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A metamodel-based design optimization scheme for minimizing energy consumption of unconditioned residential buildings considering passive features

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Summary The demand for appliances and equipment has risen as a result of emerging technologies and increasing economic growth. The outcome is high level of energy consumption worldwide, particularly in structure and infrastructure sectors. Among these sectors, residential construction stands out as one of the primary energy consumers for infrastructure development. Thus, to construct buildings that use net-zero or nearly-zero energy, architects and engineers must prioritise energy-efficient planning and implementation. This paper aims to develop a scheme to minimize the energy consumption of an unconditioned residential building based on design optimization of passive architectural design variables. Here, a parametric model is developed by using four passive architectural design variables: orientation, window-to-wall ratio, shading depth and shading angle, This generates a large number of options for the analysis of the building's energy consumption. A metamodel-based design optimisation strategy has been implemented for a single-family, single-storey, unconditioned residential building in Guwahati City, India, with the objective to minimize energy use. The results from the case study showed that by optimizing the above-mentioned passive design strategies, the energy consumption of the considered building is lower by 52% as compared to the reference design.

Keywords: nearly-zero energy buildings, passive design, parametric modelling, optimization, metamodel

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Introduction

Amid global development, the extensive use of electricity significantly contributes to substantial primary energy consumption, elevated CO_2 emissions, and global warming, with buildings playing an important role, accounting for approximately 40% of primary energy consumption in the USA and Europe, while around 30% in China, according to prior research [1]. Recent works have focused on the various energy-saving technologies that are being used all around the world to lessen the impact that buildings have on the environment. Among these methods, Net-Zero Energy Buildings (NZEB) or Nearly-Zero Energy Buildings (nZEBs) are gaining popularity [1]. The concept of NZEB has gained broad acceptance because of its ability to decrease carbon dioxide emissions and energy use in

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the buildings [2]. Similar to NZEB, the idea of nZEB has become increasingly popular globally. Without a thorough, measurable, and widely recognised definition, NZEB runs the risk of being implemented inadequately, which could reduce its efficacy in addressing social, ethical, and environmental challenges [3]. Researchers have come up with a wide range of different definitions for NZEB. Some researchers define net-zero energy building as an all-encompassing strategy for lowering carbon dioxide emissions from the construction sector [1]. Another study defines NZEBs as structures that, when assessed at the site where they were built, produce as much energy as they use in a year [4]. A study suggests that each NZEB should be customised to its own environment to achieve maximum efficiency. Despite this evolution, it is critical that the goals and criteria of NZEB models remain consistent [3]. Many aspects, including borders, measurements, and criteria, have been recognised as crucial for a universally recognised framework defining nZEB in years of intensive research, idea sharing, and debates [1]. nZEB can also be described analytically, providing an alternative to the traditional understanding [1, 5].

$$nZEB = \text{ Supply } - \text{ Demand } \geq 0 \tag{1}$$

As shown in (1), if the boundary of the building zone do not change over time, the energy balance should either be zero or positive, signifying that the energy input and output are equal or greater [1]. In this context, the term "energy" refers to operational energy, which includes fuel, thermal energy, electricity and gas.

Figure 1 illustrates the various energy-efficient techniques used to create NZEBs or nZEBs, including renewable energy, passive and active design techniques. The thermal and electrical load of buildings is often reduced as a result of a well-implemented passive design, which includes components like optimal orientation, a high-performance thermal insulating envelope, effective airtightness, and efficient shading systems [1]. Therefore, a focus on passive design methods has been given under this scheme.

Motivation and problem definition

A multi-objective optimisation using passive energy efficient features as design variables was carried out to find the best solution that balances the life-cycle cost (LCC) of a building, energy savings, and thermal comfort [6]. Incorporating and optimising passive and active approaches during the early stages of building design is an improved approach for implementing nZEBs. It is also recommended that the building's energy performance be tracked in real-time throughout the whole period of use [7]. A multi-objective optimisation analysis was performed on a pre-existing system to assess its efficacy and inform future design choices. In order to improve efficiency while decreasing lifecycle costs, a genetic algorithm (GA) was implemented into a building simulation engine and passive conservation variables were adjusted [8]. According to the results of a study, incorporating specific passive measures in the envelope of the building design during the planning, construction, or retrofitting phase can significantly lower energy consumption (up to 33 per cent) without compromising occupant comfort, highlighting the impact of solar energy and architectural elements like roof-to-wall thickness, window-to-wall ratio (WWR), and window sizing [9]. Researchers investigated enhancing energy efficiency in architectural design by integrating new information into model files, noting that Building Information Modelling (BIM) enhances design outputs with simple technological tools, and evaluated passive design strategies for Hong Kong's residential structures considering climate change implications [10]. The work developed a parametric BIM tool for LCC, examining

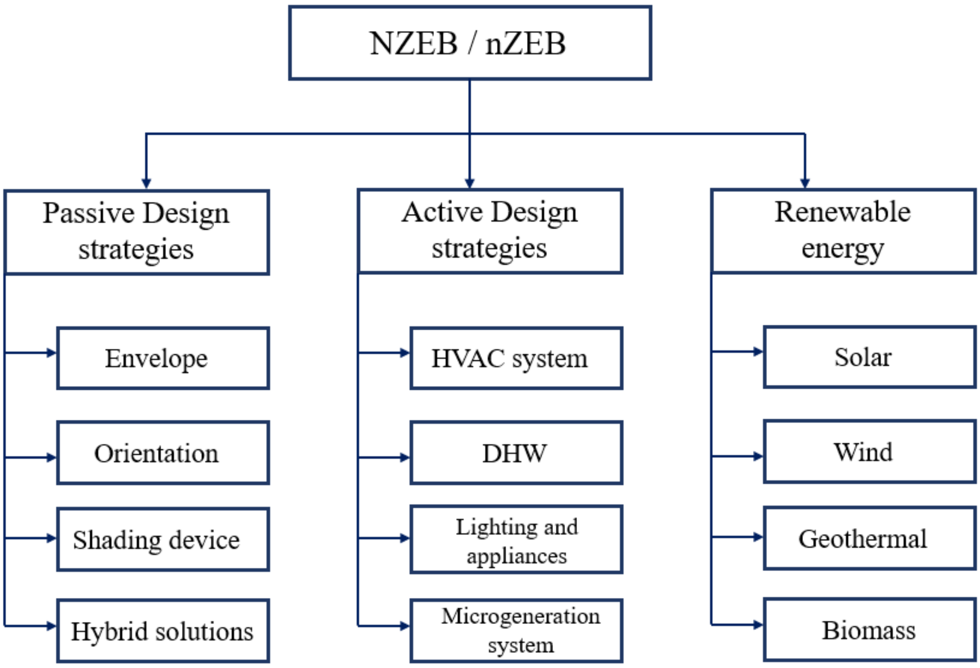

Figure 1. Strategies to achieve NZEB/nZEB.

a UK business and home to analyse operational and embodied energy perspectives [11]. In another study, BIM was employed for energy-efficient upgrades in Amazonian school classrooms, showcasing viability through 3D modelling and energy calculations [12]. The evaluation of feasible passive design techniques for residential homes in the twenty-first century involved utilising Givoni building bioclimatic charts, an adaptive comfort standard model, simulation-based sensitivity analyses, and a validated EnergyPlus model. These tools were employed to assess the dynamic performance of passive design techniques over time, considering changing climatic conditions [13]. Another study investigated two significant 20^{th} century domestic architecture cases, pioneers in parametrization, wherein digital replication and analysis of analogue figures by the architects were performed using contemporary parametric technologies [14]. The optimization strategy proposed by [15] utilizes Rhinoceros' parametric design to optimize the thermal load of a free-form building in the early design phase, demonstrating success in anticipating and enhancing heat characteristics with different building shapes. [16] studied the vital design components of passive solar office building envelopes in hot and humid climatic zones using a thorough methodology that integrated data mining methods with parametric energy simulation. A study concentrated on increasing single-family housing's energy efficiency, lowering operational CO_2 emissions, and attaining cost minimization. It notably looked at components for on-site heat and energy generation as it evaluated numerous multi-objective optimisation techniques [17]. The goal of a study was to improve the passive housing idea for single-family structures in the Southern Brazilian region. The results showed a notable improvement in thermal comfort and a significant decrease in the structures' energy requirements [18]. In another study, the thermal characteristics of the building, geometrical factors, ratios, and additional passive cooling techniques like thermal-energy storage systems, evaporative cooling, night ventilation, solar gains, and cooling from night-time sky radiation were all taken into account [19]. A simulation-based multi-criteria optimisation approach for NZEBs was developed by the researchers to evaluate the viability of cost-effective design enhancements in numerous case studies spanning climate zones in Lebanon and France [20]. In [21], a GA-based approach accounting for uncertainties during sizing was presented for sizing systems in NZEBs, considering multi-criteria performance objectives as constraints to minimize initial costs across five distinct systems. Environmental research, identification of appropriate measurements, model construction, analysis, and design judgement were all part of the procedure used to evaluate energy-efficient envelope design techniques in another study [22]. A GA-based technique stated in [21] for scaling systems in NZEBs integrated multi-criteria performance objectives as constraints to minimize initial costs across five systems, while addressing uncertainties during the sizing process. According to a study, a differential evolution system design approach for NZEBs in Hong Kong addresses climate change by optimising building system proportions based on local meteorological data to minimise LCC while satisfying user-defined performance constraints like thermostatic comfort, energy balance, and grid interaction [23]. The work provides a simplified energy analysis to assess how building orientation influences energy savings, considering solar heat gain and local factors.

The current literature lacks a comprehensive exploration of the influence of passive architectural design variables on energy consumption in unconditioned buildings, creating a gap in applying optimization techniques for such buildings. Consequently, the present work aims to address this by proposing a methodology to minimize energy consumption in residential buildings through the optimization of passive architectural design variables. To achieve this, a parametric model is created, incorporating four passive architectural design variables: orientation, WWR, shading depth, and shading angle. As the parametric study provides an extensive solution space, integrating it consistently and efficiently throughout the design process, it is challenging due to the size of the design option sets. Therefore, a metamodel-based design optimization approach is adopted. The model generates diverse options for analysing energy consumption in buildings, with a focus on reducing energy usage in a single-family, one-story unconditioned residential building.

Metamodel-based design optimization scheme for nZEB

During the early stages of a project, the designed workflow makes it possible to assess various passive design possibilities quickly. This paper describes the simulation-based workflow to minimise the energy use intensity (EUI) of a one-story single-family residential house. In this study, the simulations for parametric modelling and energy analysis have been carried out in Rhinoceros 3D Version 7, with Grasshopper along with the Honeybee and Ladybug as the plugin [24], [25], [26], [27]. EUI is defined as the amount of energy used annually per unit area, making it possible to compare energy consumption among various buildings, regardless of how different they are typically sized [28]. The workflow consists of five consecutive phases: building geometry and parametric modelling, energy simulations, design of experiments (DoE), optimization and sensitivity analysis. The framework to achieve a nZEB based on design optimization is shown in Figure 2.

Generating building energy models through parameterization

Through parametric analysis, it is possible to rapidly evaluate a large number of designs in bulk processes. This method helps to explore across the design sets, identifying all feasible parameter combinations for a specific objective, with parametric, generative, or algorithmic design aiming to offer a flexible method for describing and generating geometry through scripting [29], [30]. It involves creating linkages between geometry and decision variables to enable a dynamic relationship between them [30]. Different parameters affect the building's energy performance. To conduct a parametric study, a model has been developed that consists of the parameters to be modified and then generates a set of alternative values for each variable. After the building model is developed in parametric software, architectural design variables are then varied parametrically with number sliders to lower energy consumption. Figure 3 shows the floor plan and perspective view of the considered building.

A component is used to divide the surfaces of the zones in order to create matching surfaces between adjacent surfaces. The appropriate distribution of heat across the surfaces is ensured at this stage, which is essential for accurately calculating conductive heat flow in an energy simulation. In the next step, this component is linked to an element that helps assign rooms in energy simulation softwares to single zones, and the rooms must be a closed volume to ensure accurate volumetric calculations. In this process, the zone program is defined, for example, "Midrise apartment" and the zone status is set to be conditioned or unconditioned. Also, the zone name is set to be "Residential", "Commercial", etc. Next, it was ensured that adjoining surfaces were merged into a single surface appropriately representing internal walls. The building model is now ready with exterior walls, interior walls, roof and floor. At this stage of the workflow, the walls are ready for window and shading device creation. The model is now ready for the energy simulations.

Energy simulations for the building energy models

The simulations were conducted over a period of January to December to capture seasonal variations in energy performance. The analysis incorporated heat transfer processes through conduction, convection, and radiation along with temperature, relative humidity, and wind effects. These parameters are sourced from EPW files obtained through the ASHRAE Global Climate Data repository and integrated through Ladybug and Honeybee plugins in Grasshopper to ensure location-specific and reliable weather data. In this work, thermal comfort was addressed by utilising a reference comfort setpoint range (26.5–29.5°C, as per SP 41) based on the adaptive comfort model, which ensures acceptable indoor temperatures under varying environmental conditions. The thermal performance of the building envelope was defined using Honeybee within the Grasshopper for the given climate zone. The U–values applied were 0.45 W/m^{2}K for external walls, 0.30 W/m^{2}K for the roof, and 2.6 W/m^{2}K for single-glazed windows, which reflect the typical values for minimal insulation scenarios in unconditioned buildings. All envelope characteristics, including material layers and thicknesses, were modeled in accordance with ASHRAE standards and local construction practices. These values were consistently applied across all simulations and are critical in assessing passive performance and energy demand under parameterization. The performance indicator, Energy Use Intensity (EUI) in kWh/m^2, is evaluated for all design possibilities. Parametric modelling software, enhanced by various plugins, is used to improve simulation precision and detail. After generating the building model, the energy model is exported to simulation software where weather data in EPW format was imported to accurately evaluate energy performance for the specific location. The energy simulation is set to record data for the entire analysis period, identifying the month with the highest energy consumption and providing insights into the building's energy use. Lower values of EUI indicates improved energy performance [28].

Utilizing metamodeling for easier, accurate, and efficient solutions sets

While the parametric study offers an extensive and complete solution space, the size of the design option space makes it difficult to integrate it throughout the design process consistently and efficiently. The complex computational analysis is essential to derive the response due to the implicit nature of the precise relationship between the response and a set of input variables. The use of a metamodel, commonly referred to as RSM (Response Surface Methodology), which is a statistical approximation of the relationship, is a simple but efficient approach. With this strategy, the computing process is made easier as the response is estimated as a function of the input variables. The Design of Experiments (DoE) approach offers the essential framework for this crucial stage of Response Surface Methodology (RSM) [31]. Using this approach, computation becomes easier because the response is estimated as a function of the input variables. The ranges must be large enough to encompass all possible parameter spaces while being constrained enough to allow for simple alignment of the response surfaces with the true response using regression. DoE methods such as Full Factorial Design (FFD), Central Composite Design (CCD), Box-Behnken design (BBD), Space-Filling design (SFD), and Taguchi's orthogonal arrays (TA) can be used for this purpose [31]. A Central Composite Design (CCD) within the framework of Response Surface Methodology (RSM) is employed in the study to optimize the experimental design. CCD is chosen for its efficiency in exploring the response surface with a balanced number of simulations. A total of 25 simulations is conducted, comprising factorial, axial, and centre points. These simulations provided Energy Use Intensity (EUI) values, effectively showing the impact of the four architectural design variables on energy consumption.

Statistical validation must be done to evaluate the regression model's applicability. The accuracy and appropriateness of the model can be checked using several statistical indicators, such as the coefficient of determination (R^2), adjusted R^2 $(RA)^2$, average absolute error (%AvgErr), and root mean square error (%RMSE). The R^2 and $(RA)^2$ values should be close to 100%, showing a significant level of statistical significance, to guarantee the model's adequacy. On the other hand, optimal performance is indicated by average error (%AvgErr) and root mean square error (%RMSE) values close to zero [31]. RMSE is adopted for this work due to its ability to quantify the average magnitude of error between predicted and actual values, providing a comprehensive assessment of model performance while incorporating all data points, thus offering a robust evaluation of predictive accuracy compared to other statistical methods.

Design optimization for most optimum nZEB

In this work, DoE is adopted along with optimisation using GA. It helps to get accurate results in less duration of time. The GA is regarded as a potent tool in the optimisation field since it explores and searches for the most optimal outcome using a variety of genetic operations like selection, crossover, mutation, and more [32]. It efficiently explored the design space, identifying optimal configurations while considering all variables simultaneously including a population size of 100, a 100% crossover rate, a 2% mutation rate, and 100 child solutions, enabling precise optimization. Here, the optimization process aims at reducing the total energy consumption of the building which helps to attain and analyse the optimal results. To solve optimization issues, there are several algorithms which are capable of solving problems that are either continuous or discrete, with or without constraints.

Let f denote the objective function representing the total energy consumption to be minimized. The architectural design variables are denoted as follows:
o: Orientation.
r: Window-to-wall ratio (WWR).
d: Shading depth.
a: Shading angle.
The optimization problem can be formulated as follows:

$$\begin{aligned} \text{minimize:} \quad & \textit{f(o, r, d, a)} \\ \text{subject to:} \quad & \mathrm{o} \in [0, 360] \\ & \mathrm{r} \in [0.05, 0.7] \\ & \mathrm{d} \in [0.1, 0.75] \\ & \mathrm{a} \in [0, 60] \end{aligned} \tag{2}$$

The main goal is to minimize the total energy consumption of the building, represented by the objective function f in (2). In the process of optimisation using GA, the lower bound for the architectural design variables is set to be 0, 0.050, 0.100 and 0 respectively while the upper bound is set to be 360, 0.700, 0.750 and 60 respectively. This work do not consider any functional constraint during the optimization process. Finally, a fine-tuning dataset was created to evaluate if the achieved result from the optimization was the most optimum and the result was found to be satisfactory.

Sensitivity analysis to identify the critical architectural design variable

Sensitivity analysis determines how each architectural design variable affects overall performance. Three major types of sensitivity analysis can be categorised as screening, local and global sensitivity analysis. This work focuses on screening. Screening is an economical way of identifying and ranking the design elements that most affect output variation (e.g., energy performance) [33]. ANOVA (Analysis of Variance) is employed in the study to assess the significance of individual architectural design variables and their interactions in influencing energy consumption. This method allows to evaluate how changes in each architectural design variable affect the overall performance of the building. ANOVA provides statistical insights into the relative importance of each variable by comparing the variance in energy consumption due to changes in the design parameters. Through this process, the variables are ranked based on their impact on the output, that allows to identify the most significant factors. Interaction effects between variables are also examined, revealing how combinations of design parameters influence energy consumption in ways that individual parameters alone may not. ANOVA, is used to quantify the effects of each architectural design variable and its interactions, ensuring a more comprehensive understanding of the factors driving energy performance.

A case-study building

Site location

Located at 26.18°N and 91.76°E, Guwahati is a rapidly developing metropolitan city in the Indian state of Assam. The city is designated as a Climate Zone warm and humid.

Except for the dry winter season, the average humidity in Guwahati is constantly high, frequently topping 80%. May-June is the hottest month of the year, with temperatures typically reaching their highest point. Winter lasts from November to February, whereas monsoon season begins in June and lasts until September [34].

Building description

This study considers an unconditioned small single-family residential building as a case study building with a gross floor area of 59.85 m^2 in Guwahati, Assam. Unconditioned building here refers to a building without any mechanical heating, ventilation and air-conditioning systems. The one-story rectangular building considered here has two bedrooms (3.96 m x 3.65 m) and (4.26 m x 3.65 m) respectively, one kitchen (2.43 m x 2.74 m), one hall/dining room (5.48 m x 4.56 m) and a bathroom (2.74 m x 2.13 m). The floor height of the building is 10 m. The height of the window is fixed at 1.65 m with a sill height of 1 m as per commonly adopted architectural plans in Guwahati city. Although a small single-story building is considered as a case-study model for this study, the same workflow can be followed for any other type of building such as a multi-storied building or an unsymmetric building. In the present study, the windows were created only on the exterior walls by varying the WWR. WWR of the interior walls are not considered in this study because the solar gain received by the building is mainly due to the exterior openings in the exterior walls as the total solar gain plays an important role in evaluating the building's energy performance. Adjustable WWR and external shades with variable shading depth and angle, alongside adjustable building orientation, facilitated with number sliders.

Energy performance results and discussion

Energy performance analysis was conducted for a reference residential building with large openings, no shading devices, and an orientation of 0°, resulting in a total energy consumption of 379.95 kWh. For another random set of architectural design variables, including an orientation of 180°, a WWR of 40 %, a shading depth of 0.425 m, and a shading angle of 0°, the total energy consumption was found to be 247.17 kWh. After optimization using the GA, the most optimal configuration was achieved with an orientation of 180°, a WWR of 5 %, a shading depth of 0.600 m, and a shading angle of 38°, as shown in Figure 4. At these values of the architectural design variable, the total energy consumption of the residential building is 164.65 kWh as shown in Figure 5. While using the same values of the architectural design variables in energy simulation software, the total energy consumption of the building is found to be 182.39 kWh.

In this work, the RMSE % calculated is 9.29 % and R^2 is 0.9781 which states that the metamodel created is precisely predicted and the analysis is based on dataset consisting of 25 samples. Figure 6 shows the validation process, with the Y-axis representing actual data obtained from the simulation tool and the X-axis indicating predicted data derived from the metamodel. The 9.29 % RMSE achieved in this study reflects the average deviation between predicted and actual values, quantifying the metamodel's accuracy predictively. RMSE values below 10 % are typically considered acceptable for design optimization problems, indicating high-quality accuracy. In this case, the 9.29 % RMSE falls within the commonly reported range of 5-15 % for metamodeling studies, demonstrating the metamodel's robustness and suitability for evaluating architectural design variables [35]. The total gross floor area of the considered building is 59.85 m^2. Therefore, the achieved annual EUI of the considered building is 3.04 kWh/m^2. From the energy performance simulations, the total energy consumption of the reference building is found to be 379.95 kWh and for the same building with achieved optimum architectural design variables is 182.39 kWh. The percentage saving of total energy consumption of the building with optimum architectural design variables is 51.99%. The total energy consumption is measured in kWh which is the sum of the energy consumed from sources of that building such as lighting, electrical equipments, hot water, people gain and solar gain. The energy consumption of the single-family residential building from different sources of energy is shown in Figure 7. The energy consumption values in Figure 7 were calculated as lighting was estimated using a lighting power density of 5–8 W/m^2, electrical equipments accounts for plug loads from residential appliances (e.g., refrigerators, televisions) based on typical usage patterns, hot water usage was derived from assumptions about daily water usage and heating energy requirements, following regional standards, people gain reflects heat generated by occupants, calculated using metabolic rates (70â€“100 W/person) and occupancy schedules, and solar gain was determined through thermal simulations, considering solar radiation, glazing properties, and shading devices. Finally, the buildingâ€™s EUI value is validated from the previous literature. According to the previous literature, it is seen that according to passive house standard, the EUI of passive building has to be lower than 15 kWh/m^2 annually [7, 36]. In this paper, it is seen that for a small residential house with a floor area of 59.85 m^2 the achieved EUI is 3.04 kWh/m^2 annually which is much lower than 15 kWh/m^2. In addition to the simulation analysis, a survey was conducted to compare the energy consumption of real buildings in Guwahati with that of the simulated building, using electricity bill data from the Assam Power Distribution Company Limited (APDCL). As per the survey, the results showed a 7% higher energy consumption in the real buildings compared to the simulated buildings, which suggests that the simulation is reasonably accurate. Therefore, it can be stated that the considered building in Guwahati city is the achieved nZEB. At this stage of the scheme, statistical software is being used for screening to identify the primary factor influencing the building's overall performance.

The ANOVA table for the regression model is shown in Table 1. ANOVA results as shown in Table 1 confirm WWR as the most significant factor (F = 174.52, $p < 0.001$), with shading depth also significant (p = 0.006). Orientation and shading angle show less statistical significance ($p > 0.05$), supporting their minor influence observed in the regression model. This validates the regression structure of the model and highlights key variables for the design optimization. The metamodel obtained through DOE is a second-order polynomial equation. Table 2 shows the derived values resulting from varying a single architectural design variable while maintaining the constancy of all other architectural design variables.

The interactions between two architectural design variables were examined using the ANOVA (Analysis of Variance) experiment. ANOVA is used to assess the significant impact of individual parameters on experimental outcomes, allowing for the identification and quantification of the relative importance of each design parameter in influencing the results [37]. Every time an architectural design variable interacts with WWR, as shown in Tables 3, 4, 5, and 6, the energy consumption is minimized, highlighting WWR's significantly larger impact on reducing energy consumption in buildings compared to other passive design factors. While all architectural design variables are considered important, certain interactions, such as the combination of orientation with shading depth (as shown in Table 5), result in minimal changes, denoted by '–', indicating orientation's lesser significance relative to other architectural design variables. The regression model derived from the response surface methodology (RSM) is presented in uncoded units, incorporating all linear, quadratic, and two-way interaction terms for the four architectural design variables: orientation *(o)*, window-to-wall ratio *(r)*, shading depth *(d)*, and shading angle *(a)*. The complete equation as shown in Equation 3 predicts energy consumption (E) as a second-order polynomial. Among the design variables, WWR and its square term show the highest positive coefficients, confirming its dominant role in reducing energy consumption. The interaction between WWR and shading depth also contributes significantly, as it is reflected by a large negative coefficient. In contrast, the terms involving orientation and shading angle show negligible values, indicating limited influence within the studied range. This full formulation ensures that the regression model accounts for all relevant effects, supporting both statistical validity and predictive robustness. An ANOVA analysis can further quantify the statistical importance of these terms, showing their contributions to energy consumption. This ensures that the model captures all significant effects, including interactions and nonlinearities, ensuring the included terms are adequate to achieve a high level of predictive accuracy.

$$\begin{aligned} E = \; & 173.3 - 0.2044\, o + 272.6\, r - 1.3\, d - 0.023\, a \\ & + 0.000568\, o^2 + 37.4\, r^2 + 19.7\, d^2 + 0.00326\, a^2 \\ & + 0.0000\, o \cdot r + 0.0000\, o \cdot d + 0.000000\, o \cdot a \\ & - 133.9\, r \cdot d - 0.429\, r \cdot a - 0.407\, d \cdot a \end{aligned} \tag{3}$$

Table 1. ANOVA table for the regression model

Source	**DF**	**Adj SS**	**Adj MS**	**F-Value**	**P-Value**
Orientation	2	862	431.1	1.48	0.256
WWR	2	101407	50703.4	174.52	0.000
Shading depth	2	4201	2100.3	7.23	0.006
Shading angle	2	443	221.7	0.76	0.483
Error	16	4649	290.5		

Table 2. Main effect of energy consumption on individual variable

Orientation (in deg.)	**WWR**	**Shading Depth**	**Shading Angle**	**Energy Consumption (kWh)**
0	-	-	-	262.661
180	-	-	-	238.85
360	-	-	-	262.661
-	0.050	-	-	186.012
-	0.375	-	-	242.979
-	0.700	-	-	336.099
-	-	0.100	-	276.104
-	-	0.425	-	243.511
-	-	0.750	-	245.592
-	-	-	0	265.781
-	-	-	30	243.269
-	-	-	60	256.104

Table 3. Interaction of orientation with other variables for energy consumption

Orientation (in deg.)	WWR	Shading Depth	Shading Angle	Energy Consumption (kWh)
0	0.050	-	-	186.385
0	0.375	-	-	254.600
0	0.700	-	-	340.952
180	0.050	-	-	183.030
180	0.375	-	-	238.330
180	0.700	-	-	297.370
360	0.050	-	-	186.385
360	0.375	-	-	254.600
360	0.700	-	-	340.952
0	-	0.100	-	279.195
0	-	0.425	-	254.600
0	-	0.750	-	248.142
180	-	0.100	-	251.380
180	-	0.425	-	239.076
180	-	0.750	-	225.190
360	-	0.100	-	279.195
360	-	0.425	-	254.600
360	-	0.750	-	248.142
0	-	-	0	268.647
0	-	-	30	254.600
0	-	-	60	258.690
180	-	-	0	242.850
180	-	-	30	238.736
180	-	-	60	235.420
360	-	-	0	268.647
360	-	-	30	258.690
360	-	-	60	254.600

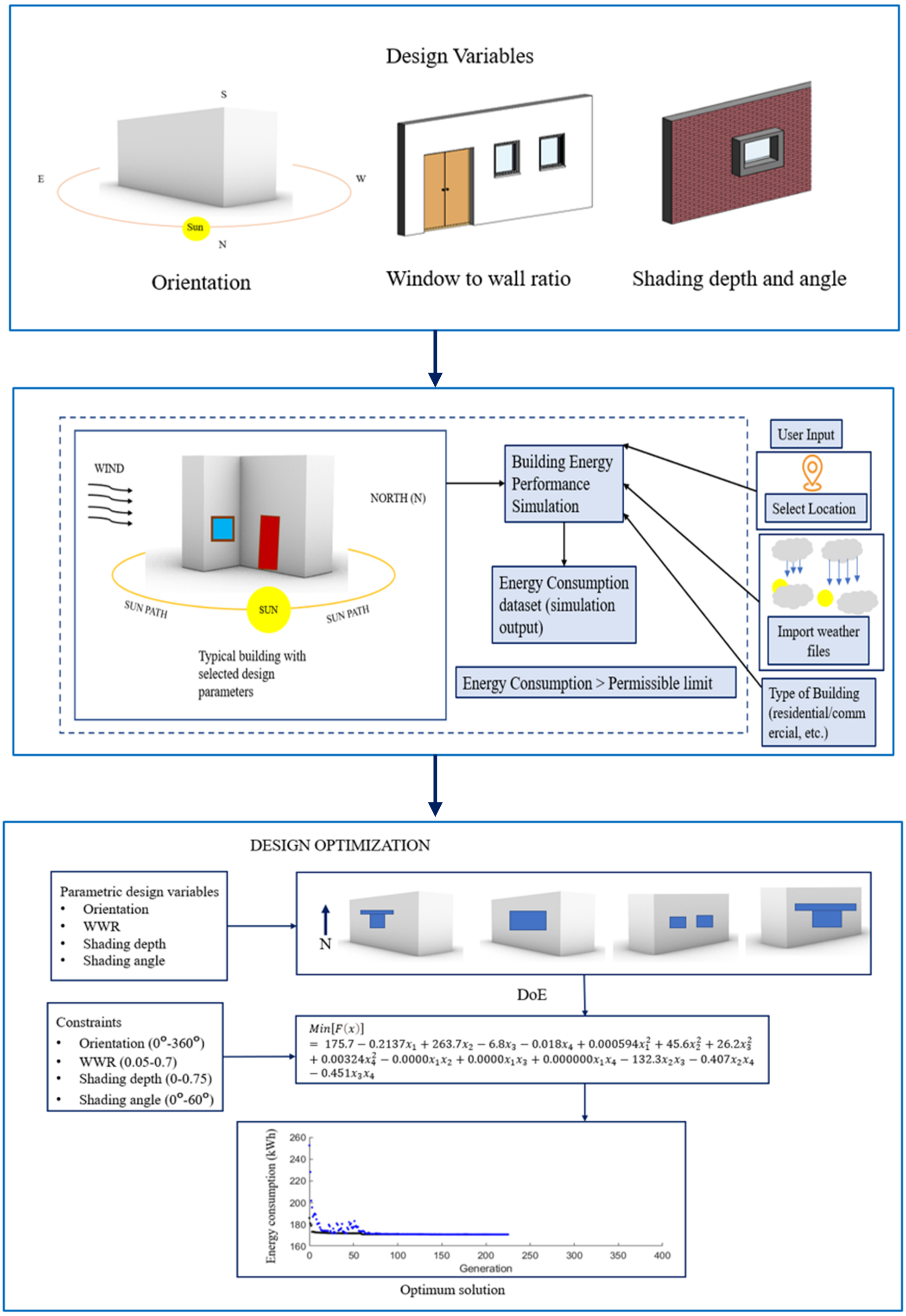

Figure 2. Scheme to achieve a nZEB based on design optimization.

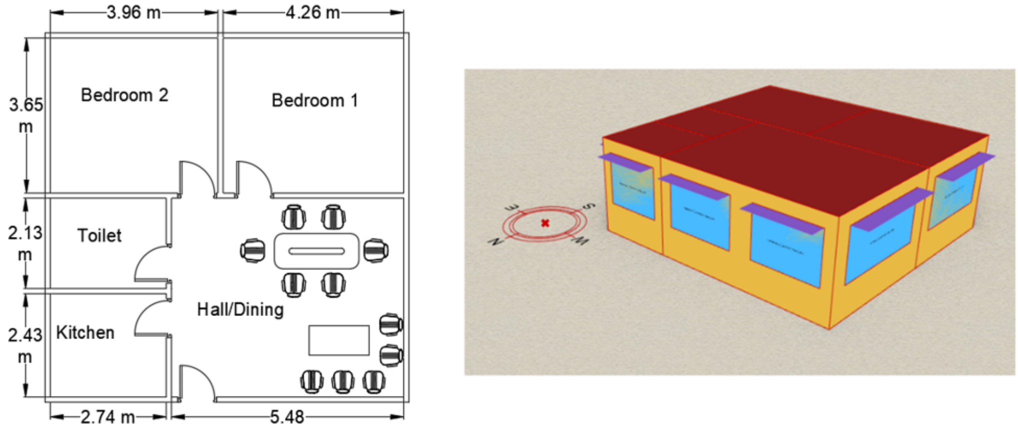

Figure 3. Floor plan and perspective view of a single-family residential house.

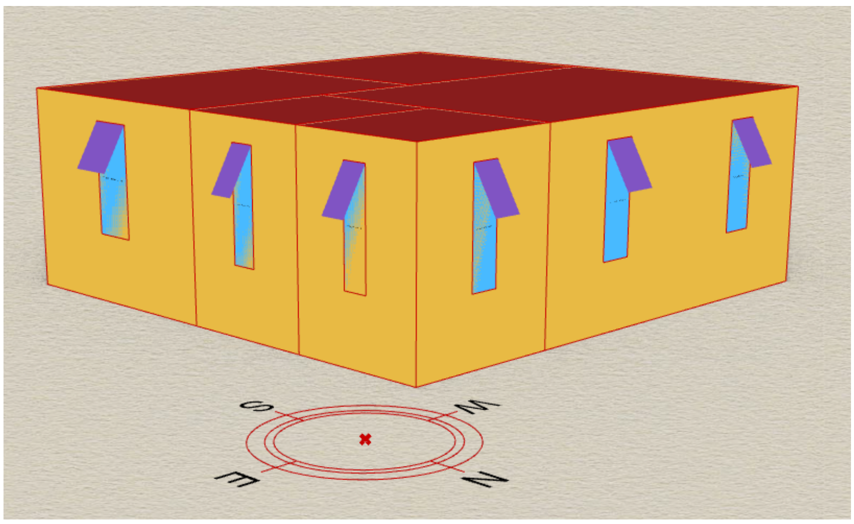

Figure 4. The single-family residential building with optimum architectural design variables.

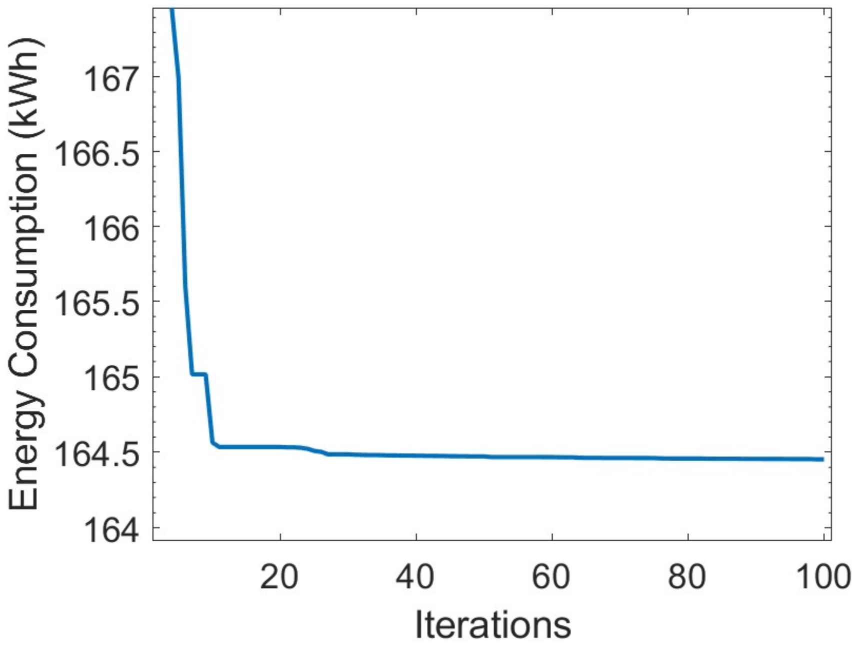

Figure 5. Total energy consumption of the building from Optimisation.

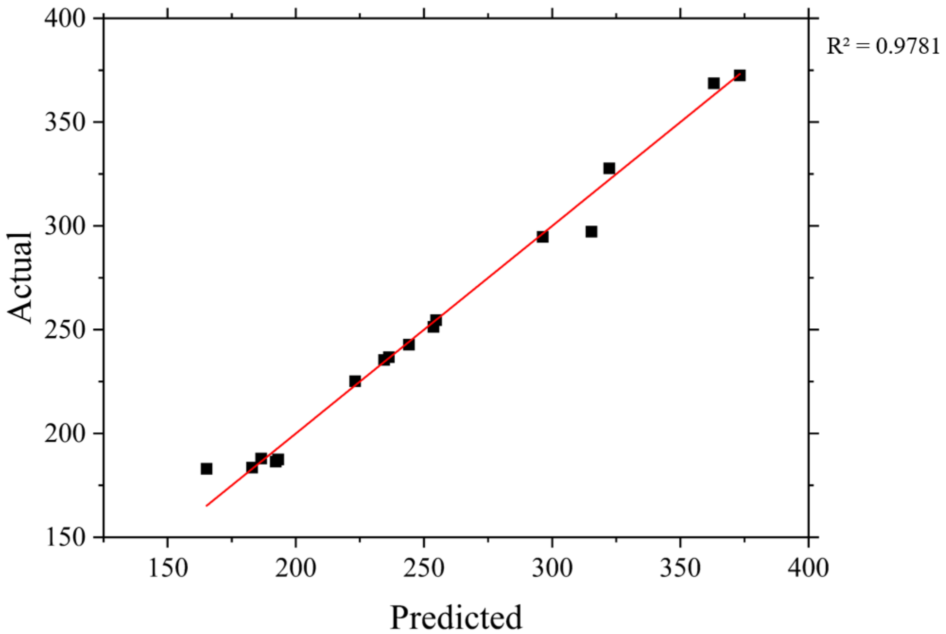

Figure 6. Validation of the metamodel.

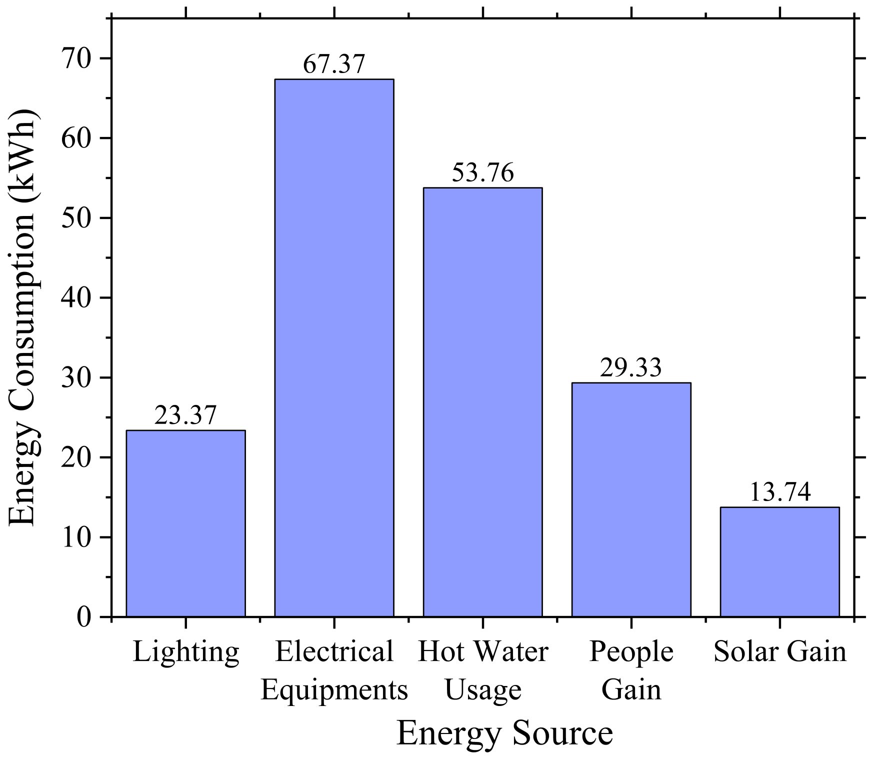

Figure 7. Energy consumption from different energy sources.

Table 4. Interaction of WWR with other variables for energy consumption

Orientation (in deg.)	**WWR**	**Shading Depth**	**Shading Angle**	**Energy Consumption (kWh)**
0	0.050	-	-	-
180	0.050	-	-	183.030
360	0.050	-	-	186.385
0	0.375	-	-	-
180	0.375	-	-	238.330
360	0.375	-	-	254.600
0	0.700	-	-	-
180	0.700	-	-	297.270
360	0.700	-	-	340.952
-	0.050	0.100	-	183.005
-	0.050	0.425	-	187.765
-	0.050	0.750	-	183.030
-	0.375	0.100	-	251.380
-	0.375	0.425	-	244.856
-	0.375	0.750	-	225.190
-	0.700	0.100	-	370.625
-	0.700	0.425	-	297.270
-	0.700	0.750	-	311.28
-	0.050	-	0	183.033
-	0.050	-	30	183.030
-	0.050	-	60	185.585
-	0.375	-	0	244.516
-	0.375	-	30	244.516
-	0.375	-	60	235.420
-	0.700	-	0	350.110
-	0.700	-	30	297.270
-	0.700	-	60	331.795

Table 5. Interaction of shading depth with other variables for energy consumption

Orientation (in deg.)	**WWR**	**Shading Depth**	**Shading Angle**	**Energy Consumption (kWh)**
0	-	0.100	-	-
180	-	0.100	-	251.380
360	-	0.100	-	279.195
0	-	0.425	-	-
180	-	0.425	-	239.076
360	-	0.425	-	254.600
0	-	0.750	-	-
180	-	0.750	-	225.1900
360	-	0.750	-	248.142
-	0.05	0.100	-	187.765
-	0.375	0.100	-	251.380
-	0.7	0.100	-	370.625
-	0.05	0.425	-	183.030
-	0.375	0.425	-	244.856
-	0.7	0.425	-	297.270
-	0.05	0.750	-	185.005
-	0.375	0.750	-	225.190
-	0.7	0.750	-	311.280
-	-	0.100	0	278.180
-	-	0.100	30	251.380
-	-	0.100	60	278.180
-	-	0.425	0	245.262
-	-	0.425	30	245.262
-	-	0.425	60	235.420
-	-	0.750	0	257.085
-	-	0.750	30	225.190
-	-	0.750	60	239.200

Table 6. Interaction of shading angle with other variables for energy consumption

Orientation (in deg.)	**WWR**	**Shading Depth**	**Shading Angle**	**Energy Consumption (kWh)**
0	-	-	0	-
180	-	-	0	242.850
360	-	-	0	268.647
0	-	-	30	-
180	-	-	30	238.736
360	-	-	30	254.600
0	-	-	60	-
180	-	-	60	235.420
360	-	-	60	258.690
-	0.050	-	0	187.185
-	0.375	-	0	242.850
-	0.700	-	0	350.110
-	0.050	-	30	183.030
-	0.375	-	30	244.516
-	0.700	-	30	297.270
-	0.050	-	60	185.585
-	0.375	-	60	235.420
-	0.700	-	60	331.795
-	-	0.100	0	280.210
-	-	0.425	0	242.850
-	-	0.750	0	257.085
-	-	0.100	30	251.380
-	-	0.425	30	245.262
-	-	0.750	30	225.190
-	-	0.100	60	278.180
-	-	0.425	60	235.420
-	-	0.750	60	239.200

Concluding remarks

Several researchers have looked into different ways to reduce building energy use and get towards NZEBs or nZEBs. However, these studies often lack a deep understanding of the design sets concerning the different stages of architectural design. Therefore, in this work, a parametric scheme has been developed to evaluate the total energy consumption and annual energy use intensity of a building. This scheme also deals with achieving the most optimum nearly-zero energy building with a very low EUI for a single-family one-story residential house. The proposed scheme has been implemented to a building situated in Guwahati, Assam.

The main outcomes of the proposed scheme are as follows:

- Based on a comprehensive literature review on passive design strategies, orientation, WWR, shading depth and shading angle are adopted for this work for their ease of acceptance by building owners and early design phase integration.
- The study incorporates parameterization, but due to the extensive number of runs involved in the process, metamodeling is employed as an alternative approach with an RMSE to be 9.29 %
- The total energy consumption of the reference building is found to be 379.95 kWh and that of the building with proposed architectural design variables is found to be 164.65 kWh.
- GA technique of optimization is carried out in the study which gives the most optimum architectural design variables as 180° orientation, 5% WWR, 0.6 m shading depth and 38° shading angle.
- Sensitivity analysis is ircarried out in the study that shows an extensive variation in the building's total energy consumption with a little change in WWR.

The scheme and integrated approach proposed in this study show applicability across various building types and climate zones. In this study, the methodology is implemented on an unconditioned single-story residential building, resulting in a favourable total energy consumption value based on the chosen architectural design variables. However, extending the application to a multi-story building could introduce additional complexities. One of the limitations of the study is that it excludes HVAC systems and thermal comfort of the occupant, which are important for a comprehensive understanding of energy consumption. Incorporating these factors for a more holistic analysis may be a future approach.

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