DOI: 10.56892/bima.v8i1.621

A Scoping Review on Building Energy Modelling

Umar Ahmed Audu[1a], Zulai Jarmai Baba Girei[2b] and Kaliat Joanna Kagai[3c, d] and Emmanuel Falude[4e]

[a]Department of Architecture, Faculty of Environmental Sciences, University of Jos
[b]Nigerian Building and Road Research Institute, Abuja, Nigeria
[c]Department of Architecture, Faculty of Architecture, Kaduna State University, Nigeria.
[d]Graduate School of Education, Department of Architecture (Doctorate-English) Okan Istanbul Universitesi Turkey
[e]Doctoral Candidate, Malaysia – Japan International Institute of Technology (MJIIT), Universiti Teknologi Malaysia, Jalan Sultan Yahya Petra,54100 Kuala Lumpur, Malaysia

Corresponding Author: auduu@unijos.edu.ng

ABSTRACT

Energy performance in buildings may now be defined during the design phase thanks to recent advancements in dynamic energy modeling technologies. However, variations in weather data processing, non-identical inputs, calculation mistakes, implementation issues, and algorithms exist throughout building energy simulation (BES) systems. Building energy modeling in many contexts during a building's life cycle is all covered in the literature this study reviewed. The goals of building performance simulation in practice, solutions achieved through building performance simulation, and the building industry were all explored in this research. One of the main topics is building performance simulation which needs to be addressed in the future. Four characteristics may be used to describe the problems and prospects of building performance simulation: obtaining high-quality data via innovative software or hardware technologies, quick and efficient modeling and optimization methods, and intelligence enhancement in large-scale modeling techniques like urban simulation and building design and operation workflows. The barriers outlined above will give rise to different kinds of theoretical or engineering problems in different building energy modeling application scenarios. The goal of engineers in business and researchers in academia is to find or enhance answers to these problems.

Keywords: Scoping, Review, Building, Energy, Modelling

INTRODUCTION

Due to increased energy consumption and carbon emissions, several governments throughout the world are pursuing carbon neutrality as a feasible response to global climate change. Because it is responsible for more than 40% of worldwide energy-related CO2 emissions, the construction industry is crucial to attaining carbon peaking and carbon neutrality objectives (Walker et al., 2020) . Currently accounting for 20% of China's total energy usage, the construction sector is one of the most polluting in the world. (Candanedo and Feldheim, 2016) . Furthermore, in the absence of stringent regulations or efficient energy-saving technology to reduce these emissions, China's building industry's energy consumption has the potential to account for a considerably growing share of total global emissions by 2050. Rapid and sustained expansion in the construction industry may jeopardize China's government's objective of achieving net zero CO2 emissions by 2060.

One of the most significant and cutting-edge carbon mitigation technologies in the construction industry, building energy modeling (BEM), is becoming a useful and helpful technique for energy-efficient designs. (Candanedo and Feldheim, 2016) operations and retrofitting of buildings, to improve energy performance and lower carbon emissions. The two types of scientific models are physical (ahead) or

Bima Journal of Science and Technology, Vol. 8(1B) Apr, 2024 ISSN: 2536-6041

DOI: 10.56892/bima.v8i1.621

data-driven (verse) models and diagnostic or prognostic models Naik et al., (2021) . Popular BEM models are prognostic physical models because they forecast the behavior of a complex system based on its characteristics, environment, and a set of well-defined principles—such as energy balance, mass balance, conductivity, heat transfer, and so forth. Physical models may represent system behavior in previously undiscovered circumstances, but they are frequently over-parameterized and need more inputs than data-driven models, which explain a system with few changeable inputs. A growing number of people are using building energy modeling (BEM) as a tool to optimize energy efficiency at various geographical and temporal dimensions, such as system, building, district, or community, and building sector levels.(Naik et al., 2021). This is owing to the fast advancement of data sensing, modeling, and visualization technologies. Academics, tool developers, and practitioners are still confronting considerable barriers and uncertainty when adopting BEM on various scales due to the extremely intricate integration of possibly involved multi-disciplinary methodologies (Homod, 2018) . As a result, the goal of this research is to provide an accurate image of current and upcoming developments in BEM and to function as a strong and useful manual or reference for researchers working in the field of BEM and its applications.

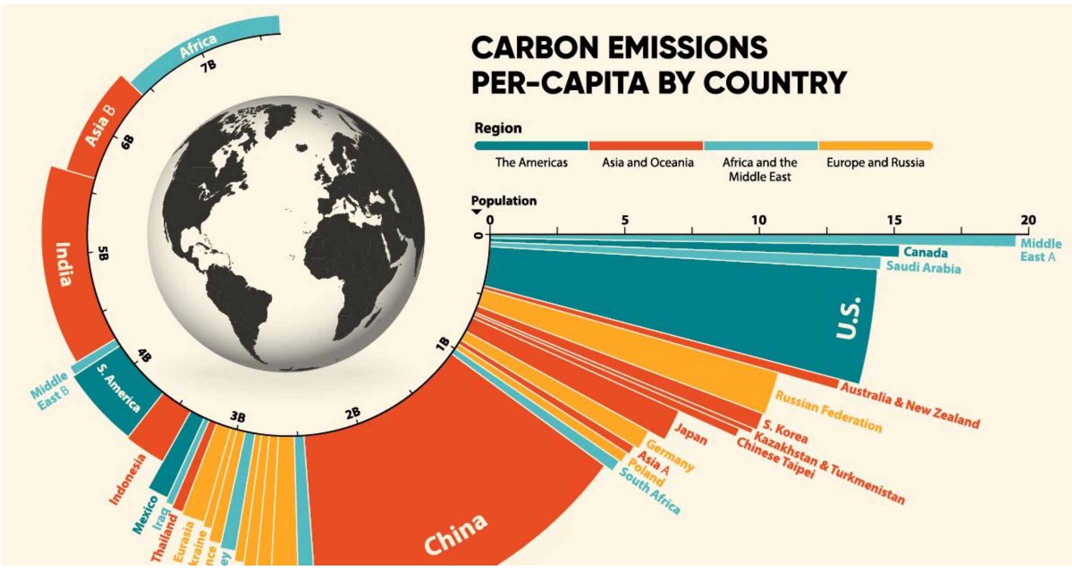

Figure 1: CO2 emissions globally.(*Visualizing Global Per Capita CO2 Emissions*, n.d.)

To do this, we compiled a list of 45 publications for evaluation. These were subsequently evaluated for relevance based on the following standards: (1) The study concentrated on the usage of building energy at various phases, including construction and operation. Performance-driven design, one of the BEM technologies, is frequently used in the building design phase to improve design procedures for low-carbon and net-zero buildings. The physics-based energy model may be used to simulate operational performance and optimize building energy system control strategies during the building operation phase. The confluence of modern digital twin technologies and classical physics-based building energy modeling (BEM) has been expedited by the availability of measured energy usage and interior environment data. This has made BEM a valuable tool for diagnosing flaws and forecasting building energy systems. BEM has been expanded beyond the operation of single structures to include district and urban scales. (Atasoy et al., 2015) . The operational effectiveness of urban energy systems may be assessed through the application of urban building energy modeling, which can support the utilization of renewable energy sources for urban sustainability. Another significant use of BEM is the balancing of energy output and demand at the metropolitan scale through the combination of modeling the building energy system and the local grid. Our analysis shows that the literature related to each scenario is evenly divided, with a smaller percentage of digital twins and a somewhat greater percentage of performance-driven design and operational optimization. The yearly trends of research on urban modeling, and building-to-grid interaction scenarios have gained considerable attention in recent years (Atasoy et al., 2015; Simsek et al., 2020).

The BEM field is going through a revolution in terms of scaling simulation and modeling approaches to bigger sizes and levels, driven by a surge in interest in cutting-edge applications like digital twins and urban modeling. In this regard, we think that one of the most important topics to address to handle the upcoming issues resulting from shifting simulation demand at different scales of energy performance modeling is differentiating between the past and present aims of BEM application research. Future studies on enhancing building and urban energy efficiency may benefit greatly from this review, which may also help other relevant researchers rapidly grasp the current state-of-the-art in BEM application studies. Our goals are as follows:

• Sort suitable BEM application material into five different application scenarios based on construction phases and research sizes.

• Create a comprehensive description of the framework, methodology, significant examples, and research needs for each application situation.

• Make recommendations on potential future paths and problems in the field of BEM.

BUILDING ENERGY MODELLING FOR URBAN BUILDINGS

There is an increasing emphasis on the city's involvement in energy system design since urbanization is bringing large-scale district heating/cooling networks and renewable energy usage closer to societal sustainability. (Atasoy et al., 2015) . Urban building energy modeling (UBEM) has been promoted because of the growing benefits of applying BEM on an urban scale (Simsek et al., 2020). Urban energy efficiency and management are promoted by UBEM, which examines the energy performance of a whole country, a city, or a block rather than modeling a single structure (Salmi, 2021) . Due to its geographical complexity, UBEM sometimes requires additional resources and work to yield reliable findings (Olgyay and Herdt, 2004). Numerous research that has looked at this topic from various perspectives in recent years have improved the methods and applications of UBEM. The UBEM workflow consists of five steps: application, simulation, calibration, model creation, and data collecting. The concept behind this is to apply energy modeling to specific buildings within the stock of urban buildings. The gathering and pre-processing of data relevant to UBEM form the basis of the whole procedure. Geometric and non-geometric variables can be used to separate the data required to create urban models. The description of the spatial and geometric properties of urban buildings requires geometric data, such as those obtained from a geographic information system (GIS) (Alves et al., 2019) . In files like geographic JavaScript object notation (GeoJSON) (Hou et al., 2014) or city geography markup language (CityGML) urban geometric data may also be generated using geographic coordinates and vectors. Additionally, Wang et al. presented a novel approach to creating 3D urban models that integrate the window-wall ratio computed using artificial intelligence elevation photos, building height determined by vertical edges and building footprint from OpenStreetMap

DOI: 10.56892/bima.v8i1.621

(Alves et al., 2019) . Any extra data needed for simulation or calibration is considered non-geometric data. To characterize building aspects, such as the input IDF files for EnergyPlus, energy-related terms are required. (Pop et al., 2018) Weather data, which may be intentionally created to include the urban microclimate or utilized as a typical meteorological year (TMY), is suggested as another essential input for UBEM (Yang et al., 2018) or sustained climatic change (Pop et al., 2018) . Furthermore, tracking building energy expenditures may be necessary for data-driven algorithm training or calibrating urban models. UBEM approaches can be broadly classified into three types based on the data inputs: (1) physics-based methods, which use data mining or machine learning algorithms to reflect energy profiles; (2) data-driven methods, which build geometric data and thermal features to explicitly simulate energy consumption; and (3) hybrid methods, which combine elements taken from physics-based and data-driven techniques.

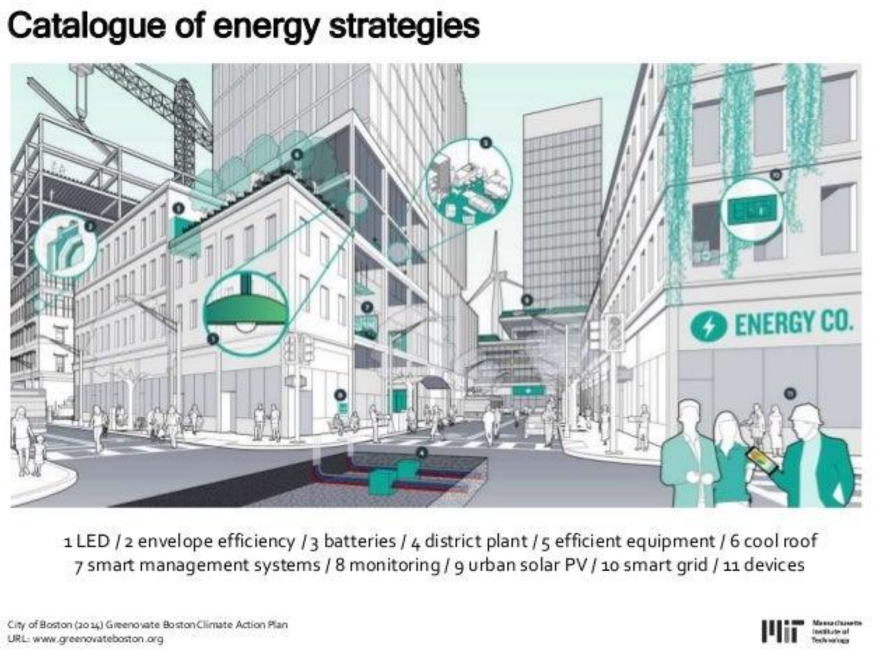

Figure 2: Catalogue of Urban Energy Strategies.

Source: (*Urban Scale Energy Simulation: Modeling Current and Future Building Demands - Carlos Cerezo Davila | PPT*, n.d.)

Building Modelling Physics-based Approach

The traditional physics-based techniques use first-principles simulations to determine the thermal dynamics of each building, and then compile the results to provide the urban energy profiles. The advantage of physics-based methods is that they offer an empirical framework for explaining the evident connection between energy efficiency and urban design elements. For example, (Naik et al., 2021) used resistance-capacitance networks to represent the building thermal process in an open-source city-scale simulation tool based on the electrical analogy (Revel et al., 2015) . Urban energy consumption was accurately predicted by the model for both a big district and a small neighborhood. The physics-based method has an intrinsic disadvantage when applied at the urban scale as it requires a substantial quantity of technical data to fully characterize structures. To reduce the computational load for simulation in UBEM, prototype models are designed to facilitate the entry of building geometry and other data. By using open-source data to automatically identify architectural archetypes, (Roselyn et al., 2019) expanded on previous physics-based techniques (Jin et al., 2021). The selected archetypes and other energy-related factors were entered into EnergyPlus for UBEM of the downtown Montreal building stock and calibrated against observed energy data, indicating the technique's good performance. Adopting architectural archetypes for UBEM simplification, however, could have an impact on the findings' correctness. To calculate the loss, (Hang-yat and Wang, 2013) assessed urban modeling performance in both complex and basic levels of building characteristics. Their results showed very little difference (about 6%) (Choi et al., 2019) . Compared to the complex models, the simple models underestimated energy performance in EnergyPlus and overestimated it in IDA Indoor Climate and Energy (IDA ICE). The most important factors influencing urban energy consumption, such as floor space, set-point temperature, outside wall U-values, and thermal system type, may also be determined to drive model simplification by conducting an uncertainty and sensitivity analysis (Young-Pil Kim et al., 2015). (Ke et al., 2018) Used the physics-based method in a Milan neighborhood with more than 600 buildings, combining it with uncertainty and sensitivity analysis. To model and assess the energy consumption patterns of residential structures in all of Algeria's provinces from 1995 to 2018, hierarchical clustering was chosen as the most sensitive input parameter (Gruber et al., 2014) , by 25%, the overestimation of the peak load of dwellings was decreased from 80% when compared to the deterministic archetype-based approach.

Building Modelling Hybrid Approach

Given their limitations, several researchers are attempting to integrate data-driven and physics-based methodologies to make use of their respective benefits and produce more thorough simulation results in UBEM. (Sittón-Candanedo et al., 2019). For instance, (Yu et al., 2015) Ten machine learning techniques were used to apply physical models created by the Urban Modelling Interface (UMI) tool to pre-simulated energy usage data to predict the energy consumption intensity of heating and cooling in Chongqing, China. In terms of urban scale findings, the Gaussian radial basis function kernel support vector regression produced the best outcomes. A surrogate modeling method based on the Nearest-neighbors algorithm applied to a pre-simulated building thermal load database was proposed by (Roselyn et al., 2019) . The hybrid approaches retain the physical description of each building, overcome data gaps that pure data-driven methods do not, and offer more accurate estimates of energy performance in building stock that lacks exact information than physics-based methods. As per the available research, there are four main uses of UBEM: (1) energy benchmarking, which involves comparing the energy use of peers; (2) urban planning, which involves providing optimal strategies for urban form and energy systems; (3) urban renovation, which aids city policymakers in making energy retrofit decisions; and (4) urban microclimate, which examines the influence of urban microclimate on energy performance. The results of selected case studies, together with their geographical dimensions, methodologies, and applications. A key use of UBEM is energy benchmarking, which is a thorough analysis of a nation's or city's energy profiles across time. A physics-based method for estimating the energy usage of Norway's building stock was presented by (Yu et al., 2015) . They found that the ultimate energy consumption is predicted to decrease by 2 to 12 TWh by 2050, or by 3% to 14% from 2020 (Khemakhem et al., 2020) . In (Hang-yat and Wang, 2013) created an urban model for commercial buildings by establishing twenty archetypes

DOI: 10.56892/bima.v8i1.621

with eight different forms of commercial usage (Yang et al., 2018) . The average annual energy use intensity for the various use types ranged from 74 to 1302 kWh/m2, according to the simulation results, giving the government scientific backing to improve building energy efficiency.

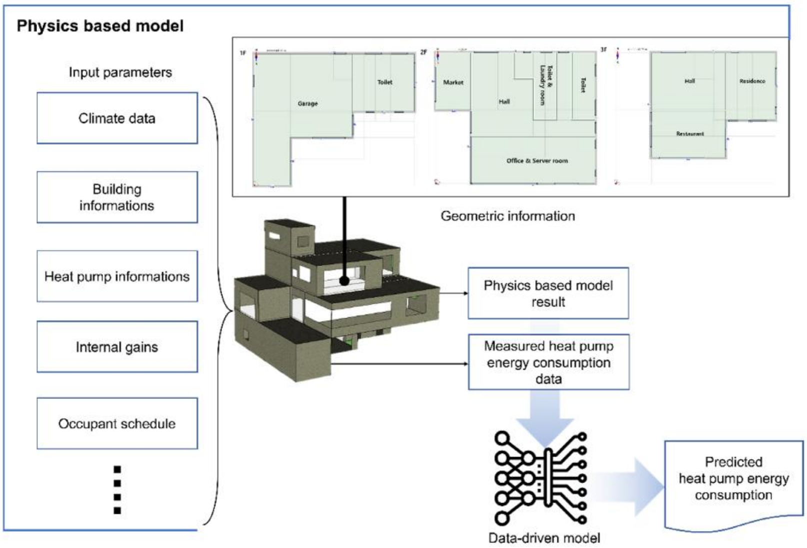

Figure 3: showing physis based model.

Source: (Oh et al., 2022)

Urban planning

Given that urban typology has a major impact on energy performance, policymakers may utilize UBEM to get insights into how energy is used in various urban forms and to provide guidance on the development of urban energy systems. Liu et al. used Grasshopper and EnergyPlus to simulate 114 cases for seven cities in four climatic zones in China, to study the impact of nearby building shadowing on the thermal energy requirements of different community kinds (Jung and Jazizadeh, 2019) . For instance, in Lanzhou, shading from surrounding buildings may cause the cooling demand to be overestimated by 45% and the heating load to be underestimated by 21%. This emphasizes the need for appropriate community design. Yu et al. identified eight key factors influencing the energy performance of urban design using the UBEM and sensitivity analysis (Salimi and Hammad, 2019) . The floor size ratio and building coverage ratio were found to be the most sensitive factors for energy consumption in Shanghai residential communities in 1963. This finding helped urban designers achieve energy-efficient layouts. On an urban scale, UBEM may assess the potential for energy savings or carbon reduction from various retrofit initiatives evaluated and simulated energy-saving options for a low-income Venice neighborhood using City Buildings, Energy, and Sustainability (CityBES) (Salimi and Hammad, 2019) . At the district level, four common retrofit approaches had an energy-saving potential of 67% and a 1.1 MtCO2 yearly reduction in carbon emissions. (Khemakhem et al., 2020) Examined the energy efficiency and potential savings of the Italian railway building stock using a hybrid methodology (Naug et al., 2022) . After several energy-saving strategies were simulated, a comprehensive analysis showed that upgrading lighting systems was the most effective approach, saving up to 26% of primary energy with a payback period of only a few months. To assess the effectiveness of energy-saving measures in a Dublin, Ireland region comprising 9000 residential buildings, Buckley et al. employed UMI to conduct the UBEM (Revel et al., 2015) . Renovation of this

DOI: 10.56892/bima.v8i1.621

example was predicted to accomplish a 60% decrease of greenhouse gas emissions by 2030 by figuring out the best cost-effective mix of envelope retrofit and on-site energy generation. The result was anticipated to support European Union Green Deal initiatives aimed at achieving a carbon-neutral economy by 2050. The local temperature created by the shape and activity of urban areas is referred to as the "urban microclimate" and is unique from the surrounding environment (e.g., the urban heat island effect and the local wind pattern affected by buildings). The least mean bias error was 6% using microclimate data but 12% using TMY data, according to research done by Xu et al. utilizing on-site observed microclimate data for UBEM of Everton Park, a residential area in Singapore (Pop et al., 2018) . The findings indicate that the urban microclimate has an impact on energy performance. UBEM and CFD modeling were used to evaluate the effects of different urban surfaces on the microclimate and energy consumption of office buildings in Trondheim, Norway (Aftab et al., 2017). An analysis of existing applications reveals that the UBEM is being used more and more to simulate the energy profile of large building stocks while accounting for the variety of their usage, shape, and structure, as well as how they interact to achieve specific research goals. In the context of the building sector's low-carbon transition, flexibility for building operators and the energy grid is now achievable thanks to demand response technology's achievement of energy resilience in energy communities. Thus, it is still recommended to incorporate new technologies and the UBEM in order to develop a mature ecosystem for energy community modeling that may help stakeholders implement more sophisticated energy-efficient and environmentally friendly solutions, even though the potential of UBEM for energy planning and building decarbonization has been thoroughly and extensively researched.

BUILDING GRID MODELING

Buildings may now employ renewable energy resources like PV panels and wind turbines to balance their onsite grid electricity and even sell excess generated electricity back to the grid as prosumers, thanks to the increasing penetration of on-site renewable energy resources. (Ke et al., 2018) . Conversely, intermittent, and uncontrollable energy sources like wind and sun are characteristics of renewable energy. Furthermore, increasing the flexibility of building power consumption is crucial due to its widespread usage. Unlike standard building performance modeling, building-to-grid (B2G) simulation requires coupling with renewable energy sources and the utility grid (Obert et al., 2020) . In recent years, many scholars have approached this topic from a variety of angles, adding to the modeling approaches and applications. As mentioned earlier, the simulation includes not only standard BPS components but also the unity grid, energy storage system, renewable energy system, and others. This section will describe the simulation approaches for the different subsystems. These days, the most common renewable energy sources used to generate building electricity are solar PV and wind (Feng et al., 2016) . Power generation estimates are typically utilized for sizing, optimization, and control in renewable energy systems. There are two categories for the techniques: The first is the easy route, Because of the streamlined approach, the model is based on the idea of power generation and incorporates meteorological factors with PV panel and wind turbine performance data. Fan et al., (2016) employed a straightforward model to determine the power production from PV and wind turbines by combining meteorological data (such as air density, wind speed, and solar irradiation) with device performance parameters (such as overall efficiency, angle, area, and capacity). Like this, (Alves et al., 2019) employed a less sophisticated method to predict the production of power; the key differences were in the model's shape and complexity as well as the input parameters (Zaki et al., 2017) . This method is unquestionably simple and does not require a significant amount of previous data (J. Y. Park and Nagy, 2018), but the quality of the forecast depends on elements related to the manufacturer of the device and numerical weather prediction (Wu et al., 2018) . Data forms the basis of the second strategy. Data-driven strategies for the renewable energy system have been proposed by several academics as computer technology has advanced. There have been several studies conducted on data-driven prediction models for energy production. A support vector machine (GASVM) model based on a genetic algorithm was presented for short-term PV power forecasting. An ANN model for forecasting solar irradiance was developed and verified by (Cheung et al., 2019) . A radial basis function network was employed to anticipate PV power output 24 hours ahead of time. A hybrid technique for probabilistic wind power forecasting based on ensemble methods, deep convolutional neural networks, and wavelet transform was proposed by (Du et al., 2022) . Historical power data or weather data are common sources of input data for these models. This strategy could be more accurate than a more straightforward one (Salamone et al., 2017), but it needs a lot of previous data.

Energy storage system

In grid-interactive buildings, electrical storage systems and thermal storage systems are the two main forms of energy storage systems. Because they both store and release energy, they could both increase the flexibility of a building's energy use. Battery storage is the most often utilized type of electrical storage equipment in buildings. While various battery systems exist, the chemical battery is the one that is most often used in conjunction with renewable energy-producing systems. (Salamone et al., 2017). On the other hand, we focus on modifications to energy storage instead of the underlying chemical process when modeling for building simulation. As a result, an energy-balanced mathematical model of the system was created, taking into consideration the loss of energy conversion between electrical and chemical sources as well as the quantity of power that enters and exits the battery to determine its state of charge (SOC) (Földváry Ličina et al., 2018). Furthermore, because the charging rate is limited during different battery stages, they frequently use this as a model restriction. A thermal storage tank is a common thermal energy storage device that uses ice or water as the medium. As with the battery system, we take great care to ensure that heat is conserved both inside and externally while building the thermal storage concept. Buildings with lower energy consumption are the aim of this field, therefore even though studies have simplified the energy storage system and mainly focused on changing its energy value, this simplification is reasonable. Due to the unpredictability of renewable energy production, the grid can also address the imbalance between supply and demand. Because of this, the utility grid plays the part of the merchant in many B2G studies, allowing buildings to purchase or sell power from it. Because of this, a lot of academics are more interested in the cost and volume of power (Zhao et al., 2014) , and they developed the energy balance model with additional subsystems like the battery and building load (Du et al., 2022). Heating, ventilation, air conditioning, lighting, and, in residential buildings, kitchenware's are a few of the components that use energy in building systems. Additionally, several studies have integrated electric vehicles (EVs) into the building system due to the fast-expanding market for EVs, and their electrical requirements should also be considered. There are three fundamental methods for modeling a building system's energy:

White-box approach

The first strategy is the "white-box method," which builds energy models by utilizing the mass and heat equations. EnergyPlus, Dymola, TRNSYS, and DOE-2 are just a few of the software programs that can readily solve these equations. Ran et al. employed this method to compute the HVAC energy consumption (Földváry Ličina et al., 2018) , whereas Wang and Wang used it to assess the heating and cooling load (Delgarm et al., 2016) . Although the white box model has a lot of possibilities for explanation, entering all the specific architectural details might take a while.

Method of the black box

The black-box approach, which is the second choice, usually entails using historical data to build the model. It does not need tangible knowledge about the structure as a result. Additionally, the complex link between the input and output may be established analytically utilizing the data (Földváry Ličina et al., 2018) calibrated the load profile of the reference day using meteorological data to provide a simplified cooling load forecast. Furthermore, the energy model is developed by a variety of machine learning techniques (Brager et al., 2015). The black-box model requires a lot of previous data, but it is easier to create than the white-box model.

Grey-box method

Moreover, the third choice is the grey-box model. This approach, which sits halfway between the white-box and black-box models, uses publicly available data and a simplified physical model to predict energy use. The resistance-capacitance (RC) model is the most often used grey-box technique. Using the 3-resistance-2-capacitance (3R2C) model, Bay et al. assessed the target buildings' thermal performance. (Brager et al., 2015) , while Dong et al. used the 2-resistance-1-capacitance (2R1C) model (Lin et al., 2016) . When the other two models need insufficient data, the grey-box model could be a preferable option since it decides between the white-box and black-box models.

Building Design

Numerous scholars highlight the combination of factors, such as the size of the energy storage system and the capacity of the renewable production system, to make the building more grid-friendly throughout the design stage. Furthermore, some research focuses increasingly on the design of net zero energy buildings (NZEBs), which requires extensive examination owing to their complex and interacting energy systems and enhanced efficiency. Sun et al. found all viable local optimums for designs using a nonlinear heuristic glow-worm swarm optimization (GSO)-based optimization, and the optimization settings performed better in terms of grid independence and cost than the default NZEB settings (Thapa, 2019) . Analysis investigated the impact of 24 significant factors in over/under voltage using global sensitivity analysis, grid reliance, and energy loss and identified the key variables influencing NZEB grid interactions (H. Park and Rhee, 2018) . To lessen the energy impact of buildings outfitted with energy storage and producing systems on the electrical grid, Salvador et al. designed and implemented a sizing strategy for a single-story home and an industrial building (Földváry Ličina et al., 2018) . The simulation's findings indicate that the proper size has a greater energy effect than the conventional size. If building simulation is completely considered throughout the design stage, the optimal parameter combination of all building components may be identified to provide a more pleasant atmosphere at a cheaper cost. Numerous studies focus on the control plan to reduce the impact on the electrical grid and operating costs when the system is in use.

They have many systems for various types of individual structures. It is divided into two categories: (1) Commercial building: A real-time optimization framework based on Model Predictive regulate (MPC) was created to regulate the power flow of a commercial building equipped with renewable energy and an energy storage system for demand response (DR) and demand flexibility (DF) programs. (Du et al., 2022) . As a result, the electric grid's maximum load ramp rate was greatly decreased. Li et al. suggested an operating approach based on a dynamic programming method to arrange the whole power flow in real-time in order to minimize the net present value in an average year (Wu et al., 2018) , (2) Residential building (Földváry Ličina et al., 2018) combined on-site energy generation with data-driven predictive demand response control for residential buildings with heat pumps, and talked about the effects of heat Two methods to DR algorithms, one rule-based and the other predictive-based, were assessed by (Wu et al., 2018) in an Irish residential building typical with the same DR pricing structure.

Additionally, the simulation results showed that the predictive-based algorithm outperformed the others in terms of carbon emissions, utility generation costs, and energy end-use expenditure. To maximize profit, which was studied with a five-story residential building employing energy scheduling carried out using GA. The findings show that, on a typical day, the profit was around 11.53 $/day (Jin et al., 2021) . However, many buildings frequently display varying degrees of simultaneous renewable energy sufficiency due to intrinsic variances in building consumption and system architecture. Numerous writers offered strategies for controlling the level of building groups to create a win-win situation inside the structures while reducing the energy impact on the grid. To achieve renewable energy sharing across three NZEBs, proposed a novel collaborative control and compared its operational costs and grid friendliness to those of traditional control. Looked at the energy management of four buildings with PV panels and thermal energy storage using two multi-agent techniques: a decentralized controller and a centralized controller. The results show that payback behavior varies significantly depending on the kind of residential buildings. Zhang et al. suggested unique control algorithms for the heat pump aggregations and offered many measures to assess building-to-grid DR adaptability (Brager et al., 2015) . Lin et al., (2016) conducted simulation research on a home communication system and presented a rule-based carbon responsive control framework to react in real-time to the grid's carbon emission signals. Additionally, it can raise the feeder's voltage profile without compromising comfort levels. Overall, testing the B2G operation method across several buildings may reduce strain on the power grid and save operating costs by encouraging building cooperation.

FUTURE PERSPECTIVES AND CHALLENGES

Based on the limitations of their theoretical or case study conclusions, researchers have proposed future directions and issues to be addressed in the field of building energy modeling (BEM). We distilled them into the following five research strategies:

(1) Performance design.

Future views and challenges related to performance-driven design are always being developed, simulated, and improved. The difficulties in encoding the design logic are the fundamental building blocks of the "generative design" idea. To meet the various demands of clients, designers need to develop algorithms that can automatically modify design parameters during the generative design process. Likewise, approaches that prioritize performance over traditional architectural design, such as idea development logic over the final product, may be the focus of performance-driven techniques. The current algorithms lack variation in geometric forms but can handle metric variables with ease. It is challenging to stay sensible while expanding the design space. In practice, architects usually parameterize the façade texture and the

DOI: 10.56892/bima.v8i1.621

massing idea. There is a shortage of extreme freeform architecture interpreted as cellular automata. The inner space structure, which is rarely studied, affects energy/ventilation performance in addition to the building shell. Even with more processing power, simulation might still take a long time for each iteration, especially when it comes to CFD.

It's challenging to improve the equation solver and physical model.

To solve the design difficulty, it may be made scalable with the right space-time resolution, or it can be utilized as a surrogate model, like the fast CFD feedback of a neural network. Another issue is whether the design document and the simulation model are compatible, particularly with geometry. For example, tessellation is required for energy modeling, and strong meshing is required for CFD to enable automatic iteration on the freeform envelope of modern structures.

The design process is guided to its completion by optimization. Upgrading the effectiveness of approximation techniques and search algorithms should be the main goal of future research. Further study is required to quantify the uncertainty of the outcome and target the sensitive variables with presumed design inputs. An integrated modeling platform like Rhinoceros may collect the data and coordinate the creation of the models, necessitating the versatility of programmers and algorithm developers in architects.

(2) Optimization of operational performance using models.

Simulation for optimization is a crucial first step toward achieving energy savings, carbon emission reductions, and thermal comfort during building operations. These days, the development of operational optimization is most often linked to model predictive control, or MPC, where the model simulation results play a major role in determining MPC's optimal performance. Building simulation performance for optimization may be improved from two directions, as various recent studies have shown that more effort needs to be made to improve the effectiveness and efficiency of model simulation. Speed of calculation and accuracy of simulation results. In engineering practice, computational speed is critical: the time step required for real-time control should be greater than the time step required for one-step optimization. The minimal temporal granularity for analysis in many application scenarios will be around 10 minutes. The simulation time for the model will be even shorter than 10 minutes when the time needed for computation to converge in the optimization phase is subtracted. This suggests that the optimization method for operational control should be limited by the calculation time.

However, to optimize processing performance, the model shouldn't be overly simple and compromise too much accuracy. The degree to which the model and its anticipated outputs match actual results will directly affect the effectiveness of MPC. As a result, finding a way to balance model processing speed and accuracy in MPC has gained popularity and is receiving a lot of attention from engineers and researchers.

(3) Data measurements are used in digital twin-integrated simulation.

A prevalent view is that digital twins are an inevitable byproduct of the development of BIM principles and the integration of data across digital and physical buildings. Technically speaking, DT is possible, but its rapid expansion is still impeded by the lack of progress in the following areas and its high cost. Viewed from a different perspective, these difficulties might be seen as the future direction of research and development for integrated simulation for DT.

The methodology is necessary to preserve the accuracy and integrity of the data. Sufficient and high-quality data are essential for the integrated DT simulation.

Throughout the building life cycle, many various types of high-quality sensors will be needed to obtain such data, placing a considerable financial strain on the industry. Additionally costly are sensor overhauls and maintenance. The next big thing in development will be more accurate sensors at reduced costs.

An additional consideration for the integrated simulation for DT is the speed of simulation and feedback performance. The present simulation frequently relies on historical data instead of real-time data and takes a long time to complete. Because of the latency resulting from historical input data and the computation process, virtual models and real-time construction conditions might occasionally be nonsensical. Look-ahead simulations should be generated fast and live to ensure an accurate representation of the physical parameter change occurring in real-time.

Furthermore, considering the expanding use of DT, the relevant scale range of the simulation approach need to be expanded.

Nowadays, most DT applications are found in single buildings or systems, and not many researchers are looking at how DT may be applied throughout a whole city. More data types and quantities are needed at the urban scale to guarantee that the virtual city correctly represents the physical metropolis. Policy directives. For instance, DT must monitor resident flow and communicate with several energy data sources on an urban scale. At the urban level, DT may be a significant factor in realizing smart cities and creating plans for future city planning.

(4) Building simulation for urban energy planning.

Urban energy profiles may be predicted with more accuracy by modeling building archetypes, according to UBEM principles and implementations. Nonetheless, model calibration and uncertainty analysis may still be utilized to improve the accuracy of archetype creation. Consequently, the important research gaps in UBEM that still need to be filled are listed below. When modeling building archetypes, uncertainty analysis may be utilized to apply a probability distribution to unknown factors (such as interior air temperature and infiltration rate). This may be further explored in future UBEM studies to determine statistically sound building parameter values. Furthermore, the reliability of the UBEM is closely linked to model calibration concerning the uncertainty associated with simplified archetypes. Many model inputs are adjusted throughout the calibration phase to bring the expected output values closer to those found through experimentation.

The effect of tenant behavior on building energy consumption is one of the topics that has been studied the most lately. Various occupant-related models are constructed, utilizing existing deterministic and stochastic building-level models to describe human activities realistically. Nevertheless, there hasn't been much research done on models that take into consideration the behavior of urban dwellers. The accuracy of the model is expected to increase with the integration of UBEM with urban mobility models, which fundamentally represent human activities in space and time.

An essential area of study for assessing the energy efficiency of existing urban building stock is the examination of infrastructure that generates energy, particularly that which is recyclable. It is especially crucial to incorporate solar systems and other building-integrated technology into UBEM. Solar potential analysis, which involves detecting roof features and giving urban-level data on viable installation sites, can be useful and improve energy system modeling during the photovoltaic system design process. Consequently, combining the UBEM with models of urban energy systems (such as municipal energy utilities and energy distribution networks) may prove advantageous for future study.

(5) Modeling demand response based on building-to-grid interaction.

There has been a lot of attention paid to understanding and managing the interaction between buildings and the grid because of the continuous advancements in building energy conservation and carbon reduction. After reviewing the relevant literature, we believe that the following concerns need to be resolved right away. The flexibility of the created environment should be fully utilized by the future modeling approach. The flexibility of the built environment is not fully used, and much of the research being done on building system models is quite rudimentary. Furthermore, the building energy consumption simulation needs to adapt to the rapid changes in solar power production conditions and grid pricing.

Therefore, utilizing architectural flexibility to its fullest and incorporating it into grid interaction is a major issue. It will be necessary to employ a large-scale model and control for the simulation. As we said in our literature review, the majority of B2G research currently being done focuses on one or a small number of buildings, with very few studies addressing larger scales. On the other hand, there is uncertainty about the effective governance and cooperation between various building types and micro-grids at a larger urban scale. Occupancy should be considered in the new B2G modeling method. It is common knowledge that occupancy has a big impact on how much energy a building uses, and a lot of research has been done to find out. Nevertheless, there is a paucity of occupancy influence on thermal comfort and energy consumption in this field as few scientists took occupancy into account in B2G modeling. Therefore, it is still unclear how occupancy affects B2G optimization.

CONCLUSIONS

The scope, condition, and application of building performance modeling in many contexts during a building's life cycle are all covered in the literature this study reviewed. This study, in general, compiled and arranged the pertinent theories, procedures, and instruments that are most appropriate for researchers and engineers, along with a few case studies of noteworthy academic or practical applications. The objectives of building performance simulation in application led to the division of this evaluation into five distinct sections: Demand response modeling of building-to-grid interaction, performance-driven design, integrated simulation employing data measurements for digital twin, and model-based operational performance improvement may all benefit from building simulation. It seems that building performance simulation is a means of continuously developing solutions, based on the research efforts reported in this work. These include demand response, digital twins, automated building design, model predictive control for optimization, and the development of a building energy model. These enhancements have the potential to improve building performance overall for the construction industry, including lower CO_2 emissions from buildings, living in, or using high-quality structures, and higher productivity among building design and maintenance personnel. This further indicates the significant role that building performance modeling will have in the future growth of the architectural sector.

One of the main topics is building performance simulation. It is unrealistic to think that a single review paper will include a comprehensive introduction to every topic covered. Because of this, the focus of this study is to present the state and direction of BEM research that has garnered the attention of most academics in the past ten years. Additionally, we came to various conclusions about the possibilities of relevant areas based on the literature analysis, including the kinds of questions that need to be addressed in the future in these research lines that are still in their infancy. Four characteristics may be used to describe the problems and prospects of

DOI: 10.56892/bima.v8i1.621

building performance simulation: obtaining high-quality data via innovative software or hardware technologies, quick and efficient modeling and optimization methods, and intelligence enhancement in large-scale modeling techniques like urban simulation, and building design and operation workflows. The barriers outlined above will give rise to different kinds of theoretical or engineering problems in different BEM application scenarios. The goal of engineers in business and researchers in academia is to find or enhance answers to these problems.

REFERENCES

Aftab, M., Chen, C., Chau, C.-K., and Rahwan, T. (2017). Automatic HVAC control with real-time occupancy recognition and simulation-guided model predictive control in low-cost embedded system. *Energy and Buildings*, *154*, 141–156. https://doi.org/10.1016/j.enbuild.2017.07.077

Alves, A., Gersonius, B., Kapelan, Z., Vojinovic, Z., and Sanchez, A. (2019). Assessing the Co-Benefits of green-blue-grey infrastructure for sustainable urban flood risk management. *Journal of Environmental Management*, *239*, 244–254. https://doi.org/10.1016/j.jenvman.2019.03.036

Atasoy, T., Akinc, H. E., and Ercin, O. (2015). An analysis on smart grid applications and grid integration of renewable energy systems in smart cities. *2015 International Conference on Renewable Energy Research and Applications (ICRERA)*, 547–550. https://doi.org/10.1109/ICRERA.2015.7418473

Brager, G., Zhang, H., and Arens, E. (2015). Evolving opportunities for providing thermal comfort. *Building Research and Information*, *43*(3), 274–287. https://doi.org/10.1080/09613218.2015.993536

Candanedo, L. M., and Feldheim, V. (2016). Accurate occupancy detection of an office room from light, temperature, humidity and CO 2 measurements using statistical learning models. *Energy and Buildings*, *112*, 28–39. https://doi.org/10.1016/j.enbuild.2015.11.071

Cheung, T., Schiavon, S., Parkinson, T., Li, P., and Brager, G. (2019). Analysis of the accuracy on PMV – PPD model using the ASHRAE Global Thermal Comfort Database II. *Building and Environment*, *153*, 205–217. https://doi.org/10.1016/j.buildenv.2019.01.055

Choi, H., An, Y., Kang, K., Yoon, S., and Kim, T. (2019). Cooling energy performance and thermal characteristics of a naturally ventilated slim double-skin window. *Applied Thermal Engineering*, *160*, 114113. https://doi.org/10.1016/j.applthermaleng.2019.114113

Delgarm, N., Sajadi, B., and Delgarm, S. (2016). Multi-objective optimization of building energy performance and indoor thermal comfort: A new method using artificial bee colony (ABC). *Energy and Buildings*, *131*, 42–53. https://doi.org/10.1016/j.enbuild.2016.09.003

Du, H., Lian, Z., Lai, D., Duanmu, L., Zhai, Y., Cao, B., Zhang, Y., Zhou, X., Wang, Z., Zhang, X., and Hou, Z. (2022). Comparison of thermal comfort between radiant and convective systems using field test data from the Chinese Thermal Comfort Database. *Building and Environment*, *209*, 108685. https://doi.org/10.1016/j.buildenv.2021.108685

Feng, W., Zou, L., Gao, G., Wu, G., Shen, J., and Li, W. (2016). Gasochromic smart window: optical and thermal properties, energy simulation and feasibility analysis. *Solar Energy Materials and Solar Cells*, *144*, 316–323. https://doi.org/10.1016/j.solmat.2015.0

DOI: 10.56892/bima.v8i1.621

9.029

Földváry Ličina, V., Cheung, T., Zhang, H., de Dear, R., Parkinson, T., Arens, E., Chun, C., Schiavon, S., Luo, M., Brager, G., Li, P., Kaam, S., Adebamowo, M. A., Andamon, M. M., Babich, F., Bouden, C., Bukovianska, H., Candido, C., Cao, B., Zhou, X. (2018). Development of the ASHRAE Global Thermal Comfort Database II. *Building and Environment*, *142*, 502–512. https://doi.org/10.1016/j.buildenv.2018.06.022

Gruber, M., Trüschel, A., and Dalenbäck, J.-O. (2014). CO 2 sensors for occupancy estimations: Potential in building automation applications. *Energy and Buildings*, *84*, 548–556. https://doi.org/10.1016/j.enbuild.2014.09.002

Hang-yat, L. A., and Wang, D. (2013). Carrying My Environment with Me. *Proceedings of the 5th ACM Workshop on Embedded Systems for Energy-Efficient Buildings*, 1–8. https://doi.org/10.1145/2528282.2528286

Homod, R. Z. (2018). Analysis and optimization of HVAC control systems based on energy and performance considerations for smart buildings. *Renewable Energy*, *126*, 49–64. https://doi.org/10.1016/j.renene.2018.03.022

Hou, C., Ouyang, M., Xu, L., and Wang, H. (2014). Approximate Pontryagin's minimum principle applied to the energy management of plug-in hybrid electric vehicles. *Applied Energy*, *115*, 174–189. https://doi.org/10.1016/j.apenergy.2013.11.002

Jin, Y., Yan, D., Chong, A., Dong, B., and An, J. (2021). Building occupancy forecasting: A systematical and critical review. *Energy and Buildings*, *251*, 111345. https://doi.org/10.1016/j.enbuild.2021.111345

Jung, W., and Jazizadeh, F. (2019). Human-in-the-loop HVAC operations: A quantitative review on occupancy, comfort, and energy-efficiency dimensions. *Applied Energy*, *239*, 1471–1508. https://doi.org/10.1016/j.apenergy.2019.01.070

Ke, Y., Zhou, C., Zhou, Y., Wang, S., Chan, S. H., and Long, Y. (2018). Emerging Thermal-Responsive Materials and Integrated Techniques Targeting the Energy-Efficient Smart Window Application. *Advanced Functional Materials*, *28*(22). https://doi.org/10.1002/adfm.201800113

Khemakhem, S., Rekik, M., and Krichen, L. (2020). A collaborative energy management among plug-in electric vehicle, smart homes and neighbors' interaction for residential power load profile smoothing. *Journal of Building Engineering*, *27*, 100976. https://doi.org/10.1016/j.jobe.2019.100976

Lin, B., Wang, Z., Sun, H., Zhu, Y., and Ouyang, Q. (2016). Evaluation and comparison of thermal comfort of convective and radiant heating terminals in office buildings. *Building and Environment*, *106*, 91–102. https://doi.org/10.1016/j.buildenv.2016.06.015

Naik, K., Pandit, T., Naik, N., and Shah, P. (2021). Activity Recognition in Residential Spaces with Internet of Things Devices and Thermal Imaging. In *Prime Archives in Sensors*. Vide Leaf, Hyderabad. https://doi.org/10.37247/PASen.2.2021.5

Naug, A., Quinones-Grueiro, M., and Biswas, G. (2022). Deep reinforcement learning control for non-stationary building energy management. *Energy and Buildings*, *277*, 112584. https://doi.org/10.1016/j.enbuild.2022.1

12584

Obert, J., Chavez, A., and Johnson, J. (2020). Distributed renewable energy resource trust metrics and secure routing. *Computers and Security*, *88*, 101620. https://doi.org/10.1016/j.cose.2019.101620

Oh, K., Kim, E. J., and Park, C. Y. (2022). A Physical Model-Based Data-Driven Approach to Overcome Data Scarcity and Predict Building Energy Consumption. *Sustainability 2022, Vol. 14, Page 9464*, *14*(15), 9464. https://doi.org/10.3390/SU14159464

Olgyay, V., and Herdt, J. (2004). The application of ecosystems services criteria for green building assessment. *Solar Energy*, *77*(4), 389–398. https://doi.org/10.1016/j.solener.2004.01.011

Park, H., and Rhee, S.-B. (2018). IoT-Based Smart Building Environment Service for Occupants' Thermal Comfort. *Journal of Sensors*, *2018*, 1–10. https://doi.org/10.1155/2018/1757409

Park, J. Y., and Nagy, Z. (2018). Comprehensive analysis of the relationship between thermal comfort and building control research - A data-driven literature review. *Renewable and Sustainable Energy Reviews*, *82*, 2664–2679. https://doi.org/10.1016/j.rser.2017.09.102

Pop, C., Cioara, T., Antal, M., Anghel, I., Salomie, I., and Bertoncini, M. (2018). Blockchain Based Decentralized Management of Demand Response Programs in Smart Energy Grids. *Sensors*, *18*(2), 162. https://doi.org/10.3390/s18010162

Revel, G. M., Arnesano, M., Pietroni, F., Frick, J., Reichert, M., Schmitt, K., Huber, J., Ebermann, M., Battista, U., and Alessi, F. (2015). COST-EFFECTIVE TECHNOLOGIES TO CONTROL INDOOR AIR QUALITY AND COMFORT IN ENERGY EFFICIENT BUILDING RETROFITTING. *Environmental Engineering and Management Journal*, *14*(7), 1487–1494. https://doi.org/10.30638/eemj.2015.160

Roselyn, J. P., Uthra, R. A., Raj, A., Devaraj, D., Bharadwaj, P., and Krishna Kaki, S. V. D. (2019). Development and implementation of novel sensor fusion algorithm for occupancy detection and automation in energy efficient buildings. *Sustainable Cities and Society*, *44*, 85–98. https://doi.org/10.1016/j.scs.2018.09.031

Salamone, F., Belussi, L., Danza, L., Galanos, T., Ghellere, M., and Meroni, I. (2017). Design and Development of a Nearable Wireless System to Control Indoor Air Quality and Indoor Lighting Quality. *Sensors*, *17*(5), 1021. https://doi.org/10.3390/s17051021

Salimi, S., and Hammad, A. (2019). Critical review and research roadmap of office building energy management based on occupancy monitoring. *Energy and Buildings*, *182*, 214–241. https://doi.org/10.1016/j.enbuild.2018.10.007

Salmi, M. (2021). Additive Manufacturing Processes in Medical Applications. *Materials*, *14*(1), 191. https://doi.org/10.3390/ma14010191

Simsek, Y., Santika, W. G., Anisuzzaman, M., Urmee, T., Bahri, P. A., and Escobar, R. (2020). An analysis of additional energy requirement to meet the sustainable development goals. *Journal of Cleaner Production*, *272*, 122646. https://doi.org/10.1016/j.jclepro.2020.122646

Sittón-Candanedo, I., Alonso, R. S., García, Ó., Muñoz, L., and Rodríguez-González, S. (2019). Edge Computing, IoT and Social Computing in Smart Energy Scenarios. *Sensors*, *19*(15), 3353. https://doi.org/10.3390/s19153353

Thapa, S. (2019). Insights into the thermal

DOI: 10.56892/bima.v8i1.621

comfort of different naturally ventilated buildings of Darjeeling, India – Effect of gender, age and BMI. *Energy and Buildings*, *193*, 267–288. https://doi.org/10.1016/j.enbuild.2019.04.003

Urban Scale Energy Simulation: Modeling Current and Future Building Demands - Carlos Cerezo Davila | PPT. (n.d.). Retrieved March 23, 2024, from https://www.slideshare.net/ClimateXMIT/urban-scale-energy-simulation-modeling-current-and-future-building-demands-carlos-cerezo-davila

Visualizing Global Per Capita CO2 Emissions. (n.d.). Retrieved March 23, 2024, from https://www.visualcapitalist.com/visualizing-global-per-capita-co2-emissions/

Walker, S., Khan, W., Katic, K., Maassen, W., and Zeiler, W. (2020). Accuracy of different machine learning algorithms and added-value of predicting aggregated-level energy performance of commercial buildings. *Energy and Buildings*, *209*, 109705. https://doi.org/10.1016/j.enbuild.2019.109705

Wu, B., Cai, W., and Ji, K. (2018). Heat source effects on thermal comfort for active chilled beam systems. *Building and Environment*, *141*, 91–102. https://doi.org/10.1016/j.buildenv.2018.05.045

Yang, J., Pantazaras, A., Chaturvedi, K. A., Chandran, A. K., Santamouris, M., Lee, S. E., and Tham, K. W. (2018). Comparison of different occupancy counting methods for single system-single zone applications. *Energy and Buildings*, *172*, 221–234. https://doi.org/10.1016/j.enbuild.2018.04.051

Young-Pil Kim, Seehwan Yoo, and Chuck Yoo. (2015). DAoT: Dynamic and energy-aware authentication for smart home appliances in Internet of Things. *2015 IEEE International Conference on Consumer Electronics (ICCE)*, 196–197. https://doi.org/10.1109/ICCE.2015.7066378

Yu, W., Li, B., Jia, H., Zhang, M., and Wang, D. (2015). Application of multi-objective genetic algorithm to optimize energy efficiency and thermal comfort in building design. *Energy and Buildings*, *88*, 135–143. https://doi.org/10.1016/j.enbuild.2014.11.063

Zaki, S. A., Damiati, S. A., Rijal, H. B., Hagishima, A., and Abd Razak, A. (2017). Adaptive thermal comfort in university classrooms in Malaysia and Japan. *Building and Environment*, *122*, 294–306. https://doi.org/10.1016/j.buildenv.2017.06.016

Zhao, Q., Zhao, Y., Wang, F., Wang, J., Jiang, Y., and Zhang, F. (2014). A data-driven method to describe the personalized dynamic thermal comfort in ordinary office environment: From model to application. *Building and Environment*, *72*, 309–318. https://doi.org/10.1016/j.buildenv.2013.11.008