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A comprehensive review on optimization challenges of smart energy hubs under uncertainty factors

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ABSTRACT

With economic development in the world and growing energy demand, the concept of sustainable energy has received more attention from energy planners in different energy sectors. To achieve sustainable energy development (SED), appropriate utilization of all types of sustainable energy resources is vital. One further requirement for this is the integration of various energy systems in the framework of a multi-energy system where all energy system elements have the possibility of synergy with others for minimizing losses and maximizing the utilization of any availabilities. Further requirements for such a highly yet wisely integrated energy system (IES) have recently been specified in the context of smart energy systems (SESs). Smart energy hub (SEH) is introduced as a novel concept that provides a distinguished framework to model SESs. The main challenge for the modeling of SEH is finding the optimal design/sizing and operation strategy of the system components based on the uncertainty of renewable sources, demands, energy market spot prices, etc. Uncertainty modeling assists in reaching a realistic optimal approach in the decision-making process and thus is a promising line of future research in the modeling of SEH. The main aim of this work is to classify and evaluate the existing methods to employ uncertainty in the design, operation, and planning of SEH to reach a better understanding of future challenges in this way.

1. Introduction

1.1. Opening

In recent years, the integration of different energy systems with multiple energy carriers has been introduced as an inevitable approach for addressing the current energy and sustainability challenges [1]. IESs can enhance the overall performance and improve resiliency and reliability. In addition, it can provide significant opportunities, such as increasing the penetration of renewable energy sources (RESs) and preparing a suitable basis for the efficiency enhancement of energy

Abbreviations: CAES, Compressed Air Energy Storage; CCHP, Combined Cooling, Heating, and Power; CHP, Combined Heating and Power; CP, Cone Program; CVaR, Conditional Value at Risk; DRO, Distributionally Robust Optimization; DRP, Demand Response Programing; ECSs, Energy Conversion Systems; EES, Electrical Energy Storage; EH, Energy Hub; ELF, Equivalent Loss Factor; EnA, Energy Analysis; EnBC, Energy Buying Cost; EnSI, Energy Selling Income; ESS, Electricity Storage System; EVs, Electric Vehicles; EVs-PL, EVs Parking Lot; ExA, Exergy Analysis; G2H, Gas to Heat; G2P, Gas to Power; GES, Gas Energy Storage; GSA, Gravitational Search Algorithm; GSS, Gas Storage System; H2C, Heat to Cold; HECS, Hybrid Energy Conversion System; HESS, Hybrid Energy Storage System; HRES, Hybrid Renewable Energy Source; HRSM, Hybrid Robust Scenario-based Model; IES, Integrated Energy System; IGDT, Information gap decision theory; IIC, Initial Investment Cost; InC, Investment Cost; IRR, Internal Rate of Return; LOEE, Loss of Energy Expectation; LOLE, Loss of Load Expectation; LP, Linear Program; LPSP, Loss of Power Supply Probability; MCS, Monte Carlo Simulation; MES, Multi-Energy Systems; MILP, Mixed-Integer Linear Programming; MINLP, Mixed Integer Nonlinear Programming; NLP, Nonlinear Programming; NPV, Net Present Value; O&MC, Operation & Maintenance Cost; P2C, Power to Cold; P2G, Power to Gas; P2H, Power to Heat; PDF, Probability Density Function; PEM, Point Estimate Method; PSO, Particle Swarm Optimization; PV, Photovoltaic; QP, Quadratic Program; RESs, Renewable Energy Sources; RO, Robust Optimization; SBA, Scenario-Based Approach; SDP, Semi-Definite Program; SED, Sustainable Energy Development; SEH, Smart Energy Hub; SEMS, Smart Energy Management System; SESs, Smart Energy Systems; SOCP, Second-Order Cone Program; TES, Thermal Energy Storage; TOC, Total Operation Cost; ToU, Time of Use.

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Nomenclature

Indices/Sets

i	Index of random variables
j	Index of output variables
k	Index of sampling
s	Index of scenario
Ω_i	Set of random variables
Ω_j	Set of output variables
Ω_s	Set of scenarios of SBA
N_{MCS}	Total number of MCS samples
N_{RV}	Total number of random variables

Parameters/Variables

P	Input vector of EH
L	Output vector of EH
C	Converter coupling matrix
x_i	Random variable
y_j	Output variable
ε_{MCS}	Relative error of MCS
p_i	Concentration points for random variable in PEM
ω_i	Specific weight for random variable in PEM
ξ_i	Standard location associated with random variable in PEM
π_s	Probability of s_{th} scenario in SBA
b_i^l	Interval of the l_{th} constraint
U^l	Interval of the uncertain vector

supply and storage units [2]. The tendency to integrate the energy networks from the conceptual point of view and the development of the required equipment for this integration from the practical point of view has caused researchers to pursue novel concepts and frameworks to deal with optimal energy management of IESs [3]. In this context, SES and SEH have been presented as promising paradigms to manage multi-energy systems (MES) [4]. Many researchers have used these concepts to operate IESs and shown these can lead to better performance than the traditional framework.

On the other hand, energy systems in real-life applications face many uncertainties. The number of uncertain parameters has increased by the integration of energy systems and interactions between different sectors [5]. Nevertheless, this integration basis can facilitate finding better solutions to deal with uncertainty, if an accurate unified stochastic scheduling is applied. Therefore, uncertainty analysis is a key point in the decision-making process of smart energy management to give a confidence level for decision-makers. This paper reviews uncertainty analysis and its challenges in the design, operation, and planning of SEH, a local energy system that is equipped energy storage system, the energy conversion system as well as connected to renewable energy recourses and upstream energy networks to supply local demand.

1.2. Contributions

The objective of this paper is to attain a precise perception of SES modeling based on the SEH concept as well as to evaluate uncertainty impacts in this modeling. SES has been introduced as a promising way to reach the goal of 100% green energy in the future and it creates a new perspective for the unified operation of MESs. Pierluigi [6] comprehensively reviewed MESs from concepts and evaluation model points of view. In this work, four types of categorization, including spatial aspects, multi-service, multi-fuel, and network perspectives, have been defined for a precise investigation of MESs. Thereafter, Nazari et al. [7] presented an updated review on MESs integrating electricity, gas, and water resources focusing on operation model and performance assessment. Lund et al. [8] explicitly defined the SES concept idea to give a scientific basis for the distinction between SESs and smart grids. They demonstrated how the SES concept could create an approach to design and operate IESs for further sustainability. O'Dwyer et al. [9] reviewed smart city challenges considering the SES concept and investigating the integration of computational intelligence and machine learning techniques to design and operation of a sustainable smart city. A macroscopic view of smart energy, a discussion of SES objectives, and the elaboration of combined objectives of the affordable sustainable green hub were presented in Ref. [10]. Xu et al. [11] reviewed the literature from an optimization point of view for the design and operation of SESs. Different optimization models, including single- and multi-objective optimizations as well as different optimization algorithms applied to solve the designing problem of SESs, were discussed in this reference.

On the other hand, SEH has also been introduced as a unit where multiple energy carriers can be converted to a different type of energy or stored for future utilization. Therefore, this concept has provided a suitable framework for the modeling of SESs. Several pieces of research have been done on this concept studying that from different visions, among which there are some review papers that collect and present the message of these works in each category in a nutshell. Mohammadi et al. [12] comprehensively reviewed different energy hub (EH) concepts and models in the literature. EH components were separately identified and studied for each of its functionality, including input, storage, conversion, and output. In Ref. [13], the optimal management of SEHs was reviewed considering separate applications of EHs in different energy consumption sectors, including residential, commercial, industrial, and agricultural sectors. Sadeghi et al. [14] did an extensive review on expansion energy planning for IESs based on EH concepts in the literature. The operation and planning of IESs were studied by Ref. [15], where the literature was systematically reviewed by considering multi-vector energy networks.

Both SES and SEH concepts have been considered in the literature as promising layouts of the future IESs to deal with sustainable energy concerns, and different review papers have focused on each of them in various aspects. Despite the fact that there is a fundamental convergence between these two concepts, however, there is no article comprehensively describing the relationship between these two concepts. Examining the fundamental and conceptual convergence of these two concepts can be very beneficial in the sense that it can create a specific and distinctive framework for future research work. Therefore, this paper firstly investigates the definition and composition of SESs and SEHs to get a comprehensive understanding of them by answering the below questions:

1 What features and properties does an SES have?
2 What is the necessity of designing modern systems in the SES concept?
3 What are the definition and specifications of an SEH?

By giving a detailed and in-depth review of the authoritative literature on the EHs and SEHs, the future trends of optimal management for SEHs will be elaborated on in this paper. Therefore, this paper presents a novel overview of recent literature on the design, operation, and planning of SEH. In this context, the following questions are rigorously answered:

1 What are the challenges in the modeling of SEH?
2 Which of the optimization models are considered more in the literature?
3 Which criteria are considered to optimize SEH?

Finally, since uncertainty analysis of SEHs can assist the

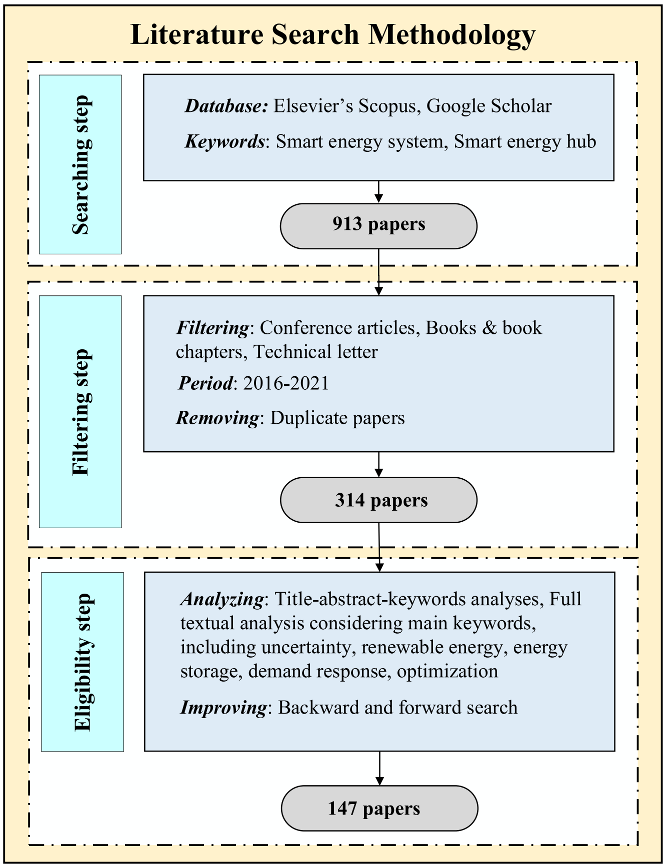

Fig. 1. The systematic principle for literature search and review applied in this paper.

compensation of renewable generation fluctuations and may smoothen the pathway to 100% green energy, as the main objective of this work, a comprehensive review of the uncertainty modeling for the design, operation, and planning of SEH is presented. Here the following questions are focused on being answered:

1 What are the elements of SEH uncertainty and how much has the modeling each of them been addressed in the literature?
2 Which methods have been employed to model the SEH uncertainty?
3 Which important areas are there for future research regarding the uncertainty modeling of SEHs?

1.3. Research methodology

The systematic principle, depicted in Fig. 1, was applied to identify the relevant literature for this review. Two approaches were taken to identify the relevant literature. Elsevier's Scopus search engine, as one of the largest databases for peer-reviewed literature, has been used firstly by mixing various search terms and boolean operators. Since the SEH concept was first introduced by Ref. [16] in 2015, the literature and works with this content have emerged after that year. Therefore, to achieve a more precise search, the limitation of the publishing year has been considered from 2016 onwards. The terms contained "smart energy system*", "energy hub*" and "smart energy hub*" have been considered for searching in the title, abstract, or keywords as following query string:

- TITLE-ABS-KEY("smart energy system*")AND PUBYEAR >2015
- TITLE-ABS-KEY("smart" AND "energy hub*")AND PUBYEAR >2015

In the second approach, the works of 10 authors, who had published more papers than others in an earlier search, were searched through the Google Scholar database and the relevant papers were picked up. According to the mentioned search procedure, 943 papers were identified in the identification step. Then, the duplicate papers are removed in the filtering step. Moreover, we have only considered research articles and review papers published in Elsevier and IEEE journals from 2016 or later, leaving out other publications, such as conference articles, books & book chapters, as well as letters. Finally, 374 papers remained as the output of this step. In the last step, title-abstract-keywords analysis, and full-textual analysis, as well as backward and forward search have been conducted on the remaining papers to reach the final main database for reviewing.

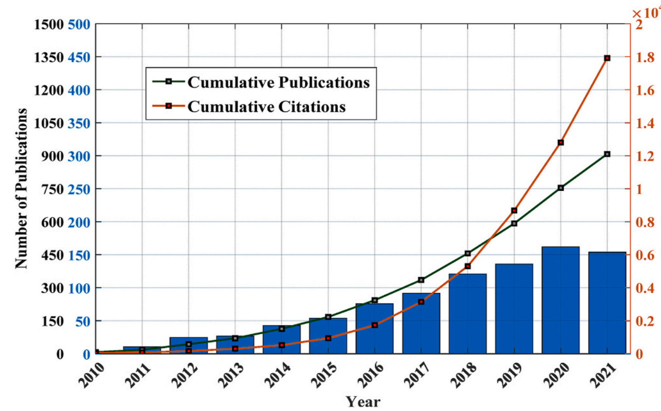

Fig. 2. The number of publications, cumulative publications, and cumulative citations on a year-on-year basis.

1.4. Publication analysis

To analyze the publications gathered by the search methodology, two analysis techniques have been carried out in this paper. The first one is the citation analysis, in which historic development and recent trends would be investigated, and the second method is keyword analysis applied to validate the main keywords associated with the eligibility step. We used the VOSviewer software, a text mining software to create bibliometric maps of scientific fields, in both analysis methods. Fig. 2 illustrates the number of publications on a year-on-year basis as a bar chart over the years, from 2010 to 2021. Moreover, the number of cumulative publications and cumulative citations of these publications are also pictured in this figure. As can be seen, the total number of publications has continuously increased in the last decade and this increment has been remarkable in the last 5 years, as the papers published after 2015 constitute 83%, of all the publications.

For the selection of the main keywords applied in the eligibility step, all the words were extracted from the title and abstract of the publications based on co-occurrence analyses, and then filtered considering a minimum limit of 10 occurrences by a built-in text mining function of VOSviewer. Finally, the co-occurrence map for the list of resulted keywords was generated to better realize their connection. Fig. 3 illustrates the network visualization of the co-occurrence map. Moreover, the keywords clustering has been demonstrated in this figure. As can be seen, three main clusters have been extracted and the keywords such as renewable energy, energy storage, demand response, optimization, and uncertainty have more overlap with different clusters. Therefore, they can be suitable keywords associated with the eligibility step.

2. Fundamentals

Each country's economic growth and development are reflected in its per capita energy consumption and consumption patterns [17]. According to the U.S. Energy Information Administration's report, world energy consumption is anticipated to increase by 44% from 2006 to

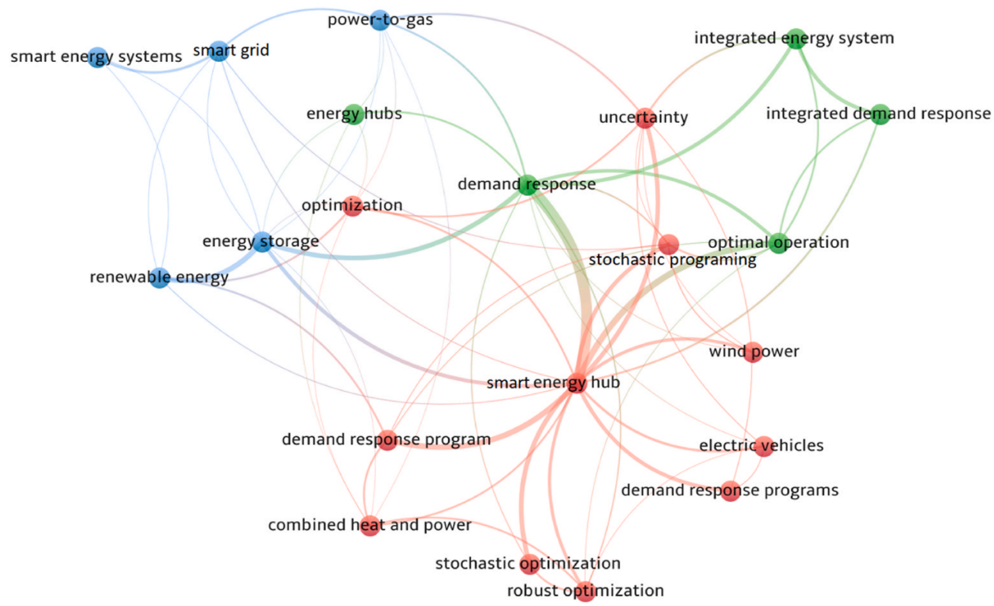

Fig. 3. The network visualization of the co-occurrence map for the list of resulting keywords.

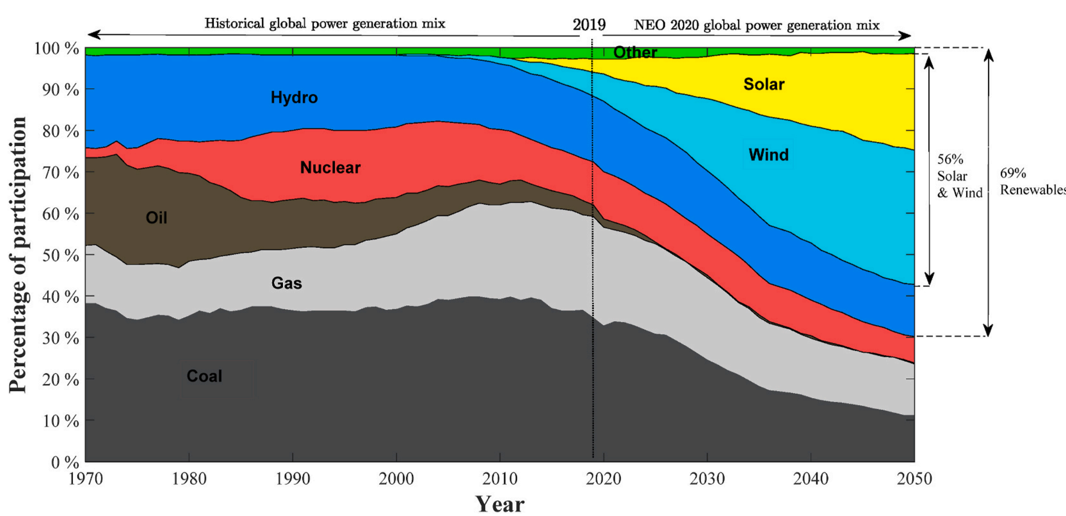

Fig. 4. Global electricity generation, 1970–2050, Source: Bloomberg New Energy Finance, New Energy Outlook [19].

2030. On the other hand, Based on the World Energy Outlook 2021 report [18], the analysis of Net Zero Emissions by 2050 Scenario, which is in line with the Paris Agreement objective, i.e., "pursuing efforts to limit the temperature increase to 1.5 °C", shows that global CO_2 emissions intensity, respectively, need to drop 56% and 91% below 2020 levels by 2030, and 2040, to reach net-zero emissions in 2050. To deal with these two challenges, the increment of RESs penetration is mandatory. Fig. 4 demonstrates the share of different primary energy in the historical and predicted power generation in the world. While wind and solar have only 9% of the global share today, they are expected to supply 56% of the world's electricity generation by 2050 [19]. However, this growth of generation share would be led to increasing power systems uncertainty and consequently getting harder conventional power plant operation, which can negatively affect system security [20]. The energy consumption growth and RESs penetration enhancement need the development of the energy sector from different points of view based on the SED principles [21]. SED causes improving energy system resiliency and reliability, increasing energy efficiency, as well as reducing CO_2 emissions [22]. In this regard, the SES concept has been introduced as the most comprehensive definition for the optimal design of future IESs based on 100% green energy which can provide a suitable basis for achieving SED in the future energy system.

On the other hand, SEH has been introduced in the literature as an upgraded concept from EH, in which intelligent devices are considered for creating a bidirectional energy flow between upstream energy networks and local energy systems [23]. Regarding the advantages of the EH model in multi-energy system modeling, SEH gives a suitable framework for the modeling and analysis of SES [24]. Fig. 5 illustrates a schematic representation of SES, in which SEH is defined as a subset of SES in an overall view.

On the other hand, SEH needs changes in the energy management system to comply with the realities from a policy implication and implementation point of view. In this regard, some recommendations, such as creating active and adaptive energy networks, providing a platform for big data acquisition and processing, and further supporting green energy by putting on emission costs, could be considered. By providing smart facilities and a competitive environment of the energy market, each SEH can be considered as a prosumer through bilateral

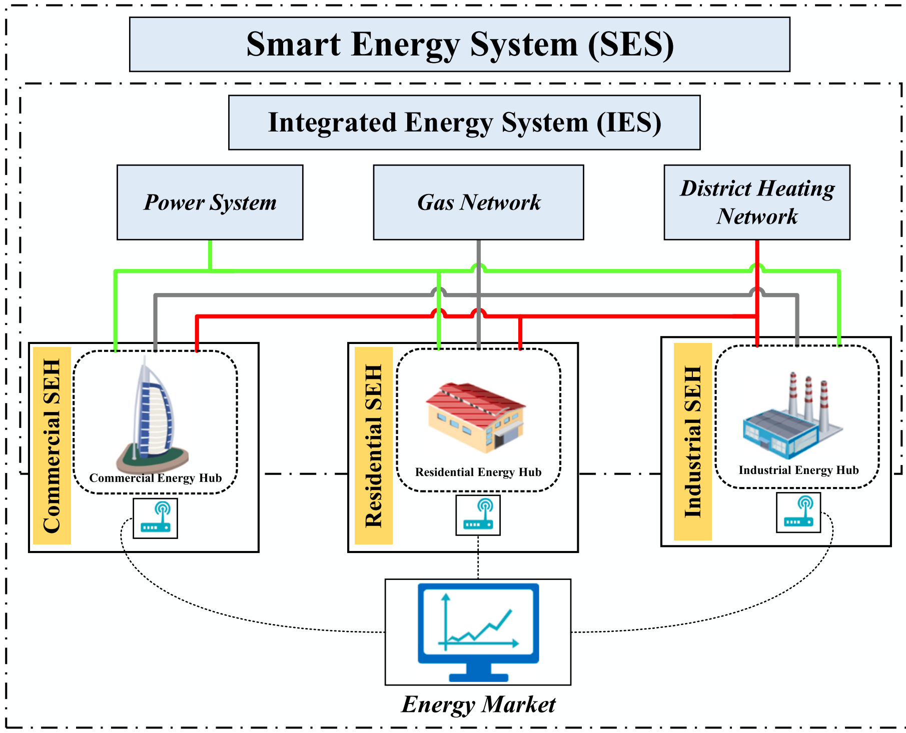

Fig. 5. A general view and schematic representation of SES, considering SEH as its subset.

energy exchange. Consideration of the prosumer role for an SEH is more achievable when it is defined for a local energy system versus an individual energy customer such as a single smart home. Because the integration of different energy carriers by HECS can provide more energy efficiency of the system and its more effective participation in an energy market.

2.1. Smart energy systems (SES)

Due to the uncertainties and fluctuations of RESs, their penetration in global energy systems is still challenging [25]. The SES concept, which is centered around a 100% share of RES in IESs, is a strong solution for addressing this challenge. This concept is the outcome of the research projects "*Coherent Energy and Environmental System Analysis*" and "*Strategic Research Centre for* 4th *Generation District Heating Technologies and Systems*" [26]. Energy storage systems (ESSs) are one of the important parts of SES to give flexibility on the operation of IES to increase RES penetration. Moreover, the energy conversion systems (ECSs), as another important part of SES, can also improve system flexibility by creating a suitable platform to support energy networks to each other. Lund et al. [8] deeply investigated how SESs can reflect a fundamental change in the future energy systems management's perception to design feasible and affordable solutions. In the literature, the SES concept has been applied at different levels from size and spatial perspectives [27]. These levels have been defined from buildings [28] to commercial or industrial areas [29], and even larger regions such as a city or a state [9]. The contribution of the top 10 countries expanding this concept in the literature is depicted in Fig. 6.

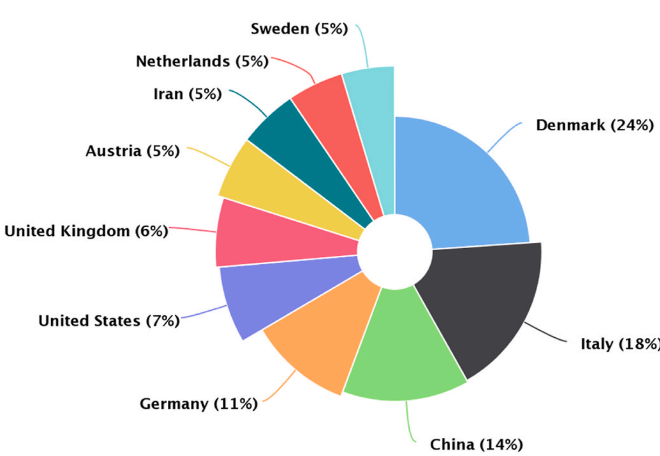

Fig. 6. The contribution of the top 10 countries most developing SES in the literature.

2.2. Smart energy hubs (SEH)

EH is a novel concept for optimal operation and energy management of IESs with the aim of sustainable MESs. For the first time, the EH concept was introduced by Ref. [30] to investigate combined economic dispatch and optimal power flow problems related to multi-energy delivery. An EH is a multi-component center with several distributed energy production, storage, and management units that makes an effective interface between stakeholders (including end-users and suppliers) and different energy carriers [31]. Many industrial facilities such as industrial parks, big buildings, bounded geographical areas, and islanded power systems can be modeled according to the EH foundations [32]. The relationship between input and output power in the EH is shown in (1) and (2). Where C is the converter coupling matrix, P and L are input and output vectors, respectively.

$$\begin{bmatrix} L_\alpha \\ L_\beta \\ \vdots \\ L_\omega \end{bmatrix} = \begin{bmatrix} c_{\alpha,\alpha} & c_{\beta,\alpha} & \dots & c_{\omega,\alpha} \\ c_{\alpha,\beta} & c_{\beta,\beta} & \dots & c_{\omega,\beta} \\ \vdots & \vdots & \ddots & \vdots \\ c_{\alpha,\omega} & c_{\beta,\omega} & \dots & c_{\omega,\omega} \end{bmatrix} \begin{bmatrix} P_\alpha \\ P_\beta \\ \vdots \\ P_\omega \end{bmatrix} \tag{1}$$

$$L = C.P \tag{2}$$

Investigation of RESs and smart energy grid technologies such as demand response programs (DRP) with the EH has created a new concept named SEH. This concept has been presented by Ref. [16] for

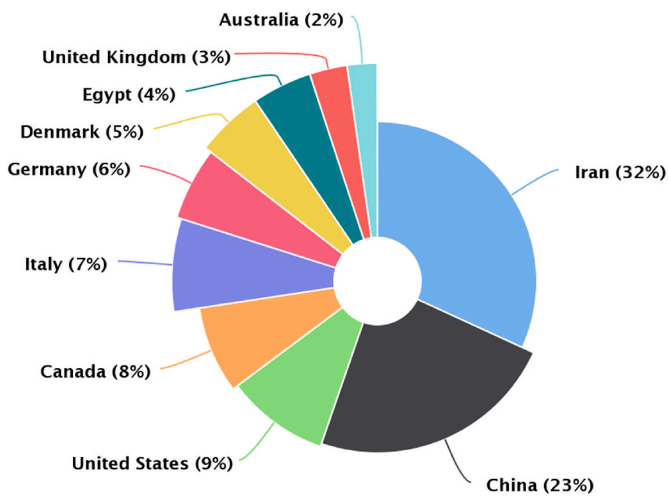

Fig. 7. The contribution of the top 10 countries developing the literature of SEH.

the first time. Moreover, Sheikhi et al. [33] investigated integrated DRP on united electricity and gas networks by proposing an ordinal potential game with a strictly concave function. Rakipour et al. [34] presented a probabilistic optimal operation of an SEH, with the participation of DRP in the electrical power and cooling sector. A new model for integrated urban energy systems based on the SEH basis was presented by Ref. [35], considering decentralized and local energy technologies. Fig. 7 demonstrates the contribution of the top 10 countries expanding the SEH concept in the literature.

A general scheme of an SEH is demonstrated in Fig. 8. As shown in this figure, this can be divided into three main parts, including hybrid renewable energy source (HRES), hybrid energy conversion system (HECS), and hybrid energy storage system (HESS), which are discussed in the following sub-sections.

2.2.1. HRESs

HRESs can be connected to upstream energy networks or stand-alone micro-grids with the aim of decreasing the dependence on fossil fuels. They can contain different RESs to generate electricity for local energy demand [36]. Depending on nature and geographical conditions, different combinations of these sources can be suggested as an ideal hybrid system for a specific case. Nevertheless, wind turbines and solar energy are particularly popular in most HRES. Furthermore, today, with investment in hydrogen production technology and governments' effort to attain an economically feasible solution for employing this energy carrier, fuel cells are also getting special importance in HRESs due to their high energy conversion efficiency and low environmental impacts [37].

Hybrid configurations can reduce the uncertainty effect of RESs on the power system, while the correlation between these sources is a major challenge in their operation. Researchers have done various quite a lot of work for optimizing and designing such hybrid systems. Optimal scheduling of an HRES based on wind, solar, and biogas has been done by Ref. [38] to deal with renewable generation fluctuation, considering thermodynamic modeling of a digester to produce the biogas from biomass. Table 1 presents a list of HRESs proposed/studied in the literature, with a different combination of renewable resources technologies. As shown in this table, wind turbines and photovoltaic (PV) are the most popular renewable energy technologies as well as fuel cells are perused more others after them, in the literature. Moreover, in most of the references, both environmental and economic assessments have been done to reach a sustainable solution.

2.2.2. HECSs

Energy conversion technologies are the most important facilities used in SEH to integrate different energy networks. For instance, the utilization of power-to-gas (P2G) facilities enables natural gas systems to consume the redundant electricity energy produced by RESs. Energy and exergy analysis is a reliable method for evaluating ECSs, defining the "value" of energy from "quantity" and "quality" aspects [52]. Although the term HECSs is less commonly used in the literature, it can be defined as the part of an SEH in which different energy carriers are converted to each other's forms. The main energy conversion technologies of SEHs may be divided into eight general categories of gas to power (G2P), gas to heat (G2H), P2G, power to heat (P2H), power to cold (P2C), and heat to cold (H2C). Different configurations of HECSs presented in the literature have been given in Table 2.

2.2.3. HESSs

SESs are expected to be highly penetrated by several energy storage

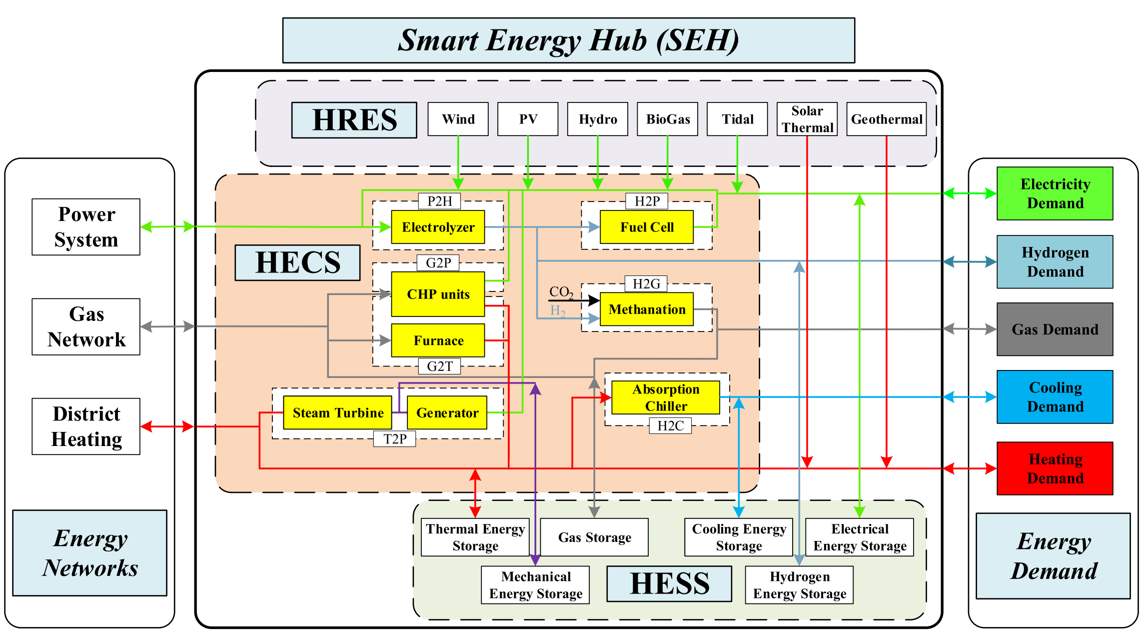

Fig. 8. General scheme for an SEH with considering a comprehensive structure that presents different SEH's parts and various energy carriers' transaction.

Table 1
HRESs with a different combination of renewable resources technologies.

Ref #	HRESs						Application
	Wind	Solar	Hydro	Fuel cell	Biogas	Tidal	
[39]	✓	✓					Optimal sizing by techno-enviro-economic assessment for large-scale reverse osmosis desalination application
[40]	✓	✓					Stochastic optimal design of an SEH in the generation section
[41]	✓	✓	✓				Optimal operation considering DRP and ESS
[42]		✓		✓			Optimal heat recovery by techno-enviro-economic assessment
[43]	✓	✓		✓			Risk-based optimal operation considering DRP and electric vehicles (EVs)
[44]		✓		✓			Stochastic operation considering load uncertainty
[45]	✓	✓		✓		✓	Optimal design for HRESs belong different regions of an energy system with remote application
[46]	✓	✓		✓		✓	Stochastic operation considering ESS
[47]	✓	✓				✓	Optimal operation by enviro-economic assessment for isolated hybrid microgrids
[48]	✓	✓		✓			Optimal design for residential load considering EVs
[49]	✓	✓		✓	✓		Techno-enviro-economic assessment to reach cost-effective hydrogen production approach for rural application
[50]	✓	✓			✓		Optimal sizing by techno-enviro-economic assessment for supplying rural application
[51]		✓			✓		Optimal design for residential SEH based on building clusters

units in different sectors based on different technologies with the aim of increasing higher renewable energy penetration. These storage units pave the way for future SESs to be operated in a flexible and cost-effective manner [64]. In general, ESSs can be divided into three main categories from the perspective of energy exchanges. 1) electrical energy storage (EES); 2) gas energy storage (GES); 3) thermal energy storage (TES). EES systems are employed to store electricity and have the largest share in the world's energy systems. They can be divided into three main categories based on the technologies being used. GES and TES systems are employed to store energy carriers in the form of gas and thermal energy for later use, respectively. Moreover, these storage systems can be used to store excess electrical power generated by renewable sources by considering P2G and P2H conversion systems. Fig. 9 demonstrates different types of ESSs based on the mentioned categorization.

HESSs usually consist of two or more energy storage devices used together to improve system performance and energy demand and supply balance. Cao et al. [65] presented a multi-objective optimal operation of SEH, including EES and TES systems, to achieve both environmental and economic purposes. A holistic proposal for SEH containing different ESSs types for each energy carrier has been given in Ref. [66] for resource scheduling problems of real-world cases. A list of HESS presented in the literature, with different configurations, is provided in Table 3. As it is seen, EES and TES have been considered more than GES by researchers in the literature.

3. Optimization challenges

The optimization problem is a specific and widely used framework for the modeling of SEHs. Knowing which kind of optimization model is applied is so important to choose the best method for solving the problem from a technical point of view. To find an optimal model of SEH, there are many challenges, which can be examined from three different perspectives, including the type of the proposed optimization problem, criteria & objectives, and application. This section describes the challenges of SEH modeling in detail, and then reviews the literature based on these perspectives.

3.1. Optimization problem model

In general, optimization problems are divided into two main types, namely convex and non-convex optimization problems. Although most problems in the real world are defined as non-convex optimization, researchers are trying to present a definition of the existing problems in a convex form. Because, unlike non-convex optimization, we always reach a global solution in a convex optimization framework. Moreover, many attempts have been made to solve convex optimization with a high degree of hardness, and different novel methods have been presented by researchers to deal with this problem. Therefore, this type of optimization problem can be so beneficial to reach a convenient result for high dimension problems.

3.1.1. Convex optimization

Convex optimization problem refers to a kind of mathematical optimization problem, in which both the objective functions and the solution space are in convex form. Defining or formulating a real problem as a convex optimization form can have many benefits. The most basic benefit is that the problem can be solved very reliably and effectively with high computational efficiency [75]. Moreover, there are also theoretical or conceptual benefits such as the dual problem, which often has an interesting interpretation in terms of the original problem as well as sometimes leads to an efficient or distributed method for solving it. The standard form of a convex optimization problem is generally defined as follows:

Table 2
HECSs configuration with different energy conversion technologies in the literature.

Ref #	HECS						Application
	G2P	G2H	P2G	P2H	P2C	H2C	
[53]	✓	✓		✓			Reliability assessment of IES considering SEH modeling
[54]	✓	✓	✓	✓	✓	✓	Optimal design and planning of EHs considering DRP
[55]	✓	✓	✓				Stochastic operation of SEH considering the coordinated P2G technology with DRP
[56]	✓	✓			✓	✓	Stochastic operation of SEH considering wind uncertainty and DRP
[57]	✓	✓			✓		Optimal design and planning of SEH by techno-enviro-economic assessment
[58]	✓	✓		✓	✓	✓	Optimal operation of SEH considering DRP and different ESS technologies
[59]	✓	✓			✓	✓	Stochastic optimal design and operation of SEH considering DRP
[60]	✓	✓	✓		✓		Energy management of a port energy system through EH modeling considering integrated DRP
[61]				✓	✓	✓	Optimal operation of regional IES considering DRP
[62]	✓	✓		✓	✓	✓	Cooperative energy management of SEH considering electrical and thermal DRP and different ESSs for power, heat, and cooling
[63]	✓	✓	✓				Stochastic operation of SEH considering DRP and EVs

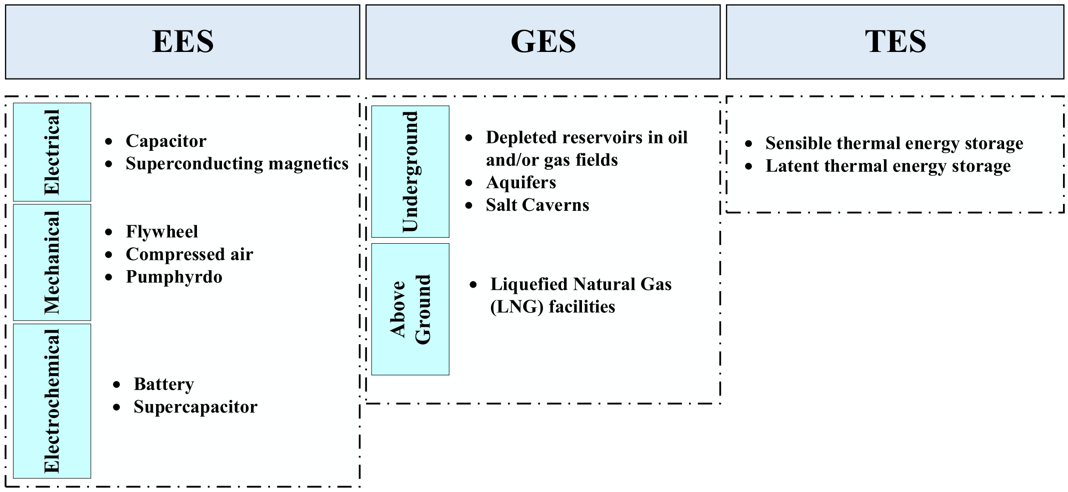

Fig. 9. The categorizations of different types of ESSs from energy exchanges point of view.

Table 3
HESS configuration in the literature. (SO: Stochastic Optimization)

Ref #	HESS			SO	Application
	EES	TES	GES		
[25]	✓	✓	✓		Optimal operation by the techno-enviro-economic assessment
[38]	✓		✓		Optimal operation considering digester's thermodynamic modeling
[43]		✓	✓	✓	Risk-based optimal operation considering DRP and EV
[55]	✓	✓		✓	Optimal operation considering the coordinated P2G technology with DRPs
[63]	✓	✓		✓	Optimal operation considering DRPs and EVs
[67]	✓	✓			Enviro-economic assessment for fuel cell/PV/battery hybrid energy system
[68]	✓	✓			Optimal operation by the techno-enviro-economic assessment
[69]	✓	✓	✓	✓	Optimal operation of SEH considering integrated DRP and HESS
[70]	✓	✓		✓	Techno-enviro-economic assessment of the coordinated operation of regional SES
[71]	✓	✓		✓	Optimal operation of virtual EH system considering thermal energy market
[72]	✓	✓		✓	Coordinated operation and power trading for CCHP microgrid with the energy market
[73]	✓	✓		✓	Optimal planning considering wind uncertainty and DRP
[74]	✓	✓		✓	Optimal planning considering wind uncertainty

$$Min \quad F(X)$$

Subject to:

$$G_k(X) \le 0, \quad H_j(X) = 0$$
$$X = [x_1, x_2, \dots, x_n] \tag{3}$$

In which, X is variable vector and $x_i \in \mathbb{R}^n$ is a decision variable. Here, the objective function of the optimization problem $F : D \subseteq \mathbb{R}^n \to \mathbb{R}$ should be convex. Moreover, the inequality constraints $G_k : \mathbb{R}^n \to \mathbb{R}$ and the equality constraints $H_j : \mathbb{R}^n \to \mathbb{R}$ should be convex and affine, respectively. Linear programming (LP), quadratic programming (QP), second-order cone programming (SOCP), semi-definite programming (SDP), and cone programming (CP) are different types of convex optimization problems. In general, each LP problem could be considered as a special case of QP problem, which is also a subset of SOCP problem. Moreover, SDP problem is a superset of SOCP problem and a subset of CP problem. Hence, these problems' hierarchy could be demonstrated by Fig. 10. This figure illustrates a hierarchy of convex programming based on comprehensiveness.

In general, a non-convex problem can be converted into convex problems by considering relaxation. But the important thing is that simplification does not cause the loss of problem information and does not take us away from the definition of the original problem. A novel day-ahead optimal scheduling for SEH based on SOCP has been presented by Ref. [76]. The original problem has been formulated as a non-convex optimization problem, and then it has been converted to a convex one by applying relaxation. Moreover, the cutting planes technique has been carried out to improve the accuracy of the relaxation. Optimal energy management for operation EVs parking lot (EVs-PL) connected to combined heating and power (CHP) unit has been investigated by Ref. [77]. At first, the original problem is introduced as a nonlinear programming (NLP), which minimizes the total energy consumption cost considering flow constraints, CHP unit, and EVs model. Then, an equivalent LP model is extracted by using the conventional piecewise linearization method to reach the global optimal point.

3.1.2. Non-convex optimization

If one of the convex optimization problem conditions is not satisfied, the optimization problem is defined in the non-convex form. Due to the complexity of IES, most of the proposed models for the design, operation, and planning of SEH in the literature have been presented as non-convex and non-linear optimization. However, solving non-convex problems is more difficult than the convex optimization problem, and also, there is no guaranty for the global optimality of a non-convex problem. Meta-heuristic methods, which may provide a sufficiently suitable solution, are employed to solve a non-convex optimization problem. A multi-period optimization based on decomposed hybrid particle swarm optimization (PSO) and interior-point approach has been introduced by Ref. [78] to improve the operation of interconnected EHs. The optimal configuration planning and operation strategies for urban SEH have been presented by using a two-layered optimization method in

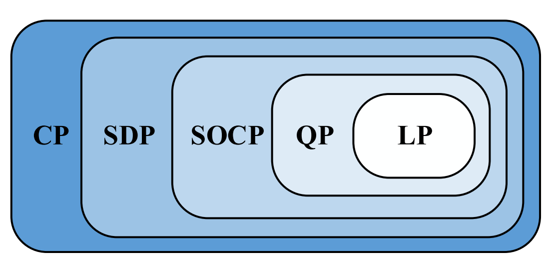

Fig. 10. Hierarchy of convex optimization problems based on comprehensiveness.

Ref. [79]. Considering valve-point effect and prohibited zones for power plants, a general non-convex and non-smooth model to reach the economic dispatch of EH has been developed by Ref. [80]. Then, a modified gravitational search algorithm (GSA) has been presented based on the time-varying acceleration coefficient, and its performance has been evaluated by implementing it on five benchmark functions as well.

3.2. Criteria & objectives

The current literature provides different criteria that can be adapted and combined regarding the specific application of a study. Overall, the objectives of SEH's energy management can be divided into three categories, including technical aspects, economic criteria, and environmental criteria, which are discussed in this section as follows:

3.2.1. Technical aspects

Energy analysis: Energy analysis demonstrates how energy is employed in different chemical or physical processes, including energy transfer or conversion. In the light of this analysis, the energy efficiency is extracted for each component of the system as a significant parameter for calculating the total energy efficiency of the system. Moreover, in order to reach intelligent management for improving the energy efficiency of an SEH, not only the utilization of high-efficiency equipment but also coordination of different parts of SEH are required [81].

Exergy analysis: Concerning the results of research on energy properties, it has been concluded that conventional energy analysis assumed from the first law of thermodynamics cannot be so impressive for analyzing the energy behavior of an SEH due to the quantity and quality attributes of energy [82]. Hence, a new concept, i.e., exergy analysis, based on the second law of thermodynamics has been given and developed to show the portion of energy that can potentially be transformed into some other kind of energy. A novel integrated optimization model has been proposed by Ref. [83] to optimize the SEH components capacity and the hourly off-design output by considering exergy loss reduction. A new multi-generation IES has also been presented by Ref. [84] to find the optimal configuration of HRES. The evaluation of the proposed system indicates that exergy and energy efficiencies are 20.16% and 5.46% more than the conventional system, respectively.

Voltage regulation: SEHs can create a suitable basis for improving the voltage of the upstream grid network by providing a bilateral energy exchange. Zhao et al. [85] presented a two-stage optimization problem to reach the optimal operation of IES considering techno-economic assessment and voltage regulation. Moreover, a novel model has been given by Ref. [86] to find the optimal dispatch of a multi-energy system considering the EH concept and data privacy preservation. In the proposed problem, the cost of energy bought from the upstream energy network, load shedding cost, energy storage degradation, and voltage regulation have been considered as objectives of the proposed problem.

Congestion management: SEHs can also prevent congestion in an upstream power network, by producing electricity through local sources. A coordinated electrical and thermal DRP has been given by Ref. [87] considering congestion management in the distribution power network. The proposed smart energy management scheduling reduced 10% and 14% the operation cost of the EHs and distribution grid, respectively. Mohamed et al. [88] proposed optimal scheduling of SEH with water, heat, and electricity demand to maximize its profit in a day-ahead electricity market and reduce dispatch cost for the power grid while taking into account the consequences of line congestions.

3.2.2. Economic issues

A novel generalized model for optimal management of SEH has been presented by Ref. [89]. System net cost, including energy buying cost (EnBC) from the natural gas system and district heating network, as well as energy selling income (EnSI) to a power system, has been considered as the objective function of the proposed problem. To minimize the EnBC for residential areas load, a novel optimization model has been introduced by Ref. [90] considering different EH structures. Moghaddam et al. [91] introduced a mixed-integer nonlinear programming (MINLP) optimization model to maximize the profit of SEH for building demands. Economic and environmental analyzes have also been performed by employing HOMER software in Ref. [92] on an SEH that uses a diesel and hydrogen backup system.

When the design or planning of an SEH with a long-term study perspective is desired, other economic indexes, such as initial investment cost (IIC), net present value (NPV), total operation cost (TOC), and internal rate of return (IRR), should be applied on the model. Zhu et al. [93] presented a novel optimization model to find the optimal design of a local SEH for a building application. The proposed problem has been given as an MINLP model and it has been solved by GAMS software. Considering main and auxiliary EHs for a distributed energy network containing electricity, gas, water, and cooling energy carriers, a cost-based planning model has been given by Ref. [94] to find the optimal energy generation dispatch.

3.2.3. Environmental issues

Jinga et al. [95] gave an MINLP model to reach the optimal design of an SEH to improve its environmental performance. Considering both environmental and economic aspects, scenario-based stochastic multi-objective optimization has been given by Ref. [96]. In the proposed model, the uncertainty of system demand, solar generation, and energy price has been considered and the Monte Carlo method with roulette wheel mechanism has been applied to generate different scenarios. Moreover, the correlation between the uncertain parameter of the system has been modeled by applying the rank correlation method. To reduce carbon emissions, a residential SEH energy model has been introduced in Ref. [97] by focusing on integration between thermal and electrical sections and considering water heater and heat pump. Optimal scheduling for the operation of an SEH has been proposed by Ref. [98] with the aim of minimizing purchase energy cost and emission tax cost considering EVs and ESSs.

3.2.4. Reliability aspects

Other indices which can play a key role in the operation of SEH belong to the reliability aspects. There are different indices, such as loss of energy expectation (LOEE), loss of load expectation (LOLE), loss of power supply probability (LPSP), and equivalent loss factor (ELF), to assess the level of system reliability. The optimal configuration of HRES has been studied by Ref. [99], considering reliability analysis. To obtain preventive maintenance scheduling under different load conditions, a two-stage stochastic optimization model has been introduced by Ref. [100], considering the random failure risk of each EH equipment. Moreover, Ghaffarpour et al. [101] developed a resilient perspective for SEH with the water utility. Energy management and water supply procedure have been studied in both system operation and planning. Reliability assessment of IES under various loads situations has been investigated in Ref. [102] by employing the loss of load expectation, the loss of load probability, and the expected energy not supplied indexes. Moreover, a generalized analytical approach has been given by Ref. [103] for the reliability assessment of SEH. Different criteria and objectives applied in the literature are listed in Table 4.

3.3. Optimization problem types for energy management of SEH

In general, three main categories can be considered for SEH energy management optimization. These categories include designing, operation, and planning. The problems regarding finding optimal sizing and configuration of SEHs can be considered in the designing category. Moreover, the short-term scheduling and long-term scheduling of SEHs are assumed in the operation and planning categories, respectively. It is worth noting that SEH's designing problem is also defined based on a long-term perspective. So, it has been considered as a part of planning

Table 4
Different criteria & objectives applied in the literature (*EnA*: Energy analysis; *ExA*: Exergy analysis; *VoR*: Voltage Regulation; *EnBC*: Energy Buying Cost; *EnSI*: Energy Selling Income; *InC*: Investment Cost; *O&MC*: Operation & Maintenance Cost; EnCr: Environmental Criteria; ReCr: Reliability Criteria).

Ref #	Technical Aspects			Economic Criteria				EnCr	ReCr
	EnA	ExA	VoR	EnBC	EnSI	InC	O&MC		
[82]		✓		✓		✓	✓	✓	
[83]		✓		✓				✓	
[104]		✓						✓	
[105]	✓	✓		✓	✓		✓	✓	
[85]			✓	✓				✓	
[90]				✓				✓	
[91]				✓	✓				
[93]				✓	✓	✓	✓	✓	
[95]				✓	✓		✓	✓	
[96]				✓				✓	
[99]				✓			✓		✓
[106]				✓	✓				✓
[100]				✓			✓		✓
[101]				✓			✓		✓
[107]				✓	✓				✓
[108]				✓	✓			✓	

problems in most research. Therefore, we also consider these two categories together in this paper.

3.3.1. SEH designing and planning

The optimal design of PV and solar thermal collector connected to a local IES has been presented by Ref. [109] to supply three building types, including hospital, office, and hotel, in seven different climate conditions. To reach the optimal sizing, the PSO algorithm has been carried out, and the average optimal performance value for each building obtained 28.95%, 22.69%, and 28.20%, respectively. Considering exergy analysis, Boyaghchi et al. [105] presented a new optimization model to obtain the best design of an SEH connected by HRES, including a concentrated PV thermal-geothermal energy system. A novel adaptive robust programming model for planning of SEH has been presented by Ref. [110] in a non-convex optimization framework and the multiple uncertainties of PV, electric loads, and also the effect of district heating/cooling network have been investigated in the proposed model. Moreover, an optimal planning model of SEH has been given by Ref. [111], considering different battery operation strategies. In Ref. [112], a novel solution methodology based on the variable-sized unimodal searching (VUS) approach was developed to get a global optimal point for SEH planning. The problem has been proposed as a bi-level optimization model and the uncertainty of load and price have been considered on the proposed model. Xiang et al. [113] also presented a new optimal planning model for an SEH considering enviro-economic assessment and price-based DRP.

3.3.2. SEH operation

A general model has been proposed by Ref. [114] to optimize the operation of an IES for the industrial production process based on the SEH concept. Cui et al. [115] investigated the impact of different types of modeling for demonstrating the internal equipment of a multi-energy grid considering the partial load ratio and constant efficiency model. Li et al. [116] presented a Lyapunov optimization-based energy management model for real-time operating of SEH by modeling energy storage and flexible electric loads as stochastic processes. An innovative methodology to design optimal incentives for paying to residential SEH has been given in Ref. [117] with the aim of improving their energy consumption. W. Hou et al. [118] developed a real-time rolling horizon chance-constrained optimization model for SEH operation.

To improve energy management in modern energy networks, DRP is used as a suitable tool for system operation. The optimal scheduling of an SEH is investigated by applying the time of use (ToU) pricing scheme for electrical energy in Ref. [89]. Moreover, An optimal dispatch model has been presented by Ref. [119] to operate a regional multi-energy system, in which the EH has been modeled as a prosumer. Based on simulation results, it has been demonstrated how prosumer modeling can assist in improving DRP and shave system peak load. An integrated DRP model has been developed in Ref. [120] by proposing a quantitative model for the energy-shifting curve of SEHs based on aggregated utility curves.

4. Uncertainty analysis

Uncertainty analysis has attracted a lot of interest in the contemporary study of decision-making processes in different fields of science. Traditionally, most optimization problems have been defined and solved in the context of deterministic form based on the predicted value of system parameters. The farther the estimated values are from the actual values, the farther the answer provided by the deterministic model can be from the actual answer. This wrong solution can increase operating costs and compromise system security. Therefore, uncertainty analysis in complex systems with high uncertainty, such as SES, can be so vital for the operators of these systems.

4.1. Uncertainty analysis from the energy sectors point of view

In the real world, each energy system faces many various random parameters. Generally, the uncertainty sources in the energy system can be divided into three main categories. The first category arises from the generation section. The generation of RESs is one of the main uncertain variables in the generation sector of an energy system. The second one belongs to the demand section. Demands are always considered as random variables in each energy system. IES faces demand uncertainty more than traditional energy systems due to the various existing demands of different energy carriers. The last category can be considered for energy prices determined by the energy market sector.

4.1.1. Generation sector

A novel operational scheduling approach, based on Mixed-Integer Linear Programming (MILP), has been investigated by Ref. [121] for SEH's energy management in the presence of the hydrocarbon natural gas system, aiming to mitigate the renewable generation uncertainties. Wang et al. [122] gave a novel scenario-based stochastic optimization to reach the optimal dispatching of an electricity-hydrogen-gas-heat IES. To deal with RES's uncertainty, a two-stage P2G technology has been considered in the proposed model as a technical solution to facilitate the integration between the power and gas network. Shahrabi et al. [123]

presented an optimal strategy determination approach for hybrid solar-wind systems. The proposed problem gives optimal planning and scheduling for an EH considering wind and PV uncertainty. However, the energy price uncertainty is neglected in the proposed problem. A scenario-based stochastic single-objective optimization has been given by Ref. [124], considering both renewable energy and energy price uncertainties. The scenario generation is done using the Monte Carlo method based on the historical data of random parameters, and then the k-means algorithm is employed to reduce the scenarios. Senemar et al. [125] proposed a dynamic structural sizing planning of residential SEH considering PV system uncertainty.

4.1.2. Demand sector

Electricity, gas, and heat have been considered as main energy carriers for the EH definition, and some other carriers, such as water, have been neglected in the literature. Nevertheless, The management of water consumption, besides other energy carriers, has been investigated by Refs. [126,127]. The proposed model in Ref. [127] has been given a stochastic enviro-economic multi-objective energy management to evaluate the role of energy storage on the EH operation. Moreover, Yan et al. [128] and Wang et al. [56] considered cooling load uncertainty for optimizing the energy management of an EH. Hydrogen is another energy carrier that is being cited as one of the most promising energy carriers in future energy systems due to its outstanding features in storage. Mansour et al. [129] introduced a hydrogen-based SEH, in which the hub operator employs integrated DRP for electricity, gas, heat, and hydrogen demand. Tri-objective optimal energy management for SEH has been investigated by Ref. [130] with the aim of DRP implementation. Integrated DRP for SEH with electric, heat, and cooling load has been presented by Ref. [131] considering operational risk and system economy using Markowitz mean-variance theory. The proposed problem is introduced as a stochastic multi-objective optimization problem and the lithium battery aging model is considered as problem constrained as well. Yuan et al. [132] studied the performance of P2G technologies with gas storage capability on increasing renewable generation penetration in SEH. They have also proposed stochastic scheduling of SEH considering integrated DRP for electric, heat, and gas load.

4.1.3. Energy market sector

The synergy created by SEHs through the integration of different energy networks can assist to reduce the uncertainty effects and stable the market energy price. A cooperative trading framework for IES has been given by Ref. [133] as an MINLP model using cooperative game theory. In the proposed model, uncertainties in energy price and consumer demand, as well as cooperative trading framework risk, were investigated. In Ref. [134], a bi-level stochastic programming problem model has been defined for operating EHs. Uncertainty was given in electricity demands, pool prices, and the electricity prices offered by the rival managers. Besides, the proposed bi-level nonlinear stochastic program was transformed into an equivalent linear single-level one, using the KKT optimality conditions and the strong duality condition. A multi-leader and multi-follower game model has been represented by Ref. [135] to investigate the interaction between energy retailers and consumers in a multicarrier energy system. Najafi et al. [136] gave a robust optimal operation for SEH considering market price uncertainty. Moreover, an innovated bi-level mathematical model has been proposed by Ref. [137] to analyze integrated energy system management from the viewpoint of a deregulated market.

4.2. Uncertainty analysis methods

The traditional and deterministic approaches to energy system optimization cannot satisfy uncertainties associated with these systems in a realistic manner. Therefore, diverse uncertainty modeling techniques to optimize SEH with random variables have been employed by researchers so far. In the rest of this part, these techniques have been comprehensively described by giving their advantages and disadvantages, and literature has been reviewed based on them.

4.2.1. Probabilistic procedure

Probabilistic procedures are one of the most widely used approaches for modeling the uncertainty of IES. These procedures are carried out by using the probability distributions of the system's random variables. There are three main methods consist of Monte Carlo simulation (MCS), point estimate method (PEM), and scenario-based approach (SBA).

Monte Carlo simulation: Considering the repeated random sampling for random variables, the MCS approach estimates a range of possible system outcomes which may happen. In this method, a sample for each random variable would be generated based on its probability density function (PDF). Then, the output variable y_j should be calculated by (4), in which $f_j(.)$ represents the system model and x_i^k is random parameter i for sample k. This process should be repeated until reaching stopping criteria. Then, the outcomes obtained in different iterations for system outputs are analyzed by applying a histogram graph and statistical criteria such as mean and variance presented by (5) and (6) [138].

$$y_j^{(k)} = f_j\left(x_1^k, x_2^k, \ldots, x_i^k, \ldots, x_n^k\right); \quad \forall j \in \Omega_j \tag{4}$$

$$E\left(y_j^{(n)}\right) = \frac{1}{n}\sum_{k=1}^{n} y_j^{(k)} \tag{5}$$

$$Var\left(y_j^{(n)}\right) = \frac{1}{n}\sum_{k=1}^{n}\left(y_j^{(k)}\right)^2 - \left(E\left(y_j^{(n)}\right)\right)^2 \tag{6}$$

Many repetitions should be done to reach a suitable answer. The relative error of this method is calculated by (7), in which N_{MCS} and N_{RV} are the total number of MCS samples and the total number of system random variables, respectively [138].

$$\varepsilon_{MCS} = \frac{1}{(N_{MCS}-1).N_{RV}}\sum_{n=2}^{N_{MCS}}\sum_{j=1}^{N_{RV}}\left|\frac{E\left(y_j^{(n-1)}\right) - E\left(y_j^{(n)}\right)}{E\left(y_j^{(n)}\right)}\right| \times 100[\%] \tag{7}$$

Point estimate method: This method works based on the concept of moments of the random variable. Unlike the MCS, this approach is a computationally efficient method with a predetermined lower number of samples. Considering k concentration points $(p_{i,k})$ and a specific weight $(\omega_{i,k})$ for each uncertain parameter, the information about the uncertainty of system outputs can be extracted. This information only includes mean and standard deviation, and the PDF shape of system outputs cannot be provided by this method. For each concentration point, one evaluation is carried out, in which other random parameters should be considered by their mean value. Here, similar to MCS, the deterministic manner is used to evaluate system outcomes for each evaluation. The two-point estimate method is presented by considering $k = 2$. The concentration points associated with the random parameters are calculated as follows [139]:

$$p_{i,k} = \mu_i + \xi_{i,k}\sigma_i;\ k = 1,2\ \forall i \in \Omega_i \tag{8}$$

In which, μ_i and σ_i are the mean and standard deviation of the random parameter x_i, respectively. Moreover, $\xi_{i,k}$ is a standard location associated with x_i, which can be calculated by (9) through the PDF skewness $\lambda_{i,3}$ of random parameter x_i. The specific weight for $p_{i,k}$ can be calculated by (10) [139].

$$\xi_{i,k} = \frac{\lambda_{i,3}}{2} - (-1)^k\sqrt{m + \left(\frac{\lambda_{i,3}}{2}\right)^2}; \quad k = 1,2 \quad \forall i \in \Omega_i \tag{9}$$

$$\omega_{i,k} = (-1)^k\frac{1}{m}\,\frac{\xi_{i,2}}{\xi_{i,1} - \xi_{i,2}};\ k = 1,2\ \forall i \in \Omega_i \tag{10}$$

After determining $p_{i,k}$ and $\omega_{i,k}$, evaluation section is done for each random variable set as follows:

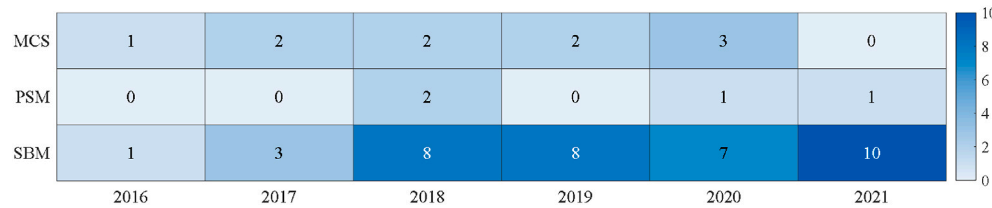

Fig. 11. The number of literature which has applied the probabilistic approach from 2016 to 2021.

$$y_j^{(k)} = f_j(\mu_1, \mu_2, \ldots, p_{i,k}, \ldots, \mu_n); \quad k = 1, 2\ \forall j \in \Omega_j \tag{11}$$

Finally, the mean and variance of system outputs can be computed as follows:

$$E(y_j) = \sum_k \sum_i \omega_{i,k} . y_j^{(k)} \tag{12}$$

$$Var(y_j) = \sum_k \sum_i \omega_{i,k} . \left(y_j^{(k)}\right)^2 + \left(E(y_j)\right)^2 \tag{13}$$

Scenario-based approach: This method is so popular in the energy management of SEH. In this approach, a limited set of scenarios with more probability are selected for uncertainty analysis. If this set is not available, it could be created by using the PDF of each random variable. To this end, many scenarios would be generated in the first step, and then the number of scenarios would be decreased by using the scenario reduction techniques. The expected value of the system outcome is computed by (14). In which, π_s is the probability of s_{th} scenario of selected set X_s.

$$y = \sum_{s \epsilon \Omega_s} \pi_s \times f(X_s) \tag{14}$$

$$\sum_{s \epsilon \Omega_s} \pi_s = 1 \tag{15}$$

The number of works in the literature, which have applied the probabilistic approach from 2016 to 2021, is pictured in Fig. 11. Moreover, detailed information about these works is presented in Table 5.

4.2.2. Possibilistic approach

The possibility approach is considered for the quantification of uncertainties with imprecise probabilities. It is derived from fuzzy sets theory, and it has a simpler implementation than the probabilistic approach. In this approach, for each random variable, a possibility distribution is used to model the epistemic uncertainty. The possibility distribution determines that how much each element x of the universe of discourse U belongs to X [171]. Depending on the application, various membership functions may be used to formulate the degree of membership of a particular uncertainty parameter [172]. In this context, Mohammadi et al. [173] proposed a fuzzy-based scheduling model to deal with multiple uncertainties in the optimal operation of the wind-integrated IES. The EH concept is carried out to model the proposed IES, and different reliability criteria, including the loss factor and the loss of energy expected, are attended to guarantee a reliable system operation.

4.2.3. Robust optimization (RO)

RO is a novel method for SEH planning and operation in the face of uncertainty. Unlike SP, no unique probability distributions for the random variables are needed. This can be seen as a benefit since probability distributions are often uncertain or difficult to obtain. When new uncertainty occurs, there isn't always enough prior data to model probability distributions. Making a mistake when calculating probability distributions can have disastrous consequences. In such cases, RO is the most preferred method to model system uncertainty. However, RO has the disadvantage of being too conservative in its results. In this method, the future uncertainty of the random parameter is presented as a lower and upper bound interval and the problem is often given as a two-stage min-max optimization problem with outer-inner structure as follows [174]:

$$Min \quad F(X)$$

Subject to:

$$\begin{aligned} &H_j(X) = \max_{c \in C} c \\ &C_1 \leq C \leq C_2 \end{aligned} \tag{16}$$

In which, X is the decision variable vector and c is the random variables of the RO model. C_1 and C_2 are also lower and upper bound of uncertainty, respectively. In this form, the two-stage min-max optimization problem could be transferred to a one-stage optimization problem through the dual approach by converting the inner maximization problem to the dual problem [174]. To describe the multi-energy carrier system uncertainties, an adaptive robust integrated bidding strategy has been presented in Ref. [175] for the EH participating in day-ahead energy markets. The proposed model has been designed as a min-max-min problem in the sense of adaptive RO, and it was solved using a new approach that included a post-event evaluation, primal cutting planes, duality theory, as well as bi-level decomposition. Distributionally RO (DRO) has been recently established as an arbitrator method to diminish the gap between stochastic programming's precision and traditional RO by unifying accessible distribution data, such as expected value, variance, and covariance, into the ambiguity set of random parameters. Thus, the result is robust to all possible states in the ambiguity set of problems based on probability distributions of the random parameter. In this context, Zhou et al. [176] gave a co-optimization of energy and reserve scheduling for IES in the presence of RES as well as ambient temperature uncertainty by applying the DRO approach. This study showed how employing more statistical data can be affected on the optimal robust solution. The robust procedures applied in the literature for modeling different uncertainties are listed in Table 6.

4.2.4. Information gap decision theory (IGDT)

IGDT is proposed as a clear, non-probabilistic, and exact risk-hedging decision-making portfolio to reliably preserve system robust output in the face of associated extreme uncertainty margins while the necessary data is missing or not informative. The ability to accurately model the difference between what is known and what is supposed to be known is at the heart of the IGDT uncertainty handling paradigm [192]. The major difference between IGDT and RO is their inputs, which distinguishes them significantly in various applications. The desired value of the cost function (the value that should be ensured) is the input of the IGDT-based system, while the boundaries of the confidence interval (the interval within which the actual pool price intends to fall) are the input of the RO. In this regard, RO belongs to the performance-enhancing category, while IGDT relates to the performance satisfying category [193]. Generally, in RO, the guaranteed profit can be determined by the user by determining the boundaries of the uncertain parameters; however, in the IGDT-based approach, the user should set the guaranteed profit (the desired profit) and the maximum length of the confidence interval is computed. Therefore, IGDT can be more understandable and

Table 5
The probabilistic procedure applied in the literature.

Ref #	Meth.	Random variables					Problem under consideration
		Wind	PV	Load	EV	Price	
[140]	MCS		✓	✓	✓		Optimal operation of a residential EH
[141]	MCS	✓	✓	✓		✓	Optimal operation considering decentralized heat pumps
[142]	MCS		✓	✓			Optimal operation of a residential EH considering DRP
[143]	MCS	✓		✓			Multi-objective operation problem by techno-enviro-economic assessment through peak load management
[144]	MCS	✓	✓				Strategic behavior of IES players in energy markets by proposing bi-level optimization model
[145]	MCS	✓		✓		✓	Optimal planning by techno-enviro-economic assessment considering DR
[146]	PEM			✓			Probabilistic energy flow for IES considering EH concept
[147]	PEM			✓		✓	MINLP model for optimal operation considering IDR
[148]	PEM	✓	✓		✓		Energy management of an island by proposing a smart water-EH model
[149]	SBA	✓	✓	✓		✓	Optimal energy management by considering different energy markets
[150]	SBA	✓	✓			✓	Optimal operation considering ice ESS
[151]	SBA		✓	✓			Optimal planning considering DRP
[152]	SBA	✓				✓	Stochastic day-ahead scheduling in the presence of gas ESS
[153]	SBA	✓		✓		✓	Risk-based stochastic scheduling considering heat market and thermal DR
[154]	SBA	✓	✓	✓			Probabilistic energy flow for IES considering EH concept
[155]	SBA	✓		✓			Risk-based stochastic scheduling considering DR and compressed air ESS
[156]	SBA	✓	✓	✓	✓	✓	Optimal scheduling of IES considering multiple downward EHs
[157]	SBA	✓	✓	✓	✓	✓	Coordinated energy management of IES in the presence of EVs
[158]	SBA	✓	✓				Stochastic operation considering different configurations for EHs and N-1 contingency model
[159]	SBA	✓	✓	✓			A two-stage stochastic optimization model considering power system and gas network security constraints and DR for heat and electric energy carrier
[160]	SBA			✓			Proposing a MILP model to calculate the market equilibrium for IES with SEH
[161]	SBA	✓	✓				Optimal operation of neighboring multi-carrier smart buildings by techno-enviro-economic assessment considering DR program
[162]	SBA	✓		✓			MILP model for the cost and risk-constrained scheduling of SEH
[163]	SBA		✓	✓		✓	Optimal designing of EH by techno-enviro-economic assessment considering DR
[164]	SBA			✓		✓	Stochastic scheduling of SEH operation using CVaR
[165]	SBA	✓	✓	✓		✓	Optimal scheduling of IES considering multiple downward EHs
[166]	SBA	✓	✓	✓	✓	✓	Optimal operation using the risk-averse approach
[167]	SBA	✓	✓	✓		✓	Optimal operation by techno-enviro-economic assessment considering IDR
[168]	SBA		✓	✓			Optimal operation using the branch-and-bound approach
[169]	SBA	✓		✓			Optimal operation considering DR using a Benders decomposition approach
[170]	SBA	✓				✓	Optimal bidding strategy for SEH in the competitive energy market

user-friendly than RO, since from a financial viewpoint, working with a consumer's benefit as input is more perceptible than the financial boundary of price uncertainty. Furthermore, IGDT can be expanded to opportunistic optimization, which is infeasible with RO optimization.

4.2.5. *Interval analysis*

Interval analysis is one of the useful alternatives for coping with uncertainties. In this approach, the lower and upper bounds are the only data accessible for random parameters. Wang et al. [194] applied interval analysis to interval mathematical programming. Without the need for precise probability distribution details, interval mathematics-based optimization can tackle uncertainties through interval numbers. It improves output bounds taking into account input intervals with a reasonable computational time [195]. It has already been used to calculate power flow boundary estimation with parameter uncertainties. A nonlinear optimization based on interval analysis can be mathematically expressed by (17) and (18); in which, U is the uncertain vector represented by interval numbers, as well as, b_i^I and U^I are the interval of the constraints and uncertain vector, respectively [195].

$$\min_X f(X, U) \tag{17}$$

$$s.t.\ g_i(X, U) \geq b_i^I = \left[b_i^-, b_i^+\right],\ U \in U^I = [U^-, U^+] \tag{18}$$

4.2.6. *Hybrid approach*

A hybrid robust scenario-based model (HRSM) has been given by Ref. [196] for achieving optimal scheduling of SEH to participate in a multi-energy market. The proposed problem presents both environmental and economical solutions by considering EVs-PL, P2G technology, thermal and electrical energy storage, and DR programing. The obtained results have shown the emission and total energy costs are decreased by up to 2.36% and 3.51%, respectively. Moreover, Nosratabadi et al. [197] investigated the effect of CHP modeling on the planning of SEH. The convexity principle with triple operational zones for the CHP nonlinear model was presented in the proposed EH model. Finally, the SEH planning model has been given as a hybrid robust/stochastic optimization problem in the frame of HRSM. Jamalzadeh et al. [198] also presented a new model for the operation of SEH considering integrated DRP and using a hybrid stochastic/interval optimization approach.

4.2.7. *Comparison of different uncertainty modeling methods*

As discussed in this section, there are different uncertainty modeling methodologies. Nevertheless, an appropriate technique should be chosen based on the type of problem under consideration, the type of random variables, and information as well as historical data availability. In this regard, the recommendations in the literature identify indicators such as accuracy, execution time, and complexity of the method to select the best methodology for uncertainty representation. Thus, each method could be evaluated through these indicators considering its attributes and limits. For instance, the MCS needs a significant number of scenarios to reach the accurate uncertainties representation and this issue leads to computational intractability in long-term planning problems of SEH. On the other hand, PEM also suffers from the computing burden for the problem with high random variables, but it is the easiest method for correlation modeling. In the meantime, although the SBA is an acceptable option for the high-dimensional problem, its accuracy is highly dependent on the availability of precise historical data of random variables as well as the type of scenario generation. A summary of the characteristics of the uncertainty techniques, as well as their merits and

Table 6
The robust procedure applied in the literature.

Ref #	Meth.	Random Variables					Problem under consideration
		Wind	PV	Load	EV	Price	
[174]	RO		✓	✓		✓	Optimal operation of multi-energy microgrids
[177]	RO		✓	✓			Optimal operation considering by enviro-economic assessment
[178]	RO		✓	✓			Stochastic energy scheduling of EH considering different time resolutions
[179]	RO	✓	✓	✓			Optimal operation considering P2G technology and DRPs
[180]	RO			✓		✓	Optimal operation considering flexible ramping products
[181]	RO				✓	✓	Optimal operation of community EH
[182]	RO	✓	✓			✓	Optimal scheduling for coordinated operation of IES considering DRP
[183]	RO	✓		✓			Optimal operation considering by techno-enviro-economic assessment
[184]	RO	✓	✓	✓			Optimal operation considering integrated demand response
[185]	RO	✓	✓	✓	✓		Energy management of SEH considering EVs, DRP, and compressed air energy storage system
[186]	RO	✓		✓			Capacity planning of IES considering DRP and user's thermal comfort
[187]	RO		✓	✓			Optimal operation of IES considering by techno-enviro-economic assessment
[188]	RO		✓				Optimal operation and planning of EH considering precise energy storage economic model
[189]	DRO					✓	Optimal operation of IES
[190]	DRO		✓				Two-stage DRO for SEH operation
[176]	DRO	✓	✓				Energy and reserve management for IES
[191]	DRO	✓	✓				Unit commitment in IES considering by multiple EHs

demerits, is listed in Table 7. As can be seen, there is no single best way to deal with SEH uncertainty, and each can be useful for some specific cases.

5. Discussion for future trends and limits

As discussed, the necessity of energy system integration based on the principles dictated by the SEH concept has been highlighted by many researchers. A lot of studies have been conducted on the modeling of SEHs to increase the energy efficiency of existing IES based on the SES concept in recent years. However, the literature for the modeling of SEH is still in its early stage and quite immature. Many problems and challenges still exist in this context. For a better understanding of how different elements for SEH modeling are taken care of, a Sankey diagram of elements participation from the perspective of the optimization problem is depicted in Fig. 12. Moreover, a word cloud chart of important keywords employed in literature for SEH modeling is illustrated in Fig. 13.

These two figures give us further information and a clearer picture of the challenges in the modeling problems of SEHs. Considering this information, the potential future research and trends in this framework can be summarized as follows:

- **Correlation Analysis:** Considering the quick development of the SEH studies, more attention to uncertainty analysis in the modeling of SEH would happen in the future. There are many uncertain variables in SEHs, where the correlation between these random variables can affect the system's operation. Temporal and spatial correlations of wind-PV, wind-load, and PV-load, as well as wind-PVload, can be considered as correlated uncertain parameters of SEHs. Although the uncertainty model of each of these parameters has been taken into account separately, correlation modeling of them is still novel.
- **Convex Optimization:** More applications of convex optimization in the design, operation, and planning of SEHs are expected to be identified in the future. Recognizing or proposing a problem in the frame of a convex optimization model has major advantages. It offers a reliable solution with high efficiency and fast response, which can be very effective for long-term studies. Not only does non-convex optimization not always provides a reliable solution, but it may not converge to any feasible solutions in problems with high dimensions and complexity. As seen in Fig. 12, the operation problem for a short-term schedule is more addressed than designing and planning problems with a long-term schedule. Therefore, the convex model can be so convenient for designing and long-term planning of SEHs.

Table 7
A summary of the characteristics of the uncertainty techniques, and their merits and demerits.

Techniques	Analysis principle	Advantages	Shortcomings
MCS	Simulation-based approach	High accuracy by simulation of real state; the correlation between the random variables can be modeled	Time-consuming; requires exact information about PDF of random variables
PEM	Analytical approach through PDF approximation	Fast; good accuracy; the correlation between the random variables can be modeled	Does not present output variable PDF; execution time depends on the number of random variables; requires exact information about PDF of random variables
SBA	Scenario-based approach	Fast; good accuracy; the correlation between the random variables can be modeled.	Does not present output variable PDF; execution time depends on the number of scenarios
Possibilistic	Applying fuzzy membership function	Useful when the historical data is not perfect; it can extract numerical values from the defective information	Time-consuming; the correlation between the random variables cannot be considered
RO	Uncertainty representation by using uncertainty sets	Useful when there is no information about the PDF of random variables and just uncertainty set exists	Correlation between the random variables cannot be considered; difficult to use in nonlinear problems
IGDT	Uncertainty representation by using forecasted values	Useful for overcoming the SEH uncertainty with severe random variables	High complexity
Interval	Uncertainty representation by using interval bounds	Useful when just an interval bound of the random variable exists	Correlation between the random variables cannot be considered; Difficult to use in nonlinear problems
Hybrid	Applying both probabilistic and possibilistic approach	Can model the real-world conditions when we have not perfect historical data for some of the random variables	Time-consuming; High complexity

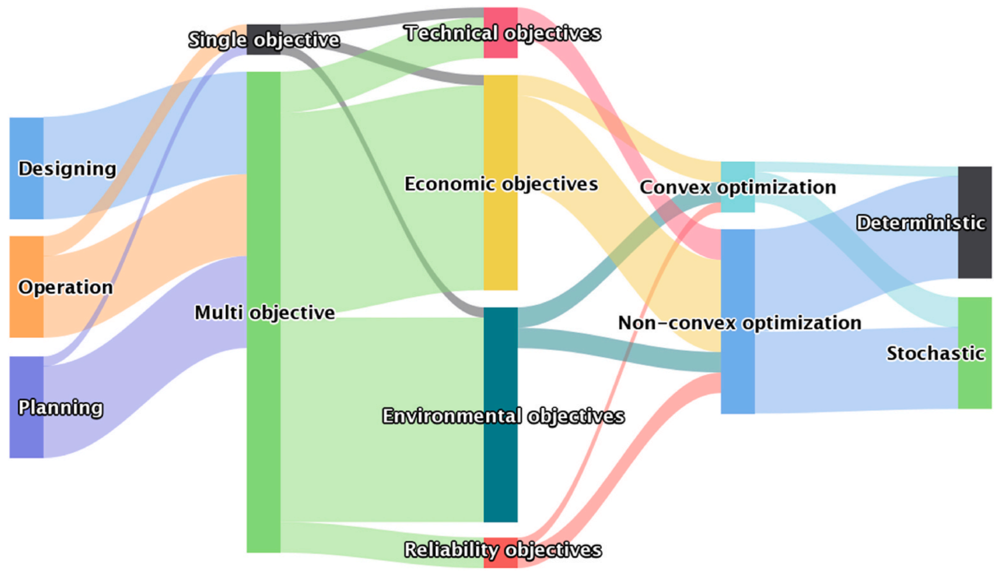

Fig. 12. The Sankey diagram of SES modeling structure based on the SEH framework in literature from optimization problem elements point of view.

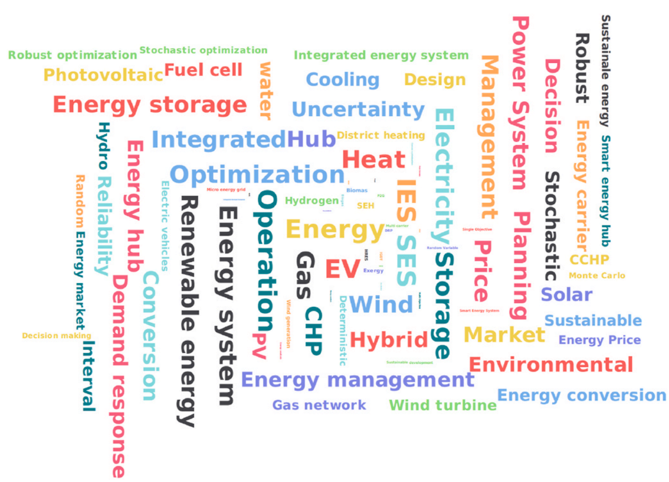

Fig. 13. Wordcloud chart of important keywords employed in literature for modeling SES.

Integrated Demand Response: Integrated demand response can be one of the important advantages of SEHs. Compared to traditional DRP, which is applied to each energy system separately, integrated demand response gives more opportunities to cost reduction and energy saving [16]. In this context, not only the load shifting is carried out on the temporal dimension, but it can also be examined in terms of energy dimension, which means that energy demands can be converted into other forms considering the energy converters equipment located in the SEHs. Although this has been recently considered by researchers, more studies are expected to be done on it in the future.

Comprehensive Energy Market: In contrast to regulated markets, energy trade monopolies and the formation of unified ownership of the energy network are prevented in deregulated markets. The energy market is often referred to as the electricity market but can also be considered for other energy carriers. Considering a comprehensive energy market consisting of different energy sectors in the context of an IES can create new and premier opportunities to achieve sustainable energy goals. Although many studies have been conducted to develop the electricity market and overcome the challenges in this market, considering the role of SEH in a comprehensive energy market is still missing. Considering the correlation of different energy prices with each other and their effects on the SEH operation and planning, as well as the role of the SEH as a prosumer in the energy market, can be some of the interesting trends for future work.

Hydrogen: Hydrogen is a clean and abundant natural source, which is considered an emerging energy carrier. It can be used as a renewable fuel for future energy systems and plays a key role in energy management. As can be seen from Fig. 13, this energy carrier has been less studied in the literature than other energy carriers, such as electricity, gas, heat, etc. The high cost of hydrogen production from renewable sources has remained the most difficult aspect of supplying this energy carrier. However, as mentioned, it is considered one of the most important energy sources in future energy networks, especially in the transportation sector. There is a massive amount of funding, especially in Europe, coming on the relevant research topics of hydrogen, i.e., Power-to-X technologies, including hydrogen generation, hydrogen storage, hydrogen processing for sub-products and fuels, etc. Therefore, further studies on the integration of this energy carrier in the IES must be and will be accomplished very soon.

Data-driven: SEH Modeling and anticipating system uncertainties would benefit from data-driven science, which is an interdisciplinary field of scientific approaches for extracting knowledge from data. Therefore, data-driven-based methods and machine learning applications would be considered as other floors for future research.

6. Conclusion

In this paper, we have examined the SEH and SES concepts and the various challenges in the modeling of SEH have been reviewed. The systematic principle has been taken to find the relevant literature for this review and then a thorough technical review was accomplished on the selected literature. Moreover, the current research trends on the application of the SEH concept for modeling IES in the literature have been investigated by keyword and citation analysis through VOSviewer software. A comprehensive definition for SEH has been then rendered and the different configurations presented by researchers in the literature were reviewed. Moreover, the optimization challenges of SEH modeling have been discussed in detail and the important findings of recent literature on the modeling of SEH from design, operation, and planning points of view have been summarized. Different uncertainty methods have been described by giving their merits and demerits and aspects of uncertainty modeling based on existing methods were critiqued. It was found that modeling of uncertainty based on RO and scenario-based stochastic optimization are the most popular ones for SEH modeling in the most recent research pieces of the literature. The robust approach would give the more suitable solution for a risk-averse decision-maker due to worst-case scenario consideration, while a probabilistic approach could present the more suitable solution for a risk-neutral decision-maker, considering all scenarios with equal probabilities. The data-driven based analysis has been performed on the collected literature and the results showed some gaps in recent studies. Based on this assessment, some recommendations for future research have been presented, which can provide beneficial visions for the research community by facilitating the path to reach more realistic SES modeling, considering future energy industry trends.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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