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Review

Modeling Approaches for Residential Energy Consumption: A Literature Review

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Abstract: The interest in sustainability and energy efficiency is constantly increasing, and the noticeable effects of climate change and rising energy prices are fueling this development. The residential sector is one of the most energy-intensive sectors and plays an important role in shaping future energy consumption. In this context, modeling has been extensively employed to identify relative key drivers, and to evaluate the impact of different strategies to reduce energy consumption and emissions. This article presents a detailed literature review relative to modeling approaches and techniques in residential energy use, including case studies to assess and predict the energy consumption patterns of the sector. The purpose of this article is not only to review the research to date in this field, but to also identify the possible challenges and opportunities. Mobility, electrical devices, cooling and heating systems, and energy storage and energy production technologies will be the subject of the presented research. Furthermore, the energy upgrades of buildings, their energy classification, as well as the energy labels of the electric appliances will be discussed. Previous research provided valuable insights into the application of modeling techniques to address the complexities of residential energy consumption. This paper offers a thorough resource for researchers, stakeholders, and other parties interested in promoting sustainable energy practices. The information gathered can contribute to the development of effective strategies for reducing energy use, facilitating energy-efficient renovations, and helping to promote a greener and more sustainable future in the residential domain.

Keywords: building energy consumption; electricity demand; energy efficiency; energy management; modeling approaches; energy systems

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1. Introduction

Residential energy consumption plays a crucial role in the overall energy landscape, and it accounts for a significant portion of global energy demand [1]. This sector encompasses various energy-intensive activities, including space heating, water heating, lighting, and the operation of electric appliances and devices in millions of households worldwide [2]. The global population continues to grow [3], which leads to an increase in the number of residential units, and subsequently to higher energy requirements in meeting basic living needs. Additionally, rapid urbanization [4] and improved living standards in many regions have resulted in increased energy consumption per household. The sector's energy demand is further influenced by factors such as population density, climate conditions, building characteristics, and socio-economic factors [5]. It is therefore crucial to understand and address the complexities of energy consumption to transition to a low-carbon future.

Energy fuels economic growth by powering industries, transportation, and essential services. As societies continuously evolve and technology becomes more pervasive, energy needs continue to increase. Nevertheless, the world is grappling with the adverse consequences of excessive energy use [6], such as greenhouse gas emissions, climate change, and resource depletion. It is therefore imperative to recognize that energy use is inextricably linked to global challenges [7], which makes it vital to explore diverse sustainable practices to find those that balance economic growth with environmental responsibility.

Improving energy efficiency and promoting sustainable energy practices have emerged as critical global priorities to reduce energy consumption in the residential sector [8]. The understanding of residential energy consumption patterns is a crucial step to design effective policies [9], implement targeted interventions, develop sustainable energy systems [10], and reduce our environmental footprint. Mitigating energy consumption in the residential sector requires a multi-faceted approach. Key strategies include the promotion of energy-efficient technologies, behavioral changes, and policy interventions. Adopting energy-efficient appliances, optimizing heating and cooling systems, implementing better insulation, and utilizing renewable energy sources are all effective measures through which to reduce energy consumption.

During our research, we studied many tools and technologies that facilitate the reduction in energy consumption in households. For example, smart meters can, depending on the technology and legal situation, enable real-time energy monitoring [11], which empowers homeowners to track and improve their consumption. Home energy management systems [12] allow for the automatic control and adjustment of energy demand and price signals based on electrical equipment. In addition, the development of energy storage and distributed energy resources offer opportunities to efficiently integrate renewable energy sources in residential systems [13].

Modeling plays an important role in shaping our understanding of energy use patterns and potential pathways toward sustainability [14]. It also provides a systematic framework through which to analyze the complex interplay of the various factors influencing residential energy use. The developed mathematical and computational models [15] that simulate energy use offer a systematic and structured approach in studying this field.

While previous studies have explored residential energy consumption and employed various modeling techniques, there remains a need for comprehensive and context specific approaches that consider the diverse factors that influence the energy use in different building types. This paper aims to address this gap by presenting a thorough examination of modeling approaches for residential energy consumption, which are divided into two main parts: (i) approaches for causal models, and (ii) models and approaches of relevance to the residential sector.

In this study, we review the existing literature on residential energy modeling and identify key studies that have contributed to the understanding of energy consumption in this sector. We highlight the advancements in modeling techniques and the insights gained from previous research.

Specifically, Section 2 will analyze the research approaches for causal models, as well as the research on models and approaches of relevance to the residential sector; meanwhile, Section 3 will provide a summary with the highlights of the research, and Section 4 will include a discussion of the findings.

2. Review of Modeling Techniques in Residential Energy Consumption

2.1. Causal Modeling

Causal models based on causal interference and analysis are powerful analytical tools that have been mainly used to identify and understand the cause and the effect relationships between the system variables. Unlike correlation, which only shows the association between the variables, causal models aim to determine the underlying mechanisms that lead to certain outcomes. In the context of modeling energy consumption in the residential sector, causal models can discover the complex interactions between various factors that influence household energy usage. Causal models, including structural equation modeling (SEM) [16], Bayesian networks [17], time series causal models [18], quasi-experimental designs [19], and randomized controlled trials (RCTs) [20], have emerged as powerful tools through which to understand the complex relationships and interdependencies influencing energy consumption in households.

Causal modeling in residential energy consumption has expanded beyond traditional techniques, with structural causal models (SCMs) [21] gaining traction. SCMs allow researchers to capture both the direct and indirect causal relationships among variables, providing a more comprehensive understanding of energy usage drivers. Additionally, the potential outcome framework (POF) [22], commonly used in causal inference, is employed to estimate causal effects by comparing the observed and the counterfactual scenarios. SCMs and the POF serve as solid foundations as they enable the consistent representation of prior causal knowledge, assumptions, and estimates. The POF takes potential outcomes as a starting point and relates them to observed outcomes, while SCMs define a model based on observed outcomes from which potential outcomes can be derived. Causal models need to fulfill seven essential tasks [23] to be valuable tools for causal inference (Appendix A).

To simulate the effects on the behavior of energy consumption in the residential sector through causal models, researchers must carefully select and collect relevant data about household energy consumption, demographic information, weather data, and details on energy-efficient technologies. Furthermore, survey data can also provide valuable insights into behavioral factors influencing energy usage. Advanced statistical software and programming languages (e.g., R and Python) are indispensable tools for data analysis and for developing causal models. When selecting libraries to build causal models, several implementation aspects should be considered, such as the license type, programming language, documentation quality, and availability of support channels. Libraries that offer support tools for creating, modifying, and converting causal diagrams enhance the usability of causal models and their interpretability. Several libraries (Appendix B) implementing previous aspects have been studied, including DAGitty [24], DoWhy [25], Causal Graphical Models [26], Causality [27], and Causal Inference [28].

Research exploring the application of SCMs and the potential outcome framework to residential energy consumption is growing. For instance, the study of [29] utilized SCMs to analyze the causal relationships between the characteristics of the buildings, occupancy patterns, and energy use in residential buildings. Their findings emphasized the substantial impact of occupant behavior on energy consumption, uncovering valuable insights for energy efficiency initiatives. Another study [30] employed the directed acyclic graph (DAG) when randomized controlled trials (RCTs) were not feasible to assess the causal effects of household energy savings. Their research demonstrated that DAGs lead to a better understanding of the processes underlying intervention programs.

2.2. Modeling of Energy Systems in Buildings

Different models that provide a comprehensive understanding of energy use across different scales are examined. The examination covers a wide range of systems, from individual buildings to complex, large-scale energy supply systems. Generally small-scale system models tend to be far more detailed than large-scale system models, but that strongly depends on their intended use.

From a modeling perspective, energy system models consist of multiple interconnected models that work within a unified framework. The level of detail in these models is different as it depends on the scale of the representation, from complex representations of valves and pipes in a building to simplified representations of building blocks. The accuracy and the quality of the obtained results are greatly influenced by modeling methodology and the available computation time.

Table 1 provides a brief overview of some of the identified models, but the list is not exhaustive. The intention is to offer readers a glimpse into the possibilities and scales of energy system models. Ten different models have been examined, each with unique characteristics and applications.

Table 1. Comparison of models for Energy Systems at Different Scales.

Load Profile Generator (Building Scale)	This modeling tool focuses on individual households and performs a comprehensive simulation of household behavior to generate load curves [31].
Energy Plus (Building Scale)	EnergyPlus is an energy analysis and thermal load simulation program that calculates building's geometry, materials, and systems [32].
EnergyPlan (Large scale energy systems)	EnergyPlan is a computer model for energy system analysis that enables the design of national energy planning strategies by analyzing the consequences of different energy systems and investments at hourly intervals [33].
MATLAB & Simulink (General Modeling Environment)	MATLAB & Simulink provide an integrated platform for data analytics and model-based design, allowing for the creation of predictive models for cost minimization [34].
Simscape Electrical Specialized Power Systems (Different scales of Energy Systems)	This software, part of the Physical Modelling product family, allows for the rapid simulation of power systems with interactions across various disciplines, including electrical, mechanical, thermal, and control systems [35].
TRaNsient SYstem Simulation program (Different Scales of Energy Systems)	TRNSYS is a flexible software environment that simulates the behavior of transient systems. It comprises an engine for system processing and an extensive library of components that model various aspects of the system [36].
RC-Building Simulator (Building Scale)	Based on the resistor capacitor (RC) model, this physics-based simulation tool accurately captures the thermal behavior of buildings using an electrical analogy [37].
ESP-r (Building Scale)	ESP-r is a building energy simulation program that allows for the integrated modeling of energy performance, through which it considers heat, air, moisture, light, and electrical power flows [38].
IDA ICE (Building Scale)	IDA Indoor Climate and Energy (ICE) is a program used to study the indoor climate of individual zones within a building, and it is used to analyze energy consumption for the entire building [39].
Modelica Building Systems (Different Scales of Energy Systems)	The Modelica Building Systems library enables dynamic simulations of energy behavior in single rooms, buildings, and districts. It accounts for the energy balance of building envelopes and can incorporate energy plant systems, such as solar heating systems [40].

The above modeling tools do not only contribute to the comprehensive understanding of energy consumption patterns, but can also analyze the impact of various interventions in residential buildings. The utilization of these models can offer valuable insights into the patterns and origins of energy consumption, the optimization of energy usage, and can help to inform the decision-making process related to energy planning and management.

2.3. Modeling the Linkage of Mobility with Residential Energy

The seamless interaction between mobility and residential energy consumption plays a pivotal role in shaping sustainable urban living. As individuals commute to work, access essential services, and partake in recreational activities, their transportation choices directly impact their household's energy usage. Electric vehicles (EVs) and the integration of smart mobility solutions introduce new dynamics to the energy landscape. With charging points being set up in homes, EVs now directly link the energy consumption for mobility with the household energy consumption.

The ever-increasing importance of sustainable urban living and energy-efficient mobility has paved the way for innovative traffic simulation models that align with the residential sector's needs. Within this context, four influential simulation models, which are examined in this review—namely SUMO, MATSim, VISSIM, and PRIMES-TREMOVE—have emerged as powerful tools through which to analyze transportation dynamics (Table 2). With a focus on energy-conscious mobility and enhanced accessibility, these models offer valuable insights to the interplay between residential mobility patterns and energy consumption.

Table 2. Noteworthy projects and models in traffic simulation and transportation modeling.

SUMO [41]	An open source, microscopic, and multi-modal traffic simulation package designed to handle large road networks and serve as a test bed for traffic research algorithms and models. While it allows interoperability with external applications during runtime, it requires an explicit definition of route steps for each citizen.
MATsim [42]	An agent-based transportation simulation framework capable of simulating large-scale scenarios. Originally focused on private car traffic, it was later expanded to include various public transportation modes, pedestrians, and cyclists.
VISSIM [43]	A microscopic simulation model based on the Wiedemann model, enabling highly accurate traffic simulations for functionally classified roadways and public transportation operations.
PRIMES_TREMOVE [44]	An economic model that combines microeconomic behavior with a detailed representation of transport technologies. It includes a transport demand module based on decision trees, and it is used to emulate consumer profile decision-making processes.

These methodologies have many proven success stories, but they have a fundamental limitation in capturing social behavior, which influences the decision of using specific transport modes. Thus, social behavior affects (i.e., time cost, comfort, monetary cost, or environmentally friendly awareness) are not included in the models. Actual platforms for road simulation do not cover these needs, either due to the impossibility to parameterize the initial system configuration according to social variables, or due to the distribution of such modules as additional commercial packages.

2.4. Modeling Approaches for Enhancing Energy Efficiency in Buildings

Improving energy efficiency in buildings is a pivotal issue for sustainable development. Modeling energy efficiency involves the use of various software tools and methodologies to simulate and analyze the energy performance of buildings. Some of the key measures that current tools consider are shown in Table 3.

Table 3. Key measures considered in energy efficiency modeling tools.

Building Envelope	Evaluates the building envelope, including walls, roofs, and floors, to assess the levels of insulation and thermal performance. Proper insulation helps in reducing heat transfer and energy loss.
Windows and Glazing	These tools analyze the type of windows and glazing used in buildings, whereby factors like the u-value, solar heat gain coefficient (SHGC), and shading devices are considered. Window replacements and glazing improvements can significantly impact the overall energy efficiency.
HVAC Systems	These models analyze heating, ventilation, and air conditioning (HVAC) systems to assess their energy consumption and efficiency. Evaluating HVAC performance helps identify the opportunities for energy savings and optimization.
Lighting	Tools that analyze lighting systems, including light fixtures and controls, to evaluate their energy consumption and potential for efficiency improvements.
Occupancy & Scheduling	Some of these tools allow for the integration of occupant behavior and schedules to simulate real-world usage patterns, which can influence energy consumption.
Appliances & Equipment	Energy efficiency models may incorporate the energy consumption of various appliances and equipment, such as refrigerators, computers, and other electronic devices.
Renewable Energy Integration	Some advanced tools consider the integration of renewable energy sources like solar panels or wind turbines to assess the potential for on-site energy generation and its impact on overall energy efficiency.

Table 3. *Cont.*

Building Orientation	Building orientation is on how the amount of sunlight received affects the energy of the building, which can impact heating and cooling loads. These modeling tools consider the orientation of the building to optimize energy efficiency.
Energy Labels & Certificates	Certain tools incorporate energy labels and certification systems to assess and rate buildings based on their energy performance and compliance with specific standards (Appendix C).
Energy Codes & Regulations	Energy efficiency models can be aligned with building codes and regulations to ensure compliance and identify relevant areas for further improvements.
Retrofit Assessment models	These specialized models play a crucial role in guiding retrofit decisions, thus enabling informed choices that result in reduced environmental impact and energy savings.

Energy efficiency modeling tools in buildings encompass diverse categories, each tailored to address specific aspects of energy consumption. Whole-building simulation tools, like EnergyPlus [45] and DesignBuilder [46], offer dynamic simulations of overall building energy performance, thus allowing for the comprehensive analysis of heating, cooling, ventilation, lighting, and other systems. Energy labeling models [47] incorporate energy labels and certificates to assess and rate the buildings based on their energy performance and compliance with specific standards. Retrofit assessment models [48] focus on assessing the impact of renovation measures on building energy efficiency, thus aiding in identifying cost-effective retrofit strategies.

While modeling tools have advanced significantly, they do have limitations such as data accuracy and integration complexity. Accurate input data [49], such as occupancy patterns [50] and weather conditions, are crucial for reliable results, but obtaining them is challenging. Moreover, the interactions between building systems might not be fully captured and lead to potential inaccuracies [51]. Nevertheless, these modeling tools have demonstrated successes in performance prediction, cost-effectiveness, and policy support. They enabled informed decision making during the design phase leading to cost savings by identifying energy-efficient measures. Furthermore, many models support policy makers in developing energy efficiency regulations and standards.

Appendix D provides an overview of the energy efficiency measures in buildings, thereby focusing on renovation measures. These measures play a crucial role in improving energy efficiency and reducing energy consumption. Understanding and incorporating these approaches into simulation models is essential for the accurate representation of energy systems. The energy performance of buildings is a crucial factor in reducing emissions.

Energy efficiency measures in residential buildings need to be considered both for renovation measures and energy labels for appliances. Energy performance certificates play a special role, with the u-value being the main factor determining thermal losses [52]. Appendix F describes the effects of different energy-efficient measures on buildings (depending on the starting condition of the building and climate conditions), and refers to two different approaches for assessing the effects of efficiency measures: rough estimation, which provides a quick and approximate assessment; and exact calculation, which involves a more detailed and precise analysis using specialized software and a consideration of multiple parameters and factors.

2.4.1. Modeling Appliances

Modeling electric appliances is crucial for various demand-side energy management applications, as well as for providing simulation results with a high temporal resolution. Accurate and representative models of these appliances are essential for optimizing energy consumption, predicting energy loads, and developing effective strategies for demand response and energy conservation. This literature review explores how electric appliances are modeled, thereby presenting the tools commonly used for appliance modeling.

Analytical models [53] form the bedrock of appliance modeling, whereby mathematical equations based on physical principles to describe appliance behavior are employed.

By simplifying the models without compromising essential characteristics, analytical approaches are effective for appliances with well-defined operating patterns, such as refrigerators, air conditioners, and electric heaters. On the other hand, empirical models utilize real-world data gathered from field measurements and surveys [54]. In leveraging machine learning techniques [55], like regression analysis and neural networks, empirical models offer greater flexibility in capturing the diverse operating conditions and behaviors of appliances (such as washing machines, dryers, and dishwashers). Hybrid models [56] represent a promising middle ground, including elements of analytical and empirical approaches to achieve a balance between accuracy and computational efficiency. By integrating physics-based principles with data-driven techniques, these models excel at representing appliances with complex operational characteristics, including smart devices and variable-speed appliances.

The literature abounds with studies focused on developing load profiles for residential buildings, which consider aggregated energy consumption from different appliances to predict overall grid load. These models incorporate various factors, such as occupant behavior, the climate, and appliance penetration rates, to enhance their predictive capabilities. Individual appliance models have also been studied. For instance, the modeling of air conditioners [57] has garnered attention due to their substantial impact on peak electricity demand. Additionally, household lighting systems [58], refrigerators, water heaters, and other appliances have been examined to understand their energy consumption patterns. In emphasizing occupant behavior and user interactions with appliances, behavior-based models have emerged to provide more accurate predictions by considering factors such as usage schedules, appliance settings, and consumer preferences.

EnergyPlus stands out as a widely used building energy simulation program that integrates detailed physics-based models for various residential appliances. Through EnergyPlus, researchers can assess the energy performance of buildings and their systems [59], which encompass HVAC, lighting, and appliances. For appliances with complex control logic and non-linear behavior, MATLAB and Simulink [60] are used for developing analytical and empirical models. These platforms offer robust simulation capabilities and provide access to various machine learning algorithms in order to tackle intricate appliance behavior. OpenDSS (distribution system simulator) [61] is instrumental for power distribution system analysis. Researchers frequently incorporate appliance models into OpenDSS to study their impact on the overall grid and to explore demand-side management.

Occupant-Driven Energy Conservation

Modeling energy sufficiency is a complex issue that involves an extensive understanding and quantifying of the energy needed to meet occupant comfort while maintaining sustainable consumption levels. Energy sufficiency entails self-regulation and self-restriction, ensuring access to and consumption of energy without exceeding environmental limits. Unlike energy efficiency, which often relies on modern and expensive equipment, energy sufficiency emphasizes low or no-cost interventions, such as behavioral changes and appropriate adjustments to existing household equipment.

For instance, the study of [62] aimed to assess and model energy sufficiency in the residential sector by analyzing occupant behavior and its impact on energy consumption. In utilizing a behavior-based simulation model, the aforementioned study estimated the energy demand for heating, cooling, lighting, and appliances by considering occupant preferences and schedules. Various energy-saving interventions were included, such as thermostat settings and the adoption of energy-efficient appliances. By comparing the simulated energy consumption with actual usage, the study examined the potential of behavior change interventions to achieve energy sufficiency while maintaining occupant comfort. The findings offer valuable insights into the role of occupants in shaping energy consumption patterns and provide evidence-based strategies for promoting energy sufficiency.

2.4.2. Modeling HVAC Systems

HVAC systems have a substantial potential to (i) provide flexibility to the energy system, and (ii) improve the energy efficiency of a building. In terms of mathematical modeling and simulation, three parts need to be considered: (i) HVAC components, (ii) HVAC control, and (iii) HVAC systems in general. HVAC control is the control mechanism that decides when the devices work, as well as the working parameters. The HVAC system describes how the different components are linked together within the building.

Table 4 provides an overview of the different models that are available for simulating heating, ventilation, and air conditioning (HVAC). The listed models encompass a wide range of technologies, from tankless water heaters to air conditioning, as well as ventilation systems. Each model represents a unique approach to simulating different HVAC components.

2.5. Modeling Energy Management Systems (EMS)

Energy management systems (EMS) utilize measured data, forecasts, and self-learning algorithms to optimize energy consumption by shifting flexible loads to times when it is more economic, ecological, or convenient. There exists a multitude of different EMS options tailored with different consumer ranges, which can be classified into clusters, namely (1) open-source EMS, (2) research EMS, and (3) commercial EMS (Table 5).

Modeling energy management systems involves considering their specific functionalities, integration capabilities, and potential applications in achieving energy sufficiency within the residential sector. The above table demonstrates the diverse range of EMS options available and the benefits they offer in terms of optimizing energy consumption, promoting energy efficiency, and fostering user engagement in energy conservation.

Table 4. Overview of HVAC System Models.

HVAC Categories	Description
Tankless Heating (gas boiler and electric resistance)	Computer simulation models for water heaters, including TANK [63], WATSIM [64], and HEATER [65]. However, these earlier models focus on tank temperature spatial distribution and are not well suited for modeling tankless instantaneous heaters. Other water heater models have been built using TRNSYS, as well as other similar general-purpose computer simulation tools [66].
Air Conditioning	Several libraries are available in TRNSYS, Modelica [67], MATLAB [68], or similar programs. The simulation models are different depending on their focus and degree of detail. For example, some models that are focused on the room climate do not model the devices but only consider a certain power for cooling. The combination of a detailed building model with detailed models of air conditioning devices is a promising strategy.
Ventilation	For ventilation systems, the methods can be separated depending on their detail. Simple ventilation models often only consider one zone (room) and calculate the ventilation depending on the air exchange rate, which can be defined by the user (as a constant or as a time series). Detailed multizone airflow models consist of nodes that are connected by flow elements. The nodes may represent room air volumes, the exterior environment, or connections in a duct system. Furthermore, they contain state variables, typically pressure, temperature, and concentrations (such as water vapor, CO_2, smoke, or pollen). The flow elements are airflow paths such as open doors and windows, construction cracks, staircases, elevator shafts, ducts, and fans. Multizone airflow models are typically used for time domain simulations of the convective energy and contaminant transport between the thermal zones of a building and to quantify stack effects in high-rise buildings. For thermal building simulations, closed door and user-estimated airflows are a poor representation of reality. Detailed multizone airflow models are, for example, available in TRNSYS [69] or in Modelica. Older well-known building models are CONTAM [70] and COMIS [71], which are both implemented in TRNSYS.

Table 4. *Cont.*

HVAC Categories	Description
MATLAB (models for general HVAC systems)	The MATLAB simulation environment Simscape [72] is widely used to build physical component models that are based on physical connections, which are directly integrated with block diagrams and other modeling paradigms. It allows for different model systems such as different HVAC devices to be assembled into a system. Simscape offers a variety of components that can be used to increase the simulation's quality and analysis possibilities. MATLAB comes with pre-defined blocks for simulating different HVAC devices. • Building Ventilation: This model for a ventilation circuit works by dividing the air volume inside a building into four distinct zones. Each of the different zones performs a different task. Between the zones, airflows and exchanges can be established. Each zone is described by a sub-system that represents the thermal resistance of the zone. These sub-systems consider the thermal masses of walls, roofs, as well as the convection and conduction. The ventilation system itself is represented by an internal air source and an external air source, both with limiters that can be applied. • Thermal Liquid Components: This library of HVAC devices contains models for actuators; pipes and fittings; pumps and motors; tanks and accumulators; utilities; and valves and orifices. Each of the components are described by sets of equations describing the behavior of each component. • Thermal Building Blocks: The modeling of components that represent the different thermal aspects of a building that need to be considered when simulating HVAC systems. Components include thermal mass, various heat transfer blocks, etc. • Heat Exchanger Solver [73]: For HVAC systems that contain heat exchangers, this modeling component provides a solver that is able to calculate the outlet temperatures of a heat exchanger using the Epsilon–NTU method. • Moist Air library: This library contains basic elements, such as reservoirs, chambers, and pneumatic-mechanical converters, as well as sensors and sources. • Thermosys Toolbox: This toolbox provides the possibility to make simulations of air-conditioning and refrigeration systems in Simulink or MATLAB. The toolbox is capable of performing both steady-state simulations and time-dependent simulations. The suite consists of a number of Simulink blocks that are appropriate for either independent use or integration into larger Simulink simulations. Each block has user-tunable parameters to allow for better simulations of practical systems. • The CARNOT Toolbox is a toolbox extension for Simulink. It is a tool for the calculation and simulation of the thermal components of HVAC systems with regard to conventional and regenerative elements. The CARNOT Toolbox is a library of typical components of these systems. It is organized in Blocksets like the Simulink Library itself. The handling of the blocks is the same as in Simulink.

Table 4. *Cont.*

<table>
<tr><th>HVAC Categories</th><th>Description</th></tr>
<tr><td>Modelica (models for general HVAC systems)</td><td>
Modelica is a simulation environment similar to MATLAB, which is composed of different libraries that represent the different parts of an HVAC system.
Modelica.Fluid.Examples.HeatingSystem [74]. This Modelica Library contains a simple exemplary heating system with a closed flow cycle. During the simulation, a valve is used to regulate the heating system as a means of simple control. This example underlies some assumptions and simplifications, such as a perfect isolation of the pipes and negligence of pressure losses between heater and pipes.
HVAC library [75]: This library allows for the development and optimization of large thermo-hydraulic HVAC systems. It provides the user with the possibilities of using components such as air ducts; adiabatic, steam humidifiers, and water extractors; borehole heat exchangers; absorption and vapor compression chillers; evaporative and dry cooling towers; boilers and combined heat and power systems; heat pumps; heat exchangers (liquid and air side), etc. The library can be used to simulate multiple different layouts of HVAC systems in different building settings.
Hydronics Library [76]: This contains all the components necessary for a detailed model of thermo-hydraulic systems, including heat exchangers for humid air and liquids. All components like pipes, bends, pumps, and valves can be insulated, non-insulated, or adiabatic. Joints, orifices, sudden expansions, contractions, and expansion vessels complete the range of model components.
TIL—Model library [77]: This contains many different components and models. It allows for the detailed analysis of individual components or to put together multiple components to form larger HVAC systems. The library can be used to simulate refrigeration cycles, including refrigeration mixtures, heat pump systems, systems with ejectors, hydraulic networks, etc. The library can be combined with the TILMedia Suite to allow for an efficient calculation of the thermophysical properties of liquids, gases, and real fluids, which contain a vapor liquid equilibrium and mixtures.
AixLib: AixLib [78] is an open-source model library for Modelica that allows for building performance simulations. It contains Modelica models for building envelope and HVAC equipment, such as boilers, radiators, heat pumps, and CHPs.
BuildSysPro [79]: This free and open-source Modelica library provides the possibility of simulating both the building envelopes and HVAC systems within a building. It can simulate air flows and also provides control algorithms for devices.
Buildings.Fluid.HeatPumps [80]: This library contains all elements needed to simulate heat pumps with a very high degree of technical detail. It provides models for different types of heat pumps.
Modelica.Electrical.Analog.Basic.HeatingResistor [81]: A model for an electrical resistor where the generated heat is dissipated to the environment via the connector heatPort, and where the resistance R is temperature-dependent.
Buildings.Fluid.Boilers—Modelica Library [82]: This package contains components models for boilers.
BuildSysPro.Systems.HVAC.Production.Boiler.Boiler [83]: This is a dynamic model of modulating condenser boilers. The gas consumption prediction model is estimated with a gray-box model. Electric consumption is determined according to the consumption of the various operation phases of the boiler (purging, pump, power on/off, standby, etc.). This model requires a limited amount of input data that is accessible from the normative tests.
Air conditioning library [84]: The Modelica Air Conditioning Library is used to design, analyze, and optimize automotive air conditioning systems during early design stages. It comes with both ready-to-use refrigeration cycle templates and a wide range of components to create non-standard configurations.
</td></tr>
<tr><td>TRNSYS Models (models for general HVAC systems)</td><td>TRNSYS is the abbreviation for the Transient System Simulation Tool, a very potent environment through which to simulate complex energy systems. The simulation tool contains multiple different libraries and tools that are used to simulate different HVAC components, as is shown in Appendix E.</td></tr>
</table>

Table 5. A brief overview of the different types of EMS.

OpenEMS (https://github.com/OpenEMS/openems) [85] (open-source code written mainly in Java and HTML)	Modular platform for energy management applications for monitoring, controlling, and integrating energy storage together with renewable energy sources, as well as complementary devices and services like electric vehicle charging stations, heat pumps, electrolysers, time-of-use electricity tariffs, etc. The code has three main parts/applications: OpenEMS Edge, which runs on site, communicates with devices and services, collects data, and executes control algorithms; OpenEMS UI is the real-time user interface for web browsers and smartphones; and OpenEMS Backend runs on a server, connects the decentralized Edge systems and provides aggregation, monitoring, and control via the Internet.
Openremote (https://github.com/openremote/openremote) [86] (open-source code written mainly in Java, TypeScript, and Groovy)	Very technical code that simplifies connecting networked assets to mobile and web applications, and it can be used as an energy management system. It can create a dynamic scheme of all available assets and their attributes in the Openremote manager. For example, for modeling an Internet-of-things system for a smart home or office, one would create building, apartment, room, and sensor assets on the domain. The rules execute actions when matching asset states or the sequences of events detected. Assets and devices are connected to the Openremote manager via Agents, which are the API (application programming interface) to 3rd-party device software, as well as service protocols. The OpenRemote FrontEnd simplifies the creation and deployment of user interfaces, such as home automation control panels and smart city monitoring dashboards.
Honda Home Energy Management System (https://www.hondasmarthome.com/tagged/hems) [87] (open-source software ready for installing)	Open-source EMS that works in dwellings that were built to be smart homes rather than those that function by adding gadgets to a conventional residence. It can monitor, control, and optimize the electricity consumption and generation of a house (batteries, EVs, lights, and HVAC systems). Its energy management tools are integrated with the smart grid to respond properly to DR.
PowerMatchSuite (https://github.com/flexiblepower) [88] (open-source code written in Java, JavaScript, HTML, Shell, and Python)	This suite comprises two disruptive open technologies: the PowerMatcher (a smart grid coordination mechanism), and the Energy Flexibility Platform and Interface (which is an operating system enabling appliances, as well as a smart grid and smart services to communicate with each other). PowerMatcher is a distributed energy system architecture and communication protocol. It facilitates the implementation of standardized, scalable smart grids. Through intelligent clustering, numerous small electricity producing or consuming devices operate as a single highly flexible generating unit, creating added value in power markets. PowerMatcher optimizes the potential for aggregated individual electricity producing and consuming devices to adjust their operation to increase the match between electricity production and consumption. The Energy Flexibility Platform and Interface (EF-Pi) is a runtime environment where smart grid applications can be deployed, and where appliances can be connected as a gateway operating system. The EF-Pi provides interfaces to interact with the environment, such as a user interface, and for connecting devices and smart grid apps. Part of the interface definitions are the control spaces and allocations. EF-Pi aims to create an interoperable platform that is able to connect to a variety of appliances and support a variety of DSM approaches.
openHAB (https://github.com/openhab) [89] (open-source code written in Java, Shell, HTML, and JavaScript)	openHAB communicates electronically with smart devices, performs user-defined actions, and provides web pages with user-defined information as well as user-defined tools to interact with all devices. To achieve this, openHAB segments and compartmentalizes certain functions and operations. Bindings provide an interface through which to interact with devices, i.e., representations of devices in the software, items that contain information about the devices, channels that connect things and items, as well as rules that perform automatic actions. Sitemap is the user interface that presents the information and allows for interaction.

Table 5. *Cont.*

Home Assistant (open-source EMS)	An open-source home automation with a strong focus on local controls and privacy. It can be run on a Raspberry Pi and provides the option for the observation, control, and automation of devices. Multiple different devices of different brands can be connected.
EnergySniffer [90] (research EMS)	EnergySniffer is a simple and flexible energy monitoring system utilizing smartphone sensors. It exploits sensors such as the magnetic sensors, light, microphones, cameras, and WiFi in smartphones to detect and monitor each operating machine in its vicinity. Energy Sniffer consists of two parts: • Energy Profile, which is a database containing machines with their corresponding energy consumption profiles and is maintained as a web service. • The multi sensing framework consists of offline learning (responsible for building fingerprint profiles for each machine) and online detection (which uses the fingerprint profiles to detect and monitor operating machines). In the online Detection and Monitoring Phase, a machine learning algorithm is used to detect and monitor running machines. Once the system detects a machine, it uses the Energy Profile database to track its energy consumption.
ALIS [91] (research EMS)	ALIS focuses on engaging the occupants involved in conservation efforts in daily activities by creating an awareness of resource use and by facilitating the efficient control of house systems. ALIS is an integrated in-home support system whose focus is set on the aware home with support for the smart occupant. ALIS is composed of three layers: house systems and resource infrastructure; software comprising a custom control system and web server; and user interfaces on several platforms (such as embedded touch panels, mobile and personal computers, and informative art). Users can enter custom energy optimizing nodes, like turning off most lights and lowering the thermostat in Sleep mode, or eliminating standby power draws in Away mode. Its goal is to make energy-saving behavior easy to enact. ALIS also provides a variety of feedback displays and analytical tools for historical, real-time, and predicted information on resource production and consumption.
Autonomous demand-side management [92] (research EMS)	The Autonomous and distributed demand-side EMS takes advantage of a two-way digital communication infrastructure. Game theory is used to formulate an energy consumption scheduling game, which is where the players are the users, and their strategies are the daily schedules of their household appliances and loads. The utility company can adopt adequate pricing tariffs that differentiate the energy usage in time and level. The proposed distributed demand-side management strategy requires each user to simply apply its best response strategy to the current total load and tariffs in the power distribution system. Simulation results confirm that the approach can reduce the peak-to-average ratio of demand, the total energy costs, as well as each user's individual daily electricity charges.
Intelligent Home Energy Management [93] (research EMS)	The intelligent EMS algorithm manages high power consumption household appliances with simulations for Demand Response (DR) analysis. The proposed algorithm manages household loads according to their preset priority and guarantees the total household power consumption to be below certain levels. Considered appliances include the following: space cooling units, water heaters, clothe dryers, and electric vehicles (EVs).
Energy Elephant [94] (makes better energy decisions) (commercial EMS)	This involves automated data insights, the importation of historical data, sensor data, a track of fuel usage, building performance comparisons, support for energy investment decisions, greenhouse gas tracking, a sustainability guide, energy price analysis, and cost reporting.

Table 5. *Cont.*

Energy Sparks (https://energyelephant.com/) [95] (commercial EMS)	Energy Sparks enables the user to perform energy analysis with a reporting application for electricity, solar generation, storage, gas, oil, and water. Available data acquisition connectors include the following: BACnet IP, Modbus TCP, Obix, Haystack, SNMP, Sedona, OPC UA, MQTT, SQL, CSV import (manual or batched), and REST API.
Home iOS (https://www.apple.com/de/ios/home/) [96] (commercial EMS)	This system allows for scheduling and control via app for functions such as air conditioning, air cleaning, bridges, cameras, bells, water, doors, ventilation, lights, locks, sockets, receivers, routers, security systems, speakers, sensors, switches, lawn sprinklers, TVs, windows, and thermostats. In addition, it can be used for notifications in case of certain events (children coming home, somebody is at the door, temperature decreases, etc.). This method focuses on control from everywhere, as well as comfortable and fancy installations.
Eagle 200—rainforest automation (https://www.rainforestautomation.com/rfa-z114-eagle-200-2/) [97] (commercial EMS)	Eagle 200 enables the user to monitor data from smart meters and connected devices. It facilitates a ZigBee connection for communication between the devices and central hub.
Opinum (https://www.opinum.com/) [98] (commercial EMS)	Opinum enhances, analyzes, centralizes, and visualizes energy-related data via a secured cloud-based platform. Devices are connected to the metadata from the cloud in order to improve event detection (Internet of things, etc.). Data processing is automated with algorithms (mainly machine learning), visualization, reports, and REST API connections.

2.6. Modeling Energy Storage

Energy storage provides energy systems with the necessary flexibility to mitigate the effects of an increasing amount of variable renewable energy. Effective energy storage models can help optimize energy usage, improve system resilience, and contribute to a more sustainable and efficient energy system design.

This study focuses on the mathematical representation of the storage system itself and the models describing its control strategy and interactions with other systems. The storage systems considered in this study are clustered according to the technology used. The relevant clusters are as follows:

- Electro-Chemical Storages
  - Classical Batteries
    - Li-Ion Technology
    -] Nickel Cadmium Technology
    - Nickel Metal Hydride Technology
    - Zinc–Air Technology
    - Sodium Sulfur Technology
    - Sodium Nickel Chloride Technology
    - Lead Acid Technology
  - Flow Batteries
    - Vanadium Redox Flow Technology
    - Hybrid Flow Technology
- Chemical Storages
  - Hydrogen
  - Synthetic natural gas
  - Biomethanation
- Mechanical
  - Flywheel
  - Pressure
- Electrical

- Supercapacitor
- Superconducting Magnetic

- Thermal
    - Sensible Heat
    - Latent Heat
    - Thermo-Chemical

With the above categorization in place, Table 6 sets the technical representation of the storage system. The models presented here show basic simulation approaches that are valid for different technologies.

Table 6. Technical representation of Energy Storage System Models.

Storage Type	Model	Description
Battery	Container Model [99]	Electrochemical processes within the battery are simplified to a container model. The container is filled and the battery is charged with a given charging efficiency. The container is then emptied and the battery is discharged with a given discharge efficiency. The size of the container and the capacity of the battery are limited. The model may also consider maximum and minimum charging and discharging powers, as well as aging effects of the battery. The model is perfectly suited for sketchy simulations and is cheap in terms of computation time.
	Open Circuit Model [100–102]	The battery is modeled as an equivalent circuit with various resistances and impedances connected in series. This model represents the electrochemical processes within the battery and yields a mathematical link between the state of charge, the current, and the voltage of the battery (which is given by differential equations). The model accuracy increases with the number of impedances included. Often, the choice of a first-order circuit, which contains one capacitor and one resistor, provides good results. The battery voltage depends on the state of charge of the battery, which is described by open-circuit voltage (OCV) lookup tables, or by empirical laws. An OCV lookup table contains characteristic values for the open-circuit battery voltage, which is dependent on the state of charge (SOC). Each battery type has a characteristic OCV lockup table that can be used as the model's input. Alternatively, empirical laws can help with approximating the correlation of the open-circuit voltage and the state of charge by simple fitting functions. The fitting parameters can be either defined from measured curves or estimated from known parameters. The temperature dependence of the state of charge and the age dependence of the capacity are given by empirical laws.
	Microscopic Models [103]	The electrochemical processes in batteries can be modeled as a diffusion process or a kinetic process. A diffusion process describes the evolution of the concentration of electroactive species in electrolytes to predict the state of charge under a given load. Diffusion processes in batteries are described by Fick's law (partial differential equations, which can be solved analytically). In the kinetic process, battery charge is distributed over two wells: the available charge well and the bound charge well. The available charge well supplies electrons directly to the load, whereas the bound charge well supplies electrons only to the available charge well. The rate at which charge flows between the wells depends on the height difference between the two wells and the conductance. Dualfoil is an open-source Fortran program, and it is widely used by researchers to validate other models due to its high accuracy.

Table 6. *Cont.*

Storage Type	Model	Description
Chemical Storage	Hydrogen Storage Model [104]	The compression for storing hydrogen is described by an isothermal process, where hydrogen is assumed to be an ideal gas. Either one compression or a multistage compressor (conducting more compressions in a row) are modeled. High-pressure hydrogen gas storages and metal hydride storages are included in the HYDROGEM library. It is compatible with TranSys and contains other hydrogen component models like advanced alkaline water electrolysis, proton exchange membrane fuel cells, alkaline fuel cells, compressors, and power conditioning equipment. In addition, hydrogen storage models can be implemented in the MATLAB/Simulink environment.
	Modeling Methanation [105]	The methanation process can be split into two parts: the mixing and preheating tank, and the process in the methanation reactor. CO_2-based methanation is modeled by assuming the chemical equilibrium and adiabatic conditions. The chemical reactions are described by four adiabatic reactors that are connected in series with intermediate gas cooling. The reactors can be simulated using the RGibbs operation block, where the chemical equilibrium of a given set of species is solved through the minimization of the Gibbs free energy. The model focuses on the description of chemical processes and the calculation of reaction rates.
Mechanical Storage	Flywheel Model [106]	An electric motor is used to drive a flywheel. Later, the rotating flywheel is used with the motor as a generator to produce electricity. A flywheel has three operational phases: the driving phase, where energy is put into the flywheel to accelerate it; the storing phase, where the flywheel is constantly rotating with small losses; and the producing phase, where electricity is generated, and the flywheel is slowed down. The mechanical relations are described by four coupled first-order differential equations or by two coupled second-order differential equations. The electromagnetic processes can be modeled with MATLAB/Simulink, where the flywheel is coupled with a built-in motor/generator. Alternatively, the system can be described analytically based on the linearization of the angular velocity. As the flywheel cannot be driven with the maximum frequency from the very beginning, an AC/AC converter is needed to gradually increase the rotational frequency and to generate electricity.
Electrical Storage	Supercapacitor—Open Circuit Model [107,108]	The model uses an equivalent circuit model. The capacitance of the capacitor is dependent on the applied voltage. This is accounted for by modeling the capacitor by two parallel capacitors. One with constant capacitance (C0), and one in which the capacitance varies linearly with the applied voltage (C). Series and parallel resistance are also used to simulate energy loss during charging and discharging. The order of the open circuit model can be increased to improve the accuracy of the description. Using fundamental physical laws, differential equations (which describe voltages and currents across the supercapacitor) are derived and solved.
	Superconducting Magnetic Energy Storage Models (SMES) [109]	A SMES is a direct current (DC) device that stores energy in the magnetic field. It consists of several subsystems: A large superconducting coil, which is used to store energy and is contained in a cryostat to keep temperature well below the critical temperature for the superconductor. An AC/DC power conversion or conditioning system (PCS), which is used to charge and discharge coil. A transformer, which provides the connection to the power system and reduces the operating voltage to acceptable levels for the power conditioning system. Additionally, a magnet protection system detects abnormal conditions that may cause a safety hazard to personnel or damage to the magnet. A detailed model of the SMES implies lumping each component. This results in complex circuit diagrams, which can be solved in, e.g., MATLAB/Simulink or PSCAD/EMTD [79].

Table 6. *Cont.*

Storage Type	Model	Description
	Superconducting Magnetic Energy Storage—simplified model [110]	A simplified model of the SMES disregards DC–AC converters and concentrates on the dynamic energy exchange between the magnet and the external power system. The electrical circuit model is translated into a mathematical model, which results in a set of differential equations that describe the dynamics of the system.
Thermal Storage	Sensible Thermal Storage—Container Model [111]	This model assumes a fully mixed tank with constant pressure and a constant volume. It describes a container full of energy, which is the analogous to a tank full of liquid with temperature that varies in time. The heat energy contained in the tank is defined by the storage volume, the actual average temperature of the liquid, and its heat capacity. Assuming a simplified process, heating the fluid in the storage is described by adding energy with a given efficiency. Supplying heat to external loads is described by subtracting energy with a given efficiency. General heat losses are calculated with an overall u-value. The model neglects thermal dynamics within the storage and is not very accurate. Its strength lies in its simplicity and small degree of computational effort.
	Sensible Thermal Storage—Variable Volume Model [112]	An alternative to the energy container model is the variable volume model, which considers a fully mixed tank with constant pressure and constant temperature. The tank is filled with a liquid of variable volume. The tank volume defines the storage capacity. In its simplest form, a single flow enters from a hot source and adds more volume to the tank. Another flow stream exits to a load and subtracts volume from the tank. Since the incoming and outgoing flows do not have to be equal, the level of fluid in the tank can vary. The model neglects thermal dynamics and is not very accurate. In addition, supply temperatures cannot vary within the model. The strength lies in the model's simplicity.
	Sensible Thermal Storage—Stratified Model [113]	This model describes the thermal dynamic behavior in a water tank. It accounts for temperature differences and the resulting heat transfer in the storage. The model is based on a computational fluid dynamics approach, wherein energy balance is formulated, which results in a partial differential equation. Due to its complexity, it is discretized via thermal stratification. The tank is horizontally split into levels, where each level is considered to be in equilibrium. Then, heat transfer occurs only between the different layers. The more layers that are chosen, the higher the accuracy of the model. The model of the storage is often combined with heat exchangers, which add energy to the lowest (coldest) temperature level and extract energy from the highest (hottest) temperature level. These processes are also described by heat transfer. Conventionally, the tank has a fixed volume. Thus, the same mass flow injected at the top of the tank leaves the tank at the bottom and vice versa. The model is commonly used in technical simulation environments like TranSys, Modelica, or MATLAB. It can be extended to models that treat storage media other than water (e.g., oil).
	Sensible Thermal Storage—3D model [114]	This model accounts for the thermal dynamic behavior within heat storage that are without discretization and simplifications. This model predicts 3D fluid motion in a thermally isolated cylindrical tank, as well as with temperature profile variation. The model is based on a computational fluid dynamics (CFDs) approach. In this model, energy balance and mass balance are formulated, and the partial differential equations are solved without discretization. This is performed so that temperature and pressure, as well as their gradients, are described by continuous field variables. The 3D-CFD model is accurate; however, it has the drawback of requiring large computational resources and computing times.

Table 6. *Cont.*

Storage Type	Model	Description
	Latent Thermal Energy Storage Model (LTES) [115]	LTES uses the phase transitions of PCM (phase change materials). When heating up a solid material, at the melting point, non-linear behavior is observed. Furthermore, latent heat is consumed to enable the phase transition. The absorption of latent heat leads to extremely high energy densities when PCMs are used as heat storages. The challenge in modeling LTES is that, during a phase change, both phases (solid and liquid) mostly exist at the same time, and the temperature is not exactly the same everywhere in the storage. This situation can be mathematically described by a boundary value problem for a partial differential equation, which aims to describe the temperature distribution in a homogenous medium undergoing a phase change. The mathematical problem can be solved via a discretization in time and space, which allows for the application of a finite element method to maintain a solution.

2.7. Modeling Generation Technologies

The increasing prominence of decentralized generation capacities has elevated the significance of accurately simulating these technologies in the household sector. Our study focuses on modeling approaches tailored to generation technologies that are relevant to residential settings, including PV generation (rooftop PV, facade PV, and bifacial PV), small-scale wind turbines, CHP technologies (gas-powered CHP, hydrogen-powered, and CHP fuel cells), and combustion engines. Each technology exhibits distinct characteristics that require unique modeling techniques to ensure accurate representation and performance simulation. To provide a comprehensive overview, as was summarized in Table 7, the different modeling approaches specific for generation technologies were considered.

Table 7. Different Modeling approaches for specific generation technologies.

Five-parameter model [116] (photovoltaic)	The photovoltaic array model is based on an equivalent circuit of a one diode model. It is described by five formulas for the photocurrent I_L, the saturation current I_D, the reverse saturation current I_S, the current through the shunt resistor I_{sh}, and the output current I (the five-parameter model). The photo current, the saturation current, and the reverse saturation current depend on cell temperature and irradiance through empirical laws. Some models assume that the cell temperature is equal to the ambient temperature, others use additional empirical laws to deduce the cell temperature from the ambient temperature, incident radiation, wind velocity, and the array type (which can be either monocrystalline, polycrystalline, or based on thin film technology). In addition to the PV model, calculations of the solar position are necessary to project the global radiation on a horizontal plane to the yield on a PV array with a given tilt and given orientation. Various methods exist to separate direct radiation from diffuse radiation and reflection. The five-parameter model is commonly used by standard simulation environments such as MATLAB, openModelica, or HYDROGEM, and it can be easily coupled to power converters, control algorithms, or larger integrated systems [117].
View Factor Model [118] (bifacial photovoltaic)	Bifacial photovoltaic systems are treated differently than regular PV systems as solar yield can occur from both sides of the PV panel. To apprehend the full backside irradiance of the PV, the view factors (i.e., the fraction of the radiation from the front side surface that hits the backside surface) are calculated. The view factor can be determined by assuming that irradiance was scattered isotropically. Alternatively, a ray tracing tool called Radiance can be used to simulate forward and backward ray tracing, as well as calculate the view factors. Modeling bifacial photovoltaic arrays additionally calls for an irradiance model, which calculates the solar position, projects the global radiation from the horizontal plane to the given orientation and tilt of the PV system, and separates the global radiation into direct, diffusive, and reflective proportions.

Table 7. *Cont.*

Quadratic Efficiency Model [119] (solar collector)	This model is identified by an empirical, quadratic, efficiency law, which originates from the theoretical equations developed by Duffie and Beckman (2013). The law accounts for the heat losses due to reflection, absorption, heat transfer, and convection. The empirical law contains three parameters. The heat losses are related to the square of the temperature difference of the collector and the ambient temperature, the linear difference, and the global radiation. For the determination of the power of the system, calculations of the solar position are necessary to project the global radiation on a horizontal plane to the yield on the collector with a given tilt and given orientation. Various methods exist to separate direct radiation from diffuse radiation and reflection. The model does not account for dynamic and microscopic effects in the solar collector. Still, it represents the behavior in the solar collector sufficiently well and has a good computational performance. Implementations of the solar collectors in libraries from TranSys, Modelica, or Soltermica are commonly based on the description above.
Hybrid Models—TranSys [120] (photovoltaic)	Hybrid models have the dual purpose of creating power from embedded photovoltaic (PV) cells and providing heat. One hybrid form consists in heating and in the air stream passing beneath the absorbing PV surface. The model then needs to operate with simple building models that can provide the temperature of the zone air on the back side of the collector, as well as provide an estimate of the radiant temperature for back-side radiation calculations. Another known hybrid form is the so-called PVT (photovoltaic thermal) method, which couples a photovoltaic array with a solar collector. For the thermal performance model, a two-node model is applied. It adds a functionality of electrical performance to the thermal model of a solar collector. A combined identification of thermal and electrical model parameters is the most suitable approach regarding accuracy and processing effort.
Models for Combustion Engines [121] (combined heat and power)	A combined heat and power unit consists of an internal combustion engine (ICE), and two heat exchangers: one picks up the heat flow from the refrigerant and the other one from the flow of exhaust gases (which have very high temperatures). The behavior of the ICE can be described via a characteristic curve that is based on the percentage load. The performance curve of the ICE describes the value of the heat flow and electric power generated for each load value of the machine. A detailed formulation for the ICE, which involves the analysis of the real thermodynamic cycle and requires the modeling of the engine and the real combustion process, can be undertaken. For example, Simulink/MATLAB provides the necessary components for such a detailed analysis. The resulting model is accurate but slow in computation.
Detailed Model for Fuel Cells [122] (combined heat and power)	A fuel cell is a combined heat and power unit, which converts hydrogen to electrical energy through the production of excess heat. The processes within a fuel cell are well described by CFD. In detail, the continuity equation; the Navier–Stokes equation; the Maxwell–Stefan equation; conservation of mass; charge and energy; and the Butler–Volmer equation form a closed set of coupled partial differential equations that mathematically express the dynamics within a fuel cell. All compounds are assumed to obey the ideal gas equation and to be in the gaseous phase. The system can be discretized and solved by a finite element method.
Generic Model for Fuel Cells [123] (combined heat and power)	This model represents a simple and efficient method through which to characterize and predict the behaviors of fuel cell modules. The state of the system is defined by the temperature of the stack, the load current, and the output voltage, (which is related to the load current by an empirical law). Those potentials are defined by other empirical laws, which need the stack temperature and the partial pressure of the hydrogen and oxygen as the input. The stack temperature is approximated by another empirical law, which relates it with time. Obviously, the generic model is computationally less intensive. The difficulty in its application is the definition of all necessary parameters from the manufacturer's datasheet or by the measured data.
Turbine with fixed rotational speed [124] (wind power)	This model assumes that the wind turbine rotates with a constant angular velocity. Then, the efficiency curve of the turbine is expressed as a function of the wind velocity. Under normal conditions, wind speed data are spikey. Therefore, the estimations of the energy produced by a wind turbine improve when using the distributions of wind velocities instead of average wind speed data. Wind speed distributions show Weibull characteristics. The power of the wind turbine can be calculated by the integral of the product of the efficiency curve and via the wind distribution over the wind speed range.

Table 7. *Cont.*

Turbine with variable rotational speed [125] (wind power)	This model studies the dynamic behavior of wind turbines with variable wind speed. The formula for the kinetic energy of wind in combination with an empirical formula for the wind turbine function is based on six specific turbine factors, the internal wind tip ratio, and the pitch angle (which all describe the mechanical behavior of the wind turbine). The turbine coefficients reflect the actual geometry of the wind blades. In addition, the mechanical model is coupled to a generator and to the grid components to accurately model the electricity production. A detailed model that considers almost every element of the wind turbine (wind source, turbine, pitch- and torque control, inverters, etc.) can be seen in Figure 1. As the model is quite detailed, the time resolution is lower. For that reason, the model works with both average data or with the distributions of the wind speed.

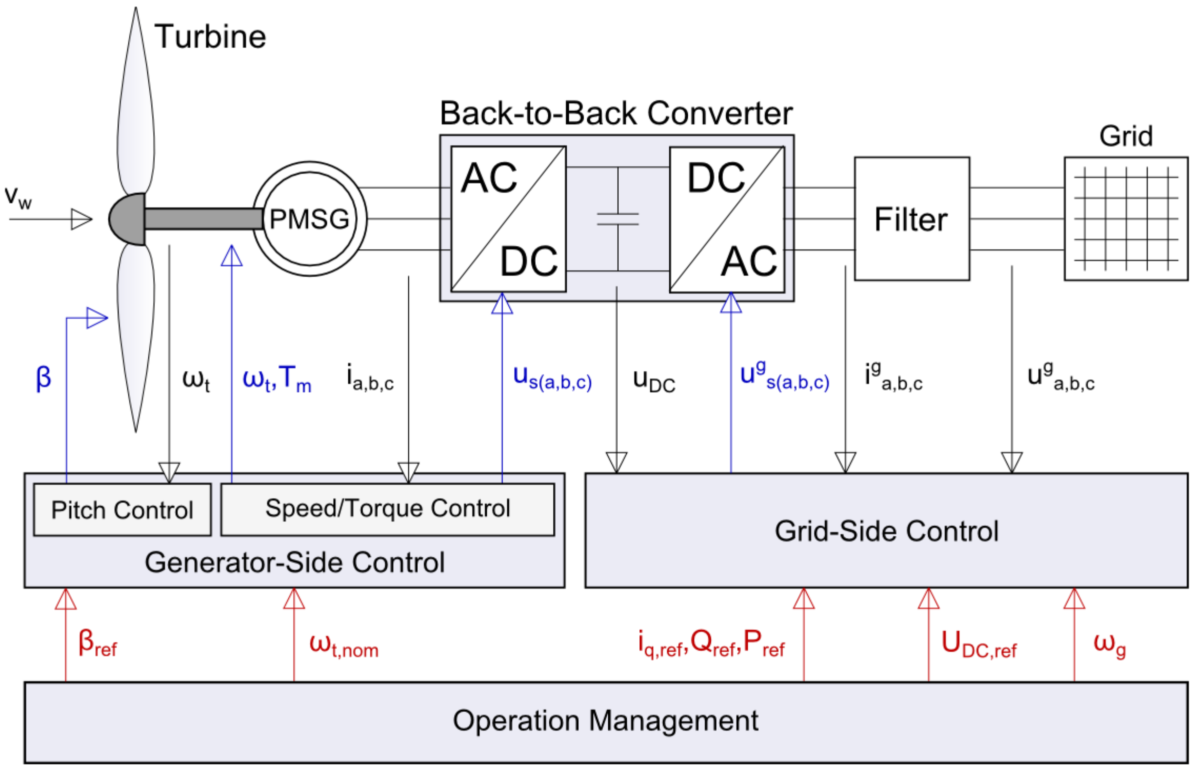

Figure 1. Detailed Model of a wind turbine [126].

2.8. Modeling Business Models in the Field of Electrical Consumption on a Household Level

The European Union's energy landscape is experiencing a transformative shift with energy consumers playing a more active role in the energy system. Decentralized generation capacities and controllable flexible loads have unlocked opportunities for consumers to interact with the energy market in innovative ways, triggering the emergence of new business models. Table 8 introduces the concept of business models in the household sector, setting the stage for the exploration of various models that offer consumers greater control over their energy consumption and costs.

2.9. Urban Energy Modeling and Microclimates

To achieve sustainability in a greater scale however, urban energy modeling techniques are being employed that consider the residential sector a pivotal factor in contributing to the urban energy canvas. The energy requirements of residential buildings such as heating, cooling, lighting, and everyday appliances reflect the city's energy footprint. Conversely, the density, the infrastructure, and the design of the urban environment exert a tangible influence on residential energy use.

Table 8. Overview of business models available to household energy consumers.

Energy as a Service (EaaS) [127]	EaaS is an innovative business model that extends beyond the traditional supply of electricity. Energy service providers (ESPs) offer various energy-related services to consumers, enabling them to optimize their energy consumption and reduce costs. These services include energy consulting, finance schemes for assets, energy management technologies, and assistance with tariff changes. By leveraging EaaS, consumers can actively participate in optimizing their energy consumption and accessing tailored services from ESPs.
Peer-to-Peer Electricity Trading (P2P) [128]	Peer-to-peer electricity trading allows consumers to directly exchange electricity surplus with each other, bypassing traditional energy suppliers. Different approaches, such as direct power purchase agreements or interconnected web-based platforms, facilitate P2P trading. Consumers become members of the platform, either through a subscription fee or other mechanisms, and engage in direct electricity trading. Although P2P trading is not yet implemented in all EU countries, recent directives have mandated the introduction of P2P and direct electricity selling, paving the way for its future adoption.
Aggregators [129]	Aggregators are service providers that represent a group of agents, such as consumers, producers, and prosumers, as a single entity in the system. Aggregators enable their agents to participate in specific market segments by reaching the required thresholds. These market segments include wholesale electricity markets and various power control mechanisms. Aggregators work in conjunction with virtual power plants (VPPs), which aggregate dispersed energy sources and flexibilities. Through information technology, VPPs optimize the use of assets based on real-time data, market conditions, and consumption trends, thus allowing aggregators to share in their agents' profits.
Community-Ownership Models [130]	Community-ownership models aim to facilitate the collective ownership, management, and utilization of generation capacities and energy-related assets. These models address barriers to individual investments in renewable energy technologies by allowing individuals to own shares in community-owned assets. There are different types of community-ownership models, including economic benefit sharing models, collective self-consumption schemes, and energy communities. These models provide financial and environmental benefits to participants and can be organized in various ways, such as cooperatives, partnerships, non-profit organizations, or community trusts.
Pay-as-You-Go Model [131]	The pay-as-you-go (PAYG) model offers a new approach through which to address energy poverty and provide access to electricity in both well-connected regions and remote areas with limited or no grid access. PAYG requires customers to pay upfront, giving them greater control over their electricity bills and consumption. This model combines decentralized and isolated energy generation from renewable sources with upfront payments, allowing users to gradually obtain ownership of devices through micro payments. PAYG models can be implemented at the household level, in a broader community, or on a neighborhood scale.
Conventional Energy Supply Models [132]	Conventional energy supply models vary across countries and energy suppliers. These models typically involve periodically measured consumption values, including energy consumption-related values, power-related values, and fixed costs. Energy bills often comprise energy tariffs, grid tariffs, taxes, and fees, with some components being unaffected by energy consumption or power usage.

Currently, urban energy modeling is progressing with improved data availability and more sophisticated simulation techniques that encompass diverse factors such as transportation, infrastructure, and land use. Recent research in urban modeling spheres underscores the significance of data acquisition techniques in refining urban building energy models. The study of [133] aggregated and analyzed data from diverse sources to gain models with the appropriate granularity in order to capture the nuances of energy consumption in different urban zones. Upon this, another study [134] explored the pertinent questions that drive the evolution of urban energy modeling. Their inquiries ranged from the impact of urban form in energy demand to the integration of renewable energy sources within urban contexts.

Urban microclimates indeed correlate with both urban and residential modeling. Microclimates are influenced by factors such as building density, vegetation, and surface materials. It impacts energy demand, heat distribution, and cooling strategies in both contexts. The integration of microclimate data enhances the accuracy of energy models for both areas. The study of [135] investigated the relevant techniques in urban thermal and wind environments, concluding that current techniques cannot pave the way for accurate strategies; furthermore, it suggested that future modeling assessments should include urban typologies and data-driven approaches for more accurate decisions. Another study [136] focused on the recent advancements of urban microclimates on urban wind and thermal environments that were found (although field measurements were the most necessary for this type of assessment, the techniques used to achieve the desired accuracy in results were missing).

3. Summary

The modeling of residential energy consumption has gathered significant attention from researchers, policymakers, and other stakeholders due to its potential to inform sustainable energy practices and policies. In this study, we examined various modeling approaches and techniques including simulation-based approaches, modeling, statistical methods, machine learning algorithms, and optimization models.

To better structure and classify the different approaches for causal models, a taxonomy of the tasks that causal models carry out is presented (Appendix A), as well as the different libraries (Appendix B) that were used to implement the causal models on these aspects. Following the classification and research conducted for causal models, we continued our research by analyzing and classifying the possibilities to address the energy-related aspects of residential buildings. The different aspects considered were very heterogeneous; thus, no common approach could be identified in how to address them.

The analysis of models for different scales of energy systems provided a deeper understanding of energy consumption (thermal or electric) in different settings. They often work as a framework where multiple different, more or less detailed models are included and soft-linked. A total of 10 different existing models were analyzed and discussed. The large-scale energy system models were neglected as the focus of this paper are residential buildings rather than entire countries (as the case in large-scale energy system models).

The option of shifting loads or using certain loads at certain times is a potential option for residential consumers. But there are certain loads (appliances) that are not available for load shifting due to technical, user behavioral or comfort restrictions. Modeling these loads generally comes down to considering pre-defined load profiles, which are applied once the device is activated. Another important option that affects the energy consumption of residential users are energy efficiency approaches, which include the following: (i) renovation measures of the building envelope, including the replacement or upgrade of windows and wall/roof thermal insulation, and (ii) purchasing and using more energy-efficient appliances with better energy labels (Appendix C).

The latter can be represented in models by using new load profiles for non-flexible appliances or improved parameters in technical models of appliances that can be used flexibly. Simulating renovation measures comes down to changing the technical parameters of buildings (e.g., the u-values of building shells). For this purpose, substantial research of different parameters has been conducted. Different technical parameters for types of insulation, wall material, window types, etc., have been identified and described in detail in this study (Appendix D).

In order to obtain more control over energy consumption and the behavior of devices, residential consumers can make use of energy management systems (EMSs). There are a multitude of different options of EMSs available on the market that differ in their price, applicability, and management options that are provided to the user. This study provides examples of EMSs for three different categories: (1) open-source, (2) research, and (3) commercial. The purpose of this research was to create an understanding of the options these EMSs provide.

Energy storage models are one of the key options to make residential consumption more flexible. In this direction, we identified a wide variety of technologies, from battery storage systems (and subtypes) over thermal storages to mechanical storages. Storage systems are modeled using mathematical equations, but there are many different approaches for the different technologies available; their differentiation is based on the degree of detail and time required to solve the underlying equations. We presented a total of 14 different approaches for 5 different storage types.

Apart from storage systems, there are certain types of devices that can be controlled by EMSs to change their operational behavior in order to meet certain goals. Amongst those, the heating ventilation air conditioning systems (HVAC systems) and electric vehicles (EV) are the most relevant for the residential sector, and these were analyzed extensively. On the one hand, for the HVAC systems, different technologies are relevant, for which a multitude of different modeling approaches exist. This study provides a summary of general approaches for these technologies, followed by a set of libraries with commonly used models for them. On the other hand, for the EVs, a review of different approaches for modeling the mobility needs are also presented and discussed.

One of the key changes to the energy system of past years was the technological advancements in the decentralized generation technologies. They provide residential consumers with the means to generate their own energy for self-consumption or other purposes. The following technologies were deemed relevant for the residential sector and are presented in this paper: (1) PV/solar generation, (2) micro-wind generation, and (3) combined heat and power generation (CHP). For the latter, the two different control strategies (electricity-led or heat-led) and the different fuels (gas-powered, biomass, or hydrogen) were considered. A total of nine different approaches used to model these three types of generation technologies were identified during the research.

The last relevant aspect considered during this research was the business models related to energy use in the residential sector. Formerly passive consumers (especially residential consumers) are slowly transitioning to becoming more active participants in the energy system, as suggested by the EU Climate Policy Package. As such, new businesses are emerging that aim at providing new services to residential consumers to generate profits for the businesses and benefits of residential consumers. The most relevant business models to be considered in this study were as follows: energy as a service, peer-to-peer electricity trading, aggregators, community ownership models, and pay-as-you-go models.

Overall, this study provides an overview of the different aspects to be considered in the modeling of residential energy consumption, as well as provides the reader with a general knowledge on different methodologies and approaches when trying to create a holistic representation of household energy consumption and the underlying decision processes.

4. Discussion

In conclusion, the research presented in this study shows a wealth of modeling approaches and techniques that are able to predict and simulate the energy consumption of the residential sector. Although the presented techniques offer valuable insights in understanding the complexities of energy usage, one question arises regarding the sufficiency of current techniques: are current techniques able to fully evaluate the residential sector's energy consumption?

The answer to this question has various aspects regarding future development. Energy efficiency is very clearly one of the most important aspects in reducing energy consumption, but the literature shows that renovation measures are often overlooked. Modeling techniques should encompass all aspects of energy efficiency to deliver a holistic understanding regarding the energy savings of residential buildings. During this research, we identified the significant role of energy sufficiency, which has limited references. Behavioral and lifestyle changes have a vital role in achieving sustainability, and modeling efforts should aim to integrate these into the current models that measure energy sufficiency.

Although the existing models address the aspects of mobility and electric appliances, current research suggests that its scope should be broadened to capture more diverse trends and other evolving elements that can accurately represent the impact of EVs and advanced appliances.

This extensive literature review revealed that the existing models are not sufficient on their own. Furthermore, to achieve a sustainable residential energy future, the integration of all approaches should be considered. This means that there is a need to develop an interconnected modeling framework so effective strategies can be developed.

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Appendix A. Seven Essential Tasks That Causal Models Need to Fulfill [16] to Be Valuable Tools for Causal Inference

I. Encoding Causal Assumptions—Transparency and Testability: Transparency enables analysts to discern whether the assumptions encoded are plausible or whether additional assumptions are warranted. Testability permits one to determine whether the assumptions encoded are compatible with the available data and, if not, identify those that need repair. Testability is facilitated through a graphical criterion, which provides the fundamental connection between causes and probabilities [16].

II. Do-calculus and the control of confounding: For models where the "back-door" (the graphical criterion through which to manage confounding) criterion does not hold, a symbolic engine is available called do-calculus, which predicts the effect of policy interventions whenever feasible [137].

III. The Algorithmization of Counterfactuals: This task formalizes counterfactual reasoning within graphical representations. Every structural equation model determines the truth value of every counterfactual sentence.

IV. Mediation Analysis and the Assessment of Direct and Indirect Effects: This task concerns the mechanisms that transmit changes from a cause to its effects, which is essential for generating explanations. Counterfactual analysis must be invoked to facilitate this identification.

V. Adaptability, External Validity, and Sample Selection Bias: Robustness is recognized by AI researchers as a lack of adaptability that comes out when environmental conditions change. The do-calculus offers a complete methodology for overcoming bias due to environmental changes. It can be used both for readjusting learned policies to circumvent environmental changes, and for controlling disparities between non-representative samples and a target population [138].

VI. Recovering from Missing Data: Using causal models of the missingness process can formalize the conditions under which causal and probabilistic relationships can be recovered from in-complete data and, whenever the conditions are satisfied, produce a consistent estimate of the desired relationship.

VII. Causal Discovery: The d-separation criterion detects and enumerates the testable implications of a given causal model. This opens the possibility of inferring, with mild assumptions, the set of models that are compatible with the data, and to represent this set compactly; in certain circumstances, the set of compatible models can be pruned significantly to the point where causal queries can be estimated directly from that set [139].

Appendix B.

Table A1. Main characteristics of the different libraries that are used to build causal models.

Aspects	DAGitty	DoWhy	Packages Causal Graphical Models	Causality	Causal Inference
Encoding Causal Assumptions—Transparency and Testability	X	X	X	X	X
Do-calculus and the control of confounding	X	X	X	X	X
The Algorithmization of Counterfactuals	X	X		X	X
Mediation Analysis and the Assessment of Direct and Indirect Effects	X	X	X	X	X
Adaptability, External Validity, and Sample Selection Bias	X	X			
Recovering from Missing Data		X			
Causal Discovery	X	X	X	X	
Support tools to write Causal Diagrams	X	X	X	X	X
License	GNU	MIT	MIT	Open	BSD
Programming Language	R	R/Python	Python	Python	Python
Documentation and support channels	X	X	X		X

Appendix C.

Table A2. Energy labels and Certificates.

LEED (USA)	LEED (Leadership in Energy and Environmental Design) is a widely recognized green building rating system that provides a framework for highly efficient and sustainable buildings. Available for virtually all building types, it provides a framework for healthy, highly efficient, and cost-saving green buildings. LEED certification is a globally recognized symbol of sustainability achievement and leadership.
BREEAM (UK)	BREEAM is an internationally recognized sustainability assessment method that certifies the sustainability performance of buildings, communities, and infrastructure projects. It recognizes and reflects the value in higher performing assets across the built environment lifecycle, from new construction, to currently used, to refurbishment.
Energy Star (US)	Energy Star promotes energy efficiency and provides information on energy consumption for various products and devices. The program provides information on the energy consumption of products and devices via different standardized methods. The Energy Star label is found on more than 75 different certified product categories, homes, commercial buildings, and industrial plants.

Table A2. *Cont.*

Rescaled EU Labels (EU)	The rescaling of EU energy labels (A–G scales) addresses the appearance of higher energy-efficient products. Class A is initially empty to leave room for technological developments in the future. Every appliance that requires an energy label needs to be registered in EPREL (European Product Registry for Energy Labeling) before being placed on the European market. A QR code is placed on the label for the client to have access to this public information. An important change in the new eco-design rules is the inclusion of elements to further enhance the reparability and recyclability of appliances, e.g., ensuring the availability of spare parts, access to repair, and the maintenance information for professional repairers.
Energy Performance Certificates (EU)	Energy performance certificates (EPCs) assess the energy performance of buildings and provide recommendations for energy efficiency improvements. Following the Energy Performance of Buildings Directive (EPBD), an EPC shall include the energy performance of a building and its reference values, as well as the recommendations for the cost-optimal or cost-effective improvements of the energy performance of a building or building unit. Within the national context, it is up to the Member States to decide on the performance rating of the representation (i.e., energy level vs. continuous scale), as well as the type of recommendations (i.e., standardized vs. tailor-made).

Appendix D.

Table A3. Energy Efficiency Approaches in Buildings (renovation measures).

Windows	Installation of Low-Emissivity Glass	Low-e storm windows with multilayer nanoscale coatings are utilized to reduce radiative heat loss and solar heat gain [101]. The primary purpose of a low-e storm window is to reduce the u-values of buildings. These low-e coatings are called solar selective or solar control low-e coatings.
	Installing Window Shading	Window shades regulate lighting and reduce solar gains, thus contributing to energy efficiency.
	Replacement with Multi-Glazed Windows	Upgrading to multiple glazes with insulation gases and efficient framing materials improves energy efficiency.
Insulation	External Thermal Insulation	Adding insulation to the exterior walls of a building with various techniques and materials enhances energy efficiency. A better insulation can be reached through multiple different approaches; for instance, by installing thermal insulation compound systems (a combination of different thermal insulation types), installing a curtain wall (often a wooden wall in front to the core wall of the building with insulation in between), or through implementing a core insulation (insulation is directly injected into the wall of a building).
	Internal Thermal Insulation	Achieved by applying insulation to the interior walls, floors, or roof of a building to reduce heat transfer. Depending on the area to which the insulation is applied, different methods and materials can be used. Regarding attics, for instance, it makes a difference whether or not it should be accessible, in which case insulation panels (on which you can walk), the installation of a raised floor, or using pour-in insulation is an option. It is important to differentiate between cavity walls, where pour-in insulation or insulation mats can be used, or—if there are solid walls—where insulation panels or insulation mats need to be used.
	Floor Insulation	This method involves insulating floors above cellars or on the ground floor, particularly when floor heating is present. The type of insulation and insulation material strongly depends on the specifics of the building and the floor, as well as whether there is floor heating installed or not. Regardless of these specifics, the insulation material must be durable due to the constant strain it has to endure.

Table A3. *Cont.*

	Roof Sealing	Thermal losses and gains of the roof area represent a very large proportion of the total losses. As such the thermal insulation of the roof plays an important role when trying to improve the efficiency of a building. Insulation options are below rafters, in between rafters, on rafters, insulation for pitched roofs, as well as internal or external insulation for flat roofs. Currently, there are multiple different materials with different properties available.
	Roof Sarking	Roof sarking is the process of installing a thin insulating membrane directly underneath the roof. It works as a sort of "reflective" insulation with the purpose of reflecting radiant heat and thus preventing it from entering the building from outside (summertime) or leaving the building from the inside (wintertime).
	Air–sealing	Sealing houses against air leakage is one of the simplest upgrades to increase comfort in a house. Air leakage accounts for 15–25% of winter heat loss in buildings, and it can contribute to a significant loss of coolness in climates where air conditioners are used. The first step is to detect leaks by inspecting the doors, windows, edges, and spots where different materials meet each other, as well as checking vents, skylights, and exhaust fans. A more professional approach is to use a blower door, which reduces the pressure in the house. In this, air from outside will enter the house because of the pressure difference. The air leakage rate can be measured this way and, through using smoke, the actual leaks can be detected.
	Insulation of Pipes	Heat losses in the pipes of the heating system account for a large (up to 50% [140,141]) of the total heat losses in central European buildings. This is due to the fact that the pipes have to be kept at operating temperature and are constantly losing thermal energy. Insulation of pipes consists of installing shells or ducts made from a thermal insulator such as glass or rock wool (from basalt) in the pipes. In addition to mineral wool, other materials such as plastic foam or vapor barrier coatings can also be used.

Appendix E.

Table A4. TRNSYS libraries and tools to simulate different HVAC components.

Libraries	Description
TYPE 753	Type 753 models involve a heating coil that is used in one of three control modes. The heating coil is modeled using a bypass approach in which the user specifies a fraction of the air stream that bypasses the coil. The remainder of the air stream is assumed to exit the coil at the average temperature of the fluid in the coil. The air stream passing through the coil is then remixed with the air stream that bypassed the coil. In its unrestrained (uncontrolled) mode of operation, the coil heats the air stream as much as possible given the inlet conditions of both the air and the fluid streams.
TYPE 917	Air-to-water heat pump—This component models a single-stage air source heat pump.
TYPE 919	Normalized water source heat pump—This component models a single-stage liquid source heat pump with an optional desuperheater for hot water heating.
TYPE 922	Two-speed air-source heat pump (normalized)—Type 922 models use a manufacturer's catalog data approach to model an air-source heat pump (air flows on both the condenser and evaporator sides of the device).
TYPE 927	Normalized water-to-water heat pump—This component models a single-stage water-to-water heat pump.
TYPE 941	Air-to-water heat pump—This component models a single-stage air-to-water heat pump.
TYPE 954	Air-source heat pump/split system heat pump—Type 954 models use a manufacturer's catalog data approach to model an air-source heat pump (air flows on both the condenser and evaporator sides of the device).
TYPE 966	Air-source heat pump—DOE-2 approach —Uses the approach popularized by the DOE-2 simulation program in which the performance of an electric air-source heat pump can be characterized by bi-quadratic curve fits.
TYPE 1221	Normalized two-stage water-to-water heat pump—This component models a two-stage water-to-water heat pump.

Table A4. *Cont.*

Libraries	Description
TYPE 1247	Water-to-air heat pump section for an air handler—This component models a single-stage liquid-source heat pump.
TYPE 1248	Air-to-air heat pump section for an air handler—Type 1248 models use a manufacturer's catalog data approach to model an air-source heat pump (air flows on both the condenser and evaporator sides of the device).
TYPE 930	Electric heating coil.
TYPE 664	Electric unit heater with variable speed fan, proportional control, and damper control—Type 664 models involve an electric unit heater whose fan speed, heating power, and fraction of outdoor air are proportionally and externally controlled.
TYPE 929	Gas heating coil—Type 929 models represent an air heating device that can be controlled either externally or set to automatically try and attain a set point temperature, much like the Type 6 models do for fluids.
TYPE 967	Gas-fired furnace—DOE-2 approach—In this model, the performance of a forced-air furnace is characterized by a constant heat input ratio.
TYPE 651	Residential cooling coil (air conditioner)—Type 651 models involve a residential cooling coil, which is more commonly known as a residential air conditioner.
TYPE 508	Cooling coil with various control modes—Type 508 models involve a cooling coil that uses one of four control modes.
TYPE 752	Simple cooling coil—Type 752 models include a cooling coil that use a bypass fraction approach.
TYPE 921	Air conditioner (normalized)—The component models of this type use an air conditioner for residential or commercial applications.
TYPE 923	Two-speed air conditioner (normalized)—The component models of this variety involve a two-speed air conditioner for residential or commercial applications.

Appendix F.

Table A5. Energy efficiency Impact of Window and Insulation Measures.

	Rough Estimation	Exact Calculation
Replacing Windows	The effect of replacing windows strongly depends on the starting position. If windows have high u-values, it is highly efficient to change them. The effect depends on the climate and weather conditions. To estimate the effects of changing windows the following rough calculation is quite useful: $J_{loss} = u \cdot A \cdot \Delta T \cdot t$ where J_{loss} is the heat loss of the building in kWh, u is the u-value in $W/(m^2\ K)$, A is the total area of the windows in m^2, ΔT is the temperature difference between inside and outside in K, and t is the considered time in hours. Taking this formula, the heat losses and heat gains can be roughly estimated before and after the window change.	In addition to the u-value, many other parameters affect the heat loss and gain through windows. For example, the alignment of the windows and their relative position to the sun, the amount of radiation penetrating through the windows, or the air leakage. Using real climate data (temperature and solar radiation) will improve the estimation accuracy. Detailed, dynamic simulations are supported by building simulation software like TranSys, EnergyPlus, or IdaICE. Simulations with the old windows should be implemented with new ones.
Storm Windows	Storm windows are the most effective when they are attached to older, inefficient, single-pane primary windows that are still in decent, operable condition. Adding an interior storm window to a new, dual-pane primary window will not improve performance much, and adding one to a decaying, old primary window will not extend the primary window's lifespan even though it will give the efficiency rating a boost. As an example, the change in the parameters due to the addition of different types of storm windows to a wood double-hung, single-glazed window is shown below. The study of [142] provided the values shown in Table A6 for the different types of windows and frames.	

Table A5. *Cont.*

	Rough Estimation	Exact Calculation
Improving Insulation	Similar to the effects of changing windows, the effect of adding insulation to a house strongly depends on the starting situation. Adding insulation to a house with old solid bricks in a cold climate will affect the energy efficiency enormously. Insulation protects from heat losses on cold days and from heat gains on hot days. In order to estimate the effects of insulation, the following formula is used: $R_{insulated} = \frac{1}{u_{insulated}} = 1/u_{not\ insulated} + th/\lambda$ The u-value is the parameter accounting for the heat loss of a building in W/(m^2 K). λ describes the thermal conductivity of the insulation in W/(m·K), and th stands for the thickness of the insulation in m. The u-value can then be used to make an estimation of the heat loss through the walls, the roof, and the floor via the formula given for J_{loss}.	In addition to the u-value, other parameters affect the heat loss and gain through walls/roof and floors. For example, the air leakage and the heat transfer resistance at the surfaces. In addition, using real climate data (temperature and solar radiation) will improve the exactness of the estimation. Detailed, dynamic simulations are supported by building simulation software like TrnSys (http://www.trnsys.com/), EnergyPlus (https://energyplus.net/), or IdaICE (https://www.equa.se/en/ida-ice). When estimating the effect of insulating houses, two simulations need to be performed: one with and one without insulation.
Adding shading	Adding exterior shades has no effect on the u-value of the building but affects its solar gains [133]. The effects of shading can, according to [134], be calculated with the solar heat gain coefficient (SHGC): $SHGC = SHGC_{ext} \cdot SHG \cdot SHGC_{glz}$ where $SHGC_{ext}$ is the heat gain coefficient for external shading, $SHGC_{int}$ the value for internal shading, and $SHGC_{glz}$ the value for glazing. The solar heat gain coefficient describes the factor of solar radiation/heat that passes into the buildings. The coefficient can reach values between 0 and 1. The solar heat gain is strongly affected by one's location and the angle at which the sun shines on a building. According to [143], depending on the type of shading and the angle of the shades, the values of 0.39 for horizontal shades, 0.7 for vertical shades, and 0.33 for combined shades can be reached. For internal shades, depending on the type of window glazing and the type of internal shade, values between 0.25 (white reflective, translucent screens in combination with 6 mm single glazing) and 0.94 (dark weave draperies in combination with low-e double-glazing windows) can be reached.	

Table A6. Example of the Representative values for different Storm Window Types [101].

Base Window	Storm Type	u-Value (W/m^{2}K)	SHGC	VT
Wood Double-Hung, single-glazed	None	5	0.61	0.66
	Clear exterior	2.7	0.54	0.57
	Clear interior	2.6	0.54	0.59
	Low-e, exterior	2	0.46	0.52
	Low-e, interior	1.9	0.5	0.54

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