Executive summary

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Overview of the Project:

Building design is a multi-criteria decision-making process that typically involves numerous design parameters, such as geometry and envelope characteristics, uncertainty in internal loads, various HVAC system characteristics, utility rate structures, etc. Extensive simulation runs are required to complete the associated combinatorial parametric sensitivity analysis, which may not be realistic due to the sheer number of design possibilities, variables, and potential design criteria (response variables or objective functions). Additionally, it is impractical to use traditional optimization techniques to conduct a thorough search for optimal and sub-optimal solutions, even though in many cases, such solutions may end up being preferable options when financial effects, site-related constraints, or aesthetic preferences are considered.

The strategy used in this work is to classify the parameters according to their significance and degree of interaction, focusing more on those that have a bigger influence and interaction through statistical methods, graphical plots and machine learning algorithms. Naturally, the outcomes determined in this work are, of course, unique to this circumstance and area and should not be generalized to other building kinds and locations.

Methodology:

1. Screening process using statistical methods to identify the influential parameters.

This approach advises visualising the two statistical indicators, μ* (Average of absolute elementary effect) and σ (Standard deviation) to help determine the relative importance of various design or input factors and to provide understanding on parameter interactions on the objective functions.

- Low Average (μ*) and Low Standard Deviation (σ) – Negligible
- High Average (μ*) and Low Standard Deviation (σ) – Linear and additive
- High Standard Deviation (σ) - Non-Linear, i.e., objective function varies non-linearly with change in those parameters, thus having greater impact on the objective function.

2. Analyzing the results through an Interactive chart along with interaction chart for the best possible combinations.

The parameters with significant impact and interactions have been further analysed and plotted on an interactive created in Python environment, where designers can apply filters / constraints on various objective functions as well as parameters to make a well-informed decision while adhering to all set limitations.

3. Training ANN (Artificial neural networks) for additional flexibility, i.e., to include additional options or make variations to design parameters at a later stage.

This step in the analysis may be optional, but it is strongly advised because it offers more flexibility in case the designer decides to use different values for design parameters than those used in the actual pre-simulated cases. This study makes use of the Keras Python library's Artificial Neural Network (ANN) model.

Design conditions and parameters:

The depicted building is a hypothetical, three-story medium office structure with five zones per floor and a total built-up area of 13,940 sq. m (150,000 sq. ft). The simulation program utilized was eQUEST, and the meteorological data used was TMY3 data for Little Rock, Arkansas as it had both cooling and heating demands with Cooling Degree Days (CDD) - 1242 deg. C days (2235 deg. F) and Heating Degree Days (HDD) – 1602 deg. C (2884 deg. F).

List of total Input Parameters / Variables considered in this project:

S. No	Input Parameters / Variables	Units	Variations
1	Orientation	Degrees	0, 90 (0 means N facing)
2	WWR	Ratio	0.1, 0.3, 0.5
3	SHGC	Ratio	0.2, 0.4, 0.6
4	Overhang Depth	Meter	0.03, 0.305
5	Wall Insulation thickness	Meter	0.025, 0.076, 0.127
6	Roof Insulation thickness	Meter	0.025, 0.076, 0.127
7	LPD (Lighting power density)	W/m^2	4.84, 6.46, 8.07
8	EPD (Equipment power density)	W/m^2	2.69, 5.38, 8.07
9	Fan Static Pressure	Pa	746.5, 1493.04
10	VAV Box Min. flow ratio (VAVMin.)	Ratio	0.3, 0.6, 0.9
11	Max. Cool Supply Air Temp. (CoolSATMax.)	Deg. C	12.78, 15.56, 18.34
12	Chiller Efficiency	COP (Ratio)	7.8, 5.4
13	Outside Air (OA) fraction	Ratio	0.05, 0.125, 0.2
14	Infiltration	$m^3/s\text{-}m^2$	0.0005, 0.002
15	Daylighting	Binary	0, 1 (No or yes)
16	Number Of Chillers	Number	1, 2
17	Chiller Variable Speed Drive (VSD)	Binary	0, 1 (No or yes)
18	Hot Water (HW) Min. Reset Temp.	Deg. C	48.89, 60
19	Chilled Water (CHW) Max. Reset Temp.	Deg. C	7.22, 10
20	Pump Min. Variable Frequency Drives (VFD)	Ratio	0.1, 0.55, 1
21	Electric Boiler	Binary	0, 1 (No or yes)
22	Economizer	Binary	0, 1 (No or yes)
23	Heat Recovery (HR)	Binary	0, 1 (No or yes)

The variations chosen typically corresponded to the useful ranges of variation in the majority of current buildings.

List of Output / Objective functions considered in this project:

S. No	Output / Objective functions	Units
1	Energy Use Index (EUI)	GJ/m2-Yr
2	Utility Cost	USD ($)
3	First Cost (Initial Investment)	USD ($)
4	LCC (Life Cycle Cost)	USD ($)

Highlights and Results:

1. Relevant parameters identified using Screening Method

Results from Morris method:

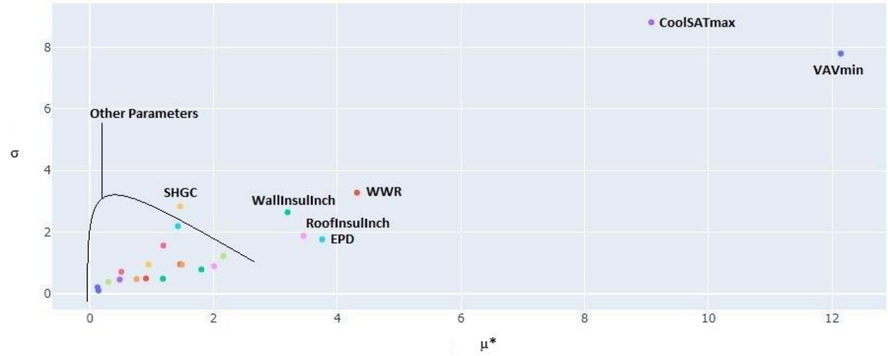

Fig 1. μ* and σ indices varying with EUI for input parameters

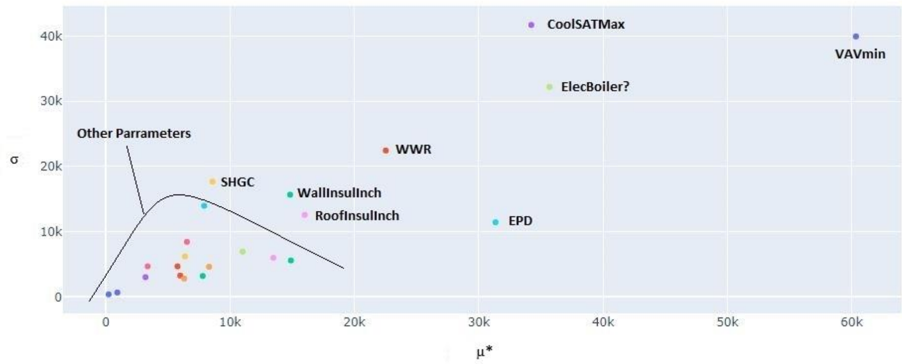

Fig 2. μ* and σ indices varying with Utility Cost for input parameters.

Increasing μ* indicates greater importance of the parameter and increasing σ indicates greater interaction between the parameters.

- *VAVMin.* and *CoolSATMax.* has high importance and interaction.
- *EPD, WWR, SHGC, Wall Insulation and Roof Insulation* has moderate importance and interaction.
- *ElectricBoiler* does not seem to influence EUI but shows high importance and interaction with Utility cost.
- ***8 out of 23*** parameters showed relevance and interaction with the input / objective functions.

Results from Sobol method:

The stability and accuracy of the screening results were validated using the Sobol Global Sensitivity Analysis. When determining the most important parameters, the findings from the screening method is very similar to Sobol method.

List of selected Input Parameters / Variables after screening process:

S. No	Input Parameters / Variables	Units	Variations
1	WWR	Ratio	0.1, 0.3, 0.5
2	SHGC	Ratio	0.2, 0.4, 0.6
3	Wall Insulation thickness	Meter	0.025, 0.076, 0.127
4	Roof Insulation thickness	Meter	0.025, 0.076, 0.127
5	EPD (Equipment power density)	W/m^2	2.69, 5.38, 8.07
6	VAV Box Min. flow ratio (VAVMin.)	Ratio	0.3, 0.6, 0.9
7	Max. Cool Supply Air Temp. (CoolSATMax.)	Deg. C	12.78, 15.56, 18.34
8	Electric Boiler	Binary	0, 1 (No or Yes)

2. Interactive parallel coordinates chart along with interaction chart for the best possible combinations.

For the 8 influential parameters, an exhaustive set of 4,374 (3x3x3x3x3x3x3x2) distinct parametric combinations were produced. It enables user to select the best combination of design variables from among the 4,374 combinatorial simulation cases. To examine and select the best options among them while adhering to all the limitations set by the user, filters can be applied interactively in real time on a variety of axes.

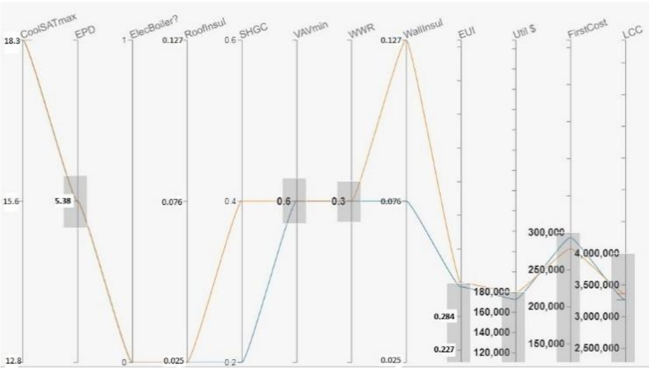

Fig 3. Parallel plot with filters applied.

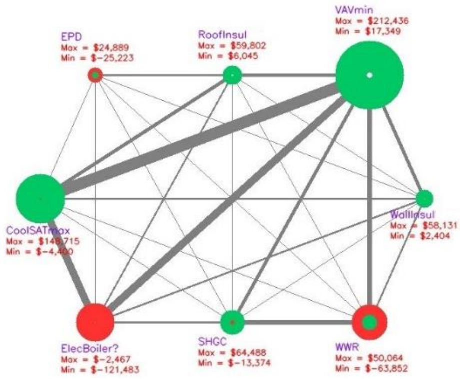

Fig 4. Interaction chart.

In Fig 3. Filters have been applied to objective functions so as to limit: EUI (0.34 GJ/m2-Yr), Utility Cost (Annual Utility Cost $180,000), First Cost ($300,000), and LCC ($4,000,000). When the variation of some of them ('EPD', 'VAVmin', 'WWR') were restricted along with the limitations on objective functions as mentioned above, the remaining solution sets represented by lines shows the latitude that available for other parameters. The two lines in Fig. 3 represent the available solutions left after applying all filters / limitations.

A parameter's importance is indicated by the size of the circles that are associated with it (i.e., the overall impact that parameter can have on an objective function while other parameters are left to vary), and the interaction between two parameters is indicated by the thickness of the line that connects them in an interaction chart as shown in Fig.4. Red and Green colours on the circles depicts the sign (negative and positive) of impact that a variable would have on the objective function, i.e., here with respect to the utility cost.

3. ANN (Artificial Neural Networks) accuracy for predictions.

An ANN model was trained using the exhaustive set of results for influential parameters and the screening results to extend the domain for parameters using machine learning. The trained model demonstrated outstanding precision, with RMSE (Rooted Mean Square Error) for EUI being 0.00636 GJ/m2-Yr (1.76%) and Utility cost being $3,327 (1.70%). Additionally, the R-squared values (Variance) for utility cost and EUI are 0.9935 and 0.9925, respectively. Therefore, it can be said that the prediction accuracy is more than acceptable for the initial design decision-making process.

Conclusions:

- The designers can explore a wide range of potential combinations based on the requirements of the building owner as this tool offers clear and better interpretation of the outcomes in addition to user-friendliness.
- With much less computing time and resources, a high level of accuracy can be achieved in the results.
- The effects of many design factors can be assessed with substantially fewer simulation runs, while also revealing information about parameter significance and parameter interaction.