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Review on Building Energy Performance

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ABSTRACT

Today, fossil fuels account for 44% of the world's energy production, endangering both human health and the natural world. The construction industry is one of the major energy users, with a significant amount of the energy used being regarded as superfluous, according to a recent analysis of global needs for energy usage within different energy usage sectors. This is a result of inadequate management techniques and the use of preventative measures against excessive energy use. To address needless use of energy and guarantee optimal living conditions for sustainable urban areas, research in both academia and industry has concentrated on several strategies over time. This study presents a review of existing literature on building energy efficiency. The study extensively discussed energy performance, building data acquisition, and strategies for twin-building energy simulation. The study further identifies strengths and weaknesses in each aspect of the building energy performance discussed.

INTRODUCTION

The indoor atmosphere of the building must be adjusted during the architectural design phase to provide sufficient comfort levels. As a result, the building's both active and passive features will need to work further to sustain indoor comfort levels in the event of unfavorable weather (Zaki et al., 2017) . Under these conditions, energy consumption often rises, which raises CO_2 emissions and has a detrimental effect on the environment (Du et al., 2022) . Data from energy usage show that 17% of all energy is used globally by the construction industry, and 25% of all electrical energy demand is met by this sector (Brager et al., 2015) . Several governments have launched various efforts in this sector intending to lower energy and CO_2 emissions, particularly in the housing stock of structures constructed before 2006, when Spain's Technological Building Code standard came into effect. Buildings and related cooling systems must adhere to the standards set out in the Fundamental Policy of Energy Efficiency (Revel et al., 2014).

The development of a set of guidelines (Wu et al., 2018) to assess the thermal performance of buildings was motivated by these laws and specifications. The use of energy-saving technology facilitates the finishing of diverse planning, building, and upkeep projects; this not only encourages the modernization of architectural design techniques but also enhances productivity (Hafeez et al., 2017; Thapa, 2019)]. Considering the present worldwide energy crisis, energy scarcity, and ongoing degradation of the surroundings, essential researchers are becoming concerned with how to use energy-saving software to execute the resource-saving design of green buildings and objectively analyze the energy-saving effect. Nonetheless, many shortcomings persist in the utilization of energy-saving technology in green buildings, including inadequate design precision and an inaccurate adaptive computing approach. A technical innovation known as an intelligent building energy control system makes use of ZigBee standards to facilitate data sharing and communication across various items over just one network that is managed by automated systems (Földváry Ličina et al., 2018; Hafeez et al., 2017; Thapa, 2019) . Research on the environmentally friendly consumption of energy in buildings is ongoing worldwide.

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To maintain the sustainability of the grid and reduce consumer energy costs, researchers have investigated several strategies for regulating and optimizing building energy consumption, including demand-side response applications, load timetables, incentives, and the incorporation of green power (Katić et al., 2020; Luo et al., 2016; J. Y. Park & Nagy, 2018; Revel et al., 2014; Salamone et al., 2017) . Furthermore, research demonstrates that a significant amount of needless energy use may be reduced with accurate human occupancy monitoring in the building to prevent energy use in vacant areas. Research on this innovation is ongoing (Salamone et al., 2017; Wang et al., 2020) , and a thorough assessment of the literature is required to identify key aspects of the current situation and potential future paths. An overview of the existing literature on building energy systems is given in this research. The energy performance is explained in Section 2; building data acquisition and analysis is covered in Section 3; building energy in digital twin simulation is explained in Section 4; and the paper is concluded in the final section.

BUILDING ENERGY PERFORMANCE

The research seeks to balance qualitative and quantitative techniques during the building design process to achieve energy performance objectives. Many nations have adopted green building standards and guidelines (Rostampour & Keviczky, 2019), which create criteria for performance assessment to direct and enhance building design and promote the development of performance-driven architecture. Building performance-driven design has the potential to improve building performance and efficiency by fortifying the bonds between different stakeholders, such as designers, users, and decision-makers in the building, as well as between the different phases of design, assessment, and decision-making. Building performance-driven design naturally connects the conditions and results of building design to provide control over building design outcomes, promoting the scientific, accurate, and effective development of architectural design. (1) building modeling and performance simulation, which includes modeling and analysis of various aspects of building performance; (2) preliminary design schemes, which include parametric setting and system selection; and (3) optimization, which primarily uses multi-objective functions to improve building performance. A survey of the literature on performance-driven building design from the viewpoints of methodology and applications is provided in the following parts.

Building Preliminary Design

The preliminary design phase is the first step in establishing a performance-driven architectural design. As previously stated, parameter setup and model generation are frequently based on standard prototypes or on-site data collection. however, (de Castro Tomé et al., 2020) conducted a parametric study on a "typical" mixed-mode office room type. They utilized the Grasshopper plug-in to simulate the issue. According to the research, balconies may be an effective shading device and solar diffuser when properly sized. (Djamila, 2017) examined how the characteristics of building energy and environmental performance are affected by climate change and summarized the relationship between design parameters and building energy and environmental performance criteria as an example of choices made in the early stages of the design process for Turkish residential buildings. (Reka & Dragicevic, 2018) performed a field test on the interior air quality of hospital buildings and developed a geometric model for a large general hospital project based on the test results. They utilized numerical simulations and CFD tools to explore the influence of three different air distributions.

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The major goal of the preliminary design stage is to develop a suitable first design plan. Performance-driven design may be separated into two categories based on target building types: new building orientation and building retrofit orientation, each with its own set of approaches. Due to a lack of relevant data, the prototype design technique must be used as a reference for new building-oriented design. It may also be separated into conventional prototypes and database prototypes, depending on the source of the prototype. Building standards (for example, businesses, hotels, residences, schools, and hospitals) serve as the foundation for the standard prototype method. Several international standards have been used as templates in simulation software. Database prototyping is like building prototypes in certain ways. Each geographic location may have one or more typical prototype structures that represent the region's limited building types (H. Park & Rhee, 2018) . Building prototyping is a strategy for creating statistically representative prototypes to examine the impact of various technology packages and give design improvement ideas (Katić et al., 2020) . On the other hand, the database prototype strategy entails choosing a template scheme that satisfies the requirements of the database produced from these prototypes (Salamone et al., 2017).

It is a self-reference approach to building retrofit-oriented design in two ways: (1) because the building retrofit is aimed at existing buildings, the modeling data is defined and measured rather than referring to other prototypes, and (2) the performance of the before-retrofit building is used to evaluate the performance of retrofit technologies. Fundamental design schemes can be chosen from four categories of building retrofit technologies: demand reduction for heating and cooling, electrical system retrofit, renewable energy technologies, energy-efficient equipment and low-energy technologies, and human considerations.

Building Simulation

For a variety of design demands, including energy performance and environmental performance, interior acoustic environment (Rodriguez et al., 2019), ventilating (Kontes et al., 2017) , and indoor thermal environment (Olgyay & Herdt, 2004) , building performance simulation is taken into consideration throughout the design stage. The simulation techniques for various building performance problems are covered in this section. To realize the aim of energy savings and emissions reductions in buildings, energy modeling is necessary for both heating and cooling load calculation and energy consumption forecast. To swiftly assess energy consumption and identify patterns, the streamlined assessment method relies on the building thermal systems' steady-state characteristic (Wang et al., 2020) , enabling more rapid calculation and simpler inputs than full physical modeling. The comprehensive physical approach utilizes many equations and physics theories to examine the interplay among different building elements, such as the HVAC system, plants, terminal equipment, and envelope. The simulation programs connected to these physical models (such as EnergyPlus, DOE2, and TRNSYS) have quickly evolved into graphical user interface (GUI) visualization tools as programming technology has advanced (Homod, 2018; Uribe et al., 2015). Regression analysis and statistics are used to examine the connections among condition factors, system architecture, and past energy data. Only retrofit-oriented building design is this strategy acceptable since it relies on past energy data. Regression and statistical methods yield highly mathematical models with good accuracy but subpar physical interpretation(Djamila, 2017).

Building Indoor Environmental Efficiency

Complete environmental performance is necessary for occupant comfort and health in addition to total energy performance. The methods of simulating three different kinds of environmental performances, together with the typical simulation tools and their application. Lighting simulation techniques are divided into three categories for lighting/daylighting performance: direct calculations, view-dependent algorithms, and scene-dependent algorithms(Aftab et al., 2017) . Municipal guidelines are using more and more direct calculations for artificial illumination. Both forward and backward ray tracing may be accomplished with view-dependent methodologies in ray tracing, which makes them suitable for picture production. Scene-dependent methodologies represented by radiosity, on the other hand, are primarily used for lighting computations due to more strict and complicated equations. The wave-based technique and geometrical acoustics are two approaches to indoor acoustics prediction. A wave-based method may be used to address sound transmission in an inhomogeneous medium in complicated contexts such as sporting stadiums (Kontes et al., 2017). Geometrical acoustics is commonly used in engineering applications because of its high processing needs and flexibility to complex building geometry. The hybrid technique obtains more accurate results at a reduced computing cost by combining the benefits of many methodologies. Environmental and energy assessments are the main emphasis of performance simulation these days. Considering overall energy use and advancement, (Rana et al., 2015) developed a performance-based design approach for almost energy-neutral structures. After examining the real-world design process, the best option for the almost zero-energy building was determined by considering renewable energy, the environment, and sources of heating and cooling. Nocera et al. (Yu et al., 2015) used an evaluation of the historical building's current lighting conditions to suggest appropriate retrofit alternatives for daylighting systems in an example classroom in a Syracuse, Italy, educational heritage building. (Rehman et al., 2018) examined the indoor air quality in five Toronto lecture halls for temperature and CO2 concentration, using one classroom as a case study for retrofitting. Additionally, methods for regulating temperature and CO2 concentration were developed and research into the reasons for discomfort in the classroom was conducted using building performance simulation, or BPS.

Physical modeling approaches for ventilation and interior thermal environment are classified into three types: computational fluid dynamics (CFD) method, zonal method, and multi-zone method (Salamone et al., 2016a). The CFD technique manages complicated air distributions and explains quantitative discoveries by integrating fluid physics, thermodynamics, numerical analysis, and computer science. (Gruber et al., 2014) . The multi-zone approach is a suitable option for speedy airflow and pollutant dispersion modeling since it reduces large processing expenses. Each zone is assumed to have homogeneous air distribution and is represented by a single node in a fluid network with doors, windows, and other openings. Based on the same assumptions as the multi-zone approach, the zonal methodology divides a zone into many sub-zones. Compared to the multi-zone approach, it provides more thorough air parameter distributions and requires less time to evaluate than the CFD method since it creates mass and energy conservation equations (Olgyay & Herdt, 2004).

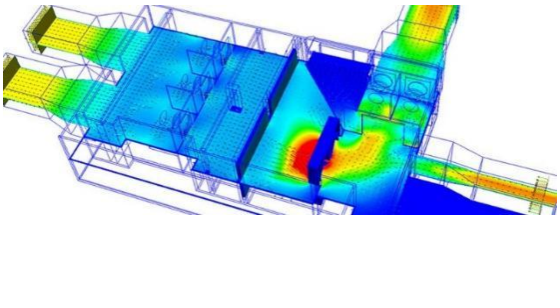

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Figure 1:Physical modeling approach "computational fluid dynamics (CFD) method"

Source: (Landguard Engineering | CFD, Computational Fluid Dynamics, Ventilation Modeling, n.d.)

According to a recent study (Young-Pil Kim et al., 2015) , performance-driven design typically necessitates optimization. Building design's many performance criteria generate a variety of optimization concerns, which are typically expressed as multi-objective nonlinear problems (Oh et al., 2014) . The software often interacts with the simulation process in each iteration to create a loop in the usual performance improvement technique (Jung & Jazizadeh, 2019) . Three components are needed to make up the optimization program: optimization methods, restrictions, and goal functions. Numerous optimization techniques have been created to address different kinds of issues. The most popular approaches for performance optimization include hybrid, metaheuristic, gradient-based, and direct search (Salamone et al., 2016b) . Discrete variables that don't need derivative information are best suited for direct search algorithms. Hasan et al. optimized two discrete variables (the sort of heat recovery and the u-value of the windows) using the brute-force search, often referred to as exhaustive search, approach to lower the life cycle cost of a detached house (Salimi & Hammad, 2019). Because of their rapid convergence, gradient-based approaches are sensitive to multi-modal functions with discontinuity in the cost function (Salamone et al., 2016b) . Using a newly developed gradient projection technique, Vakiloroaya et al. addressed the reduction of energy consumption and optimal set points of air-cooled central cooling plant systems (Hang-yat & Wang, 2013) . Meta-heuristic techniques, which do not rely largely on the algorithm's knowledge of organizational structure, may be widely used in function combination optimization and function computation. The nondominated sorting genetic algorithm-II (NSGA-II) is a prominent multi-objective meta-heuristic method (Zhai et al., 2019) . Using NSGA-II, Bre and Fachinotti's research revealed an increase in residential thermal comfort and energy efficiency of more than 80% (Elhebeary et al., 2018) . Hybrid solutions frequently combine many strategies to maximize advantages while minimizing disadvantages. The hybrid PSO-HJ approach has demonstrated excellent efficacy and durability for the optimized sophisticated fenestration system solutions. It combines the global properties of particle swarm optimization (PSO) with the high converging capabilities of the Hooke-Jeeves (HJ) algorithm (Royapoor & Roskilly, 2015).

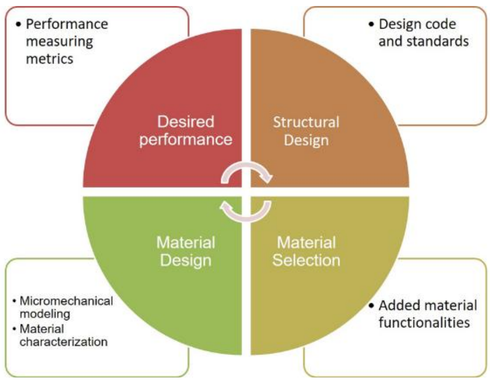

Figure 2: performance-driven design philosophy.

Source: (Dobrzański & Dobrzańska-Danikiewicz, 2019)

Building Energy Optimization

To get the optimal building design solution, identifying precise optimization targets based on performance requirements is a crucial stage in the performance-driven design process. To provide a Pareto-efficient solution for the thermal and lighting performance optimization goals, Futrell et al. (Ain et al., 2018) combined the Epsilon Constraint Method with a hybrid

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GPS Hooke Jeeves/PSO algorithm. Garcia Kerdan et al. (Blanco-Novoa et al., 2017) created a multi-objective optimization method based on energy to assess the best retrofitting procedures that minimize energy use, energy destruction, and pain from temperature changes. A primary school and an office, two UK typical case studies, were utilized to assess the viability of the proposed framework. Office building daylight efficiency may be enhanced by changing the curving façade, according to research by (Blanco-Novoa et al., 2017) Based on the typical findings of office buildings, the altered curving facade might significantly increase daylight efficiency.

Performance-driven building design assists in producing design solutions for structures that meet performance goals through modeling, simulation, and optimization. These days, improving indoor air quality and energy efficiency are the main goals of building performance. According to the previous study, performance-driven design has the potential to significantly enhance the interior environmental performance of buildings, underscoring its significance in achieving building performance objectives. Consequently, professionals may apply this technique to improve building performance at every stage of the design process. The scheme phase design of the building is closely related to how well it performs throughout usage and operation.

Building design features that directly impact thermal comfort, ventilation, and daylighting include window-to-wall ratios, envelope heat transfer coefficients, and other factors. As a result, including performance components at the plan stage can improve building performance. Given that building design is a complex process with several factors to consider, performance-driven building design will also help bring systematic components back to the design process and boost efficiency, leading to major gains in building performance. Said another way, the most advanced performance-based building design procedures used today measure building performance by employing simulation tools. To identify the best-performing designs, our computer-assisted design optimization approach rapidly generates and assesses a vast number of design options. However, this approach requires a significant level of technical proficiency for design optimization, and the time and effort needed by the user (the architect, for example) to set up and oversee the process might be a major topic for further study.

The purpose of operational optimization is to improve a given system's operational settings to achieve the intended target functions (Pop et al., 2018; Tereshchenko & Nord, 2018). Some of the goal functions of building systems include lowering building energy prices [48], emissions (Simsek et al., 2020), energy efficiency in buildings (Liang et al., 2018), and comfort for residents (Hou et al., 2014). Due to conflicting objectives, constructing operational optimization may be difficult. Building operational optimization has an additional challenge in dealing with complex, non-linear, and stochastic building systems. The system model is an effective approach to addressing these difficulties. Geometry data from building information modeling (BIM) and building energy management systems are collected, and the research shows real-time functioning. Second, the building operation pattern is established by data pre-processing and analysis. This pattern is then utilized to create the building and HVAC system models. Next, a simulation of the building and HVAC systems is performed to assess how well the best control techniques work. Optimization algorithms employ the objective function to find the optimal values of the choice variables that optimize indoor environmental conditions or reduce system energy consumption. Third, the chillers, pumps, and cooling towers' optimal

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operating parameters will be ascertained. The next subsections go into further depth about each of these phases.

BUILDING DATA ACQUISITION AND ANALYSIS

The model's performance is influenced by the quality and dependability of its inputs (Hussain et al., 2018; Salmi, 2021). Massive volumes of building operational data from building energy management systems may be acquired as current infrastructure and technologies such as smart technologies and the Internet of Things (IoT) progress.

Temperature, humidity, flow rate, pressure, equipment power, on-off states, and other parameters are among the operational data acquired. Previous research used outside temperature and humidity to assess the impact of weather interruptions (Alves et al., 2019). This data may be utilized to identify operational patterns in buildings, such as occupancy and lighting schedules (Shah & Mishra, 2016). This data may be utilized to identify operational patterns in buildings, such as occupancy and lighting schedules (Shah & Mishra, 2016). In recent years, collecting and analyzing occupancy data has arisen as a rising concern since it can influence building management, either directly or indirectly. The sensors used to collect occupancy data can be built-in temperature sensors in building dwellers' smartphones (Li et al., 2017) or a real-time video occupancy detection system (Maschi et al., 2018). Building envelope characteristics (such as U-values of walls and windows, absorptivity of walls, and G-value of windows) are needed for modeling or calibration in addition to operating data for building services systems. To ascertain the building attributes, these data are necessary for implementing solar thermal systems, heat pumps, and heat recovery technologies as active building technologies. The effectiveness of the optimization depends on pre-processing since it reduces the likelihood of oversimplifying or slowing down the procedure (Salamone et al., 2016b). Normalization (Salmi, 2021), sensitivity analysis (Young-Pil Kim et al., 2015), and data cleansing are common pre-processing techniques. It is advised to use data mining (DM) techniques to look at HVAC system operating trends and how they affect energy efficiency. Unsupervised data mining techniques for information discovery include discord detection, association rule mining, clustering, and themes (Oh et al., 2014). For instance, DM has been used to determine the appropriate control reward for changing significance and to reallocate groups of occupants with comparable occupancy patterns to the same thermal zone (Lin et al., 2016).

Building Energy Modelling

A full whole building dynamic energy model must take into consideration multiple building characteristics and features, such as internal loads and schedules and technical energy system needs, to mimic overall building performance. Simulation tools such as EnergyPlus (Jung & Jazizadeh, 2019), TRNSYS (Salimi & Hammad, 2019), DeST (Hang-yat & Wang, 2013), and Modelica (Zhai et al., 2019) are frequently used to demonstrate building performance due to the functional qualities of modular and flexible design, as well as step-by-step calculation. The capacity of the user to specify parameters that provide a good model of actual building energy usage determines how accurate these simulation programs are. Therefore, model calibration necessitates adjusting the model's parameters to match the actual physical system. Models may be validated or calibrated using observations and generic meteorological data. For example, Huang et al. adjusted the chilled water temperature, chiller performance curve coefficients, and other factors to reduce the difference between the simulated and measured chiller

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power using the actual condenser and chilled water temperatures entering the chillers (Elhebeary et al., 2018) . By calibrating a model using actual meteorological data and building energy use, (Gruber et al., 2014) produced an ideal HVAC operating plan. Optimization strategies often make use of the genetic algorithm (GA). When co-simulating MATLAB and EnergyPlus, both Functional Mock-up Interface (FMI) and Building Control Virtual Testbed (BCVTB, LBNL) are commonly utilized to exchange I/O and data (Elhebeary et al., 2018) , utilized MATLAB software to examine the effects of important cycle factors on thermodynamic and financial performance, as well as to determine the ideal CCHP system design. For instance, EnergyPlus software was utilized to calculate power, heating, and cooling demands. Then, an artificial neural network (ANN) black-box model was developed using EnergyPlus to replace the initial model, enabling quicker and more feasible GA optimization (Royapoor & Roskilly, 2015) . Using a corpus of existing expert knowledge, Gomez-Romero et al. developed a grey-box model to optimize HVAC operation in non-residential buildings. The model used differential equations to encode physical principles of mass, energy, and momentum transfer, and statistical models to fine-tune model outputs based on historical and real-time data (Oh et al., 2014). To ascertain the optimal cooling operation of an air-source heat pump-conditioned single-zone office building, a study by Djamila employed a weather-clustering approach utilizing TRNSYS and GenOpt. Next, the optimal cooling control operating strategy is used daily in the sample for all days within the same cluster (Djamila, 2017).

Building Energy Operational Optimization

Setpoints (such as thermostat setpoints, HVAC supply airflow rate, supply air temperature, and pressure setpoints) and operating modes must be optimized to minimize overall system energy consumption or operating costs while maintaining thermal comfort, according to the literature that is currently available on HVAC system control. Reka & Dragicevic, (2018) examined, for instance, five non-predictive methods, such as off-peak pre-cooling or pre-heating, and four fundamental scheduling methodologies modeled with the EnergyPlus program to maximize the performance of all HVAC subsystems in an actual non-residential building in Perpignan, south of France(Rana et al., 2015). Using a simulated-based multi-objective framework, Papadopoulos et al. modified HVAC cooling and heating parameters on typical large office buildings in seven different temperature zones in the US (Oh et al., 2014) . They investigated local control, including staging control, speed control, bypass valve control, and isolation valve control. Additionally, cooling mode control sequences and supervisory control techniques such as condenser water supply temperature reset, cold water loop differential pressure reset, and chilled water supply temperature reset were examined. Building simulation for operational optimization is now employed, according to the study, mainly to determine the optimal operational settings at three distinct levels: (1) system, (2) equipment, and (3) components. Numerous studies on system-level optimization have been conducted. Before deployment, the energy impact of suggested changes to the control system is analyzed using mostly pure simulation methods that are developed offline. Vering et al., for instance, used process intensification to assess the design and operation of heat pump systems simultaneously (Rehman et al., 2018) . The system controller is optimized in a second step employing a GA using the same dynamic simulation models after the design has been optimized in an annual dynamic building performance simulation (Ain et al., 2018) . A study showing the developed a hybrid intelligent method that uses a random forest-nondominated sorting genetic algorithm-III (RF-NSGA-III) to anticipate and optimize multi-dimensional performance. The lifetime energy consumption of air conditioning was reduced by 54% with the adjustment of setup parameters (Tereshchenko & Nord, 2018).

Using an operation optimization model, Wang et al. investigated and enhanced the hybrid solar system's combined cooling, heating, and electricity output. PRECIS and DeST were used to assess how climate change might affect solar production and energy load (Pop et al., 2018) . The complexity and dynamic nature of real-world building systems and equipment make it difficult to acquire operational data, which causes a mismatch between the simulated HVAC system and the real system. To gain meaningful information for modeling development with minimum quantifiable data, several studies used hybrid modeling methodologies for instance, Du et al. use well-established mathematical models of the pump and chiller and use TRNSYS to create real building equipment modules that more closely resemble the energy consumption of each piece of HVAC system equipment while it is in operation (Zhai et al., 2019).

Furthermore, it has been found that the difference between simulation estimates and actual energy usage is mostly due to occupant behavior (Maschi et al., 2018). To enhance HVAC control, real occupant data and comprehensive context-aware information about the target building are required; occupant characteristics are then identified and sent into the control network to make the required decisions. For example, Aftab et al. designed and assessed an automated HVAC control system for a large mosque's interior public area. The system includes real-time occupancy identification, simulation-guided model predictive control, and automated HVAC management. The onboard EnergyPlus simulator guides real-time HVAC control, which is then transferred to the embedded Raspberry Pi system platform.

Building Energy Equipment

Additionally, several research on enhancing equipment performance has been released. Most of the models in this part are hardware-in-the-loop models or are implemented in real buildings. Ideal switching points for equipment staging often deviate significantly from predetermined criteria due to measurement errors and dynamic operating conditions. Stochastic techniques are commonly utilized to address these issues. Additionally, sophisticated data analytics and machine learning are used to extract valuable information from the apparatus. A gradual pattern tower for mining strategy was introduced as a generic means of identifying usage patterns and knowledge from building operational data, and they used this technique to optimize the management of chillers and cooling towers (Simsek et al., 2020) . To maximize chiller operation, Qiu et al. suggested a model-free optimum chiller loading approach based on Q-learning. The central chiller of an office building in Shanghai is chosen as the case system, and the energy-saving potential of the method is investigated through simulation (Liang et al., 2018) . A stochastic decision-making method was developed by Zhuang et al. to assess operational risks associated with chillers and enhance their sequencing strategy. TRNSYS was used to create the virtual simulation for this study, which uses a complex primary-secondary chilled water system as its main cooling system (Hou et al., 2014) . As far as the authors are aware, there has been a lot of study on HVAC part optimization (e.g.,

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thermostat, air damper, valves, filters, evaporator coil, condenser coil, etc.). To improve pumps, pipes, filters, and dampers, several research have been conducted. The use of optimization in real components is problematic because of the difficulty in managing uncertainty in indirect computations and real system execution. Researchers depict the uncertainties as limited but random noise, or they use the input data directly from BIM or other sources, to tackle the problems. Another study found the optimal damper angle and fan pressure trajectories to lower energy consumption and provide a tube-based MPC method for multi-zone demand-control air conditioning systems (Zhai et al., 2019). By employing a grey-box model powered by the pressure drop signal, Alimohammadi et al. were able to identify clog tendencies in HVAC filters (Salmi, 2021). To assess five alternative data center cooling systems and provide recommendations for improved free cooling system designs in data centers, Alves et al. examined various pipe and pump designs, optimal control algorithms, and a steady-state model of a realistic data center cooling system (Alves et al., 2019). The use of MPC to optimize control sequences for window functioning in mixed-mode buildings was studied by May-Ostendorp et al. The best method works better by modifying windows and ventilation supply air fans(Yu et al., 2015).

BUILDING ENERGY IN DIGITAL TWIN AND SIMULATION

Information exchange and a structure's whole life cycle are intrinsically intertwined (Yu et al., 2015) . To better build design, construction, or operation, academics have regularly employed known and static building information during the past 20 years to produce virtual models, such as building information modeling (BIM) and building energy modeling (BEM) (Ain et al., 2018) . However, virtual models' limited applicability stems from their inability to accurately reflect changes in real structures over time due to a lack of real-time information intake (Blanco-Novoa et al., 2017). The emergence of advanced metering infrastructure (AMI) and the Internet of Things (IoT) provide real-time communication between virtual models and actual buildings, as well as prompt and logical decision-making for operations and issue diagnosis. With sensor technology developing so quickly, the integration of real-time data from advanced measuring technology with virtual building models gives rise to the concept of the digital twin (DT). Creating precise digital replicas of physical objects in real time is known as "building digital twins." Data integration and analysis are then used to control, simulate, validate, and forecast the whole life cycle of physical buildings, enabling intelligent decision-making and optimization (Tereshchenko & Nord, 2018) . As suggested most DT experiments concentrated on the subsequent two primary attributes:

(1) Data interaction: To create and change the virtual building, raw data—such as measured data from sensors, static design information from blueprints, and equipment nameplates—is gathered, cleaned, filtered, and sent using IoT and data analysis tools. Decision-making during the project's construction and operation phases may then be aided by the virtual model's dynamic monitoring and simulation capabilities, which may be used to infer and report back on future modifications to the parameters of the actual building.

(2) Building modeling and simulation: The use of DT requires a deep comprehension of the building's physical system. To achieve effective interaction between virtual and physical entities at different phases, the building circumstances must be appropriately defined utilizing a variety of data sources and modeling techniques. Even

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though it is still in its infancy, DT has shown incredible promise for a variety of future uses. To aid in understanding the idea of DT, this section gives a summary of the various data and modeling methodologies utilized in the sequence of the building's primary life cycles (construction and operation).

Data Interaction

DT applications in intelligent buildings are built on the foundation of dependable and informative data (Shah & Mishra, 2016) . Except for data cleaning and filtering processes, this section focuses on data collection methods and types as well as possible uses for related models. Throughout the construction process, information should be obtained in five categories: workers, materials/structures, equipment, procedures, and the environment (Li et al., 2017) . Among these are the processes, which are static data and do not need to be monitored in real-time by sensors. During the operational phase, four main categories of data need to be gathered: building constructions, interior atmosphere, occupancy, device conditions, and energy usage. The primary types of information gathered and related sensors used during the process.

Building Energy in Design and Construction Stages

Early in the building process, simulations are frequently employed to help with scheduling and process optimization. The construction simulation creates the model in four primary aspects depending on the input from the building site.

a) Geometric data relates to the shape, dimensions, and make-and-model of partially constructed structures, parts, and machinery. The geometric characteristics of the implementation process can be precisely reflected by building a high-fidelity geometric model.

b) A physical part is the material qualities and mechanical attributes of an item or device that are present during the manufacturing process. Finite element analysis tools like Midas and ANSYS are commonly used to construct physical models to describe and track changes.

c) National standards and regulations are covered in the rule section. To ensure that the equipment's operating state and the mechanical performance characteristics of its components stay within tolerances during the hoisting process, it must model and parameterize the relevant standards or specifications.

d) The behavior component deals with the associated adjustments to the mechanical properties, hoisting progress, and material characteristics brought about by changes in decision-making and system instructions.

The digital twin process during the build operation phase and the physics-based energy simulation methods now in use usually just input the shape abstraction and ignore the exact physical form and volume. It cannot replicate the settings in different interior places. Energy consumption is ignored in CFD simulations in favor of fluid dynamics parameters like temperature and air speed. The BEM is a strong basis for energy and air distribution simulations since it can incorporate all the elements needed for the simulations and link the different types of simulation to make the final virtual model more like the actual structure.

Virtual buildings in DTs can supply physical factors including HVAC systems, interior thermal characteristics, occupant behavior, and envelope materials in addition to geometrical information. To enhance the interaction link between architecture and occupancy, the DT model can use Virtual Reality (VR) in addition to CFD and BEM models.

Building Energy Applications in Artificial Intelligence

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Artificial intelligence algorithms in conjunction with virtual models might be used more frequently. A BIM model may use machine learning and optimization algorithms to enhance the efficiency of building energy usage by more precisely depicting the connection between physical elements and energy consumption. Pour et al. use Unity, BIM, and machine learning to automatically update the construction site's three-dimensional model while monitoring work progress in real time. Using DTs and an artificial neural network, predicted interior thermal comfort in the presence of energy-saving actions (Maschi et al., 2018). A structure's life cycle consists of its conception, development, usage, maintenance, and eventual deconstruction. The current study indicates that simulation is widely used in DTs for both the building and operating phases. DT is mostly utilized in the construction process for material distribution, compliance checks, worker safety management and forecasting, and progress control and monitoring. Using DTs may significantly increase information sharing, increase construction efficiency, and reduce possible construction dangers. In addition to improving the building's operational energy efficiency and internal thermal temperature, DTs are crucial in monitoring possible structural deterioration and system malfunctions. Most of the research has focused only on digital descriptions of building aspects (space or parameters), but most findings show that the use of DTs improves structures even in the absence of financial considerations. High-intensity and quick data flow between physical and virtual entities is required for DT, which is predicated on timely and high-quality building-related data. To transfer data between virtual and physical things, it must happen quickly. Data gathering, accuracy of sensors and stability, data storage device capacity, and data transmission speed are therefore too important to meet in a short amount of time to ensure a successful deployment of DT. Still, DTs remain a good choice for future system development.

CONCLUSION

Most people agree that the greatest threat to humanity is climate change. Current research demonstrates that despite the Paris Agreement, the world has not made the necessary progress to keep global warming to 1.5 °C. In this context, the construction sector must be a major actor. Approximately one-third of the world's use of energy, 30% of emissions of greenhouse gases, and 40% of natural resource usage are attributed to it. Nonetheless, recent research reveals that throughout the previous ten years, the percentage of energy consumed by buildings has somewhat decreased. This study reviews existing literature on building energy efficiency and the results of findings indicate that the majority of the literature concentrated on employing occupant scheduling activities to integrate SBEMS in commercial buildings. The results demonstrate that the literature currently in publication places a greater focus on the energy consumption of HVAC systems and less emphasis on smart lighting solutions. The outcome also shows that the increasing performance effectiveness of smart building technology has drawn more attention than any other qualitative feature. To provide a comfortable smart building experience, most smart building technologies employ actuators to carry out activities, frequently in real-time, and sensor-based monitoring to assess various building factors. A sensor and actuator of this kind are often highly time-sensitive.

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