Advancing Sustainable Architecture Through AI Technologies for Energy Efficiency: *A Literature Review*

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Abstract

Rapid, global urbanization has contributed to an expansion of the built environment and a subsequent increase in global energy consumption and carbon emissions. Examining the double-edged nature of technological development shows the unprecedented opportunities offered by the growing trend of innovation, as well as the detrimental social, economic, and environmental costs. Thus, it is important to question how the current fundamentally unsustainable fields of architecture and technology can intersect, collaborating to support environmental regeneration. A review of recent advancements highlights the potential of artificial intelligence (AI) technologies for curbing these impacts and reversing ecological destruction. This research specifically focuses on the theme of energy efficiency, delving into various studies on smart energy management systems, predictive modeling and simulation, computational design, and material design. In assessing how the goals of sustainable architecture and urban planning can be supported by AI, future research avenues for holistic approaches to sustainability are uncovered. These findings present the advantage of leveraging the rapidly developing AI technology to support a momentous shift towards regeneration. Such a transition is crucial for designing buildings and urban spaces that are seamlessly integrated into the natural environment, mitigating the effects of climate change and contributing positively to our world.

Keywords

Sustainable architecture; urban planning; sustainability; regeneration; ecological design; artificial intelligence; data science

Introduction

Human activity is producing greenhouse gas emissions at a detrimental rate, with slow action toward reduction. Insights provided by the organization Our World in Data (2023) show that the average global temperature has risen by approximately 0.8 degrees Celsius since the baseline (1961 to 1990 average). Organizations have taken steps towards mitigating these negative impacts and further global issues, most notably the United Nations' adoption of the Sustainable Development Goals (SDGs) in 2015. However, the key findings of the 2024 Sustainable Development Report by the UN's Sustainable Development Solutions Network show that "on average, only 16 percent of the SDG targets are on track to be met globally by 2030, with the remaining 84 percent showing limited progress or a reversal of progress.” It is clear that more sizable measures must be taken to combat climate change and other sustainability challenges.

Sustainability is a broad goal to allow people to thrive on Earth for a longer period of time, encompassing environmental, economic, and social needs. “Sustainability, to describe it in simpler words, is a process of making things less bad. It is not a long-term solution even if it limits the destruction of the environment to a manageable level. Nevertheless, by just becoming sustainable, one cannot bring back what has been lost” (Kadar & Kadar, 2020, p.1). Instead of just focusing on preservation, we should work towards more rigorous improvements. A forward-moving approach to achieving a prosperous society that is conducive to ecological restoration is the concept of regeneration. Instead of solely aiming to sustain, regeneration seeks to reverse environmental damage and leave a net-positive impact on the environment. This process considers design and economic approaches to “create resilient, flourishing and equitable systems that respond to the needs of society while respecting and restoring the integrity of nature” (UNESCO, 2023, page number). It involves shifting from a material culture based on fossil fuels to biomaterials and renewable energy.

Buildings can follow regenerative design concepts to reduce negative environmental impact, and actively contribute to the restoration of natural ecosystems, going beyond simply minimizing negative impact. According to Architecture 2030 (2023), an organization aimed at transforming the built environment to significantly reduce greenhouse gas emissions, the carbon associated with all building operations and infrastructure materials is responsible for about 42% of annual global emissions. A big portion of this comes from embodied carbon: the carbon emissions involved with raw material extraction, manufacturing, transportation, and end-of-life disposal; as well as the operational carbon. Regenerative design in the context of architecture focuses on environmental impacts from the very beginning of the design process, addressing issues before the embodied emissions of a project are locked in. A crucial part of regenerative design is the understanding of the interconnections of systems with their surrounding systems and the exchange of energy, water, and waste. “The regenerative system understands the human social, economic and environmental activities as ‘inter-related flows’, and the impact of the flows on each other in greater scales” (Kashkooli, 2018, p.2). This means a holistic approach, balancing environmental, social, and economic factors, which requires an evaluation of information from many sources.

Advancing technology is providing us with increasingly more opportunities for innovation. Specifically, AI is a powerful tool for processing large amounts of data and creating algorithms to be used in various applications. Its practical usage has mainly supported corporate goals of maximizing productivity, improving labor efficiency, reducing labor costs, creating new job demands, and more. In this pursuit, the very prominent harms AI has on the economy, society, and the natural environment have been overlooked. Socio-economically, AI surfaces issues regarding the collection and control of information and impacts on the labor market. This happens when corporations and governments use such technologies against workers and citizens to further profits. (Acemoglu, 2021). Ecologically, AI also has a considerable negative impact, which is rapidly increasing as AI technologies are becoming more integrated in the world (Tamburrini, 2022). The development and operation of AI requires heavy energy consumption and draining of natural resources. Making hardware such as graphic processing units relies on the unsustainable extraction of rare minerals and shipping for manufacture and distribution. Training AI models requires a lot of electricity which usually comes from burning fossil fuels. These systems run on supercomputers that produce massive amounts of heat, and cooling these systems consumes additional water and energy. AI data centers also contribute significantly to sound pollution due to the large amounts of information being processed.

Furthermore, the current trend of developing larger models for increased performance, which results in increased energy consumption, has negative implications for AI's overall carbon footprint. A big industry issue is the lack of consideration for sustainability in both product life cycles and the purpose of the final product. Often, AI technologies are used in user information processing to promote consumerism. This can be seen in social media platforms that utilize algorithms for optimizing engagement, as well as targeted ads that identify and exploit the biases of consumers. This not only results in excess waste and pollution but also contributes to social and economic inequality. Such a cultural norm fosters ignorance, selfishness, and apathy towards the current climate situation. Thus, a large percentage of companies prioritize profits over ethical considerations, turning AI into a harmful weapon instead of a tool for progression (Cafaro, 2014).

AI research should be diverted to addressing global issues such as the climate crisis, helping society, and moving towards sustainable development. An important question that should be considered during development is: how can the application of AI actively contribute to environmental regeneration? When utilized correctly, AI can allow us to understand climate change and the effects of human activity on Earth's ecosystems. The power of AI can be harnessed to process mass amounts of data related to climate, energy consumption, and societal interactions. In particular, this can be applied in architecture and urban planning to create built environments that are compromised for ecological sustainability as well as cost efficiency and functionality. "The advent of AI in urban planning and architecture is at the very beginning but offers promising incentives to accelerate the transition towards regenerative design. AI can empower architects in their day-to-day practice. Soon, architects and urban planners need to learn by analyzing nature and its complex structures to emulate how they function, through buildings" (Kadar & Kadar, 2020, p.6). To provide an example of technology successfully used to support sustainability efforts, the Edge building design in Amsterdam, utilizing smart and advanced technology, was acknowledged to be one of the world's most

sustainable buildings while maintaining comfort of the living environment (Edge, n.d.). Important features include a daylight, temperature, infrared, and motion detector to activate low-energy LEDs only when necessary; thermal energy storage pumps driven by self-generating solar power; and specific orientation that optimally exploits daylight. Similar buildings also exist, but it is clear that these energy saving principles are not being implemented on a larger scale.
Here is a brief overview of the paper, covering four main themes: smart energy management systems (SEMS), predictive modeling and simulation, computational design, and AI-supported material design. SEMS optimize energy usage in buildings by using technologies like sensors, Internet of Things (IoT) devices, and AI algorithms. They monitor energy consumption, predict demand, and automatically adjust systems like lighting, heating and cooling to minimize waste and improve efficiency. Predictive models and simulations help forecast building performance before construction. Machine learning (ML) algorithms can analyze factors like weather patterns, energy usage, and occupancy to simulate future scenarios, allowing architects to make data-driven decisions that improve the sustainability of their designs. A computational design approach uses algorithms and computational tools to generate and evaluate architectural designs. By automating parts of the design process, it allows architects to explore complex geometries and optimize structures for sustainability, efficiency, and functionality. AI technologies can also assist in developing and choosing sustainable materials by evaluating their environmental impact, cost, and performance. ML can suggest innovative materials with specific functional and sustainable objectives in mind. Thus, through these technologies, designers can gain a more direct understanding of the connection between their design choices and the construction and operational performance.

Sustainable development and regeneration have become increasingly crucial in the field of architecture and urban planning, as the world faces pressing environmental challenges with widespread urbanization. The integration of advanced technologies, such as AI and ML, has the potential to revolutionize the way we approach these issues. Through a literature review, this research paper aims to explore how AI technologies can be effectively integrated to support more sustainable and regenerative approaches in architecture.

Methodology

To achieve the objectives of this paper, a comprehensive search strategy was used to identify relevant scholarly articles and industry reports. The main databases for the search were Google Scholar and ScienceDirect, using a combination of keywords including architecture, urban design, regeneration, ecological design, machine learning, and data science. The searches were filtered to include only papers from the time frame 2020 to 2024. To ensure relevance and quality, the titles, abstracts, and keywords of selected articles were examined. Articles that did not address the intersection of AI technology, sustainable architecture, and urban planning were excluded. The remaining articles were further scrutinized to ensure a desirable depth of information. A resulting 40 papers were grouped based on specific themes and focus areas. These included the main topics of this paper: smart energy management systems, predictive modeling and simulation, computational design, and material design. The strengths, limitations and potential future research directions were evaluated to provide an insightful review of the current state of this multidisciplinary field.

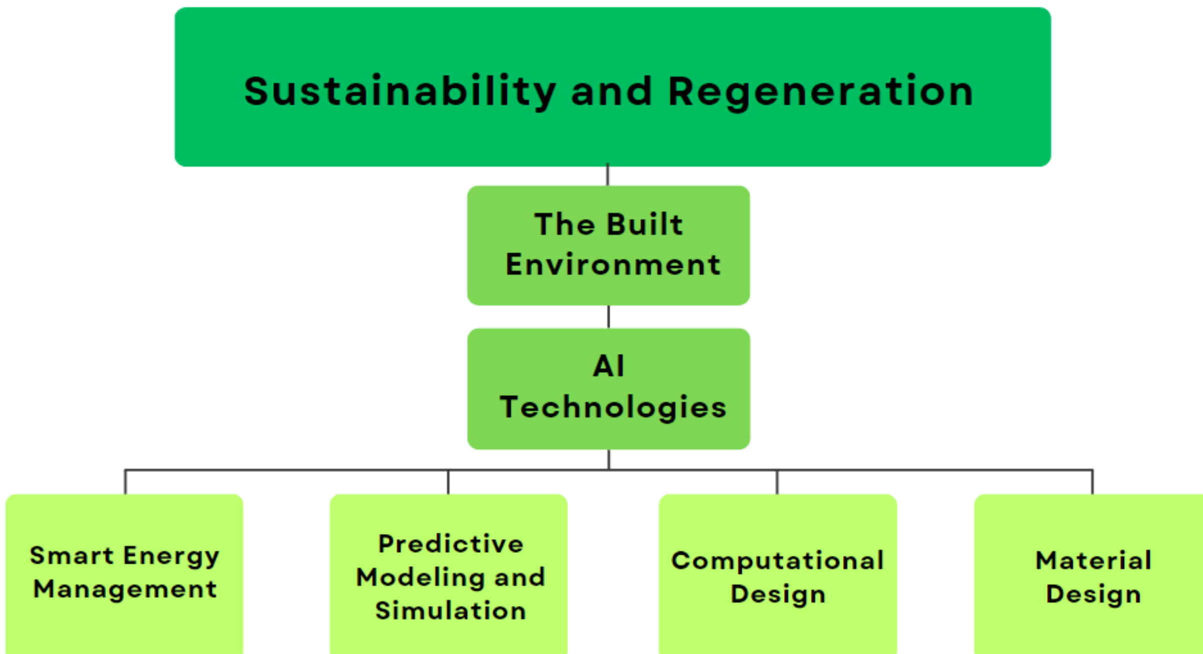

Figure 1: Emergent themes in the review of literature

Smart Energy Management Systems (SEMS)

In an era where climate change and environmental degradation are pressing global issues, the built environment emerges as a significant contributor to energy consumption. It becomes crucial to consider the energy efficiency of architectural projects throughout their entire life cycles, from design to operation. Green building principles embody this concept and are specifically designed to limit environmental impact. They extend beyond mere energy efficiency and encompass sustainable site development, water conservation, indoor environmental quality, and the use of eco-friendly materials. In designing green architecture, architects have to consider the relationship between building placement and natural lighting, shading effects of surrounding structures, the sustainability of construction materials, resource usage during building operation, ventilation and more (Bungau et al., 2022). Over the past two decades, green building projects have gained popularity among architects, engineers, and building owners with the adoption of green building standards such as BREEAM (Building Research Establishment Environmental Assessment Method) and LEED (Leadership in Energy and Environmental Design). BREEAM was first published in 1990, and is the world's longest established method of identifying the sustainability of buildings. LEED has evolved since 1998 to incorporate rising green building technologies.

SEMS have emerged as valuable tools for achieving the goals above. These systems leverage AI and IoT to facilitate real-time control of energy consumption. They are often implemented in heating, ventilation, air conditioning (HVAC) systems, lighting, and various appliances. IoT refers to a network of interconnected devices that gather and exchange data through sensors and software. Sensors can be integrated into building systems to assist with real-time data collection and monitoring of energy consumption, which enables instantaneous adjustments to optimize performance. These systems not only facilitate immediate improvements in energy efficiency but also contribute to a more extensive understanding of building dynamics. AI predictive analytics can utilize the energy consumption patterns gathered from the sensors, and relate it to data from diverse sources, such as weather conditions, occupancy rates, etc. for more efficient energy distribution, adjusting HVAC systems and lighting while considering the energy variability of the entire building (Rane 2023). ML-driven data analysis can also help predict energy future demands, allowing for a smoother integration of renewable energy (Bibri 2024). The rise of Intelligent Green Buildings (IGBs) illustrates the fusion of cutting-edge technology with sustainable architectural design for energy efficiency. They are technologically advanced structures that can moderate building conditions, utilizing SEMS (Yang et al., 2022). The principles underlying IGBs can be extended to entire urban environments, influencing the broader landscape. In other words, smart eco-cities prioritize not just individual building performance but the collective functioning of urban ecosystems. This merges smart cities, characterized by the digitalization and networking of urban infrastructure, with eco-cities, which focus on sustainability, to aim for a more holistic approach to regenerative design. Central to this vision is the development of smart power grids, and advanced electrical networks that leverage information and communication technologies (ICT) to detect and react to real-time changes. Sensors, remote sensing technologies, and data analytics are used to monitor and control environmental parameters such as air quality, water quality, and waste management, which can be applied to sustainability principles to reduce ecological harm (Bibri, 2024). Moreover, smart grids provide insight into pricing fluctuations and the availability of renewable energy. This allows for better integration of renewable energy sources, such as solar and wind, to facilitate the transition towards a more sustainable energy ecosystem, leading to more efficient usage of energy and a decreased reliance on fossil fuels (Umoh et al., 2024).

Furthermore, ML applications can address not only individual infrastructure, but also broader urban planning considerations. Climate change mitigation requires us to target absolute demand reduction, meaning the overall energy consumption and resource use must be reduced. In response to this need, Milojevic-Dupont & Creutzig (2021) proposes an algorithmic architecture called "Machine learning for Low-Carbon Urban Planning" (ML-UP), which uses ML methods to generate spatially explicit models of urban energy use and emissions. By using high-resolution data, ML-UP equips urban planners with the necessary tools to evaluate various urban planning scenarios accurately. The incorporation of data with ML's ability to capture both universal patterns and specificities can improve the granularity of climate solutions. Spatial data collected from vast sources of information helps models analyze conditions at different scales, assisting climate adaptation in specific local contexts while still being scalable to global mitigation. Instead of basing decisions on what's happening in the real time, historical data can be implemented to infer causal relationships. This approach benefits data-scarce regions, as similar cities can learn from each other's experiences.

Casali et al. (2022) discuss the applications of spatial data for sustainable urban development. There has been an increased availability of spatial data due to the rise of sensors, crowdsourcing, and real-time monitoring. In particular, geospatial data that includes geographic components like coordinates, addresses, and indexes provides the foundation for the development of more advanced geographic information systems (GIS). These systems give insight into land use, transportation networks, demographic information, and infrastructure. Deeper spatial analysis of such information enables the study of land use change, urban growth patterns, service accessibility, and the distribution of socioeconomic characteristics through visualization and mapping, which supports urban planning and decision-making. The integration of GIS with AI and ML techniques can be used for a variety of geospatial problems and applications with a specific focus on problem-solving. In sustainable development, the above-mentioned technology could be used to gain a better perception of urban cultures, social dynamics, and labor market trends. It can predict patterns of inequality, accessibility, and affordability in urban services and infrastructure, which can guide policymaking. The optimization of urban logistics and the modeling of resource flows can aid in predicting waste generation and disposal patterns for creating more circular urban systems.

To review, the integration of energy efficiency and sustainable practices in architectural projects is an urgent necessity reflecting the significant role that the built environment plays in global energy consumption. Green buildings represent a critical step in this journey, serving as models of sustainable development. However, to keep up with the rapidly growing climate crisis, revolutionary technological innovations such as AI, ML, and IoT hold potential for positive change. These tools facilitate real-time energy management, predictive analytics, and the seamless integration of renewable energy sources for better IGBs. The concept of smart eco-cities combines information and communication technologies, smart grids, and spatial data analysis to help us better understand and address the complexities of the changing climate, society, and economy to work towards creating a net positive impact.

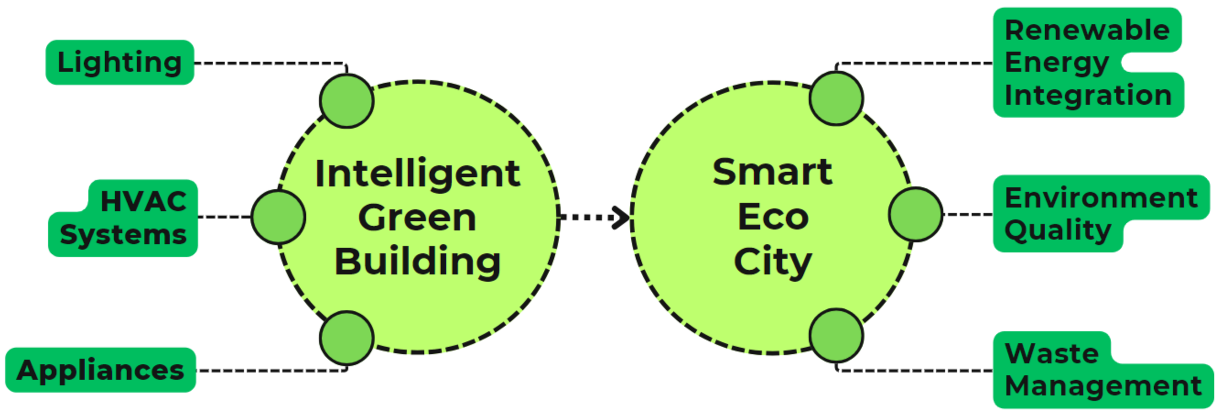

Figure 2: Role of AI and IoT technologies in supporting intelligent green buildings, as well as the transition to smart eco cities

Predictive Modeling and Simulation

This section will discuss the evaluation of environmental impacts of architectural designs, both before construction begins and during building operation. Sustainable architecture increasingly demands that environmental assessments be conducted at various stages of the design and building process, and in high detail. Predictive modeling and simulation play a crucial role by helping architects make data-driven decisions that enhance building performance, sustainability, and efficiency. Nazari (2024) describes simulation as the “process of generating data through computational modeling that involves constructing a computer-based model that represents a real system at a specific level of abstraction.” These tools allow architects to simulate and analyze various design scenarios, providing insights into building performance. The characteristics of AI and ML make them helpful tools for experimentation, modeling, and simulation. To provide an overview of the literature, several key studies are examined. Dervishaj (2023), Wang et al. (2024), Golafshani et al. (2024), and Nazari (2024) discuss how Building Information Modeling (BIM) and predictive algorithms can provide valuable information for building design, construction, and operation during the design phase. Yang et al. (2022) and Rane (2023) highlight the value of digital twins for more in-depth design visualization. These simulations offer architects a comprehensive tool for exploring different design scenarios, enabling them to foresee how changes in materials, layouts, or systems will impact a building’s energy performance, carbon footprint, and overall sustainability. Specific case studies will be reviewed to evaluate the effectiveness of simulation for increasing energy efficiency.

BIM is widely used across architecture, engineering, and construction (AEC) industries to create 3D models of buildings, allowing architects to see their design choices more clearly. It is a digital representation of the physical characteristics of a building and is often used in the planning and visualization stage of projects (Rane 2023). The primary objective of this technology is to provide valuable information for building design, construction, and operation (Dervishaj, 2023). Leveraging BIM in the initial design phases can help designers effectively gauge and improve the energy performance of their buildings (Golafshani et al., 2024). Sajjadian (2024) describes a lack of universal protocols in data management through a review of the data ecosystem in the AEC industries and outlines a performance-integrated BIM framework for energy efficiency. Ontological data, external related data, simulated performance data, and monitored performance data would be utilized in a computer simulation for evaluating building performance. To bridge the performance gap between predicted and measured performance, user behavior modeling would be needed to emulate real-world circumstances. This software replicates reality, taking input and outputting data based on physical processes.

In a case study, Wang et al. (2024) combined BIM with ML algorithms to develop a powerful prediction model based on real-world data. They specifically focused on the materialization stage of the design process, considering construction material production, component manufacturing, and on-site construction. Taking a sample of 35 typical public building foundations without basement space, this study collected and organized data related to energy consumption, material usage, and machinery adoption. This was incorporated into a foundational carbon emission calculation model, and trained with various ML techniques. The result was a powerful model that could predict materialization stage carbon emissions in foundations, effectively contributing to early-stage assessments. Furthermore, Golafshani et al. (2024) pointed out the downsides of mathematical energy optimization frameworks in the operational phase, claiming it to be too time-consuming. This issue can be combated with data-driven modeling techniques. In the study, AI models were created for predicting operational energy consumption in office buildings. Such technology was more efficient and could adapt to different types of homes and different climates. It allows for better distribution of energy usage in buildings, reducing overall energy consumption.

Building upon BIM models, digital twins provide a more comprehensive understanding of a building’s behavior and performance. They are virtual replicas of physical objects, systems, and processes. This technology is rapidly evolving with increasing adoption across various industries. While BIM provides foundational data and models, digital twins add real-time sensor data and analytics, making the process of designing buildings more dynamic and adaptive (Rane, 2023; Yang et al., 2022). Drawing on simulation models, architects and engineers can monitor, analyze, and optimize the performance of the physical counterparts, allowing for predictive maintenance and fostering better decision-making. In the context of intelligent green buildings (IGBs), digital twins can simulate different energy scenarios and promote sustainable development in smart city planning (Yang et al., 2022). Moreover, the development of virtual reality (VR) and augmented reality (AR) technologies can be combined with BIM and digital twins in design visualization. With VR, immersive virtual models of infrastructure projects can pull designers directly into their creations as if they were physically present. AR allows digital information to be overlaid in the real world, allowing for on-site visualization to examine designs in their intended environments (Rane 2023).

In the specific example of daylight design, Nazari (2024) discusses the challenges of simulation and visualization due to inherent uncertainties caused by input data quality. This can be approached by developing suitable simulation algorithms and leveraging real-time feedback and rapid tools. A simulation algorithm uses mathematical and computational approaches to model and simulate the behavior of a system, which in this case is how light interacts with surfaces. VR can enhance the visual output of simulations, allowing users to engage with the real-time virtual environment. Through this tool, architects can observe the luminance, daylight, color, and openness of their designs, as well as conduct studies on the effects of such characteristics on the overall energy efficiency of a building.

Advancements in technology give architects the opportunity to analyze and interact with their designs in real time, before operation. Prediction models and simulations can be integrated with design software for design optimization evaluation methods. This allows designers to consider the energy efficiency and understand the environmental impacts of buildings more thoroughly. With greater visualization abilities, specific issues are able to be dealt with before construction processes begin.

Computational Design

The architectural design process is framed by a considerable number of constraints, from aesthetic considerations to functional requirements and, increasingly, environmental impacts. However, architects often face the challenge of not being able to accurately assess the environmental impact of their designs at the initial stages of the design process. Traditional methods lack the efficiency and comprehensiveness that is needed to provide immediate feedback through iterations. However, recent advancements in AI and ML in architectural practice are gaining traction, offering new ways to evaluate and optimize environmental outcomes before it becomes too late to make any major changes. AI-powered computational design tools enable architects to explore many design possibilities based on predefined parameters. It can also help architects incorporate biomimicry, analyzing natural ecosystems and their resilience strategies.

For instance, the parametrization of design processes allows for rapid design evaluation and adjustment, and enables architects to explore more successful solutions for environmental objectives. It is based on mathematics and geometry, quantifying design factors into parameters, allowing designers to concurrently explore multiple design objectives (Dervishaj, 2023; Sajjadian, 2024). For instance, Alsukkar et al., 2023 emphasizes the importance of integrating different building components, such as shading and glazing, to comprehensively assess daylighting performance. Hazbei et al. (2024) discusses how parametric design tools can aid in the development of geometric patterns to take advantage of sunlight and enhance energy efficiency. A major challenge in design and optimization is that slightly changing one pattern parameter will affect the entire form, influencing building energy performance and structural designs. Having several variable parameters produces many design alternatives, making it impractical to explore each variation without these computational tools. By integrating parametric modeling, designers can balance maximizing daylight harvesting with other crucial parameters efficiently and effectively.

Building upon parametric design, generative design utilizes algorithms to explore the variants of a design beyond what is currently possible using the traditional design process. It uses iterative algorithmic frameworks to automatically propose a large number of initial designs satisfying specific user definitions and constraints, supporting human designers by automating time-consuming parts of the design process. (Chew et al., 2024). This empowers architects to focus on the innovative aspects of their projects while allowing the software to handle the technical complexities. Not only can this technology enhance design efficiency, but it can also support ecological aspects of architectural design. By aligning design generation with sustainability concepts, this approach can be utilized to create big collections of design cases that are filtered through to create optimally environmentally viable design solutions. For instance, preliminary design solutions can be generated based on specific requirements such as material selection, building orientation, and climatology. These solutions can then be systematically ranked and filtered to meet precise sustainability goals (Zang & Ding, 2024).

ML algorithms can detect repeating patterns in big sets of data and construct mathematical models that describe data behaviors. This can be used in architectural practice for environmental assessment. In 2020, a progression of three studies were done by Mazurek et al. on the use of ML and parametric design to optimize the carbon footprint of regenerative architectural design. ML models were created to generate a building shape, calculate the embodied carbon of the building, simulate the energy performance, and calculate the operational carbon footprint. The embodied carbon and operational carbon were summed to find the total carbon footprint, and the three datasets were graphed and analyzed. The results show relationships between building parameters and environmental impact and introduce the possibility of implementing carbon footprint estimates at the very beginning of the design process. The first study tackled cuboid buildings only, the second was improved to include prisms with base shapes of intersecting rectangles, and the third study incorporated entire urban layouts. Although all machine learning models were only trained on buildings between 1500-3500 square meters and lost accuracy outside of the range, the algorithms developed turned out to be sufficiently accurate as a guidance for designers.

The research above illuminated a counterintuitive finding: the designs with the lowest sum of total carbon footprint occurred at points where neither the embodied nor the operational carbon footprints individually were the lowest possible. This insight underscores the potential of AI and ML to provide information about design optimization that may not be immediately apparent to human designers. It emphasizes the necessity of considering both embodied and operational emissions without compromising one for the other. Pena et al. (2021) argues that the application of artificial intelligence should not be oriented toward finding a solution in a defined search space since the design requirements are not yet well defined. Instead, the design process should be an exploration of requirements, “searching for the space of the problem of the design as well as the space of the solution.”

The historical development of AI technologies in architecture has been monumental. It started with computer-aided design (CAD), systems that allow designers to draft their ideas digitally. Later, the rise of expert systems assisted humans in decision-making, performing structural analysis, materials selection, and space planning. The emergence of parametric design allowed architects to create adaptive systems using algorithms, and generative design evolved to explore a wide range of design options. In recent years, the integration of machine learning and neural networks has allowed for more data to be analyzed at a time. Architects can incorporate environmental data, user behavior, and building performance to discover greater nuances (Krauskova & Pifko, 2021). In the study done by Mazurek et al., it was found that AI can quickly identify connections that a human would be looking for for much longer, or would not find at all. Tools for generative design, material selection, and performance simulation can effectively be used to help human designers create more efficient, environmentally conscious buildings while maintaining functionality and aesthetics. According to Chew et al. (2024), generative design “emulates nature’s evolutionary process” by using parameters and objects to quickly explore thousands of design variants to find the best solution.

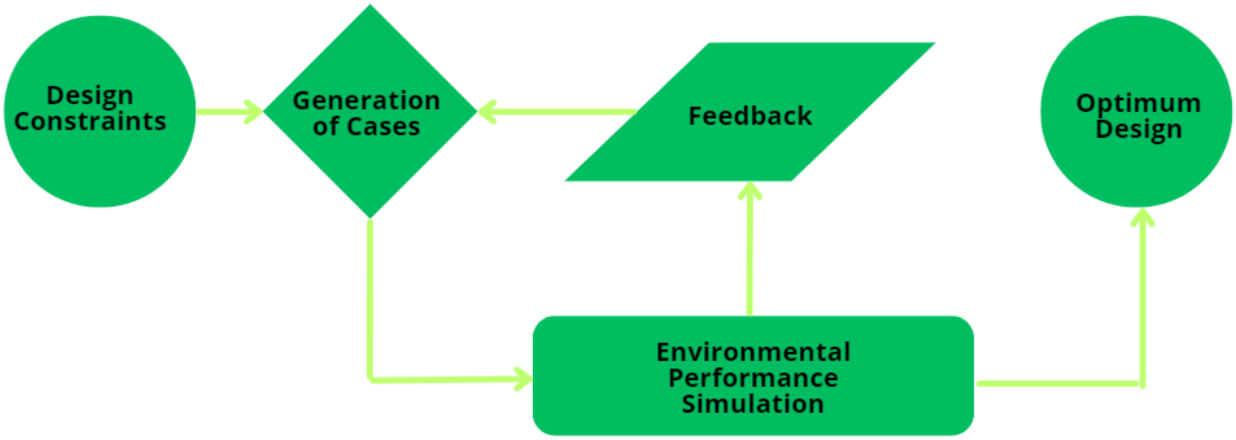

Figure 3: Generative design process

Material Design

Evaluation of materials is a crucial aspect of sustainable architecture, and AI has great potential in optimizing material selection, as well as the development of new building materials. Historically, the study and design of materials relied on rigorous strategies that often required trial and error. This involved careful observation and analysis of nature to identify nuanced properties and structures, and then advanced manufacturing techniques to validate the performance. However, with new technology, vast amounts of data can be analyzed to reveal complex correlations and patterns within material properties, structures, and compositions (Badini et al., 2023). Furthermore, AI algorithms can be developed to identify promising candidates to meet regenerative design criteria, such as designing to reduce waste and promote adaptability, longevity, and recyclability (Kadar & Kadar, 2020). Stergious (2023) and Park (2024) describe methods of material property prediction and material design. Shashwat et al. (2023), Chen et al. (2023), and Badini et al. (2023) considers AI powered material design and evaluation with specific objectives in mind. These objectives include energy efficiency in material production, the optimization of mechanical properties, and the development of materials that will adapt to changing environmental conditions.

Stergious (2023) explains how machine learning can predict material properties, minimizing the time and cost of laboratory testing as well as optimizing critical manufacturing processes. Such approaches involve training models on a mix of quantum mechanical calculations and chemical similarity notions. This has been enhanced by the increasing data availability from results of other experiments and computer simulations. By informing human designers of material behavior without the need of extensive experimentation, this model reduces energy consumption and cost. However, Park (2024) underlines the challenge of directing the design and discovery of compounds with pre-determined properties. In traditional methods, a pool of candidate materials is filtered to identify the optimal target configurations. An inverse approach requires designers to have a desired set of properties, and identify corresponding molecular structures that satisfy them. With recent advancements in materials datasets and ML, this study proposes generative AI models for creating chemical compositions and crystal structures that align with specific targets.

Shashwat et al. (2023) focuses on the design of construction materials. Thermo-physical and surface radiative properties are crucial in this context, and heat transfer mechanisms can be a source of inspiration for developing energy-efficient construction materials. These include solar reflectance, thermal emittance, thermal storage, and evaporation. Computational simulation provides a platform for conducting performance analysis while 3D printing techniques allow designers to evaluate the materials. Chen et al. (2023) studied sustainable architecture glass material (SAGM) selection. This study highlighted important factors to consider such as daylighting performance, thermal insulation performance, and explosion protection. A comprehensive criteria system was created for evaluating the sustainability of energy-efficient architectural glass materials, and a framework was designed to manage the uncertainty of algorithmic outputs.

Specifically designed for sustainability, bioinspired materials mimic structures and functions found in nature, meeting durability, flexibility, and weight requirements while utilizing sustainable materials. They can have additional properties, such as self-cleaning, self-healing, and adaptation. Badini et al. (2023) highlights how various machine learning and deep learning techniques can be employed, including supervised, unsupervised, and reinforcement learning. Models are trained on datasets containing biomaterials in order to replicate the biological design strategy. For example, in this study, AI was trained on leaf veination and trabecular bone datasets, creating a hybrid leaf/bone material that embodies the combined characteristics of the original materials.

The integration of AI algorithms can enhance the efficiency and effectiveness of material design. They can predict complex behaviors and discover new material compositions, decreasing the costs associated with material experimentation and development. With the help of computational power, scientists are able to focus solely on the most promising solution, expediting the process. By targeting specific parameters, materials can be optimized in the context of regenerative design criteria.

Research Synthesis and Insights

Through this review of literature on the potential of AI technologies in sustainable architecture and urban planning, four main themes were uncovered: smart energy management systems, predictive modeling/simulation, computational design, and material selection/design. Each of these presents a great promise for advancing sustainability efforts in the built environment. The research indicates a strong trend towards the development of wider-spread smart energy management systems, leading to the eventual integration of intelligent green building, as highlighted by Yang et al. (2022). AI-driven systems play an important role in enabling more efficient energy distribution, which reduces reliance on fossil fuels, helps with the transition to renewable energy sources, and enhances the overall sustainability of buildings (Umoh et al., 2024). Increasing the usage of predictive modeling and simulation can greatly enhance the design and operation of architectural projects. New technologies such as digital twins provide a dynamic and adaptive approach, presenting a significant advantage over traditional BIM techniques (Yang et al., 2022; Rane, 2023). The application of AI in computational design is advantageous in its ability to generate and evaluate multiple design options rapidly. This allows architects to explore a wide range of possibilities in order to optimize designs for both functional and environmental performance (Mazurek et al., 2020; Zang & Ding, 2024). Thus, the research emphasizes the potential of AI to enhance design efficiency while also reducing carbon footprints and mitigating waste. Furthermore, by leveraging machine learning algorithms, researchers can accelerate the discovery of new sustainable materials that also meet construction requirements (Badini, 2023).

Based on the review of relevant papers within the past four years, several research gaps and opportunities have been identified. Looking forward, there are several areas where further research and development are vital to targeting sustainability more holistically, including the implementation of technologies, the scalability of efforts, and the quality of data. Most technologies reviewed in this paper pose the difficulty of implementation, arising from technological, financial, and operational factors. Difficulties in scaling practices for broader urban environments and the inconsistency of data also hold back the transition from sustainability to regeneration. Notably, there are limited studies done on sustainable materials and the application of technology in material design because of how specialized the field is. The development of new materials often requires longer research timelines, garnering less attention compared to the more immediate impact of energy management, predictive modeling, and computational design.

Specifically, SEMS and predictive modeling/simulation present the greatest technological and financial barriers in implementation. SEMS require the integration of various components such as lighting, HVAC, electrical systems, and renewable energy sources. Ensuring that they function together and can be integrated within existing systems is complex. Furthermore, implementing predictive models and simulations often require a high level of expertise in machine learning and data science. Designing accurate models that can forecast energy usage and optimize systems require advanced skills that may not be available to all architectural firms. Both of these technologies have high initial costs. Installing the necessary infrastructure such as smart sensors, control systems, and data management platforms can be expensive. Predictive modeling and simulation require the development and fine-tuning of models, which can also be costly.

The effectiveness of technologies for sustainable architecture are also limited by scalability issues. In SEMS and predictive modeling/simulation, the complexity of managing data and integrating systems across larger building networks require more advanced algorithms and greater resources. The volume of real-time data generated increases exponentially, and handling and analyzing this large dataset in real time becomes more challenging. In addition, different devices and systems might be needed in different building types, leading to compatibility issues and the challenge of standardizing protocols. Moreover, computational design relies on algorithms that generate or optimize designs based on specified parameters. Scaling up these algorithms for urban development increases the number of parameters. This will often have to meet multiple, sometimes competing, objectives: structural efficiency, sustainability, aesthetics. Similarly, AI-powered material selection and design is influenced by a wide range of factors, and scaling it to larger projects requires the ability to account for a wider range of variables, increasing model complexity.

Most importantly, the accuracy of AI models are heavily dependent on the quality of data. While real-time simulation and monitoring are powerful tools, one of the major challenges of their application in sustainable architecture is the availability and integration of precise and comprehensive data, highlighted by Mazurek et al. (2020). In areas where data may be scarce or unreliable, the effectiveness of these models may be compromised. There is a need for standardized data collection methods, as well as standard protocols for integrating data from diverse sources. In addition, current models often rely on historical data, which may not accurately reflect the dynamic conditions of a building's operation. This limitation can lead to suboptimal decision-making for energy efficiency. Research should continue to explore ways to enhance the real-time capabilities of these tools, improving sensor technologies and data-sharing frameworks.

Lastly, while much of the research focuses on the environmental contributions of AI in sustainable architecture, there is a need to call more attention to the social and economic implications of these technologies. For instance, the integration of smart energy management systems may raise concerns about privacy and data security, particularly in residential settings.

Conclusion

This paper explored how sustainable architecture and urban planning can be assisted by AI technologies with a focus on applications in smart energy management systems, predictive modeling and simulation, computational design, and material design. Many research gaps have been found concerning the complexity of implementation, scalability of sustainable practices to entire urban landscapes, and the inconsistency of the distribution of data. It is also highlighted that there is a lack of research conducted on AI for material design and sustainability from a socio-economic perspective.

Future research should address these considerations, ensuring that the notion of smart eco-cities that actively contribute to ecological restoration are not only technically viable but also socially and economically sustainable. Moreover, the development and operation of AI technologies have their own environmental and ethical implications, which are often overlooked in the pursuit of innovation. The energy consumption associated with training AI models, the extraction of rare minerals for hardware, and the potential for AI to be used in ways that exacerbate inequality are significant concerns (Tamburrini, 2022; Acemoglu, 2021). Addressing these issues means developing more sustainable AI practices, such as reducing the energy footprint of AI operations and ensuring that AI applications in architecture are aligned with holistic sustainability efforts. In addition, the lack of literature on building construction materials opens a direction for exploration. AI-powered material design and selection offers possibilities for incorporating biomimicry and nature-inspired design, modeling after natural systems that inherently blend seamlessly into ecological environments. More comprehensive life cycle analysis with algorithms can ensure the contribution of materials to the circular economy. Catalano et al. (2021) address the need for multidisciplinary collaboration to gain a deeper understanding of built environments and natural systems. By engaging experts in various relevant fields to work together, more perspectives are taken into account, and new insights can be uncovered.

The field of sustainable architecture and urban planning exposes diverse research avenues through which technology can contribute to reducing environmental impact. While sustainability remains a crucial goal, the concept of regeneration goes beyond merely reducing negative impacts to actively restoring natural ecosystems. Future research should focus on developing frameworks that incorporate regenerative design principles, guiding designers to create buildings and urban spaces that are more resilient, and effectively respond to the needs of society while restoring the integrity of nature, as outlined by UNESCO (2023). Thus, not only must we consider environmental approaches, but also a holistic transition to an integrated circular economy: a model of resource production and consumption that involves sharing, leasing, reusing, repairing, refurbishing, and recycling existing materials and products for as long as possible.

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