energies

Article

Open Tool for Automated Development of Renewable Energy Communities: Artificial Intelligence and Machine Learning Techniques for Methodological Approach

Giuseppe Piras *, Francesco Muzi and Zahra Ziran

Department of Astronautical, Electrical and Energy Engineering (DIAEE), Sapienza University of Rome, 00184 Roma, Italy; francesco.muzi@uniroma1.it (F.M.); zahra.ziran@uniroma1.it (Z.Z.)
* Correspondence: giuseppe.piras@uniroma1.it

Abstract: The architecture, engineering, construction, and operations (AECO) sector exerts a considerable influence on energy consumption and CO_2 emissions released into the atmosphere, making a notable contribution to climate change. It is therefore imperative that energy efficiency in buildings is prioritized in order to reduce environmental impacts and meet the targets set out in the European 2030 Agenda. In this context, renewable energy communities (RECs) have the potential to play an important role, promoting the use of renewable energy at the local level, optimizing energy management, and reducing consumption by sharing resources and advanced technologies. This paper introduces an open tool (OT) designed for the configuration of energy systems dedicated to RECs. The OT considers several inputs, including thermal and electrical loads, energy consumption, the type of building, surface area, and population size. The OT employs artificial intelligence (AI) algorithms and machine learning (ML) techniques to generate forecast optimized scenarios for the sizing of photovoltaic systems, thermal, and electrical storage, and the estimation of CO_2 emission reductions. The OT features a user-friendly interface, enabling even non-experts to obtain comprehensive configurations for RECs, aiming to accelerate the transition toward sustainable and efficient district energy systems, driving positive environmental impact and fostering a greener future for communities and cities.

Keywords: renewable energy communities; REC; artificial intelligence; machine learning; automated development; predictive scenarios

Citation: Piras, G.; Muzi, F.; Ziran, Z. Open Tool for Automated Development of Renewable Energy Communities: Artificial Intelligence and Machine Learning Techniques for Methodological Approach. *Energies* **2024**, *17*, 5726. https://doi.org/10.3390/en17225726

Academic Editors: Alan Brent and Vítor Monteiro

Received: 23 August 2024
Revised: 31 October 2024
Accepted: 12 November 2024
Published: 15 November 2024

1. Introduction

Recognized for its critical role in improving energy security and affordability, energy efficiency is currently the focus of global policy attention to accelerate the transition to clean energy. However, despite this growing attention, the projected rate of progress in energy intensity, the main indicator of energy efficiency in the global economy, by 2023 has fallen below long-term trends, to 1.3% from 2% last year [1]. This slowdown in energy intensity improvement mainly reflects an increase in energy demand from 1.3% in 2022 to 1.7% in 2023. At the same time, the slowdown in global progress in energy intensity masks exceptional gains in some countries and regions, where strong policies, increased investment, and changes in consumer behavior have led to significant improvements well above the global average. To date, the European Union and the United States, among many others, including Korea, Turkey, and the United Kingdom, have recorded robust improvements ranging from 4% to 14% since the onset of the energy crisis [2,3]. By 2023, the global initiative to double the rate of efficiency improvement to 4% has gained significant momentum. This could result in a reduction in current energy bills in advanced countries by approximately one-third and account for approximately 50% of CO_2 reductions by 2030 [4]. However, the energy crisis has undoubtedly accelerated the energy transition to such an extent that, in response to the crisis, governments have introduced measures and initiatives aimed at achieving major improvements in energy efficiency policies, which could become substantial [5]. Since the start of the energy crisis in early 2022, there has been a significant escalation in government action, with countries accounting for 70% of the global energy demand introducing or significantly strengthening efficiency policy packages (Figure 1). The annual investment in energy efficiency has increased by 45% by 2020, with particularly strong growth in electric cars and heat pumps (Figure 2). Today, almost one in five cars sold is an electric vehicle, and global heat pump sales growth is now outpacing that of gas boilers in many markets [6]. Achieving these targets would also create 4.5 million more jobs than today in the energy efficiency sector, including manufacturing, building renovation, construction, industry, and transport [7].

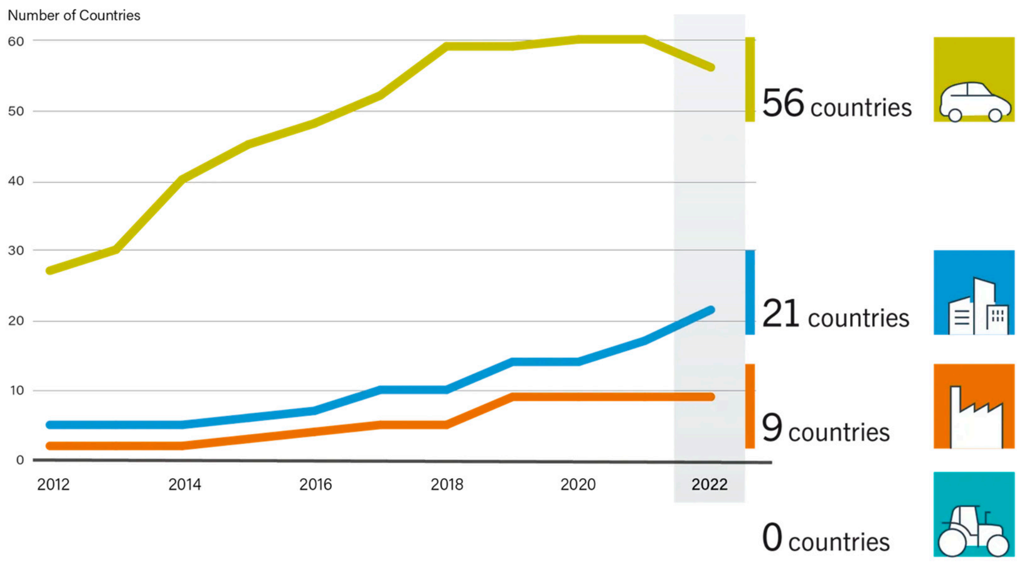

Figure 1. Countries with renewable energy regulatory policies and mandates by sector, 2012–2022 [8].

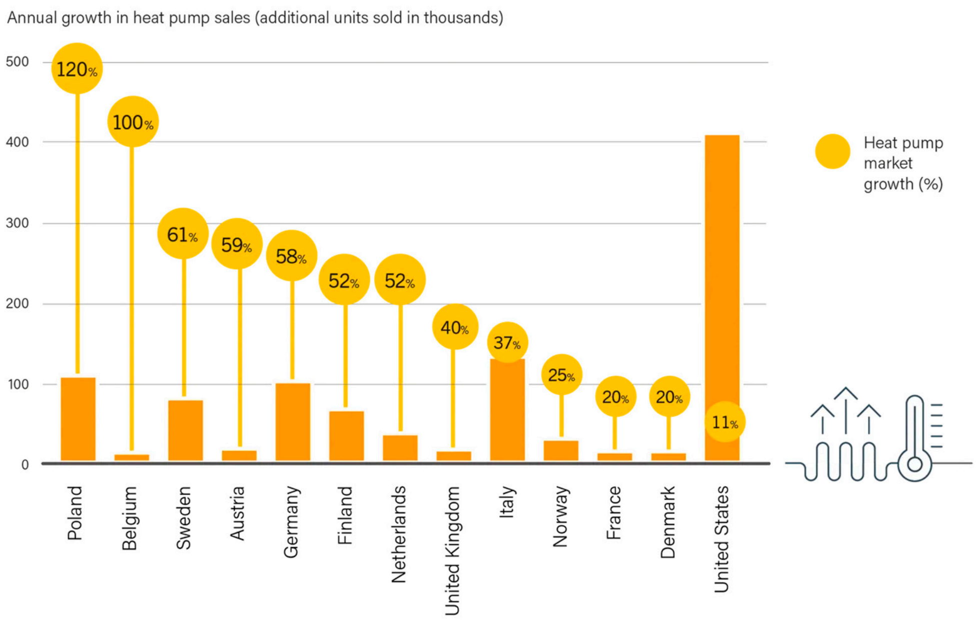

Figure 2. National heat pump markets with the largest growth in 2023 [9].

The environmental impact of buildings is a topic of growing interest in the scientific community, given their significant contribution to global energy consumption [10–12]. It is clear that buildings are responsible for a considerable percentage of the world's energy consumption and an equally considerable percentage of associated greenhouse gas emissions. The International Energy Agency (IEA) has estimated that the building sector accounts for approximately 40% of global energy consumption and 36% of CO_2 emissions related to its use (e.g., heating homes) [13]. It is therefore imperative to develop effective strategies to reduce building energy consumption and related emissions. The majority of emissions from buildings are the result of the use of energy for purposes such as heating, cooling, lighting, and other essential functions (Figure 3). However, it should be noted that the construction phase of buildings, which includes the production of materials and their processing, also contributes significantly to the overall carbon footprint. As a consequence of the accelerated process of urbanization and the concomitant expansion of urban areas, the issue is likely to intensify unless appropriate measures are implemented [14].

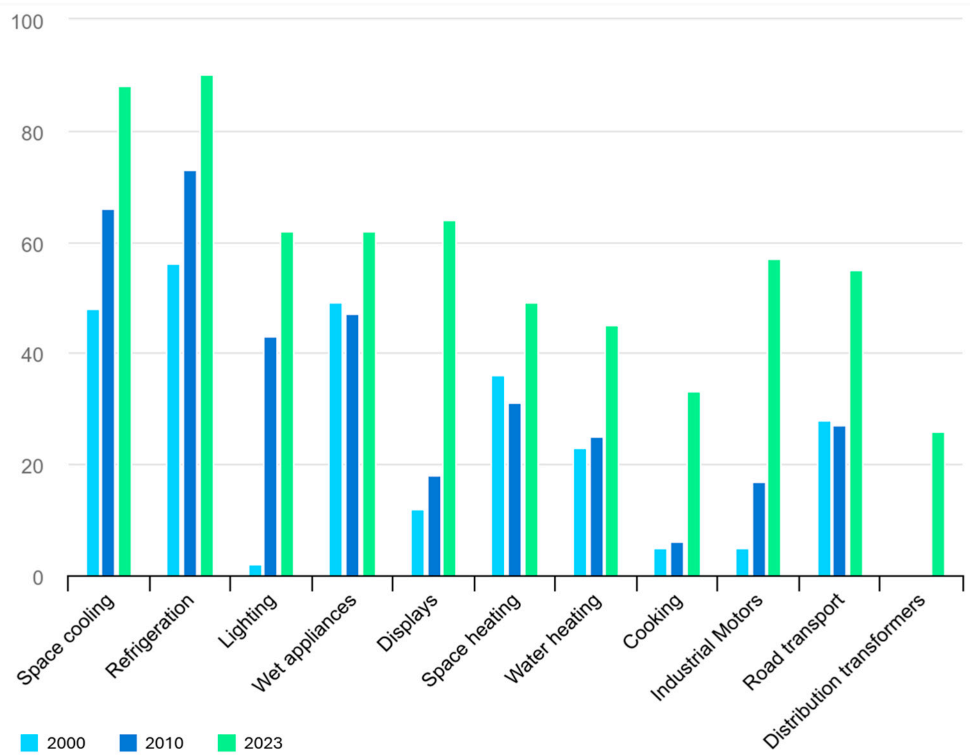

Figure 3. Global energy use coverage of minimum performance standards for major end uses, 2000–2023 [15].

The AECO sector is currently not on track to achieve net zero emissions by mid-century, with emissions growing at an average of 1% per year since 2015 [1]. Global growth in the built-up area is overcoming efforts to increase energy efficiency and decarbonization, with the consequence that the long lifecycle of buildings is reinforcing vulnerable, high-emission infrastructure. Significant change is required to achieve decarbonization of the sector while ensuring the resilience of communities. In 2023, emissions from the AECO sector will account for approximately one-third of total emissions. This includes operational emissions associated with the use of buildings (26%) and embedded emissions (7%) associated with the production of the materials needed for their construction. In order to align with the IEA's Net Zero Emissions Scenario (NZE Scenario), operational emissions must decrease by approximately 50% by 2030 in comparison to 2022 levels (Figure 4). It is important to note that in order to achieve the target of net zero emissions by 2050, all new buildings must be net zero-emitting as early as 2030.

This analysis highlights the urgent need to intensify decarbonization efforts in the AECO sector to address environmental sustainability challenges, with a focus on effective strategies that can reverse current trends and contribute to a low or zero-carbon future.

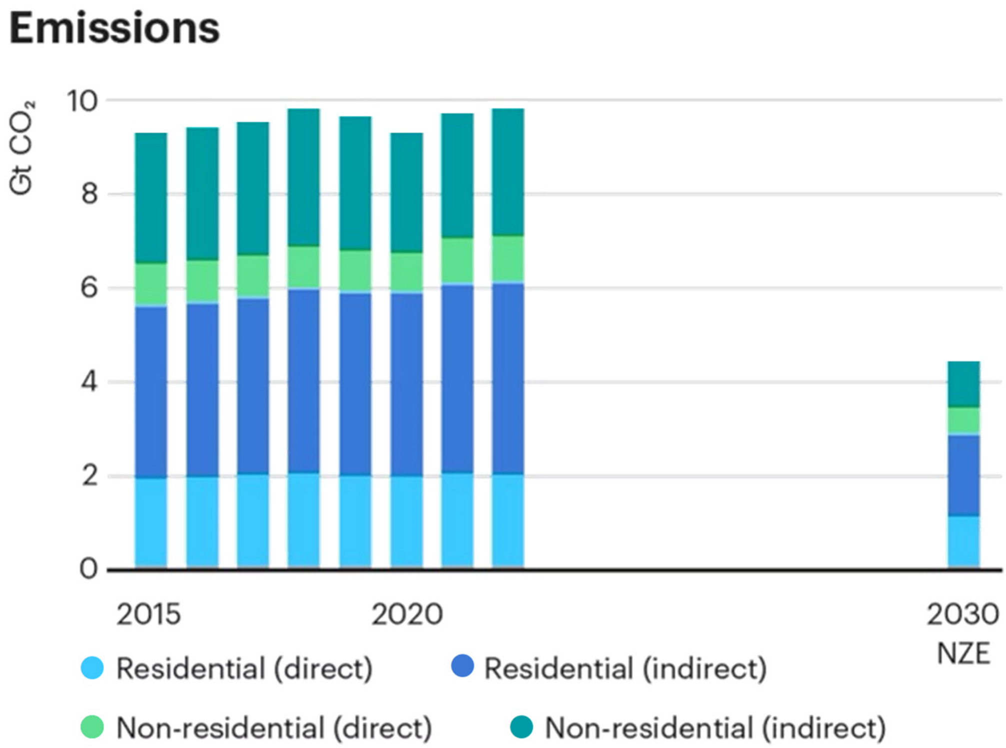

Figure 4. Global emissions from the buildings sector and NZE scenario [16].

Renewable Energy Communities

In the European context, there exists a powerful commitment towards achieving the targets outlined in the European Green Deal, which seeks to establish Europe as the first climate-neutral continent by 2050 [17]. This ambitious objective necessitates substantial reductions in greenhouse gas emissions and widespread adoption of renewable energy sources. To facilitate this transition, the European Union has set specific goals for member states, including a minimum 55% reduction in greenhouse gas emissions by 2030 compared to 1990 levels. Within this framework, Italy, as a member state of the European Union, has devised its own national strategies and plans to align with the European objectives. The Italian Long-Term Strategy on the Reduction of Greenhouse Gas Emissions provides a comprehensive roadmap towards achieving deep decarbonization by 2050 [18]. The strategy outlines ambitious targets for greenhouse gas emission reductions, the promotion of renewable energy sources, and enhancements in energy efficiency across various sectors.

To actualize these targets, Italy has implemented the National Energy and Climate Plan (NECP) and PNRR, which delineates a strategic pathway for the country's energy transition [18]. The NECP concentrates on key areas such as the deployment of renewable energy, energy efficiency measures, and the advancement of sustainable mobility. It establishes specific benchmarks for the integration of renewable energy into the energy mix, the reduction in energy consumption, and the development of energy storage and smart grid infrastructure. In alignment with European and national objectives, the establishment of energy-efficient and sustainable district energy systems has emerged as a critical aspect. District energy systems offer the potential to integrate diverse energy sources, optimize energy consumption, and minimize greenhouse gas emissions on a community scale. By harnessing local renewable energy resources, implementing energy-efficient technologies, and fostering community engagement, district energy systems can make significant contributions towards achieving national and European climate goals. Consequently, there is an urgent requirement for innovative tools and approaches that can support the design and implementation of energy-efficient district communities. These tools should facilitate the optimization of energy generation, storage, and consumption, taking into consideration factors such as thermal and electrical loads, energy consumption patterns, building characteristics, and population size. By leveraging advanced modeling techniques, data analysis, and optimization algorithms, these tools can provide invaluable insights and solutions for the efficient design of district energy systems. This includes appropriately sizing renewable energy installations and energy storage systems and estimating the resultant reductions in CO_2 emissions. By aligning with European and national objectives, the development of energy-efficient district communities can contribute significantly to overall decarbonization efforts, encourage the adoption of renewable energy sources, enhance energy efficiency, and foster sustainable development at the local level.

Renewable energy sources are reaching unprecedented levels of use in the building sector and are becoming an increasingly important part of the global energy mix (Figure 5) [19–22]. Photovoltaic (PV) solar energy is one of the main drivers of this growth, characterized by a significant expansion of generation capacity [23–26]. Wind energy is becoming increasingly important, with a growing presence both onshore and offshore [27]. Wind farms are expanding in many countries and contribute significantly to the supply of renewable electricity. Green hydrogen is confirmed as a promising technology with the potential to play a crucial role in the decarbonization of various economic sectors. The electrolysis of water, powered by renewable energy, facilitates the production of clean, carbon-free hydrogen.

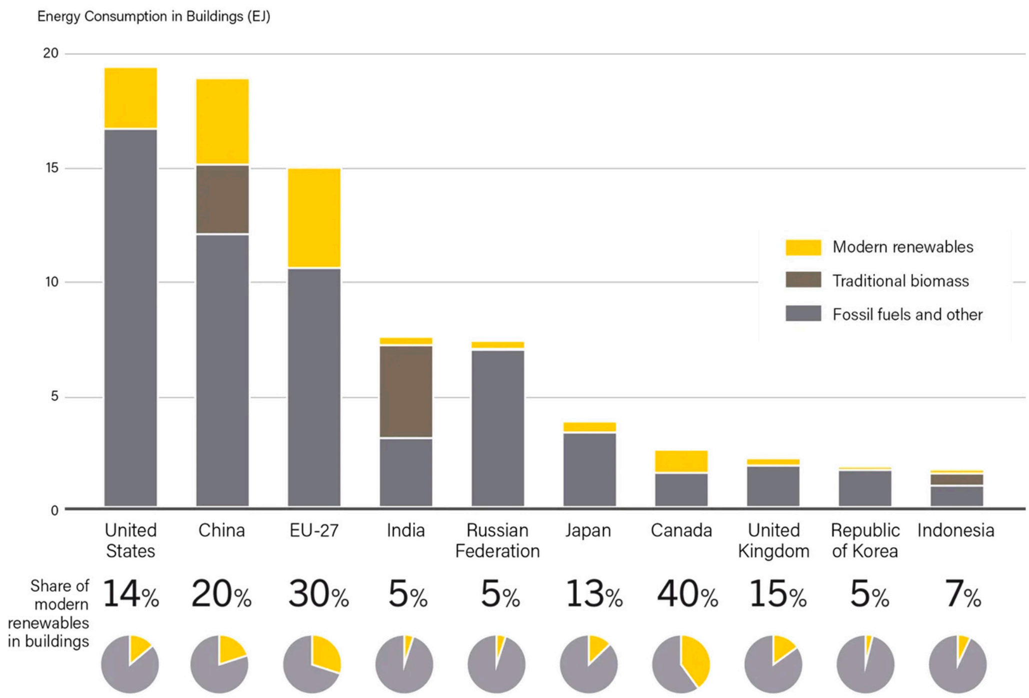

Figure 5. Share of modern renewables in buildings [28].

Leading renewable energy countries are demonstrating a strong commitment by setting ambitious targets and implementing policies that support the growth of these sources. Their initiatives are key to driving the global energy transition and accelerating the deployment of renewable energy. Directive (EU) 2018/2001, known as the Renewable Energy Directive II (RED II), is a key pillar of the European Union's strategy to promote renewable energy and meet its 2030 climate and energy targets, establishing a regulatory framework that aims to increase the share of renewable energy in Europe's energy mix, improve energy efficiency, and reduce greenhouse gas emissions [29]. One of the key components of this legislation is the adoption of transparent rules and coordination between the different bodies responsible for issuing permits for renewable energy projects. The lack of transparent rules and proper coordination between permitting bodies has been identified as a significant obstacle to the development of renewable energy. RED II addresses this issue by proposing the establishment of one-stop administrative shops to guide applicants through the application and administrative licensing process. This approach aims to reduce complexity for project developers and increase the efficiency and transparency of the authorization process. Another key aspect is the need for Member States to ensure that these communities can participate in available support schemes on an equal footing with large participants. The transition to renewable energy represents a major challenge and opportunity for communities [29].

In the context of energy transition, digital technologies and innovative systems, such as the Internet of Things (IoT) devices, smart grids, AI, and ML, with their optimization, management, and data analysis capabilities, assume a crucial role [30]. Leveraging AI and related digital technologies not only supports sustainability and resilience but also drives innovation within complex systems, such as those involved in energy transition and renewable energy management [31]. The principal applications of digital technology integration in the energy sector are the smart grid and advanced sensors, communication systems, and AI algorithms that can facilitate the real-time monitoring and management of energy distribution. For energy communities, this implies a dynamic equilibrium between supply and demand, and the integration of renewable sources into the local grid, thus ensuring a stable and continuous energy supply [32]. Khan et al. address the problem of electricity theft, which compromises public safety and causes economic losses for electricity companies by proposing a hybrid deep learning model that uses pre-processing and AlexNet techniques to improve the effectiveness of detection. Using a real dataset of smart meters, the model proposed by the authors showed promising results with high accuracy, precision, recall, and F1 score [33]. Zafar et al. discuss the importance of using AI during the fourth energy revolution to address the growing demand for energy and the depletion of fossil fuel reserves, thereby promoting the transition to smart grids. The authors use an ML model called Long Short-Term Memory (LSTM) to predict the parameters of a solar plant. They improve this model with two techniques: a combination of a convolutional neural network and LSTM, and an LSTM autoencoder, finding that the LSTM autoencoder provides the best performance; finally, they show that AI can significantly improve the accuracy of parameter predictions, helping to reduce losses and increase power generation capacity in smart grids [34]. Khalid examines energy systems from an environmental perspective and highlights emerging research trends. The rise in renewables requires infrastructure restructuring, providing opportunities for grid development and the use of AI for intermittent and distributed generation. The integration of AI and IoT into energy systems improves efficiency, sustainability, and reliability. The paper highlights the importance of a comprehensive policy and planning framework to support the transition to advanced systems and contributes to the academic debate on harnessing digital transformation to create smart and sustainable energy ecosystems [35]. Singh examines in detail the problems of integrating renewable energy sources (RESs) into distribution grid structures, highlighting their importance for modernizing the energy system and achieving environmental goals, and exploring the specific problems faced by grid-connected energy systems, including performance metrics and compatibility issues. It also provides an in-depth assessment of the characteristics of different RES hybrid systems, including solar, wind, battery, and biomass technologies. Finally, it highlights the role of advanced technologies and AI in addressing these issues, pointing to the move towards smart grids and improved distributed generation capabilities as essential components of a sustainable and robust energy future [36]. According to Wirtz, it is fundamental to highlight the dearth of adequate software tools for the simulation and optimization of energy systems at the preliminary design stage. He presents a new web-based tool, nPro, which assists in the planning of district heating and cooling systems. Once the type of system and the characteristics of the energy carrier have been selected, the system estimates the demand and the system based on the entered characteristics [37].

The present research proposes an OT that suggests different plant systems and renewable energy scenarios for the community/district. The innovative aspect of the proposal lies in the tool's capacity to foresee tailored energy systems based on consumption and geographical location, as a result of the AI and ML algorithms described in the subsequent section.

Recent advancements in ML, particularly in the realm of deep learning, have ushered in transformative changes in energy system management. Techniques such as reinforcement learning (RL) [38] and generative adversarial networks (GANs) [39] are at the forefront of this revolution. RL algorithms have been increasingly applied to optimize energy distribution and demand response strategies, enabling systems to adapt dynamically to changes in energy consumption patterns and supply fluctuations. Smith et al. demonstrate how RL can be leveraged to reduce energy consumption in commercial buildings by up to 20% without compromising occupant comfort, underscoring the potential of these algorithms to contribute to substantial energy savings and operational efficiency [40].

Moreover, the application of GANs in energy systems is a rapidly growing area of research that promises to enhance the accuracy of load forecasting and scenario planning. These networks are capable of generating simulated energy consumption data under various hypothetical conditions, providing energy managers with valuable insights into potential future challenges and enabling proactive system adjustments. The groundbreaking work by [41] Tran DT et al. illustrates how GANs can simulate electrical grid responses to extreme weather events, helping to prepare urban energy systems for increased resilience and continuity in the face of climatic anomalies. The progress in technology clearly shows how the latest AI and ML methods can enhance conventional energy management systems to achieve higher levels of efficiency and predictive accuracy. Zhimin Du et al. underscore the significance of GANs in the energy sector by addressing challenges such as imbalanced datasets in Fault Detection and Diagnosis (FDD) models. Through GAN-based adversarial learning, the model effectively generates balanced training datasets for building energy systems, ensuring accuracy and preventing missed alarms [42]. The research approach outlined in the OT initiative incorporates these sophisticated algorithms not just to improve immediate responsiveness but also to offer strategic insight into handling upcoming energy needs and situations. This strategy marks a notable advancement from current tools, distinguishing the proposed OT by its capability to leverage state-of-the-art AI for energy solutions.

A number of technological solutions are currently available on the market, which have been developed with the specific objective of enhancing methodologies for plant design or energy simulation through the use of digital tools. One such solution is HOMER (Hybrid Optimization of Multiple Energy Resources), which is a specialized software used primarily for the design, simulation, and optimization of microgrids and distributed energy systems. It is widely applied in projects involving renewable energy sources like solar, wind, and biomass, as well as traditional power generation, storage systems, and electric grids [43]. Instead, RETScreen is a software developed by the Canadian government to assess the technical and economic feasibility of renewable energy and energy efficiency projects. It is designed to help professionals and engineers design, implement, and monitor energy projects, covering technologies such as solar, wind, hydro, and biomass [44].

The OT project distinguishes itself by not only adopting but also innovating upon the latest advancements in AI and ML to deliver a tool that is uniquely capable of optimizing urban energy systems. Through the use of sophisticated data processing techniques and dynamic learning algorithms, the OT ensures that urban energy managers are equipped with a system that is both adaptive to immediate environmental changes and predictive of long-term trends. This positions the OT as a leader in the field, pushing the boundaries of what is possible in sustainable urban energy management and demonstrating a commitment to continuous improvement and technological integration in the face of global energy challenges.

2. Materials and Methods

This section describes the methodologies implemented in the OT project, designed to enhance the design and management of district energy systems. It provides a comprehensive explanation of the integration of advanced AI and ML technologies. These technologies address complex challenges in energy distribution and consumption, facilitating optimized decision-making that aligns with environmental sustainability goals.

2.1. Interdisciplinary Approach and Technical Framework

The methodology employed integrates data science, urban planning, and energy management principles, making extensive use of Python 3.13, a versatile and powerful programming language known for its robust libraries. These libraries are particularly well suited for data-intensive applications, enabling the handling of large datasets, performing complex calculations, and integrating diverse data sources. This capability ensures that OT meets the technical requirements of modern energy systems and remains adaptable and scalable as technological advancements emerge (Figure 6).

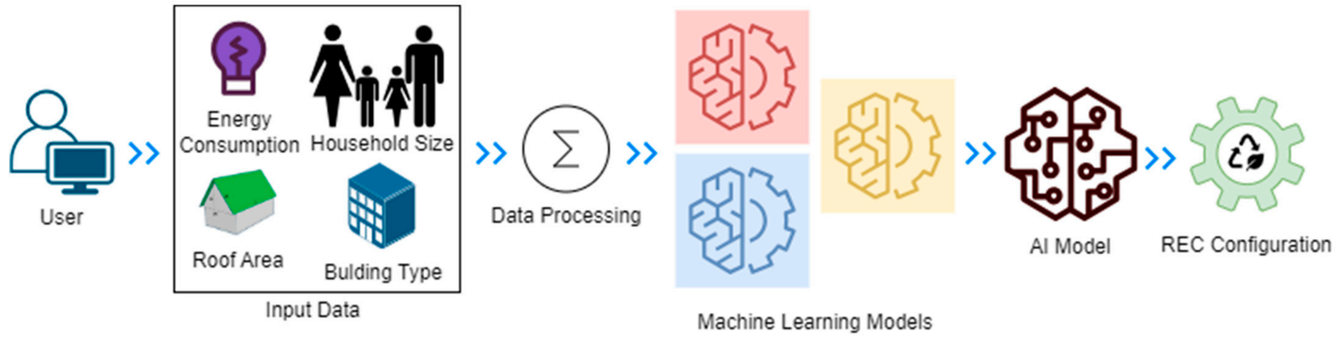

Figure 6. OT technical workflow.

2.2. AI and ML Integration for Dynamic System Adaptation

AI and ML are seamlessly integrated into OT, creating a dynamic system that can adapt to new patterns of energy use and environmental changes. This adaptability is crucial for cities aiming to reduce their carbon footprint and enhance energy efficiency. Continuous learning and improvement processes within OT provide urban planners and energy managers with actionable insights, promoting sustainable development.

2.3. User Interface and Input Data Collection

The user interface initiates the process, guiding users through a structured data input phase that is intuitive and user-friendly. This phase includes the collection of the following:

1. Thermal Loads and Electrical Loads: Data derived from utility bills measured in kWh.
2. Building Type: Users select from predefined options to ensure the energy solutions are accurately tailored.
3. Surface Roof Area and Technical Area Available: Inputs measured in square meters that influence the potential for installations like PV systems.
4. Population Size: This indicates the scale of the energy system required.
5. Location Site: This specifies whether the site is urban, coastal, or mountainous, affecting the design and energy needs.

2.4. Data Processing and System Design

Determining a building's energy demand is essential for evaluating energy efficiency and planning enhancements. A practical approach involves analyzing the energy consumption data from utility bills entered into the system by users. To standardize the data, it may be necessary to convert gas consumption from cubic meters to kWh using a conversion factor that reflects the gas's calorific value. This standardization ensures uniformity in measuring all consumed energy types. This method provides an accurate estimate of energy usage, necessitating the collection of data on electricity, gas consumption, and other fuels used throughout the year:

(1) Building-specific energy demand calculation: The energy demand specific to a building is calculated by dividing the total annual energy consumption by the building's surface area (kWh/m^2).

(2) Sizing of PV systems (1): Dimensioning a PV system involves a detailed assessment of energy requirements, site characteristics, and technical specifications of the PV panels. Initially, the building's energy demand is determined, which is influenced significantly by the site's geographical location. Solar radiation availability varies with latitude and local climate conditions, and the panel orientation—south in the northern hemisphere and north in the southern hemisphere—plays a crucial role in system efficiency. Accounting for positioning and inevitable efficiency losses from various devices, the required panel peak power value must be increased by approximately 25%.

$$W_p = (Wh/h_{eq}) \times (1/\rho) \tag{1}$$

- W_p = panel peak power
- Wh = daily consumption
- ρ = effective overall efficiency of the system

(3) Annual producibility calculation (2): The annual producibility refers to the potential energy production over one year. It is calculated using the average annual solar radiation on the site's horizontal plane (from UNI 10349 tables), the module surface area, a correction factor, and the system's effective overall efficiency.

$$E_{kWh/year} = I_{12} \times A \times f_c \times \rho \tag{2}$$

- I_{12} = average annual solar radiation (UNI 10349)
- A = module surface area
- f_c = correction factor
- ρ = effective overall efficiency of the system

(4) Sizing of electrical storage [kW] (3): Proper sizing of electric batteries is critical, especially in systems utilizing renewable energy sources like solar PV. The size of the batteries is determined based on the amount of energy that needs to be stored during low production periods to maximize self-consumption. This depends on the backup period duration and the depth of discharge (DoD), which typically is 80–90% for lithium batteries.

$$E_{storage} = Wh \times day_{storage} \times 1/\eta \tag{3}$$

- Wh = daily consumption
- η = discharge efficiency and depth of discharge

$$1/\eta = [1/(0.8 \times 0.08)] = 1/0.64 \tag{4}$$

(5) Sizing of thermal storage [V] (5): Thermal storage sizing starts with calculating the thermal load, which is the energy amount to be stored and later supplied.

$$Q = m \times cp \times \Delta T \tag{5}$$

- m = mass of the heat transfer fluid
- cp = specific heat of the fluid
- ΔT = temperature difference between the inlet and outlet of the tank

(6) CO_2 Emission reduction estimation: The OT calculates the tons of CO_2 emissions avoided by utilizing renewable energy sources, a key feature for sustainability reporting.

2.5. Optimization and Scenario Simulation

In the optimization and scenario simulation section of the OT project, AI and ML methodologies play a crucial role in forecasting and optimizing energy management systems. Here is how these technologies work in tandem with the input data to generate efficient and sustainable configurations for urban energy systems.

In this project, predictive models are central to optimizing the forecasting accuracy and operational efficiency of urban energy systems. The suite of ML technologies utilized includes the following:

I. Long Short-Term Memory (LSTM) Networks: These are specialized forms of recurrent neural networks (RNNs) that are highly effective at modeling sequential data. In the context of OT, LSTM networks are employed to capture temporal sequences and dependencies in historical energy usage data, which is crucial for accurately predicting future energy consumption.
II. Regression Models: These models are employed to predict continuous outcomes such as the output of renewable energy sources including solar and wind power. By accounting for various environmental and technical factors, these models provide precise estimations that aid in integrating renewable energy sources into the urban energy grid efficiently.
III. Ensemble Models: To enhance the robustness and reliability of predictions, OT integrates ensemble learning techniques such as Random Forests and Gradient Boosting Machines. These techniques combine the predictions of multiple models to improve forecast performance, especially in complex scenarios where single models may struggle with accuracy due to overfitting or underestimating uncertain elements.

3. Result and Discussion

The dataset used in this study represents real-world energy consumption data from urban environments, providing a robust foundation for the OT project's ML modeling efforts. The dataset and the ML model implemented in Python, ensuring reproducibility and transparency, are available on the project's GitHub "https://github.com/zahraziran/Open-tool-" (accessed on 11 November 2024) for access and further exploration. This dataset includes detailed energy usage information across various urban areas, building types, and occupancy levels, enabling a nuanced analysis that captures the complexities of urban energy demand. Figure 7 outlines the systematic approach used to handle and process data within the OT framework. This diagram illustrates the comprehensive pipeline, from the collection of data via IoT devices to the stages of data handling, feature extraction, and normalization. This workflow is critical for ensuring that the input data are both accurate and standardized, which is essential for the effective training and application of ML models. Data processing within the energy sector is pivotal, as it enables the identification of the most efficient models and approaches, potentially elevating energy management to a more advanced level. For instance, certain industrial methodologies prioritize data processing to circumvent the additional costs associated with complex analyses, thereby streamlining operations and enhancing overall efficiency [45]. By integrating tools like Python's libraries, NumPy, and Pandas, this workflow supports robust data processing capabilities necessary for real-time energy forecasting and optimization tasks.

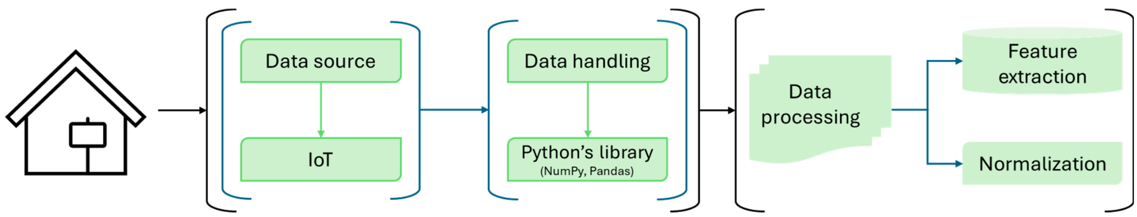

Figure 7. Data processing workflow in urban energy systems.

Achieving high predictive accuracy with such a comprehensive dataset underlines the robustness of our approach and demonstrates the potential impact of the OT. The results obtained from this research offer valuable insights and practical benefits, especially for researchers and practitioners interested in replicating or extending the OT's capabilities.

Given the promising outcomes, we have also proposed future enhancements to the OT by incorporating RL and GANs. These advanced techniques could further refine the OT's predictive abilities and adaptability, making it even more effective for dynamic urban energy management (Figure 8).

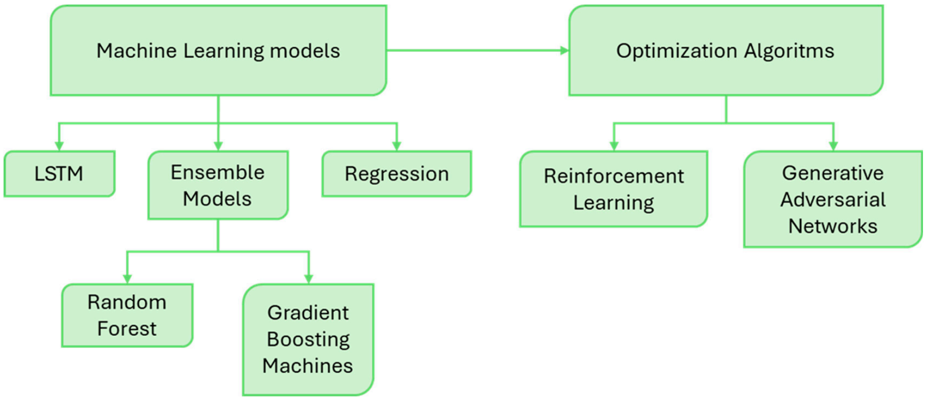

Figure 8. Architectural overview of OT's ML and optimization framework.

In this study, various ML models for energy consumption prediction were evaluated, including Long Short-Term Memory (LSTM) networks, Linear Regression, Random Forest, and Gradient Boosting models. Each model's performance was measured using standard evaluation metrics, such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2). The findings revealed that the LSTM model consistently provided the best performance, closely aligning with actual consumption patterns. This suggests that the LSTM network, with its capability to model temporal dependencies, is particularly suited to the dynamic nature of energy consumption data.

While Linear Regression served as a reliable baseline, it did not capture the complex, non-linear relationships in the data as effectively as the more advanced models. Both Random Forest and Gradient Boosting, which are ensemble methods, handled feature interactions better but lacked the temporal sensitivity necessary for time-series data. As highlighted in Figure 9, Random Forest and Gradient Boosting achieved reasonable accuracy, yet neither matched the precision of the LSTM network, especially where the variability in energy use was pronounced. The LSTM model, with an RMSE around 1.15 and an R^2 approaching 1.0, outperformed the other models, making it the preferred choice for the OT's predictive tasks.

These results are summarized in Table 1, underscoring the LSTM network's superiority in handling intricate patterns inherent in urban energy data. Table 1 presents the evaluation metrics for different ML models applied to energy consumption prediction, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-Squared (R^2). While Linear Regression achieves an R^2 value of 1.0000, indicating a perfect fit, the LSTM model demonstrates a better balance between accuracy and generalizability, making it more suitable for capturing complex temporal patterns in energy data.

Table 1. Evaluation metrics.

Model	Mean Squared Error (MSE)	Root Mean Squared Error (RMSE)	Mean Absolute Error (MAE)	R-Squared (R^2)
LSTM	2.00	1.42	1.16	0.9975
Linear Regression	0.00	0.00	0.00	1.0000
Random Forest	215.34	12.67	6.6881	0.8030
Gradient Boosting	158.20	12.38	6.8028	0.8119

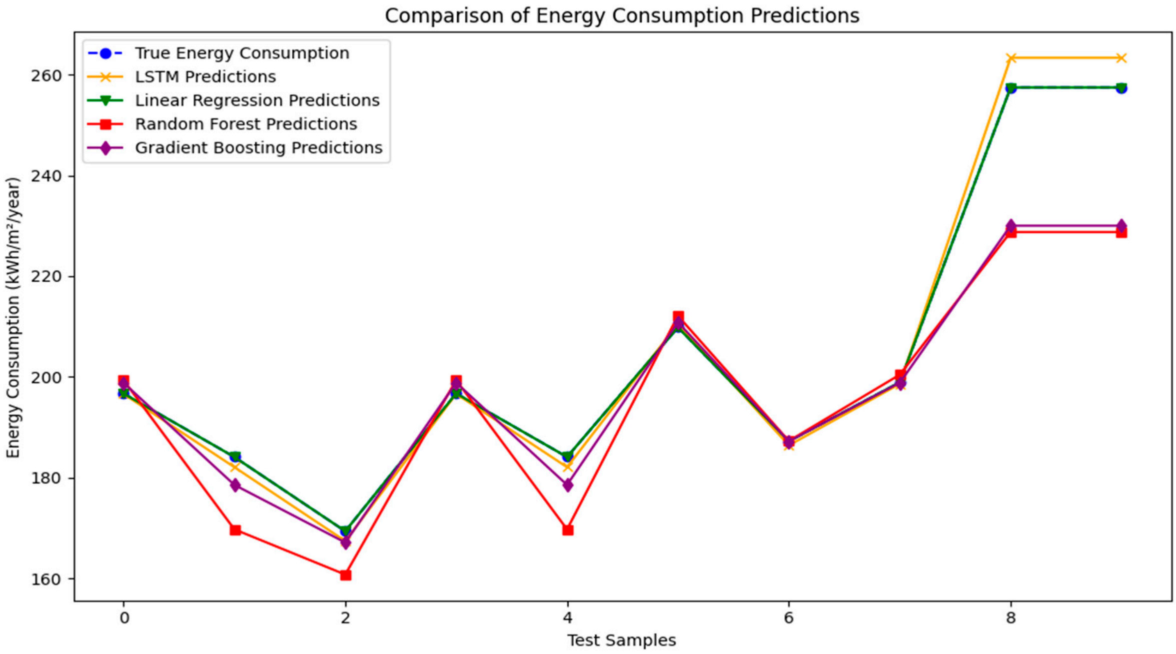

Figure 9. Predicting energy consumption with ML models.

An analysis carried out shows that although Linear Regression appears to perform best with the highest R^2 and lowest error metrics, its simplicity and tendency to overfit may make it less ideal for real-world forecasting. The LSTM network's adaptability and ability to handle complex temporal patterns suggest that it would provide more reliable results as the dataset expands or as conditions fluctuate, ensuring resilience and accuracy in a real-world deployment. The LSTM model's strong performance makes it the most viable option for the OT, as it demonstrated the highest accuracy and reliability among the models tested. The effectiveness of LSTM in this context underscores the model's suitability for similar urban energy prediction tasks. Considering these findings, we propose the integration of RL and GANs as future enhancements to the OT. RL could enable the tool to adapt dynamically to real-time changes in energy demand and supply, optimizing energy distribution in a way that responds to immediate system needs. Kim, S et al. propose an energy management algorithm based on RL, aimed at minimizing operational energy costs in smart buildings despite the uncertainty of future conditions [46], and A.T.D. Perera et al. highlight how the increasing complexity of integrated energy systems necessitates advanced control strategies, with RL emerging as a promising approach. However, they note that a direct transition to RL in energy systems faces challenges, despite RL's significant potential to manage and optimize energy flows within the renewable energy landscape [47]. This capability would be particularly valuable in demand response scenarios, where timely adjustments can lead to cost savings and improved grid stability.

GANs could further bolster the OT by generating synthetic datasets that simulate various future scenarios, thereby aiding in resilience planning. Through these simulations, the OT could better anticipate and prepare for extreme conditions or sudden shifts in energy demand. By incorporating RL and GANs, the OT would become a more adaptive and forward-looking tool, aligning it even more closely with sustainability goals and enhancing its utility for urban planners and energy managers. The proposed future work not only aims to refine the OT's accuracy but also to expand its applicability in real-world, dynamic urban energy environments.

The OT requires only basic building information and can therefore be used in a variety of areas to improve energy efficiency and promote sustainability:

- Urban energy management: It can be used by urban energy managers to monitor energy distribution and consumption in the city. Accurate forecasting and optimization strategies can reduce energy costs and improve overall system efficiency;
- Sustainable urban planning: Practitioners can use the OT to plan more sustainable districts and neighborhoods. The application can help identify the best renewable energy solutions and minimize the environmental impact of new construction;
- Commercial and residential buildings: Owners and operators of commercial and residential buildings can use the OT to monitor and reduce energy consumption, analyze the usability of renewable resources, and improve the operational efficiency of buildings, thanks to the user-friendly interface and the system itself, which does not require any special scientific knowledge to use;
- Renewable energy systems: It can be used to size design PV systems, wind, and other renewable energy systems, ensuring that these systems are designed to maximize energy production and reduce operating costs;
- Energy demand forecasting: Utilities and energy suppliers can use the OT to forecast short- and long-term energy demand, improving resource management and reducing the risks associated with demand fluctuations. After a certain training period and a sufficient amount of data, the information provided by the OT will become increasingly accurate and reliable;
- Energy policies and regulation: Regulators and energy policymakers can use the OT to analyze the impact of existing and future energy policies, and to develop new regulations that promote energy efficiency and the use of renewable energy. In summary, the OT offers a wide range of applications that can help improve energy efficiency, reduce CO_2 emissions, and promote sustainability in different sectors and contexts.

It is of the utmost importance to ensure the quality of the data used, as the efficacy of the OT is contingent upon the completeness and accuracy of the input data. In the event of inaccuracies in energy consumption data or incomplete geographical and structural information, sub-optimal predictions and recommendations may ensue. While the user interface is intuitive, the necessity for detailed energy consumption data and building specifications, for instance, can be daunting for those without experience in this field. This could restrict the accessibility and usability of the OT, resulting in incomplete data being input, which makes ML and AI models susceptible to incomplete datasets. These limitations highlight the need for the OT to be continuously refined through real-world testing and feedback, adaptive learning to accommodate new data and conditions, and perhaps a modular approach that allows for customization according to user needs and regulatory authorities.

4. Conclusions

The OT project leverages cutting-edge ML technologies within a robust framework designed to enhance the management and design of district energy systems. This framework enables a dynamic, adaptable platform that facilitates more efficient and environmentally sustainable energy distribution. The integration of advanced data science, urban planning, and energy management principles equips the OT with the versatility to address global energy challenges, providing cities with a powerful tool to achieve their sustainability goals. The OT's capacity to predict and adapt to energy consumption and environmental changes promises significant advancements in urban energy systems' resilience and efficiency.

In this research, a real-world dataset was utilized to validate the OT's capabilities, yielding promising results that underscore the potential of ML in optimizing energy consumption predictions. Through the implementation of multiple ML models, including Linear Regression, Random Forest, Gradient Boosting, and LSTM networks, we found that LSTM networks were particularly effective in capturing complex temporal dependencies in energy usage data. While Linear Regression achieved the lowest error rates in this dataset, the LSTM network's ability to model sequential data positions it as a more robust option for applications requiring detailed temporal analysis, which could be invaluable for those looking to replicate or extend OT's capabilities.

Moving forward, the OT framework could benefit significantly from integrating RL and GANs. RL could dynamically optimize energy management strategies by adjusting to real-time fluctuations in demand and supply, enhancing the system's resilience to changes. GANs, on the other hand, could aid in simulating diverse scenarios and stress-testing energy systems, preparing them for unexpected events and providing valuable insights into system performance under various conditions. This combination of predictive and adaptive capabilities would allow the OT not only to optimize energy systems but also to improve long-term sustainability and resilience.

In future iterations, integrating the OT with Building Information Modeling (BIM) could further enhance the quality of input data by incorporating detailed and accurate information on building characteristics, materials, and dimensions. This would enable OT to make even more precise predictions and develop energy distribution strategies that are finely tuned to specific building and environmental contexts. By bridging advanced AI/ML with BIM, the OT has the potential to revolutionize urban energy management, scenario planning, and sustainable development. The inclusion of RL and GANs would expand the OT's adaptability, making it an even more valuable tool for real-time energy management and policy planning, reinforcing its capacity to lead the way in transitioning towards smarter, greener urban energy systems.

Author Contributions: Conceptualization, G.P. and F.M.; methodology, G.P., F.M. and Z.Z.; software, G.P., F.M. and Z.Z.; validation, G.P., F.M. and Z.Z.; formal analysis, G.P., F.M. and Z.Z.; investigation, G.P., F.M. and Z.Z.; resources, G.P., F.M. and Z.Z.; data curation, G.P., F.M. and Z.Z.; writing—original draft preparation, G.P., F.M. and Z.Z.; writing—review and editing, G.P., F.M. and Z.Z.; visualization, G.P., F.M. and Z.Z.; supervision, G.P.; project administration, G.P. All authors have read and agreed to the published version of the manuscript.

Funding: The work was funded by Sapienza University Research Call 2022—CUP B89J21032850001, project title: Automatic electrical microgrid management system through machine learning techniques.

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. IEA. *Energy Efficiency 2023*; IEA: Paris, France, 2023. Available online: https://www.iea.org/reports/energy-efficiency-2023 (accessed on 11 October 2024).
2. Lee, C.-C.; Wang, F.; Chang, Y.-F. Towards Net-Zero Emissions: Can Green Bond Policy Promote Green Innovation and Green Space? *Energy Econ.* **2023**, *121*, 106675. [CrossRef]
3. Tiwari, A.K.; Trabelsi, N.; Abakah, E.J.A.; Nasreen, S.; Lee, C.-C. An empirical analysis of the dynamic relationship between clean and dirty energy markets. *Energy Econ.* **2023**, *124*, 106766. [CrossRef]
4. EU Energy Efficiency Directive. Available online: https://energy.ec.europa.eu/topics/energy-efficiency/energy-efficiency-targets-directive-and-rules/energy-efficiency-directive_en (accessed on 11 March 2024).
5. Piras, G.; Muzi, F. Energy Transition: Semi-Automatic BIM Tool Approach for Elevating Sustainability in the Maputo Natural History Museum. *Energies* **2024**, *17*, 775. [CrossRef]
6. Pelegov, D.V.; Chanaron, J.-J. Electric Car Market Analysis Using Open Data: Sales, Volatility Assessment, and Forecasting. *Sustainability* **2023**, *15*, 399. [CrossRef]
7. Jin, G.; Huang, Z. Statistical pathways to low-carbon cities: Analyzing renewable integration, energy-efficient design, and job creation. *Sustain. Cities Soc.* **2024**, *107*, 105429. [CrossRef]
8. Renewables 2023 Global Status Report. Available online: https://www.ren21.net/gsr-2023/modules/energy_demand (accessed on 13 March 2024).
9. AHRI. "AHRI Releases December 2022 U.S. Heating, Cooling Equipment Shipment Data". 10 February 2023. Available online: https://www.ahrinet.org/news-events/news/ahri-releases-december-2022-us-heating-cooling-equipment-shipment-data (accessed on 18 March 2024).

10. Hafez, F.S.; Sa'Di, B.; Safa-Gamal, M.; Taufiq-Yap, Y.; Alrifaey, M.; Seyedmahmoudian, M.; Stojcevski, A.; Horan, B.; Mekhilef, S. Energy Efficiency in Sustainable Buildings: A Systematic Review with Taxonomy, Challenges, Motivations, Methodological Aspects, Recommendations, and Pathways for Future Research. *Energy Strat. Rev.* **2023**, *45*, 101013. [CrossRef]
11. Vallati, A.; Vallati, A.; Di Matteo, M.; Di Matteo, M.; Sundararajan, M.; Sundararajan, M.; Muzi, F.; Muzi, F.; Fiorini, C.V.; Fiorini, C.V. Development and optimization of an energy saving strategy for social housing applications by water source-heat pump integrating photovoltaic-thermal panels. *Energy* **2024**, *301*, 131531. [CrossRef]
12. Vallati, A.; Fiorini, C.V.; Muzi, F.; di Matteo, M. Energy Simulation Scenario to Social Housing Building: Combining Heat Pump and Renewable Energy System. In Proceedings of the 2023 8th International Conference on Smart and Sustainable Technologies (SpliTech), Split, Croatia, 20–23 June 2023; pp. 1–5.
13. IEA, Building Consumption. Available online: https://www.iea.org/energy-system/buildings (accessed on 20 February 2024).
14. Nuţă, F.M.; Sharafat, A.; Abban, O.J.; Khan, I.; Irfan, M.; Nuţă, A.C.; Dankyi, A.B.; Asghar, M. The relationship among urbanization, economic growth, renewable energy consumption, and environmental degradation: A comparative view of European and Asian emerging economies. *Gondwana Res.* **2024**, *128*, 325–339. [CrossRef]
15. IEA. *Global Energy Use Coverage of Minimum Performance Standards for Major end Uses, 2000–2023*; IEA: Parism France, 2023. Available online: https://www.iea.org/data-and-statistics/charts/global-energy-use-coverage-of-minimum-performance-standards-for-major-end-uses-2000-2023 (accessed on 15 April 2024).
16. IEA. Tracking Clean Energy Progress 2023. 2023. Available online: https://www.iea.org/reports/tracking-clean-energy-progress-2023 (accessed on 11 April 2024).
17. EU, 2050 Long Term Strategy. Available online: https://climate.ec.europa.eu/eu-action/climate-strategies-targets/2050-long-term-strategy_en (accessed on 22 February 2024).
18. Italian Long Term Strategy. Available online: https://asvis.it/public/asvis2/files/Pubblicazioni/Rapporto_di_Primavera/Rapporto_ASviS_Primavera_2024_Scenari_Italia.pdf (accessed on 12 February 2024).
19. Rocha, H.R.; Fiorotti, R.; Louzada, D.M.; Silvestre, L.J.; Celeste, W.C.; Silva, J.A. Net Zero Energy cost Building system design based on Artificial Intelligence. *Appl. Energy* **2024**, *355*, 122348. [CrossRef]
20. Liao, W.; Xiao, F.; Li, Y.; Zhang, H.; Peng, J. A comparative study of demand-side energy management strategies for building integrated photovoltaics-battery and electric vehicles (EVs) in diversified building communities. *Appl. Energy* **2024**, *361*, 122881. [CrossRef]
21. Grataloup, A.; Jonas, S.; Meyer, A. A review of federated learning in renewable energy applications: Potential, challenges, and future directions. *Energy AI* **2024**, *17*, 100375. [CrossRef]
22. Shahee, A.; Abdoos, M.; Aslani, A.; Zahedi, R. Reducing the energy consumption of buildings by implementing insulation scenarios and using renewable energies. *Energy Inform.* **2024**, *7*, 1–29. [CrossRef]
23. Maghami, M.R.; Pasupuleti, J.; Ekanayake, J. Energy storage and demand response as hybrid mitigation technique for photovoltaic grid connection: Challenges and future trends. *J. Energy Storage* **2024**, *88*, 111680. [CrossRef]
24. Shi, J.; Yu, J.; Guan, J. A scientometrics analysis and visualization of the ecological impact of photovoltaic projects. *J. Renew. Sustain. Energy* **2024**, *16*, 0203786. [CrossRef]
25. Widjonarko, W.; Utomo, W.M.; Omar, S.; Baskara, F.R.; Rosyadi, M. Control energy management system for photovoltaic with bidirectional converter using deep neural network. *Int. J. Electr. Comput. Eng. (IJECE)* **2024**, *14*, 1437–1447. [CrossRef]
26. Piras, G.; Sferra, A.S. Environmental Product Declarations as a Data Source for the Assessment of Environmental Impacts during the Use Phase of Photovoltaic Modules: Critical Issues and Potential. *Energies* **2024**, *17*, 482. [CrossRef]
27. Jia, B.; Li, F.; Sun, B. Knowledge-network-embedded deep reinforcement learning: An innovative way to high-efficiently develop an energy management strategy for the integrated energy system with renewable energy sources and multiple energy storage systems. *Energy* **2024**, *301*, 131604. [CrossRef]
28. Renewables 2024 Global Status Report, Renewables in Buildings. Available online: https://www.ren21.net/gsr-2024/modules/energy_demand/02_renewables_in_buildings/ (accessed on 14 October 2024).
29. EU Directive (EU) 2018/2001. Available online: https://eur-lex.europa.eu/eli/dir/2018/2001/oj (accessed on 30 July 2024).
30. Piras, G.; Agostinelli, S.; Muzi, F. Digital Twin Framework for Built Environment: A Review of Key Enablers. *Energies* **2024**, *17*, 436. [CrossRef]
31. Berti, N.; Arman, A.; Esmaili, P.; Zeynivand, M.; Battini, D.; Bianchini, D.; Cristaldi, L.; De Giuli, L.B.; Galeazzo, A.; Gruosso, G.; et al. Sustainability and Resilience in the MICS SPOKE8 project: The role of the Digital Twin. In Proceedings of the IEEE International Conference on Metrology for eXtended Reality, Artificial Intelligence and Neural Engineering (METROXRAINE 2024), London, UK, 21–23 October 2024.
32. Piras, G.; Muzi, F.; Tiburcio, V.A. Digital Management Methodology for Building Production Optimization through Digital Twin and Artificial Intelligence Integration. *Buildings* **2024**, *14*, 2110. [CrossRef]
33. Iftikhar, H.; Khan, N.; Raza, M.A.; Abbas, G.; Khan, M.; Aoudia, M.; Touti, E.; Emara, A. Electricity theft detection in smart grid using machine learning. *Front. Energy Res.* **2024**, *12*, 1383090. [CrossRef]
34. Zafar, A.; Che, Y.; Faheem, M.; Abubakar, M.; Ali, S.; Bhutta, M.S. Machine learning autoencoder-based parameters prediction for solar power generation systems in smart grid. *IET Smart Grid* **2024**, *7*, 328–350. [CrossRef]
35. Khalid, M. Energy 4.0: AI-enabled digital transformation for sustainable power networks. *Comput. Ind. Eng.* **2024**, *193*, 110253. [CrossRef]

36. Singh, S.; Singh, S. Advancements and Challenges in Integrating Renewable Energy Sources Into Distribution Grid Systems: A Comprehensive Review. *J. Energy Resour. Technol.* **2024**, *146*, 1–37. [CrossRef]
37. Wirtz, M. nPro: A web-based planning tool for designing district energy systems and thermal networks. *Energy* **2023**, *268*, 126575. [CrossRef]
38. Arulkumaran, K.; Deisenroth, M.P.; Brundage, M.; Bharath, A.A. Deep Reinforcement Learning: A Brief Survey. *IEEE Signal Process. Mag.* **2017**, *34*, 26–38. [CrossRef]
39. Aggarwal, A.; Mittal, M.; Battineni, G. Generative adversarial network: An overview of theory and applications. *Int. J. Inf. Manag. Data Insights* **2021**, *1*, 100004. [CrossRef]
40. Smith, L.; Cao, Y.; Levine, S. Grow Your Limits: Continuous Improvement with Real-World RL for Robotic Locomotion. In Proceedings of the 2024 IEEE International Conference on Robotics and Automation (ICRA), Yokohama, Japan, 13–17 May 2024; pp. 10829–10836.
41. Tran, D.T.; Phung, D.T.; Duong, D.M.; Inoue, K.; Lee, J.-H.; Nguyen, A.Q. Privacy-preserving Face and Hair Swapping in Real-time with a GAN-generated Face Image. *IEEE Access Early Access*. **2024**. [CrossRef]
42. Du, Z.; Chen, K.; Chen, S.; He, J.; Zhu, X.; Jin, X. Deep learning GAN-based data generation and fault diagnosis in the data center HVAC system. *Energy Build.* **2023**, *289*, 113072. [CrossRef]
43. HOMER Sofware, HOMER PRO Home Page. Available online: https://homerenergy.com/products/pro/index.html (accessed on 14 October 2024).
44. Government of Canada, RETScreen Home Page. Available online: https://natural-resources.canada.ca/maps-tools-and-publications/tools/modelling-tools/retscreen/7465 (accessed on 14 October 2024).
45. Ziran, Z.; Mecella, M.; Leotta, F. A Simplified and Sustainable Approach for Energy Prediction. In Proceedings of the Intelligent Environments 2024: Combined Proceedings of Workshops and Demos & Videos Session 2024; IOS Press: Amsterdam, The Netherlands, 2024; pp. 104–113. Available online: https://ebooks.iospress.nl/doi/10.3233/AISE240022 (accessed on 10 November 2024).
46. Kim, S.; Lim, H. Reinforcement Learning Based Energy Management Algorithm for Smart Energy Buildings. *Energies* **2018**, *11*, 2010. [CrossRef]
47. Perera, A.; Kamalaruban, P. Applications of reinforcement learning in energy systems. *Renew. Sustain. Energy Rev.* **2021**, *137*, 110618. [CrossRef]