https://doi.org/10.1186/s42162-024-00374-8

REVIEW

Open Access

Simulation modeling for energy systems analysis: a critical review

M. M. Mundu[1*], S. N. Nnamchi[2], J. I. Sempewo[3] and Daniel Ejim Uti[4*]

*Correspondence: mundu.mustafa@kiu.ac.ug; daniel.ejimuti@kiu.ac.ug

[1] Department of Electrical, Telecommunication and Computer Engineering, Kampala International University, P.O. Box 20000, Kampala, Uganda
[2] Department of Mechanical Engineering, Kampala International University, P.O. Box 20000, Kampala, Uganda
[3] Department of Civil and Environmental Engineering, College of Engineering, Design Art and Technology, Makerere University, P.O. Box 7062, Kampala, Uganda
[4] Department of Research and Publications, Kampala International University, P.O. Box 20000, Kampala, Uganda

Abstract

Introduction: Energy system simulation modeling plays an important role in understanding, analyzing, optimizing, and guiding the change to sustainable energy systems.

Objectives: This review aims to examine energy system simulation modeling, emphasizing its role in analyzing and optimizing energy systems for sustainable development.

Methods: The paper explores four key simulation methodologies; Agent-Based Modeling (ABM), System Dynamics (SD), Discrete-Event Simulation (DES), and Integrated Energy Models (IEMs). Practical applications of these methodologies are illustrated through specific case studies.

Results: The analysis covers key components of energy systems, including generation, transmission, distribution, consumption, storage, and renewable integration. ABM models consumer behavior in renewable energy adoption, SD assesses long-term policy impacts, DES optimizes energy scheduling, and IEMs provide comprehensive sector integration. Case studies demonstrate the practical relevance and effectiveness of these models in addressing challenges such as data quality, model complexity, and validation processes.

Conclusions: Simulation modeling is essential for addressing energy challenges, driving innovation, and informing policy. The review identifies critical areas for improvement, including enhancing data quality, refining modeling techniques, and strengthening validation processes. Future directions emphasize the continued importance of simulation modeling in achieving sustainable energy systems.

Keywords: Energy systems, Simulation modeling, Sustainability, Optimization, Renewable energy, Data quality

Introduction

Background and context of energy systems analysis

Understanding the dynamics and functionality of energy systems is essential for addressing modern challenges such as climate change, resource depletion, and energy security (Bretschger 2024; Fashina et al. 2018). Energy systems analysis involves examining how energy is produced, distributed, and utilized across various sectors of society. This interdisciplinary approach incorporates engineering, economics, policy analysis, and environmental science (Pfenninger et al. 2014; Subramanian et al. 2018). The primary goal is to assess the efficiency, reliability, and sustainability of energy systems by examining components such as energy generation methods (fossil fuels, renewables, and nuclear), transmission and distribution networks, energy utilization patterns across different sectors (residential, industrial, transportation), and energy storage technologies (Kalair et al. 2020; Tarashandeh and Karimi 2021).

Importance of simulation modeling in understanding energy systems

Energy systems are characterized by interconnections between different energy sources, technologies, and infrastructures, along with their environmental and socioeconomic impacts. Recently, the context of energy systems analysis has evolved significantly in recent years, driven by increasing concerns about sustainability and the need for more efficient and resilient energy systems. Rapid advancements in renewable energy technologies, energy storage solutions, and digitalization have reshaped the energy scenario, offering new possibilities for optimization and innovation (Baidya et al. 2021; Çelik et al. 2022).

Undoubtedly, simulation modeling serves as a powerful tool for gripping into the behavior and dynamics of energy systems (Pfenninger et al. 2014). By creating virtual representations of real-world energy systems, simulation models enable researchers and stakeholders to explore different scenarios, assess potential outcomes, and make informed decisions. One key advantage of simulation modeling is its ability to capture the complex interactions and interdependencies within energy systems. For example, Agent-Based Modeling (ABM) has been applied to simulate consumer behavior in renewable energy adoption, highlighting how individual decisions impact overall energy consumption (Hansen et al. 2019). System Dynamics (SD) has been used to assess long-term impacts of policy interventions on energy systems, demonstrating how feedback loops and delays can influence energy transition pathways (Turner et al. 2016). Discrete-Event Simulation (DES) has optimized the scheduling of energy generation and distribution activities, effectively managing operational disruptions (Doudareva and Carter 2022). Integrated Energy Models (IEMs) combine multiple techniques to provide comprehensive analyses of energy systems, capturing sectoral interactions and informing policy decisions (Zirak et al. 2020; Subramanian et al. 2018).

Simulation modeling is a valuable tool for comprehending the intricacies of energy systems and exploring strategies for enhancing their efficiency and sustainability (Pfenninger et al. 2014; Subramanian et al. 2018; Mundu et al. 2024). It enables stakeholders to test hypotheses, evaluate alternatives, and anticipate outcomes in a virtual environment, leading to more informed decision-making and better resource allocation in the energy sector. Consequently, this review paper aims to explore the application of simulation modeling techniques in analyzing energy systems, assessing their effectiveness and relevance across various aspects of energy systems. The subsequent sections will delve into the fundamentals of simulation modeling, key components of energy systems, methodologies and materials used, results and discussions, and finally, challenges and future directions.

Objectives and scope of the review

Simulation modeling facilitates the evaluation of alternative strategies and interventions to improve energy system performance (Harish and Kumar 2016). For example, researchers can simulate the effects of deploying renewable energy technologies, implementing energy efficiency measures, upgrading infrastructure, or changing policy incentives. Testing different scenarios in a virtual environment helps stakeholders assess the potential costs, benefits, and feasibility of various options before real-world implementation. Additionally, simulation modeling enhances decision-making and risk management in energy systems planning and operations. By simulating various scenarios, stakeholders can identify potential vulnerabilities, anticipate system failures or disruptions, and develop contingency plans to mitigate risks (Deng and Lv 2020).

Simulation modeling is a valuable tool for comprehending the intricacies of energy systems and exploring strategies for enhancing their efficiency and sustainability (Pfenninger et al. 2014; Subramanian et al. 2018; Mundu et al. 2024). It enables stakeholders to test hypotheses, evaluate alternatives, and anticipate outcomes in a virtual environment, leading to more informed decision-making and better resource allocation in the energy sector.

Consequently, this review paper aims to explore the application of simulation modeling techniques in analyzing energy systems, assessing their effectiveness and relevance across various aspects of energy systems. The subsequent sections will focus into the fundamentals of simulation modeling, key components of energy systems, methodologies and materials used, results and discussions, and finally, challenges and future directions.

Methods and materials

The review process began with a broad search for articles from academic journals, conference proceedings, government reports, and industry publications pertaining to energy systems analysis and simulation modeling. The search process was conducted systematically starting from March 2024, utilizing academic databases such as Scopus, IEEE, Web of Science, and Google Scholar, chosen for their extensive repositories of scientific publications. Specific search strings were employed, including; Energy system simulation modeling, Agent-Based modeling in energy systems, System Dynamics for energy analysis, Discrete-Event simulation in energy, Integrated energy models, Challenges in energy simulation, and Advancements in energy modeling techniques. These terms were applied to the title, abstract, and keywords sections to maximize the retrieval of relevant studies. The literature selection criteria included peer-reviewed publications focusing on energy system simulation modeling, published between 2014 and 2024. The literature analysis involved a multi-step process; initial screening of titles and abstracts, full-text review of selected articles, data extraction of key points, and thematic analysis to categorize data into themes such as simulation methodologies, practical applications, emerging trends, and challenges. The initial search yielded 958 articles, which were narrowed down to 193 based on titles and abstracts, and finally, 86 articles were included in the review after full-text review. This rigorous approach ensured a comprehensive and systematic foundation for analyzing and discussing the findings in the context of energy

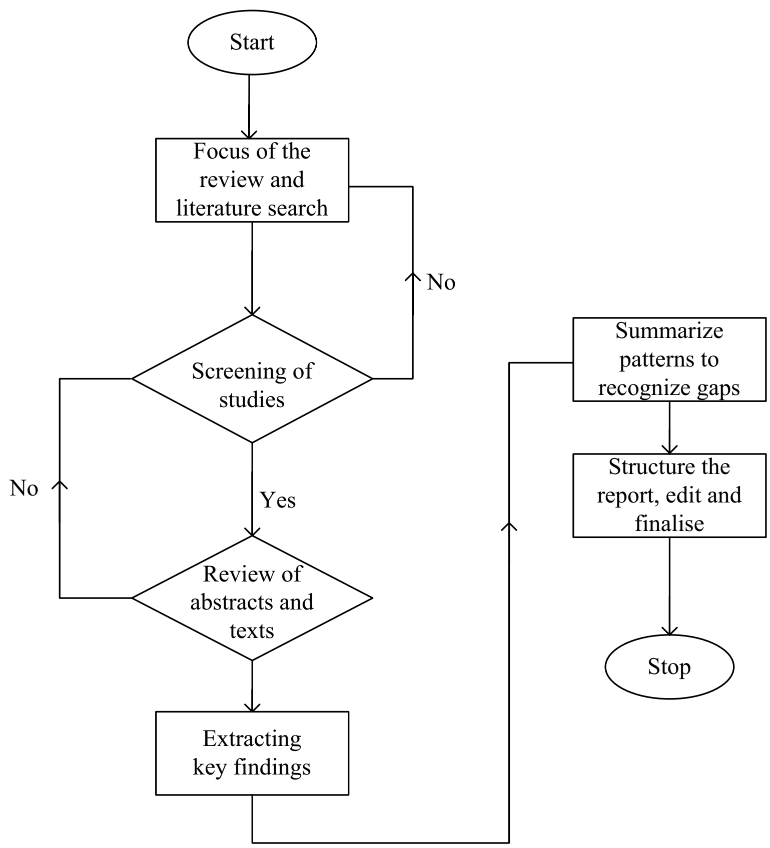

Fig. 1 Flowchart of the review process

system simulation modeling. To ensure clarity and transparency, a flowchart (Fig. 1) was created to visually represent each step of the review process.

Figure 3 outlines the literature review process starting with defining the research topic. It includes stages for searching and screening literature, selecting relevant studies, extracting data, and synthesizing findings. The final steps involve drafting and revising the report. Each step is connected by decision points that guide the progression from start to finish.

Fundamentals of simulation modeling

Definition and principles of simulation modeling

Simulation modeling involves the creation of virtual representations of practical systems to mimic their behavior over time. It employs mathematical algorithms and computational techniques to simulate the interactions and dynamics of various components within a system (Abar et al. 2017). The principles of simulation modeling revolve around the abstraction of complex practical systems into simplified models, the representation of system components and their relationships, the incorporation of stochastic elements to account for uncertainty, and the iterative simulation of system behavior to analyze performance under different conditions (Hehenberger et al. 2016). The primary goal of simulation modeling is to acquire understanding into system behavior, evaluate alternative scenarios, and inform decision-making processes.

Overview of simulation techniques used in energy systems analysis

Several simulation methods are commonly used in energy systems analysis. Firstly, Agent-Based Modeling (ABM) simulates the behavior of individual agents within a system and their interactions with other agents and the environment, enabling the modeling of consumer behavior, energy market dynamics, and the adoption of renewable energy technologies (Hansen et al. 2019; Akhatova et al. 2022; Mundu et al. 2024). For example, ABM has been used to simulate the adoption of solar panels by households, analyzing how financial incentives and social influence can drive higher adoption rates. However, ABM can be computationally intensive and requires detailed data on agent behaviors. This model is represented by Eq. (1) which gives an understanding of how individual and contextual factors interact to shape energy consumption patterns in the ABM simulated environment.

$$\begin{aligned} Agent's\ Energy\ Consumption = {} & Baseline\ Consumption + External\ Factors \\ & + Agent\ Characteristics + Social\ Influence \end{aligned} \tag{1}$$

where; the baseline represents the agent's base level of energy consumption, determined by factors such as household size, appliance usage, and lifestyle preferences. It serves as a starting point for understanding the agent's energy consumption without considering external influences or individual characteristics. The external refers to external influences that impact the agent's energy consumption, such as energy prices, weather conditions (temperature and weather patterns affecting heating and cooling needs), and policy interventions. Agent characteristics involves the individual attributes of the agent that influence its energy consumption behavior, such as income level, age, education (level of awareness and understanding of energy-saving practices and technologies), and environmental awareness. The social influence represents the effect of interactions with other agents and social networks on the agent's energy consumption, including social norms, peer pressure (influence from friends, family, or neighbors encouraging similar energy consumption habits), and information sharing.

Secondly, System Dynamics (SD) focuses on understanding the feedback loops and dynamic behavior of systems over time, representing the flow of energy through different components of the system to assess long-term impacts of policy interventions and technological changes (Turner et al. 2016; Honti et al. 2019). For instance, SD has been applied to study the long-term effects of renewable energy policies on grid stability and emissions reductions. However, SD is less detailed at the micro level and requires expertise in system dynamics. This can be given by Eq. (2).

$$\frac{dE}{dt} = Generation - Utilization - Losses \tag{2}$$

In the system dynamics model, $\frac{dE}{dt}$ represents the rate of change in the total energy stock within the system over time. The equation captures how energy availability evolves based on three key factors namely; (1) Generation which refers to the rate at which energy is produced and supplied into the system. It includes contributions from various sources, such as fossil fuels, renewables, and nuclear power, (2) Utilization represents the rate at which energy is consumed or used within the system. It encompasses energy use by households, industries, and transportation and (3) Losses which accounts for the energy lost due to inefficiencies, transmission losses, or other factors within the system. Together, these components determine the overall change in energy stock, reflecting how generation, consumption, and losses interact to impact system performance.

Thirdly, Discrete-Event Simulation (DES) models discrete events and activities within a system, optimizing scheduling of energy generation, transmission, and distribution activities, as well as simulating disruptions and emergencies (Doudareva and Carter 2022; Sykes 2022). In a DES model of an energy system, various events or activities could contribute to energy consumption, such as; operation of appliances or equipment, heating, ventilation, and air conditioning (HVAC) systems, lighting systems, industrial processes, transportation activities. Each of these events or activities would be represented as discrete entities within the simulation, and their energy consumption would be tracked individually. Additionally, optimization techniques systematically explore decision variables and constraints to find the best possible solution to a problem, applied in determining optimal investment strategies, energy resource allocation, and operational policies for efficiency and cost minimization (Fazlollahi et al. 2012). For example, DES has been used to optimize maintenance schedules for power plants, reducing downtime and operational costs. However, it only focuses on discrete events and becomes less effective for continuous processes. This model take form of Eq. (3) used in a DES model of an energy system, capturing the aggregate energy usage across multiple discrete events or activities.

$$Energy\ Consumption = \sum_{i=1}^{n} Energy\ Consumption_i \tag{3}$$

Energy consumption represents the total energy consumed within the system during the simulation period, $Energyconsumption_i$ represents the energy consumed by each discrete event or activity i within the system. Each i represents a specific event or activity that contributes to the total energy consumption. The subscript i varies from 1 to n, where n is the total number of discrete events or activities being considered in the simulation. In this case, the total energy consumption within the system would then be calculated by summing up the energy consumed by all individual events or activities over the simulation period.

Lastly, Integrated Energy Models (IEMs) integrate multiple simulation techniques and data sources to provide a comprehensive analysis of energy systems, capturing complexity and interactions between different sectors to inform decision-making processes and drive the transition to sustainable and efficient energy systems (Zirak et al. 2020; Allegrini et al. 2015). An IEM combines multiple simulation techniques and data sources to provide a comprehensive analysis of energy systems, capturing the interactions and interdependencies between different sectors such as electricity, transportation, industry, and residential. For example, IEMs have been used to analyze the impact of electric vehicle adoption on electricity demand and grid stability. However, It is data-intensive and requires integration of diverse data sources. In the context of such a model, various factors could contribute to energy demand within each sector, including population growth, economic activity, technological advancements, and policy interventions (Eq. (4)).

$$Total\ Energy\ Demand = \sum_{s=1}^{s} Energy\ Demand_s \tag{4}$$

where; *Total Energy Demand* represents the aggregate energy demand across all sectors of the integrated energy system. $Energy\,Demand_s$ represents the energy demand within each sector s of the integrated energy system and s represents the total number of sectors included in the integrated energy model. Equation (4) calculates the Total Energy Demand by summing the energy demands across all sectors. Each sector contributes to the overall energy demand, and the model integrates these sector-specific demands to provide a comprehensive view of the total energy requirements. This approach allows for capturing the interactions and interdependencies between different sectors, providing a holistic assessment of energy demand in the system. The integrated model helps in understanding how changes in one sector can impact the overall energy demand, facilitating better planning and policy-making for energy systems.

Consequently, each simulation technique offers unique advantages and limitations depending on the research question, data availability, and computational resources, enabling researchers to gain understanding into energy system behavior, and performance.

Advantages and limitations of simulation modeling in energy research

Simulation modeling offers several advantages in energy research. Firstly, it provides a cost-effective means to explore complex energy systems without the need for large-scale experiments, enabling researchers to evaluate various scenarios and interventions efficiently (Yoro et al. 2021; Fodstad et al. 2022). Secondly, simulation models allow for the analysis of system-wide impacts and trade-offs, providing insights into the interactions between different components of the energy system and their effects on overall performance (Yoro et al. 2021; Fodstad et al. 2022). Additionally, simulation modeling facilitates the assessment of long-term trends and the evaluation of the potential impacts of policy interventions and technological changes, helping to inform strategic decision-making and planning processes (Allegrini et al. 2015; Yoro et al. 2021; Fodstad et al. 2022). However, simulation modeling also has limitations that need to be considered. Firstly, the accuracy and reliability of simulation results depend heavily on the quality of input data and the assumptions made during model development, which may introduce uncertainties and biases into the analysis (Law 2009; Fodstad et al. 2022). Secondly, simulation models are simplifications of practical systems and may not capture all relevant factors or interactions, potentially leading to oversights or inaccuracies in the results (Kopec et al. 2010; Balduin 2018). Moreover, simulation modeling requires significant computational resources and expertise to develop and validate, which may pose challenges for researchers with limited access to computational infrastructure or specialized knowledge (Fonseca i Casas 2023). Overall, while simulation modeling offers interesting interpretations into energy systems and their dynamics, researchers must be mindful of its limitations and uncertainties when interpreting results and making decisions based on simulation findings.

Key components of energy systems

Generation

Fossil fuels continue to dominate global energy production, but renewables like solar and wind are rapidly growing due to technological advancements and policy incentives. For instance, global solar power capacity exceeded 700 GW in 2021 (IEA 2021). There is a strong push towards decentralized generation, particularly with solar photovoltaics (PV) and wind energy. Innovations in energy generation include advancements in offshore wind technology and the development of next-generation nuclear reactors (World Nuclear Association 2022). For example, Germany's Energiewende policy exemplifies a shift towards renewable energy, aiming for 80% renewable electricity by 2045 (Schlandt 2020).

The generalized equation for calculating electricity generation is given by Eq. (5), $Generation_i$ represents the electricity generated by each individual generation source i and n is the total number of generation sources contributing to electricity generation. The summation symbol indicates that the total electricity generation is calculated by summing the electricity output from each individual generation source. The index i runs from 1 to n, where n is the total number of distinct generation sources or units within the system.

Each generation source could be a power plant fueled by fossil fuels or renewable sources.

$$Electricity\,Generation = \sum_{i=1}^{n} Generation_i \tag{5}$$

Equation (5) calculates the total electricity generation by aggregating the output from all generation sources within the energy system. This equation is essential for understanding the system's capability to meet electricity demand and for assessing the contribution of various generation technologies. By summing the generation outputs, stakeholders can evaluate the performance and efficiency of the entire electricity generation infrastructure. The aggregated data helps in planning, optimizing energy production, and ensuring that supply meets the demand. It also aids in analyzing the impact of different generation sources on the overall energy mix and in making informed decisions about future investments and policy intervention.

Fossil fuels, including coal, oil, and natural gas, are fundamental to energy generation globally, providing a reliable source of power. These non-renewable resources are burned in power plants to produce heat, which is then converted into electricity through steam turbines or internal combustion engines. Fossil fuel-based power plants have long been favored for their capacity to meet baseline energy demands and their ability to provide continuous power supply (Zou et al. 2016; Chippada and Reddy 2023). However, their widespread use comes with significant environmental consequences, including air pollution and greenhouse gas emissions. The combustion of fossil fuels releases pollutants such as sulfur dioxide, nitrogen oxides, and particulate matter, contributing to smog, acid rain, and respiratory diseases. Moreover, the combustion of fossil fuels is a major contributor to global climate change, accounting for a significant portion of anthropogenic greenhouse gas emissions (Yu et al. 2023; Silva et al. 2013). Efforts to mitigate these environmental impacts have led to the development of cleaner technologies and policies aimed at reducing emissions, such as carbon capture and storage (CCS) and the promotion of renewable energy sources (Adams and Acheampong 2019; Withey et al. 2019). Despite these challenges, fossil fuels continue to play a dominant role in global energy generation, particularly in regions with abundant reserves and established infrastructure (Abas et al. 2015). However, the shift to cleaner and more sustainable energy sources is increasingly imperative to address environmental concerns and mitigate the impacts of climate change. The following chart (Fig. 1) illustrates the global energy generation mix (Global Electricity Mix 2023 by Energy Source 2024).

On the other hand, renewable energy sources, including solar, wind, hydroelectric, geothermal, biomass, are increasingly recognized as essential components of modern energy systems (Fig. 2). Unlike fossil fuels, renewable sources derive from naturally replenishing processes and are considered sustainable over the long term. Solar energy harnesses sunlight through photovoltaic cells or concentrated solar power systems, providing a clean and abundant source of electricity (Khan and Arsalan 2016; Nnamchi et al. 2021a, b; Kablar, 2019; Nnamchi et al. 2018). Wind energy utilizes wind turbines to convert kinetic energy from the wind into electrical power, offering widely applicable solution for electricity generation (Mundu et al. 2022; Rahimi 2018). Hydroelectric power taps into the energy of flowing water, typically through dams and turbines, to produce electricity, offering reliable and flexible power generation (Özcan et al. 2021; Catolico et al. 2021). Geothermal energy harnesses heat from the Earth's core, providing continuous and low-emission power generation (Hu et al. 2022). Biomass energy utilizes organic materials, such as wood, agricultural residues, and organic waste, to produce heat, electricity, and biofuels, offering a versatile and renewable energy source (Butlewski 2022; Muhamad et al. 2022).

Consequently, renewable energy sources offer numerous benefits over fossil fuels, including reduced greenhouse gas emissions, improved air quality, and enhanced energy security. They also provide opportunities for economic growth, job creation, and technological innovation (Overland et al. 2022; Nnamchi and Mundu 2022). However, renewable energy deployment faces challenges such as intermittency, grid integration, and resource variability. Advances in energy storage, grid management technologies, and policy frameworks are essential to overcoming these challenges and maximizing the

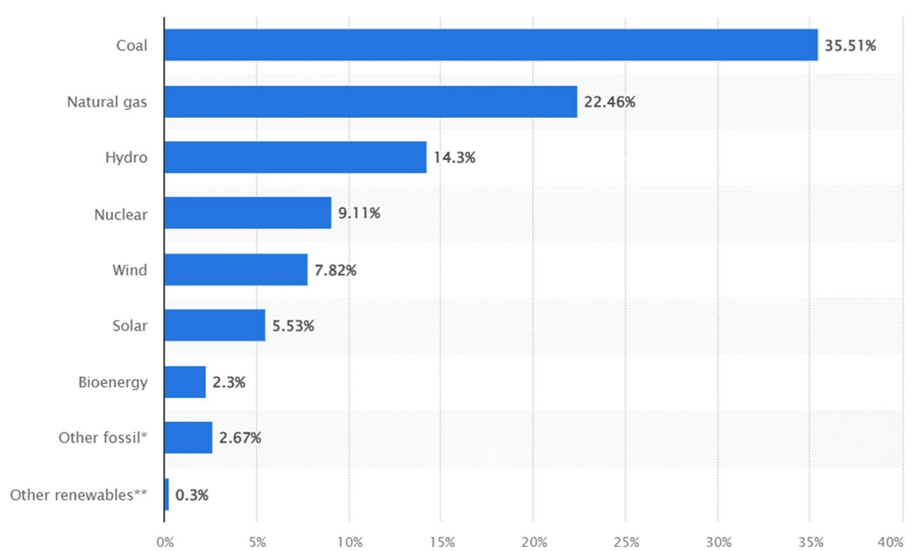

Fig. 2 Distribution of global energy generation mix

potential of renewable energy sources in the shift to a sustainable energy future (Moustakas et al. 2020; Muruganantham et al. 2017). Despite these challenges, renewable sources are increasingly competitive with conventional energy sources in terms of cost and performance, driving rapid growth and adoption worldwide. As renewable energy technologies continue to evolve and mature, they are expected to play an increasingly prominent role in global energy generation, contributing to efforts to mitigate climate change and achieve a more sustainable energy scenario.

Transmission and distribution

Transmission and distribution are essential components of energy systems, responsible for delivering electricity from generation sources to end-users reliably and efficiently. Transmission systems transport electricity over long distances from power plants, renewable energy facilities, and other generation sources to substations and distribution networks (McCalley and Krishnan 2014). High-voltage transmission lines minimize energy losses during long-distance transport, ensuring that electricity can be efficiently transmitted across regions. Transmission infrastructure includes overhead lines, underground cables, transformers, and substations, which play a critical role in maintaining grid stability and reliability (Arcia-Garibaldi et al. 2018).

Aging infrastructure and capacity limitations challenge existing transmission systems, prompting investments in upgrades to accommodate increasing renewable energy inputs. The development of smart grids and high-voltage direct current (HVDC) transmission lines enhances grid stability and efficiency, enabling long-distance transmission with minimal losses. For example, China Southern Power Grid's HVDC project transmits power over 2000 km with minimal loss, demonstrating the potential of advanced transmission technologies.

Moreover, distribution networks deliver electricity from substations to homes, businesses, and industrial facilities at lower voltages suitable for consumption. Distribution systems consist of power lines, transformers, switches, and meters, which distribute electricity to end-users while managing voltage levels and ensuring system reliability (Pimm et al. 2018; Davarzani et al. 2021).

The schematic diagram below (Fig. 3) explains the T&D network.

Equation (6) gives a simplified equation representing energy transmission and distribution.

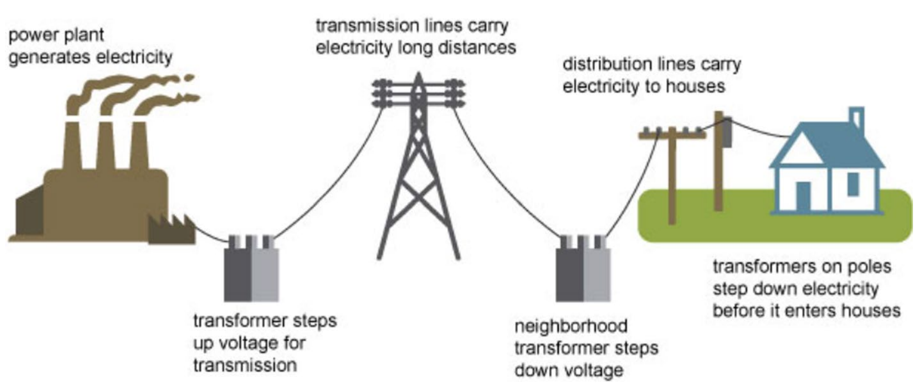

Fig. 3 Schematic network of generation, transmission and distribution

$$Energy\ Supply = Energy\ Generated - Transmission\ Losses - Distribution\ Losses \quad (6)$$

where; Energy Supply represents the amount of energy available for consumption after accounting for losses during transmission and distribution. It indicates the effective energy reaching consumers and is crucial for managing demand and ensuring reliability. Moreover, Energy Generated is the Total energy produced by generation sources. It serves as the baseline measure for assessing production capacity and system performance. More so, Transmission Losses is the Energy lost during transmission from generation to the distribution network due to resistance and inefficiencies. Minimizing these losses improves system efficiency and reduces waste. Lastly, Distribution Losses is the Energy lost during distribution from the transmission network to consumers. Reducing these losses enhances the effectiveness of the distribution system and ensures more energy reaches end-users. Equation (6) provides an important understanding into the efficiency of the energy transmission and distribution system. By subtracting Transmission Losses and Distribution Losses from Energy Generated, this equation calculates the Energy Supply available for consumption. Understanding each component allows stakeholders to identify inefficiencies in the energy system and implement strategies to minimize losses. For example, investing in advanced transmission technologies or upgrading distribution infrastructure can reduce these losses and enhance overall system performance. This equation is instrumental for energy planners, policymakers, and operators in designing and managing an efficient and reliable energy supply network.

Alternatively, in Eq. (7), the transmission and distribution (T&D) losses represent the amount of energy lost as it travels from power generation facilities to end-users. These losses occur due to various factors such as electrical resistance, equipment inefficiencies, and energy dissipation in the transmission and distribution networks.

$$T\&D\ Losses = Total\ Energy\ Generated - Total\ Energy\ Delivered \quad (7)$$

where, $T\&D\ Losses$ represents the losses incurred during the transmission and distribution of electricity, *Total Energy Generated* represents the total electricity generated by power plants or renewable energy sources and the *Total Energy Delivered* represents the total electricity delivered to end-users after accounting for losses during transmission and distribution. Equation (7) helps quantify the effectiveness of the transmission and distribution systems by measuring the energy lost before reaching the end-users. It highlights the need for infrastructure improvements and efficient operational practices to reduce losses and enhance overall system performance.

Therefore, effective transmission and distribution systems are vital for ensuring a stable energy supply, supporting economic growth, and meeting the needs of consumers (Čaušević et al. 2019). However, aging infrastructure, increasing electricity demand, and the integration of renewable energy sources pose challenges to modernizing and expanding transmission and distribution networks (Alotaibi et al. 2020). Advancements in smart grid technologies, grid automation, and digitalization are essential for enhancing the efficiency, flexibility, and resilience of transmission and distribution systems (Kulkarni et al. 2021; Aslam 2018). Moreover, investments in grid modernization, infrastructure upgrades, and grid interconnections are necessary to support the shift to a cleaner and more decentralized energy system (Aslam 2018). Overall, transmission and distribution play an essential role in the functioning of energy systems, enabling reliable and efficient delivery of electricity to consumers while facilitating the integration of renewable energy sources and supporting the transition to a more sustainable energy future.

Consumption

Consumption is a central component of energy systems, representing the utilization of energy by end-users across residential, commercial, industrial, and transportation sectors. Residential energy consumption involves the use of energy for heating, cooling, lighting, appliances, and electronic devices within households. Factors influencing residential energy consumption include household size, climate, building characteristics, energy efficiency measures, and behavioral patterns. Efforts to reduce residential energy consumption often focus on improving energy efficiency through insulation, weatherization, efficient appliances, and smart home technologies (Hu et al. 2017; Heinonen and Junnila 2014; Feng et al. 2016).

Consequently, the industrial sector is the largest energy consumer, followed by transportation and residential sectors. Energy efficiency measures are widely adopted to reduce consumption and costs. The rise of electric vehicles (EVs) and smart home technologies is transforming consumption patterns. Energy management systems (EMS) and demand response programs optimize energy use. For instance, the California's energy efficiency programs have led to significant reductions in energy consumption, demonstrating the effectiveness of policy-driven initiatives (California Energy Commission 2021).

Whereas, commercial energy consumption refers to the energy used in commercial buildings, offices, retail spaces, and institutions for lighting, heating, cooling, ventilation, and equipment operation. Commercial energy demand is influenced by factors such as building size, occupancy patterns, business activities, and energy management practices (Zaeri et al. 2022). Strategies to reduce commercial energy consumption include energy-efficient lighting, HVAC systems, building automation, and energy management systems (Lee et al. 2024; Jouhara and Yang 2018).

More so, industrial energy consumption comprises the energy used in manufacturing, processing, and production processes across various industries. Industrial energy demand is driven by factors such as production levels, technology choices, process efficiency, and energy-intensive operations. Measures to improve industrial energy efficiency include process optimization, equipment upgrades, energy audits, and adoption of energy-efficient technologies (Li 2023; Kluczek and Olszewski 2017; Binderbauer et al. 2023).

Additionally, transportation energy consumption involves the use of energy for moving people and goods via vehicles, including cars, trucks, buses, trains, ships, and airplanes. Transportation energy demand is influenced by factors such as vehicle efficiency, fuel type, travel behavior, infrastructure, and urban planning. Strategies to reduce transportation energy consumption include promoting fuel-efficient vehicles, public transit, active transportation modes, electrification, and alternative fuels (Corlu et al. 2020; Sun et al. 2021). Efforts to address energy consumption across sectors focus on improving energy efficiency, promoting renewable energy adoption, implementing demand-side management measures, and promoting behavioral changes. Achieving sustainable consumption patterns requires a combination of technological innovation, policy interventions, consumer awareness, and collaborative efforts across government, industry, and civil society.

Storage

Energy storage plays a critical role in modern energy systems, enabling the efficient management, integration, and utilization of variable renewable energy sources, enhancing grid stability, and ensuring reliable power supply (Zhou et al. 2024). Energy storage technologies comprise a diverse range of systems that store energy in various forms, including electrical, mechanical, chemical, thermal, and gravitational potential energy (Dehmous et al. 2021). Common types of energy storage technologies include batteries, pumped hydroelectric storage, compressed air energy storage, flywheels, thermal energy storage, and hydrogen storage (Menéndez et al. 2020).

Notably, Lithium-ion batteries dominate the market, with other technologies like pumped hydro and advanced thermal storage also in use. Innovations in battery technology, such as solid-state and flow batteries, are expected to enhance capacity and efficiency. Grid-scale storage solutions are crucial for supporting renewable energy integration (DOE 2020). Case Study: Tesla's Hornsdale Power Reserve in South Australia, one of the world's largest lithium-ion battery installations, has improved grid stability and reduced energy costs (Tesla 2021).

A generalized equation for energy storage is given by Eq. (8) which provides a simplified representation of the energy storage process, accounting for the input of energy into the storage system, the output of energy from the system, and any losses incurred during the storage cycle.

$$Energy\,Stored = Energy\,Input - Energy\,Output - Losses \tag{8}$$

Equation (8) measures the amount of energy stored in a system by accounting for the energy input, energy output, and losses. Energy Input is the total energy supplied to the storage system, such as from renewable sources or the grid. Energy output is the energy extracted from the storage system for use or distribution. Losses refer to energy lost due to inefficiencies during charging, discharging, or self-discharge. Understanding these components is crucial for assessing the efficiency and effectiveness of energy storage systems. High energy Input ensures adequate storage, Energy output determines the system's ability to meet demand, and minimizing losses improves the system's overall performance and reliability, which is vital for integrating renewable energy sources and ensuring energy availability.

Energy storage serves multiple purposes within energy systems, including serving as a basis for grid stability, renewable energy integration. It enables the efficient management of energy supply and demand by facilitating load shifting, allowing excess energy to be stored during periods of low demand and discharged during peak demand. Moreover, energy storage enhances grid stability by providing ancillary services such as frequency regulation and voltage support, smoothing out fluctuations in renewable energy output (Tan et al. 2021; Zhou et al. 2024). Additionally, it serves as a critical backup power source during grid outages or emergencies, ensuring uninterrupted electricity supply to essential services and communities (Čaušević et al. 2019; Bakht et al. 2024). Energy storage also accelerates the integration of renewable energy sources by storing surplus energy when generation exceeds demand and releasing stored energy when needed, thereby supporting the change to a cleaner and more sustainable energy future (Rahman et al. 2012; Zhou et al. 2024). Furthermore, energy storage plays a crucial role in the electrification of transportation, enabling the deployment of electric vehicles and supporting the development of smart charging infrastructure (Karduri 2023; Nunes et al. 2015).

Energy storage is increasingly recognized as a key enabler of the change to a sustainable, low-carbon energy future, supporting the integration of renewable energy, enhancing grid flexibility, and improving energy access. As energy systems continue to evolve and decarbonize, its role is expected to grow, offering solutions to emerging challenges and opportunities in the energy scenario.

Discussions

In this review paper, the findings from the literature review reveal significant understanding into energy systems analysis and simulation modeling. The summary of findings highlights key trends, methodologies, and advancements in the field, showcasing the diverse applications of simulation modeling in addressing complex energy challenges. For instance, Agent-Based Modeling (ABM) has been effectively applied to simulate consumer behavior and the adoption of renewable energy technologies, while System Dynamics (SD) has been utilized to analyze long-term impacts of policy interventions on energy systems.

Interpretation of results involves comparing simulation outcomes with practical data, assessing the accuracy and validity of modeling approaches, and identifying areas of convergence or divergence. For example, a case study on the integration of renewable energy in Germany demonstrated that simulation models closely predicted the actual increase in renewable energy adoption and its effects on the grid stability (Pfenninger et al. 2014).

The discussion digs into the implications of simulation findings, including their relevance for policy-making, infrastructure planning, and energy transition strategies. Simulation models have been instrumental in informing policy decisions such as the deployment of smart grids and energy storage solutions, as seen in several European countries (Subramanian et al. 2018).

Furthermore, the identification of gaps and areas for further research emphasizes opportunities for innovation and refinement in simulation methodologies, data collection techniques, and model validation practices. Emerging trends suggest a growing focus on integrating machine learning techniques with traditional simulation models to enhance predictive accuracy and computational efficiency (Baidya et al. 2021).

However, energy system simulation modeling faces several significant challenges. Model complexity is a primary issue, as simplifying assumptions can compromise accuracy and applicability. Computational capacity is another challenge; high-fidelity simulations require substantial processing power and memory, often needing access to high-performance computing facilities. Data availability and quality also pose obstacles, especially for emerging technologies and developing regions. Inaccurate data can affect model reliability. Quantifying and incorporating uncertainties, such as fluctuating demand and variable renewable energy output, is essential but challenging. Validation and verification are resource-intensive processes, requiring rigorous comparison with actual system performance data to ensure model accuracy and build trust in predictions (Pfenninger et al. 2014; Yoro et al. 2021).

Overall, the results and discussions provide feedback into the state-of-the-art in energy systems analysis, offering guidance for future research directions and practical applications in the energy sector. For instance, future research could explore the potential of hybrid simulation models that combine ABM, SD, and Discrete-Event Simulation (DES) to capture the dynamic nature of energy systems more comprehensively (Akhatova et al. 2022). Advanced modeling techniques, such as hybrid models combining different simulation methodologies (e.g., Agent-Based Modeling with System Dynamics), capture a broader range of system behaviors and interactions. Additionally, high-performance computing (HPC) and cloud-based platforms enhance computational capacity, enabling more complex simulations and reducing analysis time.

Moreover, big data analytics and machine learning are advancing data handling and predictive accuracy, enabling the processing of large datasets from smart meters and sensors. This helps in predicting patterns and optimizing energy systems more effectively. At the same time, open data initiatives and collaborative platforms address data quality and scarcity issues by promoting standardized and validated datasets and fostering knowledge exchange among stakeholders.

Advanced uncertainty quantification techniques, such as Monte Carlo simulations and probabilistic modeling, better incorporate uncertainties for a comprehensive understanding of potential outcomes. Enhanced validation frameworks using a wider range of measures and real-world data sources improve model accuracy and reliability. Continuous validation processes involving iterative updates based on new data further enhance model credibility (Boru et al. 2015; Vera et al. 2019).

Conclusion

This review has provided a broad examination of energy system simulation modeling, emphasizing its role in understanding, analyzing, and optimizing complex energy systems. Moreover, its scientific contributions lie in synthesizing various simulation methodologies and their practical applications, thereby offering a consolidated resource for researchers and practitioners. Through a systematic exploration of methodologies such as ABM, SD, DES, and IEMs, this review emphasizes the significance of simulation modeling as a powerful tool for informing decision-making, guiding policy development, and facilitating the change towards sustainable energy systems. In comparison with previous studies, this review corroborates the findings of Pfenninger et al. (2014) on the versatility and effectiveness of simulation models in capturing complex system dynamics and aligns with Subramanian et al. (2018) in identifying the importance of incorporating diverse elements such as energy sources, infrastructure, and regulatory frameworks into simulation models.

The findings reveal that simulation modeling has effectively addressed various energy challenges, including data quality, model complexity, and validation processes, as also noted by Baidya et al. (2021). Practical applications, such as modeling consumer behavior in renewable energy adoption (ABM), assessing long-term impacts of energy policy interventions (SD), optimizing the scheduling of energy generation and distribution (DES), and providing comprehensive analyses integrating multiple sectors (IEMs), demonstrate the real-world relevance of these methodologies.

Furthermore, for policymakers and practitioners, the practical implications of these findings are substantial. Simulation modeling can enhance policy formulation by providing understanding into the potential outcomes of different policy scenarios, thereby supporting evidence-based decision-making. For instance, policymakers can use simulation models to predict the impact of renewable energy incentives on market dynamics and consumer behavior, as highlighted by Akhatova et al. (2022). Practitioners, on the other hand, can use these models to optimize energy system operations, plan infrastructure investments, and improve risk management strategies by anticipating system vulnerabilities and disruptions. Moving forward, it is essential to recognize the limitations of the manuscript, which include the potential for bias in the reviewed literature, as it might not cover all geographical regions or types of energy systems uniformly.

By overcoming these challenges and capitalizing on opportunities, simulation modeling can accelerate the change to a cleaner, more resilient, and equitable energy future. Through interdisciplinary collaboration, innovation, and strategic investments, simulation modeling can play a key role in shaping the path of energy systems towards greater efficiency, sustainability, and societal benefit.

Author contributions
M. M Mundu, S. N Nnamchi, J. I Sempewo, Daniel Ejim Uti all contributed equally to the manuscript.

Funding
This review did not receive funding from any source, whether private, or public organization.

Availability of data and materials
Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Received: 25 May 2024 Accepted: 31 July 2024
Published online: 27 August 2024

References
Abar S, Theodoropoulos GK, Lemarinier P, O'Hare GM (2017) Agent based modelling and simulation tools: a review of the state-of-art software. Comput Sci Rev 24:13–33. https://doi.org/10.1016/j.cosrev.2017.03.001

Abas N, Kalair A, Khan N (2015) Review of fossil fuels and future energy technologies. Futures 69:31–49. https://doi.org/10.1016/j.futures.2015.03.003

Adams S, Acheampong AO (2019) Reducing carbon emissions: the role of renewable energy and democracy. J Clean Prod 240:118245. https://doi.org/10.1016/j.jclepro.2019.118245

Akhatova A, Kranzl L, Schipfer F, Heendeniya CB (2022) Agent-based modelling of urban district energy system decarbonisation—a systematic literature review. Energies 15(2):554. https://doi.org/10.3390/en15020554

Allegrini J, Orehounig K, Mavromatidis G, Ruesch F, Dorer V, Evins R (2015) A review of modelling approaches and tools for the simulation of district-scale energy systems. Renew Sustain Energy Rev 52:1391–1404. https://doi.org/10.1016/j.rser.2015.07.123

Alotaibi I, Abido MA, Khalid M, Savkin AV (2020) A comprehensive review of recent advances in smart grids: a sustainable future with renewable energy resources. Energies 13(23):6269. https://doi.org/10.3390/en13236269

Arcia-Garibaldi G, Cruz-Romero P, Gómez-Expósito A (2018) Future power transmission: visions, technologies and challenges. Renew Sustain Energy Rev 94:285–301. https://doi.org/10.1016/j.rser.2018.06.004
Aslam M (2018) Smart grid communication infrastructure, automation technologies and recent trends. Am J Electr Power Energy Syst 7(3):25. https://doi.org/10.11648/j.epes.20180703.11
Baidya S, Potdar V, Pratim Ray P, Nandi C (2021) Reviewing the opportunities, challenges, and future directions for the digitalization of energy. Energy Res Soc Sci 81:102243. https://doi.org/10.1016/j.erss.2021.102243
Bakht MP, Mohd MNH, Sheikh UU, Khan N (2024) Optimal design and performance analysis of hybrid renewable energy system for ensuring uninterrupted power supply during load shedding. IEEE Access 12:5792–5813. https://doi.org/10.1109/access.2024.3349594
Balduin S (2018) Surrogate models for composed simulation models in energy systems. Energy Inform. https://doi.org/10.1186/s42162-018-0053-z
Binderbauer PJ, Woegerbauer M, Nagovnak P, Kienberger T (2023) The effect of "energy of scale" on the energy consumption in different industrial sectors. Sustain Prod Consump 41:75–87. https://doi.org/10.1016/j.spc.2023.07.031
Boru D, Kliazovich D, Granelli F, Bouvry P, Zomaya AY (2015) Energy-efficient data replication in cloud computing datacenters. Clust Comput 18(1):385–402. https://doi.org/10.1007/s10586-014-0404-x
Bretschger L (2024) Energy transition and climate change abatement: a macroeconomic analysis. Resour Energy Econ 76:101423. https://doi.org/10.1016/j.reseneeco.2023.101423
Butlewski K (2022) Concept for biomass and organic waste refinery plants based on the locally available organic materials in rural areas of Poland. Energies 15(9):3392. https://doi.org/10.3390/en15093392
California Energy Commission (2021) https://efiling.energy.ca.gov/Lists/DocketLog.aspx?docketnumber=19-ERDD-01
Catolico A, Maestrini M, Strauch J, Giusti F, Hunt J (2021) Socioeconomic impacts of large hydroelectric power plants in Brazil: a synthetic control assessment of Estreito hydropower plant. Renew Sustain Energy Rev 151:111508. https://doi.org/10.1016/j.rser.2021.111508
Čaušević S, Warnier M, Brazier FM (2019) Self-determined distribution of local energy resources for ensuring power supply during outages. Energy Inform. https://doi.org/10.1186/s42162-019-0071-5
Çelik D, Meral ME, Waseem M (2022) Investigation and analysis of effective approaches, opportunities, bottlenecks and future potential capabilities for digitalization of energy systems and sustainable development goals. Electr Power Syst Res 211:108251. https://doi.org/10.1016/j.epsr.2022.108251
Chippada D, Reddy MD (2023) Optimal placement and sizing of renewable and non-renewable resources in smart grid. Distrib Gener Altern Energy J. https://doi.org/10.13052/dgaej2156-3306.38314
Corlu CG, de la Torre R, Serrano-Hernandez A, Juan AA, Faulin J (2020) Optimizing energy consumption in transportation: literature review, insights, and research opportunities. Energies 13(5):1115. https://doi.org/10.3390/en13051115
Davarzani S, Pisica I, Taylor GA, Munisami KJ (2021) Residential demand response strategies and applications in active distribution network management. Renew Sustain Energy Rev 138:110567. https://doi.org/10.1016/j.rser.2020.110567
Dehmous M, Franquet E, Lamrous N (2021) Mechanical and thermal characterizations of various thermal energy storage concretes including low-cost bio-sourced PCM. Energy Build 241:110878. https://doi.org/10.1016/j.enbuild.2021.110878
Deng X, Lv T (2020) Power system planning with increasing variable renewable energy: a review of optimization models. J Clean Prod 246:118962. https://doi.org/10.1016/j.jclepro.2019.118962
Department of Energy (DOE) (2020) https://www.energy.gov/articles/state-doe-national-laboratories-2020-edition
Doudareva E, Carter M (2022) Discrete event simulation for emergency department modelling: a systematic review of validation methods. Oper Res Health Care 33:100340. https://doi.org/10.1016/j.orhc.2022.100340
Fashina A, Mundu M, Akiyode O, Abdullah L, Sanni D, Ounyesiga L (2018) The drivers and barriers of renewable energy applications and development in uganda: a review. Clean Technol 1(1):9–39. https://doi.org/10.3390/cleantechnol1010003
Fazlollahi S, Mandel P, Becker G, Maréchal F (2012) Methods for multi-objective investment and operating optimization of complex energy systems. Energy 45(1):12–22. https://doi.org/10.1016/j.energy.2012.02.046
Feng F, Li Z, Ruan Y, Xu P (2016) An empirical study of influencing factors on residential building energy consumption in Qingdao City, China. Energy Procedia 104:245–250. https://doi.org/10.1016/j.egypro.2016.12.042
Fodstad M, Crespo del Granado P, Hellemo L, Knudsen BR, Pisciella P, Silvast A, Bordin C, Schmidt S, Straus J (2022) Next frontiers in energy system modelling: a review on challenges and the state of the art. Renew Sustain Energy Rev 160:112246. https://doi.org/10.1016/j.rser.2022.112246
Fonseca I Casas P (2023) A continuous process for validation, verification, and accreditation of simulation models. Mathematics 11(4):845. https://doi.org/10.3390/math11040845
Global electricity mix 2023, by energy source (2024) Statista. https://www.statista.com/statistics/269811/world-electricity-production-by-energy-source/#:~:text=Fossil%20fuels%20remain%20the%20greatest,coal%20used%20for%20electricity%20generation
Hansen P, Liu X, Morrison GM (2019) Agent-based modelling and socio-technical energy transitions: a systematic literature review. Energy Res Soc Sci 49:41–52. https://doi.org/10.1016/j.erss.2018.10.021
Harish V, Kumar A (2016) A review on modeling and simulation of building energy systems. Renew Sustain Energy Rev 56:1272–1292. https://doi.org/10.1016/j.rser.2015.12.040
Hehenberger P, Vogel-Heuser B, Bradley D, Eynard B, Tomiyama T, Achiche S (2016) Design, modelling, simulation and integration of cyber physical systems: methods and applications. Comput Ind 82:273–289. https://doi.org/10.1016/j.compind.2016.05.006
Heinonen J, Junnila S (2014) Residential energy consumption patterns and the overall housing energy requirements of urban and rural households in Finland. Energy Build 76:295–303. https://doi.org/10.1016/j.enbuild.2014.02.079
Honti G, Dörgő G, Abonyi J (2019) Review and structural analysis of system dynamics models in sustainability science. J Clean Prod 240:118015. https://doi.org/10.1016/j.jclepro.2019.118015
How much energy does the world consume? | nuclear-power.com (2022) Nuclear Power. https://www.nuclear-power.com/how-much-energy-does-the-world-consume/

Hu S, Yan D, Guo S, Cui Y, Dong B (2017) A survey on energy consumption and energy usage behavior of households and residential building in urban China. Energy Build 148:366–378. https://doi.org/10.1016/j.enbuild.2017.03.064
Hu X, Banks J, Guo Y, Liu WV (2022) Utilizing geothermal energy from enhanced geothermal systems as a heat source for oil sands separation: a numerical evaluation. Energy 238:121676. https://doi.org/10.1016/j.energy.2021.121676
Jouhara H, Yang J (2018) Energy efficient HVAC systems. Energy Build 179:83–85. https://doi.org/10.1016/j.enbuild.2018.09.001
Kalair A, Abas N, Saleem MS, Kalair AR, Khan N (2020) Role of energy storage systems in energy transition from fossil fuels to renewables. Energy Storage. https://doi.org/10.1002/est2.135
Karduri RKR (2023) Sustainable transportation and electrification: examining the impact of electric vehicles (EVs) on reducing greenhouse gas emissions and their role in the energy transition. SSRN Electron J. https://doi.org/10.2139/ssrn.4636512
Khan J, Arsalan MH (2016) Solar power technologies for sustainable electricity generation—a review. Renew Sustain Energy Rev 55:414–425. https://doi.org/10.1016/j.rser.2015.10.135
Kluczek A, Olszewski P (2017) Energy audits in industrial processes. J Clean Prod 142:3437–3453. https://doi.org/10.1016/j.jclepro.2016.10.123
Kopec JA, Finès P, Manuel DG, Buckeridge DL, Flanagan WM, Oderkirk J, Abrahamowicz M, Harper S, Sharif B, Okhmatovskaia A, Sayre EC, Rahman MM, Wolfson MC (2010) Validation of population-based disease simulation models: a review of concepts and methods. BMC Public Health. https://doi.org/10.1186/1471-2458-10-710
Kulkarni V, Sahoo SK, Thanikanti SB, Velpula S, Rathod DI (2021) Power systems automation, communication, and information technologies for smart grid: a technical aspects review. TELKOMNIKA Telecommun Comput Electron Control 19(3):1017. https://doi.org/10.12928/telkomnika.v19i3.16428
Law AM (2009) How to build valid and credible simulation models. IEEE Eng Manage Rev 37(2):57–57. https://doi.org/10.1109/emr.2009.5235457
Lee SH, Oh ST, Lim JH (2024) Lighting control method based on RIIL to reduce building energy consumption. Energy Rep 11:2090–2098. https://doi.org/10.1016/j.egyr.2024.01.075
Li B (2023) Modeling energy consumption in the production processes of industrial units based on load response programs in the energy market. Energy Eng 120(2):461–481. https://doi.org/10.32604/ee.2022.021877
McCalley JD, Krishnan V (2014) A survey of transmission technologies for planning long distance bulk transmission overlay in US. Int J Electr Power Energy Syst 54:559–568. https://doi.org/10.1016/j.ijepes.2013.08.008
Menéndez J, Schmidt F, Loredo J (2020) Comparing subsurface energy storage systems: underground pumped storage hydropower, compressed air energy storage and suspended weight gravity energy storage. E3S Web Conf 162:01001. https://doi.org/10.1051/e3sconf/202016201001
Moustakas K, Loizidou M, Rehan M, Nizami A (2020) A review of recent developments in renewable and sustainable energy systems: key challenges and future perspective. Renew Sustain Energy Rev 119:109418. https://doi.org/10.1016/j.rser.2019.109418
Muhamad MM, Kibirige D, Uzorka A, John UK (2022) Design and simulation of an inverter drive system with a display for a renewable energy system in the rural isolated communities of Uganda. J Power Energy Eng 10(12):1–14. https://doi.org/10.4236/jpee.2022.1012001
Mundu MM, Nnamchi SN, Ukagwu KJ, Peter BA, Nnamchi OA, Ssempewo JI (2022) Numerical modelling of wind flow for solar power generation in a case study of the tropical zones. Model Earth Syst Environ 8(3):4123–4134. https://doi.org/10.1007/s40808-021-01343-w
Mundu MM, NnamchI SN, Muhaise H (2024) Sustainable energy transitions in Uganda: influential determinants of the renewable energy landscape. IAA J Appl Sci 11(1):57–72. https://doi.org/10.59298/iaajas/2024/6.68.40.35
Muruganantham B, Gnanadass R, Padhy N (2017) Challenges with renewable energy sources and storage in practical distribution systems. Renew Sustain Energy Rev 73:125–134. https://doi.org/10.1016/j.rser.2017.01.089
Kablar NA (2019) Renewable energy: wind turbines, solar cells, small hydroelectric plants, biomass, and geothermal sources of energy. J Energy Power Eng. https://doi.org/10.17265/1934-8975/2019.04.004
Nnamchi SN, Mundu MM (2022) Development of solar isodose lines: mercatorian and spatial guides for mapping solar installation areas. Heliyon 8(10):e11045. https://doi.org/10.1016/j.heliyon.2022.e11045
Nnamchi SN, Sanya O, Zaina K, Gabriel V (2018) Development of dynamic thermal input models for simulation of photovoltaic generators. Int J Ambient Energy 41(13):1454–1466. https://doi.org/10.1080/01430750.2018.1517676
Nnamchi SN, Mundu MM, Nnamchi OA, Onochie U, Jagun ZO (2021a) Differential modelling and simulation of solar power potential: a helio-application of biharmonic model. Model Earth Syst Environ 8(2):2383–2400. https://doi.org/10.1007/s40808-021-01232-2
Nnamchi SN, Mundu MM, Ukagwu KJ, Oyagbola IA (2021b) Development and adaptation of relative sunshine hours models for the equatorial latitudes: a case study. Model Earth Syst Environ 8(1):1191–1201. https://doi.org/10.1007/s40808-021-01147-y
Nunes P, Farias T, Brito MC (2015) Enabling solar electricity with electric vehicles smart charging. Energy 87:10–20. https://doi.org/10.1016/j.energy.2015.04.044
Overland I, Juraev J, Vakulchuk R (2022) Are renewable energy sources more evenly distributed than fossil fuels? Renew Energy 200:379–386. https://doi.org/10.1016/j.renene.2022.09.046
Özcan E, Gür E, Eren T (2021) A hybrid model to optimize the maintenance policies in the hydroelectric power plants. Politeknik Dergisi 24(1):75–86. https://doi.org/10.2339/politeknik.626171
Pfenninger S, Hawkes A, Keirstead J (2014) Energy systems modeling for twenty-first century energy challenges. Renew Sustain Energy Rev 33:74–86. https://doi.org/10.1016/j.rser.2014.02.003
Pimm AJ, Cockerill TT, Taylor PG (2018) The potential for peak shaving on low voltage distribution networks using electricity storage. J Energy Storage 16:231–242. https://doi.org/10.1016/j.est.2018.02.002
Rahimi M (2018) Improvement of energy conversion efficiency and damping of wind turbine response in grid connected DFIG based wind turbines. Int J Electr Power Energy Syst 95:11–25. https://doi.org/10.1016/j.ijepes.2017.08.005

Rahman F, Rehman S, Abdul-Majeed MA (2012) Overview of energy storage systems for storing electricity from renewable energy sources in Saudi Arabia. Renew Sustain Energy Rev 16(1):274–283. https://doi.org/10.1016/j.rser.2011.07.153

Schlandt J (2020) Agora Energiewende befürchtet große Erneuerbaren-Lücke. Tagesspiegel Background Energie & Klima. https://background.tagesspiegel.de/energie-klima/agora-energiewende-befuerchtet-grosse-erneuerbaren-luecke

Silva S, Soares I, Afonso O (2013) Economic and environmental effects under resource scarcity and substitution between renewable and non-renewable resources. Energy Policy 54:113–124. https://doi.org/10.1016/j.enpol.2012.10.069

Subramanian A, Gundersen T, Adams T (2018) Modeling and simulation of energy systems: a review. Processes 6(12):238. https://doi.org/10.3390/pr6120238

Sun L, Zhang T, Liu S, Wang K, Rogers T, Yao L, Zhao P (2021) Reducing energy consumption and pollution in the urban transportation sector: a review of policies and regulations in Beijing. J Clean Prod 285:125339. https://doi.org/10.1016/j.jclepro.2020.125339

Sykes J (2022) Incorporating behaviour in health care discrete event simulation models. Int J Simul Syst Sci Technol. https://doi.org/10.5013/ijssst.a.22.04.04

Tan KM, Babu TS, Ramachandaramurthy VK, Kasinathan P, Solanki SG, Raveendran SK (2021) Empowering smart grid: a comprehensive review of energy storage technology and application with renewable energy integration. J Energy Storage 39:102591. https://doi.org/10.1016/j.est.2021.102591

Tarashandeh N, Karimi A (2021) Utilization of energy storage systems in congestion management of transmission networks with incentive-based approach for investors. J Energy Storage 33:102034. https://doi.org/10.1016/j.est.2020.102034

Tesla (2021) Tesla big battery begins providing inertia grid services at scale in world first in Australia. https://www.pv-magazine.com/2022/07/27/tesla-big-battery-begins-providing-inertia-grid-services-at-scale-in-world-first-in-australia/

Turner B, Menendez H, Gates R, Tedeschi L, Atzori A (2016) System dynamics modeling for agricultural and natural resource management issues: review of some past cases and forecasting future roles. Resources 5(4):40. https://doi.org/10.3390/resources5040040

Vera YEG, Dufo-López R, Bernal-Agustín JL (2019) Energy management in microgrids with renewable energy sources: a literature review. Appl Sci 9(18):3854. https://doi.org/10.3390/app9183854

Withey P, Johnston C, Guo J (2019) Quantifying the global warming potential of carbon dioxide emissions from bioenergy with carbon capture and storage. Renew Sustain Energy Rev 115:109408. https://doi.org/10.1016/j.rser.2019.109408

Yoro KO, Daramola MO, Sekoai PT, Wilson UN, Eterigho-Ikelegbe O (2021) Update on current approaches, challenges, and prospects of modeling and simulation in renewable and sustainable energy systems. Renew Sustain Energy Rev 150:111506. https://doi.org/10.1016/j.rser.2021.111506

Yu C, Moslehpour M, Tran TK, Trung LM, Ou JP, Tien NH (2023) Impact of non-renewable energy and natural resources on economic recovery: empirical evidence from selected developing economies. Resour Policy 80:103221. https://doi.org/10.1016/j.resourpol.2022.103221

Zaeri N, Ashouri A, Gunay HB, Abuimara T (2022) Disaggregation of electricity and heating consumption in commercial buildings with building automation system data. Energy Build 258:111791. https://doi.org/10.1016/j.enbuild.2021.111791

Zhou Y, Wang Y, Yang M (2024) Optimal integration of renewable energy in refinery hydrogen management systems: energy storage and direct utilization. Energy Convers Manag 304:118223. https://doi.org/10.1016/j.enconman.2024.118223

Zirak M, Weiler V, Hein M, Eicker U (2020) Urban models enrichment for energy applications: challenges in energy simulation using different data sources for building age information. Energy 190:116292. https://doi.org/10.1016/j.energy.2019.116292

Zou C, Zhao Q, Zhang G, Xiong B (2016) Energy revolution: from a fossil energy era to a new energy era. Nat Gas Ind B 3(1):1–11. https://doi.org/10.1016/j.ngib.2016.02.001

Publisher's Note