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Review

Modeling and Simulation Tools for Smart Local Energy Systems: A Review with Focus on Emerging Closed Ecological Systems Application

Andrzej Ożadowicz

Department of Power Electronics and Energy Control Systems, Faculty of Electrical Engineering, Automatics, Computer Science and Biomedical Engineering, AGH University of Krakow, al. Mickiewicza 30, 30-059 Krakow, Poland; ozadow@agh.edu.pl; Tel.: +48-12-617-50-11

Abstract

The growing importance of microgrids—linking building infrastructure with distributed energy resources and storage systems—is driving the evolution of Smart Local Energy Systems (SLES). These systems require advanced modeling and simulation approaches to address their increasing complexity, decentralization, and need for interoperability. This review presents a structured analysis of commonly used environments and methods applied in the design and operation of SLES across buildings, microgrids, and local infrastructures. Particular emphasis is placed on their capabilities for multi-domain integration, predictive control strategies, and smart automation. A novel contribution of this work is the identification of Closed Ecological Systems (CES) and Life Support Systems (LSS) as promising new application domains for SLES technologies. The review explores how concepts developed for building and energy management, such as demand-side management, IoT-based monitoring, and edge computing, can be adapted to CES/LSS contexts, which demand isolation, autonomy, and high reliability. Challenges related to model integration, simulation scalability, and Earth–space technology transfer are discussed. The paper concludes with a SWOT analysis and a roadmap for future interdisciplinary research. This work lays the foundation for developing sustainable, intelligent, and autonomous energy infrastructures—both terrestrial and extraterrestrial.

Keywords: smart local energy systems; closed ecological systems; life support systems; modeling and simulation tools; co-simulation; building automation and control systems; energy management systems; demand-side management; demand side response

1. Introduction

The transition toward a sustainable and decentralized energy paradigm has catalyzed the emergence of smart local energy systems (SLES), localized, flexible infrastructures that integrate renewable energy resources (RES), advanced automation, and active user participation. Although no universally accepted definition exists, SLES are typically characterized by three interrelated components: local energy generation and balancing, digitalization and control systems, and social innovation with participatory governance models [1–3]. From a technical standpoint, the integration of distributed energy resources (DER), energy storage systems, and flexible demand-side solutions is becoming increasingly prevalent in the context of SLES, with these components being organized across multiple energy vectors, including electricity, heat, and transport [4,5]. The deployment of information and communication technologies (ICT) and building automation and control systems (BACS) is pivotal to this coordination. These technologies facilitate real-time monitoring, dynamic control, and predictive optimization across both residential and district scales. In particular, home and building energy management systems (HEMS/BEMS) have become critical enablers of local energy intelligence, thereby allowing users and the systems to which they are connected to respond autonomously to changing conditions and external signals [3,6,7]. Current research in this area focuses on the application of

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artificial intelligence (AI)-driven algorithms, including deep reinforcement learning, for adaptive control. Additionally, the development of smartness indicators, such as the Smart Readiness Indicator (SRI) is important, to assess the functional performance and responsiveness of smart buildings [8–11]. These developments are increasingly converging into unified frameworks that combine energy efficiency, flexibility, and user comfort within intelligent local infrastructures.

In addition to technological advances, SLES are also grounded in evolving social and economic models that support local ownership, shared governance, and participatory innovation. Recent studies have explored the potential of emerging configurations, such as energy cooperatives, peer-to-peer trading schemes and community energy platforms, as mechanisms to democratize access to clean energy and enhance local resilience [12,13]. These structures are increasingly supported by digital platforms that facilitate transparent communication, collective decision-making, and dynamic tariff management. Latest investigations have indicated a necessity for integrated planning approaches that combine technical simulation with social engagement strategies, thereby enabling the co-design of energy systems that reflect local preferences and capacities [14]. Furthermore, the development of tailored financial instruments, including local tariffs, shared investment schemes and municipal guarantees, is recognized as a key enabler of long-term viability and equitable participation in SLES. Research in this area is advancing towards more holistic models of energy citizenship, where users are not merely passive consumers or simply data points, but active agents in shaping the function and evolution of local energy ecosystems [3,15–17].

A critical component in the development and operation of SLES is the utilization of modeling and simulation techniques, which facilitate system design, scenario analysis, real-time control, and long-term performance evaluation. Simulation tools such as EnergyPLAN facilitate cross-sectoral and national-to-local assessments of energy configurations. In contrast, platforms such as OPEN offer detailed simulation of DER dynamics, control strategies and optimization processes [5,18]. In recent years, the role of modeling has evolved beyond physical and economic dimensions, encompassing behavior prediction, uncertainty analysis, and digital twin (DT)-based system supervision. Integrated simulation environments have been shown to facilitate the testing of dynamic control mechanisms, such as model predictive control (MPC). They have also been demonstrated to assist in the evaluation of demand side management (DSM) and demand side response (DSR) strategies [7,8,19,20]. Furthermore, these environments can be used to assess the resilience of SLES under fluctuating environmental and consumption conditions. Hybrid modeling approaches, which link physical system behavior with AI-based forecasting or control, have also gained prominence. These approaches offer scalable tools for decision-making and system adaptation in real time. Co-modeling techniques, which facilitate the integration of multiple domain-specific models (e.g., electrical, thermal, behavioral) into a unified simulation framework, are increasingly employed to capture the complexity and interdependencies inherent in SLES. It is becoming increasingly evident that these capabilities are of critical importance as SLES becomes more autonomous, data-driven, and responsive to user and grid-side requirements [1,3,14].

A research direction that is both emerging and highly demanding concerns the application of SLES concepts in the context of closed ecological systems (CES) for long-duration space missions. These autonomous and fully enclosed systems integrate biological, physical, and control subsystems into a cyber-physical life-support infrastructure. This infrastructure can sustain human life in extreme environments, such as the Moon or Mars [21,22]. CES go beyond traditional microgrids by combining multi-vector energy flows with matter loops and bioregenerative processes, all within the framework of strict long-term controllability. The architectural design of these systems necessitates the integration of photosynthetic bioreactors, waste management subsystems, and dynamic environmental control mechanisms. The presence of notable parallels between CES and islanded microgrids, including the requirement for distributed generation, hierarchical control systems and multi-scale optimization, has given rise to initiatives aimed at the transfer of microgrid control methodologies, including ISA-95-based hierarchical architectures, into the domain of CES operation [21]. In this context, modeling and simulation become indispensable not only for control design and

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performance prediction but also for evaluating long-term system viability, detecting anomalies, and enabling predictive maintenance. It is imperative that models incorporate highly heterogeneous domains (electrical, thermal, biological), operate across multiple timescales, and maintain coherence between physical measurements and simulated states. The concept of CES further expands the principles of DSM and DSR by incorporating the regulation of biological rhythms, the prioritization of life-critical subsystems, and the closed-loop optimization of environmental parameters such as oxygen, carbon dioxide, and humidity [23,24]. Consequently, SLES have emerged as a unifying framework for intelligent, decentralized energy infrastructure, thereby bridging the domains of automation, environmental sustainability, and community empowerment. The extension of this work towards the extreme autonomy of CES highlights the transformative potential of modeling and simulation in enabling complex, adaptive, and resilient infrastructures, both on Earth and beyond.

Bearing in mind all these aspects, the following review makes an original contribution by identifying and framing CES and life support systems (LSS) as emerging domains of application for SLES modeling and control approaches. The extension of local energy system principles to life support environments not only opens novel interdisciplinary research frontier but also sets new expectations and challenges for existing technologies. The BACS and HEMS/BEMS, which were originally developed for the purpose of enhancing user comfort and energy flexibility in smart buildings, must evolve to support autonomous regulation of closed habitats, including critical life-sustaining parameters. In a similar fashion, modeling and simulation tools must be capable of accommodating coupled multi-domain dynamics (biological, chemical, thermal, electrical), operating across a broad spectrum of time scales, and integrating co-modeling frameworks. This ensures predictive, adaptive, and fail-safe operation under extreme autonomy conditions. These challenges necessitate hybrid, scalable, and semantically integrated solutions that span the domains of energy informatics, automation, and bio-regenerative system control. By integrating smart buildings, local energy systems, and closed-loop life support infrastructures into one analytical framework, this review establishes a foundation for future interdisciplinary research and innovation in modeling, simulation, and intelligent control of sustainable, resilient, and autonomous environments.

The rest of the review is organized as follows. Section 2 outlines the review methodology and literature selection criteria. Section 3 provides an analytical overview of modeling and simulation tools applied to SLES, microgrids, and buildings. Section 4 discusses the challenges and research trends related to extending these tools toward CES and LSS. Section 5 presents a thematic discussion on key areas of tool adaptation, integration strategies, and Earth–space technology transfer, culminating in a SWOT analysis. Finally, Section 6 concludes the paper and outlines future research directions.

2. Materials and Methods

This review was conceptually inspired by the one of the latest publications “New Horizons for Control and Energy Management of Closed Ecological Systems” [23], which outlines future directions in energy management, control, and predictive technologies within the context of CES and LSS. Drawing on this foundation, the objective of this review is to investigate how methods, tools, and systems developed for smart buildings and local energy infrastructures can contribute to the development and operation of CES platforms for long-duration space missions. In particular, the review explores the adaptation of BACS, Internet of Things (IoT), energy management, and simulation technologies to autonomous, human-centered, closed-loop environments.

The methodology applied in this review was structured in four main phases, which are presented in the following subsections.

2.1. Scoping and Framing

The review was positioned at the intersection of three interrelated domains:

- Smart building and infrastructure technologies, including BACS, BEMS, HEMS;
- SLES, including microgrids, DSM, and DT;

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- CES and LSS relevant to long-duration human spaceflight and off-Earth habitats.

The main research focus was to determine whether and how existing knowledge and technologies from the building and energy domains could be effectively transferred and adapted to the needs of CES and LSS architectures. In particular, the review investigates the modeling and simulation methods and tools employed across these domains in research and practical implementation, in order to assess their applicability to highly autonomous, human-centered, closed-loop environments. This framing was also motivated by the growing convergence of research trends in energy informatics, embedded control, and space systems engineering, which increasingly highlight the need for integrated, self-regulating platforms capable of operating in isolated, resource-limited conditions. The review therefore adopts a systems-level perspective to analyze the design, optimization, and long-term operation of energy and control subsystems. Particular emphasis is placed on cross-domain comparison and the transferability of modeling strategies, simulation environments, and analytical frameworks in both terrestrial and space-based contexts.

2.2. Literature Search Strategy

A multi-stage search strategy was adopted, combining systematic database querying with targeted selection from publisher-specific resources. The primary bibliographic databases used in the initial search phase were Web of Science, Scopus, and, to a supplementary extent, Google Scholar. The keywords used to search for relevant papers, combined using various Boolean operators, included the following: local energy systems, microgrids, modeling, simulation, building automation and control systems, life support system, closed energy system, digital twin, habitat, and demand side management.

Based on the initial filtering of abstracts and titles, full-text sources were retrieved from the following publisher platforms: ScienceDirect (Elsevier), IEEE Xplore, SpringerLink, and Wiley Online Library. The selection of papers was based on the following inclusion criteria: firstly, the research articles and conference papers had to be peer-reviewed; secondly, the primary period of publication was between 2010 and 2025; thirdly, particular emphasis was given to papers published from 2015 onwards.

2.3. Literature Search Strategy

The finalized literature set encompassed several dozen scientific publications, with the majority comprising research articles and a smaller subset consisting of review papers. Two dominant groups were identified:

- the initial group comprised articles that presented research findings and developmental work on the modeling, simulation, and control of smart buildings and energy systems. The majority of these publications were from Elsevier journals and the MDPI platform, with significant representation in the domains of energy informatics, automation, and building simulation;
- The second group encompassed studies focusing on practical applications and design of SLES, including the use of modeling and simulation tools for various use cases and operational environments. The preponderance of publications from the IEEE Xplore system within this group is notable, encompassing both conference proceedings and journal articles that pertain to the domains of embedded systems, smart grid control, and integrated energy solutions.

2.4. Identified Gap and Contribution Rationale

A significant observation during the review process was the paucity of publications directly addressing the integration of automation, energy management, and modeling tools within CES and LSS platforms, particularly in the context of human-centered space habitats. While there are numerous studies that explore smart buildings and energy systems in terrestrial settings, relatively few extend their analysis or application to closed-loop environments that are relevant for space missions.

This discrepancy has been observed even in recent publications from the last decade. Considering these facts and in order to ensure adequate contextualization of developmental trends,

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the literature review period was deliberately extended to cover approximately the last 10 to 15 years. This permitted the incorporation of a limited number of earlier, yet conceptually relevant publications that provided theoretical grounding, early modeling frameworks, and foundational perspectives on CES control strategies. While these references were not predominant in the review, they offer significant continuity with contemporary approaches. This thematic gap, together with the author's ongoing research in smart building, smart grid technologies, and space system applications, forms the foundation of the original contribution of this review. The aim is to bridge these domains by providing a systematic synthesis of tools, strategies, and knowledge streams that may inform future research and the implementation of CES-aligned infrastructures for autonomous and sustainable space missions. The initial delineation of this contribution and its underlying motivations is mentioned as well in Section 1 – Introduction.

3. Modeling and Simulations—Analytical Overview

In the context of SLES, buildings, and district-level infrastructures, modeling and simulation are foundational but distinct concepts that are frequently discussed in the reviewed literature. Modeling can be defined as the process of abstracting real-world energy systems into mathematical, logical, or agent-based representations. As discussed in [25,26], these models can capture the structure, behavior and interactions of physical components, control systems and user behaviors. By way of contrast, simulation can be defined as the process of executing these models to analyze system behavior over time under different scenarios, operational conditions or control strategies [27,28]. This distinction is discussed and emphasized in several research studies and papers. For instance, Schiera et al. [29] discuss the co-simulation frameworks and describe how domain-specific models (e.g., thermal dynamics, PV generation, user behavior) are created independently and then simulated together in a synchronized environment using platforms like Mosaik or functional mock-up interface (FMI)-based orchestration. The utilization of a modular structure facilitates the concept of plug-and-play flexibility, in addition to supporting distributed computation. This phenomenon demonstrates the separation of modeling and simulation in both logic and implementation. Furthermore, the application of simulation is conventionally linked to the evaluation of system performance, the optimization of configurations, and the testing of control strategies with hardware-in-the-loop (HIL) technics [30,31]. In contrast, modeling predominantly concentrates on conceptual design, system abstraction, or multi-domain integration [32,33].

This analytical section therefore builds upon these distinctions to classify tools according to their modeling abstraction capabilities and simulation functionality, as well as their scope, interoperability and use in decision-making processes across various smart energy, building and local microgrids applications.

3.1. Modeling—Tools, Approaches and Applications

As briefly mentioned above, modeling is the backbone of system abstraction and conceptual representation in smart energy applications. It allows researchers and engineers to formalize physical, cyber and socio-technical elements, such as energy flows, building behavior and district-level infrastructure, into logical structures that can be analyzed, optimized and simulated. Analysis of the publications selected for this review shows that the following modeling tools and methods are used most extensively. These are presented in Table 1.

Table 1. Cumulative analysis of modeling tools literature.

Modeling Tool	Occurrences	Papers/Articles
EnergyPlus	7	[27,31,34–38]
Modelica	6	[25,27,29,39–41]
TRNSYS	4	[28,30,42,43]
Matlab/Simulink	4	[28,42,44,45]
GridLAB-D	4	[46–48]

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These tools form the technological basis for modeling energy systems, ranging from detailed building simulations (e.g. EnergyPlus and TRNSYS) to modular, multi-domain representations (e.g. Modelica and MATLAB/Simulink), as well as agent-based, grid-oriented platforms (e.g. GridLAB-D). Each of these environments has its own specific strengths. For instance, EnergyPlus is ideal for thermal comfort and building envelope modeling, Modelica is perfect for component-based cyber-physical simulation, and MATLAB is excellent for integration with predictive control logic.

However, modeling approaches in energy systems research differ in more than just the tools applied; they also differ in their underlying paradigms. Five major categories emerge from the reviewed literature, as presented in Table 2.

Table 2. Cumulative analysis of modeling methods literature.

Modeling Method /Approach	Occurrences	Papers/Articles
Physical modeling	5	[25,30,34,39,43]
Optimization-based modeling	5	[31,35,36,49,50]
Geospatial / GIS-based modeling	4	[36,38,51,52]
Data-driven modeling	3	[32,53,54]
Hybrid modeling	3	[27,29,55]

Taken together, these modeling approaches reflect the diversity of challenges addressed in the design and evaluation of smart building and energy systems. Physical modeling remains dominant in building and district-level studies due to its ability to accurately represent thermal, electrical and mechanical behaviors. Optimization-based models are essential for system planning and control strategy assessment. Geographic information systems (GIS)-based methods also support spatially resolved urban and district energy planning. Data-driven and hybrid approaches are increasingly used to capture dynamic behaviors and enable integration with predictive control or AI systems.

The literature review presents a wide range of modeling practices used in various energy domains. For this review, particular attention is paid to modeling applications in the context of SLES, microgrids, and buildings. These three domains represent critical interfaces between energy generation, consumption, and management. The author reviewed the nature of the models developed for each domain, focusing on their structure, purpose, and innovative contributions.

3.1.1. SLES Modeling Domain

In SLES modeling, the emphasis is placed on capturing the multi-vector structure of local energy systems, often integrating electricity, heat, and mobility components. The models employed in this domain are designed to represent distributed infrastructures, their control hierarchies, and actor-specific behaviors within local communities.

It is a common practice among researchers and engineers to adopt modular physical modeling frameworks for the purpose of representing components and interactions. To exemplify this, one may consider Modelica-based models, which, as Qiu et al. [25] have demonstrated, facilitate the abstraction of thermal and electrical subsystems with both high temporal and structural resolution. An additional focus in SLES is on spatial and infrastructural representation, where tools such as DesignBuilder and EnergyPlus are employed to develop energy demand models at the district scale [53,56]. Rezaei et al. [50] present a district-level low-carbon planning method that combines building-level simulation and data-driven post-processing using MATLAB. Optimization-based models are also prominent, especially those incorporating investment and operational trade-offs under uncertainty. For instance, Zwicki-Bemhard et al. [31] have developed a district energy planning framework that integrates probabilistic load models and techno-economic variables. In a similar vein,

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Ascione et al. [36] propose the integration of GIS-based modeling for retrofitting scenarios, by establishing a linkage between geospatial data and demand and envelope models.

3.1.2. Microgrid Modeling Domain

The focus of microgrid modeling lies in the representation of autonomous system behavior, local energy balances, and resource complementarities. In this context, the primary objective of models is to delineate the way diverse generation and storage units interact with one another under the constraints of operational logistics at the local level.

Parejo et al. [44] employ multi-energy modeling in MATLAB to characterize the interplay between thermal and electric subsystems within a smart building microgrid. The model is designed to capture user preferences, climate conditions, and system feedback mechanisms. In this domain, physical modeling with Modelica is also employed. Wu et al. [40] construct detailed thermal and electric subsystem models of a building energy system, highlighting the capability of Modelica to handle multi-domain representations within microgrids. Furthermore, in the paper [29] Cai et al. employ the use of Modelica to represent physical models of energy components, including but not limited to heat pumps, thermal storage and electrical loads, within the context of a smart building microgrid. The modeling approach that has been developed enables scalable integration of thermal and electrical subsystems as part of a distributed simulation architecture. Another GridLAB-D, an agent-based modeling tool, is utilized to abstract microgrid components and their control rules. In the work by Chassin et al. [46], this tool is adapted to model distribution system dynamics and load control under local resource scenarios. Moreover, Wang et al. [47] have developed a testbed that integrates GridLAB-D and MATLAB to model a distribution-level microgrid that incorporates renewable energy sources and demand response mechanisms. GridLAB-D is utilized to construct detailed agent-based models of loads, DERs, and control logic, thereby enabling the exploration of self-regulating microgrid behavior in response to dynamic conditions.

3.1.3. Buildings Modeling Domain

In the field of building-focused modeling, engineers and scientists primarily seek to represent thermal dynamics, HVAC system behavior, and user-driven energy use patterns. High-resolution physical modeling is the prevailing paradigm in this field, with tools such as EnergyPlus, TRNSYS, and Modelica being utilized.

In their work, Harish et al. [34] explore a range of modeling strategies for thermal zones, airflows, and control systems in building environments. They underscore the necessity for precise envelope and occupancy modeling. In a similar manner, Dogkas et al. [43] constructed detailed TRNSYS models to evaluate the performance of hybrid heating systems in multi-family housing. In the field of structural engineering, there has been a recent focus on hybrid modeling approaches that integrate physical models with behavioral or statistical layers. This integration of physical and numerical methods has proven to be a fruitful avenue for exploring the complex interplay between infrastructure elements and their statistical properties. Duerr et al.[53] for instance, extend traditional physical models with machine-learning-based demand profiles to support responsive control. Further discussion of this topic can be found in [32]. In their seminal study, Liu et al. identify and categorize hybrid modeling approaches that combine physical models (e.g. thermodynamic equations, equipment-level logic) with data-driven layers (e.g. deep learning, graph-based models) for capturing complex energy interactions in urban buildings. These hybrid models are particularly well-suited to multi-energy systems, where electricity, heat, and cooling interact dynamically with building operations. The spatial dimension of building modeling is also a salient feature. The utilization of GIS-based models facilitates the conversion of building stock and urban morphology into zonal demand profiles and retrofit impact models, as evidenced by Hoffner et al. [51].

To summaries, the reviewed modeling efforts for various domains are characterized by three features. Firstly, there is growing integration across domains (thermal–electrical–spatial). Secondly, there is the use of optimization and control-oriented abstractions. Thirdly, there is the development

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of modular, scalable modeling platforms. Whether applied to buildings, microgrids, or community-level systems, models increasingly aim to bridge the gap between technological complexity and practical decision-making needs.

3.2. Simulation—Tools, Approaches and Applications

Simulation is a pivotal component of energy systems research, functioning as a proving ground for evaluating system behavior, validating control strategies, and comparing alternative scenarios under diverse technical and operational conditions. In contrast to modeling, which is concerned with abstracting system structure, simulation is employed to study system behavior over time, frequently with dynamic, uncertain, or complex interactions. It enables researchers and practitioners to reproduce realistic operating conditions, assess system stability, and optimize performance prior to implementation.

A review of the literature reveals the application of simulation in a variety of domains, ranging from building-level thermal efficiency to district-level load balancing and smart grid dynamics. The subsequent Tables 3 and 4 present a compendium of the most frequently employed simulation instruments and methodologies, accompanied by a selection of pertinent publications.

Table 3. Cumulative analysis of simulation tools literature.

Simulation Tool	Occurrences	Papers/Articles
EnergyPlus	6	[27,34–36,38,53]
TRNSYS	4	[28,30,42,43]
Modelica	3	[29,39,40]
MATLAB/Simulink	3	[42,44,45]
GridLAB-D	3	[46,47,57]
IDA ICE	3	[35,37,58]
OpenDSS	3	[5,52,59]
HOMER	2	[49,60]

Table 4. Cumulative analysis of simulation methods literature.

Simulation Method /Approach	Occurrences	Papers/Articles
Dynamic simulation	5	[39,40,43–45]
Building energy simulation	5	[34–36,38,53]
Thermal-energy simulation	4	[30,34,39,43]
Electric grid simulation	4	[45,48,49,52]
HIL (Hardware-in-the-loop)	4	[27,41,47,48]

The analysis identifies EnergyPlus, TRNSYS, and IDA ICE as the most frequently used simulation tools, with each supporting comprehensive and multi-layered simulations across energy domains. In such cases, the utilization of tools such as Modelica and MATLAB/Simulink is also widespread, particularly in instances where dynamic behaviors and control mechanisms represent a central focus of the study. In contrast, platforms such as GridLAB-D, OpenDSS and HOMER are designed to fulfil more specialized roles, typically focusing on specific aspects including distribution networks, power flow or techno-economic analysis. These results underscore the heterogeneity of simulation environments in energy research.

The following Table 4 provides a more detailed exploration of the dominant simulation methods and approaches that are employed across the same body of literature.

The analysis reveals that dynamic simulation and building energy simulation are the most prevalent approaches, each appearing in five distinct publications. These methods are critical for the capture of time-dependent behavior and energy use patterns, particularly in systems with control dynamics or occupant interaction. The simulations of thermal energy and electric grids are closely

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related, reflecting the significance of simulating heat flows and electrical power in local energy systems. It is noteworthy that HIL approaches have been documented in four publications, suggesting a mounting interest in real-time validation of control strategies and cyber-physical integration. This development underscores the mounting convergence of simulation with experimental and hardware-based environments in the context of smart grids and microgrid applications.

A comprehensive overview of the extant literature indicates a wide range of applications of simulation in the energy sector, including studies of grid-scale stability and detailed performance evaluations of buildings. The objective of this review is to analyze simulation approaches in the context of SLES, microgrids, and buildings. These domains illustrate how simulation is used not only for scenario testing and optimization, but increasingly for real-time validation and cyber-physical integration. The subsections that follow provide a concise overview of the observed applications and motivations for simulation across these three domains.

3.2.1. SLES Simulation Domain

In the context of SLES, simulation is utilized to evaluate multi-vector energy flows, distributed control, and interoperability of subsystems. The aforementioned studies typically utilize modular and flexible tools capable of capturing the complex interactions between electrical, thermal, and control domains.

For instance, Barbierato et al. [27] utilize EnergyPlus and FMI-based interfaces to simulate SLES interactions within a hybrid co-simulation framework, thereby enabling detailed analysis of control strategies across domains. In a similar manner, the OPEN platform, which has been validated using OpenDSS, supports the simulation of decentralized smart energy scenarios and real-time energy management [5]. In other studies, district-scale simulations have been utilized to analyze energy distribution and optimization strategies. Rezaei et al. [50] employ DesignBuilder and MATLAB to model low-carbon district scenarios, emphasizing the significance of dynamic simulations in supporting planning and decarbonization objectives. In a related application, Zwicki-Bemhard et al. integrate probabilistic elements into their simulation of district energy under uncertainty using URBANopt and optimization algorithms [31]. In addition to technical integration, numerous studies underscore the significance of simulating scalability and flexibility in SLES. For instance, Oluah et al. present a structured overview of simulation-based modeling approaches for scaling up SLES, identifying technical, economic, and social indicators used in energy system transformation scenarios. The analysis incorporates both established tools, such as EnergyPLAN, and novel modular platforms, including PyLESA [26]. Another contribution is derived from a study that focused on simulating local flexibility and performance metrics in decentralized systems. Utilizing a component-level modeling approach, the authors assess the flexibility potential, emissions, and load shifting capabilities in smart neighborhoods incorporating electric vehicles (EVs), thermal storage, and demand-responsive appliances [61]. The presented examples illustrate that simulation in SLES contexts functions as both a design instrument and an analytical framework for policy, optimization, and system architecture evaluation at local scales.

3.2.2. Microgrid Simulation Domain

The focus of microgrid simulation lies in real-time control, islanding behavior, and multi-energy integration. It is well established that tools such as MATLAB/Simulink, Modelica, and GridLAB-D are commonly utilized for the purpose of capturing dynamic responses and interactions between DERs, storage systems, and control algorithms.

In a biologically inspired application, Parejo et al. [44] simulate a homeostatic energy management system for thermal and electrical balance in a building-based microgrid using MATLAB/Simulink. Ntomalis et al. simulate grid-forming and frequency stability behaviors on Madeira Island under high renewable penetration, emphasizing the importance of dynamic simulation in non-interconnected systems [45]. It is also worthy of note that a significant number of studies have incorporated HIL approaches for the purpose of validating microgrid control in real-time. For instance, in [48] real-time

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simulators are coupled with GridLAB-D and EnergyPlus to test smart grid components under realistic operating conditions. In another case, authors utilize GridMat (a MATLAB–GridLAB-D interface) for HIL validation of microgrid controllers in a cyber-physical setting [41].

3.2.3. Buildings Simulation Domain

The application of simulation tools is most extensive at the building level, where they support performance evaluation, retrofit analysis, and integration of renewable energy and control systems. The aforementioned software, namely EnergyPlus, TRNSYS and IDA ICE, are dominant in this field, offering high-resolution models of HVAC systems, occupant behavior and thermal dynamics.

Harish et al. [62] present an overview of simulation techniques for building energy systems, comparing the strengths and limitations of different tools. Dogkaz et al. [43]utilize TRNSYS to evaluate hybrid heating configurations in multi-family buildings under cold-climate conditions, with a particular focus on seasonal efficiency. IDA ICE is distinguished by its meticulous modeling of indoor comfort and HVAC systems. In a comparative study by Meiers et al., IDA ICE was found to outperform TRNSYS and EnergyPlus in replicating measured indoor temperatures in cold climates [37]. Furthermore, Ascione et al. [36] combine GIS, EnergyPlus, and MATLAB to simulate the impacts of building retrofitting across neighborhoods, emphasizing the spatial and temporal resolution of simulation in planning scenarios. Hybrid approaches have also emerged, as evidenced by [53], where Duerr et al. integrate machine learning forecasts with physical simulations for real-time building control and energy scheduling. Furthermore, certain studies employ HIL simulation to evaluate the real-time interaction between building energy systems and control hardware. In [48] the authors implement a Smart Home HIL configuration that combines EnergyPlus with physical HVAC devices (e.g., thermostats, air conditioners) and GridLAB-D for electric system simulation. This configuration facilitates the evaluation of control strategies within a range of realistic weather profiles, electricity tariffs and dynamic thermal responses. These examples emphasize the importance of simulation in connecting building performance, occupant needs, and smart control systems through detailed and often hybrid simulation environments.

Considering these analyses, it is concluded that simulation plays a pivotal role in the analysis and design of smart energy systems, in addition to supporting performance evaluation, the development of control strategies, and the exploration of future scenarios across SLES, microgrids, and buildings. The selection of tools and methods is informed by the unique demands of each domain, encompassing temporal precision and the extent of system integration. The increased utilization of real-time and HIL methodologies underscores the transition towards more interactive, validated and cyber-physically integrated simulation environments.

3.3. Co-Modelig and Co-Simulation Approaches

Bearing in mind the progressively intricate nature of contemporary energy systems, co-simulation has emerged as a pivotal methodology for integrating multi-domain models – encompassing thermal, electrical, control, and ICT domains – within a cohesive simulation workflow. It facilitates the interoperability of tools and solvers with different time steps and numerical methods in real-time or batch simulation environments. The adoption of the FMI standard has been instrumental in facilitating cross-platform compatibility and the reusability of models.

As demonstrated in studies such as Schiera et al., the advantages of distributed multimodel co-simulation using Mosaik and FMI to link smart building subsystems in a scalable and flexible environment are apparent [29]. In a similar vein, Barbierato et al. [27] have employed a hybrid simulation approach to integrate the control, communication, and physical layers within a cohesive architecture for smart grids. At the interface of energy and ICT, Aslam et al. integrate OMNeT++ with MATLAB/Simulink using the CSMO framework to capture time delays and network dynamics in smart grid control [63]. A broader review by Palensky et al. outlines architectures and technical challenges in co-simulation of cyber-physical energy systems, including synchronization, data exchange, and real-time constraints [64].

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While the term co-modeling is occasionally encountered in the extant literature, it is notable that a standardized definition is absent. The term is typically used in a conceptual sense, for example to describe collaborative or interdisciplinary model development. Conversely, co-simulation is a well-established and increasingly necessary approach to address the modular, heterogeneous and real-time nature of smart energy systems. Its increasing utilization is indicative of the necessity for interoperability and cross-domain integration in both design and operational analysis. The relevance of co-simulation is predicated on its ability to link models from different engineering domains and software environments, even when these rely on incompatible solvers or time resolutions. This facilitates detailed and system-level analysis without compromising domain-specific accuracy. Examples of this phenomenon include:

- coupling MATLAB/Simulink with OMNeT++ for integrated control and communication analysis;
- integrating EnergyPlus with GridLAB-D to combine building dynamics with grid-side behaviors;
- using the FMI standard to interface models from tools such as Modelica, Simulink, and TRNSYS.

It is noteworthy that such configurations preserve modeling independence while supporting advanced scenario analysis, real-time testing, and holistic system validation. Consequently, this renders co-simulation a cornerstone of modern smart energy management system research.

4. Challenges of SLES and CES: Emerging Research, Engineering, and Application Trends

As it has been shortly mentioned in Section 1, the evolution of energy systems towards decentralization, intelligence and flexibility has given rise to advanced concepts such as SLES, microgrids and smart buildings. These frameworks integrate local generation, storage, flexible loads, and user-aware control, forming a mature yet continuously evolving class of solutions. In recent years, there has been an increasing tendency to utilize digital tools, predictive modeling, and multi-domain coordination with a view to enhancing energy autonomy, resilience, and sustainability [53,61].

Despite their technical sophistication, these systems are undergoing continuous development to address emergent demands pertaining to interoperability, user engagement, and integration across energy, water, mobility, and communication layers. This expanding scope creates a conceptual and technological bridge to a new class of systems like CES [27]. It is evident that CES represents a context that is fundamentally more constrained and interdependent. The development of CES can be traced back to its inception as experimental ecosystems, with subsequent adaptation for utilization in space LSS. The fundamental design objective of CES is to facilitate the sustenance of human life within fully or semi-isolated environments, achieved through the implementation of closed material and energy loops. In contradistinction to SLES or conventional microgrids, CES are required to guarantee long-term autonomy within water, air, food and energy cycles, frequently with minimal or no resupply. Recent years have seen a resurgence of interest in the fields of extraterrestrial bases, long-duration space missions, and lunar or Martian habitats. This has led to a renewed focus on research into CES, which are now regarded not only as space engineering challenges but also as extreme testbeds for sustainable system integration [65,66]. However, research and development in CES and LSS remains in its infancy, particularly regarding space-based applications, which explains the limited body of scientific literature available in this domain.

The ongoing development of smart energy systems is particularly relevant to CES, due to the convergence of technologies and control philosophies. It is evident that a significant proportion of the tools and strategies that have been developed in the context of SLES, including but not limited to hierarchical control architectures, co-simulation environments, model-predictive control, and DTs, are currently being explored or adapted for utilization in CES scenarios [23]. Furthermore, space-based CES and LSS act as paradigm models for circular economy practices and closed-loop system

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thinking, thereby providing feedback to Earth-bound applications in remote or resource-scarce regions [66,67].

4.1. SLES—Integration Potential and Toolchains

As presented in the analyses provided in Section 3, SLES employ a wide range of modeling and simulation environments that reflect their inherently multi-domain, modular nature. Recent advancements in this field demonstrate a marked convergence of simulation engines, control platforms, and data-driven architectures, thereby facilitating the integrated design, operation, and optimization of decentralized energy systems. Core simulation tools such as EnergyPlus, TRNSYS, and Modelica remain central to the modeling of building energy dynamics and district-scale interactions. It is evident that these are frequently enhanced through co-simulation with MATLAB/Simulink, GenOpt, or Python-based optimization engines [35,37]. This process serves to extend their analytical capabilities and control integration.

It is particularly intriguing to note that co-simulation frameworks are of pertinence in the context of SLES, given the necessity to establish connections between subsystems such as thermal storage, photovoltaics, EV charging, HVAC, and user interfaces. Platforms such as MOSAIK, BCVTB and FMI-based workflows facilitate the coupling of these domains, thereby maintaining solver independence whilst allowing for time synchronization and data exchange. The aforementioned process facilitates the integration of both rapid-response components and slow-varying environmental or user-related dynamics within a unified framework [27,29]. Moreover, recent platforms, including SmartBuilds and the OPEN framework, have been shown to enhance the capacity for real-time simulation, data exchange, and control logic prototyping. The integration of physical models with live or synthetic data streams is a key feature of these systems. This integration facilitates scenario testing and decision support for operators, planners and researchers [5,53].

It is also crucial to emphasize that many of these toolchains place significant emphasis on modularity, scalability, and interoperability. Standardized interfaces such as FMI facilitate the reconfiguration and expansion of SLES environments, enabling them to adapt to emergent technologies or operational objectives. Nonetheless, there are still issues to be addressed in terms of achieving concordance in temporal and spatial resolution between models, incorporating stochastic user behavior, and aligning multi-objective performance criteria across the various layers of the system [61,68]. Overall, the maturation of SLES toolchains is particularly evident in terms of co-simulation, hierarchical control, and integration of heterogeneous subsystems. This provides a robust foundation for the extension of these methods to more constrained and closed-loop systems, such as those envisaged for CES and space-based life support infrastructures.

4.2. CES—Specific Environment and Conditions for Simulation and Modeling

In contrast, CES exemplify a pronounced and highly integrated paradigm of autonomous operation, wherein the complete cycle of all resources is internally managed with minimal or no reliance on external input. This imposes a set of stringent conditions that profoundly affect the modeling and simulation of such systems. Conventional SLES may still interact with the larger grid or external infrastructure; however, CESs operate in isolated, self-contained configurations, frequently under extreme or extraterrestrial conditions. Consequently, these systems must be characterized by precision, reliability, and systemic integration across energy, environmental, and biological subsystems.

The first defining characteristic is the strict closure of material loops. It is imperative that CESs achieve high degrees of recycling for water, oxygen, carbon dioxide, and nutrients. Achieving this objective necessitates the modeling of tightly coupled biochemical and physical flows. For instance, the MELiSSA (Micro-Ecological Life Support System Alternative) developed by the European Space Agency (ESA) is composed of interconnected bioreactors, each of which simulates a specific ecological function, such as the absorption of carbon dioxide, the regeneration of oxygen, or the recycling of waste [21,22]. The modeling approaches employed in such cases must be capable of

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capturing microbial kinetics, nutrient dynamics, and gas-liquid exchanges, often across different spatial and temporal scales.

Secondly, the absence of access to external energy and data networks necessitates highly autonomous simulation and control architectures. This encompasses embedded diagnostics, prognostics, and fault-tolerant designs that are not only energy-efficient but also computationally robust under uncertain conditions. As demonstrated by Ciurans et al. [21], hierarchical control systems facilitate the integration of metabolic loads, environmental regulation, and human activity through layered and modular architectures. In a broader context, Harry Jones [24] describe the integration of decentralized sensor and control elements that provide redundancy and enable continuous reconfiguration without human intervention—a capability critical for long-duration missions. In a similar vein, the review of analogue habitats by Heinicke et al. [65] underscores the imperative for embedded automation routines and autonomous supervision systems that transcend conventional supervisory control, encompassing health monitoring and local decision-making.

Thirdly, the requirement for maximum reliability and life-sustaining precision necessitates the implementation of hybrid modeling methods that combine deterministic system equations with stochastic or adaptive layers. Bazmohammadi et al. [23] emphasize that the intricacies inherent in the behavior of the crew, the unpredictability of resource availability, and the non-linear dynamics of the system necessitate the utilization of probabilistic modeling, Markov-based control, and, with increasing frequency, the employment of digital twins to facilitate predictive planning and enhance the accuracy of simulations. As Chebbo et al. have observed [69], these approaches are of particular value in the domains of scenario-based planning and anomaly detection. This is due to the analysis of the relationship between failure propagation and system redundancy in integrated CES microgrids. Furthermore, the necessity to simulate human variability and metabolic fluctuations has resulted in a significant increase in the development of agent-based and hybrid stochastic-deterministic frameworks.

Finally, CESs require integrated modeling of energy, environment, and human factors—not only as separate domains but as interdependent subsystems. It is imperative that environmental models are capable of tracking thermal comfort, humidity control, air composition (e.g. oxygen, carbon dioxide, volatile organic compounds), and the performance of life-supporting elements such as plant chambers or water recycling systems. Ellery et al. demonstrate how these closed-loop flows (e.g., carbon, nitrogen, phosphorus, water) form the foundation of ecological balance in CES and LSS, and it is imperative that they are simulated with cross-domain awareness [22]. Similarly, the utilization of holistic modeling frameworks has been proposed as an effective strategy to support the establishment of sustainable and self-sustaining environments in long-duration space missions, thereby promoting the efficient utilization of resources and the promotion of regeneration [70].

In conclusion, it is rather clear that the application of simulation and modeling in CES and LSS extends far beyond the scope of traditional energy system analysis. The integration of biological, behavioral, and psychological factors into energy and environmental control loops introduces new layers of complexity that demand interdisciplinary approaches. The advent of emergent concepts, such as digital twins and AI-based predictive control, facilitates real-time monitoring, fault detection, and adaptive system management under conditions of elevated uncertainty and autonomy requirements. Recent studies have demonstrated the implementation of CES digital twins that incorporate sensor feedback, probabilistic crew behavior modeling, and AI-driven decision support [23]. These developments indicate new research and technological innovation directions, both in the context of future space missions and in the advancement of next-generation, human-centered SLES applications on Earth.

4.3. Transferability of SLES Modeling and Simulation Approaches to CES

In consideration of the information provided in previous subsections 4.1 and 4.2, it is evident that a significant proportion of the tools and methodologies developed for SLES demonstrate considerable adaptability to CES, notwithstanding the inherent disparities in scope, autonomy, and complexity. It is

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particularly pertinent to consider simulation environments that facilitate multi-domain coupling, modular architecture, and co-simulation integration, which are well-aligned with the system-of-systems paradigm characteristic of CES. Environments such as TRNSYS, Modelica, and MATLAB/Simulink already support detailed modeling of thermal loops, control strategies, and subsystem interaction. TRNSYS is extensible with CES-specific modules (e.g., waste heat recovery, plant lighting), while Modelica's object-oriented structure and compatibility with FMI allow for scalable integration of biological and energy models. Furthermore, the utilization of FMI is a particularly valuable asset in both SLES and co-simulation research, given its wide adoption in these fields. Indeed, it is instrumental in the creation of flexible, cross-platform simulation chains, which are of paramount importance for the design of CES [27,37]. The integration of control, energy, and communication systems is facilitated by MOSAIK, BCVTB, and CSMO, which provide further support for simulation coordination across domains. In the context of CES, where time-sensitive coordination of environmental and metabolic flows is required, such co-simulation methods are critical [63].

The availability of additional tools, such as GridLAB-D and OMNeT++, provides valuable extensions to the capabilities of the system. GridLAB-D provides a power system simulation environment that is particularly well-suited for the modeling of CES microgrids. Conversely, OMNeT++, when employed in conjunction with MATLAB, offers a framework for the development and evaluation of communication network models, with a particular emphasis on the testing of control layers [24,46,47]. Meanwhile, SmartBuilds and the OPEN platform have demonstrated the potential for real-time optimization and control. However, enhancement is required to support biological and psychological modeling layers, in particular considering LSS applications [53].

The Table 5 summarizes and compares these tools in terms of their roles in SLES, transferability to CES, and readiness for co-simulation.

Table 5. Comprehensive summary of tools transferability to CES.

Tool/Framework	Description/Role in SLES	Transferability to CES	Co-Simulation Capability
EnergyPlus	Widely used for building energy modeling; useful for thermal and ventilation modeling in CES	Moderate – limited biological/environmental coupling	Moderate – supported via BCVTB, FMI
TRNSYS	Flexible multi-domain simulation; supports custom loops and thermal subsystems	High – extensible with new CES modules	High – native support for co-simulation and FMI integration
Modelica	Object-oriented, multi-domain modeling; supports FMI and custom component libraries	Very High – strong for integrated CES models	Very High – extensive FMI and tool coupling capabilities
MATLAB/Simulink	Widely used for control systems and component modeling	High – suitable for subsystem-level modeling and integration	High – FMI, Simulink co-simulation, real-time HIL
FMI (Functional Mock-up Interface)	Standard for model exchange and co-simulation	Very High – supports modular, cross-platform integration	Core co-simulation model
Co-simulation (MOSAIK, BCVTB, etc.)	Couples models across tools and domains	High – needed for integration of energy, life support, and control	Core co-simulation model

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SmartBuilds	Real-time simulation with EnergyPlus + control/data layers	Moderate – lacks direct support for biological loops	Moderate – integrated co-simulation architecture
OPEN platform	Open-source framework for SLES coordination and simulation	Moderate – promising structure but needs CES-specific modules	Moderate – supports modular agent-based coordination
GridLAB-D	Used for modeling distributed power systems and control logic in smart grids	Moderate – suitable for electrical layers in CES microgrids	Moderate – supports coupling with EnergyPlus and real-time testbeds
OMNeT++ / CSMO	Simulates communication networks and integrates with energy models via MATLAB	Moderate – enables ICT-performance evaluation in CES scenarios	High – supports energy-ICT co-simulation with MATLAB/Simulink

It is important to emphasize that dedicated CES simulation tools are still in their development phase. Existing SLES platforms, particularly those supporting FMI, co-simulation and modular system architecture, provide a robust starting point. The incorporation of digital twins, AI-driven planning, machine learning and biological behavior layers will be instrumental in addressing the distinct requirements of long-duration, life-sustaining systems.

5. Discussion

It has been demonstrated in Sections 3 and 4 that the subjects related to the modeling and simulation of modern energy systems are multifaceted and intricate. This is especially evident in the growing prevalence of multisystem configurations, which is indicative of an integration-oriented trend. This Section 5 offers a synopsis of the salient discussion points and delineates the potential evolution of modeling and simulation tools and methods within the emergent domain of applications in CES and LSS.

5.1. Extension of SLES Modeling and Simulation Tools Toward CES and LSS Contexts

The increasing complexity of CES and LSS necessitates modeling approaches that extend beyond the conventional energy system simulation. It is evident that tools such as TRNSYS, Modelica, EnergyPlus and Simulink, which are extensively utilized for the purpose of modeling SLES, offer a promising foundation for the extension of simulation capabilities towards closed, integrated environments. The adaptation of these tools to the contexts of CES and LSS necessitates the consideration of unique challenges associated with multi-domain interactions. In contradistinction to standard building or microgrid simulations, CES necessitate the concurrent modeling of physical (energy, heat, fluids), environmental (air quality, humidity) and biological (human activity, plant growth, waste recycling) subsystems. This necessitates hybrid modeling approaches and cross-domain coupling mechanisms.

A discernible development trend is the increasing utilization of co-simulation frameworks and standardized interfaces (e.g. FMI) to facilitate interoperability between heterogeneous models. These methodologies facilitate the incorporation of thermal simulation engines, control systems, environmental dynamics, and even biological models within a cohesive framework. It is evident that tools such as Modelica and Simulink are particularly well-positioned for such integration, due to their inherent modular and equation-based modeling capabilities. In the future, the development of modeling tools for CES and LSS is likely to be characterized by an evolution towards enhanced multi-physics and multi-scale capabilities. This evolution will encompass the integration of human-in-the-loop simulation, real-time system behavior analysis, and scenario-based resilience testing. Integration with AI-based decision support and digital twin platforms is also expected to play a growing role in improving system adaptability and autonomy in long-duration space missions and extreme environments.

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5.2. Smart Building Technologies in Space Systems: From BACS/HEMS/BEMS to CES Smart Control Architectures

The development of advanced control architectures in CES and LSS is facilitated by smart building technologies, with BACS and BEMS/HEMS being of particular significance in this regard. These systems are inherently designed to manage complex interactions between subsystems such as HVAC, lighting, energy generation and storage, and indoor environmental quality, making them highly relevant to space-based habitats and other autonomous environments. The architectures of BACS and BEMS are characterized by their standardization, layered structure, modularity, and hierarchical arrangement. These features offer scalable and flexible solutions for real-time monitoring, control, and optimization in LSS. The core functionalities of these systems, which include dynamic scheduling, fault detection, occupancy-based control, and demand-side energy management, can be adapted to address the specific needs of closed-loop and resource-constrained systems.

The integration of IoT technologies and edge computing is becoming increasingly important, particularly in environments where communication latency, energy availability, and computational resources are limited [71–73]. The utilization of local processing capabilities fosters real-time responsiveness, augmented autonomy, and enhanced system resilience, all of which are imperative for long-duration space missions or isolated off-grid installations. In this context, a critical component of such systems is the dense network of sensors and monitoring modules, which continuously track environmental parameters (e.g. carbon dioxide levels, temperature, humidity), air and water quality, and resource consumption. These sensors generate substantial volumes of time-sensitive data, which must then be processed, stored, and analyzed, often in environments characterized by constrained computing power and limited bandwidth. Consequently, there is an increasing demand for lightweight, distributed data processing frameworks and on-device intelligence to ensure that essential control decisions can be made locally and reliably. In this regard, the emergence of edge computing solutions based on microcontrollers emerges as a particularly significant development, offering ultra-low-power, cost-effective platforms capable of executing fundamental analytics, anomaly detection, or control logic directly at the point of measurement. The utilization of such architectures has been demonstrated to reduce dependency on centralized computation, minimize data transmission requirements, and enhance system robustness in isolated or mission-critical environments.

Future developments in this field are expected to concentrate on IoT-driven, edge-enabled control systems, with a particular emphasis on data integration and standardization. Achieving interoperability across diverse subsystems will require unified protocols and common data models. The convergence of automation, sensing, and environmental control will result in the development of compact, scalable platforms for autonomous habitat management, supporting digital twins and adaptive decision-making in CES and LSS applications.

5.3. Energy Strategies in CES and LSS: Renewable Energy, Storage, and DSM/DSR

Energy management in the context of CES and LSS necessitates the implementation of fully autonomous, resilient, and resource-efficient solutions. In such contexts, renewable energy sources – including photovoltaics, fuel cells, and bioenergy – in combination with local storage systems (batteries, hydrogen) constitute the core of sustainable and mission-critical power supply. The systems must be designed to operate reliably under strict spatial, maintenance and energy constraints. A significant development in the field of terrestrial smart grids is the implementation of transactive energy models, which facilitate decentralized, market-like coordination of energy flows from diverse sources in real time. Such approaches facilitate dynamic balancing of generation and consumption, user-driven flexibility, and price-based prioritization. While the potential for their direct application in CES is promising, this is limited by the absence of external energy markets, user diversity, and economic drivers. However, the underlying principles of distributed control, load prioritization, and adaptive scheduling can be adapted to serve technical goals, such as maximizing system efficiency, autonomy, and resilience.

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In this context, DSM/DSR strategies are being redefined for use in isolated, mission-critical environments. Rather than relying on market signals, control algorithms are instead dependent on internal constraints, system states, and predefined priorities. In the context of constrained resources, the utilization of load classification, scenario-based forecasting, and adaptive shedding schemes has emerged as a critical mechanism for maintaining system balance and averting cascading failures. It is evident that, to facilitate the implementation of sophisticated control mechanisms within a consolidated CES microgrid, edge computing once again assumes the role of a pivotal enabling technology. The deployment of localized, low-power computing units in proximity to energy assets and sensors facilitates real-time data processing, autonomous decision-making, and system coordination without the necessity for continuous communication with a central controller. This paradigm is known as edge computing. This not only enhances the resilience and responsiveness of the energy infrastructure but also supports long-term system operability in remote and communication-limited conditions, which is crucial for long-duration missions. The insights derived from long-duration space missions offer valuable design patterns, including high-reliability architecture, redundancy planning, and fail-safe operation. These patterns are of increasing relevance to terrestrial microgrids in off-grid, remote, or high-resilience applications. These space-inspired solutions have the potential to enhance energy autonomy, fault tolerance, and system circularity. Future trends indicate a progression towards the integration of generation, storage, and intelligent control, with an escalating utilization of AI-driven energy optimization, multi-agent coordination, and DT-based simulation for the purpose of predictive system management. Concurrently, system-level trade-offs—between flexibility and stability, efficiency and redundancy—must be meticulously managed within CES, where margins for error are negligible and resource recovery is imperative.

5.4. Bidirectional Earth–Space Technology Transfer

The relationship between terrestrial and space-based technologies is increasingly bidirectional, with mutual exchange of concepts, tools, and design principles. It is evident that space missions have been instrumental in pioneering innovations in resource circularity, system autonomy, and off-grid infrastructure. These innovations have subsequently influenced the development of resilient urban systems and smart buildings on Earth. Concepts such as water and air recycling, ultra-efficient energy management, and compact, integrated system design—originally developed for life support in space—are now finding application in eco-districts, zero-emission buildings, and remote settlements.

Conversely, the rapid advancement of building automation, smart grid technologies, and IoT-based control on Earth is informing the next generation of extraterrestrial habitats. Modular BACS and HEMS systems, local energy management strategies, and edge-enabled monitoring frameworks are increasingly regarded as adaptable building blocks for LSS architectures, offering flexibility, scalability, and operational robustness under extreme conditions.

Modeling and simulation tools have been identified as playing a central role in this exchange, serving as a common language between space engineering and urban infrastructure design. The utilization of shared platforms and methodologies, including co-simulation, digital twins and scenario-based system testing, facilitates cross-domain collaboration, virtual prototyping and the transfer of validated control strategies between terrestrial and extraterrestrial contexts.

Emerging trends indicate an increasing interest in cross-sector standardization, interoperability frameworks, and open simulation ecosystems. These allow for the efficient adaptation of Earth-tested solutions to the constraints of space missions, and vice versa. It is hypothesized that, in the long term, this synergy may accelerate the development of resilient, self-sufficient systems. These systems would benefit both planetary sustainability and deep space exploration.

5.5. Summary SWOT Analysis—Smart Energy and Building Solutions in CES and LSS

To synthesize the preceding discussion, a SWOT analysis is presented in Table 6 to assess the applicability of smart energy and building technologies, including modeling and simulation tools, in

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the context of CES and LSS. The analysis under discussion highlights key technical, operational and strategic aspects relevant to both terrestrial and space applications.

Table 6. SWOT Matrix: Applicability of Smart Energy Systems and Modeling Tools in CES and LSS.

Strengths	Weaknesses
• Mature simulation tools (e.g., TRNSYS, Modelica, Simulink) adaptable to multi-domain CES models • Proven BACS/BEMS/HEMS architectures with modular, scalable design • IoT and edge computing enable real-time, decentralized control • Renewable and storage technologies validated in microgrid applications • Cross-domain modeling enables co-simulation and digital twins	• Limited readiness of existing tools for biological/environmental integration • High complexity of integrated system control in CES • Constrained computing power and energy in isolated LSS environments • Lack of market-driven mechanisms (e.g., tariffs) limits DSM/DSR adaptation • Limited standardization across tools and protocols for CES-specific use
Opportunities	**Threats**
• Transfer of space-based resource efficiency and circularity to Earth-based systems • Application of Earth-derived smart grid control in space habitats • Development of interoperable, AI-supported control and monitoring platforms • Integration of edge AI and microcontroller-based edge analytics • Expansion of simulation environments for virtual testing of extreme scenarios	• Environmental and operational extremes challenge system robustness • Failures in automation can compromise critical life-support functions (redundancy) • Data overload and communication bottlenecks in remote/off-grid settings • Cybersecurity risks in autonomous, interconnected systems • Cost and complexity of adapting existing tech to mission-specific needs

The analysis confirms a high potential for cross-domain technology transfer, particularly in areas such as modular automation, decentralized control, and multi-domain simulation. Notwithstanding the challenges associated with integration complexity, resource limitations and environmental constraints, the strategic development of interoperable, adaptive systems appears both feasible and necessary. It is vital to acknowledge the necessity of continued research and innovation in edge computing, AI-driven optimization, and co-simulation platforms if the full benefits of smart energy and building solutions are to be realized in future CES and LSS deployments.

6. Conclusions

This review provides an in-depth examination of modeling and simulation tools applied in the domains of SLES, microgrids, and intelligent buildings, focusing particularly on their applicability to the emerging and interdisciplinary context of CES and LSS. Analyses presented in Sections 3 and 4 have demonstrated that existing toolchains, such as TRNSYS, Modelica, EnergyPlus, MATLAB/Simulink, and GridLAB-D, offer a wide range of functionalities that can be partially or substantially adapted to the requirements of CES applications. These tools already support co-simulation, modularity, and cross-domain modeling, which are features essential for future space-based or autonomous infrastructures.

A fundamental contribution of this review lies in the identification and systematization of CES and LSS as novel application domains for smart energy and building technologies. Section 5 provides

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a comprehensive overview of the methodologies employed in terrestrial SLES, including demand-side management, hierarchical control, IoT-based sensing, edge computing, and digital twins. These techniques can serve as a foundational framework for the development of integrated cyber-physical-bio systems. The review emphasizes that modeling and simulation are not only useful for technical design and optimization but also act as a unifying language for the convergence of energy, environmental, and biological systems in CES.

This work thus opens a new research and development direction for the modeling community: the adaptation and extension of mature, domain-specific tools toward holistic, closed-loop system design, integrating energy flows with air, water, food, and life-support functions. The CES paradigm introduces stricter requirements on autonomy, reliability, and multi-scale system control, offering a high-impact testing ground for simulation architectures and edge-enabled decision systems.

Future work in this emerging cross-domain field should advance along multiple, complementary paths, aligned with the specific expertise of various research communities:

- for building and industrial automation engineers, the focus should be on evolving BACS, BEMS, and HEMS architectures toward fully autonomous, multi-domain control frameworks. These systems must extend beyond energy management to include environmental and biological regulation in CES and LSS applications, supported by robust, hierarchical, and fault-tolerant control logic;
- for computer scientists and data engineers, future work includes the design of edge-AI frameworks, lightweight learning algorithms, and real-time coordination platforms for distributed sensing and actuation. Key priorities involve semantic interoperability, adaptive control under uncertainty, and efficient data handling in low resource environments;
- for energy system and infrastructure engineers, challenges relate to integrating multi-modal systems (electrical, thermal, biological, environmental) within unified architectures that support optimization, resilience, and autonomy. Simulation environments should accommodate real-time adaptation, predictive diagnostics, and long-duration operation;
- for interdisciplinary research teams, there is a need to develop shared simulation platforms, digital twin frameworks, and experimental testbeds that reflect the tight coupling and constraints of CES and LSS. These platforms should support co-simulation across domains, dynamic scenario testing, and hybrid physical-virtual system evaluation.

Across all these domains, it is becoming increasingly evident that existing modeling and simulation tools require adaptation, extension, or even rethinking to meet the specific demands of CES environments. New toolchains must integrate physical, biological, and control subsystems, support variable time scales, and enable continuous supervision and optimization in isolated, life-critical conditions. Collectively, these directions establish the foundation for the subsequent generation of cyber-physical-bio infrastructures—intelligent, resilient, and self-regulating by design—capable of supporting both Earth-based sustainability objectives and future human presence beyond our planet.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
BACS	Building Automation and Control Systems
BEMS	Building Energy Management Systems
CES	Closed Ecological Systems

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DER	Distributed Energy Sources
DSM	Demand Side Management
DSR	Demand Side Response
DT	Digital Twin
ESA	European Space Agency
EV	electric vehicles
FMI	Functional Mock-up Interface
GIS	Geographic information systems
HEMS	Home Energy Management Systems
HIL	Hardware-in-the-Loop
ICT	Information and Communication Technologies
IoT	Internet of Things
LSS	Life Support Systems
MPC	Model Predictive Control
RES	Renewable Energy Sources
SLES	Smart Local Energy Systems
SRI	Smart Readiness Indicator

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