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Review

From White to Black-Box Models: A Review of Simulation Tools for Building Energy Management and Their Application in Consulting Practices

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Abstract: Buildings consume significant energy worldwide and account for a substantial proportion of greenhouse gas emissions. Therefore, building energy management has become critical with the increasing demand for sustainable buildings and energy-efficient systems. Simulation tools have become crucial in assessing the effectiveness of buildings and their energy systems, and they are widely used in building energy management. These simulation tools can be categorized into white-box and black-box models based on the level of detail and transparency of the model's inputs and outputs. This review publication comprehensively analyzes the white-box, black-box, and web tool models for building energy simulation tools. We also examine the different simulation scales, ranging from single-family homes to districts and cities, and the various modelling approaches, such as steady-state, quasi-steady-state, and dynamic. This review aims to pinpoint the advantages and drawbacks of various simulation tools, offering guidance for upcoming research in the field of building energy management. We aim to help researchers, building designers, and engineers better understand the available simulation tools and make informed decisions when selecting and using them.

Keywords: BES; simulation tool; white-box; black-box; machine learning; deep learning; building energy

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1. Introduction and Motivation

The field of building energy management is undergoing a transformative evolution, driven by the ever-increasing need for sustainable and energy-efficient solutions in the construction and operation of buildings. Recent studies like those by Doe and Smith [1] illuminate the potential of cutting-edge simulation software, underscoring a significant shift towards advanced tools that enable real-time optimization of energy use. As energy efficiency and sustainability become paramount in building design, operation, and retrofitting, the demand for accurate, data-driven decision-making has never been higher.

In this dynamic landscape, simulation tools have emerged as indispensable, offering professionals the means to model, analyze, and optimize the energy performance of buildings. This review publication explores the diverse spectrum of simulation tools available for building energy management, highlighting their strengths, limitations, and applicability, focusing on their integration into consulting practices. Zhao and Patel's [2] work on incorporating machine learning into building energy models exemplifies the progression toward data-driven methodologies revolutionizing energy management practices.

The scope of this review encompasses two fundamental categories of simulation tools: white-box models and black-box models. White-box or physics-based models rely on fundamental physics principles and engineering equations to simulate the intricate interactions within a building's energy systems. In contrast, black-box models leverage empirical, data-driven approaches, often incorporating machine learning algorithms and statistical techniques to predict building energy consumption and behaviour.

Consulting practices in building energy management necessitate a deep understanding of these simulation tools and their alignment with specific project requirements. As documented by Huang and Nguyen [3], the practical application of these tools in consulting practices is theoretical and a reality that is reshaping the industry, revealing a paradigm shift in building energy management. Their work underscores the critical role of these tools in delivering actionable insights and the added value they bring to energy consulting firms.

This review delves into the technical intricacies of these tools, highlighting their applications in consulting scenarios. Whether it is conducting energy audits, optimizing building systems, or ensuring compliance with energy performance standards, these tools have become indispensable assets for consultants. By presenting case studies and industry insights, we showcase the tangible impact of simulation tools on building energy management, contributing to the continuous improvement of energy efficiency and sustainability in the built environment.

Ultimately, this review aims to present a thorough and contemporary survey of white-box and black-box simulation tools in building energy management, assessing their practical applications in consulting practices. Our objective is to furnish a detailed comparative analysis, serving as an authoritative resource for professionals and researchers in the field. Through this, we strive to equip stakeholders with the insights required for informed decision-making, facilitate the optimization of energy efficiency, and foster a sustainable built environment, thereby propelling forward the theoretical underpinnings of the domain.

2. Literature Reviews

Statistically, cities are among the largest energy consumers and greenhouse gas emitters [4]. Therefore, predicting building energy is vital for strategizing and enhancing energy systems [2,3] and the penetration of renewable energy [5,6]. It is crucial to lower energy usage in buildings, boost efficiency, and raise the proportion of renewable energy consumption.

As energy becomes increasingly critical to countries' economies and the environment, considerable efforts are made worldwide toward its optimal use and sustainable development. The problem is associated with an energy "trilemma", defined as the need to improve the security of supply, human comfort, and accessibility. The energy is in a complex interaction with other resources like water and land. Competing demands require reducing energy costs to consumers and reducing carbon emissions for a minimal increase in the global average surface temperature [7]. Also, the load and energy management systems directly affect the occupant experience in commercial and residential buildings [8].

Due to the rapid growth of the city's inhabitants and the 40% share of building energy in energy consumption [9], it is inevitable to improve building efficiencies. Energy consumption modelling is the first step to analyzing and optimizing building efficiency. Several building energy consumption modelling tools have been developed in the last twenty years, ranging from data-driven models to web tools. Sandra et al. evaluate the effectiveness, specifically in terms of accuracy and robustness, of 60 calibration methods based on optimization for white-box models [10]. Zhengwei et al. assess approaches for comparing building energy use with its historical or expected performance, and they analyze the differences between white-box and grey-box models [11]. Finally, Xiwang et al. examine recent advancements in building energy modelling, encompassing both comprehensive building and key component modelling, for building control and operation. They discuss and compare various methods, ranging from white-box to black-box models [12].

Building energy tool selection criteria depend on factors like inputs and outputs, building or district analysis, etc. An analysis of the building performance using a new evaluation method is presented in [13]. This article determines the impact of intricate factors such as construction duration, construction expenses, annual costs based on bills, primary energy requirements, yearly CO_2 emissions from energy usage, CO_2 emissions from construction materials and activities, and thermal comfort on ultimate decision-making. Occupant behaviour is the next factor that can affect tool selection. Delzendeh et al.'s review seeks to determine prevailing research directions, pinpoint unexplored areas for future study, and identify trends in prominent journals using the Science Direct and Scopus databases [14].

Eva Schito et al. explore various methodologies and technologies to reduce energy requirements in buildings. The significant potential for energy savings in existing buildings through retrofits and renovations is emphasized, driven by global efforts to reduce energy consumption and carbon emissions in the building sector. The impact of European Union directives on energy efficiency, building design considerations, renewable energy integration, and the role of multi-objective optimization in achieving sustainable solutions are discussed. Various research contributions that address energy efficiency in buildings, focusing on optimizing energy usage while considering economic, architectural, technological, and human comfort factors, are also highlighted [15].

Gwanggil Jeon discusses the increasing role of AI models in energy management and decision-making. Various AI applications in energy systems, such as renewable energy estimation, demand forecasting, and optimization of energy consumption in public transportation, are covered. Enhanced efficiency, accuracy, and predictive capabilities are achieved through AI use in these areas, offering robust solutions for energy-related challenges. Contributions integrating AI with existing energy systems are featured in the document, showcasing AI's potential to bring stability, security, and efficiency to the energy sector [16].

Yiqun Pan et al. aimed to identify and organize the appropriate principles, methods, and tools for engineers and researchers involved in building energy management, together with case studies that could hold academic or practical importance [17]. Therefore, the review was organized into five sections, each aligning with distinct goals of building performance simulation. These sections include performance-driven design, operational performance optimization through modelling, integrated simulation with data measurements for digital twin creation, building simulation aiding urban energy planning, and modelling building-to-grid interactions for the demand response [17].

Abdo Abdullah Ahmed Gassar et al. offer a comprehensive summary of past research efforts to forecast large-scale building energy consumption through diverse methodologies, encompassing black-box, white-box, and grey-box techniques. This review covers various facets of large-scale building energy prediction, including elements influencing building energy requirements, different building categories like residential, commercial, and office structures, and prediction ranges extending from a cluster of buildings to an entire city, region, or nation [18].

The exploration of energy efficiency, renewable energy utilization, and environmental protection by Francesco Calise et al. is presented. Research from the International Conference on Sustainable Energy and Environmental Development (SEED) is showcased, including hybrid renewable energy systems, organic Rankine cycle enhancements, solar collector performance, and microgrid system design. The importance of integrating technological, economic, and environmental perspectives to meet the challenges of sustainable energy development and environmental protection is emphasized in this research [19].

Mohamed-Ali Hamdaoui et al. review two models for simulating hygrothermal behaviour in hygroscopic material buildings: white-box and black-box models. White-box models, utilizing software like COMSOL Multiphysics (V5.6) or WUFI (V6.7), focus on physical understanding and balance equations. In contrast, black-box models rely on statistical methods (ANN, CNN, LSTM) using measured data. The paper categorizes white-box models into the CFD approach, with multiple control volumes per zone, and the nodal approach, treating each zone as a uniform volume [20]. Xiaoliang Zhang et al. investigate the applications of the building simulation tool DeST (Design Simulation Toolkit) in building design and building energy efficiency research and consultation. They highlight how DeST has been used in various projects, including the development of building regulations and scientific research. The paper details DeST's role in building design consultation, commissioning, energy conservation assessment, and a building energy labelling system. They present examples from a demonstration building to illustrate how DeST aids in design processes. Additionally, the paper mentions its use in other projects and regulations, demonstrating the widespread application of DeST in building energy efficiency [21].

While the literature provides a comprehensive overview of various simulation tools, from the physics-based white-box models to the data-driven black-box approaches, there remains to be a notable disconnect between the theoretical capabilities of these tools and their practical application in consulting practices. Studies emphasize technical specifications and theoretical improvements in energy modelling. Still, they must address the real-world challenges consultants face, such as tool interoperability, user-friendly interfaces, and actionable outputs for decision-making. Moreover, there needs to be more comparative analysis that critically evaluates the performance of these tools in live consulting environments across different building types and energy systems. Furthermore, while advancements in areas like artificial intelligence present new opportunities for tool enhancement, their potential impact on consulting practices still needs to be explored. Future research must bridge these gaps by focusing on the usability of simulation tools in consulting practices, developing case studies that demonstrate their effectiveness in diverse scenarios, and assessing how emerging technologies can be harmoniously integrated to advance both the state-of-the-art and the practicalities of energy management consulting.

3. Objectives and Methodology

Efficient management of energy resources in the built environment is critical to sustainable urban development and environmental conservation. As the demand for energy-efficient buildings continues to grow, the role of simulation tools in building energy management becomes increasingly significant. These tools enable professionals to model, analyze, and optimize the energy performance of buildings, ultimately leading to reduced energy consumption and environmental impact. The review centers on these principal elements to realize the goals outlined in the introduction.

3.1. Tool Classification

This review systematically categorizes simulation tools for building energy management into two primary classes: white and black-box models. These classifications serve as a foundational framework for comprehending the diverse modelling methodologies employed by these tools. White-box models, often called physics-based models, are rooted in fundamental physics and engineering principles. They meticulously simulate building energy performance by considering the physical behaviour of various components and systems within a building. Prominent examples of white-box tools include EnergyPlus, TRNSYS, and IDA-ICE. In contrast, black-box models operate on empirical, data-driven approaches, frequently integrating machine learning algorithms and statistical techniques. These models harness historical data to predict building energy consumption and behaviour. Well-known black-box tools encompass Support Vector Machines, Random Forest, and Deep Neural Networks. This classification forms a structured basis for our analysis and highlights the fundamental differences between these modelling approaches. White-box models aim to deeply understand the physical processes governing energy consumption, while black-box models prioritize prediction accuracy, even if they are less interpretable. This fundamental distinction is pivotal in selecting appropriate tools for specific building energy management tasks.

3.2. Consulting Practices Integration Analysis

The second critical aspect of our review explores how these simulation tools are integrated into consulting practices within the realm of building energy management. Consulting in this context refers to the professional services offered to clients seeking energy-efficient solutions for their buildings, whether they are new construction projects or existing structures requiring retrofitting. Consulting practices in building energy management encompass various activities, including energy audits, predictive modelling, retrofit analysis, and performance verification (Figure 1) [22]. These practices aim to provide clients with actionable insights, data-driven decision-making, and solutions for enhancing energy efficiency while ensuring occupant comfort. The integration of simulation tools into consulting practices presents both challenges and advantages. White-box models, such as EnergyPlus and TRNSYS, offer a detailed understanding of building energy systems but demand extensive inputs and calibration efforts. Their application is particularly suited for projects where a thorough comprehension of energy behaviour is critical, such as retrofitting projects and complex building systems optimization.

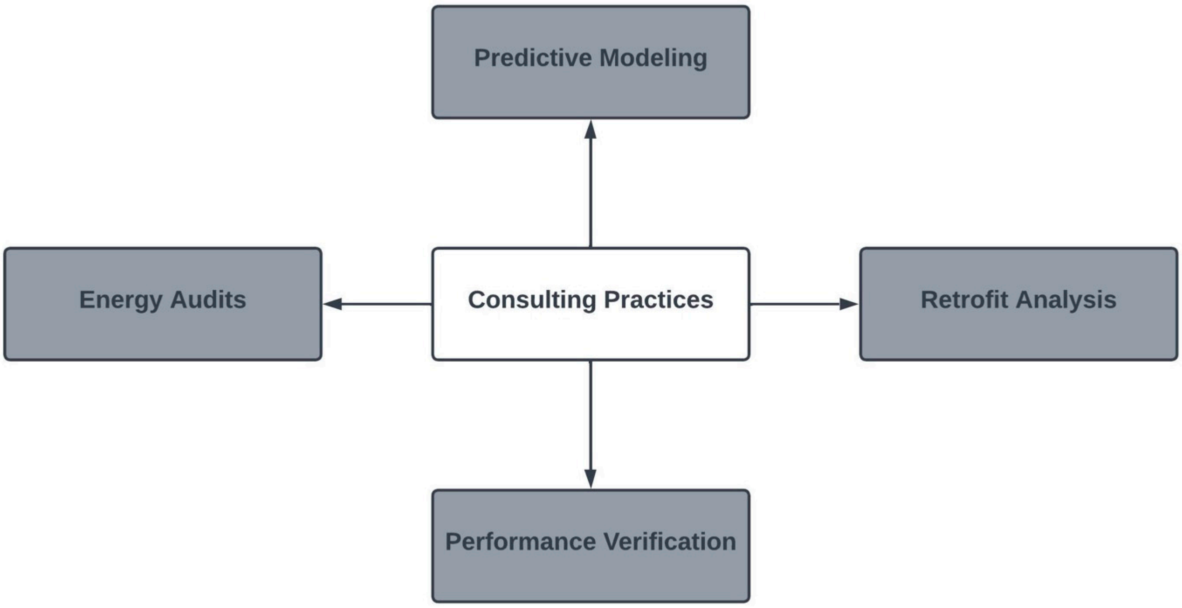

Figure 1. Specific features of consulting practices.

On the other hand, black-box models, including Support Vector Machines, Random Forests, and Deep Neural Networks, provide rapid results with less detailed input but require transparency and customization. These models excel at tasks like predicting energy consumption patterns, detecting anomalies, and optimizing building operations. They are valuable for quick decision-making in consulting scenarios.

3.3. Scalability Assessment

The third aspect of our review assesses the scalability and adaptability of these tools. Building energy management projects can vary significantly in scale, ranging from individual building components to entire urban areas [23]. Therefore, it is crucial to evaluate the suitability of each tool for different project sizes and complexities. White-box models, with their in-depth simulations, are well-suited for complex building systems and projects where detailed modelling is essential. They can accurately capture the interactions between various building components and systems, making them valuable for optimizing energy use while maintaining occupant comfort. With their data-driven approach, black-box models offer flexibility and speed in consulting practices. They can be applied to various projects, from small-scale energy audits to large-scale urban energy analysis [24]. Their ability to handle high-dimensional data and capture complex relationships between variables makes them adaptable to various building typologies and external influences, such as weather patterns. By systematically evaluating the scalability and adaptability of these tools, our review aims to assist professionals and consultants in selecting the most appropriate tool for their specific consulting projects. Whether the goal is to optimize the energy performance of a single building or develop sustainable urban energy strategies, choosing the right tool is essential for achieving accurate and actionable results.

3.4. Methodology

To achieve our research objectives, we have devised a systematic methodology that ensures the reliability and comprehensiveness of our review. Firstly, we conducted an extensive literature review encompassing peer-reviewed research articles, industry reports, and publications on building energy management simulation tools. This thorough examination guarantees that our analysis is firmly grounded in this domain's latest advancements and industry practices. Next, we categorized the identified simulation tools into two fundamental classes: white-box and black-box models. This categorization is based on these tools' underlying principles and methodologies, serving as a foundational framework that structures our analysis. It enables a clear understanding of the strengths and limitations of each tool category. Furthermore, our methodology includes an in-depth exploration of how these simulation tools are applied in the context of consulting practices. This involves meticulously examining case studies, industry insights, and best practices. Additionally, we conducted a scalability assessment of each tool, considering factors such as the level of detail they offer and their suitability for diverse consulting scenarios. This analysis aids in determining the applicability of these tools to a wide range of project scales.

Through the systematic execution of this methodology, our review aims to offer valuable insights into the evolving landscape of simulation tools for building energy management. We present a holistic perspective on these tools' capabilities, advantages, and limitations, empowering professionals in the field to make well-informed decisions and enhance the quality of their consulting services.

The system boundary in building energy management tools refers to the level of analysis and detail the tool provides. As a result, building energy management tools can operate at different system boundaries, ranging from individual building components to entire urban regions (Figure 2).

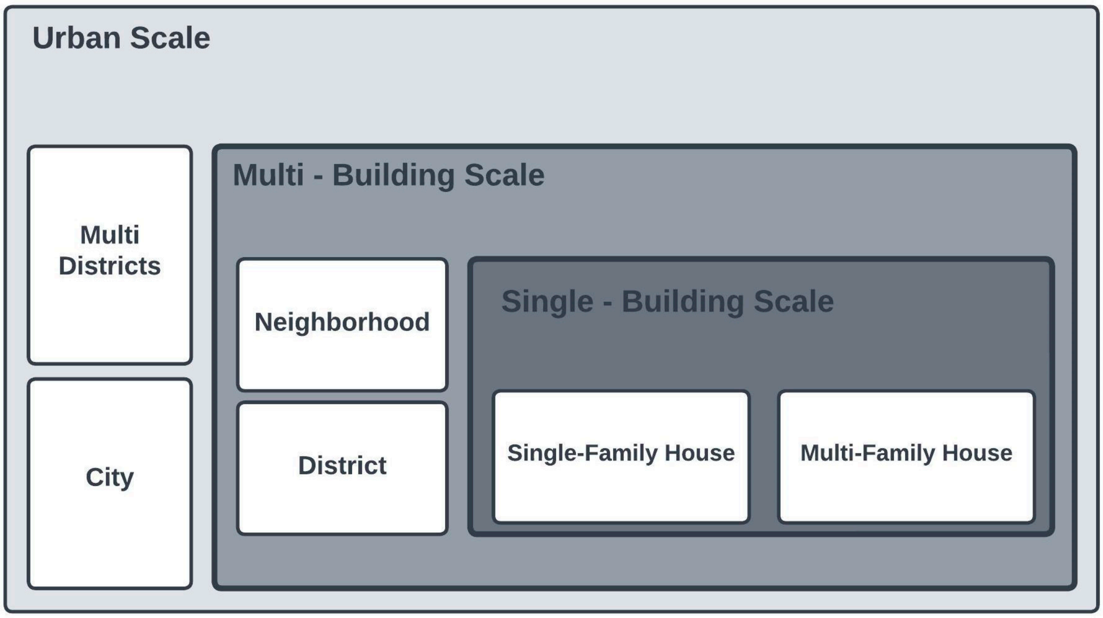

Figure 2. System boundary in BEM Tools.

At the building system boundary, tools consider the interaction between various building systems and how they affect the overall energy performance [23]. In addition, these tools often provide energy simulations and optimization capabilities to inform building design and operation decisions [17].

At the city or regional scale, tools consider large-scale urban systems' energy and environmental impacts, such as transportation, land use, and energy infrastructure. These tools may inform policy decisions about energy and climate change mitigation strategies [25].

The choice of system boundary depends on the specific application and modelling objectives. Building energy management tools can be used at multiple system boundaries to inform design and operation decisions and assess the potential for energy savings and emissions reductions [25].

This review publication examines and compares standalone and web-based models in different resolutions, from white-box to black-box, in the context of building energy simulation tools (Figure 3). Building energy simulation is an essential instrument for analyzing and enhancing energy efficiency in buildings. White-box models, grounded in fundamental physics and detailed component representations, thoroughly comprehend energy dynamics. Conversely, black-box models rely on empirical data relationships for simulating energy consumption patterns. Furthermore, we underscore the importance of web-based models, emphasizing their inclusion within both white-box and black-box modelling paradigms. By exploring the strengths and limitations of these models, we seek to provide valuable insights and guidance to researchers, practitioners, and stakeholders involved in building energy management. The review will contribute to a better understanding of the diverse modelling options available and assist in selecting the most appropriate approach based on specific project requirements and constraints.

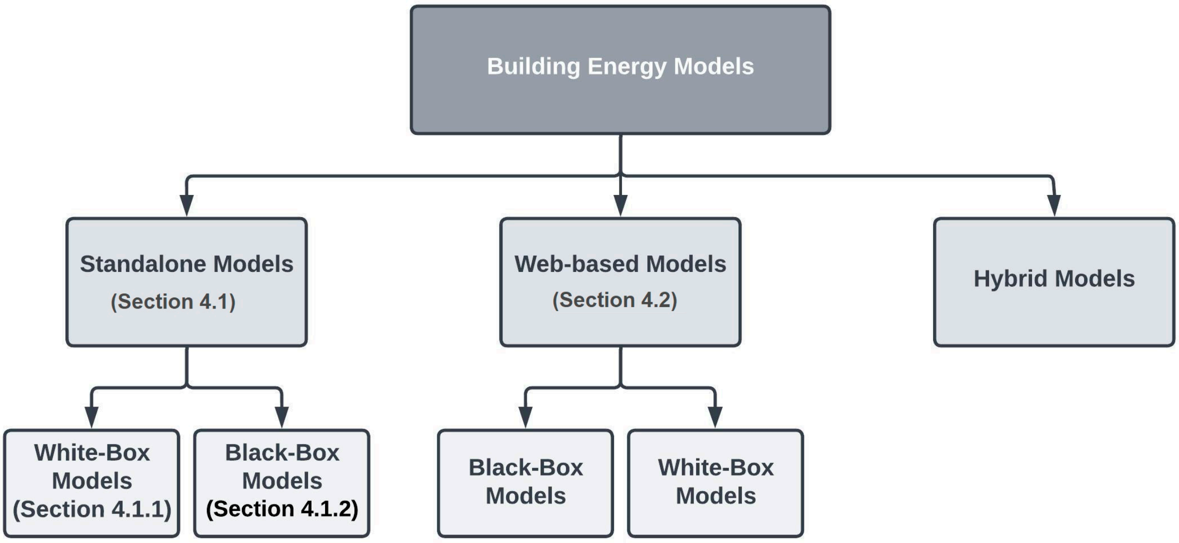

Figure 3. Structure of this review.

4. Simulation Tools for BEM

4.1. Standalone Models

4.1.1. White-Box Models

White-box tools in building energy simulation refer to software programs that use explicit mathematical models of building components and systems to simulate energy consumption and other building performance metrics. These models are derived from fundamental physical principles and engineering laws. In addition, the user can use white-box modelling to dimension specific arrangements and test the data and parameters of the different scenarios [26]. A list of white-box models can be found in Table 1.

White-box tools can be more complex than black-box tools and may require specialized knowledge and expertise to operate effectively. They may also require more detailed and accurate data inputs to produce accurate results, which can be challenging in some situations. They can predict energy consumption by establishing long-term associations between buildings' energy usage and important influencing factors [27]. Energy models based on physical principles are the most accurate, and this approach is used by software such as DOE-2 and EnergyPlus. White-box models, however, are complicated to build since they must include all the required equations and data. They need the most computing power and complexity, making their simulations slow.

Using white-box techniques can alleviate many inefficiencies and resource-intensive characteristics of conventional complex models. Besides their accuracy, white-box models offer the advantage of not requiring historical data. If the physical properties of a building are known, they can simulate a new building that does not exist [28].

The white-box building models apply heat and mass balance equations, which dynamically describe building behaviour. These equations account for three heat transfer mechanisms (conduction, convection, and radiation) between the building envelope and its surroundings. Numerous commercial and open-source software options, including EnergyPlus, Dymola, TRNSYS, and DOE-2, are available for building energy modelling. These tools efficiently formulate and solve these equations, although manual calculation of cooling and heating loads may still be necessary [29]. The details for building thermal and cooling load prediction are presented in reference [30].

To create these models, comprehensive building data is essential, encompassing details such as building envelope characteristics, HVAC system configurations, internal heat contributions, equipment specifications, occupancy patterns, thermal zones, geographical location, and meteorological data, all of which are used to construct a physical building energy model [31].

Predictive analysis and energy auditing are essential components in the consulting industry, especially regarding building efficiency [32]. White-box tools play a crucial role in these processes. These tools enable consultants to conduct thorough energy audits and predictive analyses of buildings, modelling the energy behaviour of various components with high accuracy. This precise modelling is invaluable, particularly in retrofitting projects, where understanding the impact of modifications on energy performance is critical.

White-box tools offer a significant advantage in design and retrofitting decisions. They allow consultants to simulate multiple design scenarios, providing clients with clear, data-driven insights regarding the energy implications of different design choices. This capability is crucial in the early stages of building design, where decisions can significantly influence future energy consumption. For retrofitting existing buildings, these tools are instrumental in evaluating the effectiveness of various energy-saving measures, such as upgrading insulation or HVAC systems [33].

White-box tools are invaluable when optimizing building systems, such as HVAC, lighting, and ventilation. They can simulate the dynamic interactions between these systems and the building envelope, enabling consultants to devise strategies that boost overall energy efficiency while maintaining or improving occupant comfort.

Compliance and performance verification are other critical areas where white-box tools are used. Many regions have specific energy performance standards for buildings, and these tools help consultants ensure that designs comply with these standards. They provide detailed analyses demonstrating compliance and are also used in performance verification to ensure that buildings operate as intended, achieving the designed energy efficiency levels.

White-box tools are particularly suited for modelling complex buildings, which may have unique architectural features or advanced energy systems. Their detailed nature allows consultants to develop customized solutions that address specific challenges, such as unusual building geometries or integrating renewable energy systems [33].

Lastly, client communication and education are greatly enhanced by the use of white-box tools. The detailed outputs from these tools help consultants effectively communicate complex energy concepts to clients. By visualizing energy flows and the impacts of different design choices, these tools bridge the gap between technical energy modelling and client understanding, facilitating the decision-making process.

Table 1. White-box models.

Software	Version	Developer	City, Country	Platform	Timeframe	System Boundary	Available Outputs				Pros and Cons	References
							Energy	Thermal	Daylight	Air Quality		
EnergyPlus	23.2.0	DOE, NREL	Golden, CO, USA	Win, Mac, Linux	Sub-hourly, Hourly, user-defined timeframe	Neighborhood and Districts	✔	✔	✔	✔	Pros: Highly accurate for a variety of simulations, widely used and supported. Cons: Steep learning curve, requires detailed input data, computationally intensive.	[34]
TRNSYS	18.03.0000	University of Wisconsin	Madison, WI, USA	Win	Dynamic (down to 0.01 s time-steps)	Neighborhood and Districts	✔	✔	✔		Pros: Flexible with a modular approach, good for both simple and complex systems. Cons: Requires in-depth technical knowledge, the user interface is not as intuitive as some others.	[35]
City Sim	10 October 2023	EPFL Uni	Zurich, Switzerland	Win	Dynamic (hourly basis)	Multi-district and cities	✔				Pros: Specialized for urban-scale simulations, good for assessing microclimates and district energy systems. Cons: May not capture the specifics of individual buildings as accurately, less detailed HVAC modelling.	[36]
IDA ICE	5.0	EQUA Simulation	Glasgow, Scotland, UK	Win	Hourly	Neighborhood and Districts	✔	✔	✔	✔	Pros: Detailed thermal comfort and indoor climate simulations, user-friendly interface. Cons: License cost can be high, less suited for large-scale district energy analysis.	[37,38]
Envi-met	5.6	ENVI-met GmbH	Bochum, Germnv	Win	Hourly	Single-Family and Multi-Family House	✔	✔			Pros: Strong for outdoor microclimate analysis and urban areas, good visualization tools. Cons: Focused more on microclimate than energy simulation, relatively high complexity.	[39]

Table 1. *Cont.*

Software	Version	Developer	City, Country	Platform	Timeframe	System Boundary	Available Outputs				Pros and Cons	References
							Energy	Thermal	Daylight	Air Quality		
LBNL District lib	5.3	LBNL	Berkeley, CA, USA		Hourly	Multi-district and cities					Pros: Useful for district heating and cooling analysis. Cons: Integration into broader building energy management tasks can be complex.	
Energy Pro	4.0361	EnergySoft	Novato, CA, USA	Win	Hourly	Multi-district and cities	✔	✔	✔		Pros: Certified for Title 24 compliance, user-friendly for architects and professionals. Cons: Primarily suitable for California-based projects.	[40]
Retscreen	Version 9	Gov of Canada	Ottawa, ON, Canada	Win	Monthly basis (maximum: 50 years)		✔				Pros: Simplified tool for feasibility analysis and efficiency measures, includes climate data. Cons: Not as detailed for specific system design, suited for preliminary analysis.	[41]
EnerGis	8.1	EnerGis	-	Win	Monthly		✔	✔				[42]
HOMER	3.10	UL	CO, USA	Win	Dynamic (minimum time-step 1 min)	Single-Family and Multi-Family House	✔	✔			Pros: Well-suited for optimizing microgrid designs, great for handling off-grid and renewable energy system simulations. Cons: Focused on microgrids, which may not be comprehensive for all building energy aspects.	[43]
Neplan	10.940	NEPLAN AG	Zurich, Switzerland	Win	Hourly	Multi-district and cities	✔	✔				[44]
Radiance	6.0a	Greg Ward	Berkeley, CA, USA	Win, Mac, Linux	Dynamic	Single-Family and Multi-Family House			✔		Pros: Highly accurate for daylighting and lighting simulation. Cons: Complex to use and requires significant expertise in lighting and scripting.	[45]

Table 1. *Cont.*

Software	Version	Developer	City, Country	Platform	Timeframe	System Boundary	Available Outputs				Pros and Cons	References
							Energy	Thermal	Daylight	Air Quality		
Solene	microclimat	French National Research Agency (ANR) and the ADEME (Environment and Energy Management Agency).	Lausanne, Switzerland	Win	Hourly	Single-Family and Multi-Family House	✔	✔	✔		Pros: Specialized in urban physics, it helps analyze solar radiation and its effects on buildings and urban spaces. Cons: May have a steeper learning curve for those not familiar with urban physics.	[46,47]
ESP-r	13.2.1	University of Strathclyde	Glasgow, Scotland, UK	Win, Mac	Hourly, Weekly, Monthly	Single-Family and Multi-Family House	✔	✔		✔	Pros: A versatile simulation environment capable of detailed thermal analysis, including HVAC and renewable energy systems, offers flexibility with user-defined components. Cons: Its interface is not as modern or user-friendly as some newer software, and it may require more in-depth knowledge to utilize fully.	[48]
Be10	Specific version not available	DBRI	-	Win	Hourly	Single-Family and Multi-Family House	✔				Pros: Widely used in Denmark, particularly for compliance with Danish building regulations, user-friendly with a clear interface. Cons: Its use may be more regional and not as well-suited for international contexts, the scope might be limited compared to more comprehensive tools.	[49]
BSim	Specific version not available	DBRI	-		Hourly	Single-Family and Multi-Family House	✔	✔	✔	✔	Pros: Comprehensive approach to simulating indoor environment and energy consumption in buildings. Cons: tailored to specific (Danish) standard.	[50]

Table 1. *Cont.*

Software	Version	Developer	City, Country	Platform	Timeframe	System Boundary	Available Outputs				Pros and Cons	References
							Energy	Thermal	Daylight	Air Quality		
DOE2	DOE-2.3 (release candidate)	James J. Hirsch & Associates (JJH)- eQuest	USA	Win	Hourly	Neighborhood and Districts	✔		✔		Pros: Provides a detailed and reliable simulation of building energy usage, with a strong emphasis on accuracy for HVAC and lighting systems. Cons: Interface is considered less user-friendly and more difficult to navigate.	[51]
IESVE	IESVE 2023	IES	Glasgow, Scotland, UK	Win	Hourly	Neighborhood and Districts	✔	✔	✔	✔	Pros: Comprehensive suite of tools for building performance simulation, strong for compliance and detailed HVAC analysis. Cons: Can be complex and require significant training; the full suite can be expensive.	[52]
Velux	3.0	Velux Group	Horsholm, Denmark	Win, Mac	Hourly	Single-Family and Multi-Family House			✔		Pros: Renowned for daylighting capabilities and design. Cons: Focuses primarily on daylighting solutions and may not provide extensive energy modelling capabilities for complete building analysis.	[53]
iDbuild	-	Aarhus Uni	-	Win, Mac	Hourly	Single-Family and Multi-Family House	✔	✔	✔	✔	Pros: Offers an integrated approach to energy, indoor climate, and cost analyses. Cons: Can be complex due to its broad scope, which may present a steeper learning curve for users.	[54]

Table 1. *Cont.*

Software	Version	Developer	City, Country	Platform	Timeframe	System Boundary	Available Outputs				Pros and Cons	References
							Energy	Thermal	Daylight	Air Quality		
Daysim	4.0	Reinhart	Ottawa, ON, Canada	Win	Hourly	Neighborhood and Districts			✔		Pros: Delivers advanced daylight modelling, enhancing the ability to use natural light effectively and save on lighting energy. Cons: Specialized in daylight analysis and may not cover all aspects of building energy performance.	[55]
Design Builder	7.0	Design Builder Software Ltd.	Glasgow, Scotland, UK	Win	Hourly	Neighborhood and Districts	✔	✔	✔	✔	Pros: User-friendly interface, integrates simulation and building modelling with good visualization. Cons: May not offer the same level of detail for every component.	[56]
eQuest	3.65	eQuest	USA	Win	Hourly, Weekly, Monthly	Neighborhood and Districts	✔				Pros: Free and widely used, particularly in the U.S. Cons: Interface can be less intuitive, and customization may be limited compared to more modern tools.	[57]
OpenStudio	360	NREL	CO, USA	Win, Mac, Linux	Hourly, Weekly, Monthly	Multi-district and cities	✔	✔	✔	✔	Pros: Integrates with EnergyPlus and SketchUp, offering a more user-friendly interface for these powerful engines. Cons: Still requires an understanding of EnergyPlus for complex simulations.	[58]

Table 1. *Cont.*

Software	Version	Developer	City, Country	Platform	Timeframe	System Boundary	Available Outputs				Pros and Cons	References
							Energy	Thermal	Daylight	Air Quality		
Riuska	4.9		-			Neighborhood and Districts	✔	✔		✔	Pros: Designed for climate analysis, offering detailed insights into microclimate and urban heat island effects. Cons: The focus on microclimate means it may not cover detailed energy consumption modelling within buildings.	[59]
Sefaira	Sefaire 2018	Sefaira	London, UK	Win	Hourly, Weekly, Monthly	Multi-district and cities	✔	✔	✔		Pros: Known for its real-time energy and daylighting analysis within the early stages of design, providing architects with immediate feedback on performance impacts of their design choices. Cons: May lack the depth of more detailed simulation tools.	[60]
DIVA	4.0	Rhino	Cambridge, MA, USA	Win	Hourly	Single-Family and Multi-Family House			✔		Pros: Integrates with Rhino and Grasshopper, excellent for daylight and solar analysis with a visual programming interface. Cons: Mainly focused on daylighting, requires Rhino, not as comprehensive for full energy analysis.	[61]
WatchWire	-	Energy Watch	-	Win, Mac	Hourly	Neighborhood and Districts	✔	✔		✔	Pros: Provides energy tracking and analytics geared towards operational energy management. Cons: Primarily a post-construction energy management tool, which means it is not designed for the predictive modelling of building energy performance during the design phases.	[62]

Table 1. *Cont.*

Software	Version	Developer	City, Country	Platform	Timeframe	System Boundary	Available Outputs				Pros and Cons	References
							Energy	Thermal	Daylight	Air Quality		
Sky Spark	3.1	SkyFoundry	Richmond, VA, USA	Win, Mac, Linux	Hourly	Multi-district and cities	✔				Pros: Excellent for data analytics and monitoring. Cons: More focused on data after buildings are operational.	[63]
Wattics	-	wattics	Dublin, Ireland	Win	Hourly	Multi-district and cities	✔				Pros: User-friendly, great for monitoring and analytics with a focus on identifying energy-saving opportunities. Cons: Geared more towards energy management in the operational phase than design phase modelling.	[64]
eTRM	12.2		-	Win	Hourly	Neighborhood and Districts	✔					

The time resolution for white-box simulation tools in building energy management is crucial for capturing the dynamic interactions of various building components and systems. Typically, these tools offer a range of time resolutions, from annual and monthly down to hourly or sub-hourly intervals. The finer the time resolution, the more detailed the understanding of transient phenomena, such as peak load periods or rapid changes in environmental conditions. For example, an hourly resolution can capture daily cycles of heating and cooling demand, while a sub-hourly resolution might be used to analyze the rapid fluctuations in lighting or HVAC systems due to occupancy changes. Selecting the appropriate time resolution is essential for accurate energy modelling and ensuring optimal energy conservation measures.

As shown in Figure 4, each white-box simulation tool can be used for a specific time resolution.

Figure 4. The time resolution for white-box models.

In the following sections, we describe the most common models and software from Table 1, with the pros and cons.

Among the plethora of white-box tools available for building energy management, the selection of “EnergyPlus”, “TRNSYS”, “CitySim”, and “IDA-ICE” is deliberate and strategic. These tools were chosen for their distinct strengths and versatile applications in building energy analysis.

“EnergyPlus” is selected for its exceptional accuracy in simulating building energy performance and its extensive library of building components. It is a robust choice for detailed and precise energy modelling for consultants [65]. Its broad acceptance in the industry further underscores its relevance. “TRNSYS” is a versatile tool capable of simulating various energy systems and offering customizable component modelling [66]. Its adaptability and wide range of applications make it valuable for tackling diverse consulting projects, particularly those involving complex energy systems. "CitySim" is included due to its specialization in urban energy modelling. As city-scale projects become increasingly important, CitySim's focus on this niche area makes it an essential tool for consultants engaged in projects involving multiple buildings and urban infrastructure. "IDA-ICE" brings comprehensive building energy analysis to the table, and its integration with Building Information Modelling (BIM) provides a seamless workflow for consultants. Its energy analysis and BIM integration capabilities make it a valuable tool for modern consulting practices.

The selection of "EnergyPlus", "TRNSYS", "CitySim", and "IDA-ICE" reflects a balanced approach to building energy management consulting, covering a wide range of scenarios and project types. Collectively, these tools offer the precision, versatility, urban focus, and BIM integration required to excel in the field of building energy management.

EnergyPlus

EnergyPlus is an Open-Source [9] and comprehensive building simulation software utilized by engineers, architects, and researchers to model energy usage encompassing heating, cooling, ventilation, lighting, plug loads, and water consumption within buildings [31,67].

EnergyPlus possesses a range of valuable features and functionalities, including integrated and concurrent solutions, heat balance-driven computations, flexible sub-hourly time steps, comprehensive heat and mass transfer calculations, advanced fenestration models, illuminance and glare assessments, component-based HVAC modelling, a variety of pre-defined HVAC and lighting control strategies, and support for the Functional Mock-up Interface [9].

EnergyPlus, as illustrated in Figure 5, employs a nodal approach that utilizes a one-dimensional conduction transfer function and finite-difference algorithm. Nodal methods are known for their capacity to efficiently address the extensive heat transfer calculations required for building thermal performance, enabling rapid computation [29].

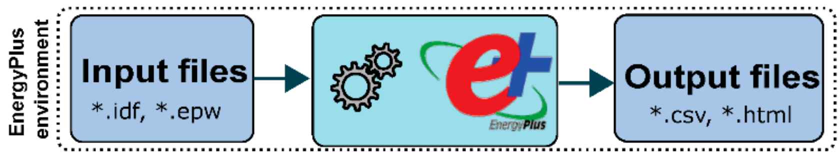

Figure 5. General EnergyPlus simulation scheme.

EnergyPlus stands out as a multifaceted tool for simulating building systems, adept in analyzing heating, cooling, and ventilation dynamics. This software excels in delivering intricate simulations that capture the nuances of thermal mass, state-of-the-art fenestration, and innovative radiant heating/cooling technologies. It adeptly handles a range of HVAC systems, incorporates renewable energy considerations, and applies advanced ventilation strategies, all while prioritizing sustainability through effective water management and thorough environmental impact studies. Additionally, EnergyPlus is equipped with robust economic analysis tools and capabilities for conducting comprehensive life-cycle cost assessments. Modelica and Python integration further enhance the software's functionality, allowing customized modelling and scripting to adapt to specific project needs. A key feature of EnergyPlus is its proficiency in processing diverse meteorological data, including projections of future climatic conditions, thereby positioning it as an essential tool for holistic building performance evaluation, particularly in energy management [68].

EnergyPlus is a highly sophisticated white-box building energy simulation tool that plays a pivotal technical role in the consulting industry, particularly in building energy management and optimization [65]. This tool stands out due to its detailed physics-based approach, enabling the precise modelling of building components and systems, including walls, roofs, HVAC systems, and lighting. Consultants rely on "EnergyPlus" for conducting energy audits and predictive analyses of buildings, benefitting from its accuracy in replicating real-world building conditions [65]. It proves invaluable in retrofitting projects, where understanding the impact of modifications on energy performance is paramount. Moreover, "EnergyPlus" empowers consultants to simulate multiple design scenarios, facilitating data-driven decision-making in the early stages of building design. HVAC system optimization, compliance with energy standards, customized solutions for complex buildings, and effective client communication are among its technical strengths. In summary, "EnergyPlus" is a technically versatile and precise tool that empowers consultants to conduct comprehensive energy analysis, optimize building systems, and provide data-driven insights to enhance building efficiency and sustainability in consulting practices.

TRNSYS

The University of Wisconsin–Madison developed this software package for simulating the behavior of transient systems using graphical interfaces [69]. TRNSYS can simulate other dynamic systems, including traffic flow and biological processes [70]. While virtual energy systems are the primary focus of most simulations, TRNSYS is also used for modelling other dynamic systems [35]. TRNSYS consists of two core components: a kernel engine and a library of 150 models. The kernel engine reads input files, iteratively solves the system, and calculates variables. It also provides utilities for regression, matrix inversion, and data interpolation. The library contains models for various components, from pumps to emerging technologies, enabling customization and expansion of the tool's capabilities [35].

TRNSYS excels in modelling various aspects crucial to building energy consulting. It supports in-depth energy audits, predictive analyses, and retrofitting projects by simulating energy behaviour and assessing modifications. In building design, it offers data-driven insights into energy implications. HVAC system optimization is a strength, ensuring energy efficiency and comfort. TRNSYS aids compliance verification with energy standards and handles complex buildings and unique systems for tailored solutions. It also simplifies complex energy data communication to clients through advanced reporting and visualization, enhancing decision-making in consulting [71].

Energy management strategies, such as optimizing ventilation systems to harness ambient energy and improve heat recovery, are critical in reducing energy consumption and maintaining thermal comfort in residential settings. While research continues to evolve in quantifying the precise energy needs for thermal comfort, TRNSYS offers a platform for such innovative investigations. As a cornerstone in energy management consulting, TRNSYS's flexible modelling framework enables consultants to devise bespoke energy simulations, combining various system components to reflect real-world building behaviours [65]. Its module-based structure is instrumental for consultants who require precision in simulating and analyzing the energy impacts of potential building modifications and exploring various design scenarios [72–74].

TRNSYS stands as a technical cornerstone in the consulting industry, particularly within the domain of building energy management and optimization. Its modular and customizable modelling approach empowers consultants to create tailored energy simulations by assembling predefined components representing various building systems and technologies. This versatility proves invaluable for a wide range of consulting applications, including energy audits, predictive analyses, and retrofitting projects. Consultants rely on "TRNSYS" to model building components and systems accurately, enabling precise assessments of energy performance and the impact of potential modifications. It excels in simulating different design scenarios, facilitating data-driven decision-making in building design's early stages [66].

The specialized features of TRNSYS, such as HVAC system optimization and energy standard compliance, underscore its commitment to delivering tailored solutions for diverse energy management projects. Its advanced reporting and visualization tools bridge the gap between intricate energy modelling and practical client comprehension. In essence, TRNSYS stands out as an adaptable, modular white-box tool that equips energy consultants with the capacity to develop custom, data-driven energy management solutions, driving the push toward more efficient and sustainable building operations [75].

CitySim

CitySim was developed to assist urban planners and stakeholders to minimize the net use of non-renewable energy sources and associated greenhouse gas emissions [36]. CitySim, a specialized tool for urban energy planning, is critical in aiding urban planners and stakeholders in drastically reducing reliance on non-renewable energy sources and mitigating greenhouse gas emissions at the urban district level. As an urban district simulation software, CitySim excels in the precise estimation of energy consumption and the potential for renewable energy generation, offering insights that span individual buildings to entire city landscapes. It distinguishes itself by providing dynamic hourly simulation results, incorporating complex interactions such as mutual shading and interreflections among buildings, which are vital for urban energy studies [26].

CitySim serves as a technical linchpin in the consulting industry. Its unique focus on urban-scale modelling equips consultants to tackle complex environments comprising multiple buildings and infrastructure. From a technical standpoint, "CitySim" provides precise building energy analysis, supports energy audits, and enables predictive analyses [76]. It aids consultants in offering energy efficiency recommendations, simulating various retrofit scenarios, and making data-driven decisions for clients. Moreover, the tool considers climate and environmental factors, helping assess their impact on building energy performance within specific urban contexts. "CitySim" offers technical customization options to adapt to project-specific requirements and is scalable to accommodate projects of varying complexities. It is pivotal in ensuring compliance with energy regulations and policies and enhances client communication through advanced visualization and reporting features. "CitySim" is a technically advanced white-box building energy tool that empowers consultants to navigate urban-scale energy management challenges effectively, making it an indispensable asset in consulting practices [77].

CitySim is a dynamic simulation tool designed for urban energy management, offering capabilities from energy consumption estimation to renewable energy potential evaluation for buildings and districts. It conducts hourly simulations accounting for daily and seasonal energy demand variations, including aspects like mutual shading and thermal exchanges. The tool also models HVAC system performance and occupant behaviour impacts on energy use, enabling realistic urban energy use portrayals. CitySim is valuable for energy audits and predictive analyses, helping forecast and optimize energy needs, including retrofit scenarios for enhanced efficiency. It integrates local climate and environmental data, supporting adherence to energy regulations. CitySim's technical adaptability, scalability, and advanced visualization tools make it a vital resource for sustainable urban energy solutions [78].

IDA-ICE

IDA ICE is a versatile building-level simulation tool utilizing the neutral model format (NMF) for equation-based simulations. It boasts an intuitive graphical user interface, the capability to import industry foundation class (IFC) models, and the ease of extending functionality by creating new components [79]. Although the application of district-level modelling has been somewhat constrained, recent developments (currently available in German) are advancing this field. These developments involve the creation of models tailored for low-temperature district heating networks with bidirectional flow, encompassing components like heat supply devices, distribution pipe segments, pumps, and borehole heat stores [23].

IDA ICE is a fundamental technical pillar in the consulting sector, specifically within building energy management and optimization. Its technical excellence lies in its ability to perform high-precision building energy modelling, allowing consultants to generate intricate simulations of building elements and systems. With support for dynamic simulations and hourly results, IDA ICE captures the dynamic nature of building energy consumption, which is vital for understanding performance variations. Moreover, the tool excels in assessing energy efficiency comprehensively, evaluating energy-saving measures and climate impacts. Technical customization options and parametric analysis empower consultants to tailor simulations to specific projects, optimizing building energy performance. IDA ICE ensures compliance with energy standards and enhances client communication through advanced visualization and reporting features. IDA ICE is a technically advanced white-box building energy tool that equips consultants with the precision and versatility needed for effective consulting practices in building energy management [80].

IDA-ICE is a comprehensive simulation software designed for energy management, providing detailed thermal comfort analysis and energy performance assessments of buildings. Its capabilities include advanced thermal modelling, which considers the building envelope, materials, and occupancy patterns to predict heating and cooling loads accurately. IDA-ICE also offers sophisticated daylighting and shading analyses, crucial for reducing reliance on artificial lighting and optimizing natural light, thus contributing to energy savings. The software's ability to model and simulate various HVAC system configurations allows for fine-tuning energy systems for maximum efficiency. Additionally, IDA-ICE supports integrating renewable energy technologies into its simulations, enabling the design and evaluation of sustainable building solutions. With features for both steady-state and dynamic simulations, IDA-ICE facilitates the exploration of energy-saving measures through retrofitting and renovation projects [81,82].

Figure 6 demonstrates how white-box models can derive hourly cooling and heating load patterns from input files, including domestic hot water profiles, domestic electricity profiles, building stock archetypes, and U-values. These hourly profiles can then serve as inputs for black-box models or assist in determining the optimal balance between supply and demand.

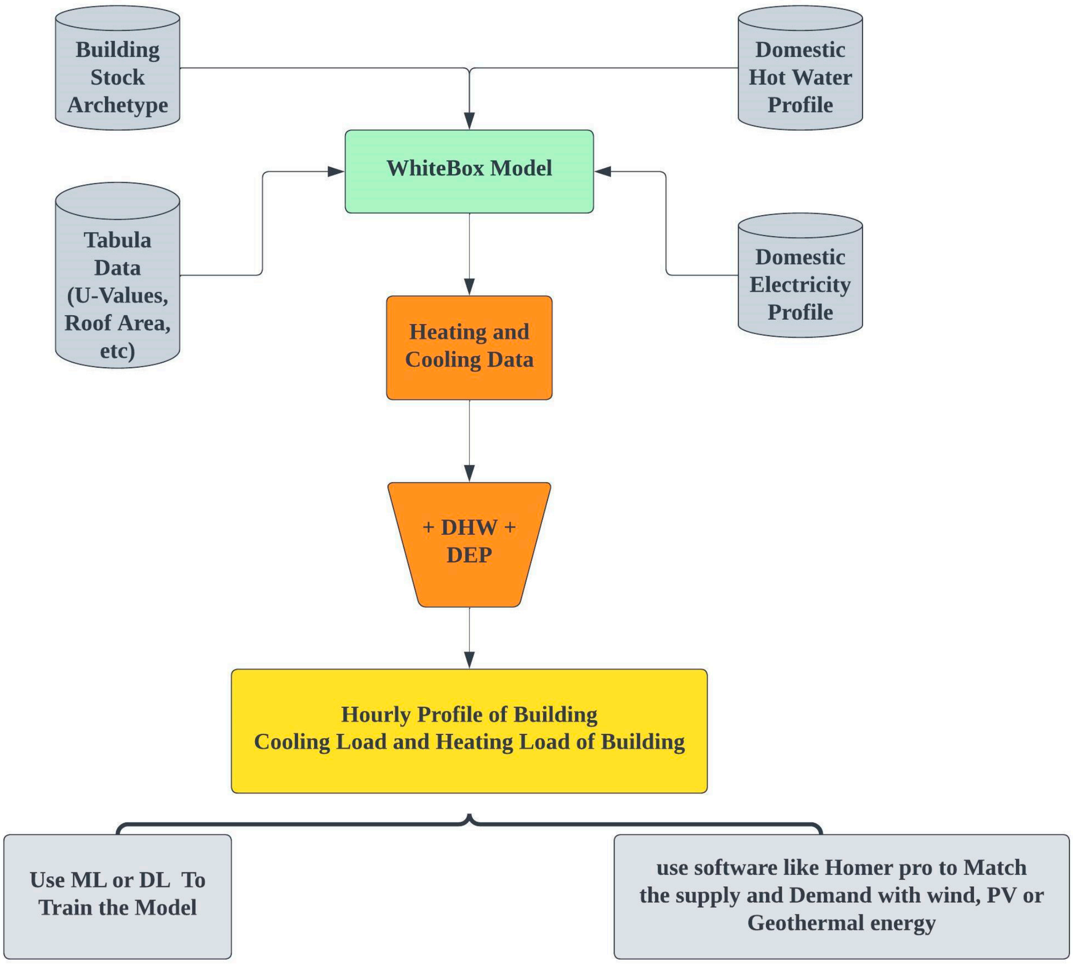

Figure 6. Different outputs using white-box (like IDA-ICE or TRNSYS) and black-box models (ML or DL).

The white-box models can extract energy, thermal, daylight, and air quality from these four outputs, as shown in Figure 7.

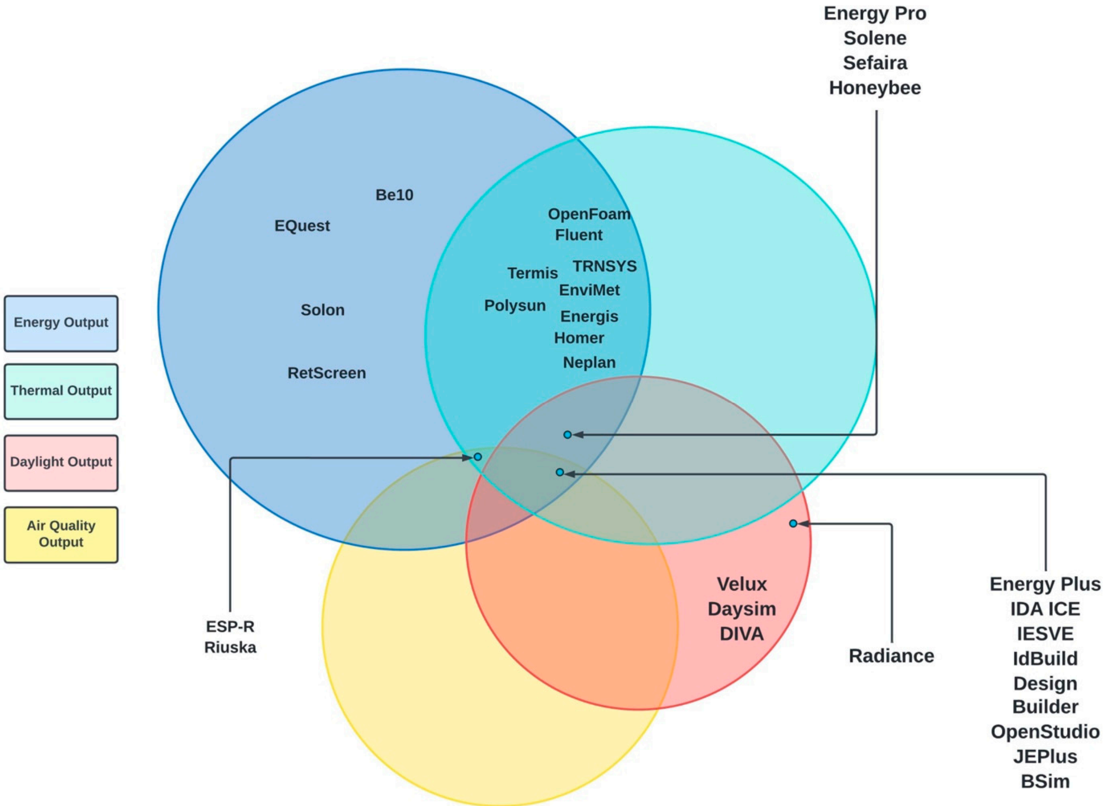

Figure 7. Outputs for white-box energy simulation tool.

4.1.2. Black-Box Models

Data-Driven Modelling (DDM) uses external data to define configurator model components and inject them into the simulations. In different application domains, data-driven models are becoming increasingly popular thanks to progress in computational intelligence and machine learning techniques. The input/output data from real-world systems are used to develop data-driven models rather than analytical or numerical models. Modelling based on data-driven inputs and outputs is described in control and systems engineering by collecting inputs and outputs, choosing a model category, estimating model parameters, and confirming the accuracy of the estimated model.

From simple linear regression [83] to more elaborate deep learning methods [84], energy calculations based on data-driven methods can be performed at various levels of intricacy. The literature [85,86] contains reviews of other methods for data-driven predictions.

Data-driven techniques can be grouped based on their statistical models (such as Support Vector Machine models and Artificial Neural Network models), the type of data they use (empirical or pre-simulated), and the variables they predict. Furthermore, these methods can be categorized according to their specific applications, including design, peak load estimation, fault diagnosis, and system tuning.

Data-driven models eliminate the need for building thermal balance equations, reducing or eliminating the requirement for detailed physical building information [29]. Through mathematical techniques, data-driven models uncover the hidden connections between output variables, such as building energy consumption, and input variables, like weather, building details, occupant behaviour, and equipment schedules. These methods readily apply to buildings that lack comprehensive physical parameters, such as those in the construction phase.

Based on Figure 8, black-box models start with loading building and meteorological datasets. Public [87,88] or private [89] datasets can be used to access building datasets. On the other hand, government meteorological platforms [90] provide access to meteorological datasets. Pre-processing the data is the next step. There is a difficulty with different algorithms, as they make assumptions about your data and may require additional transformations to be applied. However, it is also possible for algorithms to deliver better results without preprocessing when all the rules have been followed and the data have been prepared.

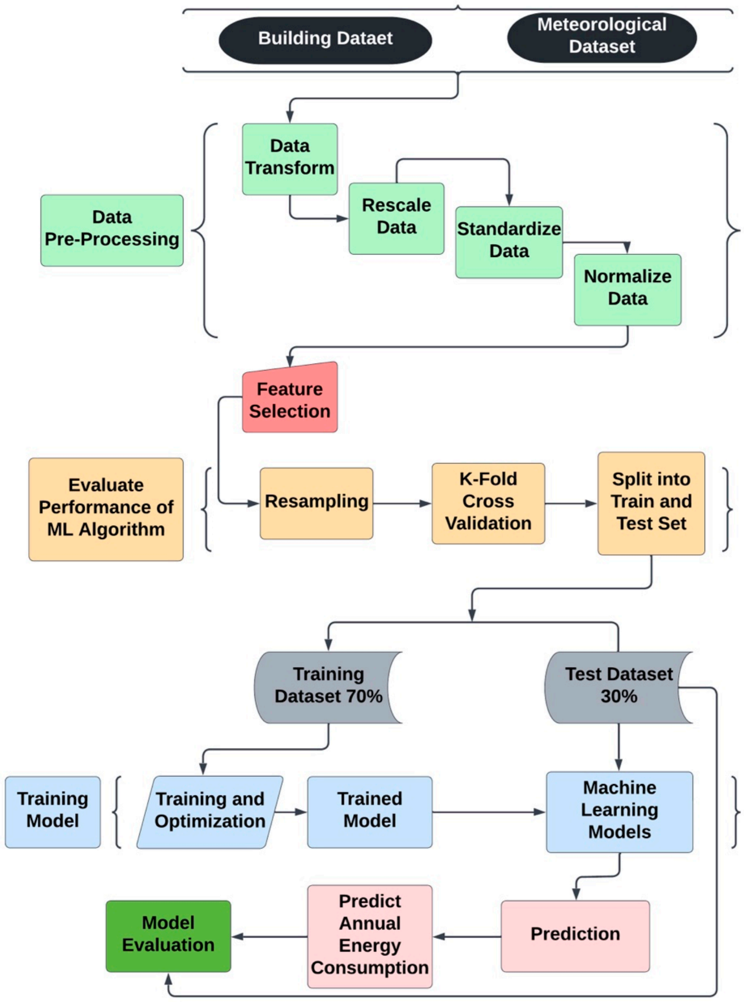

Figure 8. The procedure of black-box methods.

The data should be viewed in many ways, and then a handful of algorithms should be applied to each view. The steps for Pre-processing Data include Transforming Data, Rescaling Data, Standardizing Data, and Normalizing Data. The Data features significantly influence a machine learning model's performance [91]. Features that are unrelated or only partially relevant can have a detrimental effect on a model's performance. The feature selection process involves selecting those features in the data most likely to contribute to a prediction or output. Many models, especially linear algorithms like linear regression and logistic regression, can become less accurate when irrelevant features are present in the data [91].

Evaluating an algorithm's performance on unseen data is crucial. The most effective method is to make predictions on new data with known outcomes, followed by statistical resampling methods for accurate performance estimation. Machine learning algorithms are assessed using different training and testing datasets, where an algorithm is trained on one part of the dataset, predictions are made on the other, and these predictions are compared against expected outcomes.

The black-box model is valued for its simplicity and reliance on actual performance data, suitable for benchmarking across multiple structures. However, it needs more detailed insights into energy inefficiencies and conservation measures, and its accuracy depends on the quality and relevance of historical data. Significant deviations in the data, like major building retrofits, can reduce its predictive power. While useful for Monitoring and Verification (M&V) and forecasting, the black-box model does not provide the in-depth analysis of white or grey-box models but complements them in building energy modelling.

The current review summarizes black-box models in Table 2 below, showing detailed information on the most well-known. All black-box models, based on machine learning or programming codes, can be used on Windows, Mac, or Linux because these simulation tools do not depend on the operating system.

Black-box tools in building energy management have emerged as a cornerstone in consulting, offering empirical, data-driven solutions pivotal for quick decision-making and effective energy management strategies. These tools, grounded in statistical and machine learning models, are employed across various consulting domains, including operational optimization and predictive maintenance [24]. Operational optimization and energy profiling heavily rely on black-box tools within the consulting realm [24]. By analyzing historical energy usage data, these tools discern patterns and anomalies, aiding consultants in offering recommendations to optimize energy consumption and minimize costs [92]. The energy profiling process, which is about understanding a building's energy consumption patterns, is significantly enhanced by black-box models, thanks to their proficiency in processing extensive datasets and pinpointing trends. In predictive maintenance and fault detection, black-box tools show their strengths in building management systems. They utilize historical data to anticipate maintenance needs, averting equipment failures and downtime. These tools are also pivotal in detecting faults in building systems early on before they escalate into serious issues.

For retrofit analysis and scenario simulation in retrofit projects, black-box tools simulate various scenarios to shed light on potential energy savings and return on investment. Their rapid processing of different scenarios assists consultants in suggesting the most cost-effective and energy-efficient retrofit measures.

Real-time energy management and demand response strategies extensively leverage black-box tools. These tools enable consultants to offer instant recommendations for energy optimization and are integral in demand response strategies, where buildings alter their energy usage in response to external cues like peak demand periods or fluctuations in energy prices [92].

The adaptability of black-box tools allows consultants to provide tailored solutions for various building types and sizes, which is especially beneficial in buildings with unpredictable energy usage patterns or where in-depth physical modelling is impractical. Client reporting and visualization are other areas where black-box tools excel. Equipped with advanced reporting and visualization features, these tools help consultants communicate complex energy data to clients in an understandable manner, converting vast data into comprehensible reports and graphs. Moreover, consultants employ black-box tools for benchmarking the energy performance of buildings against counterparts or industry standards. This benchmarking is crucial for pinpointing areas for energy performance enhancement and guiding strategic planning for energy efficiency improvements.

These four tools, Linear Regression, Support Vector Machines (SVM), Random Forest, and Deep Neural Networks (DNN), have been selected for detailed explanation among various other options in the domain of black-box models for BEM. This choice has been made due to their wide adoption and effectiveness in handling diverse building energy optimization tasks. Linear Regression provides a fundamental understanding of relationships between variables and serves as a baseline model. SVM, known for its robustness in handling complex data, offers excellent classification capabilities. Random Forest is selected for its ensemble learning approach, which enhances predictive accuracy. DNN, as a deep learning model, has shown remarkable success in capturing intricate patterns and nonlinear relationships in building energy data. These four tools collectively represent a comprehensive spectrum of modelling approaches, making them crucial for consultants and professionals engaged in building energy management, thus warranting in-depth exploration.

Table 2. Black-box models.

Software/Code	Version	Developer	City, Country	Language	System Boundary	Available Outputs				Pros and Cons	References
						Energy	Thermal	Electrical	Lighting		
Open IDEAS	-		Paris, France	Modelica, Motoko, Python	-		✔	✔		Pros: Integrates with the Modelica language, allowing for flexible, physics-based modelling of building energy systems. Cons: Requires knowledge of the Modelica language.	[93,94]
TEASER	0.7.7	RWTH Aachen University	-	Python, Modelica	Single-Family and Multi-Family House	✔				Pros: Quick setup of building energy models for urban-scale simulations. Cons: Does not have the depth and detail needed for fine-tuned building-specific energy analysis.	[95,96]
CityLearn	2.1.0	Intelligent Environments Laboratory	Berkeley, CA, USA	Python	City	✔				Pros: Designed to facilitate multi-agent reinforcement learning. Cons: Requires knowledge of reinforcement learning techniques.	[97,98]
PyCity	0.3.3	RWTH Aachen University	Aachen, Germany	Python	Neighborhood, Districts	✔	✔			Pros: Python-based tool that offers flexibility and integration with other Python libraries and tools. Cons: Python proficiency is needed.	[99]
RC Building Simulator	-	Prageeth Jayathissa, et al.	-	Python	Single-Family and Multi-Family House	✔			✔	Pros: Simplifies the process of building thermal modelling using RC models. Cons: Oversimplification may miss out on more complex interactions.	[100]
Open energy modelling framework	1.0	Oemof developer team	Open source	Python	-	✔				Pros: An open-source framework that can be tailored to various energy system modelling needs. Cons: Might require more effort to set up and customize compared to out-of-the-box solutions.	[101]

Table 2. *Cont.*

Software/Code	Version	Developer	City, Country	Language	System Boundary	Available Outputs				Pros and Cons	References
						Energy	Thermal	Electrical	Lighting		
OCHRE	0.8.4	NREL	Chicago, IL, USA	Python	-	✔				Pros: Targets optimal control and hardware-in-the-loop simulation. Cons: It may not be as widely applicable or supported as more established tools.	[102,103]
ResStock	3.2.0	NREL	USA		Single-Family house	✔				Pros: Specializes in residential energy analysis. Cons: May require a large dataset for analysis.	[104]
EETBS	-		-	Python	-	✔				Pros: It is useful for educational purposes and early design decisions. Cons: It might lack the robustness required for in-depth professional use.	[105]
Building Energy Platform	-		-	Python, Java	Multi Districts, city, neighborhood, Districts, single-family house, multi-family house	✔				Pros: Potentially integrating various data sources. Cons: The platform may depend on the availability and quality of data inputs for effective energy management.	[106]
Building automation energy data analytics (BAEDA)	-	Team from Polytechnic of Turin University	-	Python	Single-Family House, Multi-Family House	✔		✔		Pros: Designed to analyze data from building automation systems to improve energy efficiency. Cons: May require complex integration with existing building automation systems and substantial data processing capabilities.	[107]

Linear Regression (LR)

LR has been widely used in many fields since it has good predictive performance and is simple. Linear and nonlinear regression methods are both regression methods [108]. Linear regression, when applied as a black-box model in building energy management and the broader energy industry, presents both advantages and challenges. At its core, linear regression seeks to model the relationship between one or more independent variables (predictors) and a dependent variable (often the energy consumption in this context). As a black-box approach, it emphasizes prediction accuracy over the interpretability of the underlying relationships. This predictive nature allows stakeholders in the energy industry to make quick, data-informed decisions about energy use and demand forecasting without necessarily understanding the intricate physical processes behind it.

Linear regression serves as a foundational analytical method within the energy management discipline, offering a straightforward and computationally efficient approach to model and forecast energy consumption. Its utility in the energy sector is underscored by its ability to inform resource distribution, enhance operational efficiency, and discern consumption trends. Energy managers frequently deploy linear regression for load forecasting and demand-side management, as well as for crafting predictive models of energy usage that facilitate swift, data-driven decision-making. While linear regression is esteemed for its simplicity and ease of use, which are advantageous for prompt analyses, it is also important to recognize its limitations in encapsulating the complex, nonlinear interdependencies typical of advanced energy systems. This recognition underscores the necessity for an eclectic array of analytical tools to comprehensively address the multifaceted nature of energy system modelling and management [109].

Linear regression is well-suited for applications involving linear or nearly linear relationships between variables, such as baseline energy consumption modelling, essential forecasting, and analyzing the influence of factors like outdoor temperature on energy usage. However, it may not effectively capture complex nonlinear relationships found in intricate building systems [83].

Technically, this tool models relationships between independent variables (predictors) and a dependent variable, often representing energy consumption. Consulting is frequently employed to create baseline energy consumption models, enabling consultants to establish reference points for energy management. Additionally, Linear Regression supports straightforward energy consumption forecasting, aiding consultants in short-term predictions and energy-efficient planning. Moreover, it helps identify critical factors affecting energy usage, such as temperature or occupancy, providing valuable technical insights for consultants. Its simplicity and computational efficiency make it a go-to choice for rapid data-driven decision-making. However, it is essential to acknowledge that Linear Regression may have limitations in capturing complex, nonlinear relationships, which are prevalent in intricate building systems. Nonetheless, its technical advantages position it as a valuable tool for consultants seeking quick and practical insights into building energy management within the consulting industry.

Support Vector Machine

Support vector machine (SVM) comprises a range of supervised learning techniques employed for tasks like classification, regression, and identifying outliers [110]. Support vector machines have several advantages, such as effectively handling high-dimensional spaces. Furthermore, this approach remains efficient even when dealing with datasets with greater dimensions than the number of samples. Additionally, the decision function relies on a subset of training points known as support vectors, ensuring memory efficiency. Finally, SVM's ability to solve nonlinear problems is one of its most essential capabilities [29,110].

Support Vector Machines (SVMs) stand out in the energy management sector for their robust predictive capabilities, particularly within building energy optimization. As a class of powerful black-box models derived from machine learning, SVMs are adept at classification and regression tasks, which are essential for analyzing and interpreting complex energy datasets. Their application in energy management is particularly valuable for forecasting consumption patterns, identifying irregularities in energy usage, and categorizing different operational states of energy systems. SVMs are prized for their proficiency in handling multi-dimensional datasets and their capacity to elucidate intricate nonlinear relationships frequently occurring in building energy systems. Utilizing the kernel trick, SVMs can transform nonlinear data distributions into a format amenable to analysis, which is particularly beneficial for modelling the dynamic interactions within building energy systems. By providing accurate and refined models of energy behaviours, SVMs contribute significantly to enhancing energy efficiency measures and optimizing operational processes, solidifying their role as indispensable assets in the strategic toolkit of energy management professionals [91].

Derived from machine learning, SVMs excel in classification and regression tasks by identifying optimal hyperplanes in high-dimensional spaces to classify or predict data points. In consulting, these tools offer several technical advantages. They are instrumental in predicting energy consumption patterns, enabling consultants to forecast and understand energy usage—a fundamental requirement in consulting. Additionally, SVMs excel in anomaly detection, helping identify irregularities or inefficiencies in energy use and contributing to efficient energy management. Moreover, they can classify building operational states, offering insights into building performance and facilitating data-driven decision-making. Their proficiency in handling high-dimensional data and capturing complex nonlinear relationships between variables is particularly relevant in building energy dynamics' intricate and multifaceted domain. Overall, SVMs are a technically powerful asset for consultants in building energy management, aligning with the industry's complex and dynamic nature [111].

SVMs, especially with nonlinear kernels, can capture intricate relationships in data. They are suitable for predicting energy consumption patterns, detecting anomalies in energy usage, and classifying the operational states of building systems. Their ability to handle high-dimensional data can be beneficial when integrating multiple sensors and systems [112].

Random Forest

Random forest algorithms combine bagging and feature randomness to create uncorrelated forests of decision trees, which is an extension of the bagging method. Three primary hyperparameters need to be set before training a random forest algorithm. There are three main factors: node size, trees, and feature samples.

The Random Forest algorithm offers advantages and challenges for classification and regression tasks. It notably reduces overfitting, a common issue in decision trees, by averaging uncorrelated trees, making it popular for accurate regression and classification tasks among data scientists [113]. The Random Forest method is crucial in the energy industry because it provides accurate predictions while mitigating overfitting, handling missing data, and determining feature importance. Its flexibility in addressing regression and classification tasks, scalability for large datasets, and capacity to capture nonlinear relationships make it a versatile tool. It plays a vital role in energy diagnostics, enabling energy consumption predictions, fault detection, and identification of key drivers for energy use. Random Forest is invaluable for optimizing energy performance and improving operational efficiency in the energy sector. A critical challenge of Random Forest is its time-consuming nature, as it processes data slowly when computing each decision tree. It also consumes more resources because it handles larger datasets, potentially limiting data storage resources. Moreover, it is more complex than a single decision tree, making predictions less straightforward to interpret [114].

Leveraging ensemble learning, Random Forest combines multiple decision trees to provide robust predictions and insights. Its key advantages include the reduction of overfitting, adaptability for various tasks (classification and regression), the ability to handle missing data, straightforward determination of feature importance, and the capture of complex relationships between variables. These qualities make it invaluable in consulting, which finds applications in predicting energy consumption, detecting system faults, and assessing feature importance. Its versatility, high predictive accuracy, and capability to handle diverse tasks make it an indispensable tool for consultants engaged in building energy management and optimization [111].

The Random Forest method is a robust ensemble learning technique widely recognized for its effectiveness in energy management. By leveraging a multitude of decision trees to generate predictions and classify data, Random Forest excels at handling the multifaceted nature of energy systems, from predicting energy demand and consumption to optimizing energy distribution and detecting system inefficiencies. Its inherent ability to manage large datasets with numerous variables makes it particularly adept at capturing the complex interactions within energy systems, such as the interplay between usage patterns and environmental factors. Random Forest's capacity for feature importance evaluation aids in identifying key predictors of energy performance, thereby informing targeted energy-saving strategies. Furthermore, its strong predictive accuracy and resistance to overfitting are invaluable for ensuring reliable decision-making in energy efficiency initiatives, renewable integration, and load forecasting. This method's comprehensive analytical strengths make it an essential component of data-driven decision-making in energy management, providing actionable insights for enhancing system reliability and sustainability [115].

Deep Neural Networks

Deep Neural Networks (DNNs- Figure 9), applied as black-box models in building energy management, excel at learning from extensive data, making them invaluable in this field. Their architecture comprises multiple interconnected layers capable of automatically extracting complex data patterns. This inherent ability allows DNNs to model building energy systems' intricate and nonlinear dynamics effectively. Whether the task involves energy consumption prediction, HVAC optimization, or anomaly detection, DNNs consistently outperform traditional models, adapting well to diverse building types, systems, and external factors like weather conditions [113].

Deep Neural Networks (DNNs) have become indispensable in the energy industry due to their capacity to handle large and complex datasets. In building energy management, DNNs are crucial in predicting energy consumption, optimizing HVAC systems, and detecting anomalies, often outperforming traditional models. Their significance lies in their ability to capture intricate patterns and relationships within energy systems, making them valuable tools for improving energy efficiency. However, their black-box nature can be a challenge, making it challenging to interpret how they arrive at their predictions. This opacity may pose issues for stakeholders seeking to uncover energy inefficiencies or meet regulatory transparency requirements. DNNs also require substantial amounts of labeled data, which can be limited in building energy contexts. Additionally, setting up and fine-tuning DNNs can be a complex task. Despite these hurdles, the substantial predictive power of DNNs and ongoing research in model interpretability ensure their continued prominence in the future of the energy industry, where data-driven decision-making and sustainability are paramount [111,116].

Deep Neural Networks (DNNs) have emerged as a powerful tool in building energy management consulting practices. DNNs, consisting of multiple interconnected layers of nodes, excel at automatically extracting intricate features and patterns from data. This inherent capability makes them well-suited for modelling the complex and often nonlinear dynamics of building energy systems. Consultants leverage DNNs for various applications, including energy consumption forecasting, optimizing HVAC operations, and detecting anomalous energy usage patterns. DNNs have demonstrated superior performance compared to traditional machine learning models, adapting to diverse building typologies, systems, and external factors such as weather patterns [117]. However, DNNs also need help in consulting. Their black-box nature, while providing accurate predictions, lacks interpretability, making it challenging to uncover the underlying physical relationships behind energy behaviours. This opacity can be problematic when stakeholders must understand the root causes of energy inefficiencies or meet regulatory transparency requirements. Training DNNs requires substantial amounts of labelled data, which may only sometimes be readily available in building energy contexts. The selection of the right architecture, hyperparameter tuning, and avoiding overfitting demand careful consideration, making the application of DNNs non-trivial [118].

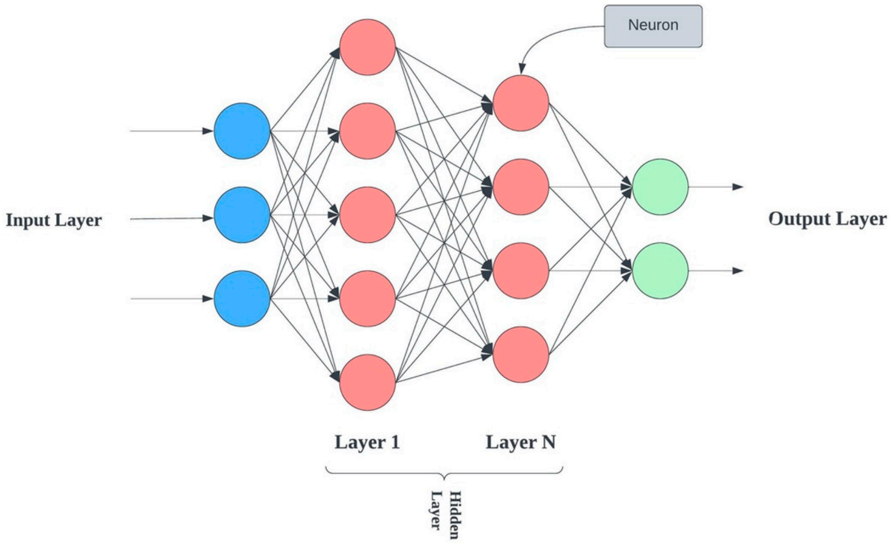

Figure 9. A Deep Neural Network with N Hidden Layers.

Despite these challenges, DNNs' exceptional predictive capabilities and ongoing research in model interpretability ensure their continued prominence in the consulting landscape of building energy management. They provide consultants with a powerful tool to analyze and optimize energy systems, ultimately leading to more efficient and sustainable building practices.

4.2. Web-Based Models

Web simulation tools can be categorized into white-box and black-box, similar to standalone simulation tools. Web-based interfaces for building energy systems have gained popularity due to their cost-effectiveness, compatibility across platforms, and ease of maintenance. These interfaces offer advantages such as cloud hosting and computing, which prevent data loss and facilitate data exchange.

In recent years, many tools have adopted web interfaces to visualize energy data, enabling benchmarking and detailed analysis of simulation results for urban buildings. These web-based tools can create 3D energy models of urban buildings and overlay colour codes to represent energy performance levels, allowing filtering by size, type, location, and building system for in-depth analysis [25].

These applications' simple interface and quick outputs dramatically lighten the load for users. Furthermore, it has several significant benefits for users. These tools are automatically updated by updating the server's source code, so users do not need to update them themselves. In addition, they are more suitable for teams since they make it easier for team members to share the project information and have little risk of losing project data. Finally, they may use cloud computation more effectively. Cloud computing technology can reduce calculation time and system processing power, which is critical to building performance simulations [25,119]. Various time resolutions, from one hour to a year, are available through the web tools, as shown in Figure 10.

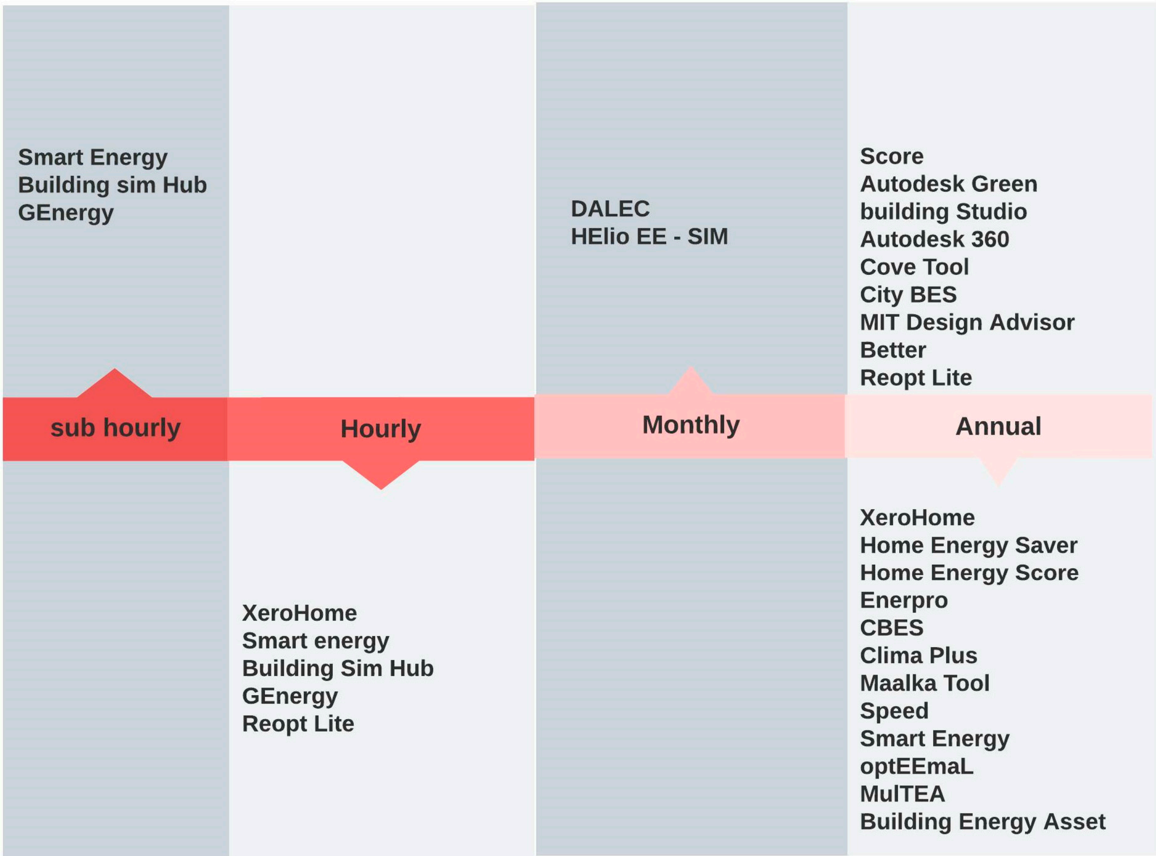

Figure 10. Time resolution for WebTools.

Compared with standalone simulation tools, web-based simulation tools also have several disadvantages. The GUI of browser-based applications (such as HTML) is limited compared to desktop applications, meaning that a single function might be repeated across multiple pages [111]. Users must navigate several pages and follow a sequence pattern to perform a simple calculation or analysis [120–122]. These applications provide slower response times because of work-wait patterns and standby modes that limit their interaction on the page refreshing [120,121,123], and the whole process is slowed down by longer response times.

A fast and stable internet connection is required for these applications to function correctly and ensure fast data transmission [124–126]. Security issues, such as the risk of reverse engineering and hijacking of source code [127], lack of management, maintenance, and modification, network connectivity limitations, limited access to local resources, and difficulties in debugging [128] are the most reported disadvantages.

Web-based tools in building energy management have become integral to consulting practices, offering a range of technical capabilities that support consultants in their energy analysis and decision-making processes. These tools are accessible via web interfaces, making them convenient and cost-effective for consultants. They have a significant impact on consulting practices by facilitating data visualization and benchmarking, offering simulation and modelling capabilities, utilizing cloud hosting and data exchange for enhanced data security, supporting collaboration and client communication, providing comprehensive energy performance analysis, and ensuring accessibility and flexibility. In summary, web-based tools enhance consulting practices by empowering consultants to provide data-driven insights, optimize building energy systems, and make informed decisions for energy efficiency improvements while effectively engaging clients in the process [129].

Table 3 summarizes the software's features, such as developer, zone analysis level, building type, available outputs, and modelling approach for webtools.

Table 3. Web Tool Simulation tools.

Software/Code	Version	Developer	City, Country	Black-Box/White-Box	System Boundary	Available Outputs				Timeframe	Pros and Cons	Reference
						Energy	Thermal	Electrical	Daylight			
Xerohome	23503	Mudit Saxena, Peter Mayostendorp, Inderdeep Dhir	CA, USA	White-Box Model	Single-Family House and Multi-Family House	✔				Dynamic	Pros: Offers detailed modelling of home energy efficiency. Cons: Only for US.	[130]
Home Energy saver	-	Berkely Lab	-	Black-Box Model	Single-Family House and Multi-Family House	✔				Annual	Pros: Provides homeowners with personalized energy use assessments and improvement recommendations. Cons: Only for US.	[131]
Home Energy score	-	U.S. Department of Energy	USA	Black-Box Model	Single-Family House and Multi-Family House	✔				Annual	Pros: Gives a quick and straightforward assessment of a home's energy efficiency and potential improvements. Cons: Simplified scoring may not reflect the complexities of individual homes' energy dynamics.	[132]
Enerpro (The Energy Profile Tool)	9.2.1	EnerSys Analytics Inc. and XModus Software Inc.	Vancouver, BC, Canada	White-Box Model	Single-Family House and Multi-Family House	✔				Annual	Pros: Allows for quick benchmarking of a building's energy performance against similar structures. Cons: May not provide detailed suggestions for energy improvements.	[133]
Senapt		Senapt Team	UK	-	Single-Family House and Multi-Family House	✔					Pros: Can assist in monitoring and managing energy consumption. Cons: May require technical expertise.	[134]
CBES	2.0	CIPSEA		Black-Box Model	Multi-Districts and City Scale	✔				Annual	Pros: Provides quick energy efficiency assessments. Cons: The tool's recommendations may be less specific than those obtained from a detailed analysis.	[22]
ClimaPlus	Climasplus 2020		MA, USA	White-Box Model	Single-Family House and Multi-Family House					Annual	Pros: Focuses on climate data analysis to inform building design and retrofit strategies for energy efficiency improvements. Cons: Its use may be limited if climate data integration is not a central component of the energy management strategy.	[135]
Maalka Tools		Maalka Inc., NY	NY, USA	White-Box Model	Single-Family House and Multi-Family House	✔	✔			Annual	Pros: Offers a platform for managing sustainability metrics and energy performance data. Cons: May require significant data input.	[136]

Table 3. *Cont.*

Software/Code	Version	Developer	City, Country	Black-Box/White-Box	System Boundary	Available Outputs				Timeframe	Pros and Cons	Reference
						Energy	Thermal	Electrical	Daylight			
Speed	2021		Wasliiiigton, DC, USA	White-Box Model	Single-Family House and Multi-Family House				✔	Annual	Pros: Designed for rapid energy modelling. Cons: The speed of analysis might come at the expense of model depth and accuracy compared to more detailed simulation tools.	[137]
Smart energy	3.0.1		USA	White-Box Model	Single-Family House and Multi-Family House	✔				Hourly, Sub Hourly	Pros: Enables detailed analysis and optimization of energy consumption, aiming to improve overall building energy efficiency. Cons: Its effectiveness greatly depends on the availability and granularity of energy consumption data fed into the system.	[138]
OptEEmAL	2019	European Union	Spain, Germany	White-Box Model	Single-Family House and Multi-Family House	✔				Annual	Pros: Offers a platform for optimizing energy-efficient building retrofit plans using integrated project delivery methods, which can enhance collaboration and efficiency. Cons: May require complex data and modelling inputs.	[139,140]
MulTEA	2018	Oak Ridge National Laboratory (ORNL) and the Lawrence Berkeley National Laboratory (LBNL)	TN, USA	White-Box Model	Single-Family House and Multi-Family House	✔				Annual	Pros: Provides a multi-scale transient energy analysis for buildings. Cons: The complexity of multi-scale analysis might not be necessary for all projects and can be resource-intensive.	[141]
Building Energy asset score	2014	Us department of Energy	USA	Black-Box Model	Single-Family House and Multi-Family House	✔			✔	Annual	Pros: Developed by the U.S. Department of Energy, it assesses the energy efficiency of building assets and provides a score, making it useful for benchmarking and understanding potential improvements, open source. Cons: Primarily focused on the inherent energy performance of the physical building assets, which may not account for operational variables.	[22]
CityBES	-	Lawrence Berkeley National Lab, under the Laboratory Directed Research and Development	Berkeley, MA, USA	White-Box Model	Multi-Districts and City Scale	✔		✔		Annual	Pros: A tool designed for urban-scale analysis, it helps in evaluating energy savings and carbon reduction strategies for city-wide building stocks. Cons: Its urban focus might make it less applicable for individual building projects or more detailed energy system design.	[142]

Table 3. *Cont.*

Software/Code	Version	Developer	City, Country	Black-Box/White-Box	System Boundary	Available Outputs				Timeframe	Pros and Cons	Reference
						Energy	Thermal	Electrical	Daylight			
Autodesk Green Building Studio	2023	Autodesk	San Rafael, CA, USA	Black-Box Model	Multi-Districts and City Scale	✔	✔		✔	Annual	Pros: Integrates with other Autodesk design software, enabling seamless energy analysis within the design process, useful for architects and designers. Cons: As part of a suite of design tools, it may not have the depth of standalone energy simulation software.	[143]
Autodesk insight 360	2023	Autodesk	San Rafael, CA, USA	Black-Box Model	Multi-Districts and City Scale				✔	Annual	Pros: Provides cloud-based energy modelling that is integrated with BIM (Building Information Modelling), offering user-friendly insights into the energy and environmental design of buildings. Cons: Might require a subscription to the Autodesk suite, and its simplified interface may not offer the granularity needed for complex engineering analyses.	[144]
BuildingSimHub	2017	Us department of Energy	France	White-Box Model	Multi-Districts and City Scale	✔				Hourly, Sub Hourly	Pros: Offers a cloud-based simulation platform that streamlines the building energy modelling process, making it accessible for collaboration across different stakeholders. Cons: Being cloud-based, it may face limitations with data security concerns or require a stable internet connection for optimal use.	[145]
Rescheck—web	-	Us department of Energy	USA	White-Box Model	Multi-Districts and City Scale	✔				-	Pros: Provides a straightforward method for demonstrating building energy code compliance, with a focus on residential buildings, and is a free web-based tool offered by the U.S. Department of Energy. Cons: While useful for code compliance, it may not offer the detailed analysis required for optimizing energy consumption beyond the minimum code requirements.	[146]
Cove Tool	2023	Covetool, Georgia, US	Atlanta, GA, USA	Black-Box Model		✔			✔	Annual	Pros: Streamlines the process of energy modelling with an emphasis on cost and performance, integrating sustainable design strategies. Cons: As a relatively new entrant, it may not have as wide adoption or comprehensive databases as more established tools.	[147]

Table 3. *Cont.*

Software/Code	Version	Developer	City, Country	Black-Box/White-Box	System Boundary	Available Outputs				Timeframe	Pros and Cons	Reference
						Energy	Thermal	Electrical	Daylight			
Edge	3.0	Team of Edge	UK	-	Single-Family House and Multi-Family House	✔				-	Pros: Focuses on sustainability and offers certifications for green buildings, with a user-friendly interface. Cons: Primarily used for certification purposes and may not be as detailed for technical engineering analysis.	[148]
DALEC	2023	DALEC Team	-	Black-Box Model	Single-Family House and Multi-Family House				✔	Monthly	Pros: Provides life-cycle carbon and energy analysis, useful for assessing the environmental impact of buildings. Cons: The focus on carbon may mean that energy efficiency measures are not as comprehensively addressed.	[149]
MIT Design Advisor	1.1	MIT Department of Architecture	MA, USA	Black-Box Model	Neighborhood and District Scale					Annual	Pros: Allows for quick assessment of design strategies on building energy use, targeted toward the early design phase. Cons: Limited in scope and may not be suitable for detailed final analysis or large-scale projects.	[150]
HeliOS EE-SIM	2017	Helios Inc.	CA, US	Black-Box Model	Neighborhood and District Scale					Monthly	Pros: Specializes in solar potential and energy simulation, aiding in the design of photovoltaic systems. Cons: Focus on solar analysis means other aspects of building energy management might need additional tools.	[22]
Better	L6.1		-	Black-Box Model	Single-Family House and Multi-Family House					Annual	Pros: Designed to analyze and compare building energy data, enabling tracking of improvements over time, open source. Cons: Its effectiveness is dependent on the quality and completeness of input data.	
Neo Net Energy Optimizer	2023	Ryan schwartz	Canada	Black-Box Model	Single-Family House and Multi-Family House	✔					Pros: Specializes in optimizing net-zero energy buildings by balancing energy production and consumption, making it valuable for sustainable design projects. Cons: Focus on net-zero energy optimization may not be as comprehensive for general energy management needs or less sustainable-oriented projects.	[151]

Table 3. *Cont.*

Software/Code	Version	Developer	City, Country	Black-Box/White-Box	System Boundary	Available Outputs				Timeframe	Pros and Cons	Reference
						Energy	Thermal	Electrical	Daylight			
SEMERGY	2016	XYLEM Technologies	-	White-Box Model	Multi-Districts and City Scale	✔	✔				Pros: Utilizes a web-based decision support system for optimizing energy efficiency in building renovation, incorporating a broad range of data including climate, building materials, and systems. Cons: May require detailed inputs and specific knowledge of renovation projects, which can limit its utility for initial design stages or new constructions.	[152]
Energinet	2021	Cebyc AS	Denmark	Black-Box Model	Multi-Districts and City Scale	✔					Pros: Aims to provide a comprehensive database and networking platform for energy market data, potentially facilitating energy trading and market analysis. Cons: Its role as a data platform means it may not directly assist in building-specific energy modelling or management tasks.	[153]
EPWMap	0.0.6	Mostapha Roudsari	-	White-Box Model	Single-Family House and Multi-Family House				Air Quality		Pros: Offers an interactive map of EnergyPlus weather data, aiding in the selection of appropriate climate data for building energy simulations. Cons: As a tool focused on climate data provision, it does not perform energy modelling or analysis itself.	[154]
Deksoft	2.1	Petr Kocian	Czech Republic	White-Box Model	Single-Family House and Multi-Family House		✔				Pros: May refer to software tools designed for specific energy management tasks, possibly including building performance analysis. Cons: Without more context on Deksoft, it is challenging to provide specific pros and cons; if it is specialized software, it may have limited applicability or require specialized knowledge to use effectively.	[155]
GEnergy	-	Donald alexander	USA	White-Box Model	Single-Family House and Multi-Family House	✔				Hourly, Sub Hourly	Pros: Can offer user-friendly interfaces for energy auditing and management, aiming to simplify the process of identifying energy-saving opportunities. Cons: May lack the depth of more specialized simulation tools for detailed technical analysis.	[156]

Table 3. *Cont.*

Software/Code	Version	Developer	City, Country	Black-Box/White-Box	System Boundary	Available Outputs				Timeframe	Pros and Cons	Reference
						Energy	Thermal	Electrical	Daylight			
EnExPlan	-	Marc Lacombe—Almiranta	Montreal, QC, Canada	White-Box Model	Neighborhood and District Scale	✔					Pros: Designed for energy exploration and planning, this tool may assist in strategizing energy distribution and conservation measures. Cons: It might be more suited for macro-level planning rather than detailed building-specific simulations.	[157]
ReOpt Lite	3.0.1	Linda Parkhill -NREL	USA	Black-Box Model	Single-Family House and Multi-Family House			✔		Hourly/Annual Analysis	Pros: Provided by the National Renewable Energy Laboratory (NREL), it helps optimize energy systems for cost and performance, focusing on renewable integration and grid reliability. Cons: As a "lite" version, it may not include all the features of a full-scale model, potentially limiting detailed analysis.	[158]
Hippo CMMS	-	Daniel Golub	Winnipeg, Canada	Black-Box Model	Single-Family House and Multi-Family House	✔					Pros: Offers a computerized maintenance management system (CMMS) that can track and manage building maintenance operations, indirectly affecting energy efficiency through optimal equipment performance. Cons: Its primary focus is on maintenance management rather than direct energy modelling or simulation.	[159]
Building performance database (BPD)	-	Robin Mitchell	USA	-	Multi-Districts and City Scale	✔					Pros: The largest publicly available source of building performance data in the U.S., useful for benchmarking and analyzing building energy performance. Cons: Primarily a database, it does not perform simulations or analyses but requires interpretation of data for application in energy management.	[160]
Snugg PRo	5.0	Sandy Michelas	Denver, CO, USA	Black-Box Model	Single-Family House and Multi-Family House	✔					Pros: A software tool tailored for home energy audits that can provide recommendations for energy efficiency improvements and detailed reports. Cons: May not be as comprehensive for commercial buildings or large-scale energy management projects, only for US	[161]

The web tool approach does not necessitate an in-depth comprehension of heat transfer and thermal behaviour in building components, as is the case with physics-based models. Therefore, this approach suits building circumstances where physical characteristics are not determined. Due to this feature, design and retrofit toolkits that use data-driven calculation methods are also ideal for non-expert users, such as designers and building owners [162].

Due to the capability and application of BES systems, several inputs and outputs for these BES tools are depicted in Figure 11.

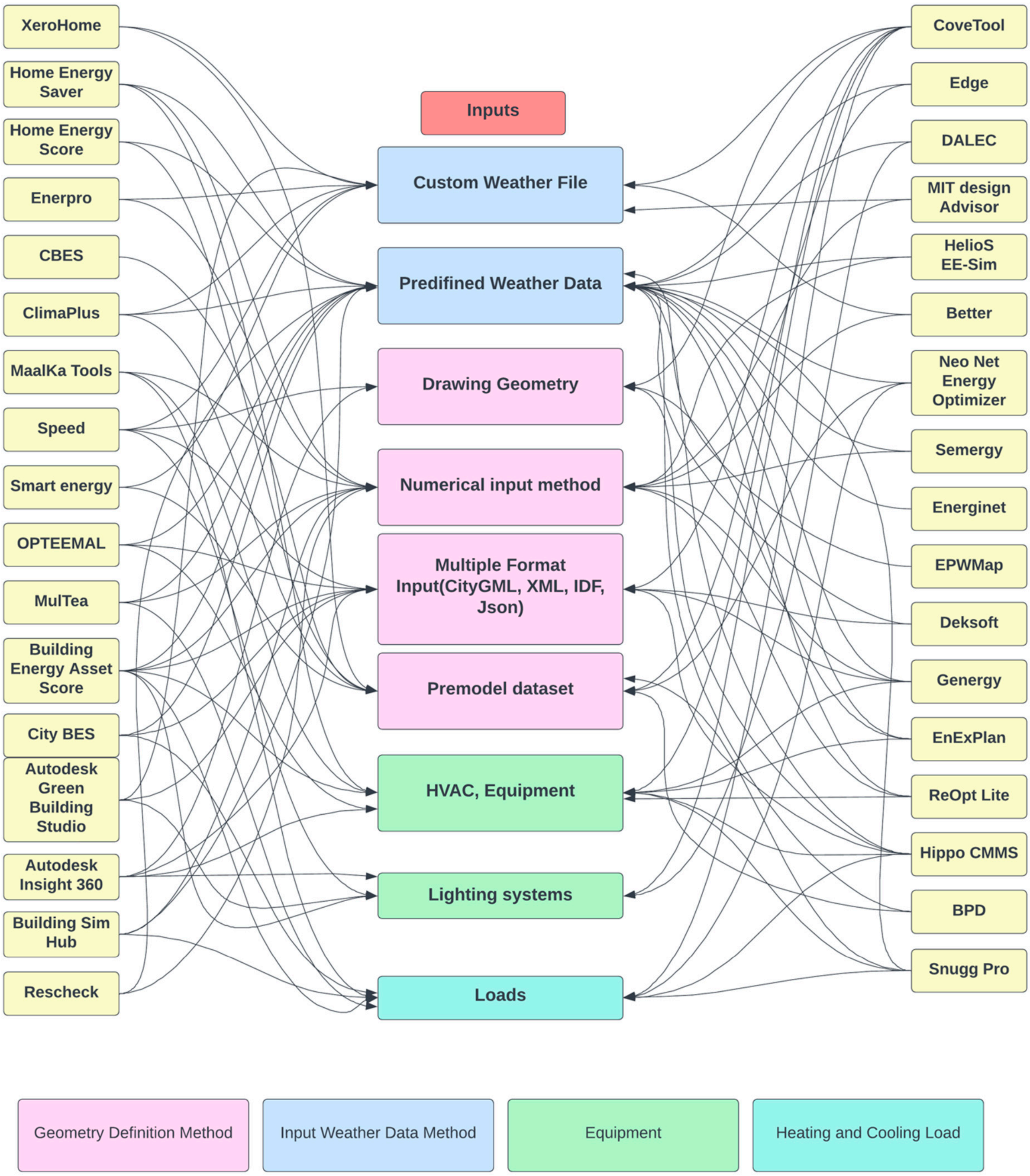

Figure 11. Input methods for WebTool Energy Simulation tool.

These toolkits have many other capabilities, as listed in [163,164]. Fourteen out of the 34 can perform load analyses based on wall, ceiling, and window materials. Building material input is possible with web applications, such as Home Energy Saver and Home

Energy Score. Enhancing and performing parametric investigations enhance the utility of toolkits, particularly during the initial stages of design when numerous design alternatives and tactics are accessible, thereby aiding decision-making.

XeroHome and Cove Tool are two of the five web-based toolkits capable of optimizing building energy management. XeroHome and Insight 360 do not implement optimization through parametric simulation, but SPEED, Cove Tool, and BuildSimHub do. These tools present users with the best design options based on all possible combinations of design features. Various toolkits provide diverse modes for defining input data, catering to users with varying proficiency levels and engagement in different phases of building design or retrofit. Examples include XeroHome, Home Energy Saver, Cove Tool, and CBES, which are suitable for users with differing levels of expertise. CoveTool has a wide range of capabilities, including water analysis, energy analysis, carbon emissions analysis, and economic analysis. It uses machine learning algorithms to analyze thousands of alternatives for better analyzing building energy systems.

Figure 12 displays various outputs for energy simulation tools within the Webtool.

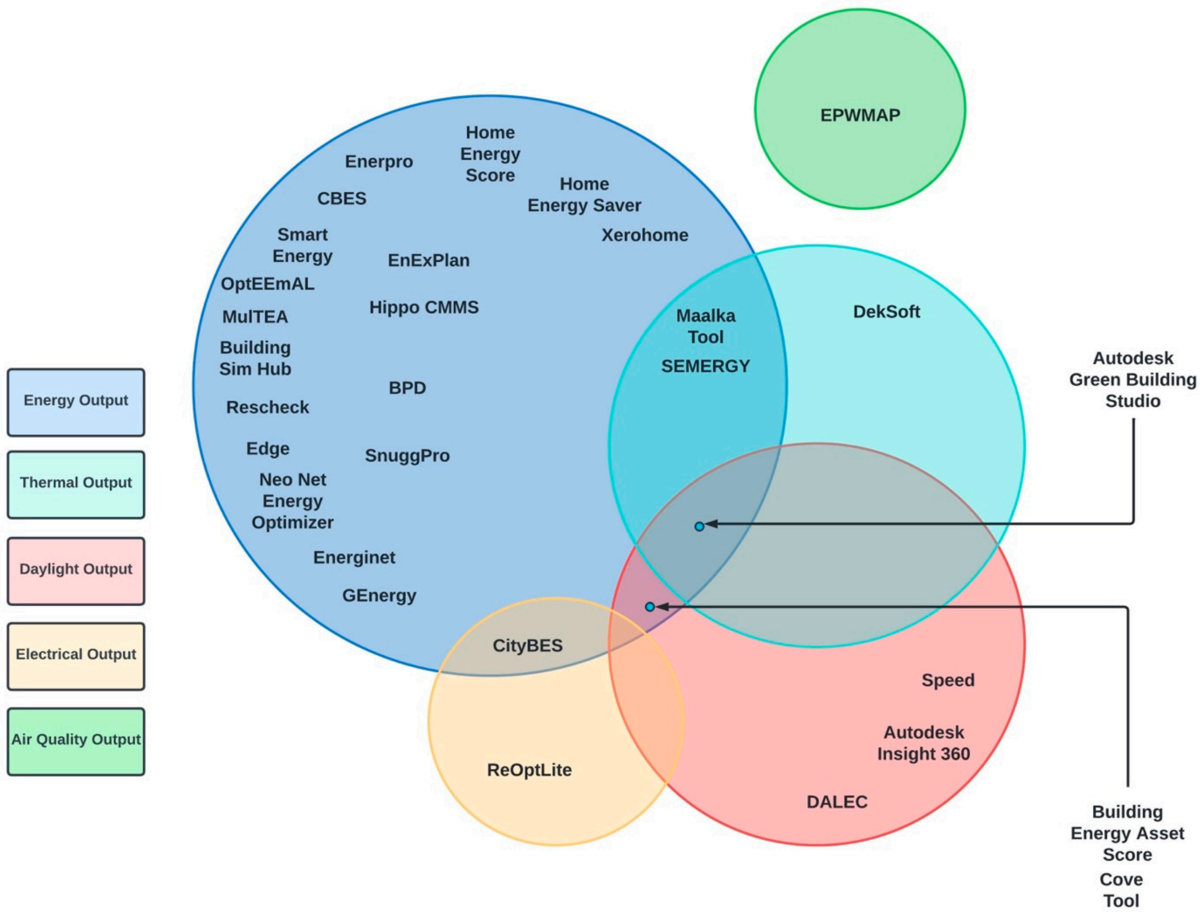

Figure 12. Outputs for WebTool Energy Simulation tool.

5. Conclusions and Recommended Future Research

5.1. Conclusions

In conclusion, this comprehensive review of building energy management simulation tools, now enriched with insights into their relevance to consulting practices, underscores the vast array of tools available to address the multifaceted challenges of optimizing energy efficiency in buildings. The tools encompass both white-box models, rooted in fundamental physics principles, and black-box models, harnessing the power of machine learning and statistical approaches. Including web-based simulation tools further expands the toolbox, providing accessibility and flexibility in data visualization and benchmarking. Consulting practices in the field of building energy management benefit immensely from these diverse tools. White-box models offer intricate insights into energy system operation and are invaluable for detailed energy performance analysis, particularly in retrofitting projects and compliance verification. On the other hand, black-box models provide consultants with rapid results, making them ideal for operational optimization, predictive maintenance, and real-time energy management.

The choice of modelling approach and tool depends on the specific consulting objectives and building complexities. Large and complex buildings demand scalable tools, emphasizing the importance of selecting the right tool for the desired level of accuracy. This review underscores the significance of a tailored approach, highlighting the plethora of tools available to support data-driven decision-making, optimize energy systems, and enhance energy efficiency in the built environment.

Furthermore, integrating these tools into consulting practices enables data scientists, analysts, and engineers to collaborate effectively, providing actionable insights and facilitating informed decision-making. As the consulting industry continues to evolve, building energy management simulation tools remains at the forefront, empowering professionals to address energy challenges, enhance sustainability, and drive innovation in the design and operation of buildings. The dynamic landscape of building energy management demands adaptability and expertise, and this review serves as a valuable resource for navigating this ever-evolving field.

5.2. Recommendation for Future Research

Based on current knowledge, several areas require further research to advance the development and application of building energy simulation tools, specifically white-box and black-box models. In addition, six knowledge gaps in building energy simulation tools can be addressed in future studies.

1. Lack of standardized methodology: Despite the availability of numerous simulation tools, there needs to be a standardized methodology for comparing and evaluating these tools. Future studies can address this gap by proposing a standardized methodology that can be used for consistent evaluation of simulation tools.
2. Limited studies on the accuracy of black-box models: While black-box models are gaining popularity in building energy management, there is a limited number of studies on their accuracy compared to white-box models. Future studies can address this gap by conducting comprehensive accuracy studies of black-box models and comparing them with white-box models.
3. Limited studies on the scalability of white-box models: While white-box models are considered accurate, their scalability to larger building complexes or districts is a concern. Future studies can address this gap by investigating the scalability of white-box models and developing methods to improve their scalability.
4. Lack of integration between white-box and black-box models: White-box and black-box models are often used separately, and there needs to be more integration between them. Future studies can address this gap by exploring ways to combine both types of models to improve accuracy and scalability.
5. Limited studies on the impact of uncertainties on model predictions: More studies are required on the impact of uncertainties on model predictions, which is crucial for decision-making in building energy management. Subsequent research endeavours have the potential to fill this void by quantifying the influence of uncertainties on model predictions and devising approaches to enhance the resilience of simulation tools.
6. Limited studies on the usability and accessibility of simulation tools: While simulation tools are becoming more advanced, there is a lack of studies on their usability and accessibility, particularly for non-expert users. Future studies can address this gap by evaluating the usability and accessibility of simulation tools and developing user-friendly interfaces for non-expert users.

In conclusion, implementing these recommendations in future studies can lead to a more precise evaluation of building simulation tools and help address the knowledge gaps identified in this review.

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Nomenclature

BEMS	Building Energy Management Systems
BES	Building energy simulation tools
BIM	Building Information modelling
BPS	Building performance simulation tools
DDM	Data-Driven Modelling
DL	Deep Learning
DNN	Deep Neural Networks
HVAC	Heating, ventilation, and air conditioning
IFC	Industry foundation class
LSTM	Long Short-Term Memory
LR	Linear Regression
LTLF	Long-term load forecasting
ML	Machine Learning
NMF	Neutral model format
PCM	Phase Change Material
RF	Random Forest
SVM	Support Vector Machine
STLF	Short-term load forecasting

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