Title

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Approach for energy efficient building design during early phase of design process

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Abstract
Energy consumption in the building sector is about 40% of total energy consumed globally and is trending upwards, along with its contribution to greenhouse gas (GHG) emissions. Given the adverse impacts of GHG emissions, it is crucial to integrate energy efficiency into building designs. The most significant opportunities for enhancing energy performance are present during the initial phases of building design, when there is less impact of other design constraints. Various tools exist for simulating different design options and providing feedback in terms of energy consumption and comfort parameters. These simulation outputs must then be analyzed to derive design solutions. This paper presents an innovative approach that utilizes user input parameters, processes them through cloud computing, and outputs easily understandable strategies for energy-efficient building design. The methodology employs Asynchronous Distributed Task Queues (DTQ) - a more scalable and reliable alternative to conventional speedup techniques-for conducting parametric energy simulations in the cloud. The goal of this approach is to assist design teams in identifying, visualizing, and prioritizing energy-saving design strategies from a range of possible solutions for each project. Furthermore, a tool 'eDOT' has been developed utilizing the discussed methodology. Unlike existing tools, eDOT leverages artificial intelligence to dynamically generate and provide design strategies during the early phases of design process. By simplifying the simulation process, eDOT enables design teams to make informed, data-driven decisions without needing to interpret complex simulation outputs. A case study simulated for two locations is provided in this paper to demonstrate the effectiveness of eDOT, further underscoring its practical impact on energy-efficient building design.

Keywords Asynchronous Distributed Task Queues, Parallel Simulations, Building Energy Analysis, Early-Stage Building Design

Introduction

Rapid urbanization around the globe is driving energy demand and the associated greenhouse gas emissions. The buildings and construction sector accounts for 36% of final energy use and 39% of energy- and process-related emissions worldwide. In 2021, about 28% of the total U.S. energy consumption was associated with residential and commercial buildings [1]. Much of the energy use in buildings is wasted because of "poor design, inadequate technology and inappropriate behavior" [2]. At the beginning of the design process, it is relatively simpler and less expensive to make design changes to arrive at the desired solution. The design process is generally phased sequentially as follows: conceptual design, schematic design, design development and construction documents. The early design phases provide more flexibility as there are fewer constraints imposed by other design decisions. There are a number of design parameters, primarily related to building form, that need to be considered during early design. Echenagucia et al. [3] discussed the importance of decisions taken in early design phase, asserting that this critical phase presents the greatest opportunity to obtain a high-performance solution for the building.

A number of building design analysis tools are currently available with varying features and functionalities that can be used to determine building energy consumption, including EnergyPlus [4], DOE-2 [5] and IES-VE [6]. Some of these tools can be used with different external User Interface (UI), For example, EnergyPlus, a whole building simulation tool developed by the U.S. Department of Energy (DOE), is included with OpenStudio [7], DesignBuilder [8] and Simergy [9]. eQUEST [10] is based on DOE-2.2, a derivative of DOE-2, and Green Building Studio [11] can serve as an interface to both DOE-2.2 and EnergyPlus. IES-VE includes both a simulation engine and a user interface. Despite the substantial number of building simulation tools available, the application of these tools is primarily restricted to the later design phases [12].

However, a number of authors have explored the use of building performance simulations in early design. One of the findings of Kristoffer Negendahl [13] emphasized that most tools and methods used in the early design stages are not sufficient to provide valid feedback while at the same time being flexible enough to accommodate a rapidly changing design process. Tian et al. [14] have compared seven energy optimization tools that can be used to identify energy efficiency solutions in the conceptual design phase. The results show that existing techniques are not able to fully address the architect's needs in the conceptual design stage and, therefore, further research and development are required. Ostergard et al. [15] have presented a robust review of building simulation tools and addressed integration challenges for early design.

Hema Rallapalli et al. [16] surveyed 100 architects in India and found that only 33% of them uses energy modeling for their projects. However, 72% of them agree that energy modeling is useful in early design. As per Hema et al., the primary reason why architects are not able to use energy modeling in their projects is a lack of energy simulation knowledge. Shady Attia et al. [17] presented a literature review and interviews with 28 optimization experts, authors pointed out that the existing limitations of the tools are computation time, the difficulty of use and the steep learning curve.

These challenges are time-consuming modeling, rapid changes in design, and conflicting requirements. Additionally, there are several limitations of the currently available tools, as follows:

- Some of the tools require the user to have programming expertise
- Some tools use input files to provide the freedom to change variables but require considerable user expertise to understand the file content and format
- Most of the tools do not harness cloud servers and task queues, due to which the simulations become onerous and time-consuming

- None of the tools produce outputs that can be readily visualized, analyzed and explained as rules or clusters that are easily understandable by users.It appears that no current tool is free of all these limitations. The use of available simulation tools in early design stage requires expertise in energy simulation. Also, if there is a requirement to run a large number of parametric simulations, the computation time will be very high. For example, if there are five parameters and each parameter needs to be simulated with five variations, then there will be over three thousand combinations. Processing and data management in such cases is difficult for users who do not have expertise in running large numbers of simulations. An additional key issue is the ineffective display of simulation results to visualize the relative performance of design alternatives. Ideally, effective visualization would provide insights into the underlying causes of performance differences.

The methodology [18] presented in this paper aims to overcome these limitations and has the following novel features:

- Distributed Task Queue (DTQ) cloud computing for modeling and processing of energy simulation results
- Presentation of results in the form of design recommendations for building energy efficiency that are easily understandable by architects.The following sections present details of the methodology for conducting early design simulations and identifying energy efficiency strategies. Following this, a pilot tool (eDOT) was developed using the methodology discussed. Further, a case study is developed using this tool.

Methodology

A methodology has been developed to make energy-efficient decisions in the early stages of building design. The methodology can be divided into seven steps, as shown in Fig. 1 and outlined in the following sections.

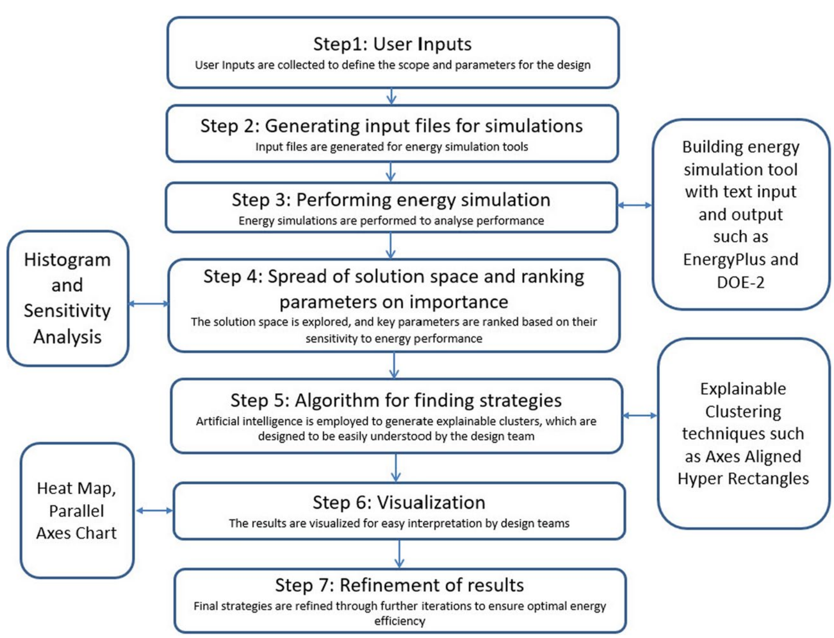

Fig. 1 Overview of the proposed methodology for early stage building energy design

Table 1 Building design parameters

Fixed design parameters	Variable design parameters
Location	Window to Wall Ratio (WWR)
Building type	Orientation
HVAC system	Glass type
Total built-up area	Aspect Ratio
Number of floors	Overhang
Window type	
Cool roof	
Daylight controls	
Heating Set Point	
Cooling Set Point	

Table 2 Range of variable input parameters

Parameter	Minimum Value	Maximum Value	Units	Explanation
Aspect Ratio	1	10	Ratio	Ratio of major horizontal dimension to minor horizontal dimension
Orientation	0	360	Degree	Angle between building face and actual North direction.
Overhang	1	45	Degree	Inverse tangent of overhang depth to window height. Measured in angle, as shown in Fig. 2
WWR	1	90	Percentage	Proportion of window to wall area in façade

Step 1: User Inputs

The step "User Input" identifies early design parameters. Some parameters can be fixed and some can be variable. The range of each variable parameter must be defined for parametric simulations to be performed. The key design attributes and the corresponding design parameters are listed in Table 1.

Fixed and variable input parameters

Input parameters can be divided into two categories - fixed parameters and variable parameters. In some cases, the parameter may be permanently fixed; for example, orientation and/or aspect ratio may be fixed by the constraints of the site. In some cases, certain parameters may be fixed in the earliest stages of the analysis to focus computational resources on other aspects of the design. An illustration of fixed and variable parameters for a typical project is presented in Table 1.

Decisions on key design parameters have a significant impact on a building's overall energy efficiency because these parameters influence factors such as heat gain, natural ventilation, daylighting, and overall thermal comfort. Each design decision, from window-to-wall ratio to building orientation, plays a role in how energy is consumed for heating, cooling, lighting, and ventilation, thereby directly influencing the overall energy performance of the building.

In this step, input parameters are identified that will be used in further processing. Typical ranges for the parameters are shown in Table 2 and described as follows:

Window-to-Wall Ratio (WWR)

The WWR is the fraction of the gross above-grade wall area that consists of fenestration. The influence of window area on different aspects of building performance depends on glass type, and on shading and orientation, whose effect varies with latitude, time of year and weather conditions. Typical trade-offs driven by WWR include daylighting and view vs. glare, solar heat gain and heat gains and losses due to thermal conduction. WWR can also have a significant effect on thermal comfort through the direct transfer of long-wave radiation between the window interior surfaces and the occupants

For instance, WWR range of 1% to 90% was chosen to encompass the broadest possible design scenarios. While typical design practices usually fall between 20% and 60%, the expanded range was included to allow flexibility and accommodate both unconventional designs and specific project needs that may push the boundaries of standard practice.

Orientation

Orientation is characterized by the azimuth angle of the normal to the main façade of the building relative to the true north. Orientation utilizes the constraints and opportunities of the given site for the co-benefits of shading to cut solar heat gain, daylighting to enhance availability while cutting glare, and the use of natural ventilation to improve energy performance and air quality. When setting up orientation ranges in simulations, common practice is to test orientations at 45° intervals or finer increments (e.g., 0°, 45°, 90°, 135°, 180°, 225°, 270°, and 315°) to capture the impact of varying orientations on energy performance. Sometimes, site conditions and neighboring buildings constraints may limit the range of orientations that can be considered.

Aspect ratio

The ratio of a building's length to its width - affects how much of the building's surface is exposed to sunlight. A higher aspect ratio may increase solar exposure on the longer facades, leading to higher cooling loads in hot climates, whereas a lower aspect ratio can reduce energy consumption by minimizing heat gain. Choosing the optimal range for such parameters is crucial, as it helps balance thermal performance, daylight penetration, and leading to a more energy-efficient design. For compact buildings, the aspect ratio typically ranges from 1:1 to 1.5:1, while elongated buildings often range from 2:1 to 4:1. Buildings with higher aspect ratios have more exposed surface area, especially on the long facades, which can be advantageous in cold climates by maximizing passive solar heating on the south-facing façade (or north-facing in the Southern Hemisphere).

Glass type

The type of glazing (glass) affects how much heat and light pass through the windows. Low-emissivity glazing can reduce heat transfer, lowering energy use for cooling or heating. The properties of a glass window are defined by U-value, Solar Heat Gain Coefficient (SHGC) and Visible Light Transmittance (VLT). Window systems typically consist of one, two or three panes of glazing, which may be identical or may have different physical properties. The space between the panes can be filled with air or with an inert gas such as argon or it can contain a vacuum. Double and triple-pane window systems may include a low emissivity coating on one of the enclosed surfaces to reduce radiative heat transfer.

Overhang

Overhangs provide shading for windows, reducing solar heat gain and cooling loads, particularly in hot climates. The depth and angle of the overhang determine its effectiveness. The overhang size is defined through the property - Profile Angle. The depth of the overhang is calculated based on the angle and window height as shown in Fig. 2.

The window overhang depth can be calculated using Eq. 1.

$$OverhangDepth = WindowHeight \times \tan(ProfileAngle) \quad (1)$$

The advantage of using profile angle as the parameter for characterizing the overhang depth is that it keeps the overhang depth proportional to the window height. It is also independent of the size of the window.Step 2: Generating input files for simulations

The next step is to generate relevant combinations to run energy simulations. It starts with entering user inputs into templates to generate input data files - text files with a predefined structure, such as the EnergyPlus Input Data File (IDF) and DOE-2 input file. A template is a text file with parameters specified as variables, which is then used to generate a separate input file for each combination of parameter values. The number of input files depends on the potential parameter variations - for example, if there are eight parameters and each has five possible values, then a total of 32,768 input files are generated. More details of EnergyPlus IDF can be found in the EnergyPlus [4] documentation.

Step 3: Performing energy simulations

Each combination needs to be simulated using a building energy simulation tool. The simulation tool provides energy consumption for each combination. To handle such a large number of simulations, parallel computing can be used. Garg et al. [19] have presented an approach to break annual simulation into several segments of smaller run period and each handled by a separate processor. The elapsed time is reduced by using multiple processors for each run. A speed gain of 3 x to 6 x was achieved in the study. Another study performed by Giannakis et al. [20] investigated simplifications in geometries and the use of co-simulation and achieved a reduction in runtime of 80%. Abhilash et al. [21] used regression to reduce computation by simulating some of the selected combinations and estimating the rest of them.

Distributed Task Queues

DTQ are a highly efficient methodology for running parallel simulations on the cloud. DTQ is recognized as a standard technique for distributing computational workloads, particularly in cloud-based environments where scalability and speed are crucial. This

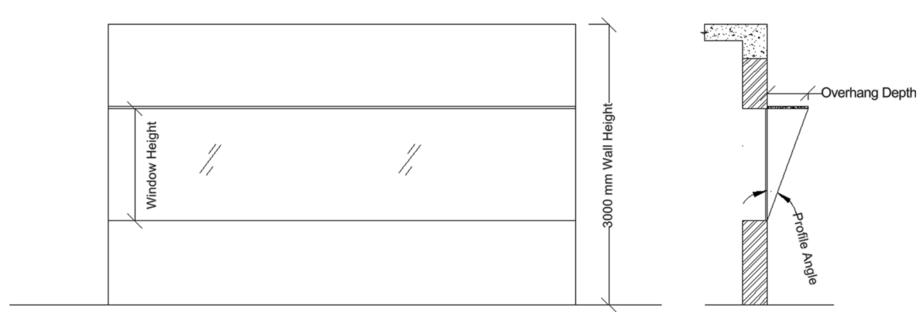

Fig. 2 Elevation and section view of window and overhang

asynchronous execution allows for simultaneous processing, which dramatically reduces the overall simulation time compared to sequential methods. Researchers have explored various techniques to handle multiple EnergyPlus simulations like multi-threading, multi-processing and parallel computing but reliable software architecture and the application of DTQ in building energy simulations still needs recognition. There are various software libraries for DTQ in different programming languages such as Huey, Celery [22], and Resque. DTQ is based on producer-consumer architecture. The producer en-queues the tasks in the message queue and the consumers de-queues it, process it and update the result in a database.

This work is novel in that it introduces DTQ to run CPU-intensive EnergyPlus programs on the web by developing scalable and fault-tolerant applications. A DTQ web application is deployed on the cloud; this application can also be deployed in research labs, universities, offices, etc for better cost savings in energy simulations.

Step 4: Spread of solution space

It is helpful for the user to review the spread of simulation results to obtain a sense of the range of energy consumption. This is achieved by providing a solution histogram. Sensitivity analysis helps user to understand the impact of design parameters on building energy performance.

Solution histogram

Plotting the distribution of energy consumption of the building based on a range of possible design solutions can provide an idea of how energy consumption is divided over an entire range of values. A sample histogram is shown in Fig. 3, plotted for Energy Performance Index (EPI). EPI pertains to the energy use per unit area of the building. This plot shows the spread of EPI based on the design solutions selected for this simulation.

Impact of parameters

Sensitivity analysis helps the user understand the impact of design parameters on building energy performance. It shows the change in energy consumption resulting from a

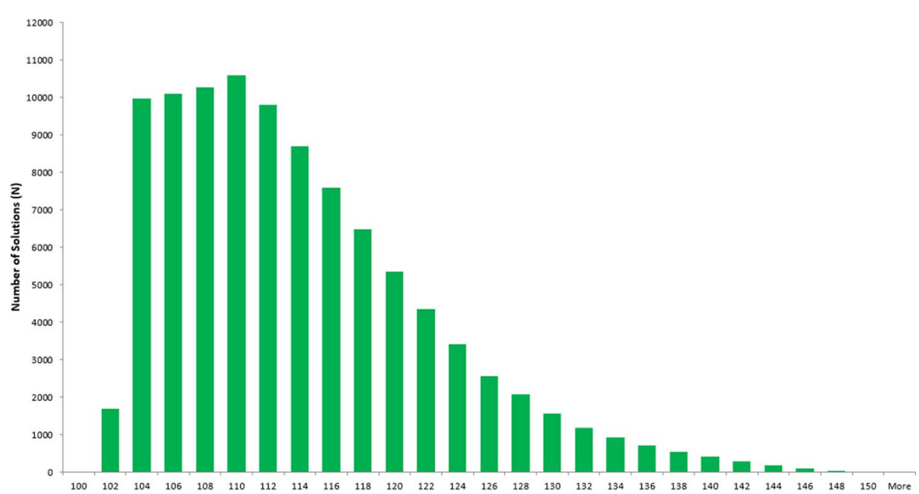

Fig. 3 Histogram of Energy Performance Index (EPI) values from the simulation results. The X-axis represents the EPI (in kWh/m2/year), and the Y-axis shows the frequency of design solutions with specific EPI values. A lower EPI indicates better energy efficiency

change in the value of one design parameter at a time, while keeping the other design parameters constant. This is equivalent to one-parameter-at-a-time sensitivity analysis at a selected point in the design space. An Algorithm 1 is used to generate parameter impact.

By quantifying the impact of various design variables-such as orientation, glazing type, and aspect ratio-on a building's energy performance, the design team can make informed decisions and prioritize attention to the most sensitive parameters.

Algorithm-1 steps are described as follows:

```
Input: A data file file containing all energy simulation results
Output: Imapact ratio
Read the data from the input file containing all simulation results
Initialize parameterlist with list of variables from the input data
paramter impact for wwr variable
 append orienList with unique values of orientation
 append glassList with unique values of glass
 append arList with unique values of aspectratio
 append overhangList with unique values of overhang
for i ← orienList do
    for j ← glassList do
        for k ← arList do
            for l ← overhangList do
                Initialize ratiolist
                for read all rows do
                    find min energy
                    find max energy
                    calculate ratio max/min
                    append ratio to ratioList;
                end
            end
        end
    end
end
find max ratio from ratioList;
return max ratio;
```

Algorithm 1 Algorithm to find impact factor for a given variable

Read the simulation output data

This step loads all the energy simulation results into memory. These results contain energy values and the corresponding design parameters.

Initialize a list of design parameters

A list of parameters to be analyzed is created in this step.

Create separate lists for each design variable

For each design variable, a list is created with all the unique values that were used in the simulations. These lists will help us loop through different design options in the next steps.

Loop through each combination

This step iterates over all possible combinations of the design variables (orientation, glass type, aspect ratio, overhang). The goal is to assess how different combinations of these variables affect energy performance.

Calculate the ratio of maximum energy to minimum energy for each combination

For each combination of design variables, the algorithm finds the highest and lowest energy consumption values. It then calculates the ratio between these values, which helps quantify the energy impact of changing design parameters.

Append the calculated ratio to the ratio list

The calculated ratio for each combination is stored in a list, which will later be used to determine the design parameters with the most significant impact on energy consumption.

Identify the highest ratio from the list

Once all combinations have been processed, the algorithm identifies the maximum ratio from the ratio list. This maximum ratio highlights the most impactful combination of variables, showing where design decisions lead to the largest changes in energy consumption.

Output the maximum ratio as the impact factor

The final result is the maximum impact ratio, which tells designers which variable has the most influence on energy consumption.

Step 5: Finding strategies

Energy simulation tools provide a large amount of output data. Careful selection of the data is required to reach useful conclusions. Once the simulations are completed, the next step is to select low-energy solutions from the design space. These selected solutions are then clustered to identify the design strategies. Clustering has become a popular machine-learning technique for identifying groups of data points with common features in a set of data points. Lemley et al. [23] provided an algorithm for finding hyper-rectangles in high dimensional data that runs in polynomial time with respect to the number of dimensions.

An algorithm 2 was developed to provide parameter strategies that generate design solutions. The goal of the algorithm is to simplify the decision-making process for architects and designers by highlighting design strategies-combinations of design parameters (such as window-to-wall ratio or orientation) that lead to low energy consumption. The algorithm works by analyzing the simulation data and determining which design parameters (e.g., orientation, glass type) can be adjusted freely without negatively impacting energy performance. It filters out combinations that do not meet a specified energy efficiency threshold and provides a list of design strategies that ensure low energy consumption.

The one-parameter strategy determines the range of values for each parameter for which each of the other parameters can take any value within its input range. For example, for a particular climate, if $WWR \leq 30\%$, any value of orientation, overhang, glass type, or aspect ratio can be chosen without any constraint, within the specified input ranges. Glass type depends on the thermal conductance of glass, Solar Heat Gain Coefficient (SHGC) and Visible Light Transmittance (VLT).

```
Input: A data file containing all energy simulation results
Output: List of strategies
Read the data from the input file containing all simulation results
Initialize parameterlist with list of variables from the input data
Initialize threshold for energy
for read all rows in csv do
    if energy < threshold then
        update value ← true.
    end
    else
        update value ← false
    end
end
for i ← parameterlist do
    uniqueList ← unique i;
    for j ← uniqueList do
        Initialize count = 0
        for read all rows do
            if value == false then
                count = count + 1;
            end
        end
        if count = 0 then
            append i,j to singlevariable list;
        end
    end
end
return singlevariable list;
```

Algorithm 2 Algorithm to find strategies from the energy simulation input data

The design sub-space defined by glazing type and WWR populated with solutions that satisfy a particular maximum energy consumption criterion is shown in Figure 4.

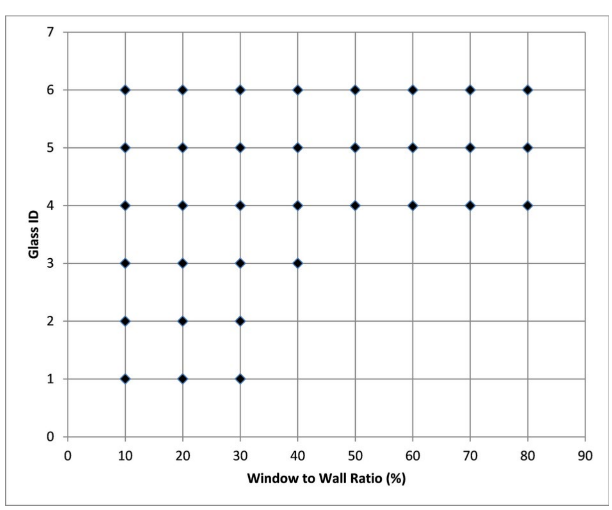

Fig. 4 Design subspace with WWR and Glass ID in energy performance simulations. Each point represents a specific combination of WWR and Glass Type (identified by Glass ID), forming a grid of design configurations. This plot helps illustrate how varying the WWR and glass type influences energy efficiency

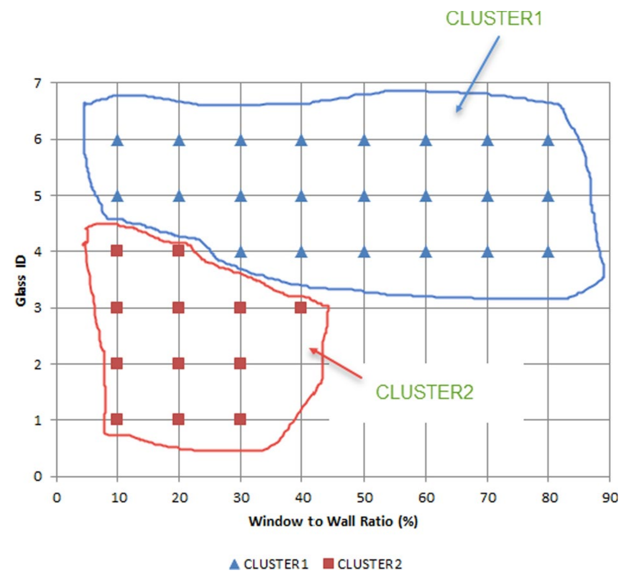

Fig. 5 Clustering of WWR and Glass ID combinations, there are two distinct clusters of design solutions: Cluster 1 (blue triangles) and Cluster 2 (red squares). Cluster 1 consists of design configurations with higher Glass IDs, on the other hand, Cluster 2 includes lower Glass IDs

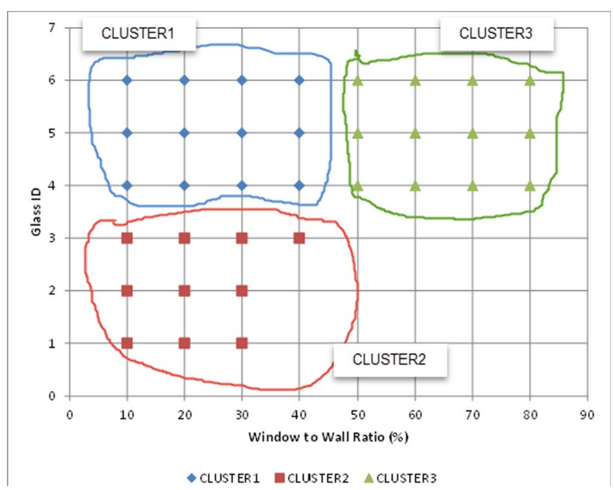

Fig. 6 Clustering of WWR and Glass ID combinations into three distinct clusters. Cluster 1 (blue diamonds) represents design solutions with WWR values from 10% to 50% and Glass IDs 4 and above, Cluster 2 (red squares) consists of lower WWR values from 10% to 30% and low Glass IDs 1 to 3. Cluster 3 (green triangles) comprises higher WWR values from 50% to 80% paired with higher Glass IDs 4 and above

Figures 5, 6 show the data points with two, and three clusters identified using the K-Means algorithm [24].

The clusters identified by distance-based clustering algorithms provide information about the effectiveness of combinations of values of different design parameters but the limitation is that they do not provide design strategies or information about design freedom, i.e. which design parameters have little effect on energy performance and so can be set based on other criteria [25].

In other words, while these clusters do indicate design solutions but these are not easily communicated to the user. For example, Cluster 2 in Fig. 5 contains points with

$WWR < 40\% and GlassID < 4$. However, choosing a low WWR should give freedom to the user to choose any Glass ID; this information is not getting captured in any cluster.

As another example, if low SHGC is chosen, then the user should be able to choose any WWR, but the sets of solutions identified by regular clustering algorithms do not capture this, so some form of synthesis is required. How or whether this synthesis should be performed depends on whether non-energy criteria are to be incorporated, even in an implicit and qualitative way.

The stipulated criteria for clusters are as follows [25].

Clusters must be explicable through simple rules such as $a_1 \leq feature_1 \leq b_1$, $a_2 \leq feature_2 \leq b_2$, and $a_n \leq feature_n \leq b_n$. Moreover, the clusters should be capable of adapting to scenarios where the number of clusters within the given space is initially uncertain and necessitates a discovery process. They are also expected to accommodate instances of overlapping clusters and account for data points that may not be categorized into any cluster. Furthermore, the methodology should arrange clusters according to their sizes, establishing a ranking based on this particular criterion. To amplify user control, the selection of clusters above a threshold defined by the user should also be feasible.

To overcome the limitation of distance-based clustering, an algorithm has been developed that identifies combinations of design solutions that can be used as strategies by designers. Referring to Fig. 6, combining clusters 1 and 2 generates the strategy Low WWR, which results in low energy consumption whatever Glass Type is selected, whereas combining Clusters 1 and 3 generates the strategy High-Performance Glazing, which results in low energy consumption whatever WWR is selected. Cluster 1 may be undesirable for non-energy reasons: High-performance glazing is more expensive and low WWR may be undesirable in terms of view, daylighting and particular aesthetics. In projects where these considerations apply, there are then two strategies that incorporate other, non-energy criteria: Use Low-Performance Glazing if Low WWR is acceptable (Cluster 2) Use High-Performance Glazing if High WWR is required (Cluster 3) Cluster 1 will have the best energy performance but the improvement over Cluster 2 or Cluster 3 may be modest and not enough to justify the extra cost or compensate for the reduced amenity. By use of algorithm-1, the single and double variable strategies can be identified. This is also a type of clustering in which we fix one dimension, which can provide Axis Aligned Hyper Rectangle (AAHR) of remaining variables, which makes for easier communication with the user.

Figures 7 and 8 show six clusters from the algorithm. The data points shown in Figs. 7 and 8 are the points for which energy consumption is less than 10% above the minimum energy consumption. These six clusters can later be merged into two clusters. The result can be easily converted into strategies that can be communicated to the user.

The six clusters are $WWR10\%$, $WWR20\%$, $WWR30\%$, *GlassID*4, *GlassID*5, and *GlassID*6. These six clusters can be combined in two clusters $WWR \leq 30$ and Glass ID 4, 5, and 6. This is very easy to communicate and understand. Let X, Y and Z be three axes in the design space and start with this three-dimensional subspace fully populated for each step of X, Y and Z. If there is a set of low energy consumption solutions that occupy a certain region of the design space that contains no other, higher energy consumption, solutions, then this set can be considered to represent a low energy design strategy. If these solutions are constrained by, i.e. are either close to or bounded by, a

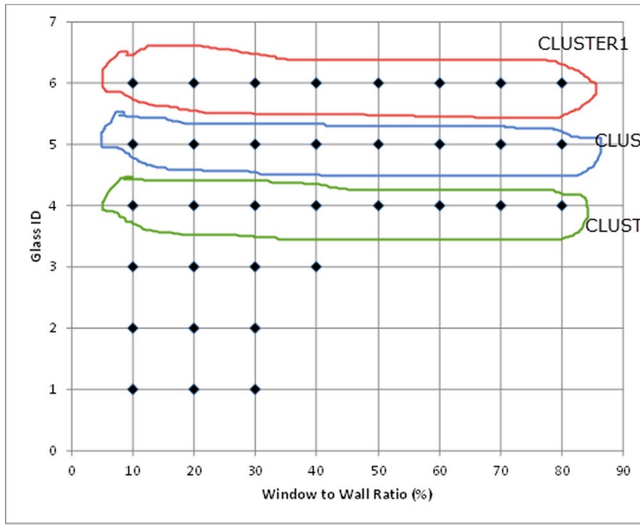

Fig. 7 Points with three clusters for Glass ID , Cluster 1 (Red): Represents a grouping where Glass ID = 6. Cluster 2 (Blue): Characterizes a range of designs where Glass ID = 5, and Cluster 3 (Green): Glass ID = 4

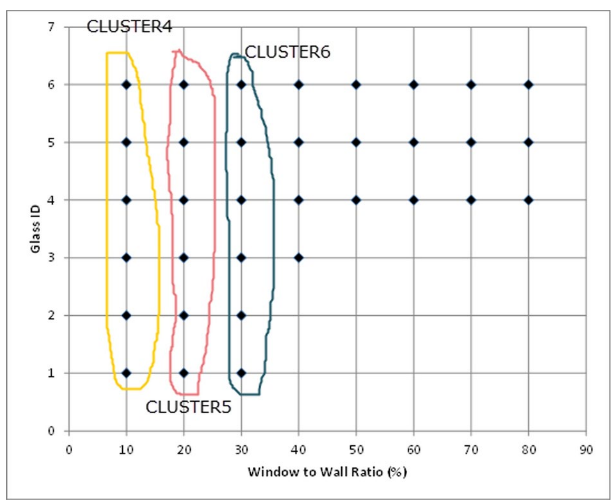

Fig. 8 Points with three clusters for WWR, Cluster 4 (Yellow): Represents a grouping where WWR=10%. Cluster 5 (Red): WWR = 20% and Cluster 6 (Green): WWR=30%

plane parallel to the Y-Z plane (X=a, say), they constitute a single variable strategy ($X = a$ or $X \geq a$ or $X < a$). Figure 9 illustrates the case where the constraint X=a defines the strategy. If there are two constraints, e.g. $X = a$ and $Y > b$, then the low energy solutions are located in the region of the X=a plane defined by $Y > b$, as shown in Fig. 10. If the Y constraint were Y=b, the solutions would lie on the line defined by $X = a, Y = b$.

If there are three constraints, corresponding to a three-variable design strategy, they can be represented graphically as follows: Three identity constraints: $X = a$, $Y = b$, $Z = c$ define a point in the design subspace Two identity constraints and a limit constraint, e.g. $X = a$, $Y = b$, $Z > c$ define a line segment, as shown in Fig. 11.

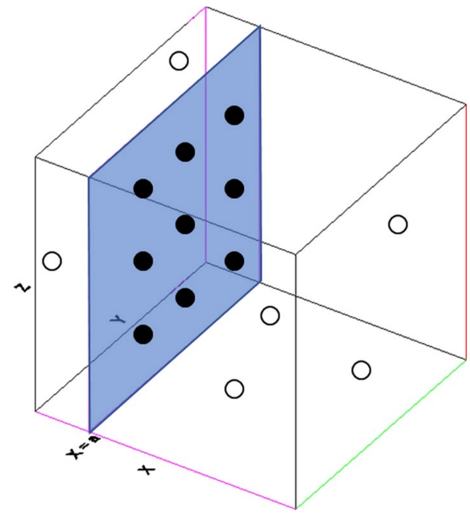

Fig. 9 Representation of one variable strategy; the solutions form a plane at X=a. Low energy solutions are represented by solid spheres and a sampling of higher energy solutions is represented by hollow spheres

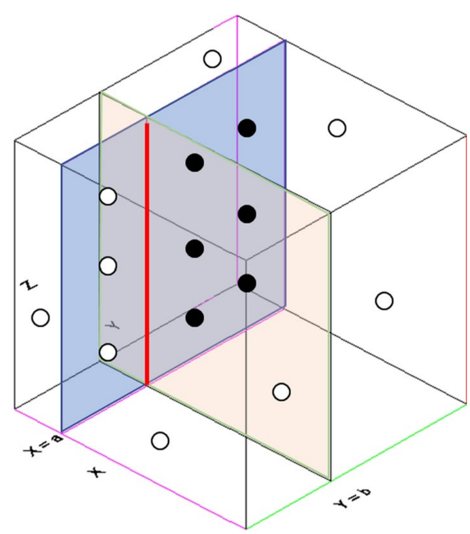

Fig. 10 Representation of a two-variable strategy defined by an identity constraint, $X = a$, and a limit constraint, $Y > b$; the solutions occupy part of a plane. Low energy solutions are represented by solid spheres and a sampling of higher energy solutions is represented by hollow spheres

Step 6: Visualization

Energy simulation tools provide a large amount of output data. Care is required in selecting the data required to reach useful conclusions. Researchers presented different data analysis and visualization techniques that can be used in the early stage of design decision-making. Yarbrough I. et al. [26] used heat maps to show energy demand in a campus. Ignacio Diaz Blano et al. [27] used a histogram for energy analytics in public buildings. Shweta Srivastava et al. [28] provided a review of different visualization techniques used in building simulations and emphasized for development of new methods that effectively represent multidimensional data to communicate simulation data among various stakeholders in the design team.

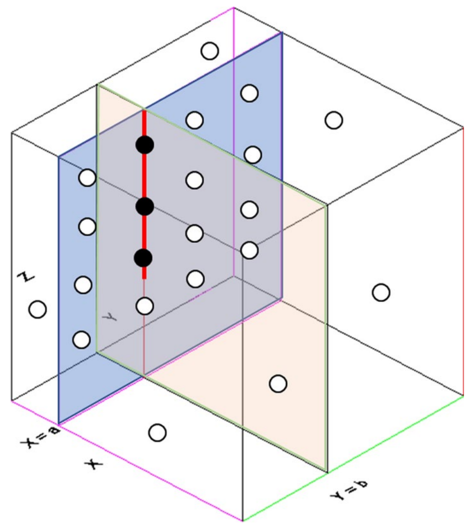

Fig. 11 Representation of a three-variable strategy defined by two identity constraints, X=a and Y=b, and a limit constraint, $Z > c$; the solutions occupy part of a line. Low energy solutions are represented by solid spheres and a sampling of higher energy solutions is represented by hollow spheres

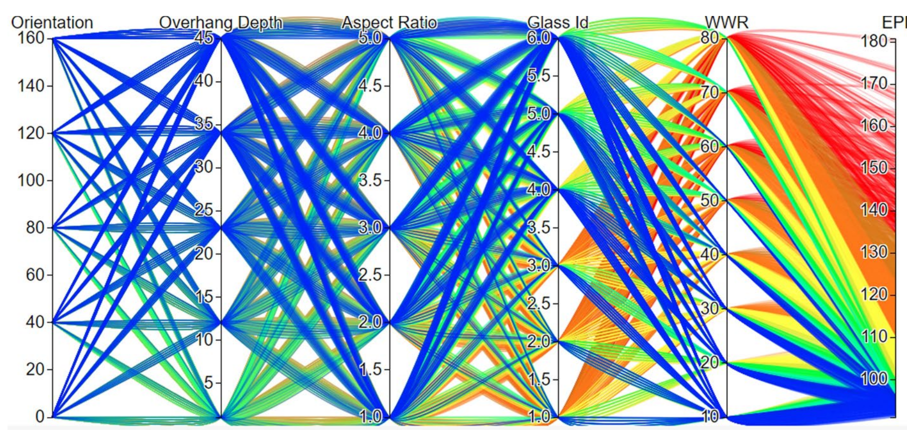

Fig. 12 Parallel coordinates graph, each vertical axis represents a specific parameter, with the corresponding values marked along the scale and the color gradient, ranging from blue to red, reflects the EPI values, illustrating ranges of high and low energy efficiency

Parallel coordinate graph

Parallel coordinates plots are one way to visualize high-dimensional data. A six-dimensional graph is shown in Fig. 12. It visualizes the relationships between key architectural parameters: Orientation, Overhang Depth, Aspect Ratio, Glass ID, WWR, and the EPI. Each vertical axis represents a specific parameter, with the corresponding values marked along the scale. The lines connecting the axes indicate how changes in these parameters correlate with one another and their collective impact on energy performance

There are a number of software tools and libraries available to generate such graphs, such as D3 [29] and python Matplotlib [30]. This type of graph can provide insights regarding the combination of design parameters that produce superior performance in terms of energy use. The user can also study the impact of various parameters on the performance of the building. Users can select ranges for different design parameters and see the impact on energy consumption. Parameters can be arranged in order of their sensitivity, e.g. with the most sensitive parameter on the right-hand side, to aid the interpretation of the graph.

Color coding of the lines by energy consumption also aids interpretation. The color gradient, ranging from blue to red, reflects the EPI values, illustrating areas of high and low energy efficiency. In Fig. 12, the blue lines indicate the solutions with the lowest energy consumption. Tracing these lines leftwards enables beneficial combinations of design parameters to be identified and provides one way of visualizing strategies. An interactive selection of lines of one color/energy range, while hiding the others, can make the graph easier to interpret. This visualization aids designers in identifying patterns and trade-offs in energy performance, ultimately guiding decision-making in building design.

Step 7: Refinement of results

The user can review the results, make changes in the ranges, and look at more possibilities. Narrowing down the ranges can help the user to understand the output results. Fine-tuning of ranges comes at the cost of simulation time.

In summary, the methodology starts with obtaining input ranges for building design variables from the user, generating input files, creating simulation models and running these using task queues in the cloud, understanding the spread of the simulation space and ranking parameters based on importance. The simulation results are then used to identify design strategies that result in performance in the lowest energy consumption range; the results are presented graphically to enable strategies to be visualized by users. Users can then refine the ranges to get more insights into design flexibility [31].

This methodology can explore and communicate energy-efficient design strategies shown in Fig. 13. The process involves capturing the design problem by selecting key parameters such as orientation, WWR, and aspect ratio. Next, distinct design strategies are identified through cloud-based simulations and cluster analysis, and finally, the energy implications of these strategies are visualized using tools such as sliders, 3D diagrams, and parallel coordinates plot. The novelty of this method is that user does not require prior knowledge of building energy simulation. User can enter input ranges in a simple graphical user interface and get design strategies for energy efficiency in design. The design strategies are generated using artificial intelligence algorithms.

Development of Early Design Optimization Tool (eDOT)

The methodology described in the paper has been implemented, in part, in a web-based pilot software framework. The computational workflow is shown in Fig. 14.

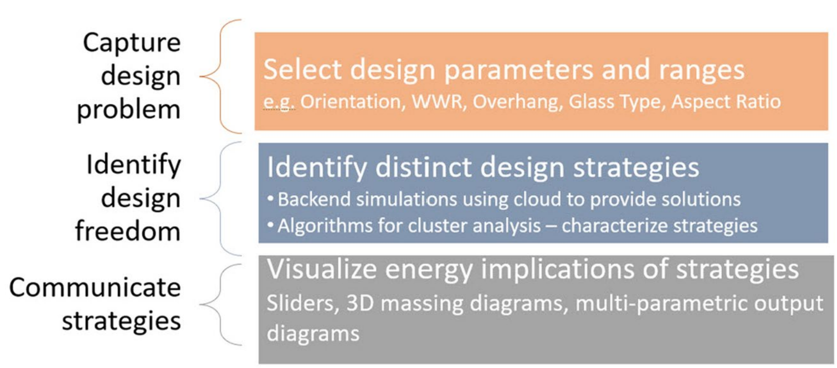

Fig. 13 Overview of the methodology used to explore and communicate energy-efficient design strategies

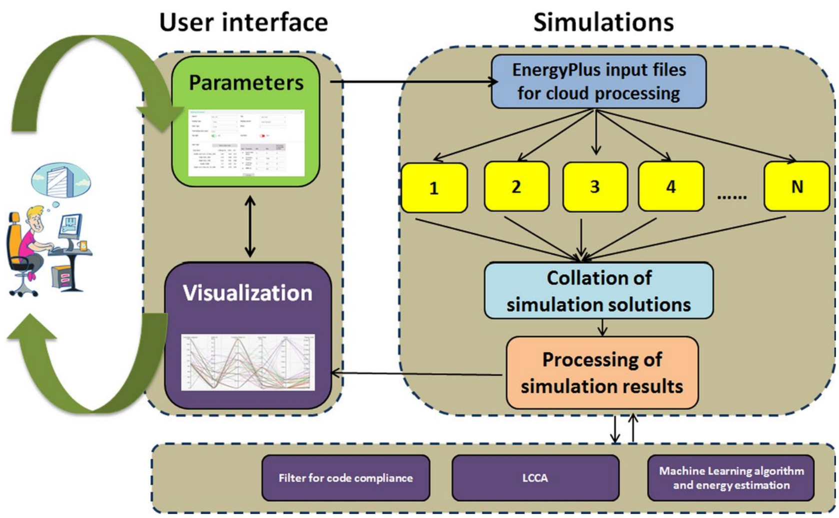

Fig. 14 Flow chart of the methodology

Description of tool

A pilot software implementation of the methodology described in section 2, named Early Design Optimization Tool (eDOT) has been developed and is described here. The pilot version is limited in that only a subset of the design variables discussed in section 2 has been implemented, the purpose being to test and demonstrate the methodology [31] and the software architecture [32]. The pilot implementation is based on US DOE's EnergyPlus whole building energy simulation program. However, the software could easily be adapted for any simulation program that uses text-based input files, e.g. DOE-2. The user selects input values such as building location, building area, Heating Ventilation and Air Conditioning (HVAC) system type. Building model and simulation parameters have been encoded in the template in templates in EnergyPlus IDF format. In the pilot version, the building form is limited to a cuboid. The purpose is to explore the relationship between basic design parameters and energy performance for a particular building size, location and usage in early design, rather than explore the consequences of more detailed architectural decisions. The tool is intended to make early-stage energy analysis available to smaller practices that do not have the resources to support more sophisticated design analysis tools. In mixed-mode energy modelling, cooling and heating loads are calculated based on the zone air temperature, zone air relative humidity and the cooling and heating set points. When conditions are favourable, natural ventilation is used to take advantage of outside conditions by opening the windows [33].

System interface

The tool has been developed on the Ubuntu Linux platform using the Python programming language [34]. Weather files are downloaded from the EnergyPlus weather data source [35]. The tool is hosted on a cloud computing platform (AWS) [36]. The UI of the tool is shown in Fig. 15.

Django [37], RabbitMQ [38], Celery [22], and Pandas have been used for data processing and visualization.

In this work, Celery [22] is used for implementing DTQ technique as the program developer need not worry about creating queues, it takes care of everything from spawning one thread per simulation to updating results in the database. RabbitMQ was used

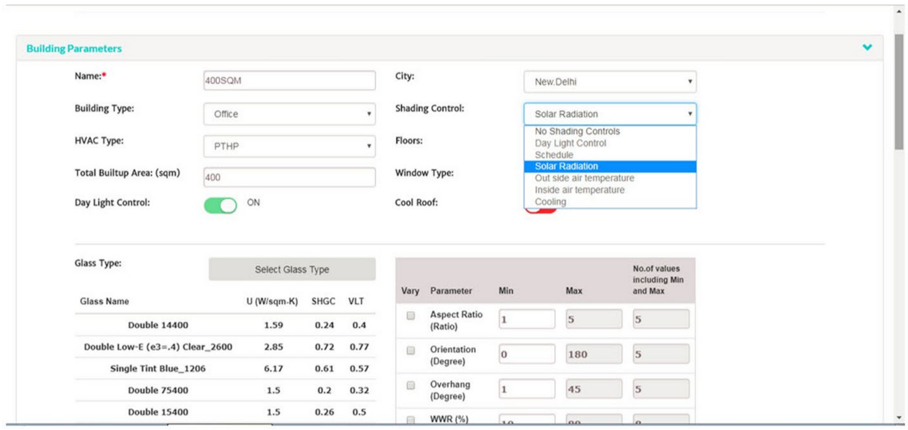

Fig. 15 User Interface of the "eDOT"

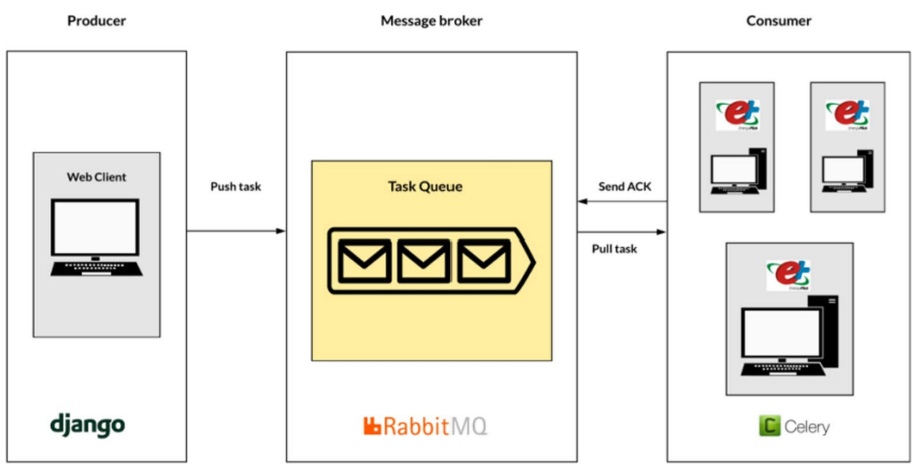

Fig. 16 Distributed Task Queue Workflow

to connect all the Celery slaves in the task queue to pass messages. Django application acts as the producer of the tasks from the user requests. Consumers on completion of tasks update the database hosted on the producer machine, which can be accessed by the Django app. Figure 16 shows the DTQ workflow used for running EnergyPlus simulations and Fig. 17 shows the system design of the application [32].

Task manager

Celery [22] is an open-source asynchronous (background) task queue which uses a distributed system for passing messages to the machines. It also supports scheduling and focuses on real-time operations. It is an easy-to-use API for building distributed Python apps. It is compatible with major messaging queues (RabbitMQ, Redis), databases (Django ORM, MongoDB, MySQL) and monitoring interfaces (Flower, Clearly). In this tool, Celery was employed to create a personalised distributed framework. Multiple Django servers which are enabled with Celery are running on slaves or workers servers. RabbitMQ [38] message queues were used to connect all the celery workers, and they are all connected to the same database as well. Whenever a free worker encounters a task on the message queue (Task queue), it dequeues that task and retrieves the simulation parameters from the common database (Simulation parameters are populated in

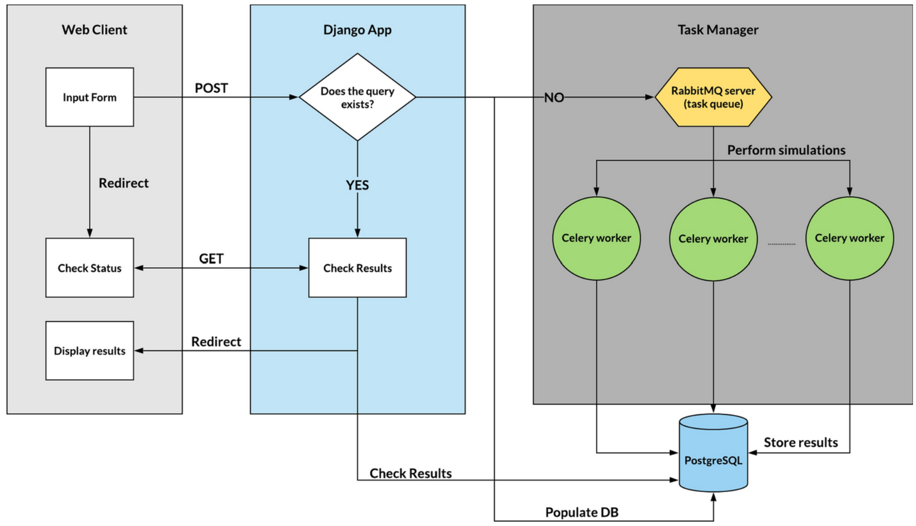

Fig. 17 System Design of eDOT

the database by Django App). Upon completion of the task, it populates the Database with results, which are later accessed by the Django App. EnergyPlus was opted to simulate building energy consumption. The ease of deploying new Celery workers makes the framework highly scalable. A new worker can be added easily by just installing the requirements and connecting to the message queue and task manager. Flower [39] was used to provide the administrator with detailed statistics about task queue usage.

Framework

The supervisor [40] is a client/server that provides a platform for users to monitor and control numerous processes in Linux based operating systems. An administrator is given the privilege of controlling Django, flower and celery app in any system/computer using this tool. This can be configured in a way which can start any program at boot time, it makes the system persistent. A supervisor is used to control the Django and Flower app at the master node and Celery worker in the slave node as shown in Fig. 18.

User scenario

An architectural team is designing an office building. The team is tasked with optimizing the building's energy performance in the early design phase. Without eDOT, they would typically need to run multiple energy simulations, manually adjust parameters, and analyze complex outputs, which can be both time-consuming and technically challenging. Using eDOT, the team can input essential parameters, such as building orientation, WWR, overhang depth, and glazing properties. eDOT then runs parametric simulations in the cloud, utilizing advanced algorithms to process thousands of combinations rapidly. After the simulations, eDOT presents the results in a clear, visual format. Moreover, eDOT's AI-driven clustering algorithm suggests specific design strategies, such as increasing insulation thickness or adjusting the window size for better thermal performance, based on the sensitivity of the input parameters. In just a few iterations, the design team can quickly visualize the trade-offs between different options and select the most energy-efficient and feasible design, reducing the time spent on manual analysis and enhancing the design process.

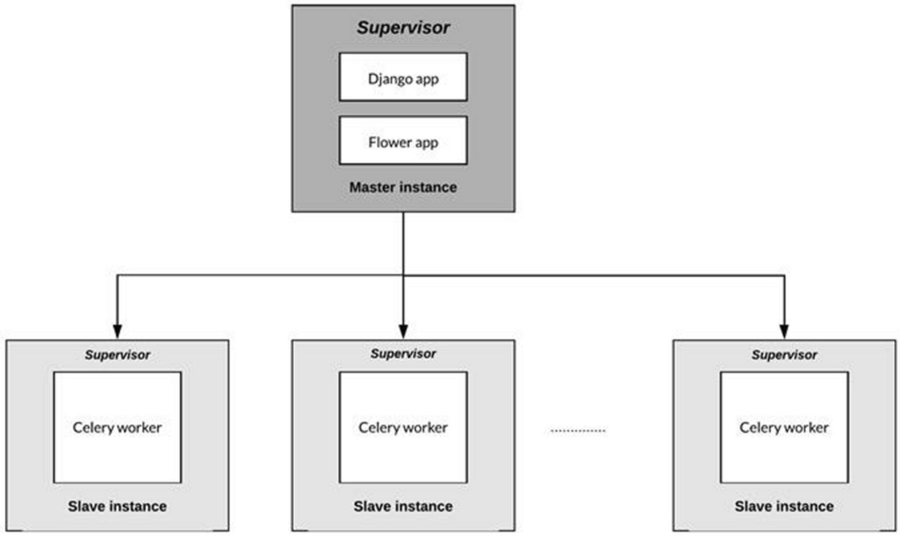

Fig. 18 Software Framework of eDOT

Table 3. Comparison of eDOT with other tools

Tool	User input file for simulation	Cloud services	Parallel computing	Need programming expertise	Output with analysis	Output strategies	Simulation engine
GenOpt [41]	Yes	No	No	Yes	No	No	Any
jEPlus [42]	Yes	Yes	Yes	Yes	No	No	EnergyPlus
COMFEN [43]	No	No	No	No	Yes	No	EnergyPlus
MIT Design Advisor [44]	No	No	No	No	No	No	EnergyPlus
BDA [45]	No	No	No	No	Yes	No	DOE-2.1e
BEopt [46]	No	No	No	No	Yes	No	EnergyPlus
MOBO [47]	Yes	No	Yes	Yes	Yes	No	Any
Ladybug [48]	Yes	No	No	Yes	Yes	No	EnergyPlus
eDOT	Yes	Yes	Yes	No	Yes	Yes	EnergyPlus

Comparison of eDOT with other tools

Another major advantage of eDOT is its ease of use in early phase of design. Traditional tools often require a high level of expertise to set up and interpret simulations, with steep learning curves for new users. eDOT, by contrast, incorporates a user-friendly interface that simplifies the process of defining design parameters, running simulations, and visualizing results. A comparison of eDOT with other tools is shown in Table 3..

Case study

Two case studies were generated utilizing the developed methodology and piloted tool implementation. These studies involved analyzing a hypothetical office building with a floor area of 400 m^2 for both San Francisco and New Delhi.

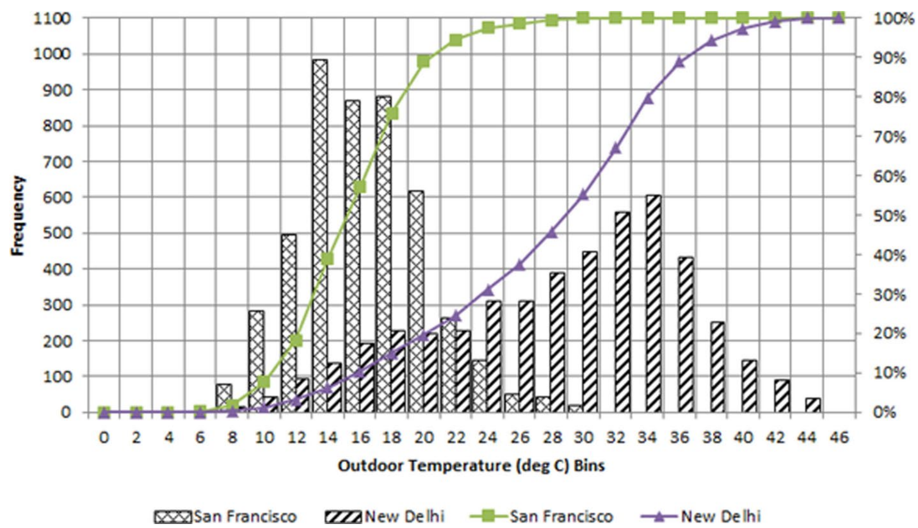

Fig. 19 Outdoor temperature distribution

Table 4 Input variable parameters for the case study

Parameter	Min	Max	No. of values
Window to Wall Ratio (WWR) (%)	10	80	8
Orientation (orien) (deg)	0	160	5
Aspect Ratio (AR)	1	5	5
Overhang Profile Angle (OPA) (Degree)	1	45	5
Glass ID (G_ID) (Refer Table 5)	1	6	6

The selection of New Delhi and San Francisco for the case studies was intentional to demonstrate the versatility and adaptability of the eDOT across two distinct climatic regions with contrasting energy performance requirements.

- New Delhi [49] represents a composite climate with significant seasonal variations, including extremely hot summers and cooler winters. This variability poses challenges in balancing cooling and heating needs, making it an ideal region to test the tool's ability to optimize designs for energy efficiency under extreme and fluctuating conditions.
- San Francisco [50]], on the other hand, has a Mediterranean climate, characterized by milder, more stable weather conditions with relatively less variation between summer and winter. Here, the focus is more on maintaining indoor thermal comfort with lower energy consumption, particularly in a mixed-mode operation that takes advantage of natural ventilation when outdoor conditions are favorable.Figure 19 shows outdoor temperature distribution for San Francisco and New Delhi for building operation hours. In San Francisco, the potential hours for mixed-mode building operation constitute about 80% when the temperature is below 18 ◦C.

Table 4 shows the variable parameters and Table 5 shows the variable glass inputs considered in this study.

The total number of combinations of parameter values for the case study is 6,000. Simulations were performed using asynchronous distributed task queues on the cloud.

Table 5 Glazing parameters for the case study

G_ID	Pane	U-value (W/m2.K)	SHGC	VLT
1	Single	6.17	0.81	0.88
2	Single	6.17	0.61	0.57
3	Double	2.85	0.72	0.77
4	Double	1.7	0.40	0.46
5	Double	2.75	0.27	0.20
6	Double	1.59	0.24	0.40

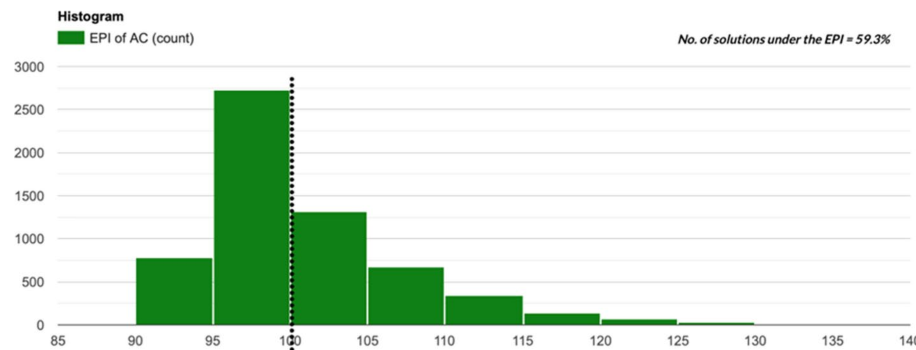

Fig. 20 Variation in energy use intensity for air-conditioned buildings in San Francisco

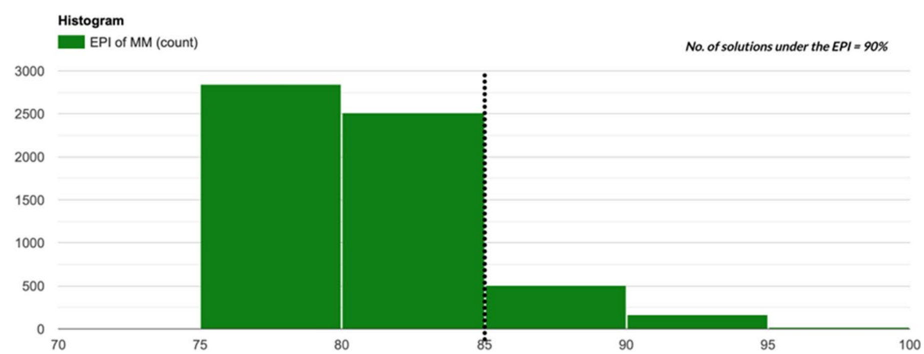

Fig. 21 Variation in energy use intensity for mixed-mode buildings in San Francisco

Results and discussion

This section discusses the findings and comparison of the air-conditioned and mixed-mode buildings in the case studies. Parallel coordinate graphs are used to showcase the solutions, allowing users to discern the spectrum of design parameters correlating with the annual energy consumption of each building.

San Francisco

Simulation of all combinations revealed a spread of energy consumption between 90 to 135 kW h $m^{-2}yr^{-1}$ for the air-conditioned buildings and between 75 to 95 kW h m^{-2} yr^{-1} for mixed-mode buildings in San Francisco. Potential energy savings of 16% to 30% were observed for mixed-mode buildings while comparing air-conditioned buildings in San Francisco. The histograms of the data are plotted in Fig. 20 and Fig. 21 for air-conditioned and mixed-mode buildings respectively. They show that most of the solutions lie in the lower energy consumption range, indicating a potential for design flexibility while achieving good energy performance.

The strategy algorithm was applied to the simulation results, identifying specific strategies. Analysis of restrictions and design freedom for building variables revealed that for a mixed-mode building in San Francisco, if WWR is restricted to 40% - 50% then all other studied parameters can be chosen in any range and building energy consumption still lies in the cut-off limit also shown in Fig. 22. For this case study, the energy consumption cut-off limit was set at 10% above the global minimum. In this regard, Cut-off EPI obtained for San Francisco for air-conditioned building is 100.1 $k\,W\,h\,m^{-2}\,yr^{-1}$ and that for Mixed-Mode building is 85.2 $k\,W\,h\,m^{-2}\,yr^{-1}$.

Restricting WWR at 60% with high-performance glazing options is suitable in both of the cases: air-conditioned and mixed-mode buildings as shown in Fig. 23. WWR is a key factor in determining the amount of heat ingress into the building. Heat gain through glazing materials can be minimized by choosing appropriate thermo-physical properties (SHGC, U, VLT) of the glazing. Hence, the optimal design combination of WWR and glazing material can reduce the annual energy consumption of the building.

New Delhi

Simulation of all combinations revealed a solution spread of energy consumption between 110 to 175 $k\,W\,h\,m^{-2}\,yr^{-1}$ for air-conditioned buildings and between 100 to 157 $k\,W\,h\,m^{-2}\,yr^{-1}$ for mixed-mode buildings in New Delhi. Potential energy savings of 8% to 15% have been observed for mixed-mode buildings when compared to air-conditioned buildings. A histogram of the data, shown in Fig. 24 and Fig. 25, depicts that most of the solutions lie in the lower energy consumption range, indicating a potential for design flexibility while achieving energy-efficient performance.

The strategy algorithm was applied to the simulation results to identify the strategies. The energy consumption cut-off limit was set at 10% above the global minimum. In this regard, the Cut-off EPI obtained for New Delhi with air-conditioned building is 122 $k\,W\,h\,m^{-2}\,yr^{-1}$ and that for mixed-mode building is 111.5 $k\,W\,h\,m^{-2}\,yr^{-1}$. 40% WWR with high-performance glazing is suitable in both cases: AC and Mixed Mode buildings as shown in Fig. 26.

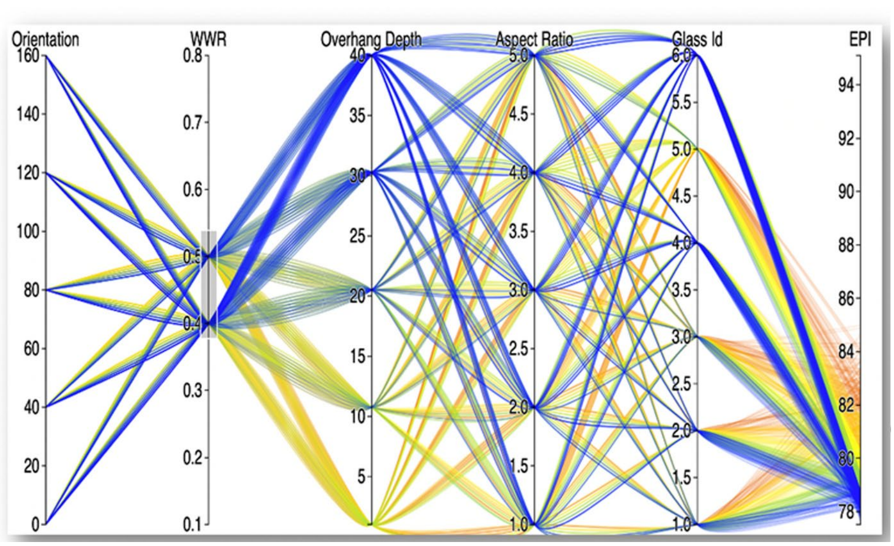

Fig. 22 Strategy: Medium WWR for mixed-mode building in San Francisco

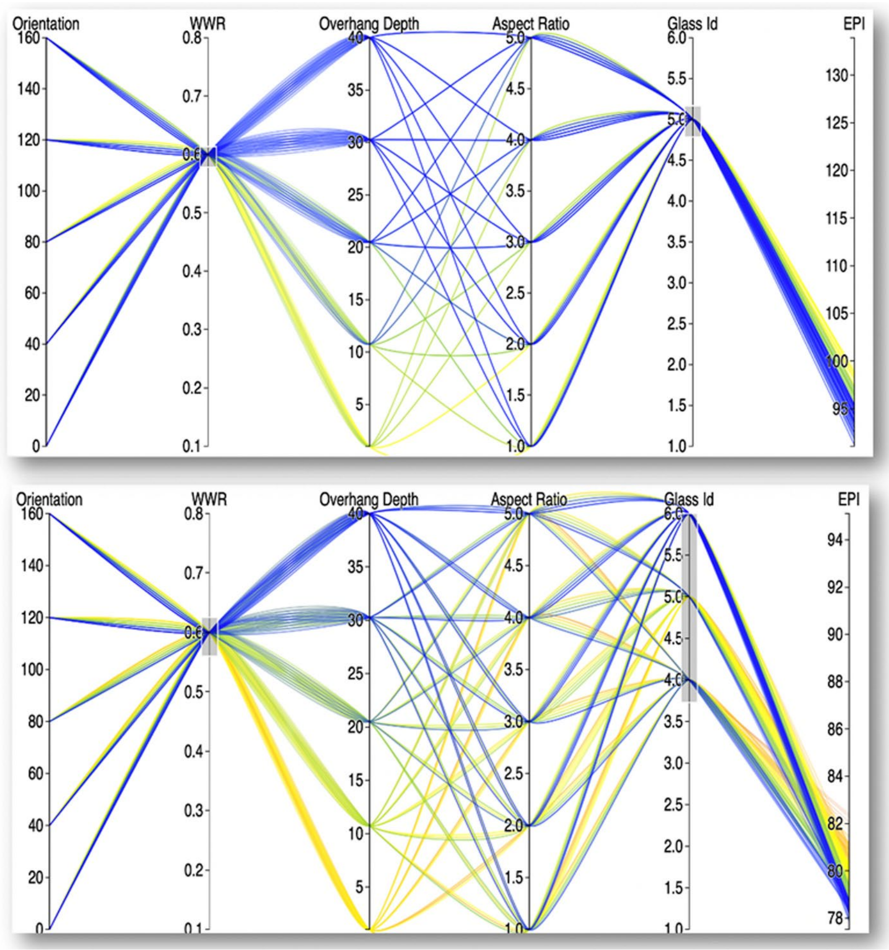

Fig. 23 Strategy: 60% WWR with high-quality glazing material for San Francisco

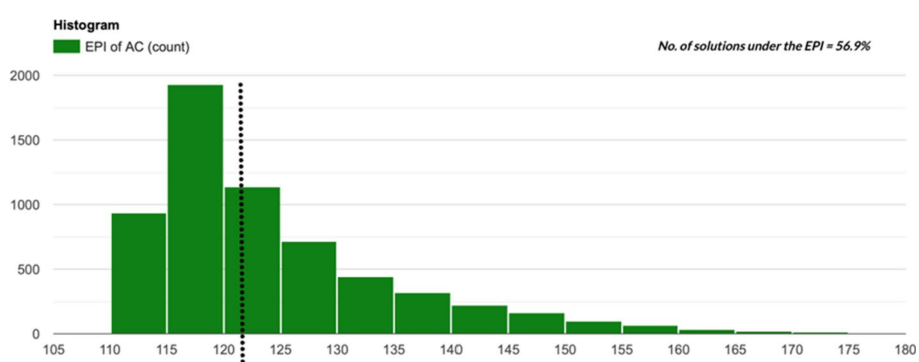

Fig. 24 Variation in energy use intensity for air-conditioned buildings in New Delhi

Further, highly efficient glazing with high Overhang depth is suitable in both of the cases: AC and Mixed Mode buildings, as shown in Fig. 27.

Discussion

The difference in simulation outputs for San Francisco and New Delhi can be attributed primarily to the distinct climatic conditions of these two regions, which influence the energy performance of buildings. New Delhi has a composite climate with extreme

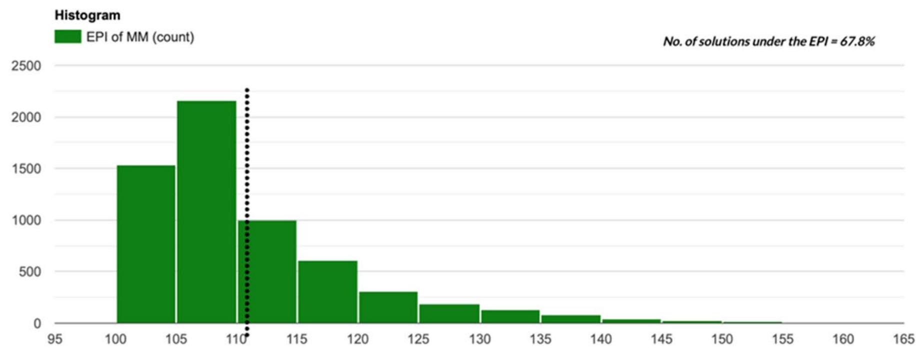

Fig. 25 Variation in energy use intensity for mixed-mode buildings in New Delhi

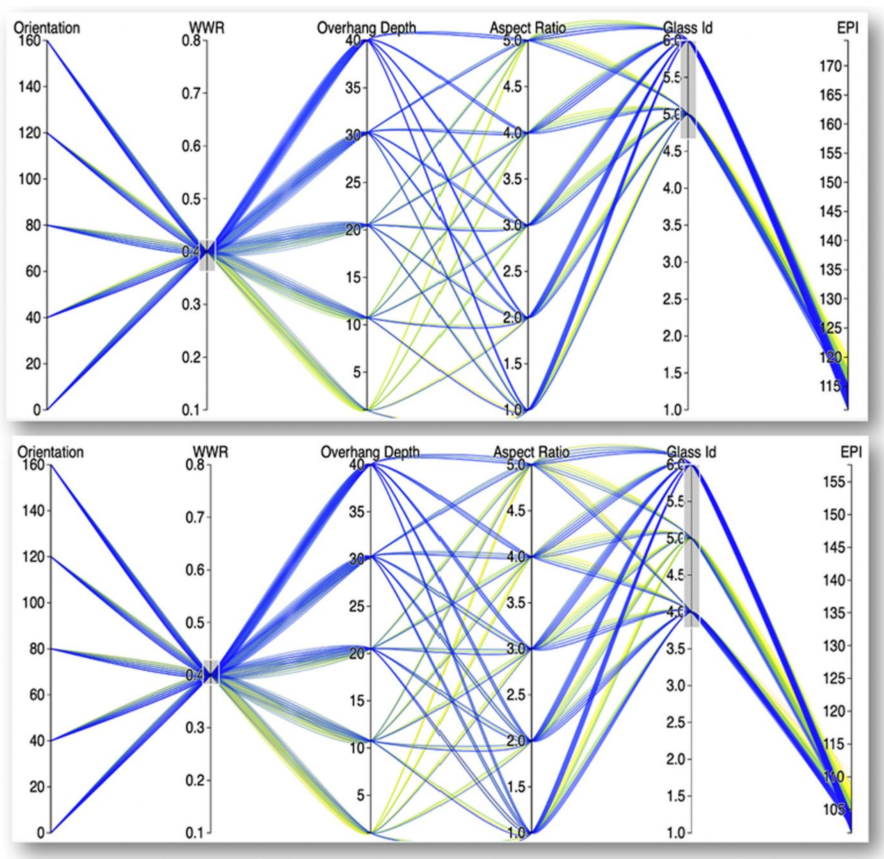

Fig. 26 Strategy: Medium WWR for mixed-mode building in New Delhi

seasonal variations, including very hot summers, a monsoon season, and relatively cool winters. Buildings in New Delhi have higher energy consumption compared to San Francisco. The building in the San Francisco case study exhibited greater energy savings with mixed-mode ventilation in comparison to New Delhi, owing to the increased number of favorable outdoor temperature hours for such ventilation in San Francisco. The insights derived from eDOT's energy simulations provide a strong foundation for design teams to make informed decisions not only about energy efficiency but also in relation to broader considerations.

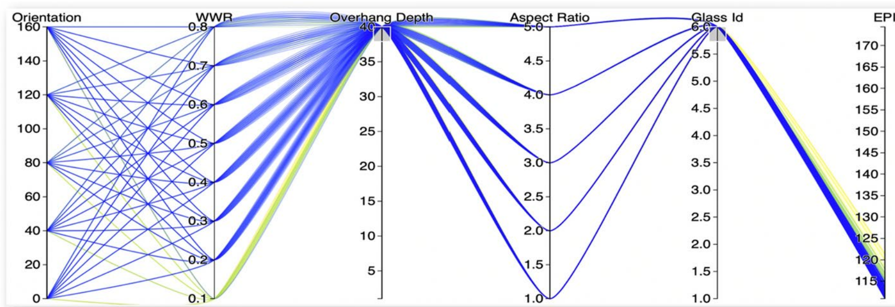

Fig. 27 Strategy: High-quality glazing material with overhangs for New Delhi

Cost-effectiveness

While eDOT primarily focuses on energy optimization, the tool's ability to highlight strategies that reduce energy consumption can have a direct impact on long-term cost savings. For example, strategies that improve insulation or glazing may come with higher initial costs but yield significant reductions in energy bills over time. Designers can make the trade-offs between capital expenditure (CapEx) and operating expenses (OpEx), enabling a more balanced decision-making process.

Design flexibility

eDOT's clustering algorithms and sensitivity analyses highlight design parameters that are most critical for energy performance, while also revealing which parameters offer more flexibility. For example, a designer might find that WWR has a significant impact on energy performance, whereas building orientation offers more design freedom. This allows the designer to focus energy optimization efforts where it matters most, while still allowing flexibility for aesthetic choices like building shape, façade design, and window placement.

Holistic decision-making

eDOT's visual outputs allow for the comparison of different design strategies, enabling the design team to evaluate multiple factors simultaneously. This holistic view ensures that non-energy-related decisions can be made within the context of overall building performance.

Practical application of eDOT in real-world building projects

In real-world building projects, eDOT provides an accessible, user-friendly platform that can be seamlessly incorporated into the early design phase to assist architects and designers in optimizing energy performance. At the conceptual stage, architects input basic building parameters such as orientation, WWR, and glazing type into eDOT. Instead of waiting for detailed drawings or mechanical system designs, eDOT can immediately process these inputs and provide feedback on energy performance, allowing design teams to explore a wide range of design solutions early in the process. eDOT's visualization methods make it easy for architects to understand the impact of each design parameter on energy consumption. For example, if a designer is considering different window configurations, eDOT can visually display which window types and placements lead to the lowest energy consumption while also meeting aesthetic or daylighting goals. This supports informed decision-making by providing clear, actionable insights.

Conclusions

A novel methodology has been developed that can help architects select design parameters for energy-efficient buildings right at the advantageous, early stages of design. This methodology entails the assimilation of program prerequisites and various constraints, the generation of combinations of permissible design parameter values for simulation, analysis of the simulation outputs, and subsequent guidance to the design team on parameter combinations yielding optimal energy performance. Furthermore, an algorithm has been developed to identify strategies that depend on a subset of design parameters, promoting energy performance while allowing design freedom to select the values of other parameters based on considerations external to energy. This methodology has been implemented into an early design optimization tool intended for use by project team members without specialized knowledge in energy simulation. Leveraging the Asynchronous Distributed Task Queue architecture, this tool provides scalable execution of a multitude of EnergyPlus simulations. Further, two case studies are presented in the paper for San Francisco and New Delhi. The demonstration of the same buildings situated in different cities with varying climatic conditions supporting different early design strategies for achieving energy efficiency illustrates the usefulness of the methodology presented in the paper.

Limitations and future research directions

The following outlines the limitations of the eDOT tool and potential directions for future research.

Simplified models in early design

eDOT focuses on early design stages, where many of the design details are still conceptual. This reliance on simplified models, assumptions, and broad design parameters may lead to some inaccuracies when translating results into real-world applications. However, as the design progresses, eDOT's outputs can be complemented by more detailed simulation tools, allowing for refined modeling that incorporates additional variables and complexities encountered in the later phases.

Speed vs accuracy

In the early phase of design, the focus is often on exploring a wide range of design possibilities rather than achieving accuracy. During this phase, it is crucial to run a large number of simulations to understand how different variables impact the overall energy performance of the building. However, running such extensive simulations can be computationally expensive and time-consuming. To address this issue, eDOT uses algorithms to reduce the number of simulations while still providing meaningful insights. While these algorithms may result in a slight reduction in accuracy compared to more detailed, exhaustive simulations, this trade-off is generally acceptable in the early design phase.

Integration with building information modeling

In real-world applications, energy optimization is just one component of the overall design process. Establishing seamless integration between eDOT and Building

Information Modeling (BIM) software would significantly streamline its application in the later phases of design, enabling a more cohesive and efficient workflow.

Optimization for non-energy metrics

Further research could focus on expanding the tool's application beyond energy efficiency, incorporating metrics such as embodied carbon, material usage, and cost to provide a more holistic optimization tool.

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Author Contributions
AB: Methodology, Formal analysis, Investigation, Writing - original draft SD: Data curation, Tool development, Case studies, Writing - review and editing VG: Conceptualization, Supervision, Writing - review and editing RS: Supervision, Writing - review and editing.

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Availability of data and materials
The code for generating IDF files is available on GitHub. https://github.com/aviruch/eDOT_Algo.

Declarations

Ethical approval
Not applicable

Competing interests
No, we declare that the authors have no competing interests as defined by Springer, or other interests that might be perceived to influence the results and/or discussion reported in this paper.

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