simulation models [1].

BESTEST provides a rigorous framework for validating simulation accuracy and identifying gaps in modeling methodologies, ensuring robust results. Leveraging this framework, the study explores how various parameters influence building performance, emphasizing their role in improving energy efficiency. By conducting sensitivity and uncertainty analyses, the research identifies key parameters with a strong correlation to performance outcomes. These critical parameters are then optimized with three targeted objectives to enhance energy efficiency and operational boundaries.

This systematic approach not only contributes to advancing building energy modeling techniques but also addresses the growing demand for efficient, data-driven methods to achieve sustainable performance in the built environment.

II. METHODOLOGY

A. Model Construction

In this research, Energy + is used as the simulation software. Both the Case 600FF and Case 600 buildings are identical simple box-shaped buildings simulated using Energyplus modeling software, and both have two double-glazed windows in the south-facing walls. The difference is that the Case 600FF building is not heated and cooled, relying only on fixed internal gains, therefore its temperature is free-floating. The Case 600 building, on the other hand, uses the Ideal Load Air system in energyplus for heating and cooling control, keeping its internal air temperature between 20°and 27°. In this research, to generate a simulation model, four aspects of data are generally considered: Environment, Building Construction, Simulation process, and Action to the building. To specify, the detail is shown in Figure 1:

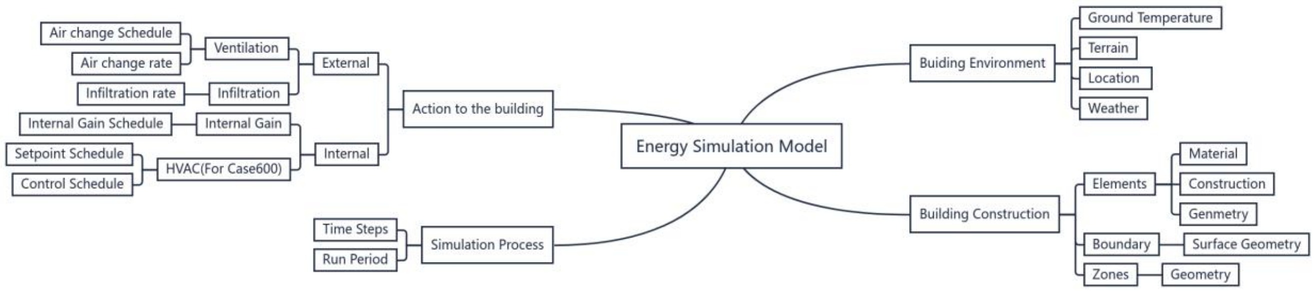

Figure 1 Considered data in this research

1) ***Build Environment:*** The location of the model is set to Denver Internal Airport. After setting the location, the weather data can be determined. Besides, Ground Temperature and Terrain type data are based on ASHRAE 140 [2], and other relative data are set to the default value.

2) ***Simulation Process:*** The Run Period of this model is set to a whole year due to the required annual result. The special days and holidays are also considered for the further schedule setting.

The time steps are positively correlated to the accuracy of the result, yet a more significant time step would increase the computational cost. Therefore, as Case600 is more complicated than Case600FF, the Time step of the Case600 model will be set to 6, and that of Case600FF will be set to 12.

3) ***Building Construction:*** To construct an analytical model of a building, as in the construction of the BIM model, the building model can be divided into Elements, Spaces, and Boundaries. Elements data can be further divided into the material, construction, and geometry data. Most of the material data are based on ASHRAE 140 [2], while the Solar Absorptance of the internal and external opaque surfaces need calculation based on its radiative properties.

As the solar absorption consists of 49.4% of infrared radiation and 50.6% of short-wave radiation [3] and the two building models, Case600 and Case600FF, are prescribed as generic models, and the radiation characteristics of their internal and external opaque surfaces are agreed to be infrared emissivity and absorptivity of 0.9, and short-wave emissivity and absorptivity of 0.6, the total solar absorption of the internal and external opaque surfaces is

$0.9 \times 49.4\% + 49.4\% + 0.6 \times 50.6\% = 0.75$. That of the rest material is set to the default value.

The space data of the building is set to the zone. The rules should be determined initially to input the boundary data into the model. The boundaries of this model are the surface, and the data is based on ASHRAE 150.

4) ***Action to the building***

a) Ventilation: daytime ventilation rate of 0.5 ach is 20% higher than at night to minimize heat impacts. Ventilation is not controlled by temperature or wind speed.

b) Infiltration: Infiltration rate of 0.5 ach per ASHRAE 140, but the effect is ignored as it is similar to ventilation and only timed differently.

c) *Internal Gain:* Modeled internal gain of 200 W, 100% sensible heat, 60% radiant, 40% convective, no latent heat, from lighting only, not considered occupancy.

d) *HVAC:* System is 100% convection cooling and constant temperature heating, no supply air temperature limitations, default values used.

B. Uncertainty and Sensitivity Analysis

Nowadays in building simulation, the main challenge is how to deal with a large variety and complex parameters [4]. Therefore, it is necessary to conduct an uncertainty (UA) and sensitivity (SA) analysis in simulation process. The purpose of it can be described as determining the relationship between the input and output of the simulation [5, 6]. The sources of uncertainty in the input parameters are identified, then the set of parameters is generated for simulation by random sampling or distributional assumptions, then the range of uncertainty in the outputs is assessed by statistical methods, and finally the relative impact of each input parameter on the outputs is quantified by applying a sensitivity analysis method (correlation analysis method).

1) Parameters and Probability Distribution

Parameters in building energy analysis can be divided into three types: design parameters, inherent parameters, and scenario parameters[7-12]. Each type of parameter has its usual distribution[13-14]. Table 1 shows the parameter types and their usual probability distributions.

Table 1 Parameters and its usual probability distribution

Parameters	Usual Probability Distribution
Design Parameters	Continuous / Discrete / Uniform distribution
Inherent Parameters	Normal / Gaussian / Triangular Distribution
Scenario Parameters	Continuous / Discrete / Uniform distribution

2) Sampling Method

Different method has different sampling strategy [15-17]. For the regression-based SA, some studies employed Latin Hypercube Sampling method (LHS) to generate samples and said that LHS has a desirable property for SA [7, 18, 19]. Moreover, LHS produces a more stable results than crude

Monte Carlo sampling with a less computational cost for complex model [20]. Besides, a study compared the SA results generated by different sampling methods, and LHS was the recommended one [21]. Therefore, LHS will be used in this research.

3) Simulation Times

As there is a marginal effect after the simulation time exceeds a certain amount [20], the number of simulations in this study will be kept within the recommended values with no more than 10 times the number of input variables [22].

4) UA Input

There are 6 inputs considered in UA, the details as shown in Table 2. Noteworthy, weather data is a very complex challenge as it includes numerous variables, to simplify the process, three weather files corresponding to hot, cold, and medium city (Resolute, Denver, Bogota) will be used [23].

Table 2. UA Input

Input	Range	Distribution	Reference
12 Monthly Ground Temperature (℃)	From 17.6-24.17	Normal Distribution	[24]
12 Monthly Ground Reflectance	0.13-0.2-0.26	Triangular Distribution	[10, 23]
Terrain	Suburbs, Country, City, Ocean, Urban	Discrete Distribution	[13]
Weather	Cold: Resolute, Medium: Denver, Hot: Bogota	Discrete Distribution	[23]
People Internal gain fraction	(0.27, 0.6)	Uniform Distribution	[20, 25]
Light Internal gain fraction	(0.25, 0.37)	Uniform Distribution	[20, 25]

5) SA Input

Six parameters will be considered in SA. The details are shown in Table 3.

Table 3 SA Input

Input	Range	Distribution	Reference
Orientation	0-0.9	Uniform Distribution	[26]
Cooling Set Point (℃)	(20,5,0.5)	Triangular Distribution	[34-37]
Heating Set Point (℃)	(15,5,0.5)	Triangular Distribution	[34-37]
Infiltration Rate (ach)	(0.5, 0.05)	Normal Distribution	[30,38]
Window width (m)	(2.1,1,1.5)	Weibull Distribution	[39]
Internal Wall thickness (m)	(0.1,0.23)	Uniform Distribution	[30]

6) UA Output

The Heating Energy will be focused on in UA. The uncertainty will be analysed based on the related parameter of the distribution diagram including mean value, standard deviation, skewness.

7) SA Output

Three targets will be focused on in SA: Heating Loads, Electricity Consumption, and Not Thermal Comfort Hour. The scatter plot of the results will be expressed. The sensitivity will be analysed by analysing the trend of the result. For analysis, two correlation coefficients will be introduced: Pearson coefficient and Spearman coefficient. The comparison of these to coefficients is shown in Table 4 [33]:

Table 4 Comparison between two correlation coefficients

	Meaning	**Scopeof application**	**Object of effect**
Pearson coefficient	Dimension measurement of covariance	Continuous, Linear input	Value
Spearmen coefficient		No restriction as Pearson	Rank of Value

Besides, several approaches have been suggested for the interpretation of the coefficients [41-43], the one proposed by Carso JC, Cliff N. which will be used in this research. Table 5 shows the conventional methods of interpreting the correlation coefficients.

Table 5 A conventional Approach to Interpreting a Correlation Coefficient

Absolute Magnitude of the Observed Correlation Coefficient	**Interpretation**
0.00-0.10	Negligible correlation
0.10-0.39	Weak correlation
0.40-0.69	Moderate correlation
0.70-0.80	Strong correlation
0.90-1.00	Very strong correlation

C. *Design Optimisation Muti-Objective Optimisation*

Building Energy simulation and Optimisation (BESO) has become a popular method for building design which aims at finding the optimal option of a large amount of candidate solutions [37-39]. In real-world building design, designers usually face the conflict design criteria simultaneously, which becomes the reason why Multi-objectives optimisation is more relevant than single-objective approach and it led to the application of the application of the relevant algorithms (MOOAs), which determine the Pareto optimum trade-off between those design objectives [40-45].

1) NSGA-II

The non-dominated-and-crowding sorting genetic algorithm II (NSGA-II) is one of the most commonly-used multi-objective optimisation algorithm [40], firstly developed by Deb [46], which is based on genetic algorithm(GA), developed by Holland in the 1970s[47]. Therefore, it will be used in this research.

2) Input Parameters and Targets

The optimisation of this research is guided by initial energy performance, and thermal comfort is the second important and indoor air quality, referencing to studies reported so far[48]. The relevant input and its range is expressed in Table 6 and Table 7:

Table 6 Inputs of the BESO

Input	Unit	Range	Reference
Heating Setpoint	℃	10-18	[27,49]
Cooling Setpoint	℃	20-28	[27,49]
Window to Wall Ratio	%	1-99	[28,29]
Infiltration Rate	Ach	0.41-7.07	[31, 50, 51]
Ventilation Rate	Ach	0.38-8	[52]
Orientation	°	0-360	[32]

Table 7 Targets of the BESO

Out put	Unit
District Cooling Energy	GJ
Zone Thermal Comfort ASHRAE 55 Simple Model Summer or Winter Clothes Not Comfortable Time	GJ
Carbon Equivalent	Hour

3) Outputs Analysis

In the field of multi-objective optimisation, the majority of studies are usually concerned with how to find the solutions that can represents as a good approximation of the Pareto-optimal set [53], which usually transformed into a single-objective problem [54]. The convergence of the indicator of each generation will be analysed.

Besides, the hypervolume indicator is the only quality indicator known to be fully sensitive to Pareto dominance [55], and it will be considered in this research.

Usually, for 2-Objectives optimisation, the hypervolume indicator is expressed as the ratio of 2-D hypervolume dominated the ideal area. In this case, 3 objectives are considered, the hypervolume indicator should be express as the ratio of 3-D hypervolume dominated the ideal volume.

However, due to the time limitation, a much rougher alternative indicator is introduced. The 3-D hypervolume will be simplified as the average volume of each generation, and the ideal volume will be simplified as the average volume of the first generation, which means the maximum volume that can be optimised. The indicator is expressed as a volume change rate:

$$indicator = \frac{\mathrm{AverageVolume}_{\mathrm{gen1}} - \mathrm{AverageVolume}_{\mathrm{geni}}}{\mathrm{AverageVolume}_{\mathrm{gen1}}}$$

III. Results and Discussion

A. *Uncertainty and Sensitivity Analysis*

1)Uncertainty Analysis

This research trying to figure out the extent to which different parameters affect uncertainty. Figure 2 illustrates a very high-level uncertainty results of all parameters with a discrete distribution, which expressed that its high uncertainty level is caused by weather data. That’s because weather data is the most complex parameter among them which consist of many variables such as temperature humidity etc. Besides, Figure 3 express the uncertainty results of the parameters without the weather data, the distribution of it is fluctuated which is caused by the combination of the terrain and ground temperature which has discrete and normal distribution. Overall, the changes of related algorithms caused by terrain differences has a sight large influence than that caused by the changes of ground temperature. Other parameters has much less influence than ground temperature as shown in Figure 4 whose distribution is a domain by the normal distribution.

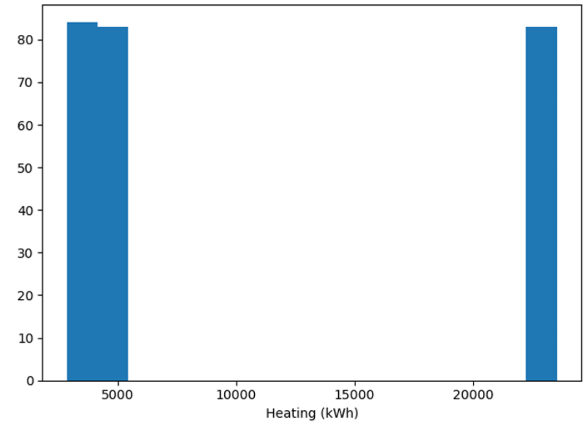

Figure 2 Result Uncertainty with all parameters

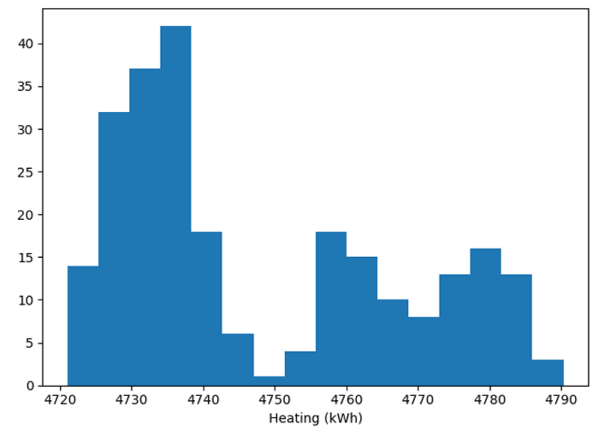

Figure 3 Result Uncertainty without weather

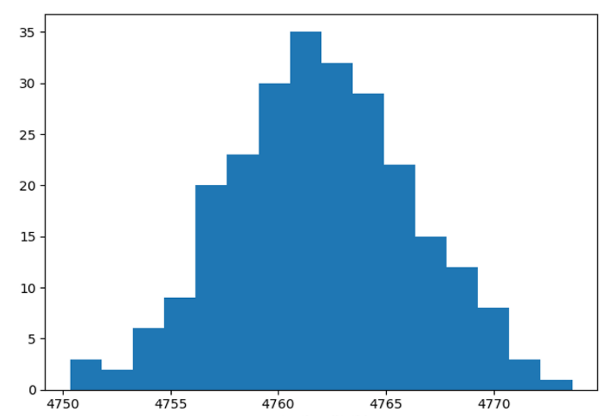

Figure 4 Result Uncertainty without weather and terrain

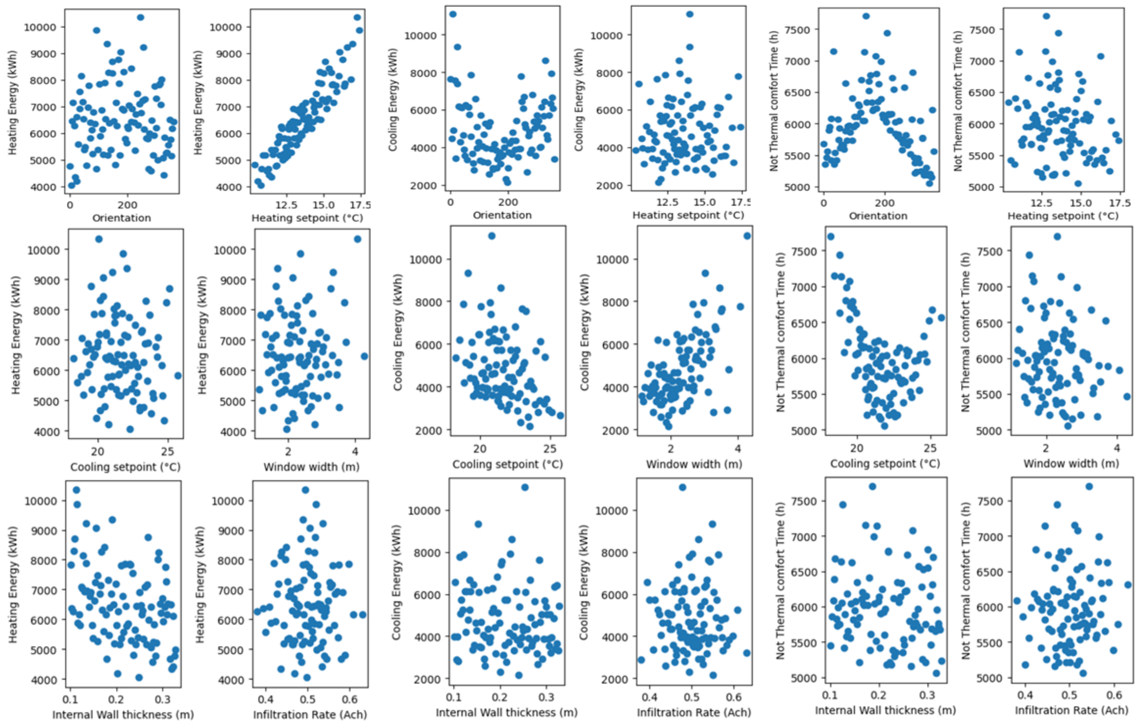

Figure 5 The sensitivity scatter plot results of 6 parameters for 3 targets

Table 8 Coefficients of 6 parameters for3 targets

	Pearson coefficient			Spearman coefficient		
	Heating Energy	Cooling Energy	Thermal Comfort	Heating Energy	Cooling Energy	Thermal Comfort
Orientation	0.01	-0.02	-0.23	-0.02	0.06	-0.23
Heating Setpoint	0.92	0.03	-0.15	0.92	0.02	-0.15
Cooling Setpoint	-0.09	-0.33	-0.42	-0.01	-0.34	-0.42
Window Width	0.085	0.60	-0.14	0.01	0.54	-0.11
Internal Wall	0.085	-0.12	-0.14	-0.37	-0.13	-0.13
Thinkness	0.085	-0.12	-0.14	-0.37	-0.13	-0.13
Infiltration Rate	-0.01	-0.01	0.05	-0.01	-0.03	0.03

2)Sensitivity Analysis

This is shown in Figure 5 and Table 8. In general, both internal wall thickness and infiltration rate have a small sensitivity of the targets. As for most of the results is affected by effective thickness of the components but internal wall thickness can only change it in a limited range. Infiltration has a less influence with a small air change rate. Heating setpoint strongly correlates to heating energy as it can directly control the heating system. Although the coefficient value expresses that orientation has a weak correlation to the results, it has a strong correlation to cooling energy and thermal comfort conversely. That's because the effect of the orientation is changed periodically as only one wall has windows which is the only way of receiving solar irradiation. Same as orientation, except for cooling energy, cooling setpoint has a strong correlation to the thermal comfort with a small coefficient value.

B. Design Optimisation

Table 9 shows some of the parameter combinations for the optimal results. Figure 6 shows the optimisation result of all generations. The 3-d results express general trend of the process, and the 2-d results shows the relationship between the targets. Cooling energy consumption has a synergy to the Carbon emission, while it has a conflict to the thermal comfort. Moreover, as shown in Figure 7, the indicator convergence in nearly 0.8, which is a relatively high value, shows that the input parameters have a relatively strong correlation to the target. Besides, according to the gradient of the result, after 4 generations 120 evaluations, the indicator converged which means the optimal solution is generated.

Table 9 Some of the parameter combinations of the optimal results

	Heating Setpoint(℃)	Cooling Setpoint(℃)	Orientation(°)	Infiltration Rate(Ach)	Ventilation Rate(Ach)
1	11.372762	25.005195	8.284403	0.371817	2.738597
2	10.173676	25.080508	34.811257	0.433600	1.007955
3	10.162740	24.794153	36.704337	0.458355	0.878162
4	10.314214	24.848106	11.473334	0.395811	1.355223
5	10.534764	24.878430	3.343706	0.360036	1.057254

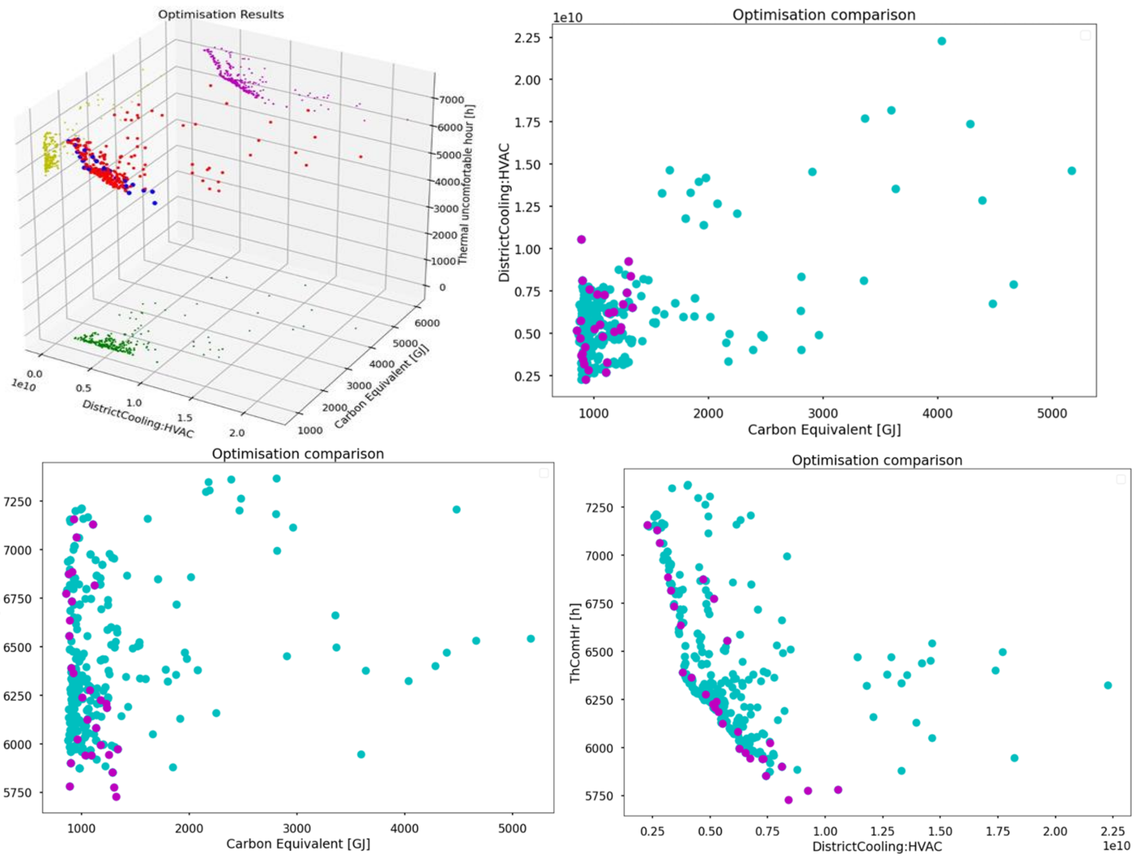

Figure 6 Optimisation results

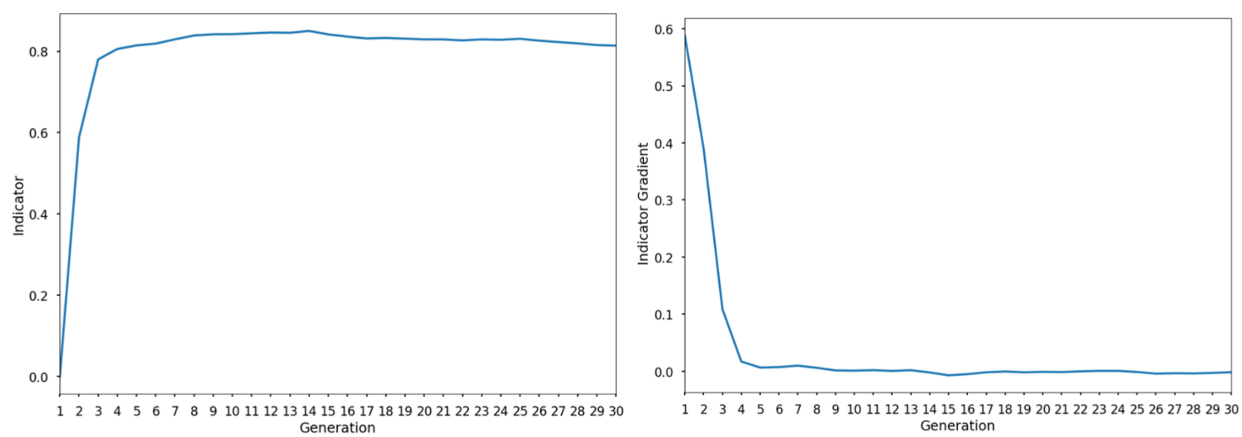

Figure 7 Indicator of generations and the gradient of change

IV. CONCLUSION

This research initially developed an Energy Plus models. Secondly, an uncertainty and sensitivity analysis were applied to the model for evaluating the correlation between the building performance and some parameter that is unclear or have no strong apparent correlation. Finally, based on the results from sensitivity analysis, the model was optimised with 3 targets by changing the parameters with significant correlation for a higher efficiency and upper limit. However, there some perspectives that need to be improved or further investigate:

1. The whole process can be applied to a more comprehensive model with detail settings such as thermal bridge, more complex HVAC system etc.

2. More parameters should be considered in the uncertainty and sensitivity analysis for figuring out the most efficient parameters to guide the future optimisation process.

3. More objectives should be considered in the optimisation as there a lot of indicators reflects the building performance. Besides, the hypervolume indicator for higher dimensional optimisation is required for evaluating the results of optimisation with more targets.

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