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Review

A Systematic Review of Sensitivity Analysis in Building Energy Modeling: Key Factors Influencing Building Thermal Energy Performance

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Abstract: Improving building thermal energy performance is essential to reducing energy consumption, minimizing carbon emissions, and enhancing occupants' thermal comfort. For this purpose, there is an increasing research interest in this field of building energy performance. This review aims to present a precise and systematic overview of the sensitivity analysis in optimizing the thermal energy performance of buildings. The investigation covers various aspects, including sensitivity analysis techniques, key measures and variables, objectives and criteria, software tools, optimization methods, climate zones, building typology, and climate change effects. The findings reveal that sensitivity analysis is a powerful technique for optimizing energy performance and identifying adaptive strategies such as dynamic shading, reflective coatings, and efficient HVAC set points to address climate change. Most of the study also highlights that the temperature set point is the key influential parameter in both heating-dominant and cooling-dominant climate zones. This review offers critical insights on advancing sustainable building design, informing policy, and guiding future research in energy-efficient building solutions.

Keywords: whole building energy simulation; sensitivity analysis; optimization tools; key input parameters

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1. Introduction

Building thermal energy modeling (BTEM) has become a crucial tool for designing energy-efficient buildings, optimizing performance for occupants' thermal comfort, and supporting decision-making in the sustainable construction of buildings. Studying the thermal energy performance of buildings is an essential aspect of modern construction and architecture, as it should consider energy efficiency, sustainability, and environmental concerns [1]. Assessing the efficiency of the thermal performance of the building is necessary to reduce energy consumption and carbon emissions without compromising the thermal comfort level [2]. To achieve this, sensitivity analysis of the building energy performance is essential, as it helps to identify the critical parameters that need attention or improvement. The accuracy and reliability of BTEM depend on the various input parameters such as weather conditions, building materials, occupancy schedule, building openings, etc. Sensitivity Analysis (SA) is widely used to identify the most influential parameters affecting building energy performance. One of the definitions of SA is a systematic and methodological approach to studying how variation or changes in a model's input

parameters affect the system's output [3]. It has become a crucial method for assessing the reliability and robustness of real-world systems and models in simulation by quantifying the degree to which the input variability impacts the outputs [4]. Figure 1 demonstrates the flow diagram for sensitivity analysis that could be adopted in building thermal energy performance analysis.

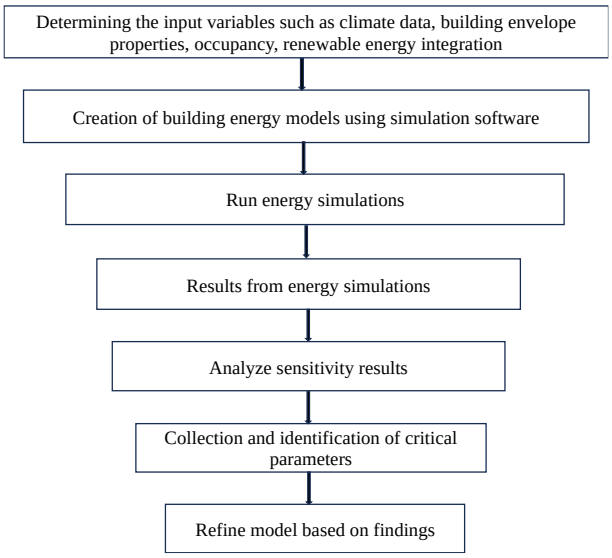


Figure 1. Flow diagram for sensitivity analysis adopted in building energy performance analysis.

It is helpful in various types of applications, such as calibrating energy models [5,6], building design [7], building energy retrofit, and climate change impacts on building energy [8]. Figure 2 illustrates the building energy simulation model, which highlights the creation of the building model, as well as several input parameters, output, and interpretation methods.

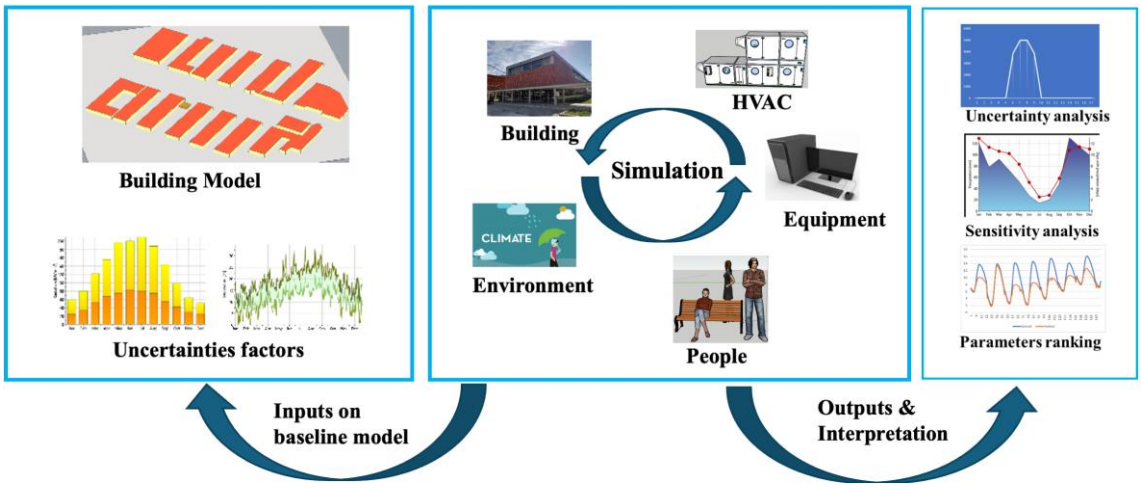


Figure 2. Illustration of a conceptual framework for building energy simulation with uncertainty analysis.

The concept of SA in building thermal energy performance was introduced after energy modeling and simulation tools were developed in the early 1980s. However, its application started prominently after developing sophisticated building energy simulation programs such as Department of Energy-Version 2 (DOE-2) and EnergyPlus (EP). The early simulation of the building energy system by varying building material and geometrical properties was performed by Manke [9] and presented at the American Society of Mechanical Engineers

(ASME) conference in 1996. In addition, one of the early papers that implemented sensitivity analysis specifically in building thermal energy performance and laid the foundation of global sensitivity analysis (GSA) was published by Saltelli [10] in the Technometrics Journal.

Despite several studies and significant achievements in the sensitivity analysis of building thermal energy performance, many areas still need in-depth exploration. The complexity of building systems and their components, evolving technologies, climate change, and their effect on the demand for building energy emphasize the necessity for continued study in this sector. Previous reviews based on the SA of building energy performances remain limited.

Wei [11] published a review article that offers a foundational review that primarily focuses on exploring the methodological framework of SA, highlighting its implementation steps and categorizing various sensitivity analysis methods. Pang et al. [12] performed a similar review, mainly emphasizing input parameter categorization, input-output nexus, sampling methods, and the uncertainties associated with the sampling methods. More recently, Mendes et al. [13] conducted a review expanding the scope by evaluating the advantages and limitations of the SA in assessing the thermal performance of buildings via energy simulations.

Despite these contributions, there remains a critical need for further review due to the rapid evolution of SA methodologies, advancements in analytical techniques, integration of emerging technologies in building energy systems, and the growing importance of climate change considerations in recent studies. The review also explored the most critical input parameters for the building's energy performance. This review endeavors to synthesize and assess the latest developments, methodologies, and applications in this field over the specified period. The primary purpose of this review is to deliver a comprehensive overview of how sensitivity analysis has enhanced and been applied to building energy performance and the corresponding evolution. By exploring the research performed, attempt to recognize trends, highlight innovative approaches, and address the implications of these outcomes for future research and practical applications.

The remainder of this paper is structured as follows: Section 2 provides the details of the literature search methodology. Section 3 overviews the publication trends and impacts of sensitivity analysis methods commonly applied in BTEM. Section 4 reviews the complete methodology of SA techniques, tools, and processes in BTEM, discussing their strengths and limitations. Section 5 critically analyzes the most influential input parameters in BTEM as identified through SA and how these input parameters vary across different climatic regions, building types, and SA methodology. Section 6 explored some of the importance of temperature adaptability due to climate change considerations in recent studies. Finally, Section 7 concludes with key findings and offers recommendations for enhancing sensitivity analysis in BTEM applications. This review aims to provide researchers and practitioners with a comprehensive understanding of SA methodologies, guiding the selection of appropriate techniques and identifying potential areas for improvement to enhance predictive accuracy in building energy simulations.

2. Literature Search Methodology

This systematic review followed a methodology to identify relevant papers from previously published works on the topic of sensitivity analysis of the building's thermal energy performance. Two databases, namely Scopus and Web of Science (WoS) core collection, were selected for the search strategy on 2 September 2024. The search was based on keywords ("Sensitivity analysis" OR "global sensitivity analysis" AND "Building energy simulation OR Building performance simulation") in the title, abstract, and keyword field of both databases. A total of 92 published papers in Scopus and WoS were thoroughly

analyzed for review assessment. The whole methodology illustrating the identification, screening, inclusion, and exclusion process is shown in Figure 3.

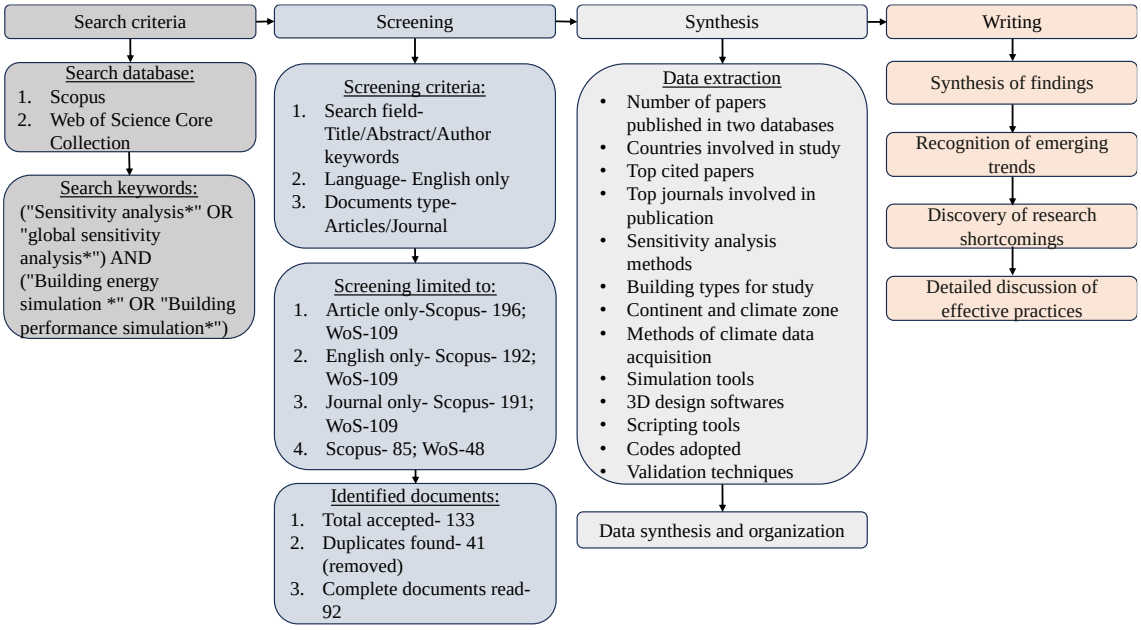


Figure 3. Flow diagram illustrating the literature search process using the keyword (*) "Sensitivity analysis" as the primary search term.

3. Overview of the Publications in Scopus and WoS

Figure 4 illustrates the overview of the number of publications related to sensitivity analysis on building thermal energy performance per year in the Scopus and WoS databases. The curve shows the increasing number of published papers with the keyword "sensitivity analysis" over time. There were very few studies and publications until 2005, and the number of publications increased from 2013 and continued to increase steadily until 2023. However, the research and publications increased rapidly from 2020 to 2023.

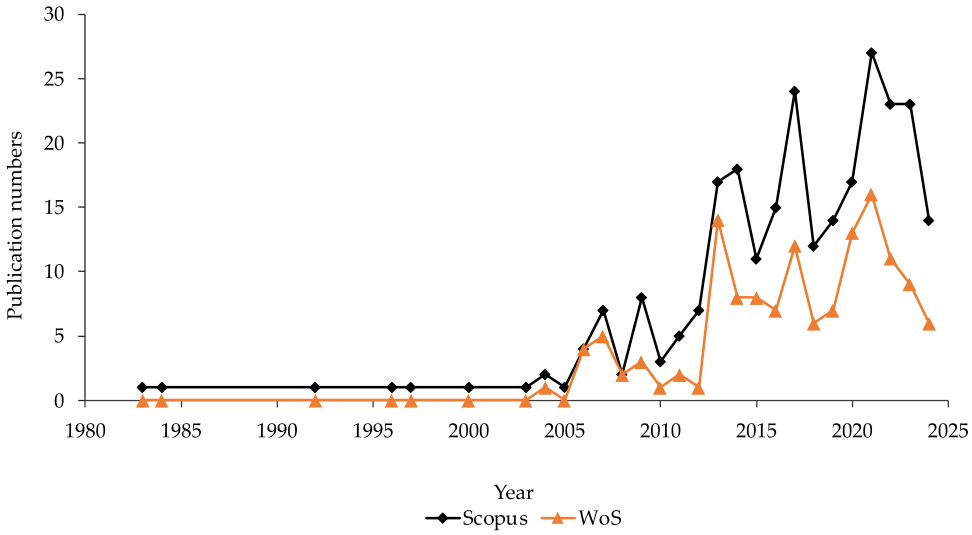


Figure 4. Publications per year related to sensitivity analysis in building energy performance in the Scopus and WoS databases.

During this period, researchers have been highly involved in studying and publishing articles related to sensitivity analysis on building energy performance. The noticeable increase in research publications in BTEM in this period can be attributed to the European

Union's strategic policy framework on climate neutrality by 2050. In addition, significant advancements in building energy simulation tools, such as EnergyPlus updates and the integration of Python APIs, have made simulations more accessible and affordable. Another important aspect is that the COVID-19 pandemic triggered the orientation of many researchers toward simulation-based research activities and increased publications.

Figure 5 depicts the Scopus keyword co-occurrence network in the sensitivity analysis, representing the number of published papers under the keyword sensitivity analysis. The figure shows the strong connection between SA and BTEM, highlighting their essence in optimizing thermal comfort, heating and cooling, and annual thermal loads. This visualization emphasizes how SA helps to improve building energy simulation models, enabling data-driven decision-making for achieving energy-efficient and thermally comfortable buildings.

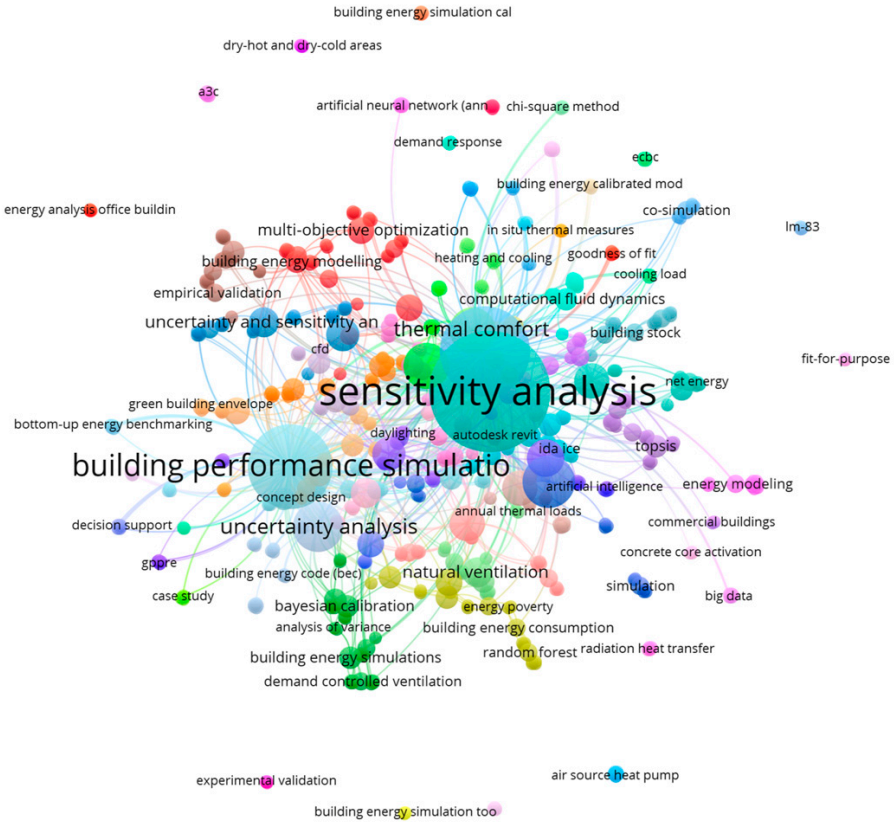


Figure 5. Scientific landscape of research on SA of BTEM, with colors representing thematic clusters of research keywords identified through co-occurrence analysis.

Researchers from many countries are involved in studying building energy performance using sensitivity analysis techniques. Figure 6 presents information about the top 15 countries that contributed the most to the publication related to the building energy and sensitivity analysis, as recorded in the Scopus database. Counting publications is based on the affiliations of first authors listed in the documents and associating them with specific countries or territories. The United States has overtaken all other countries in the publication, whereas many European countries demonstrate their interest in the subject. The USA and the UK are the two top contributors in this study area. At the same time, Asian countries such as China and Hong Kong show a growing publication trend in this research field. In turn, Table 1 illustrates the top 20 studies on the sensitivity analysis framework of building energy performance, ranked by the number of citations in Scopus and WoS from 2020 to 2024, and Table 2 presents the top 10 studies published in the journal, ranked by impact factor over a recent five-year period, according to WoS.

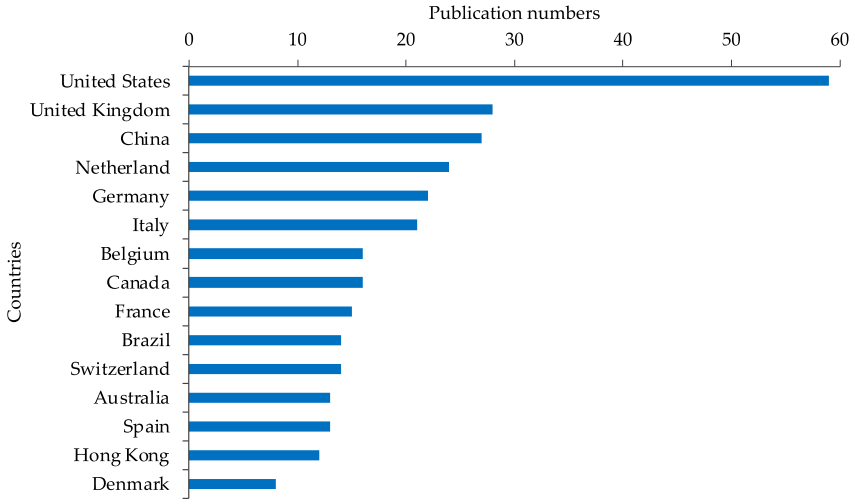


Figure 6. The top 15 countries with the highest contributions to the publications related to building energy and sensitivity analysis, based on data from the Scopus database.

Table 1. Top 20 papers ranked according to the number of citations in Scopus and WoS as of 01.09.2024.

Pos	References	Year of Publication	Number of Citations		Pos	References	Year of Publication	Number of Citations	
			Scopus	WoS				Scopus	WoS
1	[14]	2020	195	171	11	[15]	2021	36	34
2	[16]	2020	91	82	12	[17]	2022	35	29
3	[18]	2021	87	41	13	[19]	2022	34	27
4	[20]	2020	48	43	14	[21]	2020	28	23
5	[22]	2022	47	37	15	[23]	2020	27	23
6	[24]	2021	45	43	16	[25]	2021	26	25
7	[26]	2020	44	35	17	[27]	2023	25	23
8	[28]	2022	40	33	18	[29]	2021	24	19
9	[30]	2021	38	36	19	[31]	2022	21	19
10	[32]	2022	37	34	20	[33]	2021	20	17

4. SA Techniques Used in Building Thermal Energy Performance

Sensitivity analysis helps investigate how variations in input parameters (x_1, x_2, x_3, . . ., x_i) are attributed to the effect in the output (y_j). SA contributes significantly to examining the variability in the output due to the input factors. That means it can identify which input factors have the most significant effect on the output, which input parameters have minimal or negligible impacts, and how the interactions between input variables impact the output (y_j). The motivation for performing a sensitivity analysis could be model evaluation, simplification, refinement, or exploratory modeling. There are three commonly used sensitivity analysis modes to identify and rank the input factors considering their effect: factor prioritization, factor fixing, and factor mapping. Factor prioritization SA application mode identifies the uncertain factor (x_i) that has the most significant impact on the output variability (y_j), and that factor should be prioritized. On the other hand, factor fixing helps identify the input parameters that have negligible influence on the output [34]. Fixing these factors to a nominal value or even eliminating them eases the model's complexity. In addition, factor mapping aims to pinpoint the input parameters that cause the undesirable model behavior [35].

Table 2. The top 10 journals ranked according to impact factor (IF) over the most recent five-year period in WoS.

Nos	References	Journal Name	IF
1	[14]	Renewable and sustainable energy reviews	15.9
2	[26,36,37]	Applied energy	11.2
3	[31]	Automation in construction	10.3
4	[24]	Energy	8.9
5	[38]	Sustainable energy technologies and assessments	8.0
6	[19,28,39–42]	Building and environment	7.4
7	[18,43]	Solar energy	6.7
8	[20,21,23,29,30,44–51]	Energy and buildings	6.7
9	[15,32,33,52–57]	Journal of building engineering	6.4
10	[33,58]	Energy for sustainable development	5.5

4.1. Local Sensitivity Analysis (LSA) vs. Global Sensitivity Analysis (GSA)

Specifically, two SA techniques have been adopted to analyze building energy performance: local and global sensitivity analysis. LSA is a straightforward approach that implies varying only one input parameter at a time, maintaining all other parameters constant. The impact on output due to varying input will be observed, which also helps to isolate the effect of individual parameters [59]. Local sensitivity represents the first-order (or linear) sensitivity coefficients $\delta x_i / \delta y_j$, which considers a linear approximation of the dependence of the output (y_j) on the (x_i) parameter changes [56]. LSA aims to explore how small perturbations in input parameters influence model performance and is performed by varying input parameters around specific reference values. Because of its ease of use and low computational requirements, the LSA technique has been widely used in several studies related to building energy modeling [57].

However, LSA is prone to significant biases if the model is not linear. This is because LSA considers input parameters to be independent, resulting in an underestimation of the importance of interactions among input model parameters [60]. Similarly, LSA typically ignores interactions between parameters and does not account for the distribution of input parameters. Ibraheem et al. [61] conducted a sensitivity test for PV-generated electricity using One-at-a-Time (OAT) analysis. They observed that the depth-to-length ratio of the building is a more sensitive input parameter than the window-to-wall ratio, orientation, and inclination angle. Figure 7 illustrates an example of the sensitivity index for building energy use using LSA. The plot was obtained by changing the parameters' base value by ±5%, ±10%, and ±15% and the effect on the building energy use was plotted. That helps to identify the most influential parameter that affects building energy use.

Global sensitivity analysis (GSA) is a holistic approach used to assess the impact of multiple input parameters on output parameters. It also executes the analysis of the effects of interactions between the input parameters. The study of uncertainties associated with the output of a model can be attributed to various sources of uncertainties in the input of the model [62]. Figure 8 depicts the scatter plot that shows the relationship patterns between the absorption of ceiling, aspect ratio, and window-to-wall ratio and the source energy consumption using GSA techniques. GSA aims to reveal the global effects of each parameter on the output of the model, considering any interactive effects of the input factors.

However, the model requires high computational resources as it considers variations within the entire space of variability of the input parameters. In addition, the quality of the sampling strategy determines the accuracy of GSA, and when high-order indices are

significant, it is difficult to interpret the interaction effect. GSA overcomes the possible limitations of LSA, which is restricted to the linear approximation of output dependence on the variability of input factors [64]. GSA performs a comprehensive analysis, which evaluates the impacts of input factors over the entire range, considering nonlinear relationships and interactions between input factors to address the limitation of LSA, which only finds small perturbations around base values. The decision to select LSA or GSA depends on the objective of SA. LSA is preferred when a quick understanding of local model behavior is intended, particularly in a linear model, showing negligible interactions between input parameters. At the same time, GSA is selected with a nonlinear model and desired to understand the interactions between the input parameters [62].

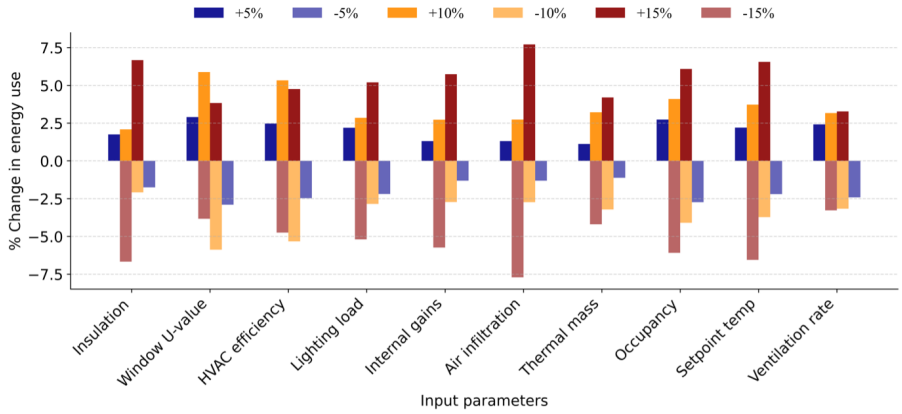


Figure 7. Sensitivity index of the building energy use with different input parameters [63].

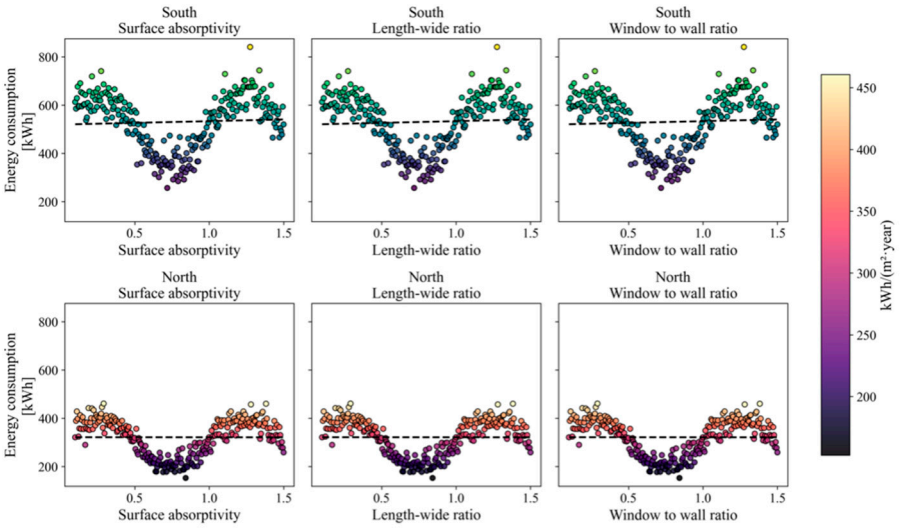


Figure 8. GSA method illustrating the variation in source energy consumption with different input parameters [65].

The GSA technique has been widely used in several studies related to building energy modeling. It has advantages over LSA in dealing with complex, nonlinear systems with interactions and full parameter exploration [64]. Furthermore, the regression-based method (RBM) [66] establishes the use of correlation coefficients to estimate the information between the uncertain factors of input and output parameters. Jans-Singh et al. [67] used the standard regression coefficient method to analyze the energy model of an archetype school building. A sensitivity analysis was performed based on linear regression and the calculation of standard regression coefficients (SRC) to evaluate the impact of reducing infiltration on discomfort time in a building design by a researcher in a review [63]. RBM is

a broader method of sensitivity analysis that uses regression models. In contrast, SRC is a specific form of RBM that standardizes the coefficients and makes them comparable.

Besides the above methods, the surrogate model, also called a metamodel, assesses a simple solution for the complex physics-based building model as an alternative option. The surrogate model is useful when the whole building energy model is computationally expensive. It can be combined with the GSA techniques for efficient sensitivity analysis. Several researchers used a surrogate model as a higher-order model for sensitivity analysis of the building energy performance [62,65]. Techniques such as artificial neural networks (ANNs) [68] and genetic algorithms [69] are also used to map input data to output. Figure 9 shows one of the surrogate models, an artificial neural network (ANN), applied to the building energy model, showing the input variables and the output performance parameters. The model comprises seven input parameters affecting energy consumption, thermal comfort, and carbon emissions. ANN provides an alternative to traditional building simulation tools such as EnergyPlus and TRNSYS, using a data-driven approach by learning patterns from historical or simulated data.

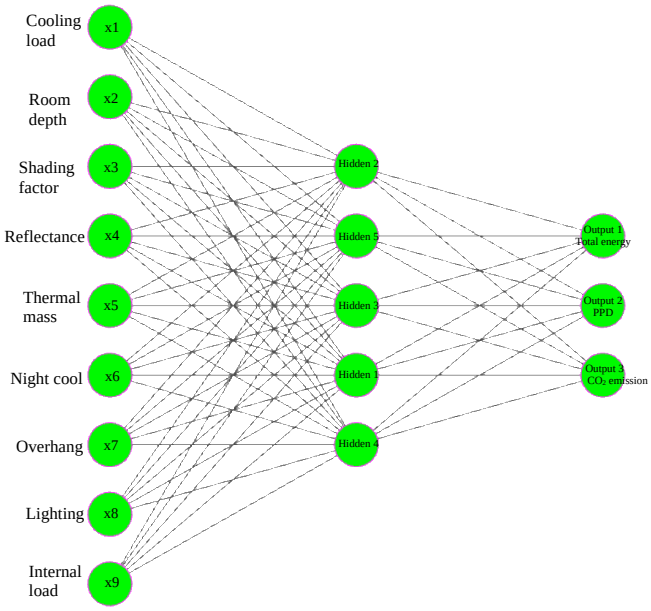


Figure 9. A surrogate model (ANN) for predicting total energy consumption applied to the building energy model, showing the input variables and the output performance parameters [70].

Figure 10 illustrates the review results, which confirm that LSA and GSA are the most widely used techniques for sensitivity analysis. Fifty-eight percent of the studies applied GSA techniques, and 25% used LSA techniques to model building energy performance. GSA is the most popular among the studies, as it considers input parameter interactions and identifies the best scenarios.

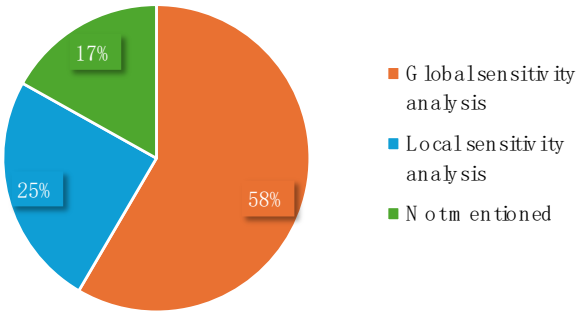


Figure 10. Percentage of local and global sensitivity analysis methods adopted in the review studies.

4.2. Sampling Methods for SA

In the sensitivity analysis of building energy modeling, sampling techniques play a significant role in exploring the input factor space and addressing how variations in these factors impact the model's output and ensure the accurate and efficient SA. Table A1 of this paper presents an overview of commonly used sampling methods, including their descriptions, advantages, and limitations observed in the review studies. Before conducting any sensitivity analysis, a sampling strategy is often required and referred to as a design of experiments.

Generally, sampling can be performed using a random or stratified method. Morris' screening method for GSA is also evident in the review by many researchers [30]. This method addresses the drawbacks of local sensitivity analysis by tabulating partial derivatives within several locations in the range of variations of input variables. The Monte Carlo method is widely used for random sampling by several authors in this review [71,72]. It uses a computational method to estimate complex mathematical behavior to assess the uncertainty and variability in model outcomes. Nevertheless, the Monte Carlo method could leave some spaces in the parameter space and affect clustering in those spaces when the parameters are in large numbers [73].

In addition, Latin hypercube sampling (LHS) is a stratifying technique used by many authors in this review. It is a method that confirms a thorough exploration of the input spaces by dividing the spaces equally, anticipating intervals, and ensuring sampling from each interval. The technique is more effective when the number of samples is much larger than the number of uncertain factors [70,74]. Among the GSA techniques, the Sobol method, a variance-based method of GSA, is prevalent in the literature in this review. This method takes into account complex and nonlinear factor interactions during sensitivity indices calculation [33]. Apart from the Sobol method, the researchers also used other variance-based methods in this review, such as the Fourier amplitude sensitivity test (FAST) [51,75] and extended-FAST [76].

On the other hand, the sample size in SA is an essential factor to be considered to obtain accurate, reliable, and computationally efficient results. An appropriate sample size is required to ensure that the model accurately captures the influence of input parameters and interactions. The choice of sample size for SA is presented in the literature. As a starting point, a rule of thumb can estimate the sample size. Sample size N is at least 10 times the number of input factors (x). However, this is not sufficient for highly nonlinear models. For variance-based methods, Monte Carlo-based sampling can be used with N in the range of 1000 to 10,000 or even more. That depends upon the complexity of the model and input parameters. For Sobol's indices, the total number of model evaluations is determined by $N(x + 2)$, where x is the number of input factors. Asadi et al. [77] used the Monte Carlo sampling techniques to run 70,000 energy models with different input samples to simulate the effects of building shape on energy performance. For Morris screening, a typical sample size N is $r(x + 1)$, where r is the number of trajectories (r = 10 to 50). In LHS, N is commonly used $N \geq 100$ to $N \geq 1000$, depending on the desired accuracy and number of inputs. Zhu et al. [32] generated 2090 samples, which are 190 times the input variables, to estimate the cooling and heating loads of the building using LHS sampling methods. Figure 11 illustrates different sampling techniques for the sensitivity analysis of the total building energy consumption. The median values obtained by various sampling techniques are almost similar; however, the upper and lower quartiles and minimum and maximum values show significant differences.

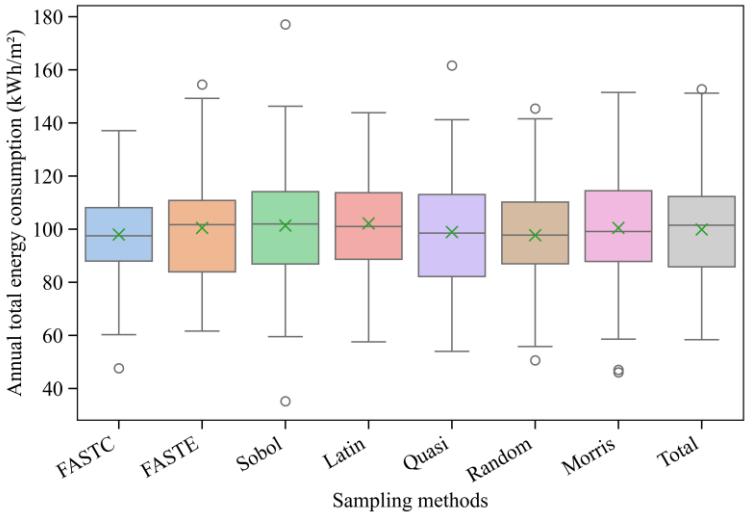


Figure 11. Different sampling methods and simulation results for building energy consumption [16].

4.3. Steps of SA for Building Energy Simulation

Once a clear objective is drawn for the SA in building energy performance, it is necessary to identify the most influential input parameters to optimize building energy efficiency. Then, define the range or distribution of each input factor. Convenient building energy simulation tools such as EnergyPlus, TRNSYS, DesignBuilder, or others can be selected to execute SA. Choosing an appropriate SA method, depending on the complexity of the model, is essential. Then, sample points will be generated using sampling methods as described in the previous section. Finally, the results will be analyzed to quantify the contribution of input parameters to the output variance and visualize the results using different charts or plots.

Visualization is one key component of the research to present and communicate after synthesizing a large amount of simulation-generated data. The guidelines for effective data visualization for research purposes are given by Kelleher and Wagener [78]. The different visualization tools help to illustrate this clearly and understandably. Table A2 of the paper shows the various names of plots to visualize the results from the sensitivity analysis, with descriptions and example plots. The examples of the plots were taken from different papers, as referenced in the table.

4.4. Energy Simulation and Post-Processing Tools in SA

Simulation tools are crucial components of SA nowadays because they allow complex systems to be solved. The interaction of multiple input parameters and nonlinear relationships often made the analytical solutions impractical or impossible. In addition, manual calculation can be very time-consuming and computationally exhaustive. Using standardized simulation software ensures faster, more efficient modeling. The simulation research group at Lawrence Berkeley Laboratory first developed a simulation program called DOE-2, funded by the U.S. Department of Energy during the late 1970s, which was used for detailed building energy simulations. The early simulation program was used for military and space applications [79]. Figure 12 depicts a bar chart related to the simulation tools used in this review's studies.

In 1971, the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) developed ASHRAE LOADS algorithms, which are a two-step calculation procedure for the dynamic heating and cooling load in a building. Later, Building Loads Analysis and System Thermodynamics (BLAST) was developed by different developers and funded by the Corps of Engineers Construction Engineering Research Laboratory.

More sophisticated simulation software, EnergyPlus (EP), was designed as a successor to DOE-2 and BLAST [80]. EP is a popular and widely used building thermal dynamics and energy simulation tool, and it is more extensively used in studies than other software. EP is a dynamic, whole-building energy simulation tool, highly detailed and open-source, developed by multiple developers and funded by the U.S. Department of Energy. EP can be easily coupled with external scripting tools such as Python to develop a sensitivity analysis framework [81]. TRNSYS (Transient System Simulation Tool), eQuest, DOE-2 (Department of Energy), and IDA ICE (Indoor Climate and Energy) are highly detailed and flexible tools for simulating building energy use. TRNSYS is suited for dynamic building energy modeling and integrating renewable energy system technologies. It can be linked with external sensitivity analysis environments, as it gives easily readable text output files by statistical software, such as MATLAB and Python [82]. In addition, software such as Apache, ANSYS Fluent, a CFD (Computational Fluid Dynamics) simulation tool, and Windows focus on fulfilling the specific aspects of the energy simulation.

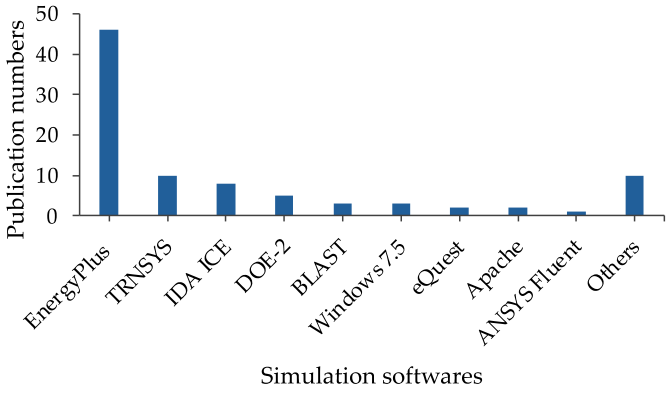


Figure 12. Different simulation software used in the papers selected for review.

Figure 13 illustrates the 3D design software that supports geometry design using other simulation software as a calculation engine. DesignBuilder is the most popular 3D design tool and uses EP as a calculation engine [83]. OpenStudio is a graphical user interface (GUI) for EP designed to work with SketchUp. SketchUp, Grasshopper, Autodesk, and CityGML are other 3D design tools widely used in conjunction with other energy simulation software.

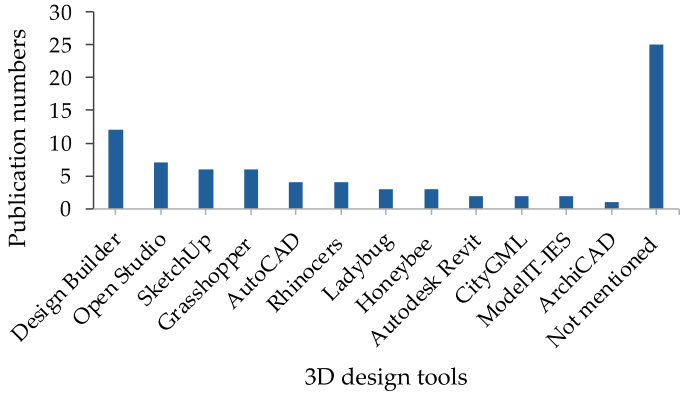


Figure 13. Different 3D design software used in the papers selected for review.

Post-processing tools are crucial for analyzing and visualizing the results from the sensitivity analysis of the building energy performance. Figure 14 shows different programming languages that help to interpret large datasets, generate meaningful insights, and facilitate decision-making by integrating, communicating, and optimizing with simulation software.

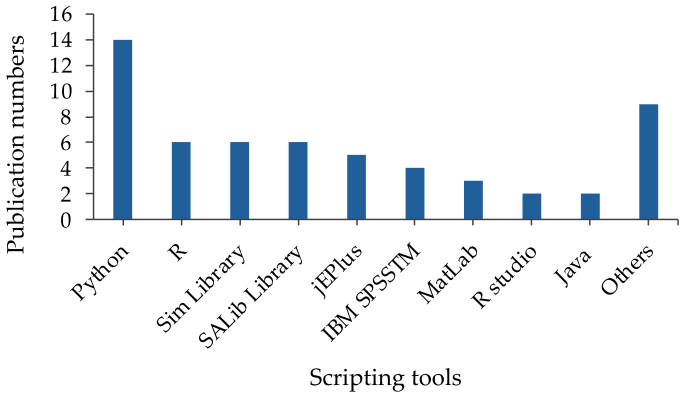


Figure 14. Different scripting tools for sensitivity analysis used in the papers selected for review.

There are standard post-processing tools, as built-in tools within energy simulation software, such as EP output viewer, TRNSYS TESS visualizer, DesignBuilder reporting module, and others; standalone and third-party tools, such as Excel, Python, MATLAB, Paraview, Dymola, and others; and GIS and BIM-based visualization tools [84,85]. Python is the most popular programming language for simulation, and it uses the SALib sensitivity analysis library in Python. A Python feature called an energy management system (EMS) allows EP to integrate and exchange data with many outside tools and libraries. Python implementations of widely used sensitivity analysis techniques, such as Sobol, Morris, and FAST, are helpful in systems modeling. In addition, other scripting tools such as R and R Studio [11], MATLAB [86], Java and MySQL [87], JSON, and jEplus [88] are also used with the integration of simulation software. Figure 15 illustrates the open-source sensitivity analysis software tools available based on programming language and the methods they support.

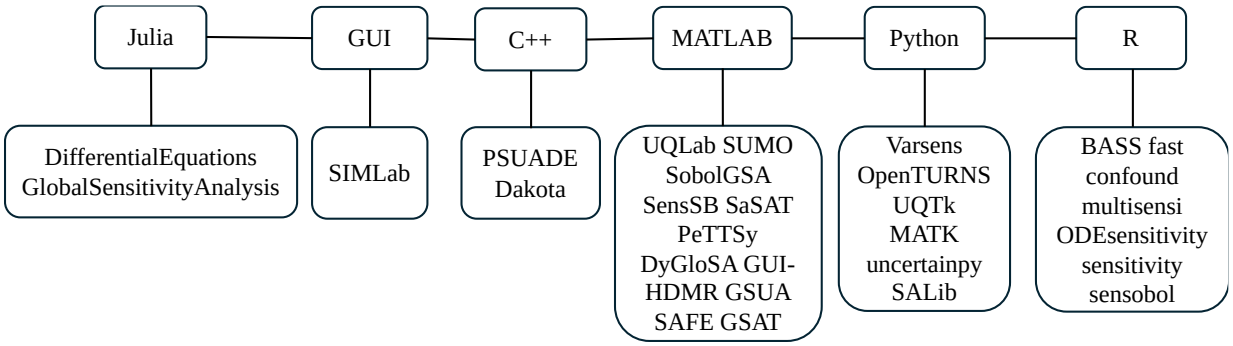


Figure 15. Open-source sensitivity analysis software tools available based on the programming language and the methods they support.

To enhance the credibility of the simulation results from the BTEM using a software tool, model calibration needs to be explicitly addressed in accordance with ASHRAE 14 guidelines [89]. Some industry-standard statistical indicators, such as Coefficient of Variation of Root Mean Square Error (CVRMSE) and Mean Bias Error (MBE), can evaluate model accuracy and measured data for validation purposes. The calibration process helps to reduce the performance gap between the real building behavior and the simulated data. Figueiredo et al. [90] performed a study to compare monitored and simulated data and reduce the performance gap in dynamic building simulation using optimization. Also, a multistage calibration technique for thermal dynamic building simulation using evolutionary algorithms was used to calibrate models in EnergyPlus. The good correlation established between the measured and simulated data gives validity to the simulated results.

4.5. SA and Codes/Standards Adopted

Following the codes in building energy simulations is necessary to meet the specific energy efficiency and performance standards. The codes are detailed, structured guidelines in compliance with energy standards to optimize the building designs for energy efficiency. Figure 16 illustrates the codes and standards that are most frequently used in the articles for the study. Codes often share mandatory compliance requirements in many cases and baseline performance metrics in some cases, against which the proposed design of buildings will be evaluated. Simulation results should exhibit that new designs of buildings meet or comply with these requirements quoted by codes. For instance, ASHRAE developed and formulated the standards and guidelines that are broadly administered and executed in the building energy efficiency sector [91]. ASHRAE periodically publishes and updates standards and guidelines related to HVAC systems.

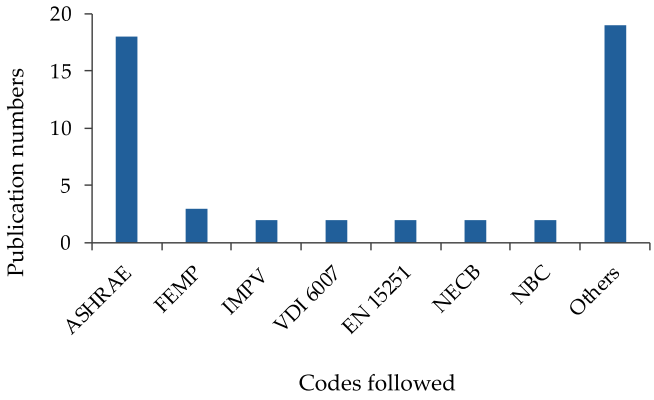


Figure 16. Different building and energy performance codes employed in the reviewed studies.

This review shows that ASHRAE standards are the most popular among designers, researchers, and engineers compared to other codes for building energy efficiency. Among the selected studies, around 36% used the ASHRAE standard, and the rest used other available standards. For instance, Carlucci et al. [29] used a small office model from ASHRAE standard 90.1 [92] and modeled it in EnergyPlus. Furthermore, each country has its standards, such as Danish building regulations and an industry guideline on indoor climate simulations [53], German standards [93], Indian National Building Code (NBC) [58], North American standards for building energy performance (NEBC) [59], Scottish building standards [71], and the Regulation of Energy Systems for Building Climatization (RSECE) in Australia [94].

5. Analysis of Sensitivity Patterns Across Building Typologies, Climate Zones, and SA Methodology to Identify Key Parameters

5.1. Methodology

A three-dimensional classification matrix was developed to identify key input parameters from the SA studies in building thermal energy modeling. Building typologies, climate zones, and SA methods are three key dimensions to analyze.

5.1.1. Building Typologies

Building stocks' heating and cooling energy demand accounts for 40% of the total energy demand [95]. The review identified the various building typologies analyzed for SA studies. The following distribution of studies was identified: residential buildings (30%), institutional buildings (19%), educational buildings (12%), and the remaining categories. The demand for heating and cooling in hospitals, institutional, and commercial buildings is generally high and cannot compromise indoor thermal comfort and air quality. Thus, more

studies are needed to reduce the energy demand by optimizing the use of energy resources and building components. Figure 17 illustrates different building typologies analyzed for BTEM in the reviewed studies. Fewer studies have been conducted on commercial, industrial, and hospital buildings than on residential, institutional, and educational buildings. However, these sectors contribute to a higher energy demand rate for heating and cooling than residential buildings. Bugenings et al. [53] studied a novel solution for school renovation by replacing the conventional retrofitting system with a combination of diffuse ceiling ventilation and a double skin façade. The result shows an 11% lower energy demand than the traditional renovation system by achieving equal indoor air quality and thermal comfort. Himmetoğlu et al. [38] studied a hospital building using a multi-objective approach to determine the most suitable green envelope design for building energy demand.

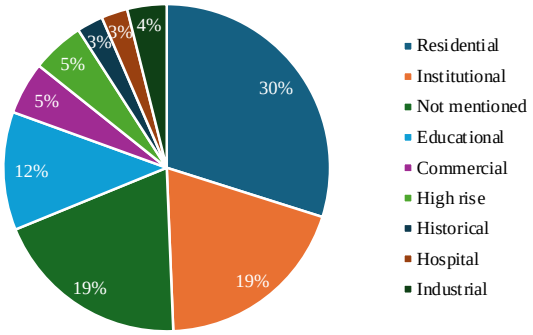


Figure 17. Different building types analyzed for BTEM in the reviewed studies.

5.1.2. Integration of Climate Zones

The energy demand for building heating and cooling may vary according to climate zones to maintain thermal comfort within an indoor environment. For the purpose of BTEM, the ASHRAE Standard 169 [96] offers a globally recognized framework of climate zones built upon long-term meteorological data, including heating degree days (HDD), cooling degree days (CDD), humidity, and precipitation. The standard serves as a foundation for climate zone categorizations into 18 distinct climate zones in building energy simulation and design. Figure 18a depicts the percentage of studies in the seven continents based on selected papers. Case studies in Asia and Europe are more dominant than those in Africa, Australia, and America. Figure 18b illustrates the percentage of studies in all kinds of hot, moderate, and cold climate zones among the selected studies. The figure shows that the studies were conducted in all climate zone types. Specifically, more studies on hot climate zones were conducted than on cold and moderate climate zones.



(**a**) (**b**)

Figure 18. Percentage of studies in the reviewed literature: (**a**) according to continent; (**b**) in different climate zones.

Climate data accuracy is fundamental for predicting a building's energy performance, optimizing energy efficiency, and ensuring indoor thermal comfort. Table 3 provides information about several climate databases and simulated data that researchers use. Climate data, which comprises input variables such as precipitation, temperature, humidity, solar radiation, and wind speed, provides fundamental inputs for building energy simulations of how a building interacts with its environment throughout the year. Figure 19 illustrates that the selected studies used 24% of climate data sourced from local weather stations, 14% from climate databases based on different national standards, and 13% from the climate database of EPW files. Furthermore, incorporating local climate data allows for assessing renewable energy potential, such as solar, wind power, and shallow geothermal energy. Climate data for building energy simulation can be accessed from multiple sources, including local weather stations, installing weather monitoring equipment, and data loggers. Standardized climate datasets such as Typical Meteorological Year (TMY) files from sources such as the National Renewable Energy Laboratory (NREL) and EnergyPlus weather (EPW) files provide reliable reference TMY files for many global locations. Additionally, satellite-derived climate data and commercial third-party weather data services, such as Meteonorm, Meteoblue, or Weather Analytics offer comprehensive historical, typical, and forecasted weather data. For instance, the hourly weather data could be obtained using the commercial software Meteonorm [91].

Table 3. Some examples of climate databases with references used in the reviewed studies.

Nos	Climate Databases and Simulated Data	References
1	Copenhagen IWEC (International Weather for Energy Calculations)	[29]
2	Chinese standard weather data (CSWD)	[32]
3	The climate data are based on the international weather measurements for energy calculations (IWEC2.0) maintained by the National Climatic Data Centre.	[36,51,61]
4	French building energy regulation (RT2012), created from observed data over the period 1994–2008.	[74]
5	The first is the CWEC, which is developed using statistical criteriafrom the Canadian Weather Energy and Engineering Datasets (CWEEDS).	[14]
6	Local to regional database with the experience of 30 years of measurements.	[97]
7	Weather file obtained from the database for the city of São Paulo, from years 1988–2021.	[42]
8	Generated according to "Climate Design Data 2009 ASHRAE Handbook" from a period of 30 years of historical data.	[55]
9	Bangkok weather data	[97]
10	Simulated deterministically using TMY weather data, the Indian Meteorological Department to develop yearly simulation weather files.	[58]
11	A microclimate model ENVI-met generated the input micro-scale weather data.	[56]
12	The information on the weather and the climate data is included in the CDWN weather file.	[98]

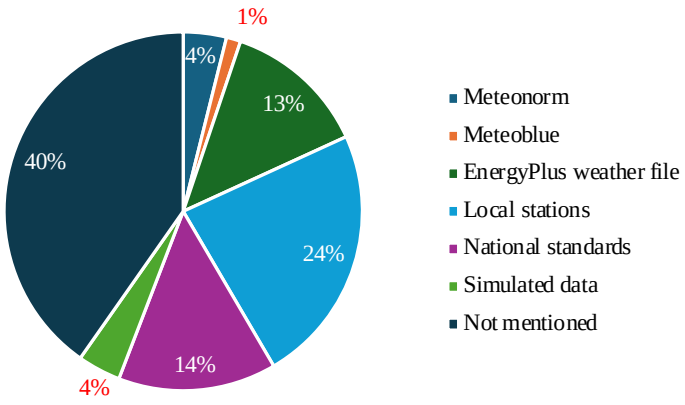


Figure 19. Different methods of climate data acquisition adopted worldwide in the reviewed studies.

5.1.3. SA Methods

Chapter 4 provides a comprehensive survey of SA techniques, highlighting the classifications and steps of SA methods in building thermal energy modeling. Pursuing that discussion, the section outlines the specific techniques employed in the review studies to analyze the influence of input parameters across various climate zones and building typologies.

5.2. Key Influential Factors

SA for building thermal energy performance considers several key input parameters to assess their influence on heating and cooling energy consumption and overall performance. Table 4 shows the standard building parameters considered in the sensitivity analysis. The range of parameters can vary depending on the building's type, location, surrounding climate conditions, and the scope of the study analysis.

Table 4. Overview of standard key input parameters considered in the sensitivity analysis of BTEM.

Input Parameters	Common Input Factors
Building envelope	Wall and roof insulation, window type, and glazing, including its U-value and solar heat gain coefficient (SHGC), and window-to-wall ratio (WWR)
Building orientation	Orientation, shape, and size
Internal loads	Occupancy density, lightening loads, and appliance and equipment loads
HVAC systems	Systems' efficiency, set point temperatures, and ventilation rates
Thermal mass	Building materials
Renewable energy	Photovoltaic panels, solar hot water systems, and shallow geothermal systems
Infiltration	Air leakage rates
Operational schedules	Occupancy schedules and systems schedules

Table 5 reveals the key influential parameters predicted by various studies for building thermal energy performance in different scenarios and considerations. The table comprehensively overviews key influential factors for building energy performance. In this review, eight studies predicted that the most critical parameter for building energy efficiency is the temperature set point [22], which is the highest recurrent parameter mentioned by researchers compared to other parameters. Temperature set points in heating and cooling systems are the target temperature values that the HVAC system aims to maintain the thermal comfort of the occupants inside the building. When the room temperature falls below the heating set point or rises above the cooling set point, the HVAC system activates to bring the indoor temperature back within the desired range.

Four typologies, including residential, institutional, educational, and hospital buildings, were selected to represent a range of occupancy patterns, internal heat gains, and operational equipment schedules. The impact of input parameters varies according to the building's intended use. Occupancy density has a lesser influence on residential buildings. However, it significantly impacts commercial buildings, schools, and office buildings [99]. According to Liu et al. [16], floor area and building coverage ratios are the most influential parameters, and envelope insulation is the least sensitive parameter in hot and humid high-rise residential buildings when assessed using Morris's screening SA method.

Also, shading devices and glazing types are key influential factors for residential buildings to minimize the heating and cooling loads. Set point temperature adjustments significantly impact the energy demand of commercial buildings as temperature fluctuations due to occupancy density require GVAC systems to compensate dynamically [100]. In the office building in mixed humid climates assessed using the variance-based SA method, window-to-wall ratio (WWR), and aspect ratio (ASR) are found to be the most sensitive

parameters [65]. Similarly, Alghamdi et al. [17] assessed the BTEM of educational buildings in warm climates using the Monte Carlo technique, and cooling set point temperatures and roof construction were identified as the most sensitive parameters.

Building thermal energy performance is highly dependent on climatic factors, as building heating and cooling demands vary when exposed to different climate conditions. Cold climate zones exhibit high heating demand and low cooling demand. At the same time, hot climate zones exhibit high cooling demand and low heating demand. In a hot climate zone such as Baghdad, the angle of inclination of a roof shows sensitive parameters for the net energy demand [61]. In a cold climate in Quebec, Canada, architectural and electrical parameters are sensitive to the building energy model [59]. Segarra et al. [91] studied energy analysis across three different climate zones: the hot climate zone of Oslo, Spain's moderate climate, and Greece's hot climate. Wind speed and outdoor temperature were identified as the most influential parameters influencing energy demand.

The temperature set point directly influences the HVAC system and the intensity of its operation in both hot and cold climate regions. In addition, the greater the differences in the indoor and outdoor temperatures, the more energy the HVAC system requires to maintain that set point [57]. Maučec et al. [33] predicted that the U-factor of a window, the solar heat gain coefficient (SHGC), and a set point temperature are the dominant factors for the prefabricated timber building in both warm and cold climate areas.

Table 5. Examples of key input factors identified in the reviewed studies that influence BTEM.

Nos	Descriptions	References
1	Glazing thermal properties (particularly SHGC) is an influential input factor in terms of cooling energy efficiency compared to other building envelope materials.	[56]
2	The combination of wall insulation, basement ceiling insulation, and a secondary window application is the most sensitive in building energy efficiency. Changing the base case with the above-mentioned combination helps to reduce the total energy consumption by 8.53%.	[20]
3	The most influential input factor in the energy demand calculation is the temperature set point, the external wall area, and the U-value of the opaque surfaces. The deviation in the energy needs calculation drops from 18% to 10%.	[22]
4	Cooling set point temperatures and roof insulation significantly reduce energy consumption by 43.7% and 41.0%, respectively.	[25]
5	Temperature set point is much more sensitive to the building's energy efficiency. Such as, if the temperature set points increased from 20 °C to 22 °C, for instance, the energy consumption for space heating increases by 11.5%.	[101]
6	The most influential parameters on energy consumption were insulation and cooling set point played a key role with the contribution of 33% and 31%, respectively.	[28]
7	The occupancy density and start/end time of working hours are highly sensitive due to their significant impact on average occupancy profiles.	[98]
8	The implementation of reflective paints on the outer wall would achieve the highest percentages of whole-building energy savings, up to 21%, for cooling demand.	[25]
9	The window-to-wall ratio and HVAC set point are the two most contributing factors for the energy savings of up to 4%.	[63]
10	The apartment's floor area, equipment load, windows-to-floor ratio, mechanical ventilation airflow, and cooling temperature set point are the most critical design parameters for energy-efficient buildings.	[30]
11	Shading and SHGC values are the most effective parameters.	[97]
12	The window-to-wall ratio is the section of passive solar design that is the most influential to energy performance.	[18]
13	The most influential component is the floor area ratio and building coverage ratio for the energy performance of residential communities.	[17]

Table 5. *Cont.*

Nos	Descriptions	References
14	The windows' U-factor, SHGC, and a set point temperature for heating are the most critical factors for heating energy demand in cold climates.	[102]
15	The solar protection strategies are still the highly sensitive strategies for building energy performance in hot climate regions.	[16]
16	The window-to-wall ratio, aspect ratio, glazing type, absorptance of the wall, and shade transmittance are major influencing parameters. However, each parameter has an impact on different proportions depending on the building orientation and performance parameters.	[62]
17	The window's SHGC, wall painted color, wall U-value, and length of roof eaves are the most effective parameters and could reduce energy consumption by up to 19%.	[42]
18	The occupant heating set point, infiltration rates, occupant density, and building thermo-physical properties have a greater impact on energy consumption.	[81]

Moreover, in hot and dry climate zones, the temperature set point is the most influential parameter in multistorey residential buildings. Windows SHGC is another influential parameter that many researchers predicted in the review studies [93]. A high SHGC of windows leads to excessive solar heat gain, which makes cooling systems cope with the cooling demand in hot and humid climates. So, reflective paint on the outer walls of the building contributes up to 21% energy savings in cooling and is very useful, particularly in hot and arid regions where solar radiation is high enough, roof insulation contributes to reducing up to 41% of cooling demand as it receives direct solar radiation [100]. In cold climate regions where the heating demand is dominant, wall insulation helps to reduce heat loss from the building and improves heating efficiency [47]. The other critical parameters are the window-to-wall ratio [31], occupants' density [103], and wall U-value [97], which significantly influence heating energy demand, particularly in colder climates.

6. Temperature Adaptability

The building should cope with the demand for cooling as climate change affects the cooling demand of buildings, especially in hot and arid regions. It is necessary to ensure the occupants' thermal comfort and that the building remains energy-efficient despite rising global temperatures. It is essential to develop climate-responsive strategies to cope with situations such as adaptive insulation, dynamic shading, efficient HVAC temperature set points, and passive solar design. These parameters should be analyzed by considering the projected climate conditions to optimize building energy performance for the future scenario. The implementation of dynamic shading systems, such as external louvers, automated blinds, or electrochromic glazing, can be an impactful strategy in response to real-time solar radiation [104]. Similarly, applying reflective coatings on the roofs and facades of the buildings helps to reduce solar absorption and surface temperature. It reveals that reflective coatings have the potential to reduce solar heat gain by about 40% [105]. Given that, SA helps uncover the most influential factors impacting heating and cooling loads under future climate change scenarios. Cooling set point temperatures become more influential in hot climates due to increased cooling demand [100].

At the same time, window shading devices play a key role in reducing the cooling demand in projected climate conditions [106]. SA also reveals the combined effect of multiple input parameters, considering future temperature increases and extreme weather events. The combined effect of cooling set point and roof insulation will significantly affect building energy performance due to future climate conditions compared to historical ones [100]. SA helps to prioritize adaptive strategies such as reflective paints [18] and glazing SHGC [82] to mitigate overheating risks in climate change scenarios. In addition,

SA gives policymakers the enlightenment to understand which input parameters are more sensitive to climate shifts, which can lead to the preparation of suitable energy codes and regulations in advance. For example, SA indicated that temperature set points and HVAC systems [65] are dominant factors under extreme future climate scenarios. So, the regulations may focus on adaptive measures for these factors. Figure 20 shows the effect of climate sensitivity on building energy consumption in five representative building models. When the percentage of energy consumption change is observed in all models, the energy consumption gradually increases from 2020 to 2100. This is because the projected climate model increases the cooling degree days.

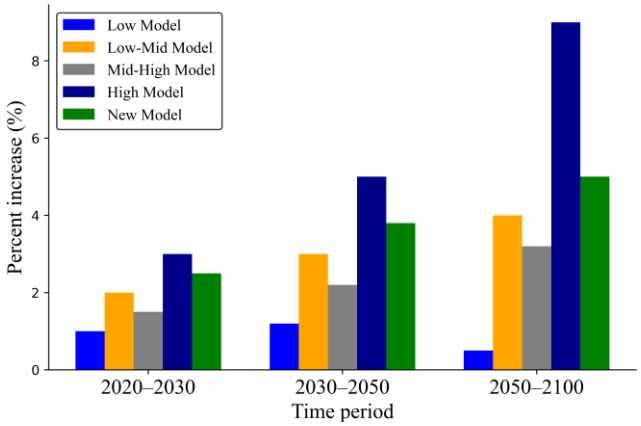


Figure 20. Total percentage energy consumption changes from 2020 to 2100 across different building models [106].

However, the climate change effect assessment heavily depends on the availability and quality of TMY data for specific locations. Several methodologies have been developed for generating TMY datasets with different priorities, such as matching statistical properties, minimizing extreme events, or eliminating anomalous years. There is the possibility of climate data uncertainties, and in many cases, the treatment of these uncertainties remains inadequate, which can lead to significant errors in model predictions [107]. Addressing these limitations needs a shift toward probabilistic, adaptive, and climate-responsive frameworks [108]. Additionally, assessing the impact of extreme weather events and evaluating uncertainty ranges would provide a more robust understanding of input parameter sensitivity under various climatic conditions [39].

7. Conclusions and Future Works

Sensitivity analysis is fundamental for optimizing building thermal energy performance through simulation, reducing energy consumption, and mitigating climate change impacts. This review highlights the importance of conducting this type of analysis with a view to improving energy performance from a sustainability perspective. This systematic review highlights key insights into the methodologies, tools, influential parameters, and adaptive strategies for the effect of climate change, incorporating BTEM and SA. The key insights are:

- Since 2005, there has been a significant rise in research using SA techniques in BTEM.
- The USA is the most involved country in studying BTEM using the SA technique, followed by China and various European countries.
- GSA is the most widely used method, surpassing LSA in analyzing building energy performance.
- The case studies of residential buildings dominate the other types of buildings, followed by institutional and educational buildings.

- Most studies focus on cases in Europe and Asia, particularly in hot climate regions.
- Climate data for BTEM is mainly extracted from local meteorological stations. However, Meteonorm software is a widely used tool, as it provides reliable data from several meteorological sources in a designated format.
- EnergyPlus and DesignBuilder are the most commonly used and popular simulation tools for BTEM.
- Python and its library, called the SALib library, are the most used scripting tools for SA.
- ASHRAE standards are the most frequently referenced codes in the studies.
- Temperature set point is the most influential input parameter, as concluded by researchers in both heating- and cooling-dominant climate zones.
- Adaptive strategies, such as dynamic shading, reflective coatings, and optimized HVAC set points, are crucial in addressing climate change effects.

Considering sustainability, some areas need improvements and focus for future research to optimize thermal energy performance in buildings. More investigations are necessary to analyze how different climate zones impact building thermal energy performance and which input parameters are most influential in each region. The Earth's temperature is continuously rising, significantly affecting building thermal energy demand, necessitating rigorous studies on adaptive strategies to maintain thermal comfort while improving energy efficiency. Future research should focus on integrating machine learning and real-time data analytics to improve SA's accuracy, applicability, and predictive capabilities in dynamic building environments.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Comparison of different sampling methods used in SA for building thermal energy analysis.

Sampling Types	Method	Description	Advantages	Limitations	References
Screening method	Morris Method	Evaluates the effect of small perturbations in input factors to identify the most impactful factors.	Computationally efficient, suited for preliminary sensitivity analysis.	Generates only qualitative sensitivity rankings instead of precise quantitative measures.	[46,109]
Random sampling	Monte Carlo sampling (MCS)	Sampling from probability distributions assigned to input factors to generate multiple model simulations.	Easy to implement, provides reliable predictions when many samples are used.	Computationally expensive, needing numerous simulations for precise results.	[110]

Table A1. *Cont.*

Sampling Types	Method	Description	Advantages	Limitations	References
Stratified sampling	Latin hypercube sampling (LHS)	Divides the input factor range into equal probability intervals and ensures that each interval is sampled once.	More efficient than MCS, leading to better coverage of input variability.	Computationally demanding, however, reduces variance compared to pure random sampling.	[111]
Quasi-random Sampling	Sobol' sequences	Uses low-discrepancy sequences to assign sample points that are more evenly distributed than solely random methods.	Improves convergence rates compared to MCS, using fewer samples to provide more accurate sensitivity estimates.	Need careful observation to ensure proper distribution of sample points.	[112]
Variance-based method	Sobol' sensitivity analysis	GSA method that decomposes the output variance to estimate contributions from each input and their interactions.	Provides detailed sensitivity indices, recording both first-order and higher-order effects.	Computationally intensive with a large number of simulations required.	[66]
Deterministic sampling	FAST (Fourier amplitude sensitivity test)	Uses Fourier transformations to quantify sensitivity indices based on spectral decomposition of model output variations.	Lower computational cost compared to Sobol' analysis to achieve similar GS insights.	Less user-friendly for interpreting interaction effects compared to variance-based methods.	[113]

Table A2. Some examples of visualization tools for sensitivity analysis results in building energy simulation.

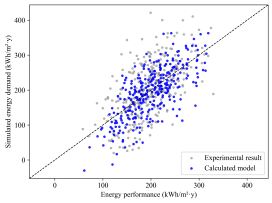
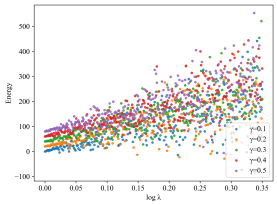
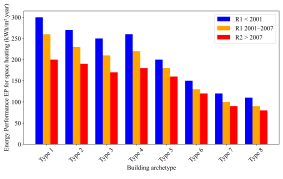
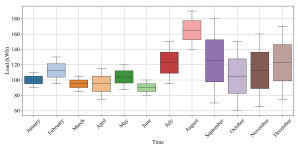
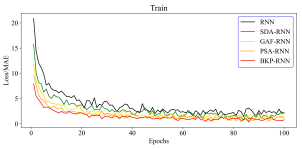
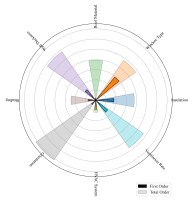
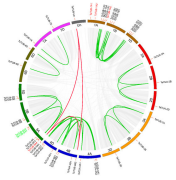
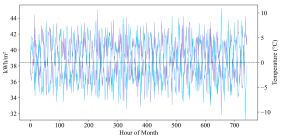
Plot Name	Description	Plots	Taken From
Scatter plots	Identify correlations and trends and conduct a preliminary analysis of input and output relationships.		[114]
Colored scatter plots	Visualize combined effects and interactions between parameters.		[115]
Bar plot	Presenting sensitivity indices with comparing relative importance of factors.		[116]
Box plot	Helps to understand variability and uncertainty.		[117]
Convergence plot	Ensures robustness of SA by assessing stability of sensitivity indices with sample size.		[118]

Table A2. *Cont.*

Plot Name	Description	Plots	Taken From
Radial convergence plot	Presents and compares sensitivity indices in a compact format.		[119]
Circos	Illustrates complex interactions in high-dimensional data.		[120]
Pattern plot	Identify patterns by summarizing multi-scenario analysis.		[86]

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