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Integrated Workflow Development for Data-Driven Neighborhood-Scale Building Performance Simulation

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As urbanization intensifies, cities are key contributors to energy consumption and carbon emissions, accounting for a significant portion of global energy use and CO_2 emissions. This paper introduces a systematic approach to support the development of urban projects with minimized operational carbon footprints through the integration of data-driven building performance simulation (BPS) tools in early-stage design. Emphasizing the necessity for a collaborative effort among designers, policymakers, and other stakeholders, we discuss the evolution of BPS toward incorporating data-driven tools for energy need reduction and informed decision-making. Despite the proliferation of modeling methods and data-related challenges, we present a theoretical workflow, supported by interactions with design firms in the US and European Union (EU) through interviews. This structured approach, demonstrating adaptability and scalability across urban contexts, foregrounds the potential for future data-driven integration in design practices. Grounded in theoretical concepts and preliminary real-world insights, our work emphasizes the transformation of standard activities toward data-driven processes, showcasing the crucial role of practical experience in advancing sustainable, low-carbon urban development. [DOI: 10.1115/1.4066565]

Keywords: cities, energy, environment, integrated design, data-driven, workflow, sustainability

Introduction

The urban landscape has undergone a systemic transformation since the industrial revolution, evolving into the epicenter of energy consumption and carbon emissions [1]. As of today, more than half of the global population resides in cities, which are responsible for a staggering 75% of global carbon emissions [2]. This percentage is projected to rise even further, given that the urban population is expected to double by 2050 [3]. Within this intricate social and urban fabric, buildings emerge as a critical component, accounting for approximately 40% of total energy consumption and 38% of CO_2 emissions in the European Union (EU) [4]. These numbers underscore the pivotal role that buildings play in the global carbon equation. The journey toward carbon emissions reduction in cities involves multiple intricacies and unforeseen factors. Tackling this issue necessitates a detailed comprehension of the energy use patterns within building clusters and the identification of effective measures to reduce this usage. A collaborative effort between architects, policymakers, building managers, and occupants is essential, harnessing collective knowledge to formulate and execute effective, cost-effective actions [1].

At the core of informed architectural design choices lies building performance simulation (BPS), as illustrated in Fig. 1. These tools influence each stage from pre-planning to the building's operational phase, with its impact most pronounced during the design development phase. In response to changing regulations that advocate for environmentally friendly and efficient infrastructure, BPS has evolved, integrating comprehensive and accurate data within the design workflow. The advent of the digital era has brought an inflow of data, which have facilitated the integration of advanced analytics, including artificial intelligence (AI) and machine learning (ML), into BPS processes. This progression heralds not just refined simulation capabilities but also their potential incorporation from the earliest design stages.

While the potential of data-driven models is unquestionable, especially with their capability to deliver quick and reasonably accurate estimates of energy consumption, it is important to recognize that surpassing traditional BPS methods is not a straightforward task. These new models, promising as they are, face challenges in fully replacing established BPS methodologies due to various complexities and entrenched practices in the field.

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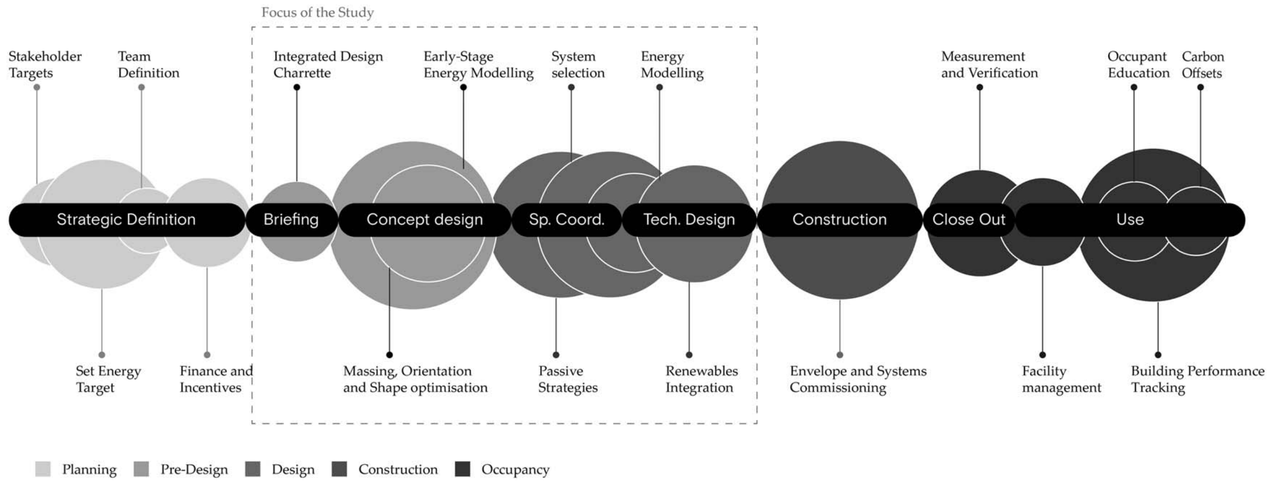

Fig. 1 Overview of the integrated design process for sustainable neighborhood-scale design, detailing stages from strategic definition to building use with a focus on energy and sustainability targets (from Ref. [40])

Numerous reviews have analyzed tools, simulation techniques, and algorithms [5,6], and related metrics and evaluation mechanism [7–9]. However, our study focuses on how data-driven instruments are incorporated into the Architecture, Engineering, and Construction (AEC) industry's practices. While numerous studies have analyzed possible integrations with design processes [10–14], there is a lack of a coherent workflow that identifies defined areas for the integration of data at the initial phases of the architectural design process at the urban scale, while identifying roles and responsibilities for each actor involved.

Literature Review

In the context of current climate urgency and the intricate urban environments we inhabit, it is increasingly vital to consider architectural design from a holistic perspective, in terms of its neighborhood and urban scale impacts. This shift reflects an evolving understanding of architecture's role within the broader picture on sustainable urban development carried on by various organizations worldwide.

As we recognize the imperative role of urban design in sustainability, it is equally important to explore the burgeoning potential of AI in enhancing these efforts. AI's capabilities to predict and optimize energy performance at an urban scale represent a critical intersection of technology and sustainable development, paving the way for regulatory measures.

The European Commission's recent proposal for a Regulation, known as the Artificial Intelligence Act [15], reflects an increasing awareness of AI's groundbreaking capacity, especially within the realm of construction and urban development. This legislation aims to establish a measured application of AI technologies, specifically for the construction industry within the European Union's borders.

Crucial considerations for the AEC domain include the formulation of standardized protocols for AI systems, setting stringent criteria for AI deemed as high risk, and fostering an environment conducive to innovation [16].

Urban clusters are becoming epicenters for AI application, as highlighted by the United Nations Habitat's report "AI and Cities" [17]. Cities stand at the forefront of leveraging AI to tackle a spectrum of social, economic, and environmental issues. Amidst the challenges of resource scarcity, administrative complexities, and escalating ecological concerns, AI's role in driving progress is becoming increasingly vital. Success hinges on a collective approach by stakeholders to cultivate an ecosystem that underpins sustainable and inclusive growth, balancing AI's benefits against potential risks.

While national AI strategies are in place [18], local authorities, urban developers, and policymakers are meticulously developing and refining AI regulatory structures specifically suitable for urban landscapes. The speed of AI advancements unlocks countless urban applications, with the United Nations pinpointing sectors such as "energy, transportation, public safety, and urban governance" for potential AI integration [17].

The energy sector, in particular, is undergoing a transformative shift through AI-enabled systems, advancing toward sustainability and reduced carbon emissions. AI supports the prediction of energy production, predictive maintenance, and optimization of energy distribution [17]. The global trend to transition toward renewable energies accentuates the necessity for data-driven forecasting and energy management within urban settings.

Datasets for BPS have become increasingly sophisticated and widely available, in part due to the establishment of a typical meteorological year (TMY) format [19]. Research has expanded to include microclimatic phenomena, like urban heat islands, within these simulations [20]. Studies such as those by Mavrogianni et al., which integrated local temperature profiles into urban building performance simulations, highlight the urban heat island effect's impact on energy use and inhabitant comfort [21]. Alongside this, there is an escalating focus on the prediction of local wind patterns [22] and the adjustment of TMYs to align with the climate predictions issued by the Intergovernmental Panel on Climate Change (IPCC) [23]. These research endeavors are crucial, with immediate implications for urban performance simulations (UPS).

Moreover, scholars have integrated the import and export capabilities of platforms like geographic information systems (GIS) and building information modeling with custom scripts. This synthesis enables the construction of thermal models, manages the simulations, and facilitates the visualization of results using spreadsheets or inside the GIS itself [21,24–27]. Some research groups have taken this a step further, enhancing and automating these simulation processes and including additional metrics to improve the utility of UPS for urban designers and planners.

The trustworthiness of UPS in shaping design and policy largely depends on the accuracy of its predictions. The discrepancies between predicted and actual energy usage, influenced by factors like actual energy use patterns, air infiltration, and occupancy patterns, may cast doubts on the capability of UPS to accurately project energy consumption on a broader scale. However, the comparison of collective data from actual yearly energy usage to simulated figures across several buildings tends to show a balancing out of individual discrepancies, with documented error margins ranging from 7% to 21% for heating loads [26,28,29] and between 1% and 19% for total energy use intensity [30–33].

In this scenario, the assimilation of artificial intelligence and machine learning into UPS has been a subject of increasing scholarly focus. Research by Nutkiewicz and Jain [34] probed into the integration of traditional physics-based simulation with machine learning, particularly transfer learning, to assess how urban retrofitting policies affect buildings. This innovative approach, termed data-driven urban energy simulation, proved effective in gauging the energy impact of retrofit interventions.

In a related study, Neumann et al. [35] investigated the establishment of positive energy districts (PEDs) within diverse urban environments in Vienna, highlighting the importance of extensive energy conservation, electrification, and renewable energy adoption to convert existing structures into PEDs. Dai et al. [36] emphasized the importance of understanding building stock on a larger scale, particularly building geometry, through a new methodology using unsupervised machine learning to evaluate building dimensions from remote sensing data. Building on these studies, Hey et al. [37] emphasized the significant impact of simulating energy retrofit adoption in urban housing stocks. Their model assigned carbon values to households, which aided in identifying the most suitable retrofit strategies. This model, combining surrogate models, optimization techniques, and neural networks, exemplifies how AI-driven simulations can influence policymaking.

Collectively, these AI-enhanced models have shown a great ability to dissect building energy demands [38], clarify the energy interplay in urban microclimates [10], and discern distinct patterns of energy consumption [39], all of which contribute to more nuanced and informed decision-making processes.

In conclusion, the landscape of urban development is witnessing the transformative influx of AI and data-driven technologies, promising unprecedented advancements in energy management, urban planning, and sustainable design. The large number of tools, algorithms, and methodologies emerging in this field reflects a robust endeavor to harness the potential of data to enhance urban sustainability. However, a critical gap persists in the practical integration of these tools into the existing workflows in architectural and urban design practices. This paper emphasizes the potential for integrating data-driven tools into "business as usual" workflows, underscoring not only the enhancement of sustainable design practices but also the stimulation of further research tailored to the specific needs of designers and urban planners. By focusing on the integration of these tools, we can bridge the gap between theoretical advancements and practical application, ensuring that the benefits of data-driven models are fully realized in the quest for sustainable and resilient urban environments. This approach facilitates the adoption of sustainable design principles at a broader scale while ensuring that the tools and models developed are directly responsive to the evolving demands of urban sustainability.

Methodology

The methodology employed to define the presented workflow unfolded in several structured phases, beginning with an in-depth examination of existing research. This step involved exploring how design processes are augmented by data integration and the flow of information, pulling insights from a variety of sources such as papers, technical reports, and interviews with industry experts in both the European Union and the United States. Specifically, interviews with design firms in the US and EU provided preliminary real-world insights into the application of data-driven tools in architectural design. This phase highlighted the growing interest in the data integration in urban energy, together with a lack of a clear framework to integrate those tools in the design process [40].

Following this, the second phase concentrated on synthesizing the collected data to map out the sequence of steps and exchanges of information that typically occur within the design process. This mapping highlights the path data travel through various stages while pinpointing the roles of different actors involved in the workflow. Key findings from this phase revealed critical points where data integration could enhance the efficiency and accuracy of the design process, especially in the briefing and concept design stages, where exchanges of information between clients and designers are required, and when the first energy assessment is conducted.

The third phase was dedicated to the creation of an analytical workflow designed to be of practical use to designers looking to embrace data-driven methodologies and to entities in the process of developing these tools. This workflow was visualized through a diagram that clearly delineated the flow of information throughout the process, detailing the requisite actions and milestones for each involved party. Partial results from this phase include a preliminary diagram that was tested and refined through feedback from industry experts.

The last phase focused on identifying and emphasizing potential opportunities for weaving data-driven tools into the workflow. This step was pivotal in highlighting where and how these advanced tools could seamlessly integrate into existing processes. Results from this phase set the baseline for improvements in design accuracy and efficiency when data-driven tools are applied at specific stages of the proposed workflow.

Workflow

The successful incorporation of advanced digital technologies in architectural and urban design hinges on their proper assimilation into the prevalent workflows of existing designers working at urban scale. In fact, mirroring the increasing inclination toward utilizing data-driven approaches [41], the recent widespread adoption of data-driven technologies across various industries can be attributed to their user-friendliness and their capability to blend into existing processes without overturning traditional approaches.

Effective implementation of advanced digital tools for data-informed and performance-driven design in urban environments necessitates a set of foundational preconditions at the design stage. A nuanced understanding of urban energy dynamics and carbon emission profiles is paramount. This encompasses a comprehensive analysis of current and projected energy consumption patterns, carbon footprints, and their implications on urban growth and policy transformations [42]. Moreover, the integration and effective utilization of digital tools in urban design are contingent on the availability of robust, structured, and scalable data. These data must accurately reflect real-world conditions to ensure the developed tools are adaptable to the evolving requirements of urban design [43].

In the process of better grasping how we can effectively integrate these tools into a design workflow, stakeholder engagement is a fundamental step. This involves the incorporation of diverse perspectives, including architectural designers, urban planners, policymakers, and community representatives in the design process. Their contributions could be helpful in shaping tools—but mainly the framework behind those—that are not only technically sound but also resonate with practical, user-friendly (from a designer perspective) applications [44]. The design approach must be versatile, capable of adapting to various urban types and scales of intervention, together with different design prerequisites. Such flexibility is essential in addressing the distinct challenges and opportunities presented by everchanging environments and different urban contexts [45].

The RIBA Plan of Work [46] is employed as the backbone of the proposed workflow, as shown in Fig. 1, due to its comprehensive and structured framework that aligns with the industry's best practices. This systematic approach demarcates the project into distinct stages, facilitating clear checkpoints, iterative assessment, and stakeholder engagement throughout the project lifecycle. Additionally, the synthesis of interview responses led to a complex and multifaceted generalized workflow definition that we set as a baseline for the future studies in this paper.

One of the pivotal findings of this research is the identification of opportunities in current workflows, particularly in the early stages, where iterations between different teams and professionals are more frequent, leading to possible errors or information losses. These areas present prime opportunities for the integration of digital tools. The proposed data-driven integration areas advocate for an integrative approach, where digital tools are not peripheral but central to the design process. This complex workflow, moreover, suggests a need for methodical integration of tools, ensuring they augment rather than disrupt the existing design process. The workflow emphasizes the importance of iterative feedback, stakeholder collaboration, and adaptability to different project scales and typologies.

Given the complexity of our proposed "business as usual" workflow, which involves multiple stakeholders, a breakdown of the key components and their interconnections is provided to support the readability of its graphic representation in Figs. 2 and 3.

(1) Stakeholders and their roles:
   (a) Client and other stakeholders: Set the scope and expectations of the project. They are the starting point of the workflow and provide overall aim and goals.
   (b) Sustainability expert: Develops sustainability strategies and collaborates with other disciplines to incorporate sustainable design elements from the onset.
   (c) Energy modeler (envelope): Focuses on defining the regulatory regime and preliminary definition of envelope. Their role is also to provide high-level, knowledge-based information to the designers regarding the role of the envelope.
   (d) Energy modeler (systems): Concerned with the systems inside the building, such as heating, ventilation and air conditioning (HVAC) and electrical systems, to ensure they meet the energy performance standards, while grasping the potential of the design in a specific urban context.
(2) Process flow and milestones:
   (a) Concept definition: This involves setting up concepts for building envelope, energy systems, and establishing the modeling rules for the whole project.
   (b) Model creation and validation: Different levels of detail models are created, and they must go through a validation process to ensure they meet design requirements and performance standards.
   (c) Data collection and analysis: Data regarding different aspects of the building, like thermal loads, lighting loads, and system information, are collected and analyzed.
   (d) Performance checks: These include checking the heating and thermal performance, cooling load, daylight analysis, and energy code compliance. Performance checks are both knowledge-based and calculus-based.
   (e) Milestones: The workflow includes several milestones where progress is reviewed, and decisions are made to move forward or revise strategies.
(3) Feedback loops
   (a) The process is iterative, with feedback loops incorporated at various stages to ensure the project adapts to new information or changes in the scope.

In the presented workflow, each phase serves a specific purpose in the overall development of a project:

(1) Briefing: This is where the client and other stakeholders, including the sustainability expert, outline the scope and high-level requirements of the project. This aligns with the role descriptions mentioned above, where stakeholders set expectations and initial goals, and the sustainability expert begins to formulate strategies.
(2) Concept design: At this stage, the concept of the buildings is defined. Energy modelers focused on the envelope and systems contribute by setting the regulatory regime, preliminary envelope design, and system configuration.
(3) Spatial coordination: This involves the detailed coordination of space, particularly the technical systems within the building. The workflow shows various tasks such as collecting detailed technical information, performing predictive analysis for energy systems, and ensuring there are no clashes or interference between different building systems.
(4) Technical design: This is a further refinement of the spatial coordination where the technical specifics of the building are finalized, including energy performance and sustainable

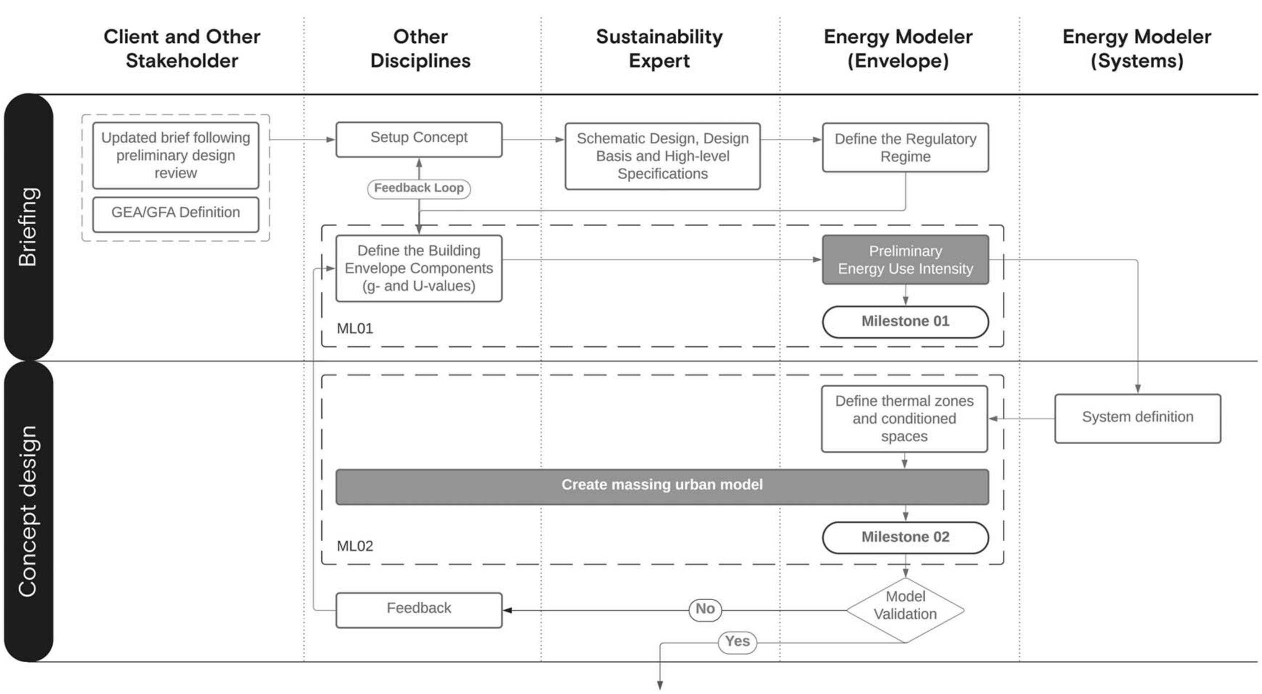

Fig. 2 Proposed workflow—briefing and concept design stages

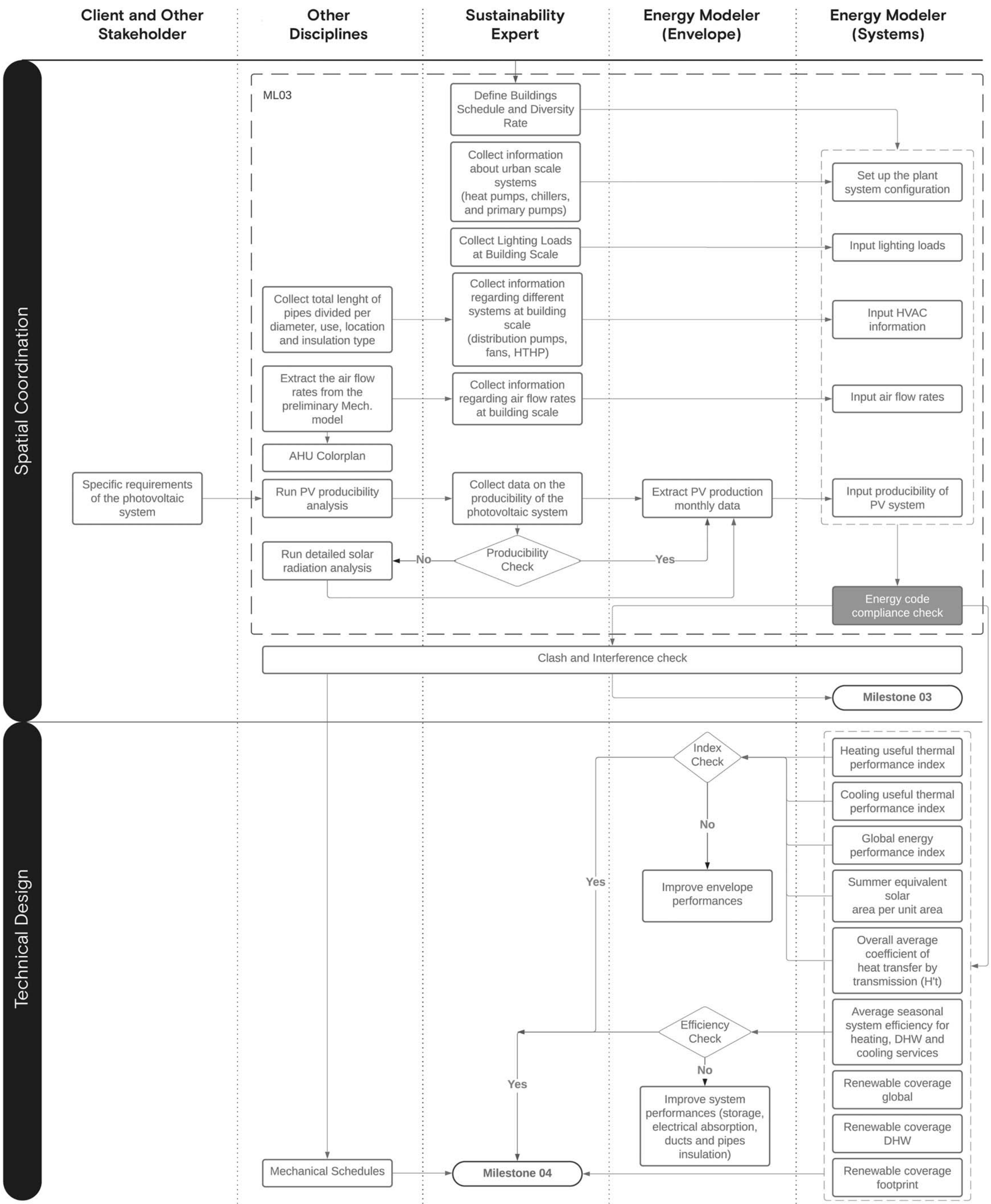

Fig. 3 Proposed workflow—spatial coordination and technical design stages

features. The workflow in the paper suggests that performance checks like thermal performance and energy compliance are key components at this stage.

Lastly, specific areas denoted as ML01, ML01, and ML03 are identified. These areas are where ML tools hold significant potential. These areas are strategic intervention points within the design process, identified for their capacity to benefit from the integration of ML technologies.

Throughout these stages, feedback loops and milestones are emphasized, reflecting an iterative design process that is adaptable to changes. The feedback ensures continuous refinement and improvement of the project, which is a critical part of the proposed workflow. The development and implementation of data-driven tools into the early-stage urban design workflow must be guided by a clear set of "guidelines" that align with existing design and regulatory frameworks. This approach facilitates a smoother transition to sustainable, performance-driven urban design practices, ensuring

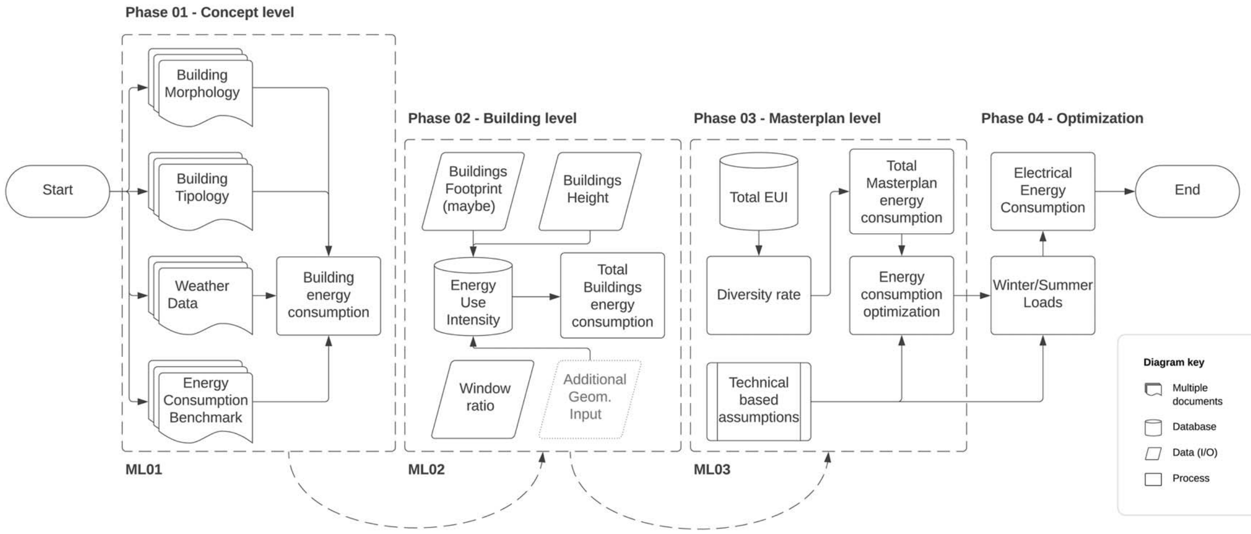

Fig. 4 Framework definition

that the new technologies and strategies are seamlessly integrated into the existing urban fabric [47]. In our workflow integration diagram, no specific tools are reported, making the workflow as adaptable as possible to different design contexts. In doing so, we highlight varying opportunities for digital tool integration across different phases of design, underscoring specific areas where such tools can significantly augment design efficiency and sustainability.

Results and Discussion

In the quest to enhance energy efficiency within urban design, conventional workflows have typically adhered to a linear progression. This traditional trajectory is segmented into different stages, starting from the briefing and advancing through to the technical design within urban settings. These stages are demarcated by pivotal evaluation activities, here referred to as "milestones," each signifying the culmination of a particular design phase.

Presently, the workflow involves multiple participants who exchange information, a process that is filled with potential inaccuracies stemming from communication breakdowns or timing discrepancies during the design progression.

The notion of "integration techniques" in this context denotes the amalgamation of disparate disciplines, data flows, and modeling activities, which collectively forge a unified and efficacious approach to urban energy design. As outlined in the previous paragraphs, the emergence of machine learning and data-centric methods signifies a transformative shift in this traditional workflow, heralding improvements across the domain.

Our proposed workflow incorporates the application of three distinct machine learning algorithms to enhance the flexibility of the workflow while maintaining the integrity of various stage assessments. The underlying principle is that each project presents unique data streams; thus, implementing a layered machine learning approach allows for the utilization of only certain segments of the model, if necessary, without necessitating a complete overhaul of the pre-existing workflow.

In the initial phase, related to ML01, the integration of machine learning can impact the schematic design stage by rapidly synthesizing and interpreting vast datasets to identify optimal design configurations (overall strategy) and energy needs (building scale). This can lead to a significant reduction in design time and enable a more informed decision-making process regarding the building envelope's performance characteristics.

Progressing to ML02, machine learning integration can refine the creation of massing and urban models. By leveraging predictive algorithms, machine learning can forecast and simulate the impacts of various design alterations, thereby minimizing risks and guiding the project toward sustainable and energy-efficient solutions (building scale).

At ML03, the focus shifts to the urban scale. Here, data-driven techniques become paramount in meticulously assessing building schedules, loads, and systems performance, without oversimplifying design processes and better assessing the multiple building influence and interaction. These algorithms can handle complex datasets, providing nearly real-time insights into energy consumption patterns and potential system inefficiencies.

The relevance of the proposed work lies in being the foundation for the development of a generalized framework—shown in Fig. 4—to enhance urban design sustainability.

Conclusion

This work advances a methodical and data-centric approach embedded within a commonly adopted design workflow and offers a robust pathway to sustainable low-carbon cities. By employing a structured workflow that hinges on the interplay of stakeholder collaboration, iterative feedback, and digital tool integration, the research advances the potential to streamline urban design processes without compromising the business-as-usual design approach. Our study illustrates that the assimilation of advanced digital technologies is not only achievable but also essential in the pursuit of operational carbon footprint reduction in urban environments. We have presented through the proposed workflow how BPS tools, when properly integrated into the design process, can significantly help improve the sustainability and efficiency of urban projects.

Through the synthesis of interviews and collaboration with design firms across the US and EU, we identified key integration points for data-driven tools within existing workflows. This underscores the importance of these tools not as peripheral add-ons but as central components that can enhance design practices at every stage. The generalized workflow presented herein serves as a foundation for further research, providing a baseline upon which future studies can build. The workflow fosters a comprehensive approach to project development.

Our research contributes a crucial narrative on the synergy between traditional design processes and the expanding field of data-driven design. By interweaving advanced digital tools within the fabric of the design stages, we offer a workflow that is practical and aligns with the dynamic needs of urban development.

Moving forward, we aim to apply the proposed theoretical framework to real-world case studies to validate its effectiveness and adaptability. This future work will involve close collaboration with design firms to implement parts of the framework in ongoing projects, allowing for iterative refinement based on practical feedback. By bridging the gap between theory and practice, we seek to demonstrate the tangible benefits of data-driven tools in enhancing urban sustainability and design efficiency.

Conflict of Interest

There are no conflicts of interest.

Data Availability Statement

No data, models, or code were generated or used for this paper.

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