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Review

Advanced Digital Tools for Data-Informed and Performance-Driven Design: A Review of Building Energy Consumption Forecasting Models Based on Machine Learning

Andrea Giuseppe Di Stefano *, **Matteo Ruta** and **Gabriele Masera**

Department of Architecture, Built Environment and Construction Engineering, Politecnico di Milano, Via Ponzio 31, 20133 Milano, Italy; matteo.ruta@polimi.it (M.R.); gabriele.masera@polimi.it (G.M.)
* Correspondence: andreagiuseppe.distefano@polimi.it

Abstract: Cities and buildings represent the core of human life, the nexus of economic activity, culture, and growth. Although cities cover less than 10% of the global land area, they are notorious for their substantial energy consumption and consequential carbon dioxide (CO_2) emissions. These emissions significantly contribute to reducing the carbon budget available to mitigate the adverse impacts of climate change. In this context, the designers' role is crucial to the technical and social response to climate change, and providing a new generation of tools and instruments is paramount to guide their decisions towards sustainable buildings and cities. In this regard, data-informed digital tools are a viable solution. These tools efficiently utilise available resources to estimate the energy consumption in buildings, thereby facilitating the formulation of effective urban policies and design optimisation. Furthermore, these data-driven digital tools enhance the application of algorithms across the building industry, empowering designers to make informed decisions, particularly in the early stages of design. This paper presents a comprehensive literature review on artificial intelligence-based tools that support performance-driven design. An exhaustive keyword-driven exploration across diverse bibliographic databases yielded a consolidated dataset used for automated analysis for discerning the prevalent themes, correlations, and structural nuances within the body of literature. The primary findings indicate an increasing emphasis on master plans and neighbourhood-scale simulations. However, it is observed that there is a lack of a streamlined framework integrating these data-driven tools into the design process.

Keywords: machine learning-based tools; building energy forecasting; data-informed design; performance-driven design; operational carbon reduction

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1. Introduction

Since the dawn of the industrial revolution, urban environments have emerged as significant influencers of energy consumption patterns. Today, as urbanisation continues its relentless march, over half of the global population resides in cities. These urban hubs, while being vibrant centres of culture and commerce, are also responsible for a staggering 75% of global carbon emissions [1]. This urban-centric carbon footprint underscores cities' dual role: they are both major contributors to the climate challenge and, simultaneously, pivotal players in its solution. A testament to this is the commitment of over 100 cities worldwide to achieve net-zero carbon emissions by 2050 [2]. Within this urban landscape, buildings stand out, playing an indispensable role in the carbon equation. Yet, while the importance of buildings in this narrative is clear, the roadmap to achieving substantial carbon emission reductions remains shrouded in complexity.

The 21st century presents a defining challenge for the built environment: constructing energy-efficient urban spaces while retrofitting existing ones to meet modern standards. Addressing this challenge demands a granular understanding of how buildings consume energy and the strategies required to minimise this consumption. Building designers, policymakers, administrators, and even tenants, must come together, pooling their expertise to devise and implement impactful, cost-efficient measures [3].

Building performance simulations (BPSs) have long been the bedrock of decision-making in building design. As shown in Figure 1, BPS plays a critical role from the initial planning stage through to occupancy, with its influence peaking during the design phase. As legislative frameworks evolve—pushing for greener, more efficient buildings—BPS has adapted, integrating richer, more reliable data streams into the design process. The digital age has ushered in an era of unprecedented data availability, paving the way for the integration of machine learning and other data-driven tools into BPS. These advancements promise not only enhanced simulation and modelling methods but also their seamless integration right from the earliest design stages. In this scenario, the recent revision of the Energy Performance of Buildings Directive (EPBD) [4] echoes this sentiment, emphasising the integration of data-informed and performance-driven tools into BPSs.

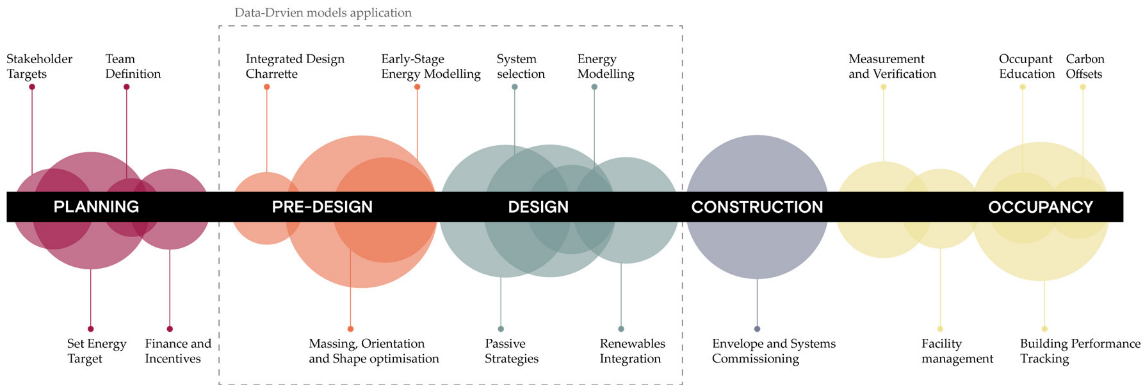

Figure 1. Phases of the building design lifecycle—each phase is depicted with a distinct colour to denote the corresponding phase, while the circle dimensions indicate their level of influence on the project's energy efficiency and sustainability outcomes.

Yet, the path is not without its hurdles. The BPS realm offers a vast array of modelling methods, creating a maze that often leaves stakeholders, from researchers to policymakers, perplexed [5]. On the other hand, the data, the lifeblood of these models, are often fragmented, unstructured, or locked behind gates of inaccessibility.

The early design stage of a building is a period of immense potential. It is during these phases that critical design parameters are set, influencing over 40% of a building's energy-saving potential [6]. To harness this potential, there is a pressing need to optimise these parameters from the earliest stages.

While the allure of data-driven models, with their promise of rapid and reasonably accurate energy consumption estimates, is undeniable, traditional BPS methods cannot be overtaken with ease. Even as data-driven BPSs evolve, challenges persist, from computational intensity to potential overestimations of the energy savings [7], from underlying biases to unclear data processing. However, recent research [8,9] shines a spotlight on the potential of data-driven methods, with techniques like Artificial Neural Networks (ANNs) [10,11], Support Vector Machine (SVM) [12,13], and Decision Tree-based models (DT) [14] gaining traction in building energy modelling [15].

While several reviews have analysed specific tools [8,16], simulation techniques and algorithms, and related indices and evaluation tools [7,17,18], this study pivots to explore the current state of the art concerning the integration of data-driven tools in the architecture, engineering, and construction (AEC) sector. The main contribution of this study lies in offering a comprehensive review of the Artificial Intelligence (AI)-based tools supporting performance-driven design and identifying an increasing focus on master plans and neighbourhood-scale simulations. Most significantly, it uncovers the absence of a streamlined framework for embedding these data-driven tools within the early stages of the design process.

Through this work, we aim to clear the mist surrounding the potential of data-driven BPS, mapping out a direction for future research and practical application, with a vision to empower stakeholders to make informed, impactful decisions for the sustainable transformation of our urban landscapes.

2. Research Methodology

Informed by the understanding that urban environments significantly influence energy consumption patterns, and the pivotal role buildings play in carbon emissions, our methodology sought to delve deep into the integration of digital tools with BPS. The pressing need to optimise design parameters from the earliest stages underpinned our analytical approach. This imperative led us to adopt a data-driven perspective, considering both traditional BPS and emerging data-driven methodologies.

To structure our exploration, we adopted a systematic literature review approach, as presented in Figure 2. Our methodology comprised of keyword identification, which was steered by the overarching aim of the paper. This process ensured a comprehensive review, encompassing advanced digital tools for data-informed design, performance-driven design concepts, and early stage energy and operational carbon assessment strategies. Recognising the importance of interdisciplinary research, multiple bibliography databases were utilised to achieve a holistic view. Further, the extraction process was not limited to a simplistic keyword search. Given the complexity and vastness of the topic, bibliometrics and data processing techniques were used to discern patterns, correlations, and thematic structures in the available literature. This approach allowed us to identify both dominant themes and gaps in the research landscape, which served as a foundation for our subsequent analyses and discussions.

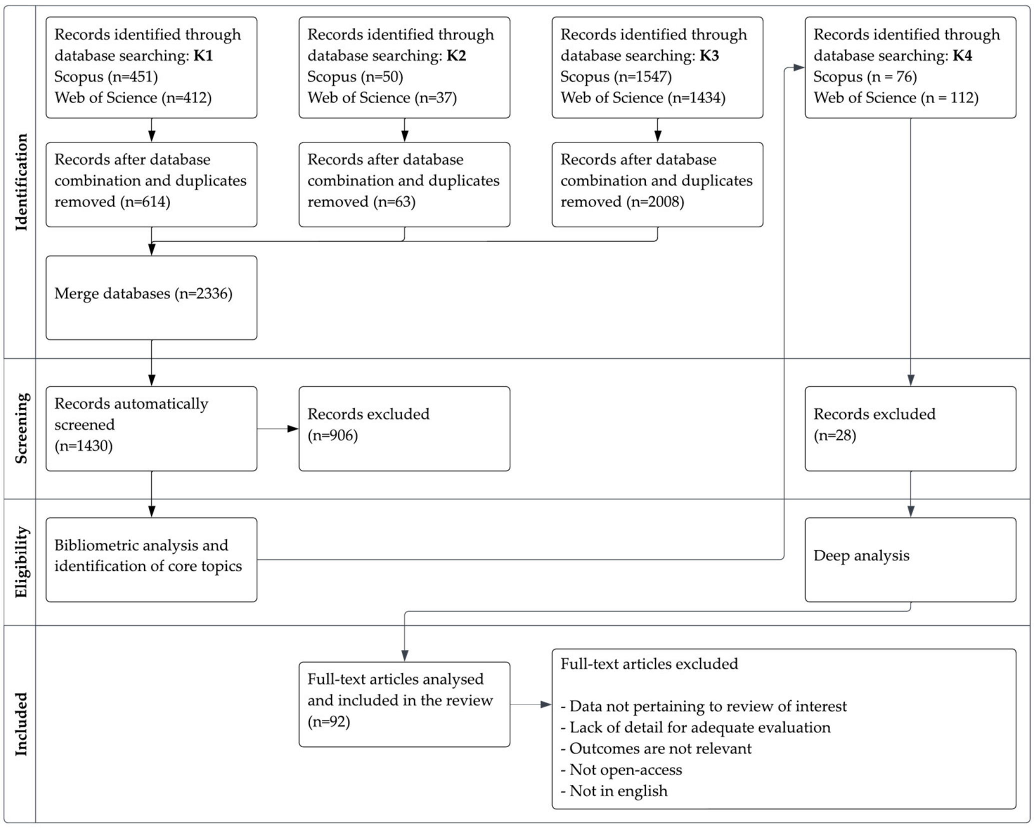

Figure 2. Literature review methodology process.

It is pertinent to note that while data-driven techniques and their application in building performance simulations are undoubtedly significant, this review will not focus on a systemic analysis of the tools and instruments, including their indexes and measurements.

Instead, the emphasis will be on the broader integration of data-driven tools into BPS, especially in the early design stages of buildings. The methodology's robustness lies in its multi-faceted approach, combining a traditional literature review with advanced data analysis techniques. It provides a balanced perspective, ensuring both breadth and depth in the exploration of the topic.

The methodology adopted for this research presents a systematic review process, ensuring a structured approach to the literature analysis. Initially, three distinct keyword searches were conducted, respectively, K1, K2, and K3. The records identified from the database searches were subsequently collated, resulting in a combined total of 2336 records. To maintain the quality and uniqueness of the data, duplicate records were removed.

Following the de-duplication process, the merged database underwent an automated analysis using specialised tools, such as VosViewer [19], to identify notable correlations, patterns, and significant themes within the literature. The insights derived from this automated analysis informed the final keyword search, designated as K4. This culminated in the identification of articles from Scopus (n = 76) and Web of Science (n = 112).

The final phase involved a scrupulous screening of the K4 search results based on their titles and abstracts to ensure their alignment with the research objectives. Out of the screened articles, 92 were identified as being of the utmost relevance, forming the foundational dataset for the review. These selected articles were incorporated into the research bibliography, providing the basis for subsequent discussions and findings.

2.1. Application of the Methodology

This section outlines how the described methodology was employed, from keyword identification to the analysis of the results. We commenced with a precise definition of the primary research question, which, in turn, naturally steered our selection of keywords by pinpointing the essential concepts relevant to the query. As described in the introductory paragraph, the aim of this paper is to analyse the current scenario in the predictive energy- and carbon-related analyses and machine learning tools for data-informed building design.

A preliminary review of the existing literature provided a baseline understanding of the dialogue within the field, identifying the terms frequently used by authors on the subject. This initial scan was instrumental in building a foundation of commonly used language and jargon in the domain of energy-efficient building design. These selected keywords were categorised into three sub-topics:

1. Advanced digital tools for data-informed design: including terms like Artificial Neural Networks, machine learning, genetic algorithm, sensitivity analysis, multi-objective optimisation, and Metamodel.
2. Performance-driven design: encompassing performance, energy consumption prediction, and building performance simulation, among others.
3. Early stage energy and operational carbon assessment: featuring early stage life-cycle assessment and operational carbon.

Bibliography databases, such as Web of Science and Scopus, along with the European Commission research project platform CORDIS, were utilised. Searches were conducted considering the intersection of different keywords to evaluate both the quantity and quality of the results. The filters applied to refine the search included open access results, specific subject areas (engineering, energy, environmental science, etc.), all document types, time periods, and affiliations.

The results from the database searches were analysed to understand the significance and temporal impact of each sub-topic. Tools like VosViewer and Bibliometrix [20] facilitated a deep semantic analysis. Preliminary findings indicate a rising interest in the confluence of these sub-topics. While performance-driven design for energy optimisation is a prevalent theme, words such as "framework", "integration", and "requirements" integrated with carbon assessment elements remains sparse, indicating a potential gap in the literature.

2.2. Bibliometrics and Data Processing

The starting phase of our research was marked by a detailed and sensitive analysis, an approach designed to identify primary sources and ensure a comprehensive, cross-disciplinary exploration across the research landscape. In this brainstorming phase, we cast a wide net for potential keywords and phrases, considering a broad range of related terms, synonyms, and variations in terminologies that might impact the search results' breadth and depth.

We formulated search strings by synthesising and Boolean combining the previously delineated keywords. Examples of these combinations include:

1. K1: ((“Artificial Neural Network” OR “ANN” OR “Neural Network”) AND (“Building Energy consumption” OR “Building Energy performance”));
2. K2: ((“Metamodel” OR “Surrogate model”) AND “Building” AND (“Energy performance” OR “Operational carbon”));
3. K3: ((“Artificial Neural Network” OR “Artificial Intelligence”) AND “Building” AND “Energy” AND “Performance”).

Using these strings, a pilot search was conducted to test the effectiveness of the keywords chosen. Based on the relevance and quality of the articles retrieved, we fine-tuned our search terms, ensuring that the literature we collated was of the utmost relevance to our research aims.

Following our preliminary review, we conducted a correlation analysis to assess the relative prominence of each keyword within the domain of our study. In the network visualisation in Figure 3, a nuanced constellation of the thematic clusters emerges, each representing a topic within the scientific literature. At the centre of the visualisation, substantial nodes in red highlight the pivotal concepts of ‘model’, ‘performance’, and ‘design’. This central clustering indicates an intensive focus on theoretical issues and performance metrics, which are foundational to the field's discourse. These nodes are not only larger, suggesting their higher frequency or importance, but are also densely interconnected, signifying a robust dialogue within the literature concerning the development and evaluation of systemic models and performance-based design methodologies. Adjacent to this core, we observe nodes in shades of green, representing the applied facets of the domain, including specific models and analytical techniques. Another discernible cluster, in yellow, punctuates the visualisation with the themes associated with energy consumption and systems' efficiency. The variance in node size and the dispersion within this group suggests a range of subtopics of variable research intensity focused on building energy-related aspects. The more dispersed light-green clusters highlight discussions on multiobjective optimisation, sensitivity analysis, and meta-modelling. This subdomain, combined with the orange one more focused on algorithms and networks for consumption predictions, signifies a rich exploration of abstract modelling processes and transformations, and their overarching significance in the broader research context.

Informed by these correlations and aiming for a more focused review, we refined our search strings. Notably, the term “Artificial intelligence” was set aside, given its ubiquity, which risked overshadowing more specific topics. The refined, primary search string was:

4. K4: ((“Metamodel” OR “Surrogate model”) AND “Building” AND (“Energy performance” OR “Operational carbon”)).

It is paramount to emphasise that this refined, targeted analysis is designed to complement, not supplant, the broader exploration based on a diverse array of keyword combinations.

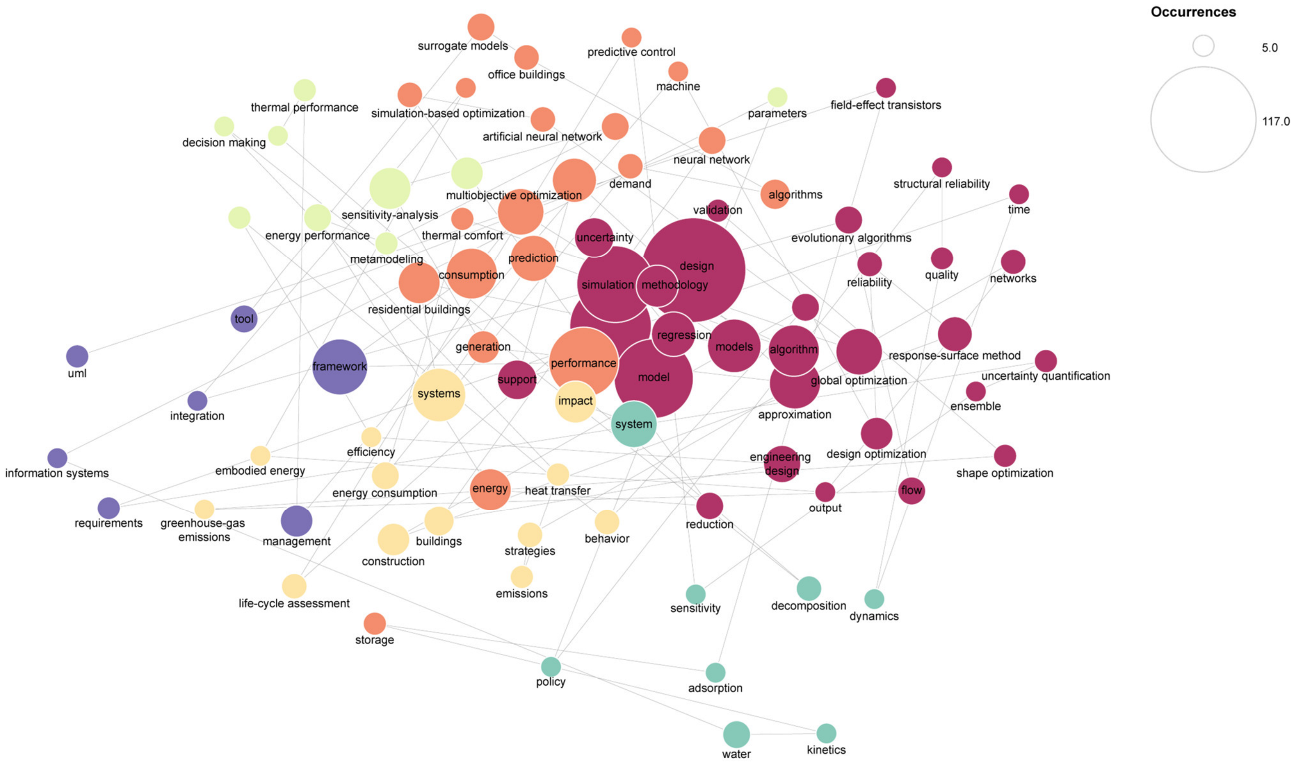

Figure 3. Correlation analysis—interconnected keyword network for AI-driven design.

3. Results

The results obtained from the analysis of the papers retrieved from the string K4 reveal that the annual production of scientific papers regarding metamodelling and surrogate modelling techniques for the energy performance and operational carbon assessment in buildings has an average annual growth rate of 8%.

Two notable observations from Figure 4 are the exponential growth around 2010 and the peak in publications on the topic in 2019. Several factors could have contributed to this surge.

The early 2010s saw a rise in environmental advocacy groups and movements, bringing attention to the importance of sustainable building practices to combat climate change. Moreover, after the 2010s—called, by Chaillou [21], the "Deep Learning Revolution" period—several other events could have influenced this growth. For instance, the Deep Learning Breakthroughs. The early 2010s marked significant advancements in deep learning. The introduction of architectures like AlexNet in 2012 revolutionised the field of computer vision. The triumph of this convolutional neural network in the ImageNet Large Scale Visual Recognition Challenge served as a catalyst, accelerating the embrace of deep learning methodologies across diverse fields, building performance simulations included. Furthermore, in 2014, Ian Goodfellow, alongside his team, unveiled Generative Adversarial Networks (GANs). GANs opened up new possibilities for generating synthetic data. In the context of building simulations, this could mean generating synthetic building designs or performance metrics to augment datasets.

On the other hand, 2019 marked another significant step in the field thanks to several factors such as:

1. Technological Advancements: By 2019, there were significant breakthroughs in computational capabilities, particularly in the realm of AI and machine learning. The development and dissemination of tools like TensorFlow and PyTorch, which made deep learning more accessible, played a pivotal role. Additionally, the proliferation of cloud computing platforms, such as AWS, provided researchers with affordable,

scalable computational resources, enabling more intricate simulations and models related to building energy performance.

2. Regulatory Changes: Around 2019, the European Union introduced the 'Clean Energy for All Europeans' package—which includes the EPBD.
3. Funding and Grants: In 2019, international bodies like the United Nations and the European Union emphasised the sustainable development goals, leading to increased funding opportunities for research on sustainable infrastructure and green building practices. Such financial injections often catalyse academic research, leading to a surge in publications.

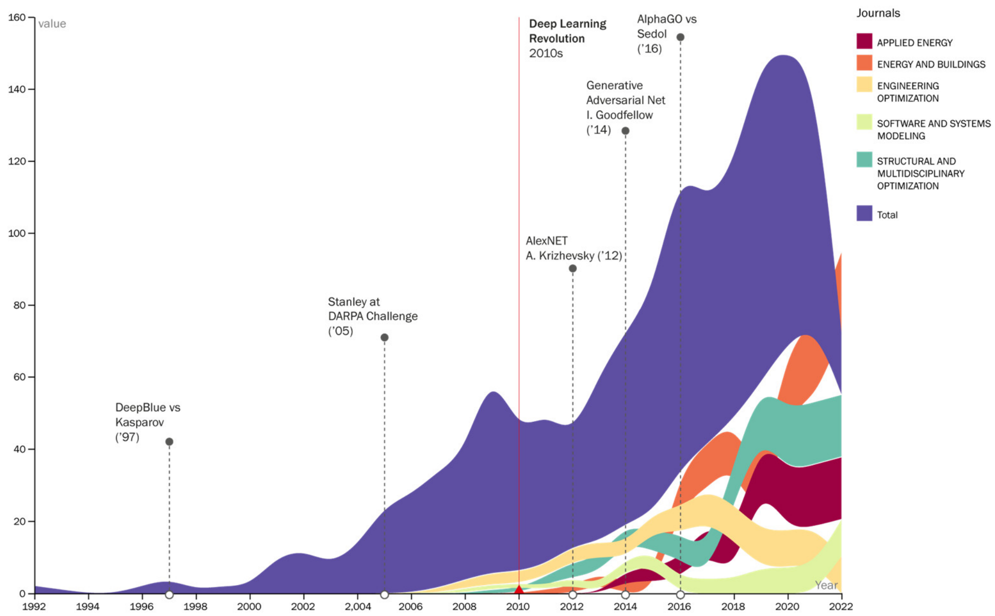

Figure 4. Growth rate and annual publications analysis by journal, with indication of the key milestones in AI development influencing scientific production.

After noting the growing interest in the researched topics, we proceeded with a more in-depth semantic analysis of the word occurrences across the titles, keywords, and abstracts of the papers obtained from the string K4, returning an initial identification of the most widely addressed topics. The treemap in Figure 5 shows the frequency of terms in the surveyed literature, helping in identifying areas of concentrated research and emerging trends.

For clarity and structured interpretation, we categorised these keywords into six thematic clusters, as depicted in the list below and visually represented in Figure 6.

- Performance—incorporating terms such as simulation, global optimisation, and parameters.
- Optimisation—covering concepts like framework, algorithm, regression, and reliability.
- Carbon—highlighting terms like impact, construction, life-cycle assessment, and emissions.
- Consumption—encompassing terms like consumption, prediction, neural network, and surrogate model.
- System—including descriptors like system, water, and storage.
- Sensitivity analysis—capturing concepts like calibration, tool, metamodelling techniques, and decision-making.

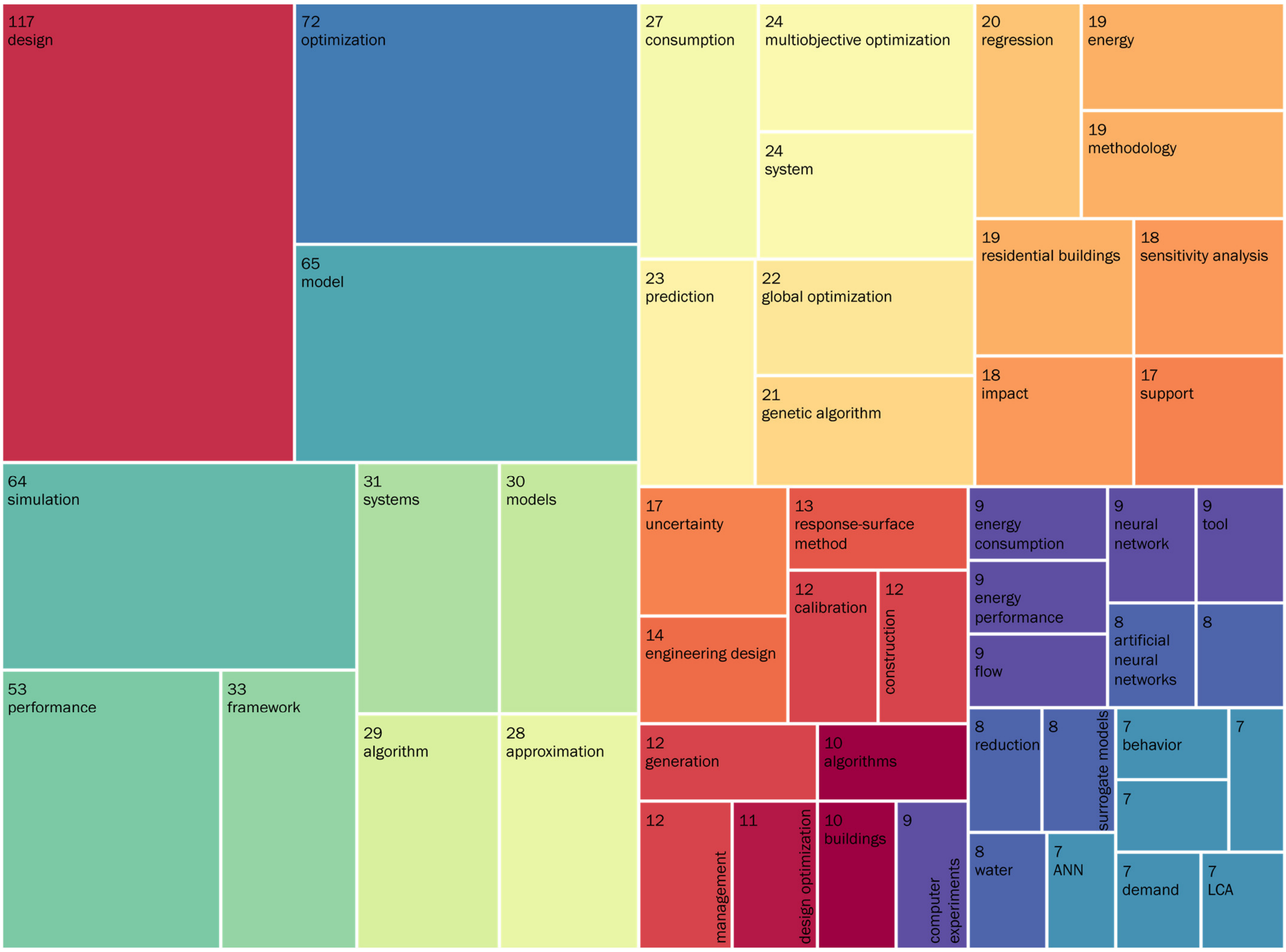

Figure 5. Keywords co-occurrence analysis of selected papers.

To evaluate the significance and coherence of these clusters, a Density–Centrality diagram was utilised (Figure 7). In this analysis, Centrality represents the degree of interaction a cluster has with other parts of the network [22]. It essentially measures the strength of the links from one research theme or community to other research themes or communities, and is an indicator of the significance of a theme or community in the development of an entire field [23]. As a cluster obtains stronger links in a network, the more central its position becomes [24]. On the other hand, Density is the measurement of a cluster's development [23]. It can be understood as the strength of all internal ties (edges) linking together the nodes that make up a theme or community [25]. Density provides a good representation of a cluster's ability to maintain itself and grow over time [26]. As a cluster increases in density, the more coherent it becomes and the more likely it is to contain inseparable nodes [22].

The analysis spotlighted "Consumption", "Carbon", and "Performance" as core themes. Within the "Consumption" cluster, emphasis is placed on neural networks and predictive models. The "Carbon" cluster seeks to merge digital tools with carbon and emission reduction analyses, while the "Performance" cluster underscores foundational elements such as global optimisation and simulation.

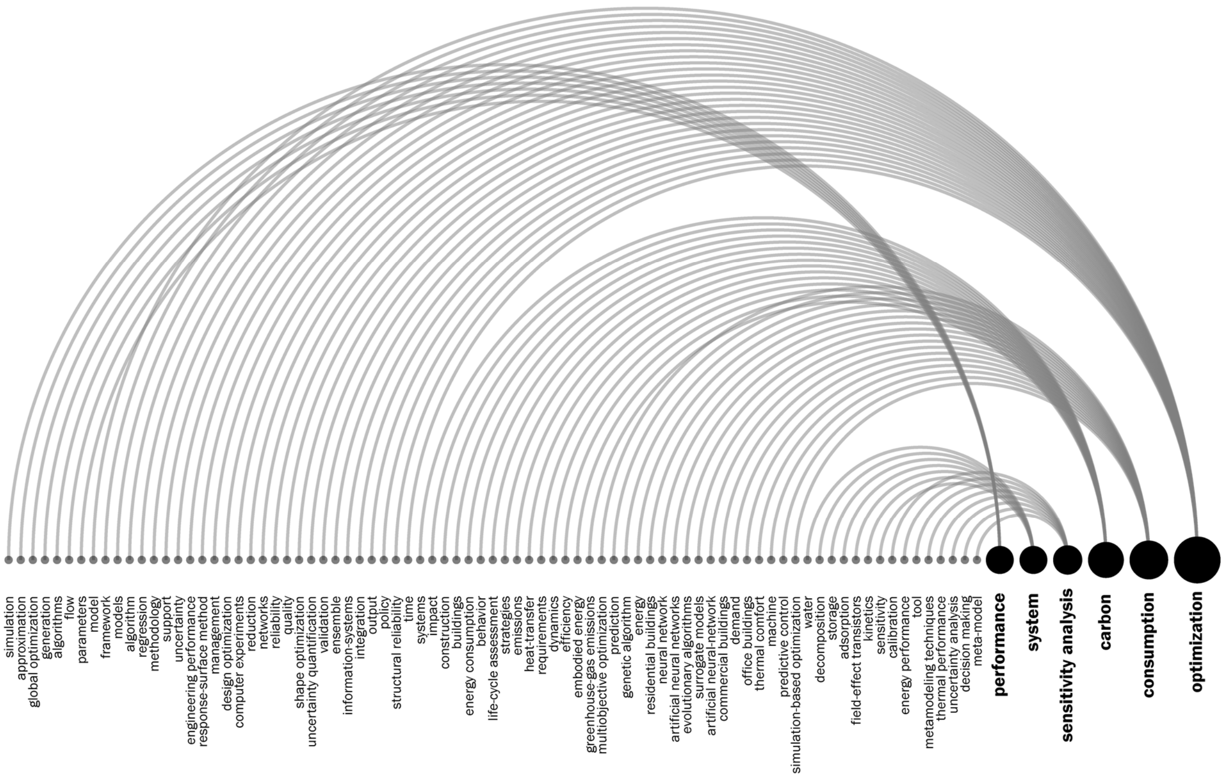

Figure 6. Keywords clustering.

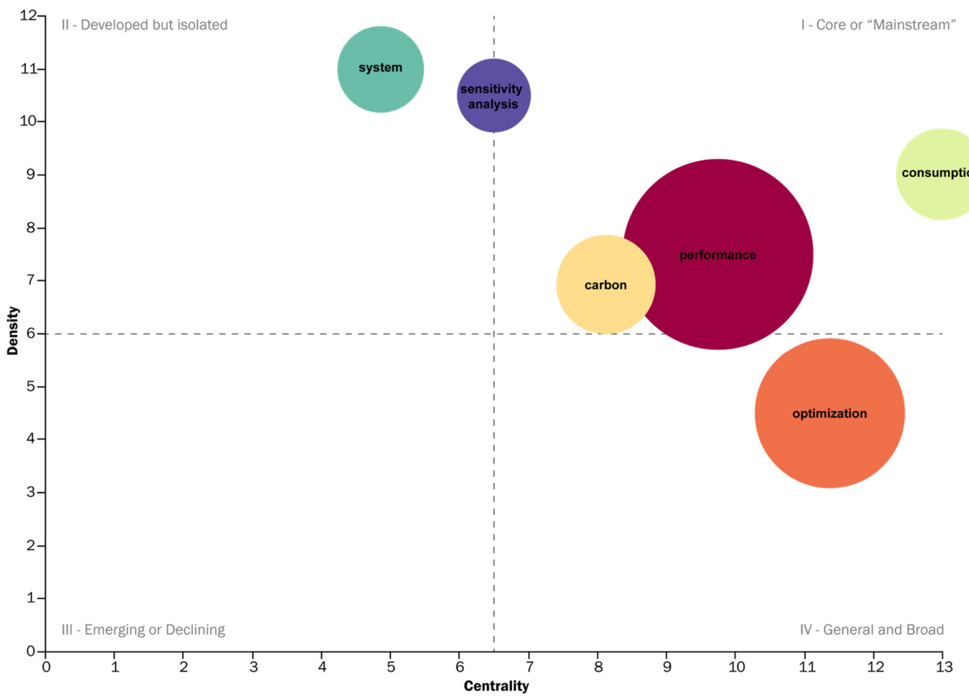

Figure 7. Density–Centrality diagram with keyword clusters.

4. Discussion

4.1. Background

The projected increase in global built floor area, projected to reach an overwhelming 235 billion m^2 by 2050 [27], stands as one of the main challenges stemming from population growth and ever-growing living standards [28]. Such a projection carries profound implications, spanning environmental, economic, and social dimensions. Given that buildings account for roughly 40% of the total energy consumption and 38% of the CO_2 emissions within the European Union [29], the global energy-saving potential is estimated at a staggering 53 Hexajoules annually by 2050 [30]. In this context, the role of building designers becomes paramount in harnessing this vast energy conservation potential. Moreover, as illustrated in Figure 8, sustainable building and city planning must face the pressing need for a holistic approach to energy and climate goals, integrating strategies for sustainable infrastructure that encompass fuel depletion, escalating energy prices, and climate finance, while also addressing the imperatives for healthier infrastructure and the urgent transition towards Net Zero Energy and Carbon buildings.

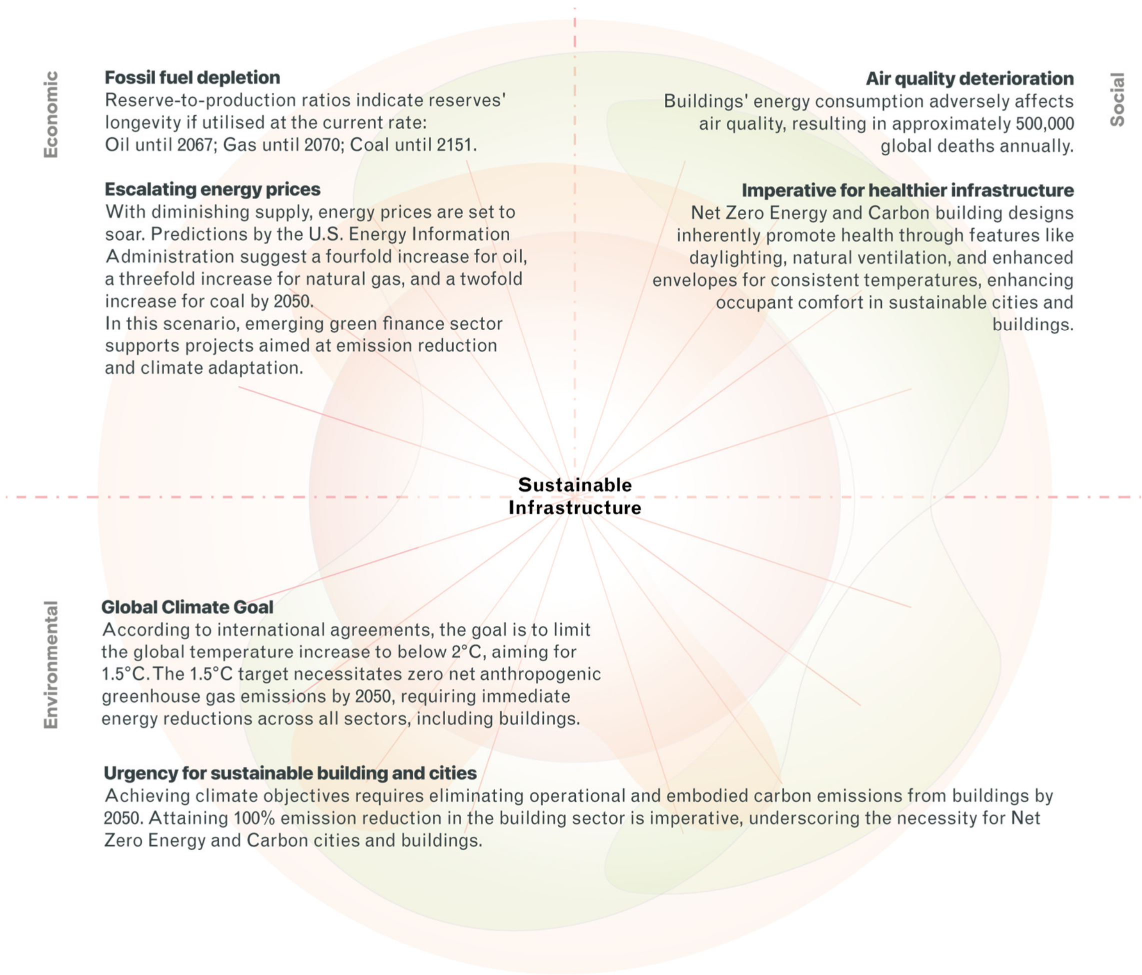

Figure 8. Sustainable infrastructure diagram.

Urban centres globally, in their pursuit of net-zero emissions, are tasked with the dual responsibility of curtailing greenhouse gas (GHG) emissions whilst also compensating for residual emissions. It is worth noting that emission reductions yield a plethora of benefits, encompassing enhanced community health, improved air and water quality, the mitigation of urban heat islands, and efficient resource stewardship.

Over the recent decades, BPSs have ascended as indispensable tools, assisting designers in navigating a multitude of design alternatives. Yet, these simulations encompass numerous variable parameters, giving rise to an expansive multi-dimensional "design space". Navigating this space necessitates significant modelling and computational endeavours, escalating costs and perpetuating inherent uncertainties [31]. Consequently, the feasibility of large-scale applications, encompassing design space exploration, uncertainty analysis, sensitivity analysis, and optimisation, remains constrained. However, the swift technological evolution, especially in the realms of data-centric and AI-driven BPS, presents unparalleled opportunities [32]. Such advancements hold promise to bolster sustainability initiatives, further carbon reduction agendas, and pave the way for more sustainable and inclusive urban development strategies.

The assimilation of AI systems emerges as a pivotal factor in addressing the multi-faceted challenges of urbanisation, spanning social, economic, and ecological dimensions. In this scenario, the European Green Deal [33] underscores the urgency for comprehensive, robust policy responses to the climate crisis, with an emphasis on optimising health, quality of life, resilience, and competitiveness dividends. Recognising the pivotal role of digital innovations, including AI, the Green Deal envisions them as instrumental catalysts in realising sustainability objectives across diverse sectors [33]. Concurrently, the EU's sustainable investment framework [34] and the revised EPBD [4] are geared towards incentivising energy sobriety in the built environment. These strategic policies are anchored in the ambition to curtail the GHG emissions and energy consumption in buildings by 2030, whilst setting sights on achieving EU-wide climate neutrality by 2050.

4.2. AI in the AEC Sector

The genesis of what we understand as AI today can be traced back to the 1940s. Pioneering work by American scientists Warren McCulloch and Walter Pitts in 1943 introduced a mathematical representation of the biological neuron, offering an early conceptualisation of an "artificial network" [35]. Over the decades, AI has evolved from isolated research endeavours in the 1950s to its current interdisciplinary nature, influencing numerous fields, including architecture [21].

As Song, Ghaboussi, and Kwon [36] have indicated, in the realm of architecture, the design process is uniquely multifaceted. The design exploration phase, often derived from abstract concepts, significantly influences various performance metrics, including energy consumption, daylight utilisation, and acoustics [37]. This initial design phase is pivotal, as it sets the trajectory for the subsequent construction and the building's entire lifecycle. AI's role in this context is not to provide definitive solutions but to aid in exploring potential design avenues [38]. While some design aspects can be quantified, many remain intangible, making it challenging to establish explicit evaluation criteria [39,40].

Beyond technological advancements, the successful implementation of AI in the AEC sector requires robust interdisciplinary collaboration. It is not just about integrating AI tools but ensuring that AI experts, environmental scientists, urban planners, and architects collaboratively harness these tools to create sustainable and efficient designs [41]. This collaborative approach ensures that the technological solutions align with the real-world complexities of urban environments and architectural challenges.

4.3. Metamodels and Data-Driven Models for Energy Forecasting

There has been a notable transition within the field of architectural design, moving away from conventional problem-solving instruments towards embracing optimisation as a tool for exploration, predominantly in the early design stages [42–48]. However, the real-world application of optimisation during these early stages remains limited. This limited application can be ascribed to various factors, including the intensive time requirements, difficulties in interpretation, constraints inherent to parametric models, and the frequently indistinct character of performance objectives in the realm of architectural design.

Buildings, throughout their lifecycle, contribute to both embodied and operational emissions. While construction primarily results in embodied emissions, operational emissions persist throughout the building's life. These operational emissions are influenced by evolving factors like climate change, electricity grid decarbonisation, and user behaviour. Notably, a discrepancy often exists between a building's design performance and its actual operational performance [49–51]. This 'performance gap' arises from complex interdependencies not accounted for during optimisation, such as building construction, supply systems, environmental parameters, and occupant behaviour. Considering the influence of global warming on the future performance of buildings, planning based exclusively on historical weather data proves to be inadequate. Therefore, it is of paramount importance to integrate uncertainty into building energy evaluations and meticulously assess the robustness of building energy systems in the face of the forthcoming conditions [50,52–54].

Metamodels, also known as data-driven models, act as approximate mathematical depictions crafted to explore the intricate relationships between inputs and outputs that are displayed by more sophisticated physics-based models [55]. Essentially, while mathematical models abstract the real world, data-driven models or metamodels abstract these mathematical models further [56]. Metamodels boast the advantage of being constructible from a modest dataset obtained through the simulation of physics-based models. These models are not only user-friendly but also allow for analytical expression in their formulations. After being adequately trained with a selected set of inputs and outputs from a physics-based model, metamodels possess the capability to forecast outputs for input values that were not part of the initial training set.

Conversely, data-driven models, which are trained using data harvested from real buildings, aim to emulate real-world scenarios rather than another model. For a data-driven approach to be effective, extensive long-term measurements across various building types are essential. Nevertheless, this method may predominantly be applicable to existing building stocks, thereby restricting the examination of alternative energy-efficient constructions. In contrast, the metamodelling approach is capable of efficiently producing the necessary database, thereby facilitating the use of virtually unlimited values for design variables.

All supervised metamodelling approaches follow a comparable procedure, which includes constructing representative samples of inputs for both training and validation purposes. For each set of inputs, a physics-based model is executed to generate the respective outputs. The metamodel is then trained with the gathered input–output samples utilising a selected technique, followed by a validation process using multiple performance indicators [32,57,58]. Upon the completion of these stages, the metamodel is ready for quick deployment in future BPS analyses.

Within the sphere of BPS applications, various techniques are prominently utilised, including polynomial regression, multivariate adaptive regression splines (MARS), the Gaussian process (also known as Kriging), SVM, and ANNs. For example, Romani et al. [59] applied polynomial models to metamodel the requirements of heating and cooling energy, contributing to the optimisation of the envelope design for a low-energy building situated in Morocco. In a similar vein, Cheng and Cao [60] devised a method for forecasting the energy performance of buildings, leveraging evolutionary multivariate adaptive regression splines. Furthermore, Rackes et al. [61] employed SVM to provide design guidance and performance labelling for passive commercial structures located in regions with hot climates. Additionally, Yuan et al. [62] utilised Gaussian processes to craft a method that simultaneously calibrates and ranks parameters for building energy models.

While the promise of AI-driven metamodels in energy forecasting is evident, it is essential to recognise their inherent challenges and limitations. The accuracy of the data, the dynamic and ever-evolving nature of urban environments, and the unpredictability of human behaviour can pose significant challenges to even the most advanced models. As the field progresses, the continuous refinement and understanding of these limitations will be crucial. Looking ahead, the intersection of AI and the AEC sector promises even more revolutionary changes. Emerging technologies and methodologies on the horizon could further refine and enhance the capabilities of AI in this field. As AI models become more sophisticated and data collection becomes more nuanced, the next decade could witness a transformative shift in how cities are planned, designed, and experienced.

4.4. AI and Cities

The European Commission's recent proposal for a regulation, known as the Artificial Intelligence Act, holds significant implications for the construction and urban development sectors. This act is a testament to the growing recognition of AI's transformative potential, especially within the construction ecosystem. It seeks to strike a harmonious balance in the deployment of AI systems, particularly for professionals in the construction sector who are increasingly relying on data-driven systems within the European Union. Key areas of concern for the AEC sector encompass the establishment of harmonised rules for AI systems, the delineation of specific requirements for high-risk AI systems, and the introduction of supportive measures to foster innovation [63].

In the broader urban context, cities are emerging as focal points in AI discourse. As underscored by the United Nations Habitat in their report titled "AI and Cities" [64], cities are uniquely positioned to harness the capabilities of AI to address a myriad of socio-economic and ecological challenges. As urban centres grapple with multifaceted issues ranging from resource constraints to governance complexities and mounting environmental threats, the infusion of AI-driven innovations is becoming indispensable. However, to truly capitalise on the transformative potential of AI, a concerted effort is required from various stakeholders to create an ecosystem that promotes sustainable and inclusive development. This necessitates a judicious balance between leveraging the opportunities presented by AI and mitigating the associated risks.

While numerous countries have proactively rolled out national AI guidelines [65], local governments, urban planners, and policymakers are navigating the intricate maze of developing, implementing, and evaluating regulatory frameworks tailored to their unique urban contexts. The rapid pace of AI advancements has opened up a plethora of potential applications in urban settings. The United Nations, in its deliberations, has spotlighted several sectors ripe for AI integration, including "energy, mobility, public safety, water and waste management, healthcare, urban planning, and city governance" [64].

One sector in which the impact of AI is particularly pronounced is energy. Data-driven systems, underpinned by AI, are poised to revolutionise energy management, propelling cities towards a more sustainable, low-carbon future. These systems are adept at forecasting the energy supply from various sources, facilitating predictive maintenance, and optimising energy distribution [64]. As urban landscapes increasingly pivot towards renewable energy sources, the role of data-driven models in forecasting, planning, and optimising energy consumption and distribution becomes paramount. These models can harness a diverse array of data to generate forecasts, offering insights into emissions and consumption patterns in intricate urban matrices.

However, for several years, climate datasets tailored to building performance simulations have been accessible, primarily due to the inception of an effective data format known as the typical meteorological year (TMY) [66]. This was further bolstered by the global availability of data in this format. Beyond merely expanding the global reach of these datasets, recent research endeavours have delved into techniques used to simulate local microclimatic events within urban landscapes, such as the urban heat island effect [67]. In a research study focused on London, Mavrogianni et al. amalgamated temperature profiles obtained locally with an Urban Building Performance Simulation (U-BPS). This integration aimed to elucidate the influence exerted by the urban heat island effect on not only the energy consumption of buildings but also on the well-being of the residents within these structures [68]. Concurrently, there is a burgeoning interest in forecasting local wind trajectories [69] and in aligning current TMYs with climate change projections from the Intergovernmental Panel on Climate Change (IPCC) [70]. These are pivotal research areas with direct ramifications for U-BPSs.

In many instances, researchers have amalgamated the export/import functionalities of existing platforms, such as Geographic Information Systems (GIS) and Building Information Modelling (BIM), with bespoke scripts. This approach facilitates the creation of a thermal model, oversees the simulations, and presents the findings through tools like spreadsheets or GIS applications [68,71–74]. Some teams have further refined and automated these simulation workflows, incorporating additional urban performance indicators to make U-BPS more accessible to urban planners and designers.

The efficacy of U-BPS models in informing design choices or policy decisions hinges significantly on the accuracy of the simulation outcomes. Considering the potential discrepancies between individual BPS predictions and actual measurements, due to variables like infiltration rates and occupant behaviours, one might question the U-BPS's capacity to authentically forecast energy consumption across numerous buildings. Yet, when juxtaposing aggregated yearly measured data against simulated energy usage spanning multiple structures, the individual model deviations appear to neutralise. This results in documented error margins of merely 7% to 21% for heating loads [73,75,76] and a range of 1% to 19% for the overall Energy Use Intensity (EUI) [77–80].

The integration of AI and machine learning models into U-BPSs has garnered considerable attention in recent years. Nutkiewicz and Jain (2019) delved into the amalgamation of physics-based building simulation methodologies and machine learning techniques, with a particular focus on transfer learning. Their exploration aimed to evaluate the effects of retrofit policies on urban structures [81]. This integrated methodology, dubbed Data-driven Urban Energy Simulation (DUE-S), showcased its potential in identifying the energy implications urban environments have on buildings undergoing retrofit processes. In a similar vein, Neumann et al. (2021) conducted an examination into the viability of establishing Positive Energy Districts (PEDs) within various urban typologies located in Wien [82]. Their work underscored the necessity of implementing extensive energy efficiency measures, promoting electrification, and harnessing renewable energy sources, as pivotal steps in the transformation of existing building stocks into PEDs. Moreover, the imperative of understanding the building stock at a larger scale, with a spotlight on building geometry, was accentuated by Dai et al. (2022) [83]. Their research unveiled a novel methodology designed to automatically gauge the building dimensions derived from remote sensing data, employing unsupervised machine learning algorithms in the process. Concluding their series of studies, Hey et al. (2022) stressed the crucial role of modelling in the adoption of energy retrofits within urban residential building stocks. They introduced an innovative concept in which carbon valuations are assigned to households, serving as a determinant for identifying optimal retrofit solutions [84]. Their approach combined surrogate models, optimisation procedures, and neural networks to evaluate building performance, offering insights into the potential of such models in informing policy decisions.

These AI-driven models are equipped to provide granular insights into the energy demand within buildings [85], elucidate energy dynamics in urban microclimates [86], and categorise distinct energy demand patterns [87], thereby facilitating more informed decision-making.

4.5. Frameworks and Workflows

The integration of artificial intelligence in the AEC sector has seen the emergence of various frameworks in recent times. Geraldi and Ghisi [88] introduced a seven-step framework that seamlessly integrates surveying, data collection, and ex-post analysis. This framework trains an Artificial Neural Network to predict a building's performance with high precision.

In contrast, Mouakher et al. [89] delved into the realm of explainable deep learning models (XAI) to address the "black box" nature of traditional neural networks. Their approach aimed to provide more transparency and an understanding of how these models make decisions.

Dong et al. [90] underscored the imperative for a framework that can intelligently automate the design process with a concentration on daylight and energy performances. Within the workflow of energy-efficient design, they identified three predominant knowledge gaps. The initial gap is the ambiguous correlations existing between different building components, resulting in repetitive modelling in the course of adjusting parameters within building information models. The subsequent gap involves the necessity for the generation of optimal alternatives that exhibit the desired performances. The third and final gap is the indispensable need for a method of decision-making that is effective, serving to sift through and select the most appropriate design plan. The task of assessing a framework's efficacy in implementing an energy-efficient design is fraught with challenges. This scenario necessitates the need for a process that is automated from start to finish, spanning from building information modelling to the final stages of decision-making. Furthermore, there is a call for a method of decision-making that is not only effective but is also seamlessly integrated with an algorithm dedicated to optimisation.

In the urban context, the rise of U-BPS tools has been notable. These tools expand the application of BPS to the urban level, leveraging physics-based methods and incorporating statistical approximations to address computational, data, and statistical challenges. The surge in U-BPS frameworks [91] can be attributed to global carbon reduction commitments, increased accessibility of urban datasets [92], advancements in computational tools, and affordable hardware.

U-BPSs are designed to provide data-driven insights applicable to a variety of urban-level scenarios, including urban planning initiatives, the development of new neighbourhoods, strategies for reducing carbon at the stock level, and the integration of buildings into the electrical grid [93]. The simulation results from U-BPSs can be aggregated and displayed at various temporal and spatial scales, contingent upon the use case in question. For example, a U-BPS that is crafted for the purpose of formulating policies for retrofitting buildings city-wide may employ an archetype approach. This approach involves simulating the distributions of energy usage for different types of residential buildings. However, to obtain accurate results at the level of individual buildings, a calibration process that is conducted building by building and is based on actual data is necessary [94]. There are various approaches available for the development of U-BPSs [95]. At its most basic, a U-BPS will incorporate the fundamental geometries of buildings, files pertaining to the relevant weather, and templates for building simulations that represent various categories of buildings [86].

Tardioli et al. (2019) introduced a novel feature engineering procedure that combines results from calibrated physics-based building energy models with traditional predictors in a forecasting framework, demonstrating improved forecasting outcomes for the heating demand in urban districts [96]. Xu and Wang (2023) presented a comprehensive methodological framework for urban decarbonisation strategies, emphasising "the integration of multi-scale energy performance evaluation within the design development process" [97]. Their data-driven methodology, utilised in a Sheffield, UK, case study, assesses scenarios of energy demand and supply at the urban level. Monien et al. (2017) highlighted the challenges in building energy evaluation tools, particularly the balance between data availability and the assumptions made [98]. Their research compared two tools based on 3D models, demonstrating the scalability of their urban simulation tool, SimStadt, from single buildings to city districts. Moreover, as encapsulated by Cappelletti and Ballarini (2021), the Building Simulation 2019 conference spotlighted recent trends in the applications of building simulation. It underscored the amalgamation of various pre-existing tools aimed at evaluating comprehensive building performance while aiding both the design and control processes of buildings [99].

5. Conclusions

This paper has conducted a literature review to chart the progression of artificial intelligence within the AEC sector, focusing on its integration into building performance simulations and its integration into the broader design process.

The review has identified a marked shift in the application of AI tools. While the use of AI for BPS at the building scale is becoming increasingly established, there is a notable emerging trend in its application for larger-scale projects, such as neighbourhood-scale developments or master plans. In these contexts, the literature highlights AI's value in facilitating complex calculations and analyses that surpass the capabilities of traditional BPS methods. This trend underscored a growing recognition of AI's potential to handle the complexities and nuances associated with achieving energy efficiency and decarbonisation objectives within the AEC sector.

Despite these advances, several open questions persist. The research has identified a large number of systematic methods for incorporating data-driven BPS in the early design stages and a need for clarity on how these tools can best support the sustainability goals. Central to the conclusions of this review is the advocacy for a coherent framework that delineates how AI-driven BPS can be embedded into design workflows. Such a framework would streamline the adoption of AI, ensuring it is effectively leveraged to optimise design choices, particularly those impacting sustainability and energy efficiency. This proposed framework would serve as a cornerstone for future research, guiding the development of actionable strategies that harness AI's full potential in the design process.

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