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Comparative analysis of simulation tools for developing, testing, and benchmarking advanced control algorithms in building energy management systems

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Buildings are an important part of the energy consumption of cities. With recent developments in integrated energy systems in buildings, the need for a smart energy management system (EMS) has significantly increased. In this regard, AI-EMS can help to enhance operational efficiency, occupant comfort, and environmental sustainability in urban areas. However, a comprehensive framework categorizing the tools and algorithms used in buildings and urban EMS is still lacking, which limits the ability to evaluate the effectiveness of these technologies. This paper addresses this gap by analyzing and comparing some of the most widely used AI tools, algorithms, and simulation environments for optimizing building energy systems, offering insights into the applications, strengths, and limitations of each tool. We provide a structured overview of AI control methods and available EMS tools, as well as a comparative analysis of their capabilities for energy management in both individual buildings and district-level systems. We aim to help researchers, policymakers, building designers, and engineers to better understand the available simulation tools for making informed decisions when selecting and using them.

KEYWORDS

artificial intelligence (AI), building energy management system (BEMS), advanced control algorithms, simulation tools, smart grids

1 Introduction

Buildings account for approximately 55% of worldwide electricity demand (International Energy Agency, 2019), making them a crucial focus for improving energy efficiency and sustainability. Intelligent buildings (IBs) are buildings equipped with advanced technologies, automation, and sophisticated control systems that enable more efficient and productive environments by optimizing both functionality and energy consumption (Bayasgalan et al., 2024). Modern IBs integrate various energy systems, including heating, ventilation, and air conditioning (HVAC), domestic hot water (DHW), lighting, energy storage, electric vehicles (EVs), and especially renewable energy sources

(RES), making them "prosumers" in energy networks—capable of both consuming and producing energy. In this context, the importance of a robust energy management system (EMS) that can effectively coordinate all energy flows to boost efficiency and flexibility, support occupant comfort, and reduce environmental impact is evident.

Recent advances in artificial intelligence (AI) applications for EMS have explored a variety of methods, from reinforcement learning (RL) to model predictive control (MPC). Current literature emphasizes that AI applications are fundamental to achieving intelligent energy management in urban environments (Mischos et al., 2023). In this context, simulation tools and platforms that replicate real-world building and district-level energy scenarios are essential for developing, testing, and benchmarking these AI-based control algorithms. Tools that model energy flow, predict resident behavior, or evaluate network interactions provide researchers with valuable insights into algorithm performance under different scenarios. For example, environments such as CityLearn facilitate RL simulations for Demand Response (DR) in urban buildings, while BOPTEST provides standardized scenarios for comparing control strategies in individual buildings. Such platforms not only help researchers evaluate algorithmic performance but also help bridge the gap between theoretical development and practical application in urban energy systems.

In addition to the papers focusing on the performance of specific algorithms to improve energy management in buildings, such as those by Yu et al. (2020), Balakrishnan and Geetha (2021), Luusua et al. (2023), Foruzan et al. (2018), Chowdhury et al. (2024), some studies combine or compare the performance of two or three algorithms and evaluate their respective benefits for EMS applications, as seen in Michailidis et al. (2024), Wang et al. (2023), Lu et al. (2019), Zhan et al. (2023), Brandi et al. (2022), or some reviews that provide insights into different control methods, their application types, and their efficiency in improving Building Energy Management Systems (BEMS). For instance, a review paper analyzed various simulation tools used in BEMS with a focus on promoting sustainable buildings and energy-efficient systems (Shahcheraghian et al., 2024). The review categorizes these tools into white-box and black-box models based on their level of detail and transparency. Another review paper highlights the need for optimal energy management and proposes a comprehensive methodology for developing improved energy models for smart cities (Calvillo et al., 2016). The review encompasses a variety of energy models and simulation tools used for urban energy management. Another paper reviews the role of AI in improving home EMS through advanced optimization techniques, comparing traditional methods with AI-powered machine learning and deep learning for more efficient demand-side management (Nutakki and Mandava, 2023). The other paper analyzes the application of AI in EMSs, renewable energy, and smart grids, and the potential of AI to improve system optimization and renewable energy forecasting (Chander and Gopalakrishnan, 2024). However, there is still a need for interdisciplinary research that bridges the gap between technological advancements and practical applications in EMS.

Despite the progress in EMS research, a comprehensive study categorizing simulation tools for AI-based EMS is notably absent from the literature. This gap creates challenges for researchers, developers, and policymakers in selecting appropriate platforms for testing and deploying AI-based control strategies. Therefore, this paper aims to address this need by providing a structured review of common tools and environments in this field, analyzing each one in terms of its specific application, advantages and limitations, and finally comparing them based on application. By presenting this overview, we aim to support the development and effective application of AI-based EMS technologies in urban and BEMSs. The rest of the paper is organized as follows: Section 2 will introduce three common AI control algorithms used in BEMS. In Section 3, we will provide a brief overview of various AI tools that are available and widely used in BEMS. Section 4 will compare these tools, and Section 5 will summarize the main goals and findings of our research as a conclusion.

2 AI control strategies in BEMS

AI-based control algorithms are often used to enhance accuracy and robustness in building energy management systems. Advanced techniques such as machine learning, deep learning, and RL, that can model complex energy patterns, predict demand fluctuations, and optimize control actions more effectively than traditional rule-based or mathematical methods. According to Blum et al. (2021), there are generally three control strategies for BEMS; RBC, MPC, and RLC.

2.1 Rule-based control (RBC)

RBC is a straightforward and the most common used control strategy in building energy management systems (Wang et al., 2023). In RBC, control decisions are made based on a set of predefined rules or conditions that dictate the system's response to various inputs, such as temperature, occupancy, time of day, or energy prices. These rules are typically developed based on expert knowledge, historical data, or regulatory requirements, and they are often expressed in simple "if-then" logic.

2.1.1 RBC strategy

1. Initialize environment parameters
2. Define control rules based on domain knowledge
3. Monitor data (e.g., indoor conditions, outdoor conditions, occupancy)
4. Apply control rules to determine control actions
5. Implement control actions by updating system setpoints
6. Monitor effects and adjust rules if necessary
7. Repeat the loop for continuous operation

While RBC is ideal for smaller systems or applications where simplicity and low cost are priorities, it is often combined with more advanced algorithms like MPC or RL in larger or more complex energy management systems to improve adaptability and optimization. Typically, baseline control is implemented using RBC.

2.2 Model predictive control (MPC)

MPC is another advanced control strategy used in building energy management that optimizes system performance by predicting and planning future actions over a specific time horizon (Wang et al., 2023). Unlike reactive control methods, MPC uses a system model to anticipate future states and calculate the best control actions based on these predictions. This approach allows MPC to achieve highly efficient, predictive control by accounting for changing conditions, constraints, and complex interactions within the building's energy systems.

2.2.1 MPC strategy

1. Initialize environment and system models [building thermal model, prediction horizon (N), control interval (Δt)]
2. Define objectives, cost function (J), and constraints
3. Gather forecast data (e.g., weather, occupancy, prices)
4. For each control interval:
   - Measure the current state (x_t)
   - Predict future states over the prediction horizon
     - Solve the optimization problem ($\min J = \sum_{k=t}^{t+N-1} c(x_k, u_k)$)
       o Subject to:
     - System dynamics $x_{k+1} = f(x_k, u_{k,} d_k)$
       - Constraints on x_k and u_k
   - Compute and apply optimal control actions u_t^*
5. Update time and iterate the process
6. End loop after the operation period

Compared to RBC, MPC offers more flexibility and performance, particularly in complex or dynamic environments. While RBC simply follows predefined rules, MPC adapts by forecasting and optimizing in real-time. In comparison to RLC, MPC typically provides more stable, predictable performance, as it relies on a well-defined model rather than learning through trial and error. However, RLC may be preferable in scenarios where building models are difficult to define accurately, and computational learning can identify effective strategies.

2.3 Reinforcement learning control (RLC)

RLC is an advanced machine learning approach that enables a system, such as a building's energy management system, to autonomously learn and adapt their control strategies through interaction with the environment (Michailidis et al., 2024). Unlike traditional control methods that rely on predefined rules or fixed models, RLC uses trial and error to identify the optimal actions to achieve specific goals, like minimizing energy consumption or reducing operating costs. This adaptability makes it particularly powerful in complex, dynamic environments where conditions change frequently.

2.3.1 RLC strategy

1. Initialize the environment: state space (S), action space (A), dynamics ($P(s'|s,a)$)
2. Initialize RL parameters: learning rate (α), discount factor (γ), exploration policy (ϵ), etc.
3. Define the reward function ($r(s,a)$)
4. For each training episode:
   - Reset the environment to the starting state
   - For each time step within the episode:

     o Select an action using the epsilon-greedy policy:

$$a_t = \begin{cases} \textit{random action} & \textit{with probability } \epsilon \\ \arg\max Q(s_t, a) & \textit{with probability } 1-\epsilon \end{cases}$$

   o Apply the action (a_t) and observe the next state (s_{t+1}) and reward (r_t)
   o Update Q-values ($Q(s_t, a_t)$) or policy ($\pi(a|s)$) using the observed experience
   o Optionally update the exploration parameter
   o Update the current state
   - End of episode: Check for convergence or save results
5. After training, extract the optimal policy π^* ($a|s$)
6. Deploy the learned policy for real-time control

RLC is particularly useful in environments where conditions are unpredictable or dynamic and where complex, nonlinear interactions. In scenarios where simpler rules suffice, or where system behavior is more predictable, RBC or MPC might be more appropriate. However, for maximizing efficiency in dynamic, high-dimensional systems such as those in smart buildings and microgrids, RLC offers distinct advantages by continuously learning and improving its strategies.

3 Simulation tools and environment

Several simulation tools and environments support the development, testing, and benchmarking of advanced control algorithms, including RBC, RLC, and MPC, for building energy management. These platforms are typically designed to model building energy dynamics, HVAC systems, renewable energy sources, energy storage, and grid interactions, making them ideal for evaluating the performance of energy management strategies. Here is an overview of some of the simulation tools and environments as well as a summary in Table 1.

3.1 CityLearn

CityLearn's Gym is an open-source Python environment and a simulation framework for the implementation of multi-agent RL for building energy coordination and DR in urban areas (Vázquez-Canteli et al., 2020). This platform was designed as a standardized tool to compare RL algorithms in the context of urban energy systems and is available as an open-source project on GitHub. CityLearn does not need any co-simulation since the buildings' energy demands can be pre-simulated and provided as CSV files. This also makes it easier for researchers to use this multi-agent RL environment, as they only need to download it from the GitHub repository, and run their RL agents as they would do with any other environment.

The primary control strategy supported by CityLearn is RL, both in single-agent and multi-agent configurations. The platform is highly flexible in allowing for the customization of the reward function, control modes (central-agent or multi-agent), and the

TABLE 1 Summary of the analyzed EMS tools.

Tools	Website	Developer	System boundary	Control Strategy	Presented in
CityLearn	https://www.citylearn.net/	Researchers	Urban districts with multiple buildings and energy systems	RLC, SAC, RBC	Vázquez-Canteli et al. (2020)
BOPTEST	https://ibpsa.github.io/project1-boptest/	International Building Performance Simulation Association (IBPSA)	Single building or collection of building types	MPC RBC	Blum et al. (2021)
Energym	https://bsl546.github.io/energym-pages/index.html	Researchers	Single-building or limited building collections	RL, RBC	Scharnhorst et al. (2021)
MPCPy	https://mpcpy.readthedocs.io/en/latest/	Researchers	Single-building energy systems	MPC	Blum and Wetter, (2019)
PyCity	https://github.com/RWTH-EBC/pyCity	RWTH Aachen University	Buildings and energy systems within a city	Optimization-based control, RBC	Schwarz et al. (2021)
eNeuron	https://eneuron.eu/	Researchers, policymakers, and energy companies	Energy hubs or neighborhoods	Optimization-based control	Morch et al. (2023)
GridLAB-D	https://www.gridlabd.org/	U.S. Department of Energy's Pacific Northwest National Laboratory (PNNL)	Distribution networks; grid-interactive buildings	ER, DER control	Chassin et al. (2008)

interaction of various building systems such as batteries, EVs, heat pumps, and electric heaters. These controls are aimed at achieving objectives like load shedding, load shifting, and overall DR optimization across the simulated city landscape.

3.2 BOPTEST

BOPTEST is a simulation framework for evaluating building energy control strategies, focusing on the comparison of control algorithms, particularly in the HVAC sector (Blum et al., 2021). BOPTEST focuses primarily on single-building simulations, though it can represent various types of buildings with differing HVAC configurations and control needs. BOPTEST supports a variety of control algorithms, with a particular emphasis on model-based strategies such as MPC. Control algorithms can overwrite the baseline supervisory and local-loop control signals to apply advanced control strategies. Additionally, the platform's modular structure and Modelica-based emulators allow for the testing of RBC, optimization-based methods, and data-driven algorithms. The platform is particularly valuable for verifying the performance of algorithms before deployment in real-world buildings, as it provides a detailed simulation environment with realistic physical dynamics.

3.3 Energym

Energym is an open-source Python-based library developed for energy management simulations and benchmarking environments to evaluate various control strategies within standardized building models (Scharnhorst et al., 2021). Energym focuses on single-building energy systems, where the simulated buildings are equipped with components and technical systems commonly found in real-world structures. This allows users to control and manage energy for individual buildings, making it ideal for testing controllers that optimize HVAC systems, lighting, and other energy-intensive building operations. Energym is specifically designed to support RL algorithms, offering a set of pre-defined KPIs and evaluation scenarios. The simulation's pre-built scenarios provide a consistent framework for evaluating controllers, enabling researchers to test their algorithms in a realistic yet reproducible setting. By including forecasts of uncertain variables, such as weather or occupancy, Energym also facilitates robust testing under conditions that reflect real-life unpredictability.

3.4 MPCPy

MPCPy is another open-source platform aimed at implementing MPC for building energy systems (Blum and Wetter, 2019). The platform offers a standardized structure for automating model setup, parameter learning, and optimization problem formulation, allowing users to implement complex MPC strategies without requiring deep expertise in coding or building-specific modeling. MPCPy operates at the building level, providing tools to model and control individual building energy systems. Its scope encompasses all essential building components such as HVAC, lighting, and other systems that can impact a building's energy profile and thermal comfort levels. Its architecture allows users to automate the learning of building parameters over time, enabling the platform to adjust to changes in building usage or environmental conditions. This makes it valuable for researchers and practitioners interested in implementing MPC for building energy optimization, especially in settings where environmental conditions and occupancy can vary, impacting energy needs and system efficiency.

3.5 PyCity

PyCity is an open-source Python simulation framework that models energy flows in urban districts, considering the interactions between buildings and energy grids (Schwarz et al., 2021). The framework is intended to help researchers and engineers address power dispatch and grid stability challenges within smart cities. PyCity supports optimization-based control strategies, with a particular focus on power scheduling and dispatch for multi-energy systems. It is designed for the development and testing of coordination algorithms that optimize energy flows based on real-time conditions and DR requirements across different buildings in a district. PyCity can model multiple energy sources, including electricity and heat, and is equipped to support flexibility in urban energy systems by facilitating demand response strategies.

3.6 eNeuron

eNeuron is an EU-funded simulation environment focusing on optimizing local energy systems and energy hubs (Morch et al., 2023). The main goal of the eNeuron H2020 project is to develop innovative tools for the optimal design and operation of local Energy Communities (ECs), integrating DERs with energy hubs to optimize resource flows across various energy carriers and consumer groups. eNeuron supports various control strategies, with a particular emphasis on the Energy Hub concept for managing multi-energy systems. This approach allows for the coordinated control of multiple energy carriers (e.g., electricity, gas, heating) and resources. The platform prioritizes strategies that promote energy optimization and flexibility, such as DR and storage coordination, aiming to balance local supply and demand dynamically. eNeuron's tools are designed to support the transition to a decentralized, low-carbon energy system by promoting energy-sharing models and integrated energy management.

3.7 GridLAB-D

GridLAB-D is an open-source platform developed by the U.S. Department of Energy for simulating distribution networks and smart grid applications (Chassin et al., 2008). GridLAB-D has evolved as a powerful tool for exploring how buildings, distributed energy resources (DER), and other grid assets can interact within the power grid. The platform supports various control strategies, particularly those suited for real-time grid-interactive applications. Key strategies include DR, distributed generation control, renewable energy integration, and load forecasting. Through its flexible modeling capabilities, GridLAB-D can simulate the impacts of different demand-side management strategies on grid performance, thus allowing users to explore control algorithms like RBC and MPC within distribution grids. Additionally, the platform is widely used to develop and test smart grid technologies and strategies, including energy storage, electric vehicle integration, and advanced metering infrastructure.

4 Comparative analysis

While all these platforms contribute to testing and optimizing energy control policies, they are in different scales (from building-level to district and grid-level), employ various control techniques, and focus on specific aspects of urban energy management (e.g., occupant behavior, RL, or grid distribution). Therefore, a comprehensive comparison can be useful for other researchers to make informed decisions for selecting and using them.

MPCPy and BOPTEST are the best for single-building energy management, typically focusing on HVAC and occupant behavior. CityLearn and PyCity enable district-level simulations, suitable for urban energy management scenarios. eNeuron and GridLAB-D support neighborhood- and grid-scale simulations, integrating DERs, demand response, and multiple energy carriers.

CityLearn and Energym specialize in RL environments for demand response and energy management. MPCPy, PyCity, and eNeuron focus on optimization and MPC approaches for energy systems. GridLAB-D supports RBC, especially for demand response and occupant-driven scenarios.

CityLearn and BOPTEST standardize and benchmark different algorithms. eNeuron and GridLAB-D support simulations relevant to energy hubs and grid-interactive buildings.

Tools like GridLAB-D and PyCity are highly flexible and support complex multi-energy systems and grid interactions. CityLearn and Energym are also user-friendly for RL research. Most tools are focused on specific aspects (e.g., RL, occupant behavior), so broader applications may require using multiple tools. Complex platforms like GridLAB-D and PyCity require a steeper learning curve, while tools like MPCPy may be limiting if the user seeks multi-building applications.

This comparison highlights some pros and cons of each tool based on their specific focus areas as summarized in Table 2. Researchers and engineers can select the most suitable platform based on their control strategy, system boundary, and application requirements.

5 Conclusion

In this paper, we critically analyzed various AI tools, algorithms, and simulation environments for building and urban energy management systems (EMS), focusing on the capabilities, scope, and unique contributions of each tool. Our comparative analysis highlights that different simulation tools are specialized for specific levels of application; single-building environments (e.g., MPCPy and BOPTEST) are typically focused on HVAC control and occupant behavior, while tools like CityLearn and PyCity facilitate district-level simulations suitable for urban energy management. Additionally, neighborhood and grid-scale simulations are supported by platforms such as eNeuron and GridLAB-D, which integrate distributed energy resources, demand response, and multiple

TABLE 2 Summary of comparative analysis.

Tools	Application	Pros	Cons
CityLearn	Benchmarking RL-based control strategies for building demand response	Easy Python-based setup for RL; customizable scenarios and reward functions; does not need co-simulation	Limited to simulated urban settings; mostly suited for RL-based control
BOPTEST	Benchmarking and comparing building HVAC control strategies	High flexibility with containerized emulators; good for comparing control algorithms	Only models HVAC; requires Modelica for emulator setup
Energym	Testing RL algorithms in standardized building scenarios	Open-source, Python-based; KPIs and standardized evaluation for fair comparisons	Focused on RL; limited pre-built building models
MPCPy	Adaptive MPC modeling and control for individual buildings	Customizable, extensible, based on open-source standards	Limited to MPC-based control; relies on user-constructed models
PyCity	Simulation and optimization of urban district energy flows	Supports multiple energy systems; Python-based and open-source	More complex setup; limited real-time control support
eNeuron	Optimizing local energy systems; supporting multi-carrier integration	Integrates DER with multiple energy carriers; aligned with EU energy community goals	Primarily focused on EU scenarios; project-specific limitations
GridLAB-D	Studying grid interactions with buildings, DERs, and storage	Robust grid-interactive control; open-source and highly customizable	Complex setup; high computational requirements; focuses more on the grid than buildings

energy carriers. We found that tools such as CityLearn and Energym are well-suited for reinforcement learning (RL) applications in demand response, whereas MPCPy, PyCity, and eNeuron excel in optimization and model predictive control (MPC) approaches. Tools such as GridLAB-D, on the other hand, offer more extensive support for rule-based and behavior-driven controls, making them effective for simulating demand response and occupant-centric scenarios. Our findings offer guidance to researchers and engineersin selecting the most appropriate simulation environment based on control strategy, scope, and application needs. Ultimately, broader applications may benefit from combining multiple tools to leverage complementary features and achieve a holistic approach to energy management in urban settings.

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Generative AI statement

The author(s) declare that Generative AI was used in the creation of this manuscript. The authors used ChatGPT, an AI language model developed by OpenAI, to improve the clarity and language of the manuscript. The authors reviewed and edited the AI-generated content to ensure accuracy and originality. The use of ChatGPT was limited to linguistic enhancement and did not contribute to the scientific content, data analysis, or interpretation presented in this work.

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References

Balakrishnan, R., and Geetha, V. (2021). Review on home energy management system. *Mater. Today Proc.* 47, 144–150. doi:10.1016/j.matpr.2021.04.029

Bayasgalan, A., Park, Y. S., Koh, S. B., and Son, S.-Y. (2024). Comprehensive review of building energy management models: grid-interactive efficient building perspective. *Energies* 17 (19), 4794. doi:10.3390/en17194794

Blum, D., Arroyo, J., Huang, S., Drgoňa, J., Jorissen, F., Walnum, H. T., et al. (2021). Building optimization testing framework (BOPTEST) for simulation-based benchmarking of control strategies in buildings. *J. Build. Perform. Simul.* 14 (5), 586–610. doi:10.1080/19401493.2021.1986574

Blum, D., and Wetter, M. (2019). *MPCPy: an open-source software platform for model predictive control in buildings*. Berkeley, CA (United States): Lawrence Berkeley National Lab.LBNL.

Brandi, S., Fiorentini, M., and Capozzoli, A. (2022). Comparison of online and offline deep reinforcement learning with model predictive control for thermal energy management. *Automation Constr*. 135, 104128. doi:10.1016/j.autcon.2022.104128

Calvillo, C. F., Sánchez-Miralles, A., and Villar, J. (2016). Energy management and planning in smart cities. *Renew. Sustain. Energy Rev.* 55, 273–287. doi:10.1016/j.rser.2015.10.133

Chander, B., and Gopalakrishnan, K. (2024). Integration of artificial intelligence techniques for energy management. *Sustain. Manag. Electron. Waste*, 1–46. doi:10.1002/9781394166923.ch1

Chassin, D. P., Schneider, K., and Gerkensmeyer, C. (2008). "GridLAB-D: an open-source power systems modeling and simulation environment," in 2008 IEEE/PES Transmission and Distribution Conference and Exposition, USA, 21-24 April 2008 (IEEE), 1–5.

Chowdhury, I. J., Yusoff, S. H., Gunawan, T. S., Zabidi, S. A., Hanifah, M. S. B. A., Sapihie, S. N. M., et al. (2024). Analysis of model predictive control-based energy management system performance to enhance energy transmission. *Energies* 17 (11), 2595. doi:10.3390/en17112595

Foruzan, E., Soh, L.-K., and Asgarpoor, S. (2018). Reinforcement learning approach for optimal distributed energy management in a microgrid. *IEEE Trans. Power Syst.* 33 (5), 5749–5758. doi:10.1109/tpwrs.2018.2823641

International Energy Agency (2019). *Global status report for buildings and construction 2019*. Paris: IEA. Available at: https://www.iea.org/reports/global-status-report-for-buildings-and-construction-2019.

Lu, R., Hong, S.Ho, and Yu, M. (2019). Demand response for home energy management using reinforcement learning and artificial neural network. *IEEE Trans. Smart Grid* 10 (6), 6629–6639. doi:10.1109/TSG.2019.2909266

Luusua, A., Ylipulli, J., Foth, M., and Aurigi, A. (2023). Urban AI: understanding the emerging role of artificial intelligence in smart cities. *AI and Soc.* 38 (3), 1039–1044. doi:10.1007/s00146-022-01537-5

Michailidis, P., Michailidis, I., and Kosmatopoulos, E. (2024). Review and evaluation of multi-agent control applications for energy management in buildings. *Energies (19961073)* 17 (19), 4835. doi:10.3390/en17194835

Mischos, S., Dalagdi, E., and Vrakas, D. (2023). Intelligent energy management systems: a review. *Artif. Intell. Rev.* 56 (10), 11635–11674. doi:10.1007/s10462-023-10441-3

Morch, A., Sæle, H., Buonanno, A., Caliano, M., Di Somma, M., and Papadimitriou, C. (2023). *Development of energy Communities in europe*. TechRxiv.

Nutakki, M., and Mandava, S. (2023). Review on optimization techniques and role of artificial intelligence in home energy management systems. *Eng. Appl. Artif. Intell.* 119, 105721. doi:10.1016/j.engappai.2022.105721

Scharnhorst, P., Schubnel, B., Fernández Bandera, C., Salom, J., Taddeo, P., Boegli, M., et al. (2021). Energym: a building model library for controller benchmarking. *Appl. Sci.* 11 (8), 3518. doi:10.3390/app11083518

Schwarz, S., Uerlich, S. A., and Monti, A. (2021). Pycity_Scheduling—a Python framework for the development and assessment of optimisation-based power scheduling algorithms for multi-energy systems in city districts. *SoftwareX* 16, 100839. doi:10.1016/j.softx.2021.100839

Shahcheraghian, A., Madani, H., and Ilinca, A. (2024). From white to black-box models: a review of simulation tools for building energy management and their application in consulting practices. *Energies* 17 (2), 376. doi:10.3390/en17020376

Vázquez-Canteli, H., José, R., Dey, S., Henze, G., and Nagy, Z. (2020). CityLearn: standardizing research in multi-agent reinforcement learning for demand response and urban energy management. doi:10.48550/arXiv.2012.10504

Wang, D., Zheng, W., Wang, Z., Wang, Y., Pang, X., and Wang, W. (2023). Comparison of reinforcement learning and model predictive control for building energy system optimization. *Appl. Therm. Eng.* 228, 120430. doi:10.1016/j.applthermaleng.2023.120430

Yu, L., Xie, W., Xie, Di, Zou, Y., Zhang, D., Sun, Z., et al. (2020). Deep reinforcement learning for smart home energy management. *IEEE Internet Things J.* 7 (4), 2751–2762. doi:10.1109/jiot.2019.2957289

Zhan, S., Lei, Y., and Chong, A. (2023). "Comparing model predictive control and reinforcement learning for the optimal operation of building-PV-battery systems," in E3S Web of Conferences, USA, 16 June 2023 (EDP Sciences). doi:10.1051/e3sconf/202339604018