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Architecting net zero: from drawings to bytes

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ABSTRACT

Every profession across the globe has been affected by computers in the last decades. Most of the day-to-day jobs are about creating and managing data and the processes include inputs, storage, transfer and output. The construction industry is no exception and has been affected by modern processes. Besides, the entire ecosystem of the construction industry from material manufacturing to usage and demolition is a carbon emitter. The role of the industry in achieving global sustainability targets is significant and the overall construction ecosystem seems to be evolving toward net-zero targets and various tools from design to construction are contributing to this goal. This research surveys the existing literature on significant data generators in the construction, and management systems and how data can be used or are used for net-zero delivery of buildings in the UK. It demonstrates a path to move away from analogy and intuition in building design to a path that is inspired by approved data-driven methods. This study highlights the lack of universal protocols in data management especially in net-zero delivery, the lack of clarity on the required data to effectively reuse building components for lower emissions and most importantly how disruptive industry 5.0 could be when interoperability issues are unsolved among AEC professionals and cloud-based data sharing is still advancing.

1. Introduction

The Fourth Industrial Revolution has undoubtedly led to an inundating amount of data in different industries and construction is no exception. In particular, data in architecture is associated with geometry, technical standards and building performance. The standards include technical information about space and building requirements and performance aspects of buildings such as energy and comfort. However, decisions in the architecture discipline can be subjective and objective depending on whether decisions are made based on data or designer intuition. Deutsch [1], in Fig. 1, shows the sequences of decision-making in architecture. In this study, architectural design covers concept, developed design and technical details containing information for the construction and operation of a building. The design is not only for aesthetics but also is an integrated activity that requires the contribution from engineers and building consultants and therefore the illustration may not be very accurate and comprehensive. For this research, we exclude the work of urban, landscape and interior designers.

The definition of data analysis is context-specific and it could be of quantitative or qualitative nature [2]. In design contexts, the visualisation of data is crucial for its interpretation and arguably visualisation is interpreted as analysis [3–5] calls the combination of data analysis with interactive visual interfaces as visual analytics even though the terminology is rarely used in architecture practices and research papers despite its popularity and significance in environmental data collection such as temperature, humidity and velocity measurements [6] and immersive applications [7].

Recent studies focused on aligning data analysis with carbon emissions and net-zero in construction [8]. reviewed data-driven forecasting methods with particular attention to occupants' behavior to reduce energy [9]. focused on Building Information Model-

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Fig. 1. Decision-making spectrum [1].

ling and the Internet of Things (IoT) and demonstrated how construction and operational efficiencies can be improved using such tools and related methods [10]. reviewed data-driven approaches used in building energy analysis including artificial neural networks, support vector machines, statistical regression, decision trees and genetic algorithms as well as K-mean clustering, self-organizing map and hierarchy clustering and demonstrated energy-saving possibilities in macro-scale. Similar studies [11–15] also used data-driven algorithms for building controls and they all reported significant energy saving potential. Data-rich models like Digital Twins (DT) are also developed and investigated in different disciplines and in AEC benefits are reported in manufacturing [16,17], improving life-cycle management [18,19] and smart operation and reducing operational energy needs [20]. National Infrastructure Commission (NIC) reported the development of DT could add 10 % to the UK economy by 2030 [20].

Furthermore [21], looked at the factors that may shape the UK's digital Built Environment and developed scenarios of how the country can reach the Sustainable Development Goals (SDG) set by the UN. Their study concluded Data Economy, DT, Data Regulation and Policy, AI, and IoT are among the vital factors. In a similar vein, the importance of Data-Driven approaches to develop a circular economy is also highlighted by [22,23]. Data-driven approaches for health and safety in BE have also been used to control the virus spreads [24–26] and assess the protocols [27]. The aim of this paper is to address the following questions that are pertinent to its focus. This paper will investigate these questions in detail and provide insights based on the current status of the research.

- How objective are the current AEC practices and how achievable are data-driven practices for net-zero delivery?
- Are the existing data foundation robust enough to achieve net zero?

In this study, applications of data in architectural design and its relevance to net zero in AEC are reviewed. The review is organized in the design stage, Information Modelling, Simulation, computational design and manufacturing, smart buildings as well as buildings post-life (demolition) It should be noted that there are overlaps in each section but each process and application are thoroughly reviewed.

2. Methods

A systematic review in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) statement is used for this paper to ensure the review process is rigorous, transparent, and replicable. To develop a foundation for the thematic analysis, key terms related to data-driven design and operations were identified based on a seminal study by Holton in the 1970s [28]. The aim of thematic analysis is to analyze qualitative data and use them to address the research questions. Fig. 2 demonstrates the overview of the overall methodology and filtering agenda. The first step involved a comprehensive search of the Google Scholar database to identify relevant studies. The second step involved screening the studies based on their titles and abstracts to exclude those that did not meet the inclusion criteria. The third step involved a full-text review of the remaining studies to assess their relevance. Finally, the data were extracted from the selected studies and analyzed using thematic analysis to identify key themes and patterns.

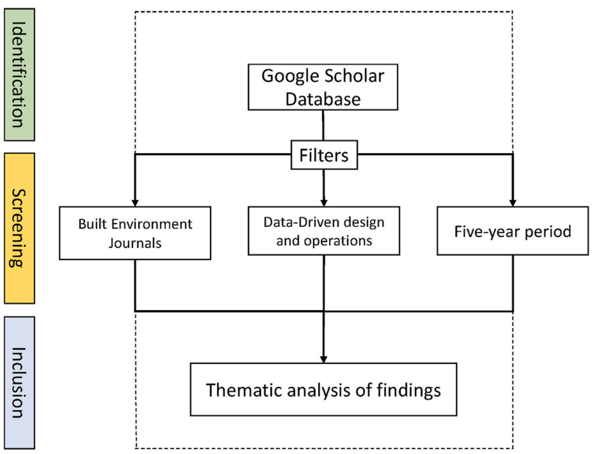

Fig. 2. Overview of the overall methodology.

3. Design stage

The use of Computer Aided Design (CAD) in the AEC industry was first established in 1962 by Charles Eastman and the commercial sale of a CAD programme incurred in 1982. From the very beginning, the CAD programme had two separate systems: entity-based (using vector graphics) and object-based (using complete parametric objects) [29]. In each system, forms are created by designers which represent a functionality and meaning even though abstract in entity-based systems. The data contained in a CAD model is a response to a client brief, site context, standards, etc. The efficiency of the model and its qualities can be judged in different stages as the process is evolutionary and fluid.

Today's architectural drawings are more than drawing sets, they are data-rich models that construction firms use to document projects as a way to supply data for downstream applications. The current ecosystem of digital tools for visualisation includes a variety of options and data sharing has been improved among construction firms even though the information sharing is rather inefficient [30]. The most common file extensions and what they generally contain in the design stage are shown in Table 1. The content of these files includes a wide range of data as shown in Table 2.

Most of the aforementioned data are used in design development and alignment with net zero lies in how Passive Design Approaches (PDAs) are utilised and how effective they might be when buildings are in operation. The significance of PDAs is well documented and since 2018 over 9000 papers have been published that highlight and quantify their impact globally. PDAs are also vital for energy ratings and building standards worldwide [32].

3.1. BIM models

Building Information Modelling (BIM), project and document management software, 4D simulations and visualisation tools are in use throughout the industry. BIM contains diverse models and semantic data of projects for users [6]. The layers in BIM models are connected and as the project develops, data size increases. The use of BIM tools in the AEC industry is growing and the data that is produced by such tools comes in many formats. Some of the formats are exclusive to certain companies and have a commercial nature and some are non-proprietary building data models. The most popular non-proprietary one is the Industry Foundation Classes (IFC) data model [33] developed by the International Alliance for Interoperability (IAI) [34]. Each IFC contains the following 4 layers [35]:

- Resource Layer (generally includes main data such as geometry and typology)
- Core Layer (includes the basic structure of the object model)
- Interoperability Layer (includes shared building elements and concepts for interoperability)
- Domain Layer (further details)

There are a number of software products that can generate IFC and other data models. Table 3 demonstrates the types of data and wherein the AEC industry they are generally produced.

Table 1
File extensions in the design stage.

DWG	The file can contain 2D and 3D drawing
SKP	Only contain 3D drawing
RVT & RFA & GSM	Contain all elements and construction information
RTE	Templates help speed up the design process, standardize designs, and retain relevant information on the styles and visualizations of projects.
PLN	Equivalent to RVT with the same content
TPL	TPL contains all the preference settings of a project, including default project elements and tools for Archicad templates.
BIMx	It can contain all the project documentation in the Archicad software, including 3D geometries, views, designs, etc.
3Ds & 3Dm	3DS is one of the most common file formats used by the Autodesk modelling, animation, and rendering software 3ds Max. The 3DM extension corresponds to files generated by the Rhino3D modelling program, based on NURBS technology.

Table 2
Data contained in architectural files.

Attributes	Qualities in any composition
Composition, Organisation, pattern and hierarchy	Elements that create any arrangement or repetition
Context	Environment or settings
Elements and Mass	Major components of a composition: color, line, shape, etc. The collective weight of elements creates Mass
Gestalt	Visual perception of whole – A Psychological term [31]
Model	A computer medium that translates ideas. A model contain a framework for any project
Plan, Section and Elevation	2D Architectural visuals containing information about boundaries, material, space sizes, etc.
Proportion	The ratio of different objects in relation to each other
Relationships	Shared features among different elements that connect them either physically or visually
Space	An area/s which functions occur
Texture	Patterns of surface
Tint, Tone and Shade	A reference to degrees of light and dark

Table 3
Types of data and their context in the AEC industry.

Sub Category of Construction	Type of Data
3D models	Graphical and non-graphical models are used for architectural design [36]
Carbon Data	Thermal simulations and LCA (WY.[37,38])
Project management	Hard clash, soft clash (rule-based), 4D clash (time management) [39]
Facility management	Point-cloud data [40]
Construction Safety	BIM-Based health and safety platforms for construction sites [41,42] (H[43])
RFID	logistics and on-site assembly construction [44]
Urban Planning and Urban Design	3D urban maps, meteorological data [45]

BIM is a shared data resource of a building and the process has widely been utilised for energy efficiency [46,47]. For example [48], proposed a performance-integrated BIM (P-BIM) framework for energy efficiency that contained building ontological data, external related data, simulated performance data and monitored performance data and through a case study, it demonstrated an improved air quality and energy costs [49]. also developed a framework by utilising data from BIM and Building Energy Management Systems (BEMS) to predict data accuracy. They used a gbXML file to transfer data between models. GbXML is now widely used by leading BIM vendors to transfer building information stored in CAD-based building information models for analysis software. Similarly, [50] utilised the interoperability potential of BIM tools and presented a framework to optimize both embodied and operational energy in buildings and [51–53] demonstrated BIM potentials for energy savings in refurbishments in various contexts.

3.2. Simulation and performance modelling

Computer simulation is an alternative method to evaluate building performance. This approach uses a software to replicate reality [54]. A wide range of simulation tools are available that run on the basis of inputs and provide data on physical processes such as heat transfer, thermal bridging, structural integrity, etc. Required inputs and potential outputs are shown in Fig. 3. The supporting mathematical models could be static or dynamic, linear or non-linear, deterministic or stochastic, discrete or continuous. One way of classifying them is on the basis of the link between their input and output. The categories are known as black box, grey box or white box. When the level of theoretical modelling is high and the level of experimental (machine learning) is low then this is a white-box category, if the level of theoretical modelling is low and the level of experimental modelling is high then it is categorized as black box and the grey box is between the white and black. Fig. 4 shows the approaches, inputs and available software in each category.

Even though simulation is one of the most commonly used tools available for building studies and the construction industry, there is an issue of a ‘performance gap’ between predicted and measured performance [55]. A wide range of factors affect the inaccuracy of simulations including data quality [56], users' physiological and psychological characteristics and behavior [57] materials defects [58] and site labour errors [59]. The success of simulation prediction is also associated with Building Management Systems (BMS) which is a combination of hardware and software layers to control and monitor building performance [60].

Data is critical to building simulation as it allows designers and engineers to create accurate models of buildings that reflect their real-world behavior. Without data, simulation models would be incomplete and inaccurate, leading to suboptimal design decisions and potentially significant energy waste [61]. used a combination of Wi-Fi-sensing and machine learning methods to increase the accuracy of simulation tools by focusing on user behaviors and found the methods are up to 7 % more accurate in a residential building

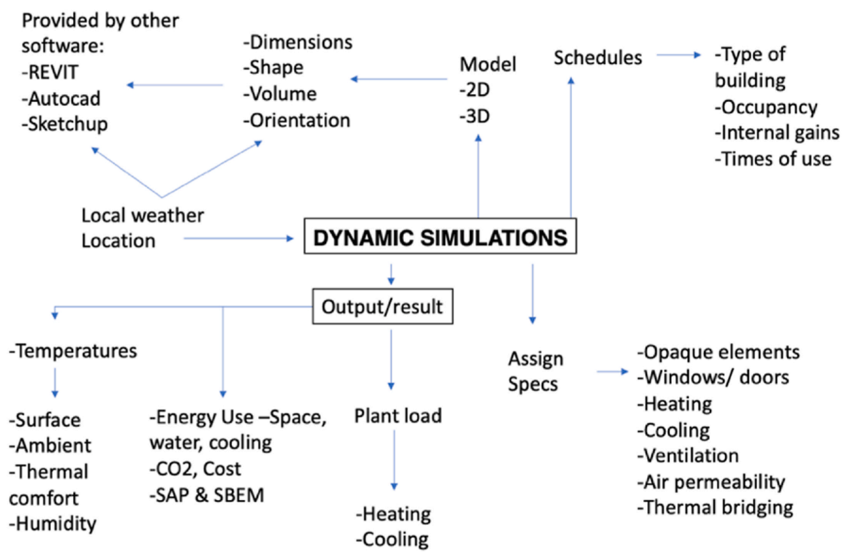

Fig. 3. Simulation tools, inputs and outputs.

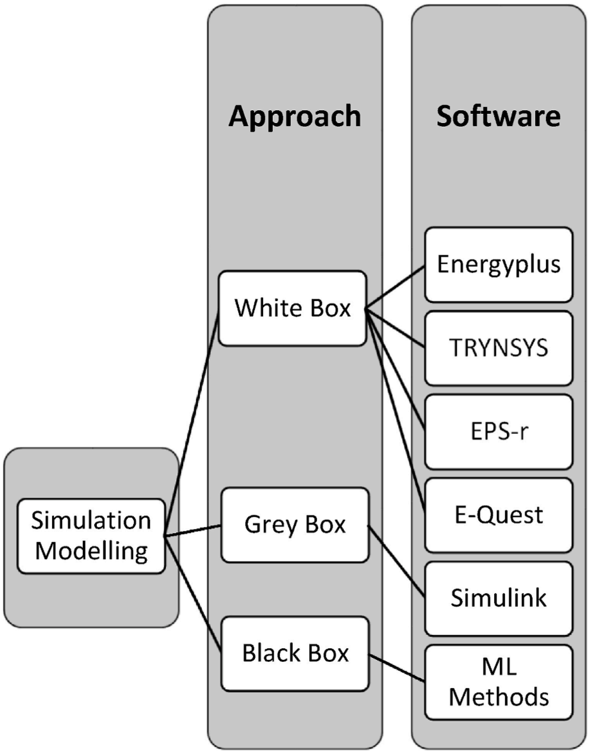

Fig. 4. Approaches, inputs and available simulation programs.

in cold climate climates. The accuracy of simulation modelling has largely been connected to user behavior modelling. The existing simulation tools seem to largely over-simplify the behaviors and the lack of accurate data led to the BPG [62]. The majority of the screened studies looked at occupant movement within different zones, window operation, lighting operation, thermostat adjustment, appliance use, solar shading operation, clothing adjustment or a combination of all. Table 4 shows the studies and their contributions.

The study of user behavior is crucial for simulation accuracy and most studies use machine learning methods to identify patterns, trends, and opportunities for improvement, and develop strategies to meet user needs and expectations. Data and user behavior are interrelated and essential components for understanding and optimizing digital experiences.

3.3. Computational design and manufacturing

Design projects based on computation have developed significantly since 2000 and are now a popular approach in some practices and among researchers across the globe. Computational Design (CD) is also known as Algorithmic Design (AD) or Generative Design (GD) and has similarities with Parametric Design (PD), the main difference is that PD does not necessarily use generative approaches [80]. Schumacher [81] noted PD is “a conceptual shift from part-to-whole relationships to component-system relationships, system-to-system relationships and system-subsystem relationships” and the process has bold themes of versioning (variations of a certain design), iteration, mass customization and differentiation.

CD and PD are both object-oriented and objects have attributes and rules that create shapes and forms. Such approaches are based on artificial intelligence, mathematics, geometry and cognitive science. Very limited literature exists to evaluate the effectiveness of CD methods on energy savings and moving toward net zero ambition. The very first attempt to use CD as an energy-saving approach was accomplished by Ref. [82] in 2004 [83]. used the CD method to optimize daylights in buildings and influence energy savings

Table 4
User-centred studies and their outcome.

Authors	Year	Focus	Outcome
[63–66]	2017, 2018, 2014, 2012	User movements	No geodetic theory and highly focus on sensors and machine learning methods for higher accuracy.
[67–74]	2017,2018,2019	Window operations and solar shading	Indoor Temperature and humidity are driving factors and machine learning methods are the main method for evaluation and modelling
[75,76]	2018, 2019	Lighting Operation	Part of the Automation process and big data analysis as a foundation for its future development
[77–79]	2018, 2019	Thermostat and clothing Adjustment	Design impact is critical and the machine learning process to record and operate can offer energy savings. ASHRAE-55 standard is the reference point in most thermal comfort studies.

[84]. used the CD method for adaptive façade design and reported a reduction in energy consumption in their case studies by 14.2–29 %.

Architectural design is a close discipline to manufacturing as both fields are based on spatial relationships. Big data, data analytics, predictive analysis, machine learning and artificial intelligence are widely used in manufacturing processes globally [85,86]. Additive manufacturing and offsite construction are where data and analytical processes are mostly used in the AEC industry [87] and traditional construction methods only rely on traditional architectural visuals.

3.4. Smart buildings

Smart buildings are defined by Ref. [88] as those run by Information and Communication Technology with relevant equipment such as sensors and actuators that generate data on building performance, occupant behavior and environmental conditions etc. The most common types of data used during the lifespan of such buildings include:

- Environmental data: This includes information on temperature, humidity, air quality, and other environmental factors that affect building performance and occupant comfort.
- Energy consumption data: This data includes information on how much energy is being used by various building systems, such as lighting, heating, ventilation, and air conditioning (HVAC), and other appliances.
- Occupancy data: This data includes information on how many people are in the building, where they are located, and how they are using the building.
- Maintenance data: This data includes information on the condition of various building systems and equipment, as well as data on maintenance schedules and repair history.
- Weather data: This data includes information on current and forecasted weather conditions, which can be used to optimize building operations and reduce energy consumption.
- Security data: This data includes information on security systems, such as cameras and access control systems, as well as data on incidents and security breaches.

The data is collected, analyzed, and used to optimize building operations and reduce energy consumption. Therefore, a large amount of data is created during the building life span [89]. Smart buildings leverage data to improve energy efficiency, comfort, and safety for their occupants. Such buildings are equipped with sensors, meters, and other devices that generate data on building performance, occupant behavior, and environmental conditions. The data is collected, analyzed, and used to optimize building operations and reduce energy consumption.

[90] looked at the smart building when integrated with PV panels and emphasized the potential of AI but the whole process requires policy development. Data from HVAC and renewable sensors can be used to optimize heating and cooling schedules, ensuring that the building is only heated or cooled when it is needed. Similarly, data from lighting sensors can be used to adjust lighting levels based on occupancy. In addition to optimizing energy efficiency, data can also be used to improve occupant comfort and productivity not only at the building scale but also at the urban scale [91]. Data can also be used to enhance building security in smart operations [92].

4. Post life

Very little literature exists to highlight the importance of demolition in the dynamics of building stocks. Outdated buildings and remaining elements are material supplies for present and future needs [93]. A very wide range of research exists that suggests the importance of recycling to reduce carbon emissions from manufacturing materials [94]. Due to the importance of the reserves, Thomsen et al. [95] referred to them as urban mining. Some of the key materials in construction like Ordinary Portland Cement are responsible for 5–7% of global Carbon Dioxide [96]. Table 5 summarises the studies looking at the data and demolition purposes.

By leveraging data, demolition professionals can make informed decisions and develop strategies that minimize the impact of the demolition process on the environment and surrounding communities.

Table 5
A summary of studies on data and demolition.

Type of Data	Relevance
Historical Data	Historical data on the building's construction, materials, and previous renovations can help inform the demolition process. This data can be used to identify potential hazards and develop a plan for safe and efficient demolition [97]
Environmental Data	Data on the surrounding environment, such as air quality and noise levels, can help ensure that the demolition process does not have a negative impact on the environment or nearby communities [98,99].
Waste Management	Data on the types and quantities of materials to be removed during the demolition process can inform waste management strategies. This data can be used to identify opportunities for recycling or repurposing materials, which can help reduce waste and minimize environmental impact [100].
Safety Data	Data on safety hazards, such as asbestos or other hazardous materials, can help ensure that proper safety protocols are followed during the demolition process. This data can also inform the use of personal protective equipment and other safety measures to protect workers and the surrounding community [101].

5. Conclusion

The world population will hit 8 billion in 2022 and new construction starts every day. In the UK, from between April 1, 2021 and March 31, 2022, 37,164 houses were completed [102]. This paper provides a much-needed review of the data ecosystem in the AEC industry, where and when data is generated and how it is been used. Compared with other industries, the use of big data is rarely used in practice and examples are limited in scope and slowly developing. However, for the net zero goal, the carbon emissions should be counted throughout the building's life cycle. This has caused the development of the ecosystem of software and data generators. This paper clarified the sources of the data in the building design and construction process which was to the best of my knowledge, the very first effort of an in-depth review of the data terminology in different construction phases, data applications and the likely size of it and how it is used for lowering emissions. Below are the key findings of this research:

- Undoubtedly the ecosystem of the data-driven approaches includes a wide range of tools to design, model, predict and construct more efficient buildings adaptable to different locations but universal protocols to use the tools are not developed enough or flexible enough for rapid expansion.
- The AEC industry lacks clarity on the data needed to effectively reuse building components, and how this impacts the modelling and design processes.
- Whilst the industry 4.0 concepts and adaption methods are progressing and underdeveloped in the AEC industry the introduction of the industry 5.0 concept is disruptive for the unprepared industry.
- The definition of 'big data' in the context of AEC requires revisions, the data analytics and approaches from other disciplines are widely used however the terminology is not well-defined.
- The well-documented problems of interoperability seem to expand and cause barriers to more advancement of Cloud-based data sharing.
- Business models in data-sharing are yet to be developed in the AEC industry. E-Sourcing and E-Procurement are not yet developed and no platform yet exists for reuse, and recycle necessities for net-zero delivery.

CRediT authorship contribution statement

Seyed Masoud Sajjadian: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

I wish to draw your attention to the following facts which may be considered as potential conflicts of interest and to significant financial contributions to this work.

I wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

I confirm that there is only one author for this paper.

I confirm that I have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing I confirm that I have followed the regulations of ENU concerning intellectual property.

I confirm that I have provided a current and correct email addresses for communications.

Data availability

No data was used for the research described in the article.

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