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Energy metaverse: the conceptual framework with a review of the state-of-the-art methods and technologies

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Abstract

The transition to green energy systems is vital for addressing climate change, with a focus on renewable sources like wind and solar. This change requires substantial investment, societal adaptations, and managing a complex energy ecosystem. However, no existing evaluation methods support this purpose. The "energy metaverse" is proposed as a digital platform that mirrors the energy ecosystem, enabling the design, trial, and assessment of new technologies, business models, and value chains before real-world deployment. Drawing from State-of-the-Art technologies and methodologies, this paper introduces a conceptual framework for the energy metaverse, comprising five essential components: a versatile energy ecosystem data space, an interoperable virtual ecosystem living lab, an energy system models and artificial intelligent algorithms sandbox, a circular value chain co-design toolbox, and an ecosystem lifecycle evaluation software tool. This paper also suggests specific methods and technologies to develop each of these five components of the energy metaverse.

Keywords: Energy metaverse, Energy ecosystem, Virtual living lab, Digital platform, Cyber-physical energy system, Lifecycle evaluation

Introduction

The green transition of energy systems is vital in combatting climate change. It reduces CO_2 emissions from conventional power plants through large-scale adoption of renewable energy technologies like wind and solar power. Such widespread adoption over a long period typically involves significant investments and societal changes. The complex and deeply interconnected nature of the energy ecosystem presents great challenges in exploring and implementing new technologies, regulatory frameworks, and business models that would guide the energy ecosystem's transition toward sustainability. The introduction of new technologies, especially system solutions, requires navigating a complex, multi-dimensional value chain, demanding robust engagement from all relevant stakeholders. It is also essential to consider the environmental, climatic, societal, technological, economic, political, and regulatory contexts under which these systems will operate. Comprehensive evaluations need to be conducted prior to their implementation. However, current methodologies are insufficient for this purpose.

The Energy Metaverse is defined in Ma (2023) as: "The Energy Metaverse is an exact digital replica of the physical energy system's ecosystem, enabling stakeholders to explore the effects of changes to the ecosystem configuration." By using data and information from smart energy meters, environment sensors, and information databases, the energy metaverse can capture the behaviors of stakeholders, infrastructure artifacts, environmental factors, and energy flows, reflecting the impact of business models, regulations, and policies.

Moreover, the energy metaverse provides a virtual living lab of the energy ecosystem. It allows the stakeholders in the business ecosystem of the smart energy sector (Ma 2022) to experiment, evaluate, and optimize new technologies, regulatory framework conditions, and business models before introducing them into the physical energy ecosystem (European Commission and European strategy for data 2020). They can investigate potential risks associated with the adoption of new technologies by exploring "what-if" scenarios before these are introduced in the physical energy ecosystem in a cost-efficient, environmentally friendly, and risk-avoided manner (Ma 2023).

Therefore, the energy metaverse can function as a digital energy ecosystem platform, facilitating the design, testing, and evaluation of technologies, business models, and value chains before they are adopted and implemented. Hence, evidence-based results can be generated, catering to local needs, aligning with political goals, and offering substantial environmental, health, climate, social, and economic benefits. These benefits include improved technological reliability, economic viability, and enhanced climate adaptation and mitigation potential.

To fulfill such a scope, the energy metaverse should employ multi-dimensional, multi-scale, multi-criteria evaluations. These encompass environmental, climate, societal, technological, economic, political, and regulatory dimensions, spanning short, medium, and long-term scenarios. They also consider the preferences and constraints of individual value chain stakeholders. Furthermore, the energy metaverse should enable a co-design process, allowing participation from all stakeholders. However, realizing such an energy metaverse is a tremendous challenge.

Ma 2023) states that the energy metaverse should be able to capture the interactions among stakeholders, tangible and intangible assets, policies, regulations, and business models. It should also predict the emergent behaviors associated with changes in the configuration of the energy ecosystems. To realize the energy metaverse, digital twin technology and Artificial Intelligent (AI) models need to be employed with the integration of multi-modeling and simulation methods. This is because the complexity of the energy ecosystem requires a comprehensive modeling and simulation approach. However, besides being able to digitally replicate the energy ecosystem and predict emergent behaviors, the evaluation and co-design functions of the energy metaverse are also essential but not discussed in (Ma 2023).

Therefore, this paper proposes a conceptual framework of the energy metaverse with five critical elements. It then investigates related state-of-the-art (SotA) methods and technologies, identifying challenges in current SotA methodologies. Subsequently, this paper proposes methods and technologies that can potentially realize each of the five energy metaverse elements. Finally, this paper discusses the scientific and practical contributions of the proposed approach, along with a recommendation for future works.

The conceptual framework of the energy metaverse

To realize the scope of allowing the design, testing, and evaluation of energy technologies, business models, and value chains across short, medium, and long-term scenarios, the energy metaverse should consist of the following five interconnected critical elements (as illustrated in Fig. 1):

- A versatile energy ecosystem data space, the foundation of the energy metaverse.
- An interoperable virtual ecosystem living lab, the infrastructure of the energy metaverse
- An energy system models and AI algorithms sandbox, the construction of the energy metaverse
- A circular value chain co-design toolbox, the landscape of the energy metaverse
- An ecosystem lifecycle evaluation software tool, the safeguard of the energy metaverse

Versatile energy ecosystem data space

The energy ecosystem data space forms the foundation of the energy metaverse. This data space should securely store and share data from multiple sources and of various types within the energy metaverse. It should also facilitate secure data exchange with third-party systems via Application Programming Interfaces (APIs). This data space ought to integrate several highly interconnected databases that aid the construction of the virtual ecosystem living lab relevant to the targeted physical energy ecosystem, support the development of energy models and algorithms, enable the design of business models and value chains, facilitate the running of what-if scenarios, and support the deployment of the ecosystem lifecycle evaluation software tool. Compliance with regulations, especially with design principles, is a fundamental requirement for this energy ecosystem data space.

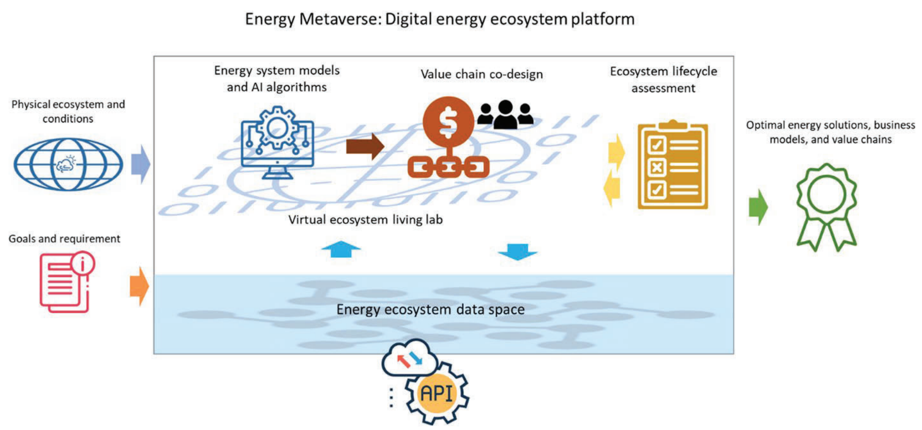

Fig. 1 Conceptual framework of the energy metaverse

Interoperable virtual ecosystem living lab

The virtual ecosystem living lab serves as the infrastructure of the energy metaverse. This living lab should digitally replicate the predefined physical energy ecosystem, encapsulating its conditions, dynamics, and trends. It should be able to allow a chosen combination of energy models and algorithms plug-and-play via well-established communication protocols and interoperability standards. It integrates the value chain co-design toolbox enabling individual users' business model development and multi-users' value chain co-design. By creating a dynamic virtual environment, the living lab enables the running of simulations to explore various hypothetical operating scenarios across different time scales. Importantly, it should be able to capture the consequences of operations and emerging behaviors resulting from the applications of energy models and algorithms, business models, and value chains. Furthermore, it integrates the ecosystem lifecycle evaluation software tool enabling the evaluation of the performance and effectiveness of energy solutions, business models, and value chains based on the simulation results.

Energy system models and algorithms sandbox

An energy solution, similar to the general concept of a product, is composed of three elements: need, technology, and form. The technological aspect can incorporate either physical components (such as hardware and facilities), cyber components (such as software and algorithms), or both. A sandbox consisting of energy models and algorithms is the construction of the energy metaverse. This sandbox should encompass various energy system models and AI algorithms. The energy system models should be capable of representing the physical components of a given energy solution, while the AI algorithms should be able to represent its cyber elements. The sandbox should allow for easy configuration and combination of these models and algorithms, significantly reducing both the time and skill needed compared to developing such systems from scratch. Moreover, the sandbox should interface with the virtual energy ecosystem living lab, thereby enabling experimentation with the selected combination of energy models and algorithms.

Circular value chain co-design toolbox

The successful deployment of energy solutions depends on coordinated efforts and well-aligned business models among all stakeholders in the value chain. In this regard, the value chain co-design toolbox forms the landscape of the energy metaverse. This toolbox should encompass a business model development tool, a value chain mapping tool, and a collection of strategies and principles. The business model development tool enables individual stakeholders to formulate their business models, while the value chain mapping tool can visually map out the value chain, complete with individual stakeholders' business models, and the flow of products, finance, information, and data. The collection of strategies and principles, which includes elements such as circular economy principles and climate mitigation and adaptation strategies, ensure that business models and value chains are sustainable, efficient, flexible, resilient, and affordable, thereby promoting and enhancing the widespread adoption of energy solutions.

Ecosystem lifecycle evaluation software tool

Evaluating the performance and efficacy of proposed energy solutions prior to the development and implementation stage is vital. This evaluation serves to minimize risks, costs, and uncertainties during the development and implementation process, ensuring that designs meet predetermined objectives and are tailored to local needs and conditions. An ecosystem lifecycle evaluation safeguards the energy metaverse, ensuring the successful adoption, implementation, and long-lasting impact of the proposed energy solutions. This ecosystem lifecycle evaluation should be holistic, encompassing all five CSTEP (Ma 2022) dimensions of the energy ecosystem: climate, environment, and geographic situation, societal culture and demographic environment, technology (infrastructure, technological skills, technology readiness), economy and finance, Policies and regulation. Besides only assessing solutions, this evaluation should also consider the interests and constraints of all stakeholders in the value chain. Furthermore, it should evaluate the cumulative effect of the co-designed value chain. The insights from the evaluation should be feasible to feedback into the design process, ensuring that an optimal solution and a harmonized value chain can be realized.

Review of the state-of-the-art methods and technologies

There are quite a few of SotA methods and technologies potentially related to each of the above five elements of the energy metaverse. They can be summarized as shown in Table 1.

Energy data space

The concept of a "data space" as defined by the European Union (EU) primarily denotes a decentralized infrastructure for trustworthy data sharing and exchange in data ecosystems, based on commonly agreed principles (European Commission and European

Table 1 Potential state-of-the-art methods and technologies related to the energy metaverse development

Focus	SotA methods and technologies
Energy data space	• Data space • Data management system • Machine Learning Operations (MLOps) platforms
Virtual energy ecosystem living lab	• Digital twin technology • Ontologies • Interoperability and Communication standards • Verification & validation testing, Model-Based Design (MBD), and In-the-Loop (ItL) testing
Energy system modeling and AI algorithms	• Cyber-physical energy system • Energy system modeling • Deep learning algorithms
Circular value chain	• Circular economy principle • Circular supply chain • Circular business model • Climate mitigation and adaptation strategies
Lifecycle assessment	• Lifecycle Assessment (LCA) • Green computing • Technology adoption • Multi-criteria decision making (MCDM)

strategy for data 2020). A European data space that interconnects different data spaces and aims to ensure extensive data sharing and usage while complying with EU values and regulations (Commission and Data Spaces 2023). The EU's data strategy has set up nine initial Common European data spaces across different domains including energy (Commission and Shaping Europe's digital future—A European Strategy for data 2023). Common European data spaces should follow specific design principles which include a common technical infrastructure and building blocks, as well as interconnection and interoperability (Commission and Data Spaces 2023). Data platform projects are running under the Big Data Value association (Association and BDVA 2023) to develop integrated technology solutions for energy data collection, sharing, integration, and exploitation, e.g., BD4NRG (BD4NRG 2023) and BD4OPEM (BD4OPEM 2023).

the SotA technology of cloud-based data management systems with microservices architectures and open APIs can support the development of an energy ecosystem data space. A cloud-based data management system refers to the utilization of platforms, tools, policies, and procedures that allow organizations to control their data in the cloud and hybrid setups (Ghosh 2023). Cloud data management platforms aim to manage data across various cloud ecosystems that are usually API-driven and delivered as microservices (Informatica and Management: Understanding the Value 2023). Cloud databases are a part of the cloud data management system for managing engagement and application data for massive networks of mobile users or remote devices (What and is a cloud database 2023).

Some commercial cloud-based data management systems support microservices architecture and open APIs, such as Microsoft Azure, Google Cloud, and Amazon Web Services. A number of open-source solutions provide similar functionalities, e.g., Apache Cassandra (2023), MongoDB (2023), OpenStack (primarily an infrastructure platform and does not support flexible data structure) (OpenStack 2023), Apache Kafka (2023) (event-based approachand does not support flexible data structure), and Apache Spark (2023) (but not directly support microservices architecture (Bouslama et al. 2017)). Both Apache Cassandra and MongoDB are powerful database technologies, and each has its unique strengths and limitations. Apache Cassandra is relatively complex to set up and manage, has limited support for aggregation, and is not so supportive if the project involves a lot of read operations. The main limitations of MongoDB are data size due to the BSON (Binary JSON (JavaScript Object Notation)) format and not transaction-friendly to handle complex operations that involve multiple data items.

data management systems are not for storing or sharing models. Therefore, the utilization of software development (DevOps) and machine learning operations (MLOps) platforms, e.g., GitLab (2023) and GitHub, for storing and sharing codes and models is necessary. Compared to GitHub, GitLab's key strength lies in its built-in continuous integration/continuous delivery (CI/CD) and DevOps workflows (Vaughan-Nichols 2023), is often seen as more secure and offers an open-source community edition repository management platform (GeeksforGeeks 2023). Furthermore, there are tools available to facilitate integration between GitLab and MongoDB (Integrate.io 2023). However, there are some key limitations of using GitLab for storing and sharing machine learning models, e.g., Size Limits (GitLab 2023) and integration with machine learning tools (Mikl and Besser 2023).

Virtual energy ecosystem living lab

According to the definition of a targeted ecosystem stated in Ma et al. (2021), energy ecosystem is a completed business ecosystem within the energy domain including elements of actors (e.g., producer, transmission system operators, distribution system operators, consumers, etc.), roles, and interactions. Digital twins are often used to model, understand, and analyze complex systems where the system's performance, reliability, and safety concerns are critical. Digital twin technology has been used in the energy domain, e.g., electricity distribution networks (Zhang et al. 2020). However, there are few applications in the context of business ecosystems due to the intrinsic complexity of the ecosystems being twinned, and the twinning process is an extremely costly undertaking requiring significant effort and time.

There are several digital twin frameworks proposed to model and simulate various systems with various methods and technologies, including production processes, infrastructure systems, supply chains, etc. Multi-agent-based digital twin framework is one of the most promising methods that can provide a comprehensive, adaptable, and scalable solution for managing and optimizing complex systems (Nie et al. 2023).

To achieve a successful integration of the digital twin application in its deployment environment, it is important to ensure interoperability between the digital twin and existing systems (Ma et al. submitted for publication). Interoperability is the ability of different systems and applications to communicate and share information effectively. The heterogeneity among energy systems makes the interoperability complex and particularly the issues of the use of different ontologies. Therefore, there is a need for full interoperability and open standards for the energy domain (Catterson et al. 2005).

An ontology is a formalized description of information, defining concepts, relationships, and categories within a given domain and offering a foundation for shared understanding and communication (Ontology in Computer Science 2007). In the energy domain, there are some generic energy domain ontologies, e.g., Harmonized Electricity Market Role Model (HRM) offering an abstract depiction of the European electricity market and the Smart Grid Architecture Model (SGAM) (Toolbox 2023) for the smart energy domain understanding. Ontologies can be categorized into three levels: upper ontologies, domain ontologies, and application ontology (Husáková and Bureš 2020). In the energy domain, ontologies for complex systems are often separated into a hierarchy consisting of an upper ontology that is connected to several lower-level ontologies representing specific subdomains (Azevedo et al. 2007). However, there is a lack of integrated ontology design, including upper ontologies, domain ontologies, and application ontologies across multiple energy systems.

There are some available standard ontology languages with stable tools for the Semantic Web community, e.g., the Resource Description Framework (RDF) (Miller 1998), RDF schema (RDFS), and the Ontology Web Language (OWL) (Christophides 2009). The OWL (Language and (OWL) 2023) is one of the most popular standard ontology languages and it is possible to be used in a variety of applications such as knowledge sharing and representation (Christophides 2009), semantic web (Kim 2007), information system (Tran et al. 2007), ontology-based reasoning (Wang et al. 2004), etc. Ontology development processes are a relatively new field of study, and there are tools for developing ontologies, e.g., Protégé (2023) and SWOOP (Kalyanpur et al. 2006). Protégé is well established and used by a large user community, and it allows to save ontology in a variety of OWL formats (Starting and Protégé 2023).

Some standards in the power systems promote interoperability between devices within substations and open interfaces between energy management systems (McArthur et al. 2007). The most widely applied standard in the power system is the IEC 61970 Common Information Model (CIM), and its distribution management extension IEC 61968 (Santodomingo et al. 2023). Some reference models and frameworks are also popularly used to achieve coherent and advantageous cooperation between different power systems, e.g., SGAM, USEF (the Universal Smart Energy Framework) (USEF Foundation.Universal Smart Energy Framework 2023), SEAS (Smart Energy Aware Systems) knowledge model (Smart and Energy 2023), OpenADR (Open Automated Demand Response) (Alliance and OpenADR. 2023) and energy@home (Energy@home. 2023). However, none of these standards cover the whole semantics involved in a flexible urban energy network on its own, and they are not formally aligned with each other (Hippolyte et al. 2016).

Digital twin interoperability can be designed using various methods, often leveraging specific standards and protocols to enable communication between different systems. The FIPA (Foundation for the Intelligent Physical Agent) provides different interoperability standards which make it possible to integrate different Multi-Agent Systems (MASs) (Foundation for Intelligent Physical Agents 2000). However, it does not mean that agents belonging to different MASs can share any useful information if the MASs use different ontologies. Furthermore, this solution is difficult to be implemented due to the challenges of the system integration including between-ontology mapping, translation mappings, etc. (Catterson et al. 2005).

Digital twin technology has been popularly used for monitoring, simulation, optimization, and control of the twinned physical system, but not for verification or validation. Verification and validation are usually achieved through Model-Based Design (MBD) which is an approach to designing and testing systems that are often used in production. Different types of In-the-loop testing, such as hardware-in-the-loop (HIL) and software-in-the-loop (SIL), are typically used during model-based verification and validation, and these tests analyze and compare the code to the original model results to ensure that the implementation accurately represents the model (Erkkinen and Conrad 2008). HIL, e.g., Power-Hardware-in-the-Loop, is common for testing physical phenomena on virtual models such as fault tolerance, active/reactive power, etc. However, HIL is not suitable for testing higher technological aggregation levels, e.g., economy or value chains, or higher levels of decision-making. SIL has been mainly used for testing and evaluation of control strategies and for optimization by utilizing a composition of digital twins in co-simulations. However, integrated approaches for the verification and validation of highly interconnected energy systems are very limited (Strasser et al. 2018). Studies usually focus on validating certain aspects of an application instead of testing the complex behavior that emerges from integrating many applications.

Energy system modeling and AI algorithms

Energy system solutions combine digital technologies with physical components to optimize the efficiency, resilience, and integration of renewable energy sources into the power grid. In the energy domain, the "cyber" component refers to using information technologies to manage and control energy systems, and the term "physical" refers to the elements of the energy infrastructure (like power generation, distribution, and end-use appliances). The optimal integration of "cyber" and "physical" elements promotes a more efficient overall performance than when concentrating solely on individual components. However, achieving this optimal integration becomes intricate and challenging due to the diversity of conditions and goals, especially the long-term objectives of individual energy communities involving multiple stakeholders.

Energy system solutions, or more accurately, Cyber-physical energy system (CPES) solutions, usually consist of different hardware and software configurations. They often include various libraries of energy system modeling and AI algorithms. Energy system modeling in CPES is often employed as an emulator (as known in software engineering) to replicate the behavior of real-world energy systems (Pham 2023). Emulation is a process where one system imitates the function of another. This allows for better control, monitoring, optimization, and understanding of the system's behavior under various conditions without having to physically test it. However, the accuracy of an emulator depends on the sophistication of the model. The more accurately the model can reproduce the behavior of the real system, the more effective the emulator will be for predicting system behavior and testing control strategies. While there are numerous energy system modeling tools and methodologies available, but also challenges within the current energy system modeling landscape (Ringkjøb et al. 2018). One of the main challenges is the growing involvement of consumers in the energy system, particularly through distributed generation and demand response, but their responses to electricity changes and policies are not captured in energy system modeling. Agent-based modelling provides the ability to represent the behaviors and choices of energy consumers (Rai and Henry 2016).

AI algorithms are crucial in cyber-physical energy systems as they effectively manage and integrate variable renewable energy sources into the grid. These algorithms not only predict energy demand and supply patterns, but they also foresee the generation of renewable energy, such as wind and solar power, and anticipate system failures or faults. Furthermore, they help optimize power generation schedules, power flows, and energy dispatch. Additionally, they can be employed in controlling various components of the energy system, ranging from individual smart devices to large-scale power plants, which enhances response times and minimizes human error. In AI algorithms, Deep learning (DL) could outperform current SotA methods, including traditional Machine Learning (ML) methods in the application of renewable energy systems.

The stability of power systems, threatened by the variability and unpredictability of Variable Renewable Energy (VRE), and the use of efficient forecasting tools can reduce such uncertainties and aid in system planning. Current VRE forecasting methods face challenges, including irregularities and fluctuations in VRE generation data (Khodayar et al. 2017), the change in daytime hours (Alanazi et al. 2016), and the lack of long-term historical weather data for specific locations (IRENA 2019). With an abundance of historical and real-time data available, various DL frameworks have been proposed for VRE forecasting that can improve the precision and temporal resolution of forecasts for VRE generation (Klaiber and Dinther 2023). Currently, deterministic VRE forecasting mainly utilizes algorithms like DCNNs (Deep Convolutional

Neural Networks) (Ghimire et al. 2019) and LSTMs (Long Short-Term Memory) (Husein and Chung 1856) for solar and wind power forecasting.

For forecasting electricity consumption and demand-side behaviors, LSTM architectures have shown considerable success at both the residential and building levels (Chen et al. 2019). However, DCNNs outperform traditional ML approaches and even LSTM due to their superior abilities in recognizing patterns and extracting features from aggregated electricity consumption patterns (Kuo and Huang 2018). In fact, the integration of DCNNs with Deep Recurrent Neural Networks (DRNN) or LSTM can elevate the accuracy of forecasting even further (Kim et al. 2019; Pramono et al. 2019).

Increased VRE penetration and the growing number of system participants, such as Electricity Storage Systems (ESS), compound the complexity of scheduling and operating electricity systems (Wei et al. 2019). Therefore, significant enhancements in scheduling are needed for solving scheduling problems quickly and optimizing responses to real-time fluctuations in VRE power generation and flexible demand. DRNNs or DCNNs have been used for balancing demand and supply, real-time dispatch, and the optimal utilization of ESS, such as microgrids' real-time management with a near-optimal scheduling policy (Alhussein et al. 2019). Extended models integrating DCNNs with Gated Recurrent Units (GRU) can further optimize the multi-day scheduling of microgrids (Afrasiabi et al. 2019). Additional technologies, such as LSTM models combined with Particle Swarm Optimization (PSO), have demonstrated cost and energy loss reductions in community microgrids (Wen et al. 2019).

Furthermore, DL has been utilized for power system frequency control to attain and maintain a real-time power balance between generation and load. LSTM has been implemented to identify power fluctuations and to enable automatic generation control (Wen et al. 2019). DCNNs increase the accuracy of power fluctuation identification under noiseless and noisy conditions (Wen et al. 2019) and can be employed to classify island events (Manikonda and Gaonkar 2019).

However, there are substantial challenges in applying Deep Learning to energy systems. For instance, the accuracy of these models is significantly influenced by the volume of training data (Lago et al. 2018). Acquiring sufficient data can be challenging or expensive. This issue becomes particularly prominent in projects like ours, where the primary objective is to assess the design prior to development when there is little to no data available. Transfer Learning (TL) techniques for renewable energy applications allow ML methods to be applied with limited or even no training data by inferring knowledge from existing energy forecasting models trained with sufficient data (Al-Hajj et al. 2023). The choice of TL techniques is based on the types of challenges that arise. There are numerous research works have focused on the application of TL to forecasting wind and solar power generation (Schreiber 2019), and load forecasting (Jin et al. 2022). However, the success of knowledge transfer, also known as domain adaptation, largely depends on the similarity between the source and target domains/tasks, but there is no standard procedure to assess the similarity of the source and target domains before initiating the transfer of knowledge (Wang et al. 2018). Concept drift detection methods that can monitor data changes that impact the model's predictions (Agrahari and Singh 2022), and domain adaptation that deals with problems where the distribution of training data (many labeled samples) is different from the distribution of test data might solve this challenge (Karimian and Beigy 2023).

The design and development of CPES solutions can be challenging due to heterogeneous hardware and software configurations, and the MBD methodology has been widely seen as a promising solution to address the associated design challenges of creating a CPES (Faruque and Ahourai 2014). Within this context, energy system modeling serves as an emulator, generating a virtual model of the energy system. DL algorithms are then utilized alongside these energy system emulators to learn the system's dynamics, predict its behavior, and make decisions for controlling the system under various conditions. The design of DL algorithms can be validated and enhanced through MBD, which incorporates iterative simulation, as well as verification and validation testing (Faruque and Ahourai 2014). This integrated approach provides a powerful framework for designing, managing, and optimizing cyber-physical energy systems.

However, this approach brings new challenges, such as emulation-simulation clock synchronization issue: traditional emulators execute real programs and its clock elapses with the real wall clock and simulators execute models with reference to the simulation's virtual clock. Furthermore, time resolutions can vary between different energy system models and DL algorithms. The time resolution refers to the temporal granularity at which data is considered or processed in models or algorithms. Some energy system models may operate at an hourly resolution, while others may work on a minute or even second basis. Similarly, DL algorithms can also be designed to process data at different time resolutions based on the specific task or application. Various time resolutions can lead to challenges such as data mismatch and incompatibility, complexity in interpolation and aggregation, and synchronization issues. These complications can consequently make performance evaluation more difficult.

Circular value chain

The Circular Economy (CE) is a model of production and consumption aiming to effectively extend the lifecycle of products by emphasizing sharing, leasing, reusing, repairing, refurbishing, and recycling existing materials and products for as long as possible (Parliament and Circular economy: definition, importance and benefits 2023). CE field is currently populated by diverging approaches and many available CE implementation strategies have been proposed. There are tools that consist of CE strategy options that support CE implementation (Kalmykova et al. 2018). However, there is little research on performance measurement in CE literature (Svensson and Funck 2019). Therefore, which performance measurement systems are most suitable for a CE and how the effectiveness of CE-specific performance indicators remain unclear (Svensson and Funck 2019). However, some studies indicate that multi-criteria decision-making techniques might be able to support CE implementation (Chauhan et al. 2021).

The circular value chain integrates the CE approach with value chain theory, often referring to the management of a circular supply chain (CSC). A CSC outlines the steps of value creation that contribute to a CE by closing material loops. These steps typically encompass product-related activities such as material sourcing, design, manufacturing, distribution and sales, consumption and use, collection and disposal, as well as recycling and recovery.

The CE implications along Porter's value chain (Porter 2011) framework show that the linear structure of the framework is not sufficient to reflect circular business practices which are primary activities in a circle (Kalmykova et al. 2018). Furthermore, Porter's framework does not sufficiently show connections between different value chain categories nor acknowledges their interrelations with external stakeholders which both are crucial requirements for CE implementation. A circular value chain framework is proposed that extends Porter's linear view to a circular business understanding and connects insights from management and CE research (Eisenreich et al. 2022).

The co-creation of circular solutions should involve the whole supply chain stakeholders (Prieto-Sandoval et al. 2019). Furthermore, stakeholder collaboration, experimentation, and platformization are proposed to be the principles for circular ecosystem innovation (Konietzko et al. 2020). However, the majority of the literature only emphasizes the necessity of collaborations without further investigation (Pinheiro et al. 2019), the roles of the stakeholders in the circular value chain in the context of different circular solutions and industries are not discussed (Lieder and Rashid 2016). Furthermore, value co-creation models could facilitate the process of co-creating circular solutions which focus on deep interactions between the providers, customers, and their resource integration (Skarzauskaite 2013). Moreover, a three-stage value co-creation process for product-service solutions is proposed with relational coping strategies (Rönnberg Sjödin et al. 2016). However, the value co-creation process does not involve the entire value chain stakeholders. Theories, e.g., business ecosystem modeling (Ma 2019) and stakeholder theory (Freeman 2010) could be applied to identifying value chain stakeholders and interactions in CSC co-creation.

There are two types of circular solutions: Closed cycle solutions create biological material cycles or technical material cycles, generated by maintenance, reuse, refurbishing, remanufacturing, or recycling (Ellen MacArthur Foundation 2013); and systemic solutions, refer to product-service systems such as leasing, sharing, or pay-per-service offers (Tukker 2015). The existing literature is primarily concerned with closed cycle solutions or CE in general, and Research on systemic solutions is less frequent which has high significance for a CE (Ellen MacArthur Foundation 2015). Some discussion on systemic solutions is mainly about how Industry 4.0 might support a CE, e.g., additive manufacturing producing goods in an additive, digital process without fixtures and tooling (Sauerwein et al. 2019) and cloud manufacturing enabling resource sharing on a cloud platform (Lopes de Sousa Jabbour et al. 2018). But no extensive knowledge of CSC for Industry 4.0. furthermore, Cyber-physical systems (CPS) are discussed in CE, but the main discussion is to track products throughout their life cycles and potentially support a product passport with the internet of things (Franco 2017). Moreover, the value chain for the software is different from the general value chain, and usually consists of eleven activities including some software specific activities, e.g., component procurement, user documentation activity, training and certification (Pussep et al. 2011).

Exploratory, experimental, and agile practices are necessary for the development of circular solutions since circular economy often requires a redefinition of business models, daily routines, and the established game rules in traditional linear systems (Hofmann and Jaeger-Erben 2020). Applying a modular design to the development process is also crucial. A modular approach breaks down complex projects into smaller, manageable components or modules, allowing quick adjustments and improvements (Tukker 2015).

In addition to the development process of circular solutions, organizations need to drive a systemic shift in core business logic and align incentives among different stakeholders. A circular economy requires businesses to design and implement models that prioritize resource efficiency, longevity, and value extraction (Geissdoerfer et al. 2020). These models, known as circular business models, are essential for successfully embracing the principles of a circular economy. Several conceptual frameworks for circular business models have been proposed in the literature which can be divided into three types: reference models, requirements, and classifications (Pieroni et al. 2019). Reference models for circular business models are frequently employed as tools supporting the conceptualization of how a business model should be structured or represented for circular economy, and classifications support the identification of how business models should be configured or changed to accommodate circular economy principles (Wirtz et al. 2016). Furthermore, a framework of key circular business model considerations is proposed to recommend the implementation of circular business model strategies, including cycling, extending, intensifying, and dematerializing (Geissdoerfer et al. 2020).

According to the definitions by EU, climate mitigation means "making the impacts of climate change less severe by preventing or reducing the emission of greenhouse gases (GHG) into the atmosphere", and climate adaptation means "anticipating the adverse effects of climate change and taking appropriate action to prevent or minimize the damage they can cause, or taking advantage of opportunities that may arise". Climate adaptation and mitigation are two critical corporate responses to climate change, each with distinct objectives, scales, planning, and implementation measures. Despite their differences, the synergy between them is crucial (Berry et al. 2015). However, there is little literature addressing climate adaptation and mitigation at the organizational level (Linnenluecke et al. 2013).

Some mitigation and adaptation options (e.g., risk assessments for operations and locations, insurance, and assessment of policy developments) has been discussed (Wittneben and Kiyar 2009), and corporate climate change mitigation actions and factors are investigated (Glienke and Guenther 2016). Nevertheless, a climate change mitigation strategy framework was proposed for carbon-intensive firms (Cadez and Czerny 2016), furthermore, companies' primary mitigation practices were proposed by the Intergovernmental Panel on Climate Change (IPCC) (The Intergovernmental Panel on Climate Change (IPCC) 2023) including e.g., energy efficiency, emission efficiency, reuse and recycling of materials, and reducing demand for product services. Furthermore, companies can implement corporate carbon strategies that encompass organizational engagement, risk management, carbon measurement and policy, product improvements, process improvements, and carbon offsetting to increase their carbon competitiveness (Perlin et al. 2022).

There is limited literature in cooperating climate mitigation strategies because adaptation strategies are often seen and linked as the responsibility of the government and the public sector (Rao and Thamizhvanan 2014). Adaptation options strongly depend on the adaptation objective of each sector or environment. Adaptation practices are usually specific to local conditions and developed locally from relevant action plans to reduce climate-related risks, including, e.g., information-sharing practices, developing early warning and preparation plans, and developing strains and cultures that can withstand various climatic conditions (Todaro et al. 2021).

Therefore, climate mitigation and adaptation strategies significantly influence companies' business models. Companies vulnerable to natural disasters amplified by climate change can experience significant hindrances to their profits and market efficiency (Hong et al. 2019). Meanwhile, companies may seek to develop new products or enter new markets to mitigate climate risks and costs which can lead to economic opportunities and improved societal roles (Hsu and Wang 2013). However, general business model strategies including circular business model strategies do not incorporate climate adaptation and mitigation strategies. Hence, the value of the solutions does not always align with climate adaptation and mitigation objectives.

In the energy domain, energy system solutions are closely linked to climate adaptation and mitigation objectives referring to the focus on sustainability, efficiency, flexibility and resilience. Sustainability, efficiency, and flexibility can contribute to the climate mitigation objective that reduces GHG emissions, such as renewable energy sources, and energy efficiency in power generation and grid operations, battery technologies and demand response (Kang et al. 2020). Resilience along with flexibility can contribute to the climate adaptation objectives, such as nature disasters and other extreme weather driven threats with, e.g., infrastructure design, planning, emergency response and post-event recovery (Jessen et al. 2022). The design of an energy solution typically does not encompass all climate adaptation and mitigation objectives. The strategies often represent a trade-off among these objectives and the interests of various stakeholders that increase the complexity and difficulty for the business model development and value chain design.

Lifecycle assessment

Evaluating the performance and effectiveness of designed energy solutions and their value chains is crucial to ensure the design fulfills pre-defined goals and adapts to local needs and conditions. This evaluation should encompass all perspectives to guarantee the success of adoption, implementation, and long-term effects. Consequently, the evaluation should consider all five critical CSTEP business ecosystem dimensions: Climate, environment, and geographic situation, Societal culture and demographic environment, Technology (Infrastructure, technological skills, technology readiness), Economy and finance, Policies and regulation (Ma 2022). Moreover, the evaluation should be conducted prior to the development and implementation phase. This allows for valuable feedback that can improve the design and reduce risks, costs, and uncertainties associated with the development and implementation process. To realize such an evaluation, it not only needs to capture the above dimensions, but also all value chain stakeholders' interests and constraints.

The currently accepted definition of Life Cycle Assessment (LCA) is the "compilation and evaluation of the inputs, outputs, and potential environmental impacts of a product system throughout its life cycle" (Hellweg and Milà I Canals 2014). There are typically four steps in LCA: (1) the description of the goal and scope, (2) inventory analysis, (3) life-cycle impact assessment, and the interpretation of the inventory and impact assessment results. The LCA method is based on a detailed inventory of input and output flows of processes across the life cycle stages of products or services, converting the overall flow balance into several environmental impact categories, and these impacts may potentially be further consolidated into a single score (Blass and Corbett 2018). Current LCA practices as standardized by International Organization for Standardization (ISO) (2023), and the ISO 14040:2006 standards are a broadly accepted set of principles and guidelines for performing a LCA analysis (Curran 2013). there are many LCA software and only two open-source LCA software: OpenLCA (2023) and Brightway (2023). OpenLCA is a Java application that is popularly used for LCA. Brightway is written in the Python programming language and designed for large datasets.

The applications of LCA can be from product design, process optimization, supply chain management, cooperates' strategies, and national environmental policies. In the energy sector, LCA has been deployed as a standardized tool to understand the environmental effects of energy generation technologies, especially renewable energy technologies, and most of the studies have been conducted in Europe (Barros Murillo et al. 2020). LCA is mainly applied to conventional product development, potential can be applied in the software engineering domain to determine the environmental impact of a software product and the environmental impact of a software development process. However, LCA in software engineering is rarely discussed in the literature. Simultaneously, there is no literature in LCA for digital technology and only one short conference paper (less than 3 pages, published in 2005) discussed eco-design factors of software product content and commercialization (Kawamoto et al. 2005).

Accompanying the increasing focus on Industry 4.0, there is growing interest in environmental awareness within cyber-physical systems. This typically refers to the environmental impact assessment of these systems. The environmental impact assessment of cyber-physical systems is usually to assess the environmental footprint of devices and their use, and data management and lifecycle (Cortes-Cornax et al. 2023). There is a framework proposed for the maintenance of cyber-physical systems incorporating LCA methods (Sénéchal and Trentesaux 2019). However, the climate impact of Information and Communications Technology (ICT) is underestimated with few studies (Freitag et al. 2022).

In the field of ICT, the concept of green computing or green IT refers to the practice of utilizing computing resources to their maximum efficiency to mitigate the environmental impact (Harmon and Auseklis 2009). The literature has proposed numerous classifications of green computing metrics, covering an array of categories such as carbon footprint, population, and green energy usage (Gürbüz and Tekinerdogan 2016). In addition, metrics considering other aspects like performance and cost have also been incorporated. In the context of software development, certain strategies can enhance the green computing practice. For example, a reengineering process that promotes efficient software recycling, and green software engineering that optimizes energy consumption (Kutscher et al. 2020). Engineering software as a Software Product Line (SPL) is a strategy to improve efficiency that allows software modules to be configured or deselected, thereby enabling the creation of various distinct software products from a single code base (Clements and Northrop 2002). This not only facilitates reuse but also diminishes the effort required for maintenance.

In the value chain domain, there are some practices in LCA of a specific sector's value chain and mainly from cooperates' value chain decision making perspective (Geibler et al. 2016) incorporating cooperates' internal metrics (Meinrenken et al. 2014). In the supply chain domain, an LCA of the supply chain constitutes a full LCA, involving all activities associated with a product or service, especially including logistics (transportation and vehicles), rather than only focusing on the product's material life cycle (Browne et al. 2005). A decision tree approach with 19 environmental criteria is proposed for LCA and decision making of sustainable transport processes (Greschner Farkavcova et al. 2018). Furthermore, supply chains always involve several actors, and the majority of LCA studies may acknowledge the presence of these actors but seldom explicitly take each stakeholder's incentives into account (Blass and Corbett 2018) Agent-based modeling methods are recommended to address the complexity of this topic (Batten 2009).

Life Cycle Cost Analysis (LCCA), or Life Cycle Costing (LCC), is typically considered in the LCA process to ensure a holistic, long-term evaluation of costs associated with a product, service, or infrastructure (Kubba and Kubba 2010). LCC can be divided into three different types: conventional, environmental, and societal, and it aids in making informed decisions about the total costs over the lifetime of the asset (Yang et al. 2020). LCA and LCC were often used together along with a range of other methodological aids, e.g., cost–benefit analysis (Jeswani et al. 2010). There are methods proposed for the use of LCA together with LCC (França et al. 2021). Recently, LCC was implemented in the LCA software – openLCA, but focused on environmental Life Cycle Costing, not operational costs.

Besides LCA, there is increasing research in Social Life Cycle Assessment (S-LCA) aiming to evaluate the social and socio-economic aspects of products, as well as their positive and negative impacts throughout their life cycle (Jørgensen 2013). S-LCA is an addition to LCA, but it can be used individually without combining it with LCA. Stakeholders play a crucial role in the S-LCA methodology and the S-LCA evaluation indicators are developed and selected according to the stakeholders' life cycle activities (UNEP, SETAC Life Cycle Initiative 2009). There are several S-LCA frameworks and methods including both economic and social aspects of S-LCA (Wu et al. 2014), and indicators (Kühnen and Hahn 2017). The primary methodologies used for Social Life Cycle Assessment (S-LCA) are derived from Life Cycle Assessment (LCA). However, there are challenges when deploying LCA methods in S-LCA, such as impact assessment and handling of data (Petti et al. 2018). Dealing with semi-quantitative and qualitative indicators poses a challenge in S-LCA, particularly because these impacts are not expressed in relation to the functional unit (Wu et al. 2014). S-LCA has been applied for renewable energy technologies, such as solar power (Corona et al. 2017), offshore wind (Tseng et al. 2017), and hydrogen power (Adami Mattioda et al. 2017).

Based on LCA, LCC, and S-LCA, Life Cycle Sustainability Assessment (LCSA) has been proposed to incorporate the three pillars of sustainable development (environmental, economic, and social impacts) into one formulation, while retaining a life cycle perspective (Fauzi et al. 2019). There are two main formulations of LCSA: (1) the LCSA model consisting of LCA + LCC + S-LCA (Kloepffer 2008), (2) acts as a framework with a similar definition as first formulated, but with a broader and deeper scope (Guinée et al. 2011). Eight research challenges in LCSA are identified, and mainly due to the different perspectives of LCA and S-LCA (Fauzi et al. 2019).

There is a S-LCA database, PSILCA (PSILCA 2023), which can be imported into and used in LCA software—openLCA, however, it is not for free. In addition, other tools are also used with the LCA-LCC approaches, such as a multi-criteria approach to account for environmental, social, and economic impacts (Balasbaneh and Marsono 2020). A widely used technique is Multi-Criteria Decision Making (MCDM), including e.g., mathematical modeling, Analytic Hierarchical Process (AHP), and fuzzy logic approach that has been used in LCA studies (Zanghelini et al. 2018).

Furthermore, Policy and regulation need to be considered in LCA in several ways, e.g., defining assessment boundaries and scenario analysis (such as waste regulations included end-of-life disposal scenarios), and incentives and penalties for reduced environmental impact (e.g., tax credits for renewable energy). Therefore, the Life Cycle Impact Assessment (LCIA) is recommended to integrate with another assessment modelling, e.g., regulatory assessment practices and policy support tools (Pennington et al. 2004).

Moreover, results from LCA can be used to inform policy and regulatory decisions, offering insight into the potential environmental policy and regulation making. Policies play a critical role in shaping the life cycle of a product or service by establishing guidelines and regulations to influence how products are designed, manufactured, used, and discarded (Rebitzer et al. 2004). Especially product-oriented environmental policies, e.g., the EU's Communication on integrated product policy—building on environmental life-cycle thinking (Commission and Building on Environmental Life-Cycle Thinking 2003), and the proposal for establishing a framework for the setting of eco-design requirements for energy-using products (European Commission 2003).

In addition to considering environmental, social, economic, and political factors, successful implementation of technology requires its widespread adoption to truly achieve the anticipated benefits. Technology adoption theories and models have been introduced in the literature to describe the adoption behavior toward new technology and help to develop business models aiming to achieve a fast and/or high adoption (Ma et al. 2022). The adoption and diffusion of green energy technologies are impacted by various factors at the individual, corporate and societal levels. The determinants of green energy adoption can be categorized into the technical matter, adopter level, corporate promotion and environmental challenge. Cost [expense of adopting green technologies (Higueras-Castillo et al. 2019)], performance [the functional reliability and effectiveness (Sopha and Klöckner 2011)], infrastructure (infrastructure readiness and facilitating conditions (Girod et al. 2017)), visibility of technology (Parkins et al. 2018), technological capabilities (Fu et al. 2018) and environmental regulation are the main determinants in the category of technical matters.

The performance of the energy solutions in the literature is usually regarding end-users' perceptions and experiences of use, e.g., charging time and driving distance of electric vehicles, which usually associate with the determinant of consumers' environmental concerns. However, the performance associated with climate concerns is barely discussed. Climate concerns include climate adaptation and mitigation, and the performance of a renewable energy solution should consider both climate mitigation and adaptation measures. Mitigation measures are associated with adaptive actions in response to climate change by society and business (West and Brereton 2013), and there are significant analytical challenges associated with mitigation and adaptation assessments. However, the boundaries of mitigation measures are more clearly defined because there is a straightforward metric (GHG emission reduction) to assess the effectiveness of such determinations (Perlin et al. 2022). There are several examples of adaptation measures, such as developing integrated risk assessment tools in the insurance sector; and investing in drought prevention measures (Perlin et al. 2022). Climate resilience can be used as the adaptation measure, which is defined as "The ability of the system and its component parts to absorb, accommodate and recover from both short-term shocks and long-term changes. These shocks can go beyond conditions covered in standard adequacy assessments" by International Energy Agency (IEA) (2020).

Challenges in SotA technologies and methods

The energy ecosystem data space

The concept of a "data space" has been defined by the EU, but not practically implemented. Therefore, no practical common data space design principles exist. Several challenges and limitations exist in implementing data spaces in practice:

- Data platform projects are running under the Big Data Value association, but they are way too complex to deploy in practice.
- Commercial data and model management platforms are too expensive and less flexible for deployment.
- Open-source platforms, including cloud-based data management systems and MLOps platforms, present their own limitations, particularly in their ability to handle complex operations and integration.

Despite these challenges, the SotA methods for cloud-based data management systems and MLOps platforms with APIs and microservices have been developed and refined to high degrees. However, the challenge lies in their integration to create a versatile and secure energy data space that complies with the data space design principles.

The interoperable virtual ecosystem living lab

Digital twin technology is emerging within the context of business ecosystems, with a focus on the energy sector. However, the application of this technology faces several challenges and limitations:

- Complexity and availability: The applications of digital twin technology are primarily limited to physical energy systems. There are only a few digital twin applications designed for business ecosystems due to their inherent complexity. The intrinsic complexity of the ecosystems also hampers integrated ontology design and application across multiple energy systems.
- Standards and Interoperability: An integrated approach to ontology and interoperability design is currently lacking, as well as open standards across multiple energy

systems. There's some literature on the interoperability of digital twins, but there's a notable absence of standards to ensure this interoperability. None of the common reference models or frameworks (e.g., SGAM, USEF, SEAS, and OpenADR) cover the whole semantics in energy and are not formally aligned with each other.
- Testing methods: SotA methods utilizing digital twins are present for monitoring, simulation, optimization, and control of physical systems. However, there is no method using digital twin technology specifically for the verification and validation of highly interconnected energy systems. Different types of In-the-Loop testing, such as hardware-in-the-loop and software-in-the-loop, are used for model-based verification and validation. Still, an integrated approach for highly interconnected energy systems is missing.

These challenges necessitate the development of a virtual energy ecosystem living lab that can connect various energy system models and AI algorithms. This would enable the creation of more robust digital twin applications, specifically suited for highly interconnected energy systems.

Energy system modeling and AI algorithms

Energy system modeling tools and DL algorithms are being used for energy systems, but several challenges and limitations persist:

- Complexity of behavior and choices: The central challenge of energy system modeling is its inability to accurately capture the growing complexities of consumer behavior and choices. Existing tools and methodologies are also incapable of capturing the growing involvement of consumers in the energy system.
- Data acquisition challenges: DL requires sufficient data for effective implementation. However, collecting data from targeted energy communities can be difficult or expensive. This remains a main challenge for applying DL algorithms, particularly in the use of CPES.
- Synchronization issues: There are problems with clock and time resolution synchronization between energy system models and DL algorithms, further complicating interoperability. This includes challenges with differences in emulation-simulation clock and time resolutions.
- Algorithm limitations: though DCNNs and LSTM algorithms outperform current SotA methods in renewable energy systems, there are no standard procedures for domain adaptation available to assess the similarity of source and target domains. TL techniques are present but are not fully adapted to the context.

Circular value chain co-design toolbox

The main challenges in integrating circular value chain design practices with CPES solutions, particularly in connecting these with climate mitigation and adaptation goals, can be summarized as:

- Lack of focus on CPES solutions: Only a few circular values chain design practices exist for CPES solutions and no systemic approach has been developed to streamline circular value chain co-design for CPES solutions. While a circular value chain framework exists, it lacks a detailed exploration of stakeholder identification, its roles, and the flows among these stakeholders within a CSC.
- Lack of focus on climate objectives: While there is a growing emphasis on corporate climate adaptation and mitigation, these efforts are not yet linked with the value of the business model. Presently, circular business model strategies don't incorporate climate mitigation or adaptation goals. Also, the design process of an energy solution usually does not encapsulate all climate adaptation and mitigation objectives.
- Limited linkage and systematic approaches: The value propositions of CPES solutions, encompassing sustainability, efficiency, flexibility, and resilience, have not been properly linked. Furthermore, these initiatives remain isolated, without a comprehensive or standardized approach.
- Lack of collaborative tools: Additionally, there is a lack of tools to facilitate collaboration in integrating circular value chain practices with CPES solutions and climate objectives.

Lifecycle assessment

There are significant shortcomings in the LCA studies related to CPES solutions, especially concerning the assessment of value chains:

- Limitations in LCA and LCC: LCA is mainly applied to conventional product development, and LCA of digital technology is rarely discussed. Most LCA studies in supply chains seldom explicitly take each stakeholder's incentives into account. LCC tends to focus only on environmental costs, not operational costs.
- Neglect of cyber aspect: The existing studies primarily address the "physical" component and neglect the "cyber" aspect. Additionally, there is a lack of LCSA or LCA studies focusing specifically on software.
- Geographical focus: LCSA studies (including LCA, LCC, and S-LCA) have been conducted mainly in Europe. This regional focus limits the applicability of findings to diverse and global contexts.
- Absence of climate measures: Measures for climate mitigation and adaptation are absent in existing studies. Consequently, the climate effectiveness of CPES solutions and their circular value chains remains immeasurable. No studies have combined these measures with LCA.
- Lack of comprehensive studies: No studies assess CPES solutions or value chains from all five CSTEP dimensions. This leaves gaps in understanding the full impact and effectiveness of CPES solutions, particularly in the context of climate mitigation and adaptation.

Recommendation of energy metaverse development methods and technologies

Versatile energy ecosystem data space

To create a dynamic and versatile energy ecosystem data space, the open cloud-based platforms MongoDB and GitLab could be considered for storing and sharing data and AI models. To solve limitations of MongoDB and GitLab, e.g., size limits, unfriendly transactions and integration, the data space could encompass various interconnected databases, with each database operating as an independent service and maintaining its own lifecycle. These databases could include:

- Physical energy ecosystem inventory database describing typical cases (e.g., energy communities) or cases that have been investigated before. The description could include the cases' conditions (e.g., populations, potential renewable energy resources, etc.).
- Energy production and consumption database containing historical data for electricity production and consumption at the physical energy ecosystems. In the case where no historical data is available, synthetic data generation can be used to compensate for the missing data.
- Weather database containing historical weather data for the physical energy ecosystems.
- Energy technology catalog describing the potential energy technologies and systems that might be used for experiments. The catalog is used to select the technologies for the alternative energy system configurations that will be evaluated in the virtual ecosystem living lab.
- Algorithms database containing potential AI algorithms for energy management system operations.
- Scenario and results database containing scenario information and resulted energy production and consumption data, and evaluation results of energy solutions and value chain.

An energy data space framework and internal and external data exchange protocols with the employment of the microservices architecture equipped with standard API interfaces (e.g., OpenAPI 2023) are recommended to ensure interoperability. This design will facilitate secure and seamless interactions with the internal systems and third-party APIs, broadening the ecosystem's utility and functionality.

Interoperable virtual ecosystem living lab

The architecture for the interoperable virtual ecosystem living lab is recommended to be designed based on ecosystem architecture design and analysis methods (Ma et al. 2021; Ma 2019) which can ensure the virtual ecosystem living lab captures the fundamental ecosystem elements. Digital twin technology with multi-agent-based simulations could be used to develop the virtual environment including actors, objects (facilities, systems), and the dynamics and evaluation of the whole virtual ecosystem. For a typical virtual electricity ecosystem living lab, it should include digital twins of electricity grids (Værbak et al. 2021), energy sources and production (Clausen et al.

2022; Sørensen et al. 2022), energy consumption (Howard et al. 2021), and electricity markets (Fatras et al. 2022). The web-based tool Energy Metaverse platform (Ma 2023) can be utilized to build the foundation of the virtual ecosystem living lab.

Hierarchical ontologies and existing standards and communication protocols in the energy domain are recommended to be used in the development of the virtual ecosystem living lab. The interoperability standards can support the plug-and-play functionality of energy solutions and enable integration with the circular value chain co-design toolbox and ecosystem lifecycle evaluation. Furthermore, the set of communication protocols will guarantee seamless communication with external systems. Protégé (2023) and Protégé Ontology Web Language (OWL) API (Programmer's and Guide 2023) are recommended for ontology development which also can ensure semantic consistency and reasoning capabilities throughout the entire ontology lifecycle.

Energy system models and algorithms sandbox

Energy system models and algorithms sandbox should comprise various energy system models and an array of DL algorithm libraries. These energy system models could include energy generation system models, energy storage system modeling, energy network modeling, etc. They function as digital emulators that mirror the corresponding physical energy system. The open-source Modelica-based modeling and simulation software OpenModelica (2023) can be utilized for energy system modelling.

The DL algorithm libraries could include forecasting, scheduling, and control libraries that can operate on energy system emulators. This setup allows for learning system dynamics, predicting system behavior, and making decisions to control the system. DCNNs and LSTMs have been popularly used in the energy system. The DL algorithms (DCNNs and LSTMs) can be built with Keras (2023) and PyTorch (2023), and experimented and documented with Jupyter Notebook (2023) to ensure a systematic working flow. For the physical energy ecosystems that only have minimal or no data, TL techniques along with concept drift detection methods can be used to create DL algorithms.

A flexible framework is recommended to ensure interoperability between energy system models and DL algorithms. This setup will allow for easy configuration and modification of both energy system models and DL algorithms. The framework should also apply multi-time resolution and a container-based virtual time system to achieve efficient synchronization between the energy system models and DL algorithms. Moreover, this framework can implement the designed communication protocols and interoperability standards to ensure compatibility with the virtual living lab.

Circular value chain co-design toolbox

The circular value chain co-design toolbox is recommended to consist of three interconnected tools: a business model development tool, a strategies tool, and a value chain design tool. The business model development tool should be considered to be built upon a business model framework, e.g., the business model canvas (Strategyzer. 2023), and the value proposition component can be linked with the strategies tool. The strategies tool could consist of CE implementation, climate mitigation, and adaptation strategies. A set of customized mitigation and adaptation options could be designed to align with the objectives of sustainability, efficiency, flexibility, and resilience.

The value chain design tool could be employed with the circular value chain framework and value co-creation models. The business ecosystem modeling method (Ma et al. 2021) can be used in the value chain design tool to identify value stakeholders and their interactions, and the web-based tool, Ecosystem Map Generator (Map and Generator 2023) can support this objective. Furthermore, the web-based Energy symbiosis designer (Energy symbiosis designer 2023) can be utilized to analyze the value chain and investigate the optimal circular value chain. Moreover, a collaborative user interface with a real-time collaboration feature could be deployed to enable individual users for the business model development and multiple users' value chain co-design.

Ecosystem lifecycle evaluation software tool

Ecosystem lifecycle evaluation software could be built upon the CSTEP ecosystem analysis and evaluation method (Ma 2022; Ma et al. 2022) and MCDM models to evaluate the scenario results. Furthermore, the ecosystem lifecycle evaluation could employ LCSA methods (including LCA, LCC, and S-LCA) and green computing metrics to capture five dimensions of Climate and environmental, Social and cultural, Technological, Economic and financial, policy and regulatory (Ma 2022), as well as the preferences and constraints of individual value chain stakeholders. The web-based tool, CSTEP Business Opportunity Identifier (Business Opportunity and Identifier 2023) can be employed to define long-term future scenarios together with scenario design and analysis in LCA, thus enabling the evaluation of the enduring effectiveness of energy solutions and their value chains.

Moreover, open-source LCA software, e.g., OpenLCA and Brightway, and python libraries for MCDM models, e.g., PyMCDM (2023), can be utilized and integrated with the virtual energy ecosystem living lab. It will not only evaluate the results but also provide feedback, improving the design of the energy solutions and value chains.

Discussion and conclusion

This paper proposes a conceptual framework of the energy metaverse with five critical elements (as illustrated in Fig. 1). Based on the review of the State-of-the-Art methods and technologies, this paper recommends the development of the energy metaverse should consider the methods and technologies shown in Table 2. Compared to Table 1. the potential State-of-the-Art methods and technologies related to the energy metaverse development in Table 2 are more practically feasible to be implemented for realizing the energy metaverse development with reliable software and tools.

Scientific contributions

The recommended approaches for developing the energy metaverse are built up the State-of-the-Art methods and technologies, and significantly enhance the State-of-the-Art as:

Energy ecosystem data space

The proposed data space features an array of interconnected databases, facilitating secure data and information exchanges within the energy metaverse and with third-party

Table 2 Recommended methods and technologies for the energy metaverse development

Energy metaverse element	Deployed methods and technologies	Software and tools
A versatile energy ecosystem data space	• Open source cloud-based data management system • Open DevOps and MLOps platform • Interconnected databases • Microservices architecture • Standard API interfaces	MongoDB (2023) GitLab (2023) OpenAPI (2023)
An interoperable virtual ecosystem living lab	• Digital twin technology • Ecosystem architecture design and analysis methods • Multi-agent-based simulations • Hierarchical ontologies • Communication protocols and Interoperability standards	SDU-CEI Energy Metaverse platform (Ma 2023) Protégé (Protégé. 2023) Protégé Ontology Web Language (OWL) API (Programmer's and Guide 2023)
An energy system models and AI algorithms sandbox	• Energy system models • Deep learning algorithm libraries (DCNNs and LSTMs) • Transfer learning techniques • Communication protocols and interoperability standards	OpenModelica (2023) Keras (2023) PyTorch (2023) Jupyter Notebook (2023)
A circular value chain co-design toolbox	• Business model framework • Circular economy implementation strategies • Climate mitigation and adaptation strategies • Circular value chain framework • Value co-creation models • Ecosystem architecture design and analysis methods	Business model canvas (Strategyzer 2023) Ecosystem map generator (2023) Energy symbiosis designer (2023)
An ecosystem lifecycle evaluation software tool	• CSTEP ecosystem analysis and evaluation method • Multi-Criteria Decision Making (MCDM) models • Life Cycle Assessment (LCA) methods (including social LCA and Sustainability Assessment) • Green computing metrics	CSTEP Business Opportunity Identifier (2023) OpenLCA (2023) and Brightway (2023) PyMCDM (2023)

systems or APIs. This innovative design will effectively address the capacity limitations and integration challenges inherent in State-of-the-Art methods.

Virtual ecosystem living lab

The proposed approaches take digital twin technology a step further. It employs this technology in an innovative virtual ecosystem living lab that allows for the verification and validation of interconnected energy systems. To address the challenges of interoperability, a dynamic digital replica of predefined physical energy communities and systems is proposed. This architecture pushes the boundaries of the state-of-the-art by leveraging existing interoperability standards and communication protocols. This approach enables seamless integration and communication between different digital twins and existing systems. Furthermore, the proposed approaches move beyond static analyses and instead adopt dynamic, scenario-based simulations. Therefore, they enhance the depth and breadth of evaluations of energy solutions, especially cyber-physical energy system solutions, allowing for more comprehensive value chain co-design and multi-criteria lifecycle assessments.

Energy system models and AI algorithms sandbox

This paper proposes the first energy system models and AI algorithms sandbox that combines a variety of energy system models and deep learning algorithm libraries. This approach advances energy system modelling by deploying agent-based simulation models to accurately capture the growing consumer involvement in energy systems. Furthermore, the use of Transfer Learning techniques alongside concept drift detection methods to create deep learning algorithms for targeted physical energy ecosystems with minimal or no data is a significant leap beyond existing models. Moreover, the proposed flexible framework can ensure interoperability, easy configuration and modification, and efficient synchronization between energy system models and deep learning algorithms through multi-time resolution and a container-based virtual time system.

Circular value chain co-design toolbox

The proposed approach can ensure the integration of energy solutions, especially cyber-physical system solutions, with circular value chains and circular business models, focusing on the missing linkage between climate adaptation and mitigation strategies and business model values. The employment of the business ecosystem modeling for value stakeholder identification, facilitating collaboration and co-creation, a notable upgrade from existing isolated efforts. The innovative combination of circular business model development, climate strategies, and circular value chain design into a co-design toolbox, aligns business and climate objectives such as sustainability, efficiency, flexibility, and resilience. It allows the seamless development and execution of energy solutions.

Ecosystem lifecycle evaluation software tool

This paper proposes an ecosystem lifecycle evaluation method that is tailored to offer a comprehensive evaluation of energy solutions and their corresponding business models and value chains. This method integrates a variety of methodologies, including methods of Life Cycle Assessment, Life Cycle Costing and Social Life Cycle Assessment, regulatory and policy assessment practices, and technology adoption theories with climate mitigation and adaption measures. This method ensures the comprehensive capture of the five CSTEP dimensions of Climatic, environmental, Social, cultural, Technological, Economic, and Policy and regulatory thus providing a holistic evaluation of energy solutions and value chains. Furthermore, the green computing metrics are also deployed in this method to fill the research gap of missing Life Cycle Assessment of software. This method also incorporates Multi-Criteria Decision Making models into the evaluation framework. This allows the encapsulation of diverse stakeholder preferences and constraints, adding depth and inclusivity to the decision-making processes. Furthermore, the deployment of the web-based tool, CSTEP Business Opportunity Identifier, and scenario design & analysis in LCA can ensure the reliability and credibility of the evaluation of the long-term effectiveness of energy solutions and their circular value chains.

Practical contributions

The use of the energy metaverse can facilitate a transformative shift in the energy sector, primarily targeting key players and stakeholders who are at the forefront of the sector's evolution. The focus will be on the active participants in the renewable energy sector, energy technology developers, policymakers, and the scientific community. These groups are not just interested but are deeply involved in enhancing the economic and environmental performance of the energy sector. These professionals understand the benefits of incorporating innovative technologies, advanced business models, and effective policy measures in promoting sustainable energy. Their expertise, insights, and influence are vital in overcoming the challenges that the sector currently faces. The stakeholders who can benefit directly from the applications of the energy metaverse can be outlined as:

Energy technology providers

They will benefit significantly from the outcome related to the development and optimization of energy solutions and AI-based operational models. These outcomes provide concrete steps for energy technology providers to refine their existing technologies or develop new ones, ultimately enhancing their offerings' reliability and cost-effectiveness.

Energy services companies and business consulting firms

The novel business models, value chains, and AI-based operational strategies can guide them to refine their consultancy services, potentially driving revenue growth and competitive advantage.

Utility companies

The AI-enhanced efficiency aspect of the economic/technological outcome can serve as a model for these companies to optimize their grid operations. The innovative business models and value chains from the same outcome may provide insights into optimizing their resource allocation, leading to cost reductions and improved service reliability.

Local Communities and energy consumers

The optimized energy solutions will provide reliable and affordable energy, fostering local economic development, and improved living standards. Also, CO2 emission reduction will contribute to cleaner, healthier environments.

Regulatory bodies and policymakers

The evidence-based optimization strategies and ecosystem lifecycle evaluation methodology can be highly valuable for policy development. The societal outcome's emphasis on quantifying impacts can provide them with robust data to guide policy decisions and regulatory measures related to renewable energy use.

Non-Governmental Organizations (NGOs)

NGOs focusing on climate change, energy, and social development. The ecosystem lifecycle evaluation methodology can guide their initiatives and advocacy. They can also use the societal outcome's emphasis on quantifying environmental, health, social, and economic impacts to measure the effectiveness of their programs.

Scientific community

The scientific community will directly benefit from the scientific outcomes, including the advanced knowledge on the co-design of value chains, business models, and ecosystem lifecycle assessment methodologies. They can leverage these outcomes to guide their research directions and potentially open new frontiers in the integration of cyber-physical systems, artificial intelligence, and renewable energy technologies.

Limitations and future works

The development of the energy metaverse is extremely complex and requires great effort to deal with the following challenges:

The main technological challenge is the digital replication of each targeted physical energy ecosystem which requires demands substantial manual preparatory activities, such as gathering and analyzing information and data. The information and data collection not only includes the technical specifications and constraints (e.g., existing energy systems), climate and environmental conditions (e.g., solar radiation, wind speed) but also the behaviours of all involved stakeholders. Furthermore, to ensure the virtual representation of targeted physical energy ecosystems remains realistic and precise, there's a need for comprehensive long-term trend analysis and forecasting. However, executing such multi-faceted ecosystem trend evaluations can be labor-intensive, and current state-of-the-art methods don't present efficacious solutions. A recommended approach is to employ the CSTEP ecosystem evaluation technique (Ma et al. 2022) and its associated CSTEP Business Opportunity Identifier tool (2023), complemented by the scenario design and analysis in LCA for long-term trend prediction. However, this approach is qualitative rather than quantitative, which poses its own set of challenges. While qualitative analyses offer valuable insights into system behaviors, stakeholders' motivations, and potential system evolutions, they might not provide the precise numerical data needed for some technical simulations or decision-making processes. Quantitative data is essential for making accurate forecasts, optimizing system performance, and conducting rigorous risk assessments. The absence of exact numerical values can make it challenging to gauge the full impact of certain decisions, measure return on investments, or ensure the most efficient allocation of resources.

Another technological challenge is to integrate pre-existing software into the energy metaverse platform. Although some software is open-source, due to the diversity in their foundational architectures, compatibility issues might arise. This can lead to divergences in data exchange, misalignment in functionalities, and potential operational inefficiencies. Furthermore, closed-source software brings along its set of challenges such as limited access to source code, which can constrain customization and seamless integration efforts. Addressing these challenges requires a comprehensive understanding of software interoperability, as well as the development of standardized protocols and middleware solutions to bridge the gap between varying software architectures. However, the implementation of the existing interoperability standards and communication protocols reveals difficulties for software developers and stakeholders to adopt them. This is primarily because these standards and protocols, while universally designed, might not account for the specific differences and unique requirements of every application or system. Moreover, the dynamic nature of the technological landscape means that standards can quickly become outdated, requiring frequent updates and adaptations. Additionally, a lack of comprehensive documentation or training resources for these standards can impede their widespread acceptance and use.

Cost is the main economic challenge for developing and operating such an energy metaverse platform. Each of the five critical elements in the energy metaverse platform requires significant financial resources for research, development, deployment, and maintenance. Firstly, the foundational infrastructure, being the backbone of the platform, demands robust hardware and software components, which often come with high initial investments. Secondly, the data management and storage systems necessitate state-of-the-art security measures and large-scale storage solutions, which can be expensive to implement and maintain. Thirdly, integration tools and APIs for ensuring seamless interoperability among different systems introduce costs associated with licensing, customization, and continuous upgrades. Fourthly, user interfaces, while vital for user engagement and experience, need ongoing design and user research to stay intuitive and relevant. Lastly, the analytics and reporting tools require advanced algorithms and computational power, representing another significant expense. All these elements combined underscore the financial challenges involved. To mitigate these costs, it's essential to explore diversified funding sources, partnerships, and scalable design solutions that can adapt to changing technological landscapes without frequent and costly overhauls.

While there are considerable advantages for stakeholders in using the energy metaverse platform, as highlighted in the "Practical contributions" section, certain stakeholders, particularly energy technology providers, may be hesitant to adopt it. This reluctance can come from the platform's potential to disrupt established R&D procedures. Consequently, the usage of the energy metaverse platform might need a re-evaluation of existing infrastructural systems, processes, and practices. In addition, the transparency provided by the metaverse platform might expose certain inefficiencies or proprietary methods, causing concerns among stakeholders who view these as competitive advantages. Additionally, there might be concerns related to data security, intellectual property rights, and the high learning curve associated with understanding and navigating a new digital platform.

Abbreviations

AHP	Analytic hierarchical process
API	Application programming interface
AI	Artificial intelligent
BSON	Binary JavaScript Object Notation
CE	Circular economy
CIM	Common information model
CPS	Cyber-physical systems
CPES	Cyber-physical energy system
CSC	Circular supply chain
CSTEP	Climatic and environmental, social and cultural, technological, economic and finance, and political and regulatory
DCNNs	Deep convolutional neural networks
DevOp	Software development
DL	Deep learning
EU	European Union
ESS	Electricity storage systems
FIPA	Foundation for the intelligent physical agent
GHG	Greenhouse gases
GRU	Gated recurrent units

HRM	Harmonized electricity market role model
IEA	International energy agency
ItL	In-the-loop
IPCC	Intergovernmental panel on climate change
ISO	International Organization for Standardization
JSON	JavaScript object notation
LCA	Lifecycle assessment
LCC	Life cycle costing
LCCA	Life cycle cost analysis
LCIA	Life cycle impact assessment
LCSA	Life cycle sustainability assessment
LSTM	Long short-term memory
MAS	Multi-agent systems
MBD	Model-based design
MCDM	Multi-criteria decision making
ML	Machine learning
MLOp	Machine learning operations
NGOs	Non-Governmental Organizations
OpenADR	Open automated demand response
OWL	Ontology web language
PSO	Particle swarm optimization
RDF	Resource description framework
SEAS	Smart energy aware systems
SGAM	Smart grid architecture model
SotA	State-of-the-art
S-LCA	Social life cycle assessment
TL	Transfer learning
USEF	The Universal Smart Energy Framework
VRE	Variable renewable energy

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