Enhancing the Resilience and Sustainability of Integrated Energy Systems Exposed to Extreme Natural Hazards by Means of Artificial Intelligence, Advanced Simulation, and

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Review

Enhancing the Resilience and Sustainability of Integrated Energy Systems Exposed to Extreme Natural Hazards by Means of Artificial Intelligence, Advanced Simulation, and Optimization Methods, Within an Integrative Systems Framework: A Critical Review of Literature

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Abstract

Re-engineered fourth-generation management (R4thGM) emerged in 2022 as an innovative systems approach to make production systems more contemporary (e.g., more sustainable and open to diverse stakeholders), while complex system governance (CSG), as a systems approach, enables the control, coordination, communication, and integration of smart energy systems. However, there remains a lack of literature: (i) discussing how R4thGM, integrated energy system (IES) governance (as CSG), artificial intelligence (AI), advanced simulation, robust optimization methods, and stakeholders should be taken into account in the task of enhancing IES's resilience and sustainability, particularly against extreme natural events; (ii) discussing the role of IES governance in enhancing control, coordination, integration, and communication of IES infrastructures; (iii) emphasizing the role of R4thGM for enhancing the resilience and sustainability of an IES; (iv) presenting an integrated energy meta-system (IEM) resulting from IES governance and relying on three technical enablers, i.e., (resilience) robust optimization, AI, and advanced simulation methods. This study aims to propose a novel integrative systems approach based on R4thGM and IES governance, using AI, advanced simulation, and optimization methods to enhance the resilience and sustainability of IES infrastructures in the design and operational phases. To achieve this goal, we have reviewed 85 Scopus- and Web of Science-indexed papers published in 2017–2025. The novelty of this study lies in presenting an integrative systems approach best suited to resilient and sustainable IES infrastructures against extreme natural hazards. Moreover, propositions are formulated to reflect on the suggested framework. Finally, research implications and future directions are provided.

Keywords: integrated energy systems; integrated energy meta-system; climate change-induced extreme weather conditions; artificial intelligence; natural disasters; advanced stochastic simulation; re-engineered fourth-generation management; integrated energy system governance; integrated energy system resilience; integrated energy system sustainability

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1. Introduction

A transition toward a contemporary energy sector that mitigates environmental impacts and promotes social and economic development has recently gained traction amid growing concerns about climate change and energy sustainability [1]. Energy system resilience is often debated in academic works alongside themes such as energy sustainability

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and energy transition [2]. The nexus between resilience and the sustainability of energy systems is rooted in the first definition of resilience, introduced in 1972 as a concept in ecological systems, which refers to a measure of the persistence of systems and their ability to absorb change and disturbances while maintaining the same relationships between populations or state variables [3,4]. Energy systems belong to the category of critical infrastructure systems whose inability or destruction would negatively affect national security, economic security, public health or safety, or any combination of such matters [5]. Extreme natural hazards and disruptions, including climate change-induced extreme weather events (e.g., natural disasters), pose serious threats to energy systems and other critical infrastructure [6–8]. According to Katina et al. [5], energy systems operate under conditions of *uncertainty*, such as extreme natural hazards and other high-impact, low-probability events, thereby characterizing the volatility, uncertainty, complexity, and ambiguity (VUCA) of the operating environment for 21st-century energy systems. *Volatility* describes instability; *uncertainty* means the lack of predictability (e.g., low-probability threats), the prospect of surprise, and the sense of awareness and understanding of concerns; *complexity* signifies the interplay of diverse factors, the overlap of issues without cause-and-effect chains, and the confusion surrounding 21st-century engineered systems—including energy critical infrastructure systems such as integrated energy systems (IESs); and *ambiguity* refers to the haziness of reality, the potential for misinterpretation, and the multifaceted meaning of conditions, leading to cause-and-effect confusion [9,10]. From a *leadership*, *management*, and *governance* perspective, the contemporary VUCA landscape necessitates adopting more robust, adaptable, and anticipatory approaches to navigate incessant transformations in different sectors [11], including the energy sector. A truly resilient and sustainable energy sector needs to extend beyond mere survival and recovery; it should embrace a proactive, systems approach that fosters continuous improvement, adaptation, and transformation in the face of an ever-changing landscape [12].

IESs (Figure 1) are systems-of-systems (SoSs) and a crucial solution for the next-generation energy structure, offering multi-energy complementary advantages, augmented efficiency, reduced emissions of greenhouse gas, and enhanced air and water quality while integrating and coordinating multi-energy carrier systems to provide customers with flexible, resilient, clean, affordable, and sustainable energy [1,13–21]. From a *design* and *analysis* perspective, IESs are often referred to as multi-energy systems [22,23]. Depending on the landscape and stakeholders' focus, IES's naming is typically influenced by its outputs, inputs, or functionality. As illustrated in Figure 1, IESs encompass interdependent multi-energy infrastructures [24–32] and can be categorized into five categories—*(i) the category of power-centric IESs* within which an IES can be an integrated gas and power system (IGPS) (e.g., [29,33–39]), an integrated electricity, gas, and heat system (IEGHS) (e.g., [40–45]), an integrated electricity, heating, cooling, gas, and water system (IEHCGWS) (e.g., [46]), an integrated electricity, gas, and water system (IEGWS) (e.g., [28]), an integrated electricity-heat system (IEHS) (e.g., [47–49]), a building-to-vehicle-to-building (B2V2B) (e.g., [50]), or another type of power-centric IESs; *(ii) the category of thermal and cogeneration-based IESs* that includes combined cooling, heat, and power (CCHP) systems (e.g., [51]) and district IESs (e.g., [52]); *(iii) the category of renewable and hybrid energy systems* where an IES can be a hybrid renewable energy system (HRES) (e.g., [53,54]), a nuclear-renewable hybrid energy system (e.g., [55]), an integrated energy park (e.g., [56]), or another configuration of renewable and hybrid energy systems; *(iv) the category of hydrogen-IESs* where an IES can take the form of hydrogen production with nuclear power (e.g., [57–59]), an electricity-hydrogen integrated energy system (EHIES) (e.g., [60]), an electricity-hydrogen-heat integrated energy system (EHHIES) (e.g., [24]), an electric-thermal-hydrogen integrated energy system (ETHEIS) (e.g., [61]), or another type of hydrogen-IESs; and *(v) the category of storage, flexibility, and* *sector-coupling integration* within which an IES can be a microgrid (e.g., [62–66]), energy storage integration (e.g., [67]), energy storage and demand response integration (e.g., [68,69]), or another type of IESs from the same category (Figure 1).

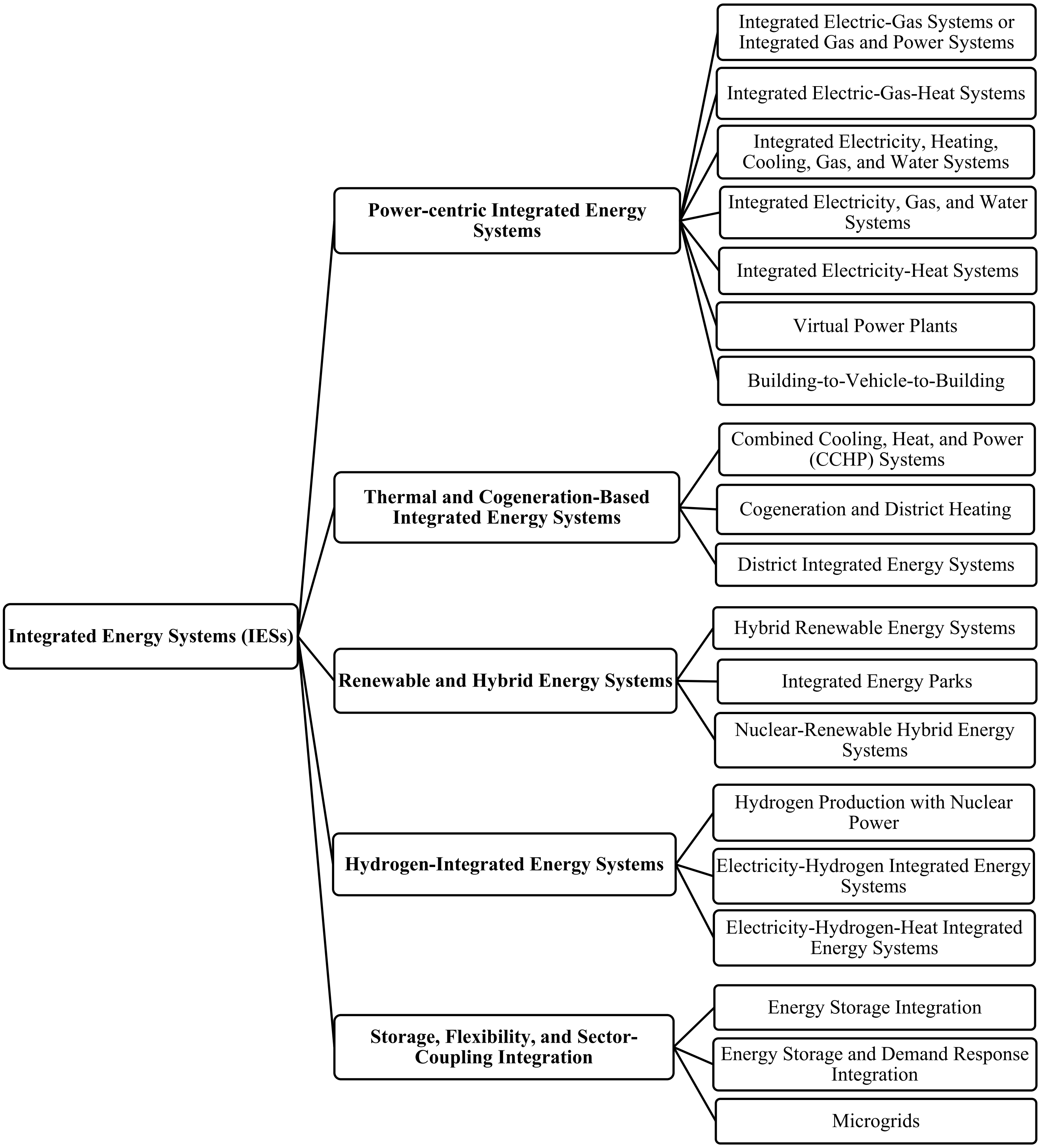

Figure 1. The most common types of integrated energy systems (IESs) and their categories.

An IES is a contemporary energy-critical infrastructure and a way to improve resilience to extreme natural hazards [41,70]. It is a viable solution from environmental and energy-supply perspectives [71]. IESs have emerged as a viable way and a promising, resilient, and sustainable solution to address the challenges of multi-energy supply; however, they are *vulnerable* to *extreme natural hazards*, which can disrupt the whole energy infrastructure and lead to energy shortages [42,48,72]. Global climate change, extreme natural hazards (e.g., extreme weather), and advances in digital technology (e.g., AI) are major considerations for the resilience of energy-critical infrastructures [73]. Due to escalating climate change, the world has witnessed a progressive increase in the frequency and intensity of extreme weather events [15,26,63,74–82] as triggers for natural technological (NaTech) incidents [17,83,84]. Sustainable energy systems generally catalyze energy supply reliability, stability, security, and resilience to extreme natural hazards [85]; however, these latter can pose a significant threat to the resilient and sustainable operation of IESs [64,86–90]. Furthermore, natural calamities resulting from climate change go beyond IES infrastructure faults and engender large-scale energy anomalies, including power outages in temporal and spatial dimensions [24,61,91–100].

Developing, implementing, managing, or governing an IES requires the involvement of *stakeholders*, including energy operators and policymakers [1]. Stakeholders have the capacity to influence the outcomes (e.g., efficiency, time to recover after an extreme natural hazard, pressure/temperature/voltage stability, losses, renewable energy share, carbon footprint, carbon dioxide removal, etc.) of an energy project to a large extent [101]. In this study, based on the conception of diverse stakeholders provided by Hallioui et al. [9], diverse stakeholders of an IES are people who can affect or be affected by the resilience and sustainability of its infrastructures (e.g., power, gas, heat, cooling, hydrogen, water, nuclear, or other interdependent infrastructures). The United Nations Development Programme [12] recommends stakeholder inclusion for enhancing the resilience and sustainability of energy systems—including IESs—through actively involving diverse stakeholders, such as governments, the private sector, civil society, and local communities, in open and transparent processes of decision-making and shaping the energy transition, which fosters trust, cooperation, and shared responsibility for a resilient and sustainable energy future. For a resilient and sustainable IES, diverse stakeholders generally include: (i) governments and regulatory bodies at the local, regional, and international levels; (ii) energy companies and utilities such as generation systems, transmission systems, distribution systems, gas, and heat operators; (iii) investors; (iv) engineers and technology developers; (v) consumers; (vi) local communities; (vii) researchers; (viii) builders; and (ix) non-governmental organizations.

From a *digital technology perspective*, AI has become a fundamental catalyst for energy transition, especially as nations struggle to meet global climate goals and strive for carbon neutrality [102]. Machine Learning (ML) algorithms can lead the smart-sustainable energy transition while supporting IES resilience against climate change-induced extreme weather [103]. The authors of [103] used a machine-learning microgrid restoration technique based on hybrid autoregressive integrated moving average-deep reinforcement learning (HARIMA-DRL) to support post-disaster electricity recovery. Furthermore, AI is a revolutionary digitalization technology, helping harden and modernize IESs [104–106], enhancing IES infrastructure coordination [107], challenging the dominance of traditional numerical weather prediction [108], strengthening predictive maintenance [109,110] and its framework of contemporary maintenance or Industry 4.0 technology-based sustainable maintenance [111,112], leveraging automated recovery (i.e., self-healing capabilities) [113], supporting accurate forecasts of energy demand [114], reducing operation costs [115], and ensuring adaptive operations for IESs [116]. Integrating AI, remote sensing, and ML can enhance the control and monitoring of resilient and sustainable IESs under extreme weather conditions [117]. From a *computational* and *simulation viewpoint*, *stochastic simulation* enables scenario analysis, risk quantification, and robust resilience optimization for different IES infrastructures under uncertainty (e.g., extreme natural hazard uncertainty) in both the design and operational phases [51,66,118–120]. The recent literature (e.g., [121,122]) presents advanced (stochastic) simulation as a computational framework integrating physics-based modeling, uncertainty quantification, and possibly AI techniques (e.g., ML and Deep Learning (DL)) for capturing complex, dynamic, and uncertain real-world behavior, often emphasized in modern frameworks studying and optimizing the resilience of complex systems such as IESs. The integration of AI and stochastic simulation techniques (e.g., Monte Carlo methods) has enabled more efficient and adaptive solutions for complex real-world challenges, including IESs exposed to extreme natural hazards [8,123]. While advanced stochastic simulation methods (e.g., affine invariant, interacting, and multi-source Markov Chain Monte Carlo-MCMC samplers) are not strictly AI-based [8], advanced MCMC can serve as a core foundation for several AI systems (e.g., Bayesian ML and generative models) [124]. In addition, ML, DL, and AI tools (e.g., neural networks) significantly accelerate and enhance advanced stochastic simulation while improving both approximation accuracy and computational efficiency [125,126]. AI methods and tools, on their own or combined with advanced stochastic simulation methods, can enhance proactive, predictive control; coordinated multi-energy dispatch under uncertainty; fast and adaptive decision-making; real-time resilience optimization; self-learning and adaptive control; and support the real-time operation of resilient and sustainable IES infrastructures against extreme natural hazards [8,64,85,123,127–132].

At the *management* and *governance* scales of contemporary complex production systems, including IESs, and in alignment with the United Nations Development Programme [12] and sustainable development goals (SDGs) defined in the United Nations 2030 Agenda for Sustainable Development [133], (i) in 2022, Hallioui et al. [9] created a systems approach, which is a management style or management paradigm called R4thGM. R4thGM, based on Hallioui's triangle (Figure 2), aims at making organizations more contemporary (i.e., more sustainable and open to diverse stakeholders) while orienting them toward sustainability and the customer [9,111]. (ii) Katina et al. [5] discussed the concept of governance for smart energy systems, which harness state-of-the-art technologies (e.g., AI) and infrastructures. Indeed, the authors of [5] described the governance of smart energy systems using CSG, a systems approach grounded in systems theory and management cybernetics, aiming to control, coordinate, communicate, and integrate smart energy infrastructure systems as SoSs. CSG involves the nine governance functions of the meta-system (i.e., the governing system or the brain of the system-of-systems (SoS)) [5,134,135], extending the four meta-system functions of Beer [136]'s viable system model (VSM). The recent literature discusses IES governance in frameworks that address legal uncertainty, regulatory risks, stakeholder inclusion, policies, and energy justice principles to enable cross-energy-sectoral coordination among infrastructure operators—as stakeholders—and to achieve a clean-energy-systems-driven transition [137].

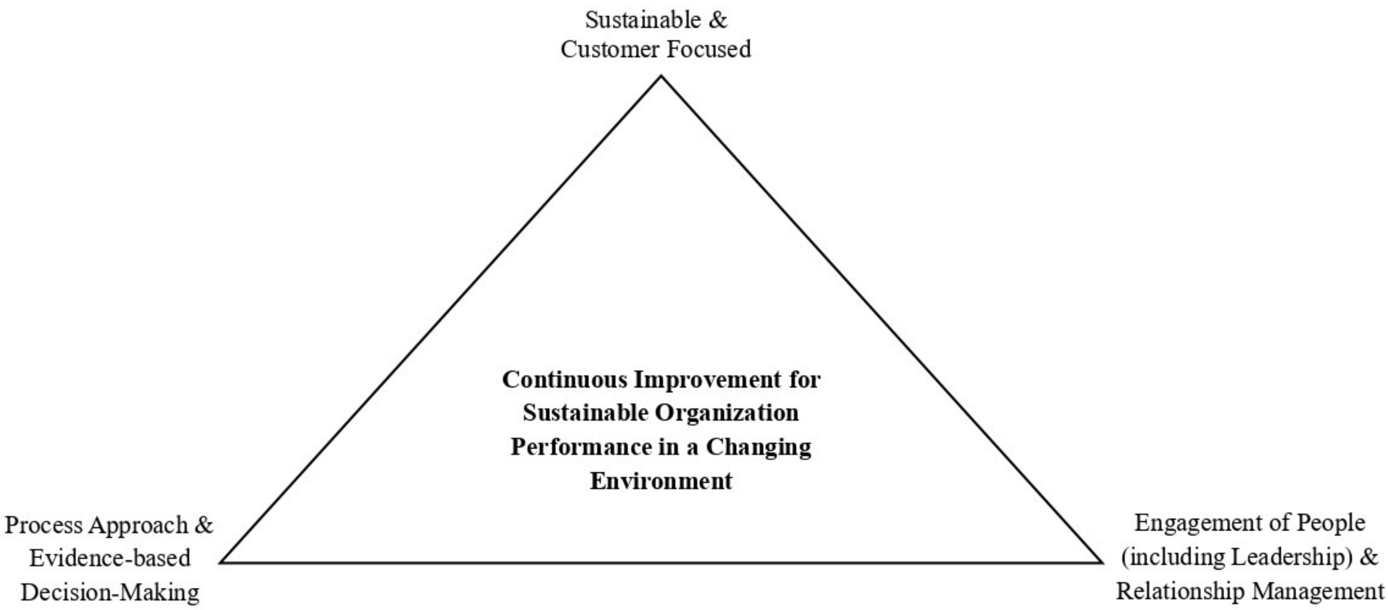

Figure 2. Hallioui's triangle—basis for re-engineered fourth generation management (R4thGM) (based on [9,111]).

However, as shown in Figure 3, until today, there remains a lack of literature: (i) discussing how R4thGM, IES governance (as CSG in the sphere of IESs), AI, advanced simulation, robust optimization methods, and stakeholders (as contemporary concerns) should be accounted for in enhancing IES's resilience and sustainability against extreme natural hazards; (ii) discussing the role of IES governance in enhancing control, coordination, integration, and communication of IES infrastructures against extreme natural hazards; (iii) emphasizing the role of R4thGM for enhancing the resilience and sustainability of IESs exposed to extreme natural hazards; and (iv) presenting an integrated energy meta-system (IEM) resulting from IES governance and relying on three technical pillars, i.e., AI, advanced simulation methods, and robust optimization of IES resilience. Therefore, the main aim of this critical review article is to propose an integrative systems approach (or meta-systems approach) based on R4thGM and IES governance, which is best suited for enhancing the resilience and sustainability of IESs (in the design and operation phases) against extreme natural hazards, using AI, advanced simulation, and optimization methods. This paper presents: (i) R4thGM founded on the new tool PoliTo's triangle as an application of Hallioui's triangle (Figure 2) to IESs exposed to extreme natural hazards and (ii) IES governance based on the new model, the so-called resilient and sustainable integrated energy system model (RS-IES-M) built upon IEM. The core challenge for this study is to gather R4thGM, IES governance, IEM, AI, advanced simulation, robust optimization methods, and stakeholders under the umbrella of a novel integrative systems approach to enhance IES resilience and sustainability. The rest of the paper is organized as follows: Section 2 describes the research methodology. Section 3 discusses the proposed integrative systems approach. Section 4 presents propositions for enhancing resilient and sustainable IES control, coordination, communication, and integration in the face of extreme natural hazards through the proposed integrative systems approach, as well as research implications. Conclusions with a practical roadmap for grid operators, research limitations, and future research are provided in Section 5.

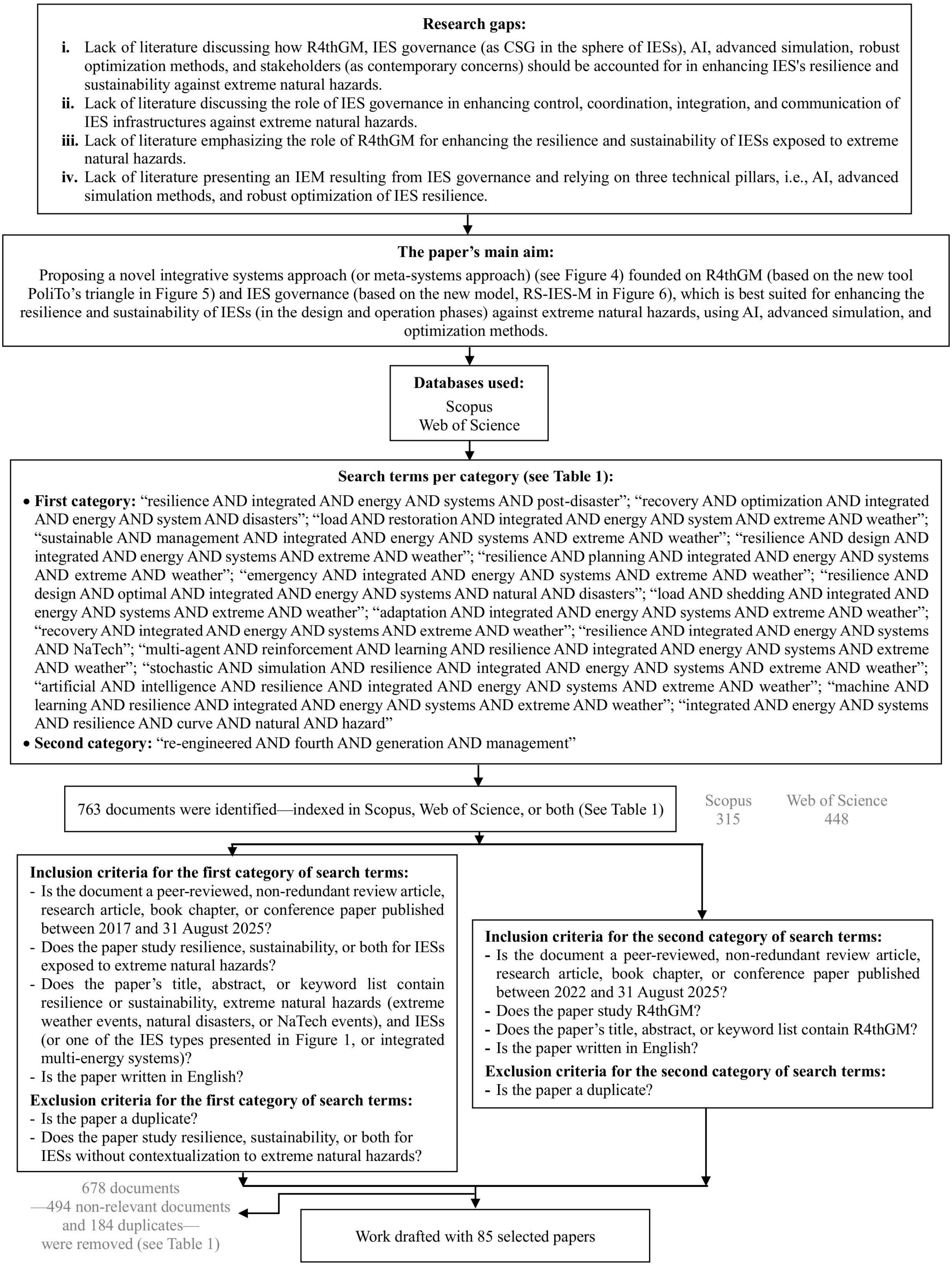

Figure 3. Diagram of research methodology.

2. Materials and Methods

This study utilizes a two-search-term category and a two-inclusion/exclusion-criteria qualitative research methodology (Figure 3). A literature review is ideal for synthesizing research findings and constructing theoretical frameworks [9,111,138,139]. The Scopus and Web of Science databases are utilized to identify peer-reviewed papers and construct and reflect on the proposed theoretical framework (Sections 3 and 4.1). A total of 18 search terms, grouped into two categories, were considered (Figure 3 and Table 1). By searching within the field "Article title, Abstract, and Keywords" in Scopus and the field "Topic" in all editions within Web of Science Core Collection, the search terms result in 315 documents indexed in Scopus and 448 documents indexed in Web of Science, making a total of 763 identified documents (Figure 3 and Table 1), including books, editorial materials, conference reviews, review articles, research articles, book chapters, conference papers, and other types of documents.

As shown in Figure 3, the inclusion criteria for the documents identified through the search terms of the first category consisted of: (i) peer-reviewed, non-redundant review articles, research articles, book chapters, or conference papers published between 2017 and 31 August 2025; (ii) papers that study resilience, sustainability, or both for IESs exposed to extreme natural hazards; (iii) papers whose title, abstract, or keyword list contain resilience or sustainability, extreme natural hazards (extreme weather events, natural disasters, or NaTech events), and IESs (or one of the IES types presented in Figure 1, or integrated multi-energy systems); and (iv) papers written in English. To guarantee relevance, exclusion criteria (for documents retrieved through search terms of the first category) are implemented to remove (i) duplicate papers and (ii) papers studying resilience, sustainability, or both for IESs without contextualization to extreme natural hazards (Figure 3).

The inclusion criteria for the documents retrieved through the search term constituting the second category consisted of (i) peer-reviewed, non-redundant review articles, research articles, book chapters, or conference papers published between 2022 and 31 August 2025; (ii) papers that study R4thGM; (iii) papers whose title, abstract, or keyword list contain the concept of R4thGM; and (iv) papers written in English. To ensure relevance, only one exclusion criterion is applied to these documents (duplicate papers are removed) (Figure 3).

For each search term in Table 1, records from Scopus in BibTeX format and Web of Science in plain text file format were merged and deduplicated using the bibliometrix package [140] in R version 4.5.2 [141], executed within the RStudio integrated development environment (version 2025.09.2, Build 418). Based on the two groups of inclusion and exclusion criteria, 678 documents—494 non-relevant documents and 184 duplicates—were removed, and 85 papers were selected from 763 documents (Figure 3 and Table 1).

Table 1. Number of relevant papers per search term in the Scopus and Web of Science databases.

Category of Search Terms	Search Term	Documents in Scopus	Documents in Web of Science	Duplicates Per Search Term in Scopus and Web of Science	Number of Relevant Papers	Relevant Papers
First category	resilience AND integrated AND energy AND systems AND post-disaster	42	46	28	18	[29,30,34,39,40,42,43,48,50,62,80,87,88,99,103,142–144]
	recovery AND optimization AND integrated AND energy AND system AND disasters	42	35	19	10	[26,27,37,44,49,61,89,91,145,146]
	load AND restoration AND integrated AND energy AND system AND extreme AND weather	14	21	11	7	[15,36,38,45,70,76,147]

Table 1. *Cont.*

Category of Search Terms	Search Term	Documents in Scopus	Documents in Web of Science	Duplicates Per Search Term in Scopus and Web of Science	Number of Relevant Papers	Relevant Papers
First category	sustainable AND management AND integrated AND energy AND systems AND extreme AND weather	31	33	12	6	[148–153]
	resilience AND design AND integrated AND energy AND systems AND extreme AND weather	18	51	10	6	[46,63,72,74,78,154]
	resilience AND planning AND integrated AND energy AND systems AND extreme AND weather	34	69	22	6	[118,155–159]
	emergency AND integrated AND energy AND systems AND extreme AND weather	24	32	11	5	[54,81,160–162]
	resilience AND design AND optimal AND integrated AND energy AND systems AND natural AND disasters	5	7	3	4	[28,41,163,164]
	load AND shedding AND integrated AND energy AND systems AND extreme AND weather	13	16	11	4	[32,165–167]
	adaptation AND integrated AND energy AND systems AND extreme AND weather	35	61	22	4	[131,168–170]
	recovery AND integrated AND energy AND systems AND extreme AND weather	33	34	16	3	[47,90,171]
	resilience AND integrated AND energy AND systems AND NaTech	4	4	3	3	[17,83,84]
	multi-agent AND reinforcement AND learning AND resilience AND integrated AND energy AND systems AND extreme AND weather	2	3	2	2	[64,127]
	stochastic AND simulation AND resilience AND integrated AND energy AND systems AND extreme AND weather	6	13	6	2	[23,65]
	artificial AND intelligence AND resilience AND integrated AND energy AND systems AND extreme AND weather	6	9	4	1	[128]
	machine AND learning AND resilience AND integrated AND energy AND systems AND extreme AND weather	2	11	1	1	[85]
	integrated AND energy AND systems AND resilience AND curve AND natural AND hazard	2	1	1	1	[31]
Second category	re-engineered AND fourth AND generation AND management	2	2	2	2	[9,111]
Total		315	448	184	85	
The total number of documents retrieved from the Scopus and Web of Science databases was 763.						
The total number of non-relevant documents based on the inclusion and exclusion criteria (see Figure 3) was 494.						

3. An Integrative Systems Approach to Resilient and Sustainable IESs

This section constitutes the core contribution of the paper. Section 3.1 presents the proposed integrative systems approach, or meta-systems approach, based on R4thGM and IES governance, while Section 3.2 describes its triad, founded on optimization methods, AI, and advanced simulation.

3.1. The Suggested Integrative Systems Approach (Meta-Systems Approach)

In the context of the organization of unthinkable systems—i.e., systems too complex to fathom—in the sense that they are difficult or impossible to fully conceptualize, model, predict, or control using current human cognitive, technological, or societal frameworks, Beer [136] defined the Greek prefix meta as over and above. The literature on cybernetics, systems theory, management science, and CSG refers in several works to the operational and scientific construct of meta-system—a system above the system in question [5,136,172–181], in other words, a system beyond the SoS [134]. In cybernetics, Turchin [181] introduced the concept of meta-system transition to describe the evolutionary emergence of a higher level of control and organization from a set of interacting subsystems. From a control systems-based decision-making viewpoint, Van Gigch [178], Kickert [179], and Kickert and Van Gigch [180] forged the meta-system paradigm as a decision-making framework. Control systems-based decision-making predated meta-decision-making [182], which was conceptualized in the second half of the 20th century as systems thinking and decision sciences matured [183–185]. To increase the understanding of the meta-system and differentiate it from the concept of a complex system or SoS, Hallioui et al. [138], Katina et al. [134], Keating and Katina [186], Reza et al. [187], Keating et al. [188], and Beer [136] defined the meta-system as a governing structure that allows the formation of an SoS and the achievement of its evolutionary goals and missions. Furthermore, based on Keating and Bradley [135]'s theoretical conception of CSG, the meta-system is a set of higher-level functions that govern a complex system to maintain its viability (i.e., its existence). Inspired by systems science, an integrative systems approach, also known as a meta-systems approach, can be presented as a higher-order framework, founded on existing systems approaches, that builds on or synthesizes their principles to achieve a set of goals [189]. Indeed, an integrative systems approach is a systems approach of systems approaches.

The suggested integrative systems approach (Figure 4) combines R4thGM and IES governance as contemporary enablers of resilience and sustainability-driven systemic decision-making, philosophies, and frameworks for resilient and sustainable IESs against extreme natural hazards. AI, advanced simulation, and methods for optimizing resilience form the triad of the proposed integrative systems approach (Figure 4). In the energy field, R4thGM aims to orient IESs toward a resilient and sustainable multi-energy supply (Figure 5). From a systems thinking viewpoint, IES governance is an application of CSG as a systems approach [175], embraces cross-energy system complexities and interactions [137,172,190], strengthens resilience to increasing climate and weather extremes [191], and emphasizes holistic design, such as resilience-based design (RBD) [5] and different lifecycle operation phases for integrating, controlling, coordinating, and communicating the infrastructures of a resilient and sustainable IES. Sections 3.1.1 and 3.1.2 describe the mechanisms for both systems approaches (i.e., R4thGM and IES governance), which form the basis of the proposed meta-systems approach (Figure 4).

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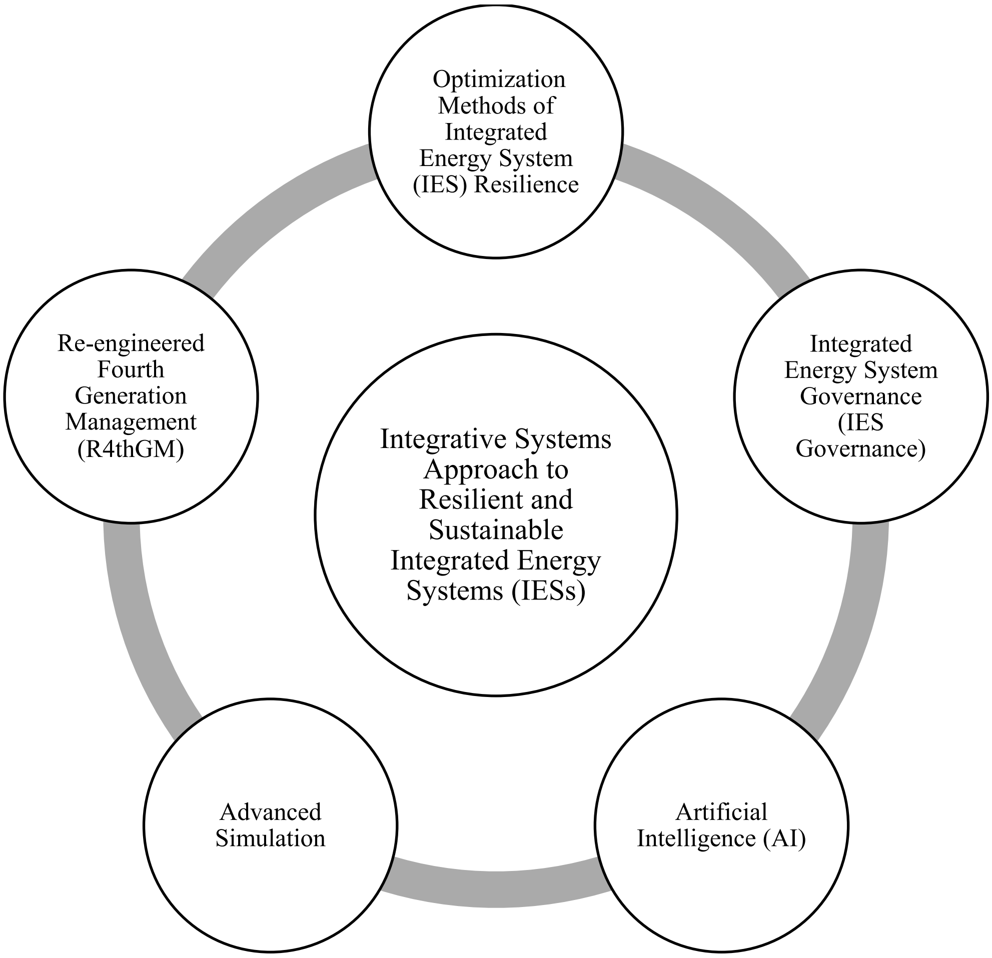

Figure 4. The proposed integrative systems approach for enhancing the resilience and sustainability of integrated energy systems (IESs) against extreme natural hazards.

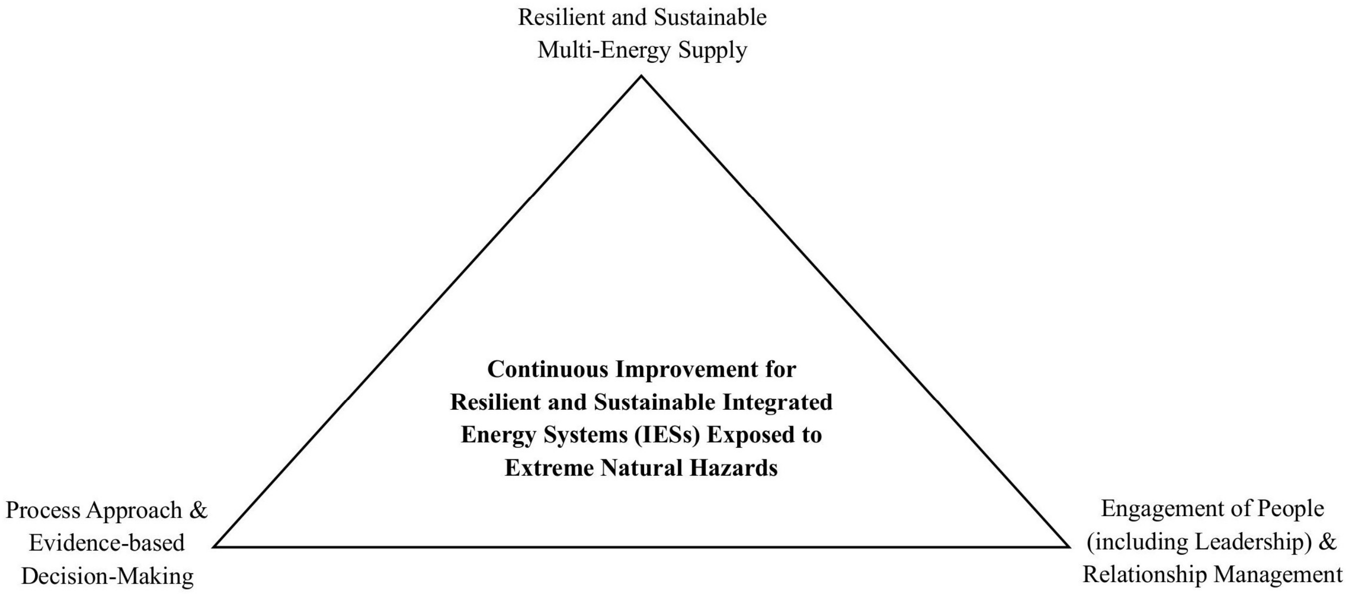

Figure 5. PoliTo's triangle for resilient and sustainable integrated energy systems (IESs) in the face of extreme natural hazards. It is an application of Hallioui's triangle [9,111] to IESs exposed to extreme natural hazards.

3.1.1. IES Governance

IES governance being a CSG can improve system performance (e.g., resilience, sustainability, and effectiveness) through designing, executing, and developing the nine meta-system functions crucial for providing IES control, communication, coordination, and integration [5,135,175,176,186,192–194]. The nine governance functions of the meta-system usually discussed in the domain of SoSs engineering [5,134,135] are derived from Beer [136]'s four meta-system functions (i.e., system identity, development and learning and transformation, operations and monitoring, and coordination)-based VSM, also known as Beer [136]'s approach to viability, which explains how organizations can remain viable (i.e., exist, adapt, and thrive) in complex and changing environments. These functions are assigned across five key bottom-up systems or subsystems (Systems 1–5), with Systems 2–5 representing different layers of control and adaptation (i.e., meta-system layers). VSM is still a general concept [195]. VSM is the entire system, and the meta-system (i.e., Systems 2–5) is its brain—the governance part, situated above the operational system (i.e., System 1 in the VSM's basis), to ensure coherence, adaptability, and survival [136]. Indeed, from a bottom-up perspective, Beer [136] founded VSM on autonomous operational units within System 1, which are governed in the sense that they are served, stabilized, and supported by four crucial layers in the meta-system's top-down architecture (i.e., Systems 5–2). Keating and Bradley [135] upgraded the VSM meta-system by expanding its four functions to nine interrelated meta-system functions, thereby developing a CSG reference model. According to the authors of [5,134,135], these nine governance functions are dispatched on the four layers of the VSM meta-system (i.e., Systems 5–2 in the VSM meta-system) as follows: (i) meta-system five (M5)—policy and identity; (ii) meta-system five star (M5*)—system context; (iii) meta-system five prime (M5′)—strategic system monitoring; (iv) meta-system four (M4)—system development; (v) meta-system four star (M4*)—learning and transformation; (vi) meta-system four prime (M4′)—environmental scanning; (vii) meta-system three (M3)—system operations; (viii) meta-system three star (M3*)—operational performance; (ix) meta-system two (M2)—information and communication.

In the context of the novel integrative systems approach, or meta-systems approach, illustrated in Figure 4, IES governance is suggested in this work as a promising novel systems approach, or systemic paradigm, based on a resilient and sustainable IES model (RS-IES-M) (Figure 6), to enhance IES sustainability and resilience against extreme natural hazards in the design and operation phases. The RS-IES-M, as a new tool and a foundation of IES governance, is built upon nine integrated energy meta-system functions (IEM-Fs) (Figure 6 and Table 2), which, within an IEM, govern the infrastructures of the resilient and sustainable IES (Figure 6). Figure 6, Table 2, and the nine IEM-Fs are supported by the works of Katina et al. [5], Katina et al. [134], Keating and Bradley [135], and Beer [136]. IEM, or the meta-system within RS-IES-M (Figure 6), encompasses the triad (i.e., optimization methods of IES resilience, AI, and advanced simulation) of the suggested integrative systems approach (Figure 4), along with stakeholders (e.g., maintenance/repair crews, energy operators, managers, consumers, governments, research institutions, experts, and other interested physical and moral persons) as crucial policymakers to enhance resilience and sustainability of IESs exposed to extreme natural hazards.

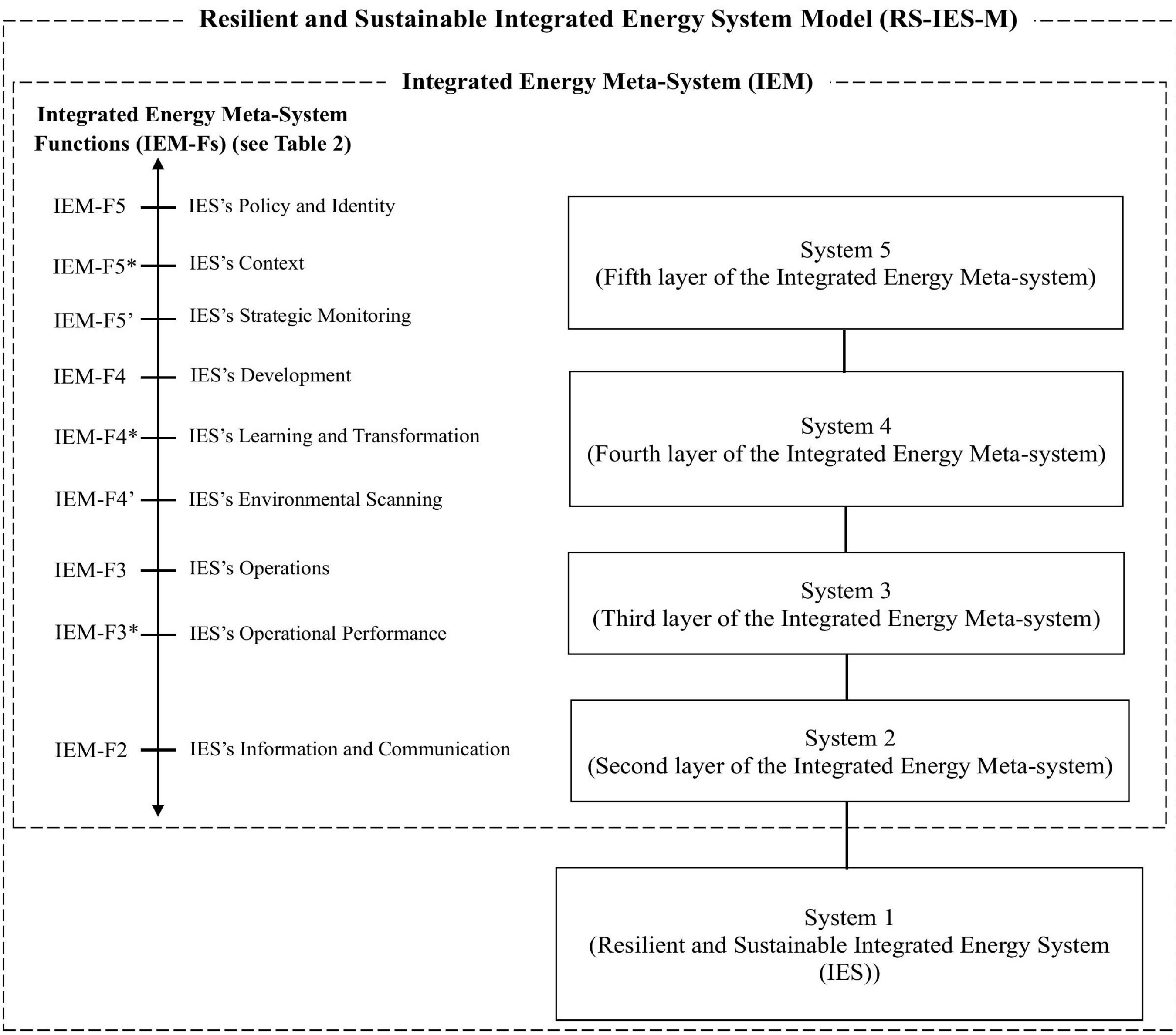

Figure 6. Resilient and sustainable integrated energy system model (RS-IES-M)—a basis for integrated energy system governance (IES governance) against extreme natural hazards.

Table 2. Integrated energy meta-system functions (IEM-Fs).

Integrated Energy Meta-System's (IEM) Layer	Integrated Energy Meta-System Function (IEM-F)	Description
System 5	IEM-F5—IES's policy and identity	Defining resilience- and sustainability-related policies, goals, values, vision, accountability, oversight, and strategic direction for the IES, aligning all decisions and actions to foster the IES's sustainability and resilience against extreme natural hazards.
	IEM-F5*—IES's context	Controlling the set of circumstances, patterns, and conditions that shape the IES's context or environment, enabling or constraining the IES's resilience/sustainability to proactively address its external environment and thereby strengthen its sustainability and resilience under extreme natural hazards.

Table 2. *Cont.*

Integrated Energy Meta-System's (IEM) Layer	Integrated Energy Meta-System Function (IEM-F)	Description
System 5	IEM-F5′—IES's strategic monitoring	Ensuring oversight of the IES's performance indicators at a strategic level to address future resilience and sustainability challenges and uncertainties, which enables IES to anticipate vulnerabilities and implement timely adjustments to enhance its sustainability and resilience against extreme natural hazards.
System 4	IEM-F4—IES's development	Establishing future scenarios, RBD's solutions, and adaptive plans to anticipate changes and adapt (i.e., upgrade) IES to resilience and sustainability-related future dynamics of its technological, meteorological, managerial, ecological, economic, social, cultural, and geopolitical environments and trends. Indeed, this IEM-F ensures that IES evolves to withstand and recover from extreme natural hazards while guaranteeing its long-term economic, social, and ecological sustainability.
	IEM-F4*—IES's learning and transformation	Ensuring continuous improvement-driven learning and transformation of the resilient and sustainable IES, and suggesting RBD and sustainability planning. This IEM-F permits the IES to integrate past experiences into improved strategies that leverage the IES's sustainability and resilience against extreme natural hazards.
	IEM-F4′—IES's environmental scanning	Sensing the IES's external environment for trends, circumstances, events, or patterns that involve present/future negative impacts on the IES's resilience and sustainability. In fact, this IEM-F enables early detection of emerging threats from extreme natural disruptions and proactively strengthens the IES's resilience and sustainability.
System 3	IEM-F3—IES's operations	Maintaining the day-to-day operations of the IES and ensuring continuous control of its operational performance, while also guaranteeing an efficient resource allocation to cope with extreme natural hazards. This IEM-F enables the IES to maintain stability and quickly recover from disruptions caused by extreme natural hazards, thereby enhancing its overall resilience and sustainability.
	IEM-F3*—IES's operational performance	Conducting audits to systematically assess IES's operational performances (including operational or short-term resilience) and sustainability performances and detect abnormal or emergent conditions. This IEM-F enables the early identification of weaknesses and emerging risks, allowing for timely actions that enhance the IES's sustainability and resilience to extreme natural hazards.
System 2	IEM-F2—IES's information and communication	Ensuring coordination, communication, and the flow of information between the IES's infrastructures, thereby strengthening the IES's sustainability and resilience during extreme natural hazards.

3.1.2. The Role of R4thGM in Leveraging IES's Resilience and Sustainability

From both a general and a chronological standpoint, management literature has witnessed five generations of management styles. To interpret the convergence of management evolution and quality revolution in the last decade of the 20th century, Joiner [196] defined the first four successive generations: (i) first-generation management—management by doing; (ii) second-generation management—management by directing; (iii) third-generation management—management by results; and (iv) fourth-generation management—systems approach orienting complex, contemporary socio-technical organizations or systems toward the customer (i.e., quality). The fifth-generation management is re-engineered fourth-generation management (R4thGM)—a recent, promising 21st-century systems approach based on the triangle in Figure 2 to manage more complex systems (including IESs), while orienting them toward sustainability and the customer in a context of Industry 4.0 digitalization technologies (i.e., AI), diverse stakeholders, circular economy, and competitiveness [9]. R4thGM was a pioneering management style that integrated sustainability as an orientation for 21st-century production systems, making them more contemporary within their landscape [9,111]. Indeed, through R4thGM, Hallioui et al. [9] introduced a new generation of production systems and distinguished between (i) first-era contemporary production organizations, defined as customer-oriented systems managed through fourth-generation management, and (ii) second-era contemporary production organizations, defined as sustainability- and customer-oriented systems that are characterized by Industry 4.0 technologies and circular-economy principles and managed through R4thGM.

In the scope of the resilience-sustainability nexus, it is obvious that sustainable IESs are often resilient, while resilient IESs are better able to be sustainable in the face of extreme natural hazards [7,82,197–199]. The literature has long shown the importance of resilient and sustainable management for more complex, contemporary energy systems such as IESs [73,85,149]. The resilient and sustainable operation and management of IESs are crucial to guarantee economic efficiency, environmental cleanliness, and well-being [148]. A resilient and sustainable proactive management approach, strategy, or management style (e.g., R4thGM) enhances economic performance and operational reliability for IESs, including renewable resources, under volatile market conditions and extreme natural hazard scenarios [150,152], which supports the trade-off between IES resilience and economic sustainability [200] as a response to the increasing need for high resilience, operational flexibility, low carbon emission, and cost-effective IESs [78]. Moreover, maintaining a resilient multi-energy supply based on IES is essential to successfully implementing the sustainable, net-zero energy transition and adapting to spatially heterogeneous climate impacts [153,154].

From an R4thGM viewpoint [9,111], besides the necessity of sustainability orientation for more contemporary (i.e., more resilient, sustainable, and open to diverse stakeholders) IESs, resilient multi-energy supply should be an orientation for the 21st century's IES infrastructures, which explains the first and foremost corner—*resilient and sustainable multi-energy supply*—of PoliTo's triangle (Figure 5) proposed as a foundation of R4thGM for resilient and sustainable IESs against extreme weather events. PoliTo's triangle bridges the gap between the seven quality management principles—customer focus, process approach, evidence-based decision making, engagement of people, leadership, relationship management, and continuous improvement—defined by the International Organization for Standardization [201] and the understanding of sustainable multi-energy supply [202]. This triangle incorporates resilience as a quality of IES-based multi-energy supply and a customer focus (i.e., people/consumer focus) to leverage sustainability's social, economic, and environmental pillars (i.e., the triple bottom line of sustainability). PoliTo's triangle (Figure 5) is an application of the triangle in Figure 2 to the field of energy, in general, and to IESs exposed to extreme natural hazards in particular.

The second corner of PoliTo's triangle (Figure 5) is the *systemic/process approach and evidence-based decision-making*, which can be described in this study as using a scientific approach [9,196] to manage the different, interdependent IES's infrastructures, such as electric, gas, heating, cooling, hydrogen, and water infrastructures or subsystems, in a resilient and sustainable way in the face of extreme natural hazards. The second corner of PoliTo's triangle revolves around optimization methods for IES resilience, AI, and advanced simulation-based decision-making (Section 3.2). The third corner of PoliTo's triangle (Figure 5) is *inclusive engagement of people (including leadership) and relationship management*. This corner involves managing the collaborations, total involvement, and openness to diverse and multi-level stakeholders, such as governmental and non-governmental organizations and other energy decision-makers and policymakers (e.g., energy consumers, energy operators, engineers, researchers, investors, etc.) from the public and private sectors (Section 1) [12,75,130,203], in the continuous improvement process of resilience and sustainability for IESs exposed to extreme natural calamities.

3.2. Triad of the Suggested Integrative Systems Approach

3.2.1. Optimization Methods of IES Resilience

IES resilience can be defined as the capacity of a set of interconnected energy systems to anticipate, withstand, respond to, and recover from a disturbance to a normal state (Figure 7) [8,43–45,103,143,145,169,204–207]. It is often summarized as the ability to withstand and rapidly recover from uncontrollable processes, including extreme natural hazards [29,73,146,208]. Beyond IES's RBD (i.e., the design stage of IESs), IES resilience enhancement strategies for the resilience-oriented operation stage can be analyzed from three dimensions—pre-disruption defense, disruption response, and post-disruption recovery [42,80,87,209,210]. Fostering grid resilience entails proactive actions before disruptions (i.e., avoidance), efficient reconfiguration during incidents (i.e., survival), and strategic recovery planning post-natural disasters [211]. From the IES management and governance perspective (Sections 3.1.1 and 3.1.2), the resilience curve serves as a basis for pre- (including RBD) and post-natural hazard modeling and simulation [39].

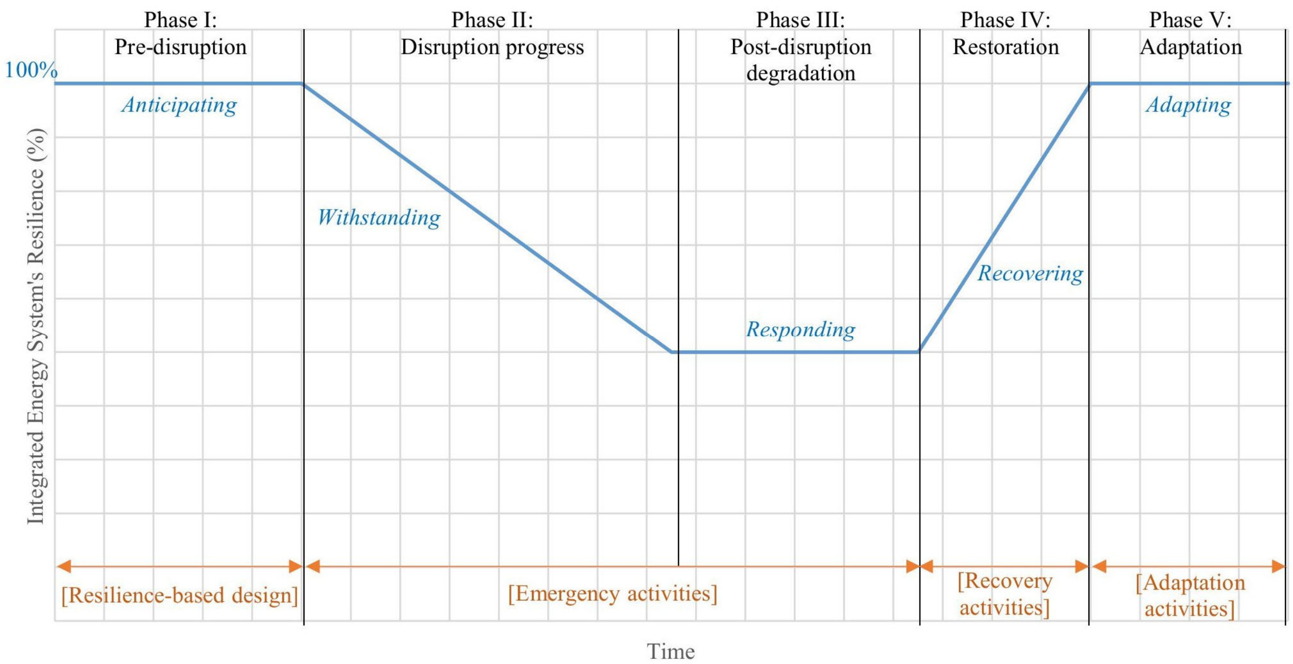

Figure 7. Curve of integrated energy system (IES) resilience.

As shown in Figure 7, in the proactive phase of pre-natural-disruption, i.e., during phase I—the useful life phase featured by long-term resilience actions spread over years or months—including RBD, redundancy planning, and infrastructure reinforcement—and days/hours off operational or preventive responses (i.e., short-term resilience actions) [78,85,118,156,212,213], IES is safe, operating with its normal loads [45]. Indeed, anticipation in phase I (Figure 7) is about: (i) proactive resilience planning—a long-term activity to enhance IES robustness and intelligence in pre-planning for natural disruptions [144,212]. Pre-planning, or proactive preparation, is the set of technical, organizational, and strategic actions carried out in phase I, bridging RBD that considers the total cost of the critical infrastructure as one of the design parameters [41,53,163,164,214] with operational readiness to minimize the IES's degradation in phases II and III and accelerate restoration [215]. (ii) preventive responses encompassing short-term measures, such as IES hardening, reserve scheduling, resource (e.g., mobile generators, repair crews, water pumps, and spare parts) pre-positioning, preventive maintenance, early warning protocols, adjusting grid topology (i.e., network reconfiguration) ahead of a natural disruption, pre-natural-disruption collaborative dispatch of emergency resources, and proactive scheduling and deployment of emergency resources [54,118,151,155,157–159,162,216]. According to Hafeznia and Stojadinović [28], proactive resilience planning and preventive responses are pre-natural-hazard resilience enhancement measures. Natural disruption occurs, and emergency activities such as IES protection, load shedding, and emergency islanding start in phase II (Figure 7) [32,165–167,217]—the IES performance significantly declines in this phase. Over the post-disruption degradation phase (i.e., phase III), IES begins absorbing and resisting the negative consequences of the natural hazard [212]. In phases II and III, emergency activities or short-term emergency responses, such as emergency dispatch, prosumer-centric microgrids (in phase III), and emergency mobile energy storage (EMES) allocation, are reactively deployed to directly support critical loads (e.g., hospitals, water pumps, and shelters), slow down the degradation in phase II, and stabilize performance at a degraded level before the restoration phase (i.e., before phase IV) [54,81,127,160,161]. The IES's effectiveness and stability improve progressively and are inversely proportional to decreasing energy load losses during the restoration phase (i.e., phase IV), witnessing recovery activities such as the mobile compressor dispatch, topological reconfiguration, microgrid formation, maintenance, fast fault isolation, remote-controlled service restoration, coordinated operation of energy subsystems, and leveraging energy storage [34,36,39,70,76,90,171]. The IES adaptation phase (i.e., phase V) goes beyond restoration. In phase V, the IES effectiveness, safety, and stability return to or exceed the original state in phase I (Figure 7). Phase V involves long-term, continuous improvement-driven adaptation strategies and future resilience, such as IES's redesign, strategic reconfiguration, transformation, resilience upgrades, and reinforcements [168]. The long-term resilience measures or adaptation activities in phase V include diversifying energy sources to incorporate more renewables and microgrids, decentralizing energy production, investing in robust and flexible infrastructure, e.g., energy storage and innovative and sustainable grid technologies, and incorporating AI and smart control to improve demand management and enhance IES response to extreme natural hazards [131,170,204,218,219].

In the sphere of IES resilience optimization, the suggested integrative systems approach (Figure 4) focuses on optimizing RBD and post-natural hazard restoration. Indeed, it focuses on optimizing IES resilience in phases I and IV of the resilience curve (Figure 7). As detailed in Supplementary Table S1, the recent literature has long demonstrated the effectiveness of optimizing RBD [41,53,163,164] and post-natural disruption restoration [26,28,29,35–39,42–45,49,142] in improving functionality performance for IESs [88,220]. To optimize IESs' RBD and post-natural hazard restoration, single- and multi-objective approaches, diverse constraints, and optimization methods or algorithms must be considered (Supplementary Table S1). Supplementary Table S1 presents contributions emphasizing optimal restoration after disruption and optimal RBD for IESs exposed to natural disruptions, based on peer-reviewed papers published between 2022 and 2024 and indexed in Scopus, Web of Science, or both databases.

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3.2.2. Artificial Intelligence (AI) and Advanced (Stochastic) Simulation as Enablers of IES's Resilience and Sustainability

Modern IESs, characterized by high penetrations of variable RESs, distributed energy resources (DERs), and complex interactions among electricity, heating, and mobility sectors, exhibit profound stochastic variability and uncertainty that traditional models cannot adequately capture. To assess resilience (the ability to withstand and recover from disruptions) and sustainability (long-term, reliable operation under environmental and economic constraints), it is essential to efficiently explore vast state spaces that encompass system operational conditions, component failures, extreme weather events, and market fluctuations. Classical stochastic methods, such as Monte Carlo simulation (MCS), remain foundational for probabilistic uncertainty quantification and risk assessment, as they approximate the distributions of outcomes by repeated random sampling from uncertain inputs, enabling the evaluation of resilience and sustainability metrics in stochastic contexts [221]. However, the computational cost of direct MCS grows prohibitively for low-probability event analysis (such as that of interest to the present paper, involving extreme natural hazards), necessitating *hybrid* and *adaptive* approaches that leverage machine learning (ML) and AI to enhance efficiency and insight.

AI has emerged as a transformative technology and pivotal force capable of leading the transition toward more innovative, resilient, and sustainable IESs [222,223], which supports the energy efficiency revolution, enhances grid resilience, ensures energy supply security, and optimizes the integration and consumption of economically, environmentally, and socially sustainable energy [224]. In the AI-sustainability nexus, R4thGM encourages incorporating AI into the circular economy as a sustainability foundation for more contemporary production systems, including more contemporary IESs (Section 3.1.2), and using AI to foster the holistic behavior of these systems [9]. AI methods (e.g., ML) are expected to enhance decision-making processes by optimizing IES resilience to extreme climates, efficiency, and cost-effectiveness [128]. Furthermore, integrating ML and remote sensing can strengthen IES resilience and sustainability [117]. ML can be incorporated into frameworks that combine AI and simulation techniques to optimize investments in IES generation, storage, and transmission; integrate extreme natural hazards; and improve grid resilience through long-term, proactive resilience planning (Section 3.2.1) [225]. Oikonomou et al. [225] suggested a machine-learning, scenario-based simulation framework for planning power infrastructure resilience. In fact, the authors of [225] proposed a framework that employs a machine-learning-based model trained on historical loads and meteorological variables to parametrize heatwave-induced loads for each Western Electricity Coordinating Council (WECC) region. ML techniques, such as reinforcement learning (RL), have been considered a valid, innovative solution for real-time decision-making problems concerning the energy load recovery or restoration phase (Figure 7); for instance, instead of building the optimization problem, RL can formulate the decision-making problem as a Markov decision process and solve it [131]. Focusing in more detail on the specific methodologies, recent literature highlights that advances in AI/ML have fundamentally transformed the analysis and management of IESs by enabling effective (data-driven) resilience and sustainability assessments across *multiple spatial* and *temporal scales* [129,226–230]. At the core of these advancements are *supervised* learning methods, such as Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM) networks, Random Forests (RFs), Support Vector Regression (SVR), and gradient boosting frameworks (e.g., eXtreme Gradient Boosting-XGBoost) [227], which have been widely adopted for accurately estimating component failures or degradation patterns, predicting state-of-health and SOC for storage, and forecasting renewable generation and load demand, thereby mitigating variability and enhancing the reliability of decentralized systems over time scales ranging from minutes to days [228,231]. Complementing these predictive models, Deep Learning (DL) approaches extend conventional (neural) architectures to capture complex nonlinear dependencies in high-dimensional operational data, making them effective for real-time grid optimization and anomaly detection [129]. (Multi-Agent) RL and its deep variants further contribute to resilience by enabling adaptive control strategies in Energy Management Systems (EMS) and microgrid environments, where agents learn optimal policies through interaction with stochastic environments, enable systems to adapt to disruptions or changing conditions, and improve long-term performance without explicit mathematical models, balancing objectives such as cost, emissions, and reliability *in real time* [229,232–234]. For anomaly and fault detection, *unsupervised* and *hybrid* techniques (including Siamese networks, Autoencoders-AEs, Variational Autoencoders-VAEs, One-Class Support Vector Machines-OCSVMs, Isolation Forests-IFs, and recurrent models such as LSTM) have shown effectiveness in quickly identifying deviations from normal operation that may indicate failures, cyber-physical threats, or equipment degradation [235,236]. Also, clustering techniques (e.g., k-Means and Density-Based Spatial Clustering of Applications with Noise-DBSCAN) have shown effectiveness in identifying and grouping similar patterns of IES evolution towards critical conditions [233]. One issue with pure data-driven AI/ML models (black-box models) lies in the fact that they can miss *physical constraints* in energy systems; in this respect, *hybrid* models blending data-driven learning with *physics* or *domain knowledge* have been proposed. For instance, unlike data-driven models, in a direct application to integrated gas and power systems (Figure 1), where AI and stochastic/dynamic simulation interact, He et al. [237] recently proposed a physics-informed neural operator that embeds differential and algebraic physical constraints into the AI model to enhance energy flow calculations in IESs. Physics-Informed Neural Networks (PINNs) [237,238], Graph Neural Networks (GNNs) [239], and combinations of the two concepts [240,241] integrate physical constraints and laws (e.g., power, mass, and information flow equations) and system topology, respectively, into learning processes, improving generalization across spatially (and temporally) interconnected energy grids and production systems, and enhancing interpretability essential for sustainability analyses [233]. The *multi-scale* and *multi-level* version of GNNs, i.e., Hierarchical Graph Neural Networks (HGNNs), introduces multiple levels of representation, often by pooling or clustering nodes into "super-nodes" to capture long-range structural information and multi-scale dynamics. This addresses limitations of "flat" GNNs, such as the over-smoothing problem and the inability to capture interactions between distant parts of a large IES [242,243]. Additionally, multi-objective optimization and metaheuristic methods (Section 3.2.1), such as genetic algorithms and particle swarm optimization, are frequently coupled with AI/ML predictors to explore (efficiently and with a relatively low computational effort) large search spaces and identify trade-offs between resilience metrics (also including reliability, availability, vulnerability, and robustness) and sustainability goals (e.g., emissions minimization) over long planning horizons [244]. These algorithm classes collectively support a comprehensive framework that spans component-level diagnostics, system-level forecasting, and real-time adaptive control, facilitating the design and operation of energy infrastructures that are both resilient to disruptions and aligned with sustainability objectives [227]. Thus, such a technological convergence presents substantial potential for enhancing the operation and maintenance of IESs, particularly through autonomous operation supported by Digital Twins (DTs) and the implementation of data-driven (possibly, physics-enhanced) condition-based and predictive maintenance methodologies [245–250].

However, challenges remain in: (i) data quality and availability; (ii) computational scalability (since training complex models, e.g., deep reinforcement learning-DRL and large ANNs, is resource-intensive); (iii) model interpretability, which must be addressed to fully leverage AI/ML in practical IES deployments: actually, providing transparency and interpretable decisions is critical for system operators and policy compliance, and represents a key for AI/ML adoption in safety-critical energy infrastructures and regulatory environments; (iv) integration across different domains (e.g., combining models across supply, storage, market, and resilience domains) and across decentralized systems (e.g., local energy communities and Internet of Things (IoT) sensing networks) without sharing raw data to protect sensitive operational information, which is ideal for distributed energy markets and privacy constraints [129,228,229,234,235,251–253].

With respect to advanced (stochastic) simulation, it plays a central role in analyzing resilience and sustainability in IESs, particularly in quantifying uncertainty, rare-event probabilities, and complex scenario spaces that arise from high penetrations of variable RESs and multi-scale infrastructure interactions. At the foundation of such analyses lies the classical Monte Carlo simulation (MCS), which uses repeated random sampling to model the behavior of systems with stochastic inputs and to estimate metrics such as Loss of Load Expectation (LOLE) and Expected Energy Not Supplied (EENS) under uncertainty, providing a probabilistic view across differing temporal and spatial resolutions [221]. However, naïve MCS can be computationally prohibitive when evaluating low-probability, high-impact events (e.g., extreme natural hazards) or when exploring high-dimensional state spaces (typical of IESs). To address these challenges, variance reduction and advanced sampling techniques such as Quasi-Monte Carlo (QMC) [254], Stratified Sampling [255], Subset Simulation (SS) [256–258], Line Sampling (LS) [259,260], Splitting methods [261], the RESTART approach [262,263], and Importance Sampling (IS) [264] have been adopted, enabling more efficient estimation of rare event probabilities and reducing the number of required simulations by focusing computational effort on the most relevant regions of the IES state space [254]. Within the IS context, several techniques in various fields of research have been proposed to optimize the approach, i.e., maximize the accuracy and maximize the precision (resp., minimize the estimation variance): see, e.g., the Adaptive Kernel (AK) [265], the Cross-Entropy (CE) [266], the Variance Minimization (VM) [267], and the Markov Chain Monte Carlo-Importance Sampling (MCMC-IS) [268] methods. Affine invariant, interacting, and multi-source MCMC methods extend MCS by generating correlated sample sequences that can better capture complex probability distributions, functional and dynamic dependences, for deeply exploring the system state space and discovering those combinations of factors (i.e., of component failures, physical parameter variations, environmental conditions, repair strategies, spares allocations, etc.) leading to unexpected critical system configurations (disrupted performance states) [269] or to restored system configurations (recovered performance states). For these reasons, MCMC has been successfully applied in multi-area reliability and resilience assessment and probabilistic security studies of power systems, where spatial correlations and intermittent generation patterns must be captured [270,271]. Hamiltonian Monte Carlo and other physics-informed sampling schemes represent further advances, reducing correlation in the sampled trajectories and improving convergence in high-dimensional spaces common to system state exploration, including voltage stability and contingency analysis [272]. Additionally, QMC approaches, which replace purely random sampling with low-discrepancy sequences (e.g., Sobol, Halton), often yield faster convergence rates and have been shown to enhance efficiency in probabilistic power system studies compared to traditional Monte Carlo, especially under constraints of limited computational resources [254,273,274]. More sophisticated frameworks, such as multi-level Monte Carlo, exploit *hierarchies* of *model fidelity* to achieve further computational savings when estimating expectations across scales, which is particularly relevant for coupling *short-term* operations with *long-term* planning in IESs [275]. Together, these stochastic simulation methods can enable comprehensive exploration of system dynamics under *uncertainty*, providing both *granular* and *system-wide* insights for identifying critical accident scenarios, resilience bottlenecks, and sustainability trade-offs in integrated energy infrastructures [276].

Based on the above-mentioned literature, it is evident that *each* of the methods analyzed, i.e., AI/ML approaches, optimization techniques (e.g., metaheuristics, swarm intelligence, and local search), decision-making methods (e.g., Markov decision processes), game theory, and statistical and probabilistic methods (e.g., Bayesian networks, Hidden Markov models, and stochastic simulation), can play a crucial role in empowering the resilience of IES infrastructures with respect to extreme natural events [105,277]. In this study, efficient and intelligent *combinations* of these approaches are considered for enhancing the resilience and sustainability of IESs within the proposed integrative systems framework (Section 3.1).

One prominent *hybridization* involves adaptive sampling strategies such as IS, which selectively biases samples toward regions of the input space that contribute most to a quantity of interest (e.g., failure events), thus substantially reducing variance and the number of required simulations compared to standard MCS. Advanced implementations of adaptive importance sampling have been developed with physics-informed, system-aware proposal distributions [262,278], enabling real-time estimation of failure probabilities in large networks with relatively few samples [279]. When combined with surrogate modeling techniques such as Gaussian process emulation [269,280–283], neural network approximators [284], or SVR [285], these methods offer a two-fold benefit: surrogate models provide a computationally cheap representation of expensive physical simulations, while adaptive sampling focuses computational effort on critical regions of the state space, further accelerating rare-event and accident scenario discovery [286,287]. Beyond sampling acceleration, deep AI/ML models are increasingly used to generate realistic stochastic scenarios that preserve temporal and spatial correlations inherent in complex energy systems. For example, deep generative architectures such as Generative Adversarial Networks (GANs) and their Bayesian variants have been applied to produce high-fidelity renewable energy and load scenarios without explicit probabilistic model assumptions, capturing both temporal diversity and conditional behaviors relevant to extreme or rare operational conditions [288–291]. Similarly, normalizing flows, a class of deep probabilistic models that directly approximate multivariate distributions, have been proposed for producing scenario-based forecasts that preserve joint uncertainties across multiple correlated variables, such as wind, solar, and load profiles, facilitating robust planning and risk assessment [292]. Complementary approaches employ Gaussian Processes (GPs) and other Bayesian non-parametric models to not only forecast uncertain system behavior but also quantify predictive uncertainty, making them valuable components of hybrid frameworks for risk-aware decision-making and resilience analysis. Gaussian Process models provide probabilistic predictions with well-calibrated uncertainty estimates that can guide stochastic sampling and AI/ML-based scenario clustering, enhancing robustness in multi-scale applications ranging from distribution-level microgrids to regional transmission networks [293]. In parallel, clustering, classification, and dimensionality reduction methods (e.g., global sensitivity analysis, feature selection, k-Means, Spectral Clustering-SC, Hierarchical Clustering-HC, Principal Component Analysis-PCA) are frequently used to reduce the complexity of the IES under analysis [269,294] and/or the complexity/size of scenario sets generated either by stochastic simulations or deep generative models [295–297], enabling efficient exploration of representative "macro-scenarios" for both planning and real-time resilience assessment [298–300]. DRL constitutes another hybrid frontier wherein learning-based agents interact with stochastic simulation environments to discover adaptive control policies that maximize system resilience under uncertainty. Although primarily applied to energy management and operational optimization (e.g., adaptive dispatch of storage and distributed resources in microgrids), DRL agents implicitly explore state spaces to identify failure-prone regions and adaptive interventions, bridging simulation and learning in a closed-loop fashion [102]. Such learning frameworks enhance operational decision-making by effectively navigating high-dimensional action and state spaces where traditional optimization struggles to scale across multiple temporal resolutions (e.g., minutes to seasons) and spatial hierarchies (e.g., feeders to regional grids) [301]. Another key class of hybrid strategies integrates stochastic simulation with deterministic system solvers, such as coupling MCS with Newton-Raphson power flow analysis, to efficiently evaluate system reliability under probabilistically generated stress conditions, thereby synthesizing probabilistic risk profiles with physically accurate system responses [302]. In such frameworks, stochastic simulations generate a diverse set of operational states, while deterministic solvers accurately assess stability and feasibility, enabling identification of critical vulnerability scenarios with both computational tractability and physical fidelity. Hybrid simulation and ML/AI approaches also extend to scenario reduction and optimization, in which high-dimensional stochastic forecasts are distilled into compact, representative ensembles for integration into stochastic programming or multi-stage optimization frameworks used in resilience planning. Techniques such as strategic sampling guided by ML-informed insights or clustering have demonstrated substantial efficiency gains in solving chance-constrained problems and managing uncertainties associated with RESs integration and storage dynamics [299,303]. By combining stochastic sampling and data-driven model reduction, these methods reconcile the need for scenario diversity with computational limits, facilitating multi-objective analyses that can incorporate sustainability metrics such as emissions, cost, reliability, and resiliency [304]. In synthesis, iterative and adaptive hybrid frameworks that marry stochastic simulation and ML/AI (e.g., adaptive importance sampling with ML surrogates, deep generative scenario generation conditioned on environmental stressors, RL integrated with stochastic environments, and stochastic-deterministic simulation couplings) offer powerful tools for resilience and sustainability analyses of IESs. These hybrid approaches enable efficient exploration of complex state spaces, identification of rare accident scenarios, and robust decision-making across granularities from component to system levels and temporal scales from real-time operations to long-term planning [305,306].

In this respect, in a framework proposal titled *ARtificial Intelligence and STOchasTic simulation for the rEsiLience of critical infrastructurES (ARISTOTELES)* [8], stochastic simulation for the resilience of IESs under extreme natural hazards (e.g., climate change-induced flooding) involves creating models that incorporate uncertainties in weather event occurrences and component failures, then using simulation techniques to evaluate IESs' ability to withstand and recover from such events [17]. Regarding different classes of disrupted and recovered system states, with varying magnitudes and speeds of system performance loss or recovery, Di Maio et al. [8] affirmed the feasibility of deploying AI methods, such as DL, clustering, and regression techniques, in information retrieval and synthesis. IES modelling techniques encompass human-knowledge-based ML models, requiring specific expertise in physical mechanisms [85], i.e., underlying physics (e.g., power flow, heat transfer, gas flow, losses, current-voltage relations, fluid dynamics in pipes, compression, storage, charge-discharge dynamics, and coupling constraints) that govern how energy is stored, transported, converted, and generated across multiple energy carriers (Supplementary Table S1). ML can serve as a predictive tool to enhance IES's preventive response to extreme natural hazards, enabling efficient resource allocation and preventive scheduling in the pre-disruption or anticipation phase (Figure 7). For example, it can be integrated into an outage prediction model to identify vulnerable parts of the IES's power infrastructure based on extreme weather forecasts and the power infrastructure's operational history (i.e., historical data) [132]. Since some IESs, such as hybrid renewable energy systems (HRESs) [53], include wind turbines, state-of-the-art ML regression techniques, including SVR, ANNs (multi-layer perceptron and extreme learning machines), and GPs, can be applied for predicting extreme weather-induced wind power ramp events [307].

Focusing on IES' resilience enhancement in post-natural disruption in general and the restoration phase in particular (Figure 7), AI and stochastic simulation have recently been effectively combined by Liu et al. [127] to develop an advanced resilience optimization framework for EMES allocation based on multi-agent deep reinforcement learning, learning optimal energy storage allocation strategies under uncertainty. Indeed, the authors of [127] used simulated microgrid-integrated distribution networks and probabilistic disaster models, such as the joint probability density of rainfall and wind speed, to train and evaluate the DRL algorithm. These authors presented four recovery scenarios to simulate and compare distinct post-natural disaster recovery strategies for the microgrid-integrated distribution network. Das et al. [64] developed a novel, efficient, parallelized reinforcement learning (PRL) technique based on probabilistic events to handle microgrid energy scheduling under extreme-weather uncertainty. They performed two simulation investigations—stochastic optimization and online testing—to compare them with well-established RL methods. Therefore, the authors of [64] demonstrated that their new PRL method can achieve up to 20% improvement in optimization performance, with a computational cost up to 28 times lower than Q-learning with experience replay and multi-agent Q-learning. Shang et al. [308] developed a framework to jointly evaluate reliability and resilience, simulating the combined effects of natural disruptions and gradual component degradation or aging. The authors of [308] employed MCS and ML-enabled forecasting to predict power infrastructure performance and develop proactive operational solutions in the anticipation phase (Figure 7), which can enhance stability, robustness, and longevity-driven proactive resilience, as well as address ecological, social, and economic trade-offs (i.e., the triple bottom line of sustainability) for IESs.

4. Propositions and Research Implications

To reflect on the suggested theoretical framework (Figure 4), Section 4.1 presents propositions to enhance the resilience and sustainability of IESs against extreme natural hazards through the proposed integrative systems approach. The research implications are discussed in Section 4.2.

4.1. Propositions for Enhancing Resilient and Sustainable IES Control, Coordination, Communication and Integration Through the Suggested Integrative Systems Approach

To enhance resilient and sustainable IES control, coordination, communication, and integration against extreme natural hazards, through the suggested integrative systems approach (Figure 4), it is crucial to be aware that R4thGM, as a management style [9,111], aims at making the IES—as a complex socio-technical system or organization—more resilient, sustainable, and open to diverse stakeholders against extreme natural hazards, while catalyzing its orientation toward resilient and sustainable multi-energy supply in the operation phase (Section 3.1.2). This section focuses on IES governance and the role of IEM-Fs (Figure 6 and Table 2) that characterize IEM (Figure 6) in strengthening the control, coordination, communication, and integration of resilient and sustainable IES's infrastructures against extreme natural hazards in the design and operation phases of the IES, while considering the roles that optimization methods of IES resilience, AI, and advanced simulation can play in the sphere of IEM as a part of RS-IES-M (Figure 6) suggested in this study. Indeed, this section presents propositions that describe the interplay between IEM and the triad of the proposed integrative systems approach (see Figure 4 and Section 3.2), based on: (i) the recent literature using resilience optimization methods for control, coordination, communication, or integration of IESs under extreme natural hazards (for Proposition 1 in Section 4.1.1), and (ii) Sections 3.1.1 and 3.2.2 (for Propositions 2 and 3 in Sections 4.1.2 and 4.1.3).

4.1.1. Proposition 1: Resilience Optimization Methods-Based IEM for IES Coordination and Integration Against Extreme Natural Hazards

The recent literature has consistently demonstrated the feasibility and effectiveness of coordinating and integrating the infrastructures and sometimes the maintenance personnel of an IES to enhance its flexibility, preparedness, and robustness in both pre- and post-natural disruption phases (Figure 7), based on several optimization methods of IES resilience (Section 3.2.1) [22,26,39,45,50,60,93,147]. In this respect, Wen et al. [60] proposed a post-disaster recovery strategy for a multi-region electric-hydrogen IES that incorporates cross-regional resource sharing, with synergistic cooperation among maintenance personnel, mobile electric energy storage, hydrogen-fueled power generation vehicles, and the hydrogen energy infrastructure. From an IEM's perspective (Figure 6), Wen et al. [60]'s framework implies a highly interdependent, multi-actor, and multi-region coordination problem. It directly and critically involves the following relevant (i.e., most critical) IEM-Fs (Figure 6 and Table 2): (i) IES's information and communication (IEM-F2)—it is crucial for multi-agent coordination and integration to synchronize cross-regional resource sharing, ensure consistent situational awareness, and facilitate cooperative resilience and sustainability-driven decision-making; (ii) IES's operations (IEM-F3)—it handles the operational integration of diverse resources (i.e., it executes the actual post-disaster recovery operational plan for IES) by assigning maintenance crews, managing cross-regional dispatching, and allocating mobile storage and mobile hydrogen power generators; and (iii) IES's operational performance (IEM-F3*)—it ensures the effectiveness perennity for the post-disaster recovery plan as conditions evolve around the IES by detecting bottlenecks in cross-regional resource sharing, monitoring success of deployment solutions, and identifying unpredicted conditions during the recovery activities (Figure 7).

L. Sun et al. [93] presented a flexible emergency resource coordination for optimal IES operation under ice disasters. In the sphere of RS-IES-M and IEM (Figure 6), the most relevant coordination- and integration-focused IEM-Fs (Figure 6 and Table 2) to L. Sun et al. [93]'s framework are: (i) IES's information and communication (IEM-F2)—it is essential for synchronizing emergency activities (Figure 7), while supporting coordinated dispatch of emergency resources, ensuring effective communication of the infrastructure status, and enabling real-time integration of diverse IES's subsystems for optimal operation under ice disasters; (ii) IES's operations (IEM-F3)—it executes the coordination logic across IES as a whole by allocating backup resources, ensuring stable operations despites outages and facility/line icing, dispatching flexible emergency resources, and managing rerouting of energy flows; and (iii) IES's operational performance (IEM-F3*)—it guarantees the IES's real-time adaptation as the ice disaster progresses during phase II in the resilience curve (Figure 7) by identifying underperforming infrastructures and zones of the IES, detecting operational anomalies and failures due to icing, and triggering IES's optimal resilience-focused corrective operational actions.

Tutus et al. [50] proposed a synergistic home energy management system (SHEMS) that integrates DERs and B2V2B operation to enhance community resilience by minimizing the total loss of demanded services (LODS) during the post-disaster phase (Figure 7). From the lens of RS-IES-M based on IEM and its IEM-Fs (Figure 6 and Table 2): (i) SHEMS significantly relies on real-time coordination between homes, DERs, electric vehicles (EVs), and community controllers, which directly involves IES's information and communication

(IEM-F2) as a crucial function for multi-home coordination and various DERs collaboration, while enabling B2V2B communication between EVs and home systems and synchronizing the scheduling of DERs; (ii) IES's operations (IEM-F3) is fundamental for handling the real-time operation of integrated DERs–EVs–home resources by executing cooperative post-disaster energy sharing, dispatching and coordinating DERs, manage B2V2B operation, and prioritizing critical loads to minimize LODS; and (iii) IES's operational performance (IEM-F3*) is necessary to continuously check for the SHEMS's suboptimal performance by assessing the performance of DERs, battery availability for EVs, satisfaction of real-time loads, and effectiveness of energy sharing.

L. Wang et al. [147] enhanced distribution system restoration after extreme weather events such as hurricanes, storms, and wildfires by coordinating repair crews, EVs, and RESs. From an IEM's viewpoint (Figure 6), the most relevant IEM-Fs (Figure 6 and Table 2) to L. Wang et al. [147]'s multi-agent, cross-resource coordination and decision-making framework dedicated to accelerating distribution system recovery and supplying critical loads are as follows: (i) IES's information and communication (IEM-F2)—it is crucial for aligning all actors during the restoration phase (Figure 7) by enabling synchronized restoration actions, dynamic dispatching, EVs routing/charging coordination, and real-time condition monitoring; (ii) IES's operations (IEM-F3)—it serves as the operational brain coordinating the set of working components through dispatching repair crews, routing EVs for supplying critical loads, and coordinating the availability of renewable generation; and (iii) IES's operational performance (IEM-F3*)—it ensures the distribution system's adaptation when restoration conditions shift rapidly by monitoring the effectiveness of the ongoing post-natural disruption restoration, identifying bottlenecks or delays over the restoration process, determining EVs charging constraints/shortages, detecting renewable intermittency, and performing the necessary real-time feedback-based resource allocation adjustments.

Lu et al. [26] proposed a combined electrical and heat load restoration (CEHLR) model for IEHSs that coordinates the recovery of electrical and heat loads after extreme events, such as natural disasters. In the optic of IEM (Figure 6), the most relevant IEM-Fs (Figure 6 and Table 2) to Lu et al. [26]'s framework are: (i) IES's information and communication (IEM-F2)—it is indispensable for coupling the IEHS's electrical and heat infrastructures in phase IV (Figure 7) by allowing joint decision-making between electrical and heat networks, synchronized restoration priorities, and consistent IEHS situational awareness among all operators and control units of electrical and heat infrastructures (e.g., the IEHS's coordinated restoration remains aligned and coherent among people conducting the recovery activities); (ii) IES's operations (IEM-F3)—it executes the integrated recovery activities across both infrastructures of IEHS by ensuring that the restoration in one IEHS's infrastructure does not destabilize the other, dispatching CHP units, coupling electricity- and heat flows-related constraints across IEHS, rerouting electrical power, scheduling the IEHS's heat supply and circulation pumps; and (iii) IES's operational performance (IEM-F3*)—it is necessary for ensuring dynamic correction during the IEHS's coordinated recovery since CEHLR requires continuous performance monitoring to identify electrical overloads, thermal bottlenecks, miscoordination issues-induced mismatches between electrical demand and heat availability, and equipment limits during the restoration phase (Figure 7) for IEHS sensitive to cascading failures.

Gazijahani et al. [39] outlined a pre- and post-disaster management model to enhance the resilience of distribution systems against hurricanes, integrating energy systems—electricity and natural gas grids—with distinct spatial and temporal characteristics. The most relevant IEM-Fs (Figure 6 and Table 2) that leverage coordination and integration for the framework outlined by the authors of [39] are: (i) IES's information and communication (IEM-F2)—it is fundamental for the integration of energy carriers with different topologies and behaviors by coordinating between electricity and gas operators, unifying situational awareness, and ensuring synchronized modeling of both infrastructures for the integrated power and natural gas distribution system exposed to hurricane; (ii) IES's operations (IEM-F3)—it executes all cross-energy, cross-temporal operational strategies over pre- and post-hurricane phases (Figure 7) through ensuring the coordination of pressure management and gas flow routing, gas-fired electricity generators' dispatch, electric feeder reconfiguration, emergency load prioritization, and controlled islanding; and (iii) IES's operational performance (IEM-F3*)—it is essential for ensuring dynamic correction of the tightly coupled electricity–natural gas system. Indeed, during the hurricane and restoration phase (Figure 7), IEM-F3* (Figure 6 and Table 2) continuously assesses the distribution system's operational performance by identifying vulnerable or overloaded power lines, detecting pressure drops across gas pipelines, monitoring stability during reconfiguration, and adapting dispatch to unexpected anomalies.

Li et al. [45] proposed a multi-energy coordination solution to restore energy supply to most electricity, heat, and gas loads in an urban area after an extreme event while ensuring and improving the complementarity among power, heat, and gas sources in the urban integrated energy system (UIES). From an IEM's perspective, the most relevant IEM-Fs (Figure 6 and Table 2) to the UIES's resilience improvement-driven multi-energy coordination framework suggested by the authors of [45] are as follows: (i) IES's information and communication (IEM-F2)—it is crucial to manage the UIES's multi-energy carrier complementarity by coordinating load restoration priorities, aligning operational decision-making across power, heat, and gas infrastructures, and cross-carrier information sharing-based consistent cross-energy situational awareness; (ii) IES's operations (IEM-F3)—it executes the coordinated restoration across the power, heat, and gas carriers by ensuring real-time operational coordination of CHP units' dispatch, heat pump scheduling, pressure management for the gas network, power distribution reconfiguration, cross-energy balancing to exploit the complementarity among power, heat, and gas sources, and the operation status of the coupling elements such as CHP and gas turbine within UIES after the extreme event; and (iii) IES's operational performance (IEM-F3*)—it maintains the UIES's stability during dynamic restoration, which is sensitive to cascading effects, by detecting aberrant conditions over the gas network (e.g., abnormal gas pressure), identifying electric overload, detecting heating network bottlenecks, and ensuring real-time adjustments to maintain the UIES's resilience.

4.1.2. Proposition 2: AI- and Advanced Simulation-Based IEM for IES Control and Coordination Against Extreme Natural Hazards

The interplay between (i) RS-IES-M and its brain IEM (Figure 6) and (ii) AI and advanced simulation is described for each of the nine IEM-Fs (Figure 6 and Table 2) in Table 3 to build an AI- and advanced simulation-based IEM (i.e., combined AI- and advanced simulation-based IEM-Fs) for enhancing the control and coordination of resilient and sustainable IESs against extreme natural hazards.

Table 3. AI- and advanced simulation-based integrated energy meta-system (IEM) for resilient and sustainable integrated energy system (IES) control and coordination against extreme natural hazards.

Integrated Energy Meta-System Function (IEM-F)	Contribution of AI	Contribution of Advanced Simulation	Combined AI- and Advanced Simulation-Based Role of the Integrated Energy Meta-System Function (IEM-F)
IEM-F5—IES's policy and identity	- Learning the correlations between policies (e.g., reserve margin, energy storage target, demand response activation, and cross-carrier coordination policies) and IES-level resilience and sustainability outcomes (e.g., time to recover after an extreme weather event, pressure/temperature/voltage stability, efficiency, losses, long- and short-term carbon dioxide emissions, renewable energy share, and energy supply cost). - Providing stakeholders, acting as policymakers, with decision support.	- Running thousands of long-run scenarios that combine diverse policy choices, extreme weather events, and technology plans. - Generating risk metrics (e.g., expected energy-not-served and probability distributions of emissions).	IEM-F5 serves as a strategic controller that is AI-assisted and simulation-informed, setting resilience- and sustainability-oriented goals, policies, and values for IES exposed to extreme natural hazards in the operation phase (Figure 7). Through IEM-F5, AI can process simulation outcomes as training data to deduce which high-level coordination and control policies are best suited (i.e., robust and accountable) for future extreme natural hazard scenarios.
IEM-F5*—IES's context	- Using forecasting machine learning (ML) models to update an extreme natural hazard-aware environment or context proactively and continuously. - Automatically analyzing the real-time IES's context (e.g., natural hazard forecasts, loads, grid stress, and weather), clustering the IES's context into a regime or category (e.g., normal, stressed, or extreme regime), and driving the best-suited strategy or mode of control (e.g., efficiency-based control, preventive control, and emergency control).	- Discovering possible trends of the IES's context—a set of diverse possible future situations for IES—(e.g., multi-energy demand patterns, climate trajectories, and shocks related to the energy resource price). - Quantifying how the IES's context regimes influence the control and coordination requirements for the IES's infrastructures.	IEM-F5* leverages context-aware modes of control and coordination for the IES. Through this integrated energy meta-system function, advanced simulation can map the space of possible contexts, while AI can use the mapped context space to learn the necessity of changing the modes of control based on the IES's operating regime and recognize the regime in real time.
IEM-F5′—IES's strategic monitoring	- Developing predictive models that map strategic performance indicators (e.g., long-term resilience indices, sustainability, and greenhouse gas emissions) to support control and planning decision-making in pre- and post-natural disruption phases (Figure 7) for IES. - Detecting the gradual, long-term changes—slow drifts—in the IES's operating conditions (e.g., emerging demand patterns, infrastructure aging, and a slow increase in the frequency of extreme weather events), indicating the insufficiency of a part or the set of existing control policies against climate change-induced evolving extreme natural hazards threatening the IES's resilience and sustainability at the strategic scale.	- Providing a probabilistic baseline for each strategic performance indicator.	IEM-F5′ serves as an early-warning IEM's function for control/coordination incompatibility under climate change-induced evolving extreme natural hazards. Through this integrated energy meta-system function, AI can compare real data with simulation-based baselines to: (i) assess whether IES is drifting toward a strategically non-resilient/unsustainable trend and (ii) recommend control-policy improvements.
IEM-F4—IES's development	- Using reinforcement learning (RL) to suggest candidate control architectures and coordination schemes to enhance the IES's resilience and sustainability against extreme natural hazards. - Generating RBD solutions for IES by exploring and optimizing alternative control and coordination architectures.	- Assessing every control/coordination design under a set of extreme natural hazard scenarios. - Generating comparative IES's resilience–sustainability metrics for each candidate future control architecture or coordination design (i.e., for each alternative).	IEM-F4 serves as an IES's resilience/sustainability design lab for future control and coordination structures, with an emphasis on RBD for designing a resilient and sustainable future for IES in phase I (Figure 7) against extreme natural hazards.

Table 3. *Cont.*

Integrated Energy Meta-System Function (IEM-F)	Contribution of AI	Contribution of Advanced Simulation	Combined AI- and Advanced Simulation-Based Role of the Integrated Energy Meta-System Function (IEM-F)
IEM-F4*—IES's learning and transformation	- Analyzing the IES's operational history to detect systemic weaknesses in IES's control/coordination strategies. - Learning root-cause failure patterns relating to extreme natural hazards threatening IES during the operation phase (Figure 7) and enhancing RBD and sustainability planning for the IES's multi-energy infrastructure. - Identifying transformation, improvement, and redesign pathways for IEM (Figure 6) itself (e.g., redesigning control/coordination hierarchies, improving demand response policies, new reserve rules, etc.), based on the analysis of different factors, including extreme natural hazard evolution, renewable behavior, and long-run trends in the IES's loads.	- Validating the best-suited robust candidate transformations across a wide range of scenarios of extreme natural hazards threatening IES.	IEM-F4* creates self-improving control and coordination-driven IEM, ensuring continuous transformations of design and strategies to maintain the IES's high resilience and sustainability against extreme natural hazards.
IEM-F4′—IES's environmental scanning	- Using AI techniques (e.g., ML) to scan weather forecasts, climate projections, and satellite data, the change of the IES's control/coordination policies, market trends, and emerging technologies that are sustainable and resilient to extreme natural hazards. - Identifying the correlations between natural disruptions and the abnormal operation of the IES's infrastructures—impacting the IES's stability or ecological/economic/social sustainability—as crucial signals for the control and coordination of resilient and sustainable IES.	- Converting the AI-extracted signals relevant for the IES's control/coordination into a set of updated scenarios that all controllers and planners should consider. - Quantifying the likely IES's control complexities associated with new natural threats.	IEM-F4′ ensures the continuous alignment between the resilient and sustainable IES's coordination and control actions and the emerging natural disruption-induced external risks.
IEM-F3—IES's operations	- Deploying AI controllers (e.g., DRL and ML surrogate) for coordinating the dispatch of energy resources in a resilient and economically sustainable way and enforcing the IES's resilience constraints under extreme natural hazards. - Learning resilience- and sustainability-oriented coordination policies between the IES's carriers/regions, in order to minimize the risk of extreme natural hazard-caused cascading failures.	- Providing offline training environments for the IES's AI controllers (e.g., ensembles of high-variety scenarios without risking the real energy grids of IES).	IEM-F3 enables AI and advanced simulation to operate IES resiliently and sustainably directly from a control and coordination perspective against extreme natural hazards. Through this integrated energy meta-system function, AI can execute the IES's coordination and control in real time, while advanced simulation can train, calibrate, and validate the IES's coordination/control policies under extreme natural hazards.
IEM-F3*—IES's operational performance	- Using predictive models for flagging abnormal physical quantities (e.g., abnormal pressures, temperatures, and voltages), energy flows, and deviations from the IES's expected resilience responses (e.g., insufficient energy storage) or sustainable behaviors (e.g., unexpected carbon dioxide emissions, energy consumption, energy waste, and operation costs). - Categorizing extreme natural hazard condition-induced events into distinct scales of severity for IES, involving appropriate coordinated responses.	- Providing reference performance distributions across various extreme natural hazard scenarios and control policies for IES. - Enabling consistent assessments of the IES's ongoing operational state with the acceptable score of risk under extreme natural hazards.	IEM-F3* is the operational watchdog for the IES's resilience and sustainability performances under extreme natural hazards.

Table 3. *Cont.*

Integrated Energy Meta-System Function (IEM-F)	Contribution of AI	Contribution of Advanced Simulation	Combined AI- and Advanced Simulation-Based Role of the Integrated Energy Meta-System Function (IEM-F)
IEM-F2—IES's information and communication	- Determining the most critical information (i.e., AI-based information prioritization) for the IES's control decisions during natural disruptions (Figure 7). - Learning adaptive data-reduction [309] to allow the local, regional, or IES's wide algorithmic controllers to acquire only the necessary (i.e., the most relevant) information for real-time adaptive control and fast and reliable coordination during extreme natural hazards, i.e., in phase II (Figure 7).	- Quantifying the effect of information loss on the control performance and coordination of IES exposed to extreme natural hazards.	IEM-F2 designs and maintains the architecture of information flow and coordination between the infrastructures of the resilient and sustainable IES under extreme natural hazards.

4.1.3. Proposition 3: AI- and Advanced Simulation-Based IEM for IES Integration and Communication Against Extreme Natural Hazards

The interplay between (i) RS-IES-M and its brain IEM (Figure 6) and (ii) AI and advanced simulation is described for each of the nine IEM-Fs (Figure 6 and Table 2) in Table 4 to build an AI- and advanced simulation-based IEM (i.e., combined AI- and advanced simulation-based IEM-Fs) for enhancing the integration and communication of resilient and sustainable IESs against extreme natural hazards.

Table 4. AI- and advanced simulation-based integrated energy meta-system (IEM) for resilient and sustainable integrated energy system (IES) integration and communication against extreme natural hazards.

Integrated Energy Meta-System Function (IEM-F)	Contribution of AI	Contribution of Advanced Simulation	Combined AI- and Advanced Simulation-Based Role of the Integrated Energy Meta-System Function (IEM-F)
IEM-F5—IES's policy and identity	- Synthesizing data from the IES's infrastructures to identify integration opportunities, supporting the IES's sustainability and resilience against extreme natural hazards. - Using AI tools such as natural language processing (NLP) and knowledge graphs to align standards and policies across diverse stakeholders (i.e., regulatory, technical, institutional, and societal stakeholders) of the resilient and sustainable IES.	- Testing the resilient and sustainable IES's infrastructure integration policies (e.g., multi-energy hubs, cross-sector backup, power-to-gas and power-to-heat coupling, coordinated outage and restoration strategies, hybrid storage solutions, etc.) under several extreme natural hazard scenarios. - Assessing the impact of data exchange and communication policies between the operating and managing stakeholders on the IES's resilience and sustainability outcomes (Table 3) during extreme natural hazards.	Through IEM-F5, AI can suggest extreme natural hazard-aware integration and communication policies, while advanced simulation can demonstrate which policy options are best suited for the IES's resilient and sustainable performance across numerous scenarios of extreme natural hazards.

Table 4. *Cont.*

Integrated Energy Meta-System Function (IEM-F)	Contribution of AI	Contribution of Advanced Simulation	Combined AI- and Advanced Simulation-Based Role of the Integrated Energy Meta-System Function (IEM-F)
IEM-F5*—IES's context	- Building a context map of all the IES's infrastructures, diverse stakeholders/actors (e.g., major consumers, gas operators, heat operators, regulators, city authorities, etc.), and data sources (e.g., sensor data, hazard data, operational data, forecasts, etc.). - Identifying the enablers and constraints for the communication and integration of the resilient and sustainable IES's infrastructures in the design and operation phases (Figure 7). - Classifying the IES's context into normal/stressed/extreme regimes and determining when enhanced cross-infrastructure integration and more intensive communication are required.	- Exploring how the changes in the IES's context (e.g., climate trends) impact the feasibility/benefit of infrastructure integration. - Assessing the impact of degradation/loss of the IES's infrastructure communication channels in different operating conditions (i.e., normal, stressed, and extreme natural hazard conditions) on the IES's resilience and sustainability performances.	Through IEM-F5*, AI can recognize the IES's current context and recommend the best-suited integration links and communication pathways that should be engaged or strengthened to enhance the IES's resilience and sustainability against extreme natural hazards, while advanced simulation maps the space of the possible IES's infrastructure communication/integration contexts.
IEM-F5′—IES's strategic monitoring	- Monitoring the resilient and sustainable IES's long-term indicators (e.g., cross-carrier energy exchange, interoperability concerns, and data-sharing frequency). - Monitoring long-term changes in climate and natural hazards and the IES's technologies and operations, and identifying when the existing IES's infrastructure integration/communication policies or the existing stakeholders' communication agreements are gradually becoming insufficient or inadequate for resilience and sustainability, exacerbating the need for new integration/communication policies to cope with climate change-induced evolving natural hazards.	- Providing probabilistic baselines for how an appropriately integrated and well-communicating resilient and sustainable IES's infrastructure should operate under future extreme natural hazards. - Signaling the necessity of strategic redesign/RBD—when observed, IES's infrastructure integration/communication performance falls outside those baselines.	IEM-F5′ enables tracking the IES's strategic resilience and sustainability performances and signaling when multi-energy infrastructures' integration/communication is no longer aligned with the IES's future resilience and sustainability under climate change-induced extreme/evolving natural hazards. Technically, through IEM-F5′—AI can carry out a comparison between the actual IES's communication and integration performance with advanced simulation-based expectations, determining when the IES needs new integration projects or communication protocols to remain resilient and sustainable.
IEM-F4—IES's development	- Using reinforcement learning (RL) to suggest future integrated configurations (e.g., multi-energy hubs and electricity–gas–heat coupling points) to strengthen the resilience and sustainability of IES against extreme natural hazards. - Supporting the design of the overall structure of information exchange between stakeholders and infrastructures in the IES.	- Stress-testing the architecture designs of the resilient and sustainable IES's integration and communication against several extreme natural hazard scenarios. - Locating weak integration links and critical communication pathways whose failure would affect the IES's resilience in a significant way.	IEM-F4 allows for the design of the resilient and sustainable IES's future integrated architectures and high-level communication structures against extreme natural hazards. Through IEM-F4, AI can generate IES candidate architectures and communication schemes, while advanced simulation can identify the best-suited future designs for resilient, sustainable (e.g., low-carbon) performance across many extreme natural hazards.

Table 4. *Cont.*

Integrated Energy Meta-System Function (IEM-F)	Contribution of AI	Contribution of Advanced Simulation	Combined AI- and Advanced Simulation-Based Role of the Integrated Energy Meta-System Function (IEM-F)
IEM-F4*—IES's learning and transformation	- Learning from past extreme natural events where the IES's infrastructure integration failed and where communication breakdowns occurred between those infrastructures. - Suggesting integration/communication transformations (e.g., new interconnection points, additional cross-infrastructure flexibility, reviewed data-sharing policies, and clean energy/carbon-neutral technology integration) to enhance the IES's resilience and sustainability against extreme natural hazards.	- Performing pre-implementation tests for these integration/communication transformations under various extreme natural hazards to determine how well they can enhance the IES's resilience and sustainability. - Exploring the effect of bringing structural changes to the IES—e.g., adding a regional energy hub or strengthening data links between stakeholders such as transmission system/distribution system/gas/heat operators.	IEM-F4* ensures continuous improvement and transformation of the resilient and sustainable IES's infrastructure integration and communication against extreme natural hazards in the operation and design phases (Figure 7). Through IEM-F4*, AI can identify communication/integration issues in the IES and suggest transformation solutions; at the same time, advanced simulation can validate the optimal (i.e., most effective) transformations to enhance the IES's integration and communication, thereby improving economic/social/environmental sustainability and resilience against extreme natural hazards.
IEM-F4′—IES's environmental scanning	- Scanning the literature, policy documents, technology trends, and external data (e.g., local/regional/national/global energy generation mix, hydrogen economy, and transport electrification) to identify emerging opportunities for cross-sector integration and exchange of data between the entire IES's infrastructure. - Detecting emerging natural hazard patterns that will require more effective/sophisticated integration and communication of the IES's infrastructures.	- Integrating these trends into updated groups of scenarios and assessing how those shifts impact the need for new information flows and communication links within the IES. - Quantifying the gains in terms of resilience and sustainability of early adoption of specific IES's infrastructure-integration strategies under future extreme natural hazard patterns or regimes (e.g., frequency, intensity, duration, spatial extent, etc.).	IEM-F4′ enables the scanning of the IES's external environment for new integration and communication opportunities, requirements, and constraints.
IEM-F3—IES's operations	- Orchestrating real-time integration actions (e.g., gas-to-power, power-to-heat, and multi-energy balancing) for the IES's infrastructures in the pre- and post-extreme natural event (Figure 7), based on shared information, which includes real-time operational data, forecasts, and sensor signals (i.e., information exchanged by stakeholders such as different energy operators) across these infrastructures. - Managing operational data flows between the IES's infrastructures and control centers, while supporting the operational decisions of these control centers.	- Providing training and test environments that include integrated multi-energy (e.g., electricity, gas, heat, and hydrogen) models and real-world communication bottlenecks under natural hazards (Figure 7). - Assessing the effectiveness of diverse data exchange policies and IES's infrastructure-operational integration strategies across numerous scenarios of natural hazards.	Through IEM-F3, AI can use advanced simulation-trained policies to ensure the real-time operation of integrated energy flows and information exchange for the IES's infrastructures, enhancing the ability of these infrastructures to support each other effectively during the occurrence of an extreme natural hazard (Figure 7).

Table 4. *Cont.*

Integrated Energy Meta-System Function (IEM-F)	Contribution of AI	Contribution of Advanced Simulation	Combined AI- and Advanced Simulation-Based Role of the Integrated Energy Meta-System Function (IEM-F)
IEM-F3*—IES's operational performance	- Monitoring the IES's cross-carrier flows (e.g., power supporting heat, gas backing up power, etc.) and shared assets, as well as data exchange quality in terms of consistency and completeness. - Detecting the failures in the integration of the IES's infrastructures and anomalies in communication (e.g., missing energy data, missing coupling equipment status, time delays in equipment responses, and sensor data corruption) between these infrastructures, affecting the IES's resilience during extreme natural hazards (Figure 7).	- Providing reference performance envelopes for the IES's infrastructure-integrated operations and communications under given contexts of extreme natural hazards. - Supporting the classification of integration/communication anomalies in the IES's infrastructures.	IEM-F3* enables monitoring the performance of the resilient and sustainable IES's infrastructure-operational integration and communication while detecting anomalies requiring IES-level (i.e., IES's multi-energy infrastructure coordinated) response. Through IEM-F3*, AI can compare the IES's infrastructure-integration/communication performance in real-time with advanced simulation-driven expectations and trigger IES-level responses when infrastructure communication/integration is likely to be affected, thereby impacting resilience/economic, social, and environmental sustainability.
IEM-F2—IES's information and communication	- Filtering, prioritizing, and routing cross-infrastructure information for the IES. - Detecting communication bottlenecks between the IES's infrastructures and supporting shared situational awareness, and therefore, enhancing integrated operation during extreme natural hazards (Figure 7).	- Stress-testing communication links (i.e., operational communication channels) between the IES's infrastructures under many extreme natural hazards. - Generating baseline performance envelopes and identifying vulnerabilities in the information flow over the IES's infrastructures.	IEM-F2 ensures designing and maintaining the operational information architecture and communication channels between the IES's infrastructures. Indeed, the combination of AI and advanced simulation in IEM-F2 ensures hazard-aware, timely, and reliable information exchange among the IES's infrastructures, leveraging the IES's integrated operations, sustainability, and resilience against extreme natural hazards.

4.2. Discussion

Since its creation by Hallioui et al. [9], R4thGM has not been studied or applied to IESs (Table 1). Since the development of the CSG reference model by Keating and Bradley [135] and the upgrading of Beer [136]'s VSM meta-system by expanding its four functions to nine interconnected meta-system functions (Section 3.1.1), no study has presented an IEM resulting from IES governance and based on optimization methods of IES resilience, AI, and advanced simulation (Table 1). Furthermore, we confirmed that in the literature, no work: (i) has discussed the way in which R4thGM, IES governance, AI, advanced simulation, robust optimization methods, and stakeholders as contemporary concerns can be accounted for in enhancing IES's resilience and sustainability against extreme natural hazards, and (ii) has discussed the role of IES governance in leveraging control, coordination, integration, and communication of IES infrastructures against extreme natural hazards (Table 1). The main goal of this study was to propose an integrative systems approach based on two well-established systems approaches—R4thGM and IES governance— which is best suited to enhancing the resilience and sustainability of IESs against extreme natural hazards in the design and operation phases, using resilience optimization methods, AI, and advanced simulation (Figure 4). The overall study process (Figure 3) was designed to support the resilience and sustainability of IES exposed to extreme natural hazards. It allowed us to select 85 relevant papers—review articles, research articles, book chapters, and conference papers—published between 2017 and 31 August 2025.

Through this work, the concepts of resilience, sustainability, IES, extreme natural hazards, R4thGM, IES governance, IEM, optimization methods of IES resilience, AI, advanced simulation, and stakeholders are gathered in the proposed theoretical framework (Figure 4). This latter, as a novel meta-systems approach (Section 3.1), builds upon: (i) R4thGM, founded on the new tool called PoliTo's triangle (Figure 5), which is an implementation of Hallioui's triangle (Figure 2) to IESs exposed to extreme natural hazards. Indeed, to make IESs more contemporary—i.e., more resilient, sustainable, and open to diverse stakeholders—(Section 3.1.2), and (ii) IES governance based on the novel model termed RS-IES-M and its component IEM (Figure 6) featured by the nine IEM-Fs (Figure 6 and Table 2) to govern the resilient and sustainable IES's infrastructures (Section 3.1.1), i.e., to ensure control, coordination, communication, and integration for these infrastructures (Section 4.1), based on the elements of the triad—optimization methods of IES resilience, AI, and advanced simulation (Figure 4 and Section 3.2).

The recent literature demonstrates the effectiveness of several methods or algorithms for optimizing the resilience of distinct IESs across the design and operation phases (Supplementary Table S1 and Section 3.2.1), notably in the pre- and post-extreme natural hazard phases—to anticipate, withstand, respond, recover, and adapt—in general (Figure 7). In the optic of the proposed integrative systems approach (Figure 4), the design and post-extreme events should be regarded as the target phases for enabling optimal RBD and optimal post-extreme natural hazard restoration, respectively. Therefore, this study affirms the cruciality of those methods in optimizing RBD and post-natural disruption restoration for IESs (Supplementary Table S1). Indeed, optimization algorithms (Supplementary Table S1) play a centric enabling role in enhancing IES infrastructure resilience in the face of extreme natural hazards, as they leverage and operationalize coordination, integration, resource allocation, and recovery strategies under complex physical, temporal, and interdependency constraints. In addition, the recent literature shows that the combination of AI, either on its own or in combination with advanced simulation (i.e., AI and AI-based stochastic simulation or advanced simulation), is a lever for the resilience and sustainability of IESs exposed to extreme natural hazards (Section 3.2.2). Based on the existing, recent works that use resilience optimization methods for coordination and integration of IESs under extreme natural hazards, and in light of Sections 3.1.1 and 3.2.2, we suggested three propositions for enhancing resilient and sustainable IES control, coordination, communication, and integration against extreme natural hazards, through the proposed integrative systems approach (Section 4.1): Proposition 1—resilience optimization methods-based IEM for IES coordination and integration (Section 4.1.1); Proposition 2—AI- and advanced simulation-based IEM for IES control and coordination (Section 4.1.2); and Proposition 3—AI- and advanced simulation-based IEM for IES integration and communication (Section 4.1.3).

On the one hand, we found that resilience optimization methods can enhance the RS-IES-M in general and its IEM (Figure 6) in particular by supporting the coordination and integration of resilient and sustainable IES infrastructures against extreme natural hazards at the operational scale through roles relevant to IEM-F2, IEM-F3, and IEM-F3* (Section 4.1.1). On the other hand, in each of the nine IEM-Fs (Figure 6 and Table 2), within the IEM—the combination of AI with advanced simulation can strengthen this IEM by leveraging the control, coordination, integration, and communication of resilient and sustainable IES infrastructures against extreme natural hazards at the strategic, developmental, and operational levels of the IEM through roles relevant to IEM-F5, IEM-F5*, IEM-F5′, IEM-F4, IEM-F4*, IEM-F4′, IEM-F3, IEM-F3*, and IEM-F2 (Tables 3 and 4). In other words, in each IEM-F (Figure 6 and Table 2), AI will provide adaptive, learning-based decision support, monitoring, and control, while advanced simulation will enable probabilistic stress testing, the quantification of extreme natural hazard uncertainty, and scenario diversity. So, together, they will foster extreme natural hazard-aware, robust control, coordination, integration, and communication across resilient and sustainable IES infrastructures (Figure 8) at the strategic (i.e., the fifth), developmental (i.e., the fourth), and operational (i.e., the third and second) layers of the IEM (Figure 6 and Table 2), involving (i) IEM-Fs 5, 5*, and 5′; (ii) IEM-Fs 4, 4*, and 4′; and (iii) IEM-Fs 3, 3*, and 2, respectively (Tables 3 and 4).

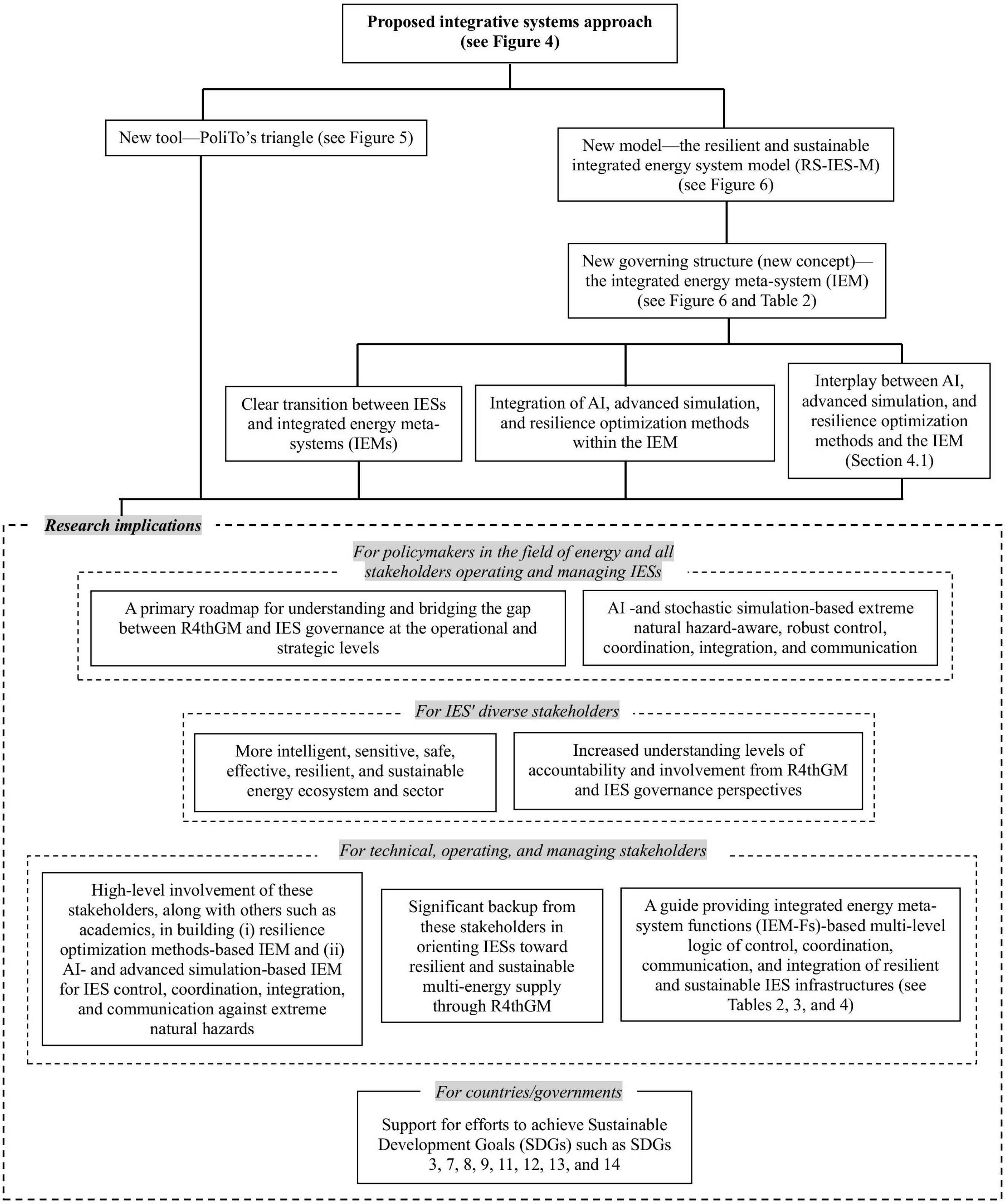

Figure 8. Diagram of the main research implications.

This work is a pioneer in proposing an integrative systems paradigm that combines R4thGM and IES governance and uses resilience optimization methods, AI, and advanced simulation to enhance the resilience and sustainability of IES against extreme natural hazards. Furthermore, this study is pioneering the presentation of the new tool called PoliTo's triangle as a basis for R4thGM applied to IESs; the new model called RS-IES-M—impressed by the four meta-system functions-based approach to viability (i.e., VSM) and its meta-system and the nine meta-system functions-based CSG reference model—and the new governing structure called integrated energy meta-system (IEM) as a new concept based on the nine IEM-Fs, enabling resilient and sustainable IES control, coordination, communication, and integration against extreme natural hazards. This research will lead the transition from focusing on resilient and sustainable IESs in the face of extreme natural hazards to an increased focus on integrated energy meta-systems (IEMs) from an IES governance perspective (Figure 8), as IEMs operate at a higher abstraction level for ensuring and enhancing the control, coordination, communication, and integration of resilient and sustainable IES infrastructures, while incorporating cross-system interactions, meta-level decision-making, and systemic resilience and sustainability. It is the first research contribution in the IES literature to encompass the components AI, advanced simulation, and resilience optimization methods under the umbrella of a meta-system for the resilient and sustainable IES (i.e., under the umbrella of the IEM) and to find the interplay between these components and the IEM (Section 4.1).

As shown in Figure 8, for policymakers in the field of energy and all stakeholders operating and managing IESs, this paper will serve as a primary roadmap to understand and bridge the gap between the roles of resilient and sustainable management style—R4thGM—and governance of resilient and sustainable IESs—as a CSG—in an era of increasing frequency of natural disruptions impacting IES resilience and sustainability in the short term (i.e., at the operational scale) and climate change-induced evolving extreme natural hazards threatening the resilience and sustainability of IES infrastructures at the strategic scale. This work will increase understanding of IES' diverse stakeholders' levels of accountability and involvement from R4thGM (during the operational lifespan of the IES) and IES governance (during the IES design and operational phases) perspectives, thereby building a more intelligent, sensitive, safe, effective, resilient, and sustainable energy ecosystem and sector leveraged by AI, advanced simulation, and resilience optimization methods to address extreme natural hazards, climate change threats, and the evolving environment of IESs (Figure 8). Indeed, it will serve as a guide, providing the technical stakeholders (e.g., technology developers) and operating and managing stakeholders with IEM-Fs-based multi-level (i.e., strategic, developmental, and operational) logic of control, coordination, communication, and integration of resilient and sustainable IES infrastructures in the face of extreme natural hazards (Figure 8), from the IES's policy and identity (i.e., IEM-F5) to the IES's information and communication (i.e., IEM-F2) (Tables 2–4 and Section 4.1.1).

Moreover, significant backup from technical, operating, and managing stakeholders in orienting IESs toward resilient and sustainable multi-energy supply through R4thGM (Figure 8), known for its substantial implications on considering and advancing the triple bottom line of sustainability and realizing the 17 SDGs [9,111], in addition to the high-level involvement of these stakeholders along with others such as academics in building (i) resilience optimization methods-based IEM for IES coordination and integration; (ii) AI- and advanced simulation-based IEM for IES control and coordination; and (iii) AI- and advanced simulation-based IEM for IES integration and communication against extreme natural hazards, will leverage country efforts (i.e., government efforts) toward achieving SDGs (Figure 8) such as SDG3 (ensure healthy lives and promote well-being for all at all ages), SDG7 (ensure access to affordable, reliable, sustainable and modern energy for all), SDG8 (promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all), SDG9 (build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation), SDG 11 (make cities and human settlements inclusive, safe, resilient and sustainable), SDG12 (ensure sustainable consumption and production patterns), SDG13 (take urgent action to combat climate change and its impacts), and SDG14 (conserve and sustainably use the oceans, seas and marine resources for sustainable development).

5. Conclusions with a Practical Roadmap for Grid Operators, Research Limitations, and Future Research

5.1. Conclusions with a Practical Roadmap for Grid Operators

This paper reviewed 85 papers to present an R4thGM- and IES Governance-based integrative systems approach for enhancing the resilience and sustainability of IESs exposed to extreme natural hazards, using resilience optimization methods, AI, and advanced simulation. It presents the new tool, PoliTo's triangle, to make IESs more contemporary during their operation phase in the face of extreme natural hazards, while orienting them toward a resilient and sustainable multi-energy supply. On the other hand, this study proposes an RS-IES-M, built upon an IEM, to govern resilient and sustainable IES infrastructures through the nine IEM-Fs, thereby enabling and supporting the strategic, developmental, and operational control, coordination, integration, and communication of these infrastructures during the design and operation phases of IESs in the face of extreme natural hazards. Furthermore, this work strengthens the nexus between long- and short-term resilience and sustainability for IES's infrastructures while enhancing the holistic behavior of IESs and, therefore, hardening the interdependencies among these infrastructures, which supports the resilience- and sustainability-based viability of IESs. This contribution addresses the challenge of making the proposed integrative systems-based approach a compromise between resilience, sustainability, R4thGM, IES governance, IEM, AI, advanced simulation, and stakeholders as contemporary constructs to enhance IES's resilience and sustainability against extreme natural hazards. The use of resilience-optimization-based IEM for IES coordination and integration and AI- and advanced-simulation-based IEM for resilient and sustainable IES control, coordination, integration, and communication against extreme natural hazards remains at the proposal level for future research contributions.

The proposed theoretical framework is inclusive, involving IES's diverse stakeholders, from IES operators (grid operators) to governments. Here is a 10-step practical tomorrow roadmap, in the light of which grid operator-level stakeholders can effectively engage in enhancing the resilience and sustainability of IES infrastructures against extreme natural hazards in the operational and design phases: (1) stand up an R4thGM resilience cross-functional cell (after implementing R4thGM)—this is aligned with IEM-Fs 5 and 5′ for ensuring a natural hazard-ready, resilient, and sustainable multi-energy supply/operation, while defining operational (real-time/hours–days), tactical (days–weeks), and strategic (months–years) key performance indicators (KPIs) related to the resilience, sustainability, control, coordination, integration, and communication of IES infrastructures; (2) create a hazard-triggered operating mode—this aligns with IEM-Fs 5 and 5* and can be implemented by publishing an operating mode table for normal, stressed, extreme, and restoration conditions, each with clear, pre-approved actions or interventions (e.g., SOC targets, islanding readiness, demand response readiness, etc.); (3) build the minimum cross-IES infrastructure data sharing pack—this is in alignment with IEM-F2 and related to agreeing on a minimum viable dataset (e.g., voltage risk, availability of DERs, pressure at key nodes, compressor status, SOC of thermal storage, extreme weather alerts, etc.) exchanged periodically, e.g., every few minutes and faster during an emergency; (4) create a stochastic simulation-based hazard scenario library and run daily stress tests for the next 24–72 h—this is aligned with IEM-Fs 4 and 4′; (5) use AI to turn scenarios into tomorrow's playbook—this is in alignment with IEM-Fs 3 and 3* and can be performed through training/using ML surrogate to rapidly rank scenarios and identify supportive feedback (e.g., top vulnerability clusters and recommended preventive actions per cluster); (6) set preventive operating constraints for the next day—this is aligned with IEM-F3 and can be carried out by transforming the playbook into operational constraints (e.g., demand response readiness thresholds and activation conditions, and islanding readiness for critical microgrids); (7) deploy anomaly monitoring related to simulation baselines that aligns with IEM-F3* and combines AI and advanced simulation; (8) run a 15–20 min hazard drill within the IES's control room—this aligns with IEM-Fs 2 and 3 and can be performed by doing a short drill before peak risk hours; (9) post-action learning loop within 24 h after a stress—this is a crucial continuous improvement-driven learning and transformation action (organizational learning process in the sphere of resilient and sustainable IES infrastructures) of the IEM. It is the role of IEM-F4* to ensure that the integration action that helped or failed, the missing or late signals, and the procedure that influenced (e.g., slowed) the response are captured, and that AI models and the library of simulation scenarios are updated accordingly after any disruption, including extreme natural hazards; and (10) create a weekly transformation backlog—this in alignment with R4thGM and IEM-Fs 4 and 4*, and it is about ensuring the availability of a prioritized backlog of transformation technical and procedural items, each linked to simulated risk mitigation and sustainability impact (e.g., revised emergency data-sharing policy, sensor addition at critical nodes, new training disruption scenarios, etc.).

5.2. Research Limitations and Future Research

The qualitative research process used to write this critical review article (Figure 3) enabled us to identify potential research limitations arising from the scarcity of secondary data in the literature, which were justified by the novelty of the research topic and its elements. To date, Refs. [9,111] are the two works discussing R4thGM in the existing literature (Table 1). Although R4thGM has been considered to create sustainable total productive maintenance (STPM) in 2023 as a substitute for the Japanese total productive maintenance in the context of the more complex, smart, and sustainable manufacturing sector [111], no studies have emphasized it or provided experimental evidence (e.g., case study outcomes) on its implementation in the energy sector. There remains a scarcity of frameworks that use AI methods/tools, advanced simulation, or a combination of AI and advanced simulation to enhance the resilience/sustainability of IESs against extreme natural hazards (Table 1), which explains the scarcity of literature discussing the technological aspect relating to AI- and advanced simulation-based control, coordination, communication, and integration of IES infrastructures exposed to extreme natural hazards. Indeed, while AI and advanced (stochastic) simulation offer powerful tools to build and leverage an efficient integrated energy meta-system (IEM) (Tables 3 and 4) as a foundation for the resilient and sustainable integrated energy system model (RS-IES-M) (Figure 6 and Table 2) to enable and enhance resilient and sustainable IES autonomous control and coordination (Table 3) and integration and communication (Table 4) against extreme natural hazards, the real world deployment of these two technical enablers (i.e., AI and advanced simulation) remains limited by data scarcity (Table 1), deep uncertainty, computational constraints, safety and explainability concerns, regulatory barriers, and interoperability challenges. A comparative study of AI methods, assessing their advantages and disadvantages for building an IEM, is outside the scope of this work. Moreover, the literature lacks resilience optimization frameworks for the control and communication of IES infrastructures under extreme natural hazards, and no work has been reported on applying the resilience optimization methods or algorithms presented in Supplementary Table S1 to IES governance. No studies have been found that investigate the effectiveness of resilient and sustainable management approaches (e.g., R4thGM) involving diverse stakeholders for IESs under extreme natural hazard conditions (Table 1). Therefore, the role of these stakeholders in enhancing the resilience and sustainability of IESs in the face of extreme natural hazards remains underexplored among researchers.

Further contributions are needed to conduct case studies that implement the proposed meta-systems approach for IESs and multiscale energy systems, and assess the effectiveness or impact of R4thGM in improving their resilience and triple bottom line of sustainability through good practices (e.g., resilience standards, incentives, multi-sector coordination, hardening infrastructures, flexible operations, DTs, participatory risk mapping, resilience- and sustainability-oriented awareness programs/culture, transparent reporting, and shared KPIs) among diverse stakeholders (e.g., governments/regulatory bodies, energy operators, researchers, technology providers, and local communities and municipalities), in the short- and long-term. Each IEM-F in Tables 3 and 4 might be studied in future works as an independent research framework that can deploy AI techniques/tools, advanced simulation, or a combination of AI and advanced simulation to enable or enhance coordination, control, communication, and integration of smart, complex energy infrastructures and boost their sustainability and resilience against extreme natural hazards, including climate change-induced extreme weather events. Furthermore, future comparative frameworks that study RS-IES-M should evaluate the strengths and weaknesses of different AI techniques when combined with advanced stochastic simulation in engineering/developing IEMs to enhance the control, coordination, integration, and communication of resilient/sustainable IES infrastructures. Future comparative assessments of optimization methods are also necessary to support the transition between IESs and IEMs. These assessments might be conducted based on the effectiveness of resilience, computational tractability, and interpretability of decisions.

Future research might apply IES governance to help us identify the effects of RS-IES-M on Industry 5.0, RBD, and the leadership of the smart, resilient, and sustainable energy sector. Empirical studies might assess the impact of RS-IES-M on anticipating, withstanding, responding to, recovering from, and adapting to natural disruptions threatening IESs, or investigate its role in leveraging environmental, social, and economic sustainability for a region. Studies could implement the proposed integrative systems approach to evaluate its role in promoting smart and sustainable cities from a more complex, resilient, multi-stakeholder, and advanced-energy-sector perspective. Further qualitative and quantitative research should be conducted to examine the crucial role that RS-IES-M-based IES governance could play in fostering human-centered AI design principles, balancing resilience- and sustainability-driven human-AI expertise within the context of an IEM, and supporting the ethical and accountable deployment of generative AI within IESs and the energy sector as a whole.

From the *technical* points of view of both (research) *themes* and *methods*, several issues are still open and, thus, deserve attention [310]. In the contemporary context of rapid technological advancement and transformation—particularly in the *energy* and *digital* sectors, also driven by growing concerns over climate change—smart IESs are pivotal in supporting other infrastructures and society as a whole in a scenario of energy transition. In this respect, they must be *adapted* to support *multiple* and *diverse* energy sources, systems, and production units: renewable energy sources (e.g., solar and wind); electric vehicles; integrated power/water/gas distribution systems; energy transportation systems; different energy vectors, such as electricity, natural gas, and hydrogen; energy storage systems, such as accumulators and batteries; hydrogen tanks; and other technologies, including innovative designs for fission-based nuclear power systems, such as Small Modular Reactors (SMRs) and Micro Reactors (MRs), prototype fusion-based facilities for energy generation, while also maintaining reliability, availability, resilience, and sustainability. This requires significant *upgrades*: new infrastructures for transmission and storage; sensors and software for real-time management of supply and demand; smart meters that provide detailed information to utilities and consumers; and the repurposing of existing fossil-fuel infrastructure to ensure a stable, secure, and clean energy supply for the future. In this respect, in the context of classical risk assessments for existing *multi-unit* facilities and forthcoming smart IESs, two critical and yet unresolved challenges remain: the comprehensive evaluation of *multi-hazard* and *multi-unit* risk. Addressing these issues is essential to ensure a scientifically robust assessment of the *aggregated* site risk [311]. This also highlights the importance of assessing the risk contributions arising from *external events*, such as earthquakes and extreme meteorological phenomena. In particular, the increasing influence of *climate change* underscores the growing significance of such hazards and the need to evaluate the *resilience* and *sustainability* of new IESs accordingly [16,312]. Risk aggregation (alongside resilience and sustainability aggregation) refers to the *systematic integration* of information resulting from multiple sources, including (i) 'diverse contributing factors' (e.g., different hazard *types*: internal failures, fires, earthquakes, and other disruptive events) and (ii) 'multiple spatial or operational units' (e.g., distinct power generation *facilities* within the *same* site), for producing an *overall* assessment of risk, resilience, and sustainability. Conventional approaches typically handle these issues in a fragmented manner. Specifically, (i) *expected* contributions to the target metrics from distinct hazard types are often aggregated through simple *summation*, and (ii) risks associated with individual system units are usually analyzed *separately*, with interdependencies and interactions introduced a posteriori in an informal and case-specific way. At the site level, large-scale events, such as the nuclear accident at the Fukushima Daiichi plant in Japan in March 2011, have drastically increased the need for more robust, systematic approaches capable of addressing multi-hazard, multi-unit risk and resilience. Several key challenges complicate the "aggregation process." First, the analytical methods used across different hazard categories and system units often vary in *maturity*. Second, the modeling approaches employed to develop risk and resilience assessments may rely on different *simplifying assumptions*, adopted to varying *degrees* to enable tractable analyses across hazards and locations. Third, the *nature* and *scale* of *uncertainty* can differ substantially among analyses; for instance, some hazards are associated with extremely rare or historically unobserved environmental conditions, leading to uncertainty levels that may undermine the applicability of conventional probabilistic statistical methods [313,314].

From another perspective, continuous advancements in *sensor electronics* for component and *process state monitoring*, AI analytics, and ML algorithms for data processing—coupled with the increasing availability of computational power to support such analyses—are driving significant transformations in the energy sector. This convergence of technologies presents a wealth of opportunities for enhancing the operation and maintenance of smart IESs, including the implementation of autonomous systems supported by DTs and data-driven approaches for condition-based or predictive maintenance [245–250].

However, the *qualification* and *Verification and Validation* (V&V) of AI models and ML algorithms—often regarded as "black-box" systems—remain unresolved challenges for ensuring their safe and reliable application, even when such models are employed solely to assist operators and decision-makers rather than for fully autonomous operation [315]. On one hand, this necessitates rigorous treatment of *uncertainty* in model predictions used for decision-making [316–318], for instance, through Bayesian Neural Networks [319], Deep

GPs [320], Dropout Monte Carlo [321], Mean-Variance Estimation [322], Conformal Prediction [323,324], or Evidential DL [325]. On the other hand, the safety-critical nature of AI and ML applications in the energy domain demands ongoing research to improve the transparency and interpretability of model outputs, fostering trust in their use [233]. Approaches such as the integration of *physical knowledge* into learning algorithms [238–241], *post-hoc sensitivity analyses* (Local Interpretable Model-agnostic Explanation-LIME, SHapley Additive exPlanations-SHAP, Integrated Gradients, Feature Importance, and Counterfactual Explanations) [227], and *advanced visualization techniques* [326,327] should be further developed to provide interpretability from multiple perspectives, explaining learned input-output relationships, individual predictions, and the underlying reasoning processes leading to those predictions. In this respect, transparency and explainable decision-making are critical to supporting system operators, ensuring regulatory compliance, and fostering trust in AI/ML-aided safety-critical energy infrastructures. Additional challenges include:

(i) limitations in *data quality and availability*;
(ii) computational *scalability*, as the training of complex models (e.g., DRL frameworks and large ANNs) is computationally demanding;
(iii) cross-domain and cross-system *integration*, which encompasses the *coordination* of *multiple* (AI/ML) *models* across supply, storage, market, and resilience *domains*, as well as across *decentralized architectures* (e.g., local energy communities and IoT-based sensing networks) and *heterogeneous granularities* at the spatial (component, feeder, regional, national) and temporal levels (milliseconds-protection, minutes-control, hours/days-operation, years-planning) [328,329]. Achieving such integration (e.g., by Federated Learning and/or Multi-Fidelity Metamodeling) without sharing raw data—thereby preserving sensitive operational information—is particularly important for distributed energy markets operating under privacy and data-protection constraints [129,228,229,234,235,251–253].

In the context of DTs, a key challenge lies in their seamless *integration* with existing systems and processes. Achieving effective *data communication* and *interoperability* between DTs and established operational frameworks often requires developing new interfaces and communication protocols. Nonetheless, interoperability also represents one of the most promising capabilities of Digital Twin (DT) technology, as it enables the effective sharing and use of data to support decision-making and control functions. Finally, the role of *operators* and *end-users* in deploying and interacting with DTs must be carefully addressed to ensure that *human factors* are appropriately incorporated into the design and implementation of these advanced systems [6,245,246].

Moreover, the ongoing digitalization of the energy industry has brought increased attention to the *cybersecurity* of installations and infrastructures for energy production and distribution [330]. Cyber risk analysis for digitalized assets remains a developing discipline, characterized by *methodological immaturity* and a *lack of validated techniques*, partly due to the rapidly evolving nature of cyber threats. Nevertheless, as integrated smart energy-critical infrastructures continue to adopt digital technologies, it becomes increasingly critical to develop and apply analytical methods capable of informing risk management decisions. Such methods should enable the implementation of *prioritized security controls* that effectively prevent and mitigate cyber risks while accounting for the specific operational and regulatory constraints inherent to the energy industry [230,235,245,271,331].

Considering the pivotal role of safety in the advancement of nuclear power and integrated energy critical infrastructures as contributors to sustainable development, substantial progress—both theoretical and practical—is expected to be achieved in the aforementioned areas.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/en19040957/s1, Table S1: Contributions emphasizing optimal restoration after disruptions and optimal resilience-based design (RBD) for integrated energy systems (IESs) exposed to natural disruptions between 2022 and 2024.

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

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Data Availability Statement: The data presented in this study are available from the corresponding authors upon request.

Conflicts of Interest: The authors are aware of no personal or financial conflicts that might have affected the research reported in this study.

Abbreviations

The following abbreviations are used in this manuscript:

IESs	Integrated energy systems
AI	Artificial intelligence
R4thGM	Re-engineered fourth generation management
CSG	Complex system governance
IES	Integrated energy system
IEM	Integrated energy meta-system
VUCA	Volatility, uncertainty, complexity, and ambiguity
SoSs	Systems-of-systems
ML	Machine learning
DL	Deep learning
RL	Reinforcement learning
ANNs	Artificial neural networks
NPP	Nuclear power plant
IGPS	Integrated gas and power system
HRES	Hybrid renewable energy system
IEGHS	Integrated electricity, gas, and heat system
B2V2B	Building-to-vehicle-to-building
EHIES	Electricity-hydrogen integrated energy system
EHHIES	Electricity-hydrogen-heat integrated energy system
ETHEIS	Electric-thermal-hydrogen integrated energy system
IEHS	Integrated electricity-heat system
IEHCGWS	Integrated electricity, heating, cooling, gas, and water system
IEGWS	Integrated electricity, gas, and water system
VPPs	Virtual power plants
CCHP	Combined cooling, heat, and power
NaTech	Natural technological
HARIMA-DRL	Hybrid autoregressive integrated moving average-deep reinforcement learning
MCMC	Markov chain Monte Carlo
SDGs	Sustainable development goals

SDG	Sustainable Development Goal
VSM	Viable system model
PoliTo	Politecnico di Torino
RS-IES-M	Resilient and sustainable integrated energy system model
RBD	Resilience-based design
IEM-Fs	Integrated energy meta-system functions
IEM-F	Integrated energy meta-system function
PV	Photovoltaic
WT	Wind turbine
MT	Microturbine
FC	Fuel cell
BESSs	Battery energy storage systems
V2G	Vehicle-to-grid
H2	Hydrogen
SOC	State-of-charge
IESHWGS	Integrated electricity, steam, hot water, and gas system
MILP	Mixed-integer-linear programming
ESS	Energy storage system
CHP	Combined heat and power
ETIES	Electric-thermal integrated energy system
PDS	Power distribution system
DHS	District heating system
EB	Electric boiler
HB	Heating boiler
TSAA	Two-stage acceleration algorithm
MISOCP	Mixed-integer second-order cone programming
SOCP	Second-order cone programming
DRO	Distributionally robust optimization
IEEE	Institute of Electrical and Electronics Engineers
DHN	District heating network
NNC	Normalized normal constraint
TOPSIS	Technique for order of preference by similarity to ideal solution
BSS	Beetle swarm search
BAS	Beetle antennae search
PSO	Particle swarm optimization
GTPP	Gas turbine power plant
CCPP	Combined-cycle power plant
ES	Electric substation
NGPP	Natural gas processing plant
LNG	Liquefied natural gas
LSTM	Long short-term memory
EMS	Energy management systems
AEs	Autoencoders
VAEs	Variational autoencoders
OCSVMs	One-class support vector machines
IFs	Isolation forests
DBSCAN	Density-based spatial clustering of applications with noise
PINNs	Physics-informed neural networks
GNNs	Graph neural networks
HGNNs	Hierarchical graph neural networks
LOLE	Loss of load expectation
EENS	Expected energy not supplied
QMC	Quasi-Monte Carlo
SS	Subset simulation

LS	Line sampling
IS	Importance sampling
AK	Adaptive kernel
CE	Cross-entropy
VM	Variance minimization
MCMC-IS	Markov chain Monte Carlo-importance sampling
GANs	Generative adversarial networks
GPs	Gaussian processes
SC	Spectral clustering
HC	Hierarchical clustering
SMRs	Small modular reactors
MRs	Micro reactors
V&V	Verification and validation
LIME	Local interpretable model-agnostic explanation
SHAP	Shapley additive explanations
DT	Digital twin
PCA	Principal component analysis
IoT	Internet of Things
DTs	Digital twins
RFs	Random forests
SVR	Support vector regression
NGCS	Natural gas compressor station
WSF	Water supply facility
WPS	Water pump station
NGGS	Natural gas gate stations
WST	Water storage tank
BSUs	Building stock units
SDN	Smart distribution network
FRVPPs	Flexible renewable virtual power plants
FRVPP	Flexible renewable virtual power plant
RESs	Renewable energy sources
DRP	Demand response program
SOP	Soft open point
DSRs	Distributed series reactors
ARISTOTELES	Artificial intelligence and stochastic simulation for the resilience of critical infrastructures
HRESs	Hybrid renewable energy systems
EMES	Emergency mobile energy storage
DRL	Deep reinforcement learning
PRL	Parallelized reinforcement learning
SHEMS	Synergistic home energy management system
DERs	Distributed energy resources
MCS	Monte Carlo simulation
LODS	Loss of demanded services
EVs	Electric vehicles
CEHLR	Combined electrical and heat load restoration
UIES	urban integrated energy system
NLP	Natural language processing
WECC	Western Electricity Coordinating Council
KPIs	Key performance indicators
STPM	Sustainable total productive maintenance
IEMs	Integrated energy meta-systems

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