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A review of neighborhood level multi-carrier energy hubs—uncertainty and problem-solving process

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ABSTRACT

The energy hub (EH) is a promising concept that can accurately evaluate the performance of multi-carrier integrated energy systems (IESs), ranging from a building to a district, city, region, country, or even an international level. Multi-carrier EH-based IESs available in the literature have reached a desirable level of maturity for broad scales. However, there is confusion in the literature that misleads readers regarding multi-carrier EH-based IESs located on limited scales (e.g., buildings or neighborhood level). Furthermore, multi-carrier EH-based IESs studies that involve complexities such as discrete, continuous, or mixed decision-making variables, multiple conflicting objective functions, non-linearity, non-convexity, and discontinuity are affected by different techno-economic, environmental, and social parameters that are uncertain. Ignoring such uncertain input parameters (UIPs) in these studies leads to less adaptable results to realistic conditions. However, their integration is a challenging process intensifying these complexities during studies' modeling, optimization, and decision-making processes. Therefore, this review paper aims to fill these gaps by identifying, classifying, assessing, and prioritizing different UIPs, their analyzing techniques, and solution approaches, solvers, and software for addressing relevant optimization problems to achieve a deeper understanding of current challenges and potential future research, trend, and capacities in multi-carrier EH-based IESs studies.

1. Introduction

1.1. Background and motivation

Global energy crises (e.g., the OPEC oil embargo of 1973); policies related to climate change (e.g., Paris Agreement and Kyoto Protocol); gas dignity upgrade; nuclear generation dilemma; expanding the use of renewable energy resources (RERs); and technological progress of co- and tri-generation units acted as a trigger for a considerable number of countries to integrate their independent infrastructures of energy carriers and construct multi-carrier energy ones with interoperability, multi-carrier integrated energy systems (IESs) [1]. From technical, economic, and environmental (TE&E) as well as security perspectives, multi-carrier IESs can be more efficient than independent energy infrastructures, and this is now well-proven and recognized by a wealth of research publications [1–3]. However, the existence of various energy carriers and the integration of their interactions and interdependencies increase the complexity of these systems from different aspects. Therefore, more powerful tools are needed to model and analyze multi-carrier IESs. One of the most efficient concepts for analyzing multi-carrier IESs is the multi-carrier energy hub (EH). This concept was introduced in a project called "a vision of future energy networks (VoFEN)" as an efficient tool to facilitate the move towards non-hierarchical innovative multi-carrier IESs systems to benefit from the synergistic of different energy carriers [4]. The multi-carrier EH is determined in a system where different carriers can be converted, conditioned, stored, and distributed to satisfy multi-carrier energy demands [4,5].

Regarding spatial scales, the multi-carrier EH can be applied from a building to a district, city, province, country, or even at an international level. However, its implementation depends on various factors, the most important of which are the resources and energy carriers available, the desired level of complexity, and others [3]. The multi-carrier EH concept

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was used in many research projects to scrutinize multi-carrier IESs. As a result, about 4663 and 4963 articles are listed in the Scopus and Web of Science platforms for the “energy hub” keyword, respectively. This number of research activities demonstrates this concept’s importance, popularity, and growing trend in recent years. With this growing importance, it becomes necessary to scrutinize the principal features available in the literature that make the multi-carrier EH the revolutionary tool it is. Therefore, several review papers have been done over the last decade to classify these research publications systematically. Table A1 lists some of the top ones [1,3,5–17].

A retrospective view of review papers presented in Table A1 illustrates that the classification of multi-carrier EH-based IESs in them can still be used, although some modifications may be necessary to adjust them for new criteria. Nonetheless, when there is a need to focus on a unique and in-depth audit (e.g., uncertainty, problem-solving process) of a specific type of multi-carrier EH-based IESs (e.g., rural, local, urban, or industrial multi-carrier EH-based IESs), the effectiveness of these review articles is impaired and confuse researchers. Therefore, as technical publications in the field of multi-carrier EH-based IESs expand, finding and filling the existing gaps in the literature by providing an accurate classification for each class of these systems can serve as a precious resource for researchers and engineers.

1.2. Contribution

This paper develops and presents a taxonomy of research publications that have modeled buildings (*e.g.*, industrial, residential, commercial, office, or public buildings) as multi-carrier IESs using the EH concept, so-called micro multi-carrier EH-based IESs (μMEHs). The main contribution of the article is to scrutinize μMEHs from two perspectives, including uncertainty and problem-solving process, to provide a holistic understanding and classification of them by answering the following questions.

- What are the uncertainties and their analyzing techniques in μMEHs’ studies?
- What optimization models and solution methods are considered in μMEHs’ studies?
- What attractive paths can be envisioned for μMEHs’ studies from the perspective of uncertainty and problem-solving process?

1.3. Why μMEHs?

Approximately 60% of energy consumption can be attributed to residential buildings, while the remaining portion is accounted for by commercial buildings [18]. Traditionally, buildings were only consumers, passive end-users connected to the energy supply infrastructures of different carriers (e.g., electricity, district heating, green gas, district cooling, and district hydrogen networks). New paradigm shifts, however, are occurring due to unbundling and deregulation of power systems, TE&E advances in small-scale RERs, emerging new multi-carrier energy conversion and storage technologies, global environmental policies, and others.

These modifications will shake traditional notions about multi-carrier energy supply infrastructures and IESs. Buildings are the central core of these new paradigms. Their role has transited from the consumer to the prosumer, an active one that can consume, produce, store, and supply different energy carriers [19,20]. This way, active buildings will improve the balance of multi-carrier infrastructures via multi-carrier demand side management programs (DSMPs), increase the efficiency of future local energy markets of different carriers, reduce greenhouse gas emissions by increasing the uptake of small-scale RERs, create new business opportunities, and others [19,20]. Furthermore, according to International Energy Agency, multi-carrier DSMPs should be the top priority of research activities in sustainable energy systems [21]. Overall, providing an intelligent classification of μMEHs can help researchers to pave new and innovative paths toward adapting buildings with multi-carrier energy infrastructures to embrace their countless benefits.

1.4. Why uncertainty and problem-solving process?

With the integration of interactions and interdependencies between different energy carriers, increasing development of small-scale RERs, electric vehicles (EVs) connection, and updating local multi-carrier energy markets rules, and others, new uncertainties are introduced to studies related to multi-carrier IESs, especially μMEHs, and the existing ones have been escalated [22]. Regarding uncertainty, technical studies under the μMEHs concept can be categorized into two central policies: deterministic and non-deterministic [23]. In the deterministic policy, the μMEH is modeled for the most critical condition (maximum value) of all parameters (i.e., multi-carrier energy prices and demands, available budget, and the production capacity of RERs), irrespective of their probability of occurrence. Implementing studies related to μMEHs under the deterministic policy has the benefit of simplicity; however, it cannot present an actual (or close to actual) image of behavior related to different parameters in real-world conditions and consequently leads to unrealistic and impractical results (less adaptable results to realistic conditions). Therefore, the rational decision to eliminate this significant shortfall inherent in deterministic policy is to investigate these studies under the non-deterministic policy [24]. In this policy, the μMEH is modeled for all possible cases that may occur in the future for all parameters with stochastic nature, considering their occurrence’s probability. This policy is much more flexible than the deterministic and can reflect more realistic results in the μMEHs’ studies. However, the non-deterministic policy is frequently surrounded by an aura of esoterism and ignored by planners and decision-makers in different fields of science that prefer to find a unique (certain) outcome. As a result, some may be tempted to give up and accept that the non-deterministic policy is not amenable to evaluating models quantitatively or qualitatively.

Nevertheless, the emergence of new theories, the improvement of the existing ones, the development of powerful computational tools, and others prove the opposite opinion and facilitate the use of this policy as a must to make studies more realistic. Furthermore, it is widely recognized that most of μMEH’s studies are formulated in the form of different types of optimization problems. These problems involve complexities such as discrete, continuous, or mixed decision-making variables, multiple conflicting objective functions, non-linearity, non-convexity, discontinuity, and others. Moreover, uncertainties integration is extremely tough, intensifying these complexities during the modeling, optimization, and decision-making processes in the μMEHs’ studies. Under this circumstance, identifying and classifying different techniques and the problem-solving process (solution approaches, solvers, and software) for analyzing these uncertainties and solving the relevant optimization problems, respectively, help new research to find and fill the current challenges by relying on efficient ones.

1.5. Paper outline

The remainder of this article is divided into five sections. In section two, selected articles are classified based on the analysis methods. Besides, section three investigates μMEHs’ studies regarding uncertainty concepts, including uncertainty definition, uncertainty matrix, and widely used sensitivity analysis and uncertainty analysis techniques to examine the effects of uncertain parameters. Moreover, section four categorizes the μMEHs’ studies regarding the problem-solving process. Next, section five presents and discusses the limits and prospects of μMEHs’ studies in uncertainty and problem-solving process. Finally, section six summarises the identified research gaps, potential research directions, and future works for μMEHs’ studies.

2. Publication analysis

A filtering step is applied using the keywords "energy hub" plus "building", "energy hub" plus "neighborhood", "residential energy hub", "industrial energy hub", and "commercial energy hub" on the available articles in the Scopus and Web of Science platforms that investigate the multi-carrier EH-based IESs to build a database of relevant publications for this review paper. Then, an additional filtering process is performed to ignore duplicate papers on two platforms, descriptive papers, conference papers, technical letters, book chapters, and books. Finally, an exhaustive analysis (e.g., the title-keyword-abstract investigation, full-text review, forward and backward search) is used to create raw materials for the database. The output of this three-step filtering process results in about 100 papers, Refs. [25–123], which are reasonably consistent with the objective of this paper. A classification of these articles in terms of analysis methods of μMEH's studies is presented in Table A2.

3. μMEHs' studies based on the uncertainty concepts

3.1. Uncertainty definition

Uncertainty is not simply the absence of knowledge. Instead, it can be defined as insufficient information, which can be of three sorts: inexactness, unreliability, and border with ignorance [124].

Moreover, uncertainty can prevail when much information is available. Furthermore, new information can either decrease or increase uncertainty. For example, new knowledge in complicated procedures may reveal previously unknown or understated uncertainties. In this way, more knowledge illuminates that our understanding is more limited or that procedures are more complex than thought before. As a general definition, therefore, uncertainty can be defined as any departure from the unachievable ideal of complete determinism [124].

3.2. Uncertainty matrix

μMEHs' studies have considered different uncertain input parameters (UIPs) in their models. However, the main drawback of these studies is the unclear reasons for choosing these parameters. The determination of these reasons requires the classification of UIPs by considering different aspects. Nevertheless, considering these parameters can be categorized from various criteria, it is challenging to systematically map them into a holistic categorization. Also, there is no specific guideline in the relevant literature to determine these criteria and consequently perform the classification of UIPs. Existing classifications for UIPs in multi-carrier IES studies have concentrated on only one dimension of these parameters, the nature of UIPs [6,15,17,22]. However, other dimensions and features of UIPs can be valuable to categorizing these parameters orderly. This paper presents a three-dimensional concept to classify UIPs in the μMEH's studies, inspired by concepts presented in Ref. [124], as follows (see Fig. 1).

- The nature of a UIP: This dimension distinguishes between two extremes: epistemic and variability uncertainties. The first item refers to our insufficient knowledge, which is declining with the advancement of research and experimental attempts. The second item, by contrast, refers to inherent variability. Therefore, this dimension determines whether the uncertainty of a parameter stems from the imperfection of our knowledge or its inherent variability.
- The level of a UIP: This dimension distinguishes between different levels of uncertainty: i) statistical uncertainty, ii) scenario uncertainty, and iii) recognized ignorance. The first item refers to a condition in which the UIP can be defined and formulated adequately in statistical terms. In contrast to the first item, the second one relates to the condition in which the occurrence of a range of outputs is possible; however, the formulation of the probability of the occurrence of a specific outcome is very complex and sometimes impossible. Finally, the third item refers to the condition in which there is a fundamental ignorance of the functional relationships and/or statistical properties. In this item, the scientific foundation to define different scenarios is very fragile. It should be noted that these levels are located between two limits, including determinism and absolute ignorance (indeterminacy). Determinism refers to a condition in which everything is precisely known. In real-world cases, this condition is not attainable. Absolute ignorance, however, refers to a deep level of uncertainty. As a general result, this dimension determines where uncertainty stands in the spectrum that extends from deterministic knowledge to absolute ignorance.
- The location of a UIP: This dimension attempts to identify generic locations where uncertainty manifests itself and are: i) context, ii) model uncertainty, iii) inputs, iv) parameter uncertainty, and v) model outcome uncertainty. The first item refers to defining the system's boundaries to be modeled. The second item relates to two classes of uncertainties: model structure uncertainty and model technical uncertainty. Model structure uncertainty arises from the model itself, whereas model technical uncertainty stems from the implementation process of the model using computers. The third item refers to data that define the base system and external driving forces that alter this system and its performance from various perspectives. This item can be divided into two classes of uncertainties: uncertainty related to the external driving forces and uncertainty associated with system data. The first class produces changes within the system and the magnitude of the forces. The second class, however, drives the model and typically quantifies relevant features of the reference system and its behavior. The fourth item refers to the data and strategies employed to calibrate different parameters of the model. Finally, the fifth item refers to the accumulated uncertainty related to the model outcomes. As a general result, this dimension determines where the uncertainty is in the model.

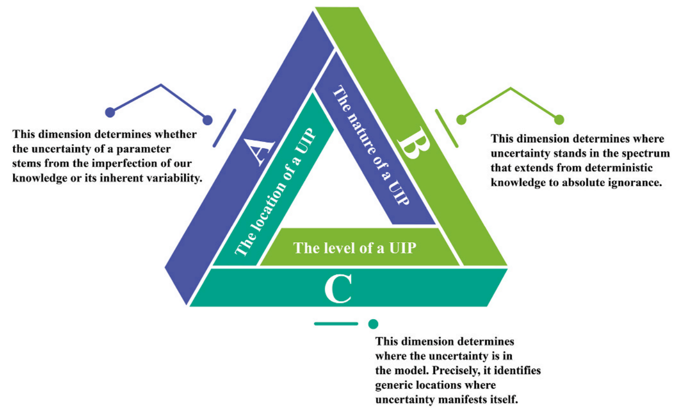

Fig. 1. A three-dimensional concept to classify UIPs in the μMEH's studies.

For further descriptions of these dimensions, please refer to Ref. [124].

An analytical tool, the uncertainty matrix, can be defined using these dimensions to classify and report different UIPs in μMEHs' studies. This matrix can meet the need of decision-makers for an effective and powerful tool to identify, classify, assess, and prioritize the critical features of different UIPs involved in μMEHs' studies systematically and graphically. It is necessary to mention that in filling in the uncertainty matrix, the level and nature of a UIP that occurs at any location can manifest itself in various forms simultaneously. Also, UIPs found in a specific section of the matrix may not hold greater significance compared to UIPs in other sections of the matrix. Furthermore, this matrix looks generally compact. However, the level and nature of each UIP must be estimated for any location in the model structure. This process needs significant efforts if UIP must be identified, classified, assessed, and prioritized in detail. Moreover, this matrix may characterize UIPs only at a certain point in time and must be updated with more information and the development of new circumstances. Next, this matrix must be reapplied in any field using experts because those performing the uncertainty studies may have overlooked some relevant UIPs. For instance, some experts may not be aware of the incompleteness of the model structure in a particular system, which may be emerged by other experts in the field or in a self-evaluation process. The insights derived from the use of such a matrix can help determine how best to allocate project resources to reduce the detrimental effects and/or embrace the positive effects of UIPs in the estimates of the outcomes of interest (e.g., would it be more worthwhile to concentrate on the model's structure or to gather more data to estimate the model's parameters?). The formation of the uncertainty matrix for all UIPs in μMEHs' studies is presented in Table A3. The uncertainty matrix in Table A3 illustrates that a remarkable part of μMEHs' studies has focused on the most common, significant, and influential uncertainties, such as multi-carrier energy prices and demands and the output power of RERs. However, with the increasing level of interaction between different energy carriers arising from the use of an updated cluster of multi-carrier energy conversion technologies, changing local multi-carrier energy market rules, EVs connection, to name a few, the severity, importance, and effect of uncertainties in μMEHs' studies are constantly evolving. Therefore, it is necessary for new studies to move away from the excessive focus on a confined number of uncertainties and to adapt their models to real-world conditions as much as possible by integrating new and high-impact uncertainties. As a result, scrutinizing the effect of new uncertainties in μMEHs' studies to update the uncertainty matrix can be a suitable path for new studies in this field.

3.3. Analysis of the effect of UIPs

In general, sensitivity analysis (posterior) and uncertainty analysis (prior) techniques can be used to investigate the effect of changes in UIPs on the model output [125]. Sensitivity and uncertainty analysis techniques are closely linked but distinct from each other.

3.3.1. Sensitivity analysis techniques

From a technical perspective, sensitivity analysis techniques investigate how model output variations can be apportioned to different UIPs. These techniques, thus, measure the change in the model output in a localized region of the space of UIPs. Precisely, these techniques address how the model's optimal solution(s) and the optimal decision made by the decision-maker would change with changes in UIPs' values, the level of restrictions and target output requirements that depend on UIPs, and others. In addition, this kind of analysis can estimate the cost of a specific change in a particular UIP places on the optimal solution(s) and decision. This information is of value to those making decisions in different phases of a complex procedure. In the relevant literature, there are various techniques for sensitivity analysis. Each technique has several advantages and disadvantages regarding its properties, computational costs, application ranges, and how to implement it.

Well-known examples of sensitivity analysis techniques include i) local sensitivity analysis, ii) screening experiments, and iii) global sensitivity analysis [125]. The first technique relies on the local effects of UIPs, measured through partial derivatives of the output. Some engineering fields, especially chemistry, are good examples of successfully applying this technique, but it is inappropriate for models that are computationally expensive to evaluate and have many UIPs. The second technique can be a suitable alternative to cope with the pitfalls of local sensitivity analysis. This technique needs a low computational burden to identify the factors subset that controls most output variability. This technique provides qualitative sensitivity measures. It means it ranks UIPs in order of importance and does not quantify how much a specific UIP is more important than another. There is a trade-off between computational burden and information. Unlike previous techniques, the global sensitivity analysis considers the full range of variation of UIPs along their joint distribution [125,126]. Since UIPs vary simultaneously, this involves multidimensional averaging. The global sensitivity analysis uses variance-based methods to calculate the contribution of each UIP or a group of UIPs to the total output variance. For a particular UIP, $\gamma_n; \forall\{n \in \Omega_N\}$, the first-order sensitivity measure (importance measure) can be defined using Equation (1):

$$s_n = \frac{V(E(y|\gamma_n))}{V(y)}; \forall\{n \in \Omega_N\} \tag{1}$$

In this Equation, $E(y|\gamma_n)$ is the expected value of the output variable y when γ_n is fixed, and $V(y)$ is the unconditioned variance of the output variable y. For independent UIPs, the importance measure equals the first-order sensitivity index of Sobol. This Equation demonstrates the expected reduction in the variance of the output variable y when $\gamma_n; \forall\{n \in \Omega_N\}$ is fixed. It should be noted that the sum of the first-order Sobol sensitivity indices cannot exceed one. In this technique, the output variance is univocally decomposed in orthogonal terms of increasing dimensionality. For instance, in a model with three UIPs, the total variance $V(y)$ is decomposed using Equation (2):

$$V(y) = V_1(y) + V_2(y) + V_3(y) + V_{12}(y) + V_{13}(y) + V_{23}(y) + V_{123}(y) \tag{2}$$

The first-order terms quantify the impact of each UIP. The second-order terms represent the impact due to the interaction between a particular pair of UIPs that is not amenable to the linear combination of the effects due to each of them. The third-order term is similarly derived. It is a complete representation since UIPs' capacity to appreciate all the interaction effects are considered, which is significant for nonlinear and nonadditive models. However, the number of terms in Equation (2), by raising the number of UIPs, is exponentially increased. It can be the main disadvantage of variance-based techniques (curse of dimensionality). The total sensitivity indices can be used to cover this drawback. In the same three UIPs case, these indices are defined using Equation (3):

$$\begin{aligned} s_{T_1} &= s_1 + s_{12} + s_{13} + s_{123} \\ s_{T_2} &= s_2 + s_{21} + s_{23} + s_{213} \\ s_{T_3} &= s_3 + s_{31} + s_{32} + s_{312} \end{aligned} \tag{3}$$

In a model with N UIPs, the decision-maker need to investigate N total sensitivity indices, unlike the previous method, which requires to compute $2^N - 1$ terms in Equation (2). It should be noted that $s_{T_n}; \forall\{n \in \Omega_N\}$ can be calculated independently from the summands that compose it. In the relevant literature, other methods exist to compute global sensitivity indices. Interested readers may look at [126–128] for further information. Among all μMEHs' studies in the database, twelve articles have used sensitivity analysis techniques independently or in combination with uncertainty analysis techniques to investigate the effect of changes in diverse UIPs on their model output [46,61,70,87,92,95,98,101,104,112,116,119]. Details of UIPs of each study can be followed in Table A3. It is important to note that all these studies have presented relatively comprehensive descriptions of the sensitivity analysis process, which can be helpful from different aspects. However, almost all these studies investigated bounded fluctuations of UIPs on the objective function(s) value. It means their methods to execute the sensitivity analysis are not based on a global exploration of the space of UIPs. In addition, these studies have examined the sensitivity of the objective function(s) to the UIPs individually (varying one UIP at a time).

Furthermore, they do not consider the correlation between different UIPs, which is abundantly found in practical models. All these things cause uncertainty and sensitivity to be wrongly estimated in most of these studies. Detailed examination of these cases is beyond the scope of this article. However, the interested reader may look at [129] which presents a systematic review of sensitivity analysis practices in different branches of science and describes why many of these analyses are false.

Therefore, the need to heed the cases mentioned above, which causes a move towards using more efficient techniques to investigate sensitivity, is fully felt, and it can be an attractive study path for future research.

3.3.2. Uncertainty analysis techniques

In a broad sense, uncertainty analysis techniques attempt to answer this question: How uncertain is the prediction? These techniques attempt to map what a model does when selected UIPs are left free to vary over their range of existence [127,130]. In a more precise definition, these techniques aim to quantify the overall uncertainty associated with the response due to uncertainties in the model input. Different uncertainty analysis techniques have been used to model and examine UIPs in multi-carrier IESs studies, especially μMEHs' studies, that can be classified into six main categories, see Fig. 2.

3.3.2.1. Probabilistic techniques. Probabilistic techniques rely on statistical distributions such as the Weibull probability distribution function (PDF) and normal PDF to scrutinize UIPs. For example, let y be a multivariate function of N UIPs, $y = f(\gamma); \forall \gamma = \{\gamma_1, \ldots, \gamma_n, \ldots, \gamma_N\}$. In these techniques, the decision-maker seeks to determine the PDF of the output variable y, assuming that the PDF of UIPs is known, which is the critical assumption. Probabilistic techniques are comprised of two major classes, numerical and analytical approaches. Numerical approaches rely on making different guesses at the solution and investigating whether the answer to the problem is acceptable enough to terminate the problem-solving process. The analytical ones, by contrast, require framing the problem using algebraic equations. Although analytical approaches lead to accurate solutions, their implementation for large-scale and complicated problems is challenging and sometimes even impossible.

On the contrary, numerical ones are easier to implement, especially for large-scale and complex problems. Numerical approaches give approximate solutions; however, obtained solutions are acceptable in various problems, especially problems related to engineering subjects. The Monte Carlo experiment (MCE) is the most well-known and widely used iterative numerical approach that uses repeated random sampling of UIPs to attain numerical results for the output variable(s) [131]. The implementation processes of the MCE vary but tend to track steps of the same general pattern as follows.

- Step 1: Define a domain for each member of the vector of UIPs, $\gamma = \{\gamma_1, \ldots, \gamma_n, \ldots, \gamma_N\}$.
- Step 2: Set the counter of the MCE: $k = 1$.
- Step 3: Generate a sample for each member of the vector γ based on the relevant PDF over the pertinent defined domain in Step 1.
- Step 4: Compute the output variable y for the generated sample of the vector γ in the previous step, supposing that $\gamma = \gamma_k = \{\gamma_{k1}, \ldots, \gamma_{kn}, \ldots, \gamma_{kN}\}$, according to Equation (4):

$$y_k = f(\gamma_k); \forall \gamma_k = \{\gamma_{k1}, \ldots, \gamma_{kn}, \ldots, \gamma_{kN}\} \tag{4}$$

- Step 5: Compute the expected value and the variance of the output variable y, using Equations (5) and (6), respectively:

$$\mathrm{E}(y) = \sum_k \frac{y_k}{k} = \mathrm{Mean}(y_1, \ldots, y_k, \ldots, y_K) \tag{5}$$

$$\sigma(y) = \mathrm{E}(y^2) - \mathrm{E}^2(y) = \mathrm{STD}(y_1, \ldots, y_k, \ldots, y_K) \tag{6}$$

- Step 6: Check the stopping criterion. If this criterion is satisfied, go to the next step; otherwise, set $k = k + 1$ and go to Step 3.
- Step 7: Stop.

The MCE has been used as the chosen strategy to examine diverse UIPs (see Table A3) in almost half of the μMEHs' studies available in the database dealing with uncertainties, including operation [28,63,68,84,93,94,106,109], planning [83,87,90], design [61], resilience [76,91]. These studies have shown that the MCE can handle uncertainties with acceptable accuracy in various problems related to μMEHs with different sizes and complexities. However, the high computational burden and the total reliance on PDFs of UIPs have been stated as shortcomings of this method in these studies. It must be recognized that to relieve the second weakness, the model reported in Ref. [93] uses the Gaussian mixture model alongside the MCE to generate different scenarios for UIPs that do not follow any commonly used PDF. Several enhanced versions of the MCE (e.g., non-sequential, pseudo-sequential, and sequential MCEs) are developed to improve the performance of this method in engineering-related studies; however, their explanation is beyond the scope of this paper. Interested readers may look at [6,22,130,131].

Analytical approaches are broken down into linearization- and PDF approximation-based groups [6,22,130]. Different methods of the former group (e.g., convolution, cumulant, Gram–Charlier a series, Edgeworth expansion, Cornish–Fisher expansion, Taylor series, first-order second-moment) lie in the computation of the PDF of a linearized combination of UIPs [6,22,130]. The accuracy of these methods strongly depends on selecting the appropriate linear function, which is a challenging task. These complexities have resulted in the development of the latter group. Different methods of this group, such as the point estimate (PE) method, unscented transformation, scenario-based decision-making (SDM) method, and others, dwell on

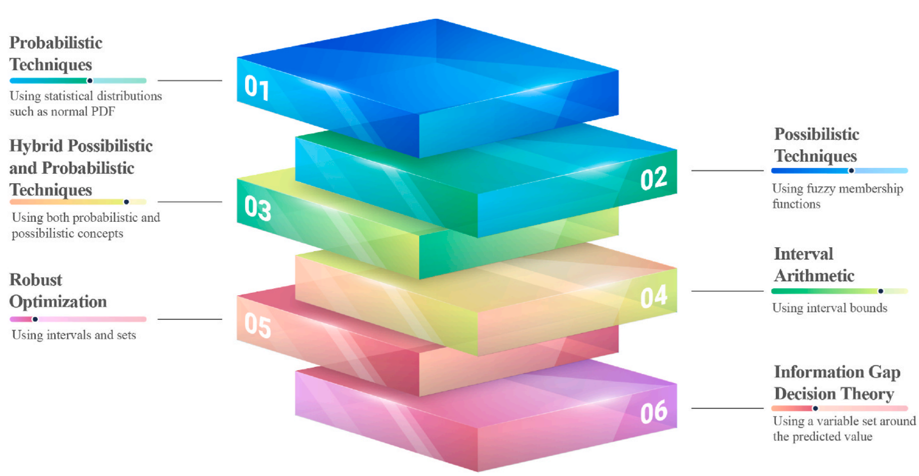

Fig. 2. The classification of different uncertainty analysis techniques to model and examine UIPs in μMEHs' studies.

how to create suitable samples of the UIPs that can maintain an acceptable level of information about UIPs' PDFs [6,22,130]. Among analytical approaches, the SDM and two-point estimate (2PE) methods have been used in the μMEHs' studies to examine different UIPs.

UIPs have countless realizations. However, the decision-maker cannot examine all of them. In this situation, a logical solution is to transform the continuous infinite uncountable realization space into countable finite sections (scenarios) with related weights (probabilities), which is the basis for the SDM method. Precisely, based on the PDF of each member of the vector γ, a limited list of scenarios is generated. Next, the expected value of the output variable y is calculated using Equation (7):

$$\mathrm{E}(y)=\sum_{s}^{\mathrm{S}}\pi_s.f(\gamma_s);\forall\gamma_s=\{\gamma_{s1},\dots,\gamma_{sn},\dots,\gamma_{s\mathrm{N}}\};\forall\{s\in\Omega_\mathrm{S}\} \tag{7}$$

In this Equation, π_s is the probability of scenario s. It must be recognized that the probabilities of scenarios are different, but their sum must equal 1. Among μMEHs' studies available in the database concerning uncertainties, nine studies have used the SDM method to incorporate and examine the impacts of various UIPs (see Table A3) on different μMEHs' studies, including operation [40,69,70,81,106,118], planning [108], design [75], resilience [73]. The findings of these research publications demonstrate that the SDM method is easily implementable in various μMEHs' studies. However, it needs detailed data on UIPs. Furthermore, the SDM method cannot deliver the output variable(s) PDF and only gives its expected value.

The PE method relies on calculating the statistic moments of a random quantity that is a function of one or multiple UIPs [132]. For example, let y be a multivariate function of N UIPs, $y=f(\gamma);\forall\gamma=\{\gamma_1,\dots,\gamma_n,\dots,\gamma_\mathrm{N}\}$ and assume that UIPs' PDFs are available. This method needs 2^N probability concentrations located at 2^N different points to replace the original joint PDF of UIPs by aligning the second-order and third-order non-crossed moments. In real-world and large-scale problems where the number of UIPs is large, implementing the PE method leads to a drastic computational burden, which in many cases is not economical and even possible. An applicable variation of the PE method entitled the 2PE method was suggested to cope with this drawback [133]. In contrast to the PE method, the 2PE one requires only 2N probability concentration points, which leads to a sharp reduction in the computational burden. A step-by-step procedure for the 2PE method is provided as follows:

- Step 1: Set the number of UIPs equal to N.
- Step 2: Set the first and second moments of the output variable y, according to Equations (8) and (9), respectively:

$$\mathrm{E}(y)=0 \tag{8}$$

$$\mathrm{E}(y^2)=0 \tag{9}$$

- Step 3: Set the counter of UIPs: $n=1$.
- Step 4: Calculate the skewness coefficient associated with the UIP n, according to Equation (10):

$$\lambda_{\gamma_{n,3}}=\mathrm{E}\left[\left(\gamma_n-\mu_{\gamma_n}\right)^3\right]\Big/\left(\sigma_{\gamma_n}\right)^3 \tag{10}$$

In Equation (10), μ_{γ_n} and σ_{γ_n} are the mean and variance of the UIP n, respectively. Also, $\mathrm{E}[(\gamma_n-\mu_{\gamma_n})^3]$ is calculated using Equation (11):

$$\mathrm{E}\left[\left(\gamma_n-\mu_{\gamma_n}\right)^3\right]=\sum_{t}^{\mathrm{T}}\left(\gamma_{n,t}-\mu_{\gamma_{n,t}}\right)^3.p\left(\gamma_{n,t}\right);\forall\{t\in\Omega_\mathrm{T}\} \tag{11}$$

In Equation (11), T and $p(\gamma_{n,t})$ are the number of observations of the UIP n and the probability of observation t related to the UIP n, respectively.

- Step 5: Calculate the location and probability (weighting) of two concentration points related to the UIP n, using Equations (12) and (13), respectively:

$$\zeta_{\gamma_{n,i}}=\frac{\lambda_{\gamma_{n,3}}}{2}+(-1)^{3-i}.\sqrt{\mathrm{N}+\left(\lambda_{\gamma_{n,3}}/2\right)^2};\forall\{i\in\{1,2\}\} \tag{12}$$

$$p_{\gamma_{n,i}}=\frac{(-1)^i.\lambda_{\gamma_{n,3}}}{2\mathrm{N}.\sqrt{\mathrm{N}+\left(\lambda_{\gamma_{n,3}}/2\right)^2}};\forall\{i\in\{1,2\}\} \tag{13}$$

In Equation (13), the value of each probability, $p_{\gamma_{n,i}};\forall\{i\in\{1,2\}\}$, can vary from 0 to 1; however, their sum always equals 1.

- Step 6: Calculate two concentration points according to Equation (14):

$$u_{\gamma_{n,i}}=\mu_{\gamma_n}+\zeta_{\gamma_{n,i}}.\sigma_{\gamma_n};\forall\{i\in\{1,2\}\} \tag{14}$$

- Step 7: Calculate the output variable y concerning the UIPs' vector, using Equation (15):

$$y=f(\gamma);\forall\gamma=\left\{\mu_{\gamma_1},\mu_{\gamma_2},\dots,u_{\gamma_{n,i}},\dots,\mu_{\gamma_{\mathrm{N}-1}},\mu_{\gamma_\mathrm{N}}\right\};\forall\{i\in\{1,2\}\} \tag{15}$$

- Step 8: Update $\mathrm{E}(y)$ and $\mathrm{E}(y^2)$, using Equations (16) and (17), respectively:

$$\mathrm{E}(y)\cong\sum_{n=1}^{\mathrm{N}}\sum_{i=1}^{2}p_{\gamma_{n,i}}.f\left(\mu_{\gamma_1},\mu_{\gamma_2},\dots,u_{\gamma_{n,i}},\dots,\mu_{\gamma_{\mathrm{N}-1}},\mu_{\gamma_\mathrm{N}}\right);\forall\{i\in\{1,2\}\} \tag{16}$$

$$\mathrm{E}(y^2)=\sum_{n=1}^{\mathrm{N}}\sum_{i=1}^{2}p_{\gamma_{n,i}}.f\left(\mu_{\gamma_1},\mu_{\gamma_2},\dots,u_{\gamma_{n,i}},\dots,\mu_{\gamma_{\mathrm{N}-1}},\mu_{\gamma_\mathrm{N}}\right)^2;\forall\{i\in\{1,2\}\} \tag{17}$$

- Step 9: Calculate the mean (expected value) and the standard deviation of the output variable y, using Equations (18) and (19), respectively:

$$\mu_y=\mathrm{E}(y) \tag{18}$$

$$\sigma_y=\sqrt{\mathrm{var}(y)}=\sqrt{\mathrm{E}(y^2)-(\mathrm{E}(y))^2}=\sqrt{\mathrm{E}(y^2)-(\mu_y)^2} \tag{19}$$

- Step 10: Set $n=n+1$. If $n\le\mathrm{N}$, go to Step 4; otherwise, go to the next step.
- Step 11: Stop.

The 2PE method is simple-to-use and straightforward; however, it lacks high accuracy in real-world and large-scale problems. Furthermore, this method does not give any information about the shape of the PDF of the output variable(s) and only provides its mean and standard deviation. Among μMEHs' studies available in the database concerning uncertainties, three studies have used the 2PE method to address the impact of different UIPs on μMEHs' operation process [51,94,97]. The model reported in Ref. [51] has used the 2PE method to handle uncertainty related to the output power of the rooftop photovoltaic system. This reference has shown that considering the photovoltaic system with its relevant uncertainty improves the synergy between the output power of the photovoltaic system and electricity consumption. This improvement has been made by transferring the controllable demands to sunny hours as much as possible. Thus, the μMEH's energy cost and power demand during peak hours have been significantly reduced. The framework presented in Ref. [94] has considered the output power of the photovoltaic system and electricity price as UIPs and modeled them using the 2PE method. The simulation results have demonstrated that it is impossible to reach the optimal operation cost without consideration of these uncertainties. Also, test results implied that the 2PE method performs better than the MCE. A hybrid framework consisting of the 2PE method and information gap decision theory (IGDT) has been proposed in Ref. [97] to scrutinize the impacts of UIPs on the μMEH's operation. Modeling uncertainties associated with the output power of RERs (photovoltaic panels and wind turbines) and energy demand has been done using the 2PE method, whereas the IGDT has been used to formulate the severe uncertainty related to gas prices. The primary outcome of this reference is the reduction of the complexity of the uncertainty modeling process through the IGDT by handling a portion of them with the 2PE method.

Stress again that probabilistic techniques rely on the assumption that sufficient information is available to construct PDFs related to UIPs. In the absence of this information, these strategies will collapse.

3.3.2.2. Possibilistic techniques. Possibilistic techniques use linguistic categories with fuzzy boundaries to examine UIPs in a wide range of domains where information is incomplete and imprecise [134]. These techniques use different membership functions (MFs), such as triangular, trapezoidal, Gaussian, and others, to scrutinize the membership degrees of possibilistic UIPs. Regardless of the shape of MFs, the main question is "How to determine the MF of the output variable y if MFs of UIPs are known, which is the key assumption in these techniques?". How to answer this question has led to the development of different methods (e.g., the α-cut, defuzzification). The possibilistic output variable y of a model of epistemic UIPs is usually represented in the form of a multivariate function, $y = f(\gamma); \forall\gamma = \{\gamma_1, \ldots, \gamma_n, \ldots, \gamma_N\}$. If the possibility distribution of UIPs is known, the possibility distribution of the output variable y can be determined using the well-known α-cut technique. The α-cut technique is based on fuzzy logic and fuzzy set theory [135]. The fuzzy set A is characterized by an MF mapping element of a domain, space, or the universe of discourse γ_n to the unit interval $[0, 1]$, see Equation (20).

$$\mathrm{A} = \{(\acute{\gamma}_n, \mu_{\mathrm{A}}(\acute{\gamma}_n)) : \acute{\gamma}_n \in \gamma_n, \mu_{\mathrm{A}}(\acute{\gamma}_n) \in \mathrm{U}_n\}; \forall\{n \in \Omega_{\mathrm{N}}\} \tag{20}$$

Equation (20) describes that A is a function from domain γ_n to co-domain U_n, and each element $\acute{\gamma}_n \in \gamma_n$ of the domain maps to element $u_{\acute{\gamma}_n} \in \mathrm{U}_n$ of the co-domain, which means that $\mu_{\mathrm{A}}(\acute{\gamma}_n) = u_{\acute{\gamma}_n}$. Precisely, $\mu_{\mathrm{A}} : \gamma_n \rightarrow [0, 1]$ is a mapping called the degree of the MF of the fuzzy set A and $\mu_{\mathrm{A}}(\acute{\gamma}_n)$ is the membership value of $\acute{\gamma}_n \in \gamma_n$ in the fuzzy set A. These membership grades are often represented by real numbers ranging from $[0, 1]$. Let the fuzzy MF of UIP n be a symmetric trapezoidal type, as depicted in Fig. 3.

The fuzzy MF depicted in Fig. 3 is characterized by Equation (21) through (25):

$$\mathrm{support}(\mathrm{A}) = \{\dot{\gamma}_n \in \gamma_n | \mu_{\mathrm{A}}(\dot{\gamma}_n) > 0\}; \forall\{n \in \Omega_{\mathrm{N}}\} \tag{21}$$

$$\mathrm{core}(\mathrm{A}) = \{\dot{\gamma}_n \in \gamma_n | \mu_{\mathrm{A}}(\dot{\gamma}_n) = 1\}; \forall\{n \in \Omega_{\mathrm{N}}\} \tag{22}$$

$$\mathrm{boundary}(\mathrm{A}) = \{\dot{\gamma}_n \in \gamma_n | 0 < \mu_{\mathrm{A}}(\dot{\gamma}_n) < 1\}; \forall\{n \in \Omega_{\mathrm{N}}\} \tag{23}$$

$$\mathrm{crossover}(\mathrm{A}) = \{\dot{\gamma}_n \in \gamma_n | \mu_{\mathrm{A}}(\dot{\gamma}_n) = 0.5\}; \forall\{n \in \Omega_{\mathrm{N}}\} \tag{24}$$

$$\mathrm{bandwith}(\mathrm{A}) = \{|\dot{\gamma}_{n,1} - \dot{\gamma}_{n,2}| | \mu_{\mathrm{A}}(\dot{\gamma}_{n,1}) = \mu_{\mathrm{A}}(\dot{\gamma}_{n,2}) = 0.5\}; \forall\{n \in \Omega_{\mathrm{N}}\} \tag{25}$$

Equations (21) and (22) represent the support and core of the fuzzy set A, respectively. The support of the fuzzy set A is the crisp set of all points $\dot{\gamma}_n \in \gamma_n$ such that $\mu_{\mathrm{A}}(\dot{\gamma}_n) > 0$ (nonzero membership grades). It should be noted that the support of the fuzzy set A is its strong 0-cut. The core, however, is the crisp set of all points $\dot{\gamma}_n \in \gamma_n$ such that $\mu_{\mathrm{A}}(\dot{\gamma}_n) = 1$ (membership grades equal 1). The fuzzy set A is normal if its core is non-empty (the high\highest membership value equals 1); otherwise, this set is sub-normal. Equation (23) describes the boundary of the fuzzy set A. This boundary comprises those elements $\dot{\gamma}_n \in \gamma_n$ of the universe such that $0 < \mu_{\mathrm{A}}(\dot{\gamma}_n) < 1$. The boundary of a fuzzy set is the difference between its support and core. Equations (24) and (25) describe the crossover point and the bandwidth of the fuzzy set A, respectively. The crossover is a point $\dot{\gamma}_n \in \gamma_n$ such that $\mu_{\mathrm{A}}(\dot{\gamma}_n) = 0.5$, whereas the bandwidth (width) is the distance between the two unique crossover points.

For the fuzzy set A of UIP n, the α-cut can be defined using Equations (26) and (27):

$$\mathrm{A}^{\alpha} = \{\dot{\gamma}_n \in \gamma_n | \mu_{\mathrm{A}}(\dot{\gamma}_n) \geq \alpha, 0 \leq \alpha \leq 1\}; \forall\{n \in \Omega_{\mathrm{N}}\} \tag{26}$$

$$\mathrm{A}^{\alpha} = [\,\underline{\mathrm{A}}^{\alpha} \quad \bar{\mathrm{A}}^{\alpha}\,] \tag{27}$$

In Equation (27), $\underline{\mathrm{A}}^{\alpha}$ and $\bar{\mathrm{A}}^{\alpha}$ are the lower and upper bounds of the A^{α}, respectively. For different values of α, we get different crisp sets. In general, if $\alpha_1 > \alpha_2$, then $\mathrm{A}^{\alpha_1} \subseteq \mathrm{A}^{\alpha_2}$. Consider two values for the α-cut, as depicted in Figure (3). The set A^{α_1} contains all the elements from $\dot{\gamma}_{n,1}$ to $\dot{\gamma}_{n,2}$, including both end values. The set A^{α_2} contains all the elements from $\dot{\gamma}_{n,3}$ to $\dot{\gamma}_{n,4}$, including both end values. It should be noted that the α-cut converts to the strong the α-cut by replacing Equation (26) with Equation (28).

$$\mathrm{A}^{\alpha+} = \{\dot{\gamma}_n \in \gamma_n | \mu_{\mathrm{A}}(\dot{\gamma}_n) > \alpha, 0 \leq \alpha \leq 1\}; \forall\{n \in \Omega_{\mathrm{N}}\} \tag{28}$$

Having the α-cut of each UIP, the α-cut of the output variable y can be described using Equation (29) through (31):

$$y^{\alpha} = [\,\underline{y}^{\alpha} \quad \bar{y}^{\alpha}\,] \tag{29}$$

$$\underline{y}^{\alpha} = \inf\left[f\left(\mathrm{F}^{\alpha}_{\gamma_1}, \ldots, \mathrm{F}^{\alpha}_{\gamma_n}, \ldots, \mathrm{F}^{\alpha}_{\gamma_N}\right)\right]; \forall\{n \in \Omega_{\mathrm{N}}\} \tag{30}$$

$$\bar{y}^{\alpha} = \sup\left[f\left(\mathrm{F}^{\alpha}_{\gamma_1}, \ldots, \mathrm{F}^{\alpha}_{\gamma_n}, \ldots, \mathrm{F}^{\alpha}_{\gamma_N}\right)\right]; \forall\{n \in \Omega_{\mathrm{N}}\} \tag{31}$$

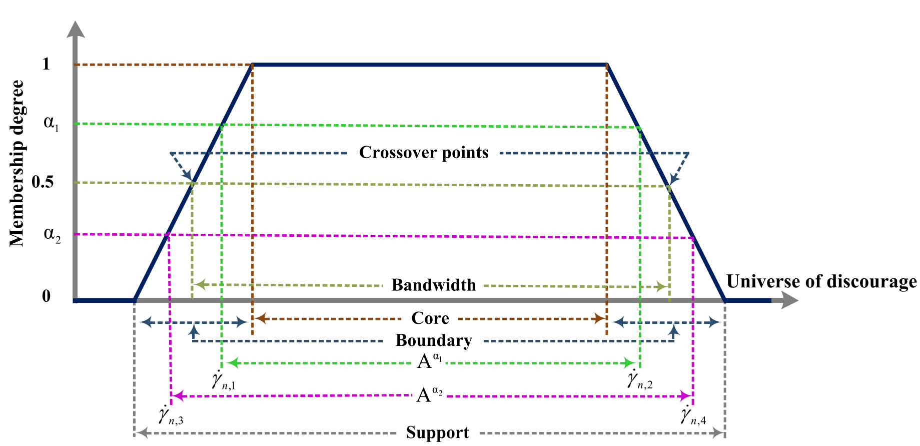

Fig. 3. The symmetric trapezoidal fuzzy MF of UIP n.

In Equations (30) and (31), $F^{\alpha}_{\gamma_n}$ is the α-cut of the UIP n. In each α-cut, one minimization and one maximization will be done to obtain the lower and upper bounds of the output variable y, $\underline{y}^{\alpha}$ and $\bar{y}^{\alpha}$, respectively. Readers refer to Ref. [135] for further information about possibilistic techniques. None of the studies in the database that have investigated uncertainties has focused on the possibilistic techniques. Using these techniques to model UIPs and compare them with probabilistic techniques can be a new research path for μMEHs' studies.

3.3.2.3. Hybrid possibilistic and probabilistic techniques. Hybrid possibilistic and probabilistic techniques are developed to deal with UIPs, some of which can be modeled probabilistically, and the rest can be described possibilistically. These techniques combine probabilistic and possibilistic concepts in a bi-loop structure (a probabilistic technique in the outer loop and a possibilistic one in the inner loop) to represent and manage UIPs in modeling, optimization, and decision-making processes. In these techniques, UIPs are represented by probability distributions and fuzzy sets, which capture the likelihood of events and the degree of possibility of their occurrence, respectively. The probabilistic loop of the bi-loop structure is used to model random variabilities and uncertainties that probability distributions, such as Weibull and normal PDF, can describe. On the other hand, the possibilistic loop is used to model uncertainties arising from incomplete or imprecise information, vagueness, and ambiguity (e.g., uncertainty in the data quality, variability in human susceptibilities) that a probability distribution cannot represent. This bi-loop structure allows for more robust and flexible modeling of uncertainty, as it can handle both types of uncertainty in a complementary way. It also enables decision-makers to incorporate their subjective judgments and domain knowledge into the modeling process, which can be helpful when data is limited or unreliable. Examples of the most well-known hybrid possibilistic and probabilistic techniques include i) the α-cut-MCE, ii) the α-cut-SDM method, and iii) α-cut-unscented transformation. Consider the α-cut-MCE. In this technique, the outer loop is MCE, and the inner is the α-cut. Details related to MCE and α-cut are presented in previous sections of the paper. For a thorough discussion regarding hybrid probabilistic and possibilistic techniques, interested readers are directed to Refs. [6,22,130]. These techniques have not been used in any of the papers available in the database that deal with uncertainties. However, since they provide valuable insights into the behavior of complex models and help decision-makers make more informed and robust decisions in the face of different kinds of uncertainty, their implementation in μMEHs' studies can be an attractive research path.

3.3.2.4. Interval arithmetic. Interval arithmetic was introduced to compute the exact solution and error as a single entity (interval) [136]. This technique can be used to model uncertainty because it provides a rigorous and systematic way to represent and manipulate intervals of real numbers, which can be used to represent uncertainty in measurements or calculations. The idea behind this technique is straightforward. First, the distance between the bottom and top edges of each UIP is defined using an interval (a range of possibilities). Then, the decision-maker tries to find the lower and upper bounds for the output variable(s). This technique performs arithmetic operations on closed intervals (interval numbers). Each interval number represents some fixed real number between the lower and upper endpoints of the closed interval. Therefore, an interval arithmetic operation produces two values for each result. These values correspond to the lower and upper endpoints of the resulting interval such that the true result certainly lies within this interval, and the resulting interval's width indicates the result's accuracy. This process makes interval arithmetic helpful in solving problems in which the exact value of a solution is not known, but instead, only a range of values for UIPs is available. Let y be a multivariate function of N UIPs (real numbers whose values are uncertain), $y = f(\gamma); \forall \gamma = \{\gamma_1, \ldots, \gamma_n, \ldots, \gamma_N\}$. In addition, assume there is sufficient information about an acceptable range of γ_n, $\underline{\gamma}_n < \gamma_n < \bar{\gamma}_n; \forall\{n \in \Omega_N\}$, $\left\{\underline{\gamma}_n, \bar{\gamma}_n \in \mathbb{R}\right\}, \left\{\underline{\gamma}_n \leq_{\mathbb{R}} \bar{\gamma}_n\right\}$, in which the true value of γ_n is estimated to lie. Therefore, the closed (bounded) nonempty real interval (interval of certainty or confidence) of the UIP n can be defined using Equation (32):

$$[\gamma_n] = \left[\underline{\gamma}_n \quad \bar{\gamma}_n\right] = \left\{\gamma_n \in \mathbb{R} | \underline{\gamma}_n \leq_{\mathbb{R}} \gamma_n \leq_{\mathbb{R}} \bar{\gamma}_n\right\}; \forall\{n \in \Omega_N\} \tag{32}$$

This Equation describes that the true value of $[\gamma_n]$ lies within the interval $\left[\underline{\gamma}_n \quad \bar{\gamma}_n\right]$. The lower and upper interval boundaries for the interval $[\gamma_n]$ are returned by the infimum and supremum operators, according to Equations (33) and (34), respectively:

$$\inf([\gamma_n]) = \min\left(\left[\underline{\gamma}_n \quad \bar{\gamma}_n\right]\right) = \underline{\gamma}_n; \forall\{n \in \Omega_N\} \tag{33}$$

$$\sup([\gamma_n]) = \max\left(\left[\underline{\gamma}_n \quad \bar{\gamma}_n\right]\right) = \bar{\gamma}_n; \forall\{n \in \Omega_N\} \tag{34}$$

If $\underline{\gamma}_n = \bar{\gamma}_n$ then $[\gamma_n]$ is a thin or point interval. In addition, $[\gamma_n]$ is negative if $\bar{\gamma}_n < 0$, positive if $\underline{\gamma}_n > 0$, and symmetric if $\underline{\gamma}_n = -\bar{\gamma}_n$. The width\diameter, radius, and midpoint of $[\gamma_n]$ can be described using Equation (35) through (37):

$$w([\gamma_n]) = \sup([\gamma_n]) - \inf([\gamma_n]) = \bar{\gamma}_n - \underline{\gamma}_n; \forall\{n \in \Omega_N\} \tag{35}$$

$$\text{rad}([\gamma_n]) = \frac{w([\gamma_n])}{2} = \frac{\left(\bar{\gamma}_n - \underline{\gamma}_n\right)}{2}; \forall\{n \in \Omega_N\} \tag{36}$$

$$\text{mid}([\gamma_n]) = \frac{(\inf([\gamma_n]) + \sup([\gamma_n]))}{2} = \frac{\left(\underline{\gamma}_n + \bar{\gamma}_n\right)}{2}; \forall\{n \in \Omega_N\} \tag{37}$$

This technique considers the range of possible instances represented by an interval model. In interval arithmetic, given a $\mathbb{R}^N$ to $\mathbb{R}$ continuous function $y = f(\gamma); \forall \gamma = \{\gamma_1, \ldots, \gamma_n, \ldots, \gamma_N\}$, the interval united extension $[f]$ of f corresponds to the range of f-values on its interval argument $([\gamma_1], \ldots, [\gamma_n], \ldots, [\gamma_N])$ in $I(\mathbb{R}^N)$ can be defined using Equation (38):

$$\begin{aligned}[f]([\gamma_1], \ldots, [\gamma_n], \ldots, [\gamma_N]) &= \{f(\gamma_1, \ldots, \gamma_n, \ldots, \gamma_N) | \gamma_1 \in [\gamma_1], \ldots, \gamma_n \in [\gamma_n], \ldots, \gamma_N \in [\gamma_N]\} \\ &= [\min\{f(\gamma_1, \ldots, \gamma_n, \ldots, \gamma_N) | \gamma_n \in [\gamma_n]\}, \max\{f(\gamma_1, \ldots, \gamma_n, \ldots, \gamma_N) | \gamma_n \in [\gamma_n]\}]\end{aligned} \tag{38}$$

For example, Fig. 4 shows the case $N = 2$, $y = f(\gamma); \forall \gamma = \{\gamma_1, \gamma_2\}$. Intervals for these two UIPs are defined as $[\gamma_1] = \left[\underline{\gamma}_1 \ \bar{\gamma}_1\right]$ and $[\gamma_2] = \left[\underline{\gamma}_2 \ \bar{\gamma}_2\right]$. These intervals represent the possible range of values each UIP can take over the given domain.

The output variable at each point in the rectangular domain is evaluated by substituting the interval values for γ_1 and γ_2 into the function. This results in a new interval output for each point in the domain. For instance, at the top-left corner of the rectangle of certainty,

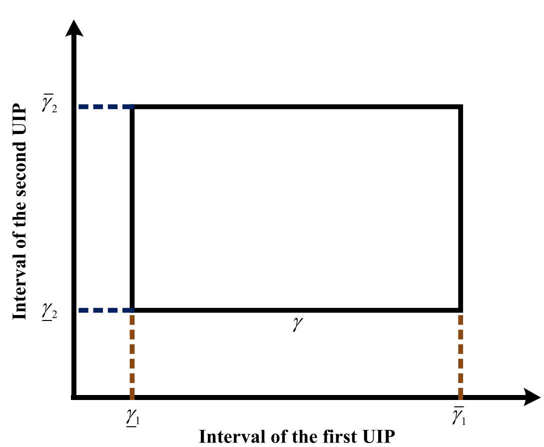

Fig. 4. A 2-dimensional parallelotope of certainty.

where $\gamma_1 = \underline{\gamma}_1$ and $\gamma_2 = \overline{\gamma}_2$, the output variable evaluates to $y = f\left(\underline{\gamma}_1, \overline{\gamma}_2\right)$. Therefore, it represents the range of values the function can take over the given domain. This technique keeps track of all UIPs simultaneously because an interval arithmetic operation produces an interval of certainty within which the true real-valued result is guaranteed to lie.

Operations applied to the ordinary number system can be extended to cover interval numbers. Let $[\gamma_n] = [\underline{\gamma}_n \quad \overline{\gamma}_n]$ and $[\gamma_m] = [\underline{\gamma}_m \quad \overline{\gamma}_m]$ be the interval of two UIPs and $\circ \in \{+ - \times \div\}$ and $0 \notin [\gamma_m]$ when$\circ = \div$ be one of the four basic arithmetic operators. The generic form of basic algebraic operations for interval numbers can be defined using Equation (39):

$$[\underline{\gamma}_n \quad \overline{\gamma}_n] \circ [\underline{\gamma}_m \quad \overline{\gamma}_m] = \{[\gamma_n] \circ [\gamma_m] | \gamma_n \in [\underline{\gamma}_n \quad \overline{\gamma}_n], \gamma_m \in [\underline{\gamma}_m \quad \overline{\gamma}_m]\}; \forall \{n, m \in \Omega_{\mathrm{N}}\} \tag{39}$$

This form can be used for addition, subtraction, multiplication, and division of these two UIPs according to Equation (40) through (44):

$$[\underline{\gamma}_n \quad \overline{\gamma}_n] + [\underline{\gamma}_m \quad \overline{\gamma}_m] = [\underline{\gamma}_n + \underline{\gamma}_m \quad \overline{\gamma}_n + \overline{\gamma}_m]; \forall \{n, m \in \Omega_{\mathrm{N}}\} \tag{40}$$

$$[\underline{\gamma}_n \quad \overline{\gamma}_n] - [\underline{\gamma}_m \quad \overline{\gamma}_m] = [\underline{\gamma}_n - \overline{\gamma}_m \quad \overline{\gamma}_n - \underline{\gamma}_m]; \forall \{n, m \in \Omega_{\mathrm{N}}\} \tag{41}$$

$$[\underline{\gamma}_n \quad \overline{\gamma}_n] \times [\underline{\gamma}_m \quad \overline{\gamma}_m] = \left[\min\left(\underline{\gamma}_n\underline{\gamma}_m, \underline{\gamma}_n\overline{\gamma}_m, \overline{\gamma}_n\underline{\gamma}_m, \overline{\gamma}_n\overline{\gamma}_m\right) \quad \max\left(\underline{\gamma}_n\underline{\gamma}_m, \underline{\gamma}_n\overline{\gamma}_m, \overline{\gamma}_n\underline{\gamma}_m, \overline{\gamma}_n\overline{\gamma}_m\right)\right]; \forall \{n, m \in \Omega_{\mathrm{N}}\} \tag{42}$$

$$[\underline{\gamma}_n \quad \overline{\gamma}_n] \div [\underline{\gamma}_m \quad \overline{\gamma}_m] = [\underline{\gamma}_n \quad \overline{\gamma}_n] \times \left[\frac{1}{\overline{\gamma}_m} \quad \frac{1}{\underline{\gamma}_m}\right]; \forall \{n, m \in \Omega_{\mathrm{N}}\} \tag{43}$$

$$\frac{1}{[\underline{\gamma}_n \quad \overline{\gamma}_n]} = \left[\frac{1}{\overline{\gamma}_n} \quad \frac{1}{\underline{\gamma}_n}\right]; \forall \{n \in \Omega_{\mathrm{N}}\}, 0 \notin [\underline{\gamma}_n \quad \overline{\gamma}_n] \tag{44}$$

Full details of properties related to the algebraic operations of interval numbers (e.g., associative commutative and distributive features) are out of the scope of this paper; readers refer to Ref. [136] for further information in this regard.

In interval arithmetic, intervals calculated from arithmetic are guaranteed to include all possible combinations of real values within the respective input intervals. This vital property ensures the completeness of range estimations. However, when UIPs are not independent, the output results will overestimate the actual ranges. In this condition, only the soundness of estimations is affected, not their completeness. Therefore, overestimation caused by interval dependency and wrapping is the main drawback of interval arithmetic. To eliminate these drawbacks, different versions of this technique were developed (please refer to Refs. [136,137]).

Almost all μMEHs' studies are presented in the form of optimization problems. Therefore, a step-by-step procedure to apply the interval arithmetic technique in the optimization process can be summarized as follows.

- Step 1: Defining the optimization problem: The objective function, constraint, and decision-making variables will be defined. These variables should be represented as intervals to capture the uncertainty in their values.
- Step 2: Determining the search domain: The search domain for each decision-making variable will be determined as an interval. This domain is the range of values that the decision-making variable can take.
- Step 3: Evaluating the objective function: The objective function will be evaluated at each point in the search domain defined by the intervals of decision-making variables. The result is a range of possible values for the objective function.
- Step 4: Finding the optimal solution: The range of possible values for the objective function over the entire search domain will be found, and then the interval with the smallest (or largest) possible value will be selected. This interval represents the range of values for the objective function corresponding to the optimal solution.
- Step 5: Checking for sensitivity: The objective function at different points near the optimal solution will be evaluated to determine how sensitive the solution is to small changes in the input decision-making variables. If the solution is sensitive, go to the next step; otherwise, go to Step 7.
- Step 6: Refining the search domain or modifying the objective function: The search domain for the input decision-making variables will be refined, or the objective function will be modified to obtain a more accurate solution. This process can be done by repeating Steps 3–5 with a smaller search domain for the input decision-making variables.
- Step 7: Validating the solution: The solution will be validated by verifying that it satisfies any constraints or requirements imposed by the optimization problem and is physically feasible.

The reader may look to Ref. [138] for a thorough explanation of interval arithmetic. Unfortunately, none of the articles in the database has relied on this technique for modeling uncertainties. However, considering this technique's powerful features in uncertainty modeling, its use in μMEHs' studies can be a rational choice for future research.

3.3.2.5. Robust optimization. Robust optimization (RO) examines the fluctuation effects of UIPs on the output of different optimization problems through uncertain sets [139]. As long as UIPs' values are within the permissible bounds of the uncertain set, the feasibility of the optimization problem's solution(s) can be guaranteed. The uncertain set selection is the key to this technique to address UIPs since it can be defined in different forms such as box, ellipsoidal, polyhedral, cone (closed, convex, pointed), convex, and others [139]. The concept of this technique has continued to develop and adapt. Nowadays, different versions and applications are being seen in various branches of science, such as engineering, marketing, and business management, that can be categorized into three models: i) engineering game, ii) two-stage, and iii) distributed RO models. The first model is related to the UIPs that try to worsen the performance index of the system while the decision-maker attempts to adopt a policy to optimize this index under all possible conditions [140]. This model has strong applicability to engineering problems. However, decisions taken by the decision-maker are overly conservative. The two-stage RO model can be used [141] to eliminate this weakness. The concept behind this model is to partition decision-making variables into adjustable and non-adjustable for staged decision-making. The decision-maker uses non-adjustable decision--making variables to make relevant decisions before UIPs are realized while altering adjustable ones according to UIPs. This process takes place based on affine adjustable RO or two-stage adaptive RO. The former utilizes an affine function to create affine links between adjustable decision-making variables and UIPs that they depend on. The latter has a more complex structure. However, it can provide more freedom to adjust the operational point (higher adaptation to UIPs), especially in the real-time exploration phase. The distributed RO model can also overcome the weakness related to relatively conservative decisions in other models [142]. In this model, the decision-maker creates an ambiguous set of PDFs according to a portion of UIPs' information and makes an optimal decision for the worst PDF of the fuzzy set. The distributed RO model relies on constructing fuzzy sets based on statistical moments and distance-based PDFs. To represent a generic description of the RO model, let y be a multivariate function of vectors γ and w, $y = f(\gamma, w); \forall \gamma = \{\gamma_1, \ldots, \gamma_n, \ldots, \gamma_{\mathrm{N}}\}, w = \{w_1, \ldots, w_m, \ldots, w_{\mathrm{M}}\}$, which is linear in γ and nonlinear in w. In contrast to the vector w that has known values, the values of the vector γ are subjected to uncertainties and defined using uncertainty set $\gamma \in \mathrm{U}(\gamma) = \{\gamma_1, \ldots, \gamma_n, \ldots, \gamma_{\mathrm{N}}\}$. Precisely, the vector γ can take values from the relevant set $\mathrm{U}(\gamma)$. Then, the general description of the RO model can be defined using Equations (45) and (46):

$$\underset{w}{\text{Maximize}}\ y = f(\gamma, w); \forall \gamma = \{\gamma_1, \ldots, \gamma_n, \ldots, \gamma_N\}, w = \{w_1, \ldots, w_m, \ldots, w_M\} \tag{45}$$

where:

$$\gamma \in U(\gamma) = \{\gamma_1, \ldots, \gamma_n, \ldots, \gamma_N\} \tag{46}$$

With a linear relationship between y and the vector γ, the RO model defined in Equations (45) and (46) can be rewritten as Equation (47) through (50):

$$\underset{w}{\text{Maximize}}\ y \tag{47}$$

subject to:

$$y \leq f(\widetilde{\gamma}, w); \forall \widetilde{\gamma} = \{\widetilde{\gamma}_1, \ldots, \widetilde{\gamma}_n, \ldots, \widetilde{\gamma}_N\}, w = \{w_1, \ldots, w_m, \ldots, w_M\} \tag{48}$$

$$h(\widetilde{\gamma}, w) = V(w).\widetilde{\gamma} + g(w); \forall \widetilde{\gamma} = \{\widetilde{\gamma}_1, \ldots, \widetilde{\gamma}_n, \ldots, \widetilde{\gamma}_N\}, w = \{w_1, \ldots, w_m, \ldots, w_M\} \tag{49}$$

$$\widetilde{\gamma} \in U(\gamma) = \{\gamma \| \gamma - \overline{\gamma}| \leq \dot{\gamma}\}; \forall \gamma = \{\gamma_1, \ldots, \gamma_n, \ldots, \gamma_N\}, \widetilde{\gamma} = \{\widetilde{\gamma}_1, \ldots, \widetilde{\gamma}_n, \ldots, \widetilde{\gamma}_N\}, \overline{\gamma} = \{\overline{\gamma}_1, \ldots, \overline{\gamma}_n, \ldots, \overline{\gamma}_N\}, \dot{\gamma} = \{\dot{\gamma}_1, \ldots, \dot{\gamma}_n, \ldots, \dot{\gamma}_N\} \tag{50}$$

In these Equations, $\widetilde{\gamma}$, $\overline{\gamma}$, and $\dot{\gamma}$ are the vector of uncertain values, the vector of estimated values and the vector of maximum possible deviation of γ from $\overline{\gamma}$, respectively. This technique aims to find a solution(s) that maximizes the objective function y and ensures the decision-maker that its value remains optimal with a high probability when some forecast errors exist about the values of the vector γ. A counterpart version of the RO model presented in Equation (47) through (50) should be built and solved to reach this target. The robust counterpart is described using Equation (51) through (55):

$$\underset{w}{\text{Maximize}}\ y \tag{51}$$

$$y \leq f(\gamma, w); \forall \gamma = \{\gamma_1, \ldots, \gamma_n, \ldots, \gamma_N\}, w = \{w_1, \ldots, w_m, \ldots, w_M\} \tag{52}$$

$$f(\gamma, w) = V(w).\overline{\gamma} + g(w) - \underset{u_i}{\text{Maximize}} \sum_{i=1}^{I} v_i(w).\dot{\gamma}_i.u_i; \forall \gamma = \{\gamma_1, \ldots, \gamma_n, \ldots, \gamma_N\}, w = \{w_1, \ldots, w_m, \ldots, w_M\}, \overline{\gamma} = \{\overline{\gamma}_1, \ldots, \overline{\gamma}_n, \ldots, \overline{\gamma}_N\}, \{i \in \Omega_I\} \tag{53}$$

$$\sum_{i=1}^{I} u_i \leq \psi; \forall \{i \in \Omega_I\} \tag{54}$$

$$0 \leq u_i \leq 1; \forall \{i \in \Omega_I\} \tag{55}$$

According to the robust counterpart structure, see Equation (51) through (55), two nested optimization problems must be solved. Equation (53) is linear with respect to u_i, and its dual form that can be described using Equations (56) and (57):

$$\text{Minimize} \left[\psi.\alpha + \sum_{i=1}^{I} \delta_i\right]; \forall \{i \in \Omega_I\} \tag{56}$$

$$\alpha + \delta_i \geq v_i(w).\dot{\gamma}_i; \forall \{i \in \Omega_I\} \tag{57}$$

Inserting dual form into the robust counterpart structure gives the model presented in Equation (58) through (61):

$$\underset{w,\alpha,\delta_i}{\text{Maximize}}\ y \tag{58}$$

$$y \leq f(\gamma, w); \forall \gamma = \{\gamma_1, \ldots, \gamma_n, \ldots, \gamma_N\}, w = \{w_1, \ldots, w_m, \ldots, w_M\} \tag{59}$$

$$f(\gamma, w) = V(w).\overline{\gamma} + g(w) - \psi.\alpha + \sum_{i=1}^{I} \delta_i; \forall \gamma = \{\gamma_1, \ldots, \gamma_n, \ldots, \gamma_N\}, w = \{w_1, \ldots, w_m, \ldots, w_M\}, \{i \in \Omega_I\} \tag{60}$$

$$\alpha + \delta_i \geq V(w_i).\dot{\gamma}_i; \forall \{i \in \Omega_I\} \tag{61}$$

A detailed discussion of the RO technique is outside the scope of this paper. For a complete overview of this technique, please refer to Ref. [139]. Among μMEHs' studies available in the database, four studies have focused on the RO strategy to address the effect of UIPs on the design and operation process of the μMEHs [32,84,112,119]. The authors of [32] have investigated the impact of UIPs (CO_2 cost, primary energy saving, fuel tariff, and electricity prices) on designing different technologies for a μMEH. By examining different levels of conservatism on the mean and standard deviation of the objective function and analyzing the results, this reference has concluded that the deterministic model is preferable. However, it seems that this result is not so much resealable. Reported models in Refs. [84,112,119] have incorporated different UIPs (see details in Table A3) in the operation process of μMEHs. The simulation results in these studies have converged to the conclusion that using the RO model to deal with the effects of UIPs can assist the operator in improving the operation process of the μMEH from different perspectives.

3.3.2.6. Information gap decision theory. The IGDT is a potent and radically different tool for making rational decisions under a severe lack of information (e.g., the deficiency or absence of historical data to construct PDFs or MFs of UIPs) [143]. The main difference between the IGDT and other techniques is how UIPs are modeled. Unlike other techniques that rely heavily on PDFs, MFs, uncertain sets, and others, this theory uses information gaps to model these parameters. In this theory, each UIP is modeled as an information gap (the distance between prediction and reality), not a probability [143]. Therefore, there is no need for any initial data from the UIP (e.g., PDF, MFs, and uncertain sets). Let us define the general form of an optimization problem related to the μMEHs' studies using Equation (62) through (66):

$$\underset{x,\gamma}{\text{Minimize}}\ f(x, \gamma) \tag{62}$$

subject to:

$$g_b(x, \gamma) = 0; \forall \{b \in \Omega_B\} \tag{63}$$

$$h_e(x, \gamma) \leq 0; \forall \{e \in \Omega_E\} \tag{64}$$

$$x = \{x_1, \ldots, x_m, \ldots, x_M\}; \forall \{m \in \Omega_M\} \tag{65}$$

$$\gamma = \{\gamma_1, \ldots, \gamma_n, \ldots, \gamma_N\}; \forall \{n \in \Omega_N\} \tag{66}$$

Equations (63) and (64) describe the equality constraint b and inequality constraint e of the optimization problem. In addition, Equations (65) and (66) represent certain and uncertain decision-making variables. Also, let us define the UIP n using the envelope-bound model of IGDT, as described in Equation (67):

$$U^n(\Delta_n, \gamma_n) = \left\{\widetilde{\gamma}_n : \frac{|\widetilde{\gamma}_n - \gamma_n|}{\gamma_n} \leq \Delta_n\right\}; \forall \{\Delta_n \geq 0\}, \{\widetilde{\gamma}_n \in U(\Delta_n, \gamma_n)\}, \{n \in \Omega_N\} \tag{67}$$

Equation (67) describes the length of the information gap of the UIP n between the expected (predicted) value, γ_n, and the value that may occur (actual value), $\widetilde{\gamma}_n$. If the actual value of UIP n is equal to the predicted value of this uncertain parameter, the interval of UIP n, Δ_n, will be equal to zero; otherwise, this parameter will be equal to a positive value. It should be noted that the magnitude of deviation related to this parameter from the predicted value will not exceed the length of the relevant information gap Δ_n [143]. Fig. 5 Illustrates how the robustness region of this parameter is described using Equation (68):

$$\upsilon_n = [\,(1 - \Delta_n).\gamma_n \quad (1 + \Delta_n).\gamma_n\,]; \forall \{n \in \Omega_N\} \tag{68}$$

Now, a key question is raised: How the optimization problem should be handled if realized values of UIPs differ from the predicted ones? In

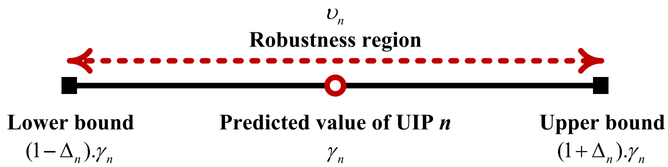

Fig. 5. The robustness region associated with the UIP *n*.

such circumstances, the decision-maker can use two different policies, risk-averse and risk-taker policies, to puzzle out the optimization problem.

- Risk-averse decision-making policy: Robustness function

This policy scrutinizes the detrimental effects of UIPs on optimizing the μMEHs' studies. The decision-maker tries to obtain optimal decision-making variables (robust decisions) to hedge her\his decisions against risks arising from severe UIPs. In this condition, the robustness function addresses the greatest level of UIPs, such that the maximum value of the objective function cannot be greater than a predetermined critical value. The robustness function is, therefore, the degree of resistance against UIPs and immunity against smaller values of the objective function at which defeat cannot arise. It means that a large value of the robustness function is desirable in the optimization problems in the minimization form. The robustness function for the optimization problem presented in Equation (62) through (66) can be expressed using Equation (69) through (73):

$$\Upsilon(x,\varpi_c)=\underset{\Delta_n}{\text{Maximize}}\left\{(\Delta_n):\underset{\tilde{\gamma}_n\in\Pi^n(\Delta_n,\gamma_n)}{\overset{x}{\text{Maximize}}} f(x,\tilde{\gamma}_n)\le\varpi_c\right\};\forall\{\Delta_n\ge 0\},\{n\in\Omega_N\} \tag{69}$$

subject to:

$$\underset{\tilde{\gamma}_n}{\overset{x}{\text{Maximize}}}\ \{\text{Equation (62)}\le\varpi_c\};\forall\{\tilde{\gamma}_n=(1+\Delta_n).\gamma_n\},\{n\in\Omega_N\} \tag{70}$$

$$\tilde{\gamma}_n\le(1+\Delta_n).\gamma_n;\forall\{n\in\Omega_N\} \tag{71}$$

$$\tilde{\gamma}_n\ge(1-\Delta_n).\gamma_n;\forall\{n\in\Omega_N\} \tag{72}$$

$$\{\text{Equation (63) through Equation (66)}\}|\tilde{\gamma}_n;\forall\{\tilde{\gamma}_n=(1+\Delta_n).\gamma_n\},\{n\in\Omega_N\} \tag{73}$$

In Equation (69), the predetermined critical value of the objective function, ϖ_c, is obtained using Equation (74):

$$\varpi_c=(1+\omega_c).\varpi_b \tag{74}$$

In Equation (74), the base value of the objective function, ϖ_b, is obtained by solving the optimization problem of the μMEHs' studies presented in Equation (62) through (66) by considering the predicted values for UIPs (deterministic\risk-neutral decision-making policy). It is necessary to mention that ω_c is the critical cost deviation factor of the optimization problem determined by the decision-maker.

- Risk-taker decision-making policy: Opportunity function

This policy examines the propitious face of UIPs in the optimization process of the μMEHs' studies. The decision-maker tries to obtain optimal decision-making variables (opportunistic decisions) to take advantage of the risks arising from severe UIPs. In this condition, the opportunity function illustrates the smallest level of the UIPs, such that the objective function's minimum value can be as small as a predetermined target value. Therefore, the opportunity function is immunity against a windfall reward, where sweeping success can occur. It means that a small value of the opportunity function is desirable in the optimization problems in the minimization form. The opportunity function for the optimization problem presented in Equation (62) through (66) can be described using Equation (75) through (79):

$$\Gamma(x,\varpi_t)=\underset{\Delta_n}{\text{Minimize}}\left\{(\Delta_n):\underset{\tilde{\gamma}_n\in\Pi^n(\Delta_n,\gamma_n)}{\overset{x}{\text{Minimize}}} f(x,\tilde{\gamma}_n)\le\varpi_t\right\};\forall\{\Delta_n\ge 0\},\{n\in\Omega_N\} \tag{75}$$

subject to:

$$\underset{\tilde{\gamma}_n}{\overset{x}{\text{Minimize}}}\ \{\text{Equation (62)}\le\varpi_t\};\forall\{\tilde{\gamma}_n=(1-\Delta^n).\gamma_n\},\{n\in\Omega_N\} \tag{76}$$

$$\tilde{\gamma}_n\le(1+\Delta_n).\gamma_n;\forall\{n\in\Omega_N\} \tag{77}$$

$$\tilde{\gamma}_n\ge(1-\Delta_n).\gamma_n;\forall\{n\in\Omega_N\} \tag{78}$$

$$\{\text{Equation (63) through Equation (66)}\}|\tilde{\gamma}_n;\forall\{\tilde{\gamma}_n=(1-\Delta_n).\gamma_n\},\{n\in\Omega_N\} \tag{79}$$

In Equation (75), the predetermined target value of the objective function, ϖ_t, is obtained using Equation (80):

$$\varpi_t=(1+\omega_t).\varpi_b \tag{80}$$

The calculation process of the base value of the objective function (ϖ_b), in Equation (80), is like the process described in the risk-averse decision-making policy. Furthermore, ω_t is the target cost deviation factor of the optimization problem determined by the decision-maker.

Among μMEHs' studies available in the database, only two studies have used the IGDT to examine the effect of UIPs on the operation process of the μMEHs [97,118]. The objective function of both studies is to decrease the operation and emission costs. These studies show that the IGDT assists the decision-maker in making robust decisions against severe UIPs, especially the gas price, to reduce operation and emission costs.

As a result, a deep understanding of appropriate and powerful strategies for modeling and integrating different types of uncertainties in mathematical models and adapting these models as much as possible to actual conditions is felt. To cover this need, Table A4 presents each technique's main idea, well-known examples, strengths, and weaknesses and reviews the literature based on them. It is evident from Table A4 that most of the μMEHs' studies have relied on traditional techniques for scrutinizing UIPs. These techniques have the appropriate speed, acceptable accuracy, and a relatively simple implementation process. However, they suffer from a fundamental weakness. These techniques require the PDFs and/or MFs of UIPs to scrutinize them. In real-world conditions, however, there is insufficient data to construct PDFs and/or MFs with acceptable accuracy for most UIPs. There is a need, then, for powerful techniques such as interval arithmetic, RO, and especially IGDT to model severe UIPs whose PDFs and/or FMFs are unknown.

4. Problem-solving process

The problem-solving process in μMEHs' studies can be investigated from the optimization problem structure and solution method. Technically speaking, most optimization problems related to μMEHs' studies are complex, practical, nonconvex problems embracing a non-linear and blended-integer essence [5,10,17]. However, with the increase of interactions between different energy carriers because of the use of new multi-carrier energy conversion technologies, updating of local multi-carrier energy market's rules, moving towards maximum use of RERs, clarification of new environmental standards to reduce greenhouse gas emissions, and others, finding an optimal solution(s) for these optimization problems can be much more complicated than before. Most research publications abide by two distinct policies to tackle the complexities of the optimization problems of μMEHs' studies. In the first policy, publications examined only a primitive structure of optimization problems.

These publications rely on a single-objective and single-level optimization model, disregard risks resulting from severe uncertainties, regard hypothetical case studies, and neglect practical limitations–to name a few. Accordingly, such models of μMEHs lack adequate efficiency to adapt to real-world conditions. In the second policy, however, publications consider a more complex structure of optimization problems. Nevertheless, solving such complex optimization problems is fraught with different challenges. Instead of embracing and handling these challenges, most publications summon some relaxation (e.g., linearization of non-linear models). These relaxations cause the outputs obtained from the solving process to be inconsistent with the actual conditions. Most of the considered simplifications in optimization problems related to μMEH's studies are due to current shortcomings in the second aspect of the problem-solving process (solution methods).

4.1. Solution method

Table A5 presents a comprehensive classification of the solution methods, including solution approaches, solvers, and software used to solve optimization problems related to μMEHs' studies. In the broadest sense, solution methods used to solve the optimization problems concerning μMEHs' studies can be categorized into three major classes: i) deterministic methods, ii) stochastic-based methods, and iii) stochastic-learning methods (see Table A5).

4.1.1. Deterministic methods

From Table A5, deterministic methods that include different solution approaches are the most widely used class for handling the relevant optimization problems. However, it should be noted that each solution approach of this class has been developed to solve a narrow range of optimization problems, and no specific one can solve a wide range of problems. Among all solution approaches, solvers, and software related to the deterministic methods, the mixed-integer linear programming approach, CPLEX solver, and GAMS software are the most popular combination. Full details associated with deterministic methods can be seen in Table A5. Most solution approaches in the class of deterministic methods follow an exact process and rely on objective function(s) derivatives to handle the optimization process. However, the objective function of optimization problems related to practical cases of μMEHs' studies involves complexities such as mixed decision-making variables, non-differentiability, non-linearity, high multimodality, and discontinuity, as well as comprise many local minima. Moreover, the search space and/or dimensions of the optimization problem may be so large that the global optimum cannot be found in a reasonable amount of time. In this condition, deterministic methods may not be efficient enough to find a quality solution. Precisely, the solution obtained from these methods relates to the optimization problem with a simplified structure and cannot be considered the optimal solution for the original non-simplified optimization problem. Hence, stochastic-based methods relying on the random search process can be a promising alternative.

4.1.2. Stochastic-based methods

Stochastic-based methods consist of two submethods: i) heuristic and ii) meta-heuristic. The heuristic submethod relies on the trial-and-error process to find the solution to the optimization problem.

This submethod can reach an acceptable solution to optimization problems, especially large-scale and practical ones, in a reasonable time. However, since its stopping criterion is often the lack of improvement in two consecutive solutions, it may stop even though it has not reached the optimal solution. Therefore, the heuristic submethod cannot guarantee the optimality of the obtained solution(s). None of the papers in the database used a heuristic submethod to solve the optimization problem μMEHs' studies. Meta-heuristic submethod was suggested to eliminate the weaknesses of the heuristic one. These techniques solve the optimization problem regardless of its structure. Therefore, they can solve a more comprehensive range of optimization problems. These techniques rely on a memory of data obtained from previous iterations to search the feasible search space and find the globally optimal solution (s). Further information about the structure and the differences between various techniques of this submethod can be found in Ref. [144]. It is clear from Table A5 that the use of the metaheuristic submethod in μMEHs' studies is much less favoured compared to exact ones despite their relatively acceptable performance. It may be due to the complexity of implementation optimization problems related to μMEHs' studies with this submethod. Different techniques of this submethod have been used to solve various structures of the optimization problem related to the design [38,64,65,74,80,85,96,98,99,101,115], operation [58–60,79,94,109,114], and resilience [73,76,91] of μMEHs' studies. By examining the results of references related to the design problem of μMEHs' studies, it can be found that these techniques have obtained a well-suited cluster of equipment for the μMEH that meets TE&E criteria. This suitable performance for metaheuristic techniques is also observed in operation and resilience of μMEHs. More precisely, these studies show that metaheuristic techniques offer several advantages. First, they are flexible and can be applied to various optimization problem domains or structures of μMEHs' studies, from design to operation and even resilience. Next, they can quickly and efficiently explore large search spaces and find the optimal or near-optimal solution(s) in a reasonable amount of time. In addition, they can handle optimization problems with noisy or incomplete data and continue searching for the optimal solution(s) even when faced with unforeseen changes or disruptions. Furthermore, they do not require prior knowledge of the problem structure or search space (suitable for problems where the underlying structure is unknown or difficult to model). However, the main drawback of these techniques is that their performance depends on the parameter settings. Therefore, the initial value of these parameters significantly impacts the speed, efficiency, and quality of the solution(s) found by the technique. As a result, the proper choice of the technique and its parameters setting should be carefully considered based on the specific optimization problem of μMEHs' studies to ensure the best possible results. In practical cases, it is also necessary to experiment with different parameter settings and evaluate the technique's performance using appropriate metrics to select better initial values.

4.1.3. Stochastic learning methods

In optimization problems based on the decision maker's preference, the decision maker's actions can affect the immediate reward, the following situation, and the subsequent reward. Practically speaking, μMEHs' studies, especially the operation of the μMEH, are entirely compatible with the structure of such optimization problems. The stochastic learning methods, therefore, can be a suitable option to solve such optimization problems. These methods solve the optimization problem related to μMEHs' studies by updating the solution over time; hence, they do not depend on the details associated with the μMEH's dynamic. However, only one study from the relevant database of research papers has used the reinforcement learning method to solve the optimization problem associated with the operation of the μMEH [33]. This study has shown that the reinforcement learning method does not require any details about the dynamic of the μMEH. More precisely, this method swiftly converges to a near-optimal solution and updates the solution during the time; hence, it does not face any impediments by changing the dynamic of the μMEH. Another strength of this method is its high adaptability to implement in the real-time frame to optimally control all significant energy loads, storage, and generation devices by considering the customers' comfort level. The simulation results have confirmed the efficiency of the reinforcement learning method by demonstrating up to 40% reduction in the electricity and gas cost and a 17% and 50% reduction in peak load and carbon dioxide emission, respectively. As a result, since optimization problems of μMEHs' studies are complex, practical, non-convex problems embracing a nonlinear and blended-integer essence, it is acceptable to use simplifications at different levels to use various solvers of exact methods. However, researchers can avoid oversimplifications that cause a drastic transformation between the structure of the original optimization problem and the simplified one. These oversimplifications enormously reduce the compatibility of the solution(s) obtained from the simplified optimization problem with the actual condition of the original one. Using stochastic and stochastic learning methods and comparing results with the results of exact methods to determine the more efficient methods for solving the optimization problems of μMEHs' studies can contribute to covering gaps in the problem-solving process.

4.2. Decision-making analysis

Different models reported in the literature of μMEHs' studies contain several non-commensurable, conflicting, and correlated objective functions. Therefore, these studies consider two schemes for decision-making analysis in their optimization problems: single-objective and multi-objective. Table A6 categorizes μMEHs' studies from the standpoint of the scheme used for decision-making analysis.

In the first scheme that most of the μMEHs' studies have relied on (see Table A6), different objective functions are combined to form an equivalent objective function and solved with a typical single-objective solver. This scheme's principal target is to find a specific minimum or maximum value for the equivalent objective function (optimal solution) under the predetermined limitations, if any. This scheme simplifies the problem-solving process by moving the decision-making phase before the optimization phase. However, this transfer forces the decision-maker to adopt his/her preferences without knowledge. Therefore, the solution obtained from solving the single-objective optimization problem cannot provide a realistic view of the main structure of the optimization algorithm. In the second scheme, however, different objective functions are simultaneously optimized. Precisely, the main goal of this scheme is to find the Pareto-optimal solution set and then select the most satisfactory solution from them, considering the decision maker's preferences. Therefore, in this scheme, the decision-making phase is located after the optimization one or combined with it to create a hybrid phase. This scheme enables decision-makers to determine their preferences with a higher understanding of the optimization problem; scrutinize the interdependencies between decision-making variables, objective functions, and constraints; and finally, make a more knowledgeable choice among the Pareto-optimal solution set. Therefore, the final solution from the Pareto-optimal solution set aligns better with real-world conditions and matches the decision maker's preferences. In the presence of multiple non-commensurable, conflicting, and correlated objective functions in optimization problems related to μMEHs' studies, the most rational decision is to use the second scheme to solve the optimization problem. However, it increases the complexity of the solving process considerably. For more information about multi-objective optimization and decision-making analysis, please refer to Ref. [145]. From Table A6, only 16 and 3 out of 97 papers have used the bi- and tri-objective decision-making analysis in their optimization problems, respectively. As a result, according to the existing capacity, it is expected that new studies in the field of the μMEH will be more inclined to use the multi-objective optimization process to solve their optimization problems to embrace its benefits.

Many multi-objective optimization techniques have been developed in related literature to find the Pareto-optimal solution set and select the final optimal solution. In a general sense, these techniques can be broken down into non-interactive and interactive according to the role of the decision-maker in the solution process [146–148]. Non-interactive techniques do not require any involvement from the decision-maker during the optimization process. Instead, they generate diverse and non-dominated solutions, and the decision-maker selects the solution that best meets their needs [148]. Interactive techniques, however, involve the decision-maker in the optimization process. The decision-maker provides feedback on their generated solutions, which guides the search process towards the desired solution [147]. It is necessary to mention that evolutionary multi-objective techniques can be either interactive or non-interactive, depending on the implementation method to involve the decision-maker's decisions in the optimization process [146]. Detailed discussion about multi-objective optimization techniques and decision-making can be found in Ref. [145]. Table A7 presents each technique's fundamental idea, advantages, disadvantages, and familiar examples and reviews the literature of μMEHs' studies that used multi-objective decision-making analysis in their optimization problems based on them. From this table, it can be found that μMEHs' studies that focused on the use of multi-objective decision-making schemes in the optimization process used the basic category (e.g., weighting and ε-constraint methods) or evolutionary multi-objective techniques in the form of a non-interactive technique to obtain the Pareto optimal solution set. These studies have preferred the simplicity of implementing these techniques to their weaknesses against interactive techniques. However, future research is expected to use interactive techniques to solve the optimization problems of μMEHs' studies and obtain Pareto optimal solution set since these techniques facilitate decision-making and enable decision-makers to explore the trade-offs between conflicting objectives dynamically.

5. Limits and prospects

In the last decade, many studies have documented the necessity of integrating different energy infrastructures to achieve security, technical, economic, and environmental objectives. To pave this direction, a considerable part of these studies is focused on introducing, applying, and developing the EH concept as an efficient tool for modeling multi-carrier IESs. Therefore, an acceptable level of maturity can be seen in the literature related to multi-carrier EH-based IESs. In recent years, modeling buildings (e.g., industrial, residential, commercial, office, or public buildings) in the form of multi-carrier IESs using the EH concept, μMEHs, has become an attractive trend in energy studies. However, maturity is lost when the literature on multi-carrier IESs is narrowed down to μMEHs, and different problems and challenges will appear. In this paper, the authors have examined these systems from perspectives of uncertainty and problem-solving process. A Sankey chart is illustrated in Fig. 6 to create an accurate understanding of the relevance of μMEHs' studies in these perspectives. It should be noted that the description related to the abbreviations used in Fig. 6 is like the description in Table A5.

By using this figure and analysis done in previous sections of the paper, the main existing challenges and potential future research, trend, and capacities in μMEHs' studies can be expressed as follows.

- Uncertainty: Uncertainty considerations have been ignored in most μMEHs' studies. Ignoring uncertainties leads to results that are the least compatible with real-world conditions and, as a result, presents an unrealistic image of the μMEH's performance. In the first step, future studies are expected to be conducted with different uncertainties. Multi-carrier energy prices and demands are integral to uncertainty modeling in μMEH's studies. Existing studies have also examined them in detail. However, increasing interaction between different energy carriers due to using new equipment and rules changes the severity, importance, and effects of uncertainties. Therefore, in the second step, future research is expected to update uncertainties with efficient tools (e.g., uncertainty matrix) and use

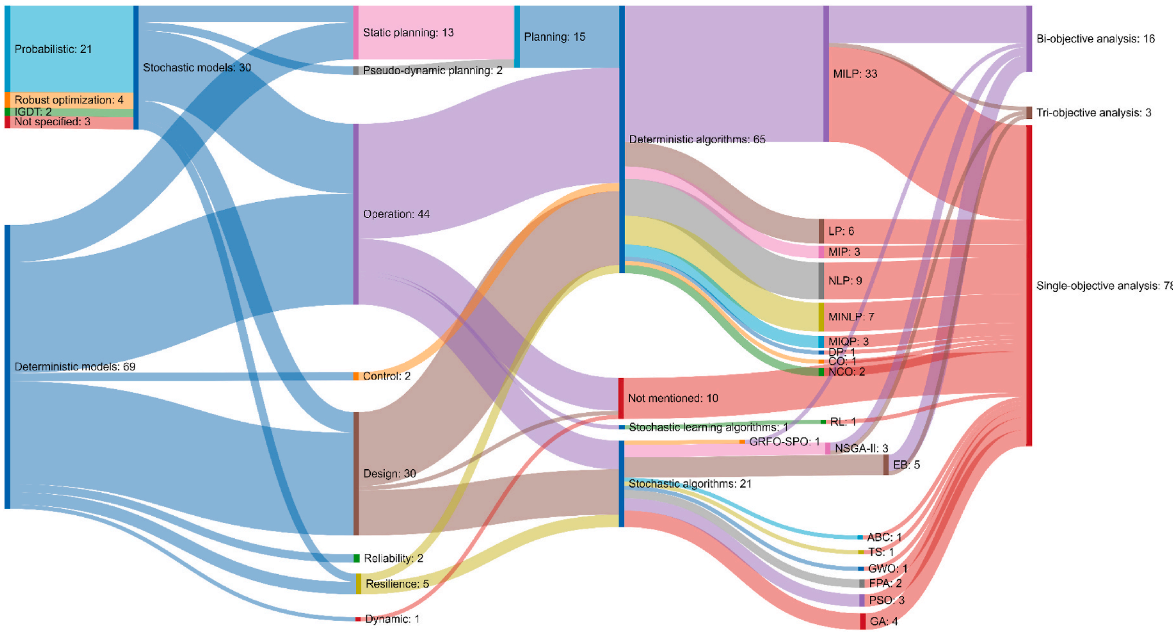

Fig. 6. The Sankey chart for classifying and linking μMEHs' studies from different perspectives.

an updated combination of uncertainties instead of focusing on common ones.

- Sensitivity analysis techniques: Sensitivity analysis in most of μMEH's studies was wrongly estimated because they investigate bounded fluctuations of UIPs on the objective function(s) value, examine the sensitivity of the objective function(s) to the UIPs individually, and do not consider the correlation between different UIPs, which are common features of practical models. Therefore, future research in μMEH's studies is expected to use more efficient techniques to investigate sensitivity considering all aspects of practical models.
- Uncertainty analysis techniques: An overemphasis on using traditional techniques to model uncertainties is observed in μMEHs' studies. These techniques need the PDFs and/or MFs of UIPs to model and investigate them. However, access to such data is impossible in many real-world cases. Therefore, using modern techniques (e.g., interval arithmetic, RO and IGDT) that integrate, model, and scrutinize the effects of uncertainties without access to their initial data can be an attractive path for future research in μMEHs' studies.
- Solution approach: Different solvers from deterministic methods have been widely used to find the solution(s) to the optimization problems related to μMEHs' studies. These solvers require different levels of simplifications in optimization problems depending on the procedure to find the solution(s). Under this circumstance, the founded solution(s) is optimal for the simplified optimization problem structure and cannot be generalized to the original structure of the problem. Therefore, it is suggested to rely on alternative methods (e.g., stochastic method and stochastic learning method) to solve optimization problems associated with μMEHs' studies in future research or on using solvers that require lower levels of simplifications. This process makes the founded solution(s) more compatible with the original structure of the optimization problem.

- Decision-making analysis: The single-objective analysis is the dominant scheme for decision-making analysis in optimization problems related to μMEHs' studies. This scheme transfers the decision-making phase to before the optimization phase. Under this circumstance, the decision maker's preferences are chosen without knowledge, which reduces the obtained solution's adaptability with the optimization problem's original structure. Therefore, more studies are expected to be done using multi-objective analysis. Also, all μMEHs' studies used non-interactive techniques to solve the multi-objective optimization problem and obtain the Pareto optimal solution set. These techniques have many weaknesses (see details in Table A7); therefore, future research is expected to rely on interactive techniques.

6. Conclusion remarks

The main driver for this work was that, despite a maturity in the multi-carrier EH-based IESs that are located on broad scales, there is confusion in the literature for readers regarding a unique and in-depth audit (e.g., uncertainty and problem-solving process) of limited scales multi-carrier EH-based IESs (e.g., buildings or district scales). Therefore, this article has aimed at bridging this gap by presenting a critical review of the principal features and modeling techniques of uncertainties as well as the optimization problem structure and solution methods (approach, solver, software) in multi-carrier EH-based IESs applications, focusing on the neighborhood level, backed by the recent publications in this field. The obtained review outcomes demonstrate that several open questions have still remained in μMEHs' studies regarding uncertainty and problem-solving process.

Of these problems in μMEHs' studies, ignoring uncertainties through developing models based on the deterministic policy, disregarding new and high-impact UIPs through an excessive focus on common UIPs, omitting powerful techniques to scrutinize UIPs via an overemphasis on traditional ones, neglecting the powerful solution methods to handle the original structure of the optimization problem by relying on solution methods that require oversimplifying the optimization problem's structure, and dismissing the multi-objective analysis by transferring the decision-making phase before the optimization in the single-objective analysis seem outstanding. Based on the above discussion, this paper presented potential future research, trend, and capacities to relax these problems. These capacities can pave new paths to reach more realistic frameworks in future μMEHs studies. Future research to back this review aims to investigate the structure (multi-carrier energy resources and demands as well as energy conversion and storage technologies) and analysis methods (dynamic, operation, control, design, planning, reliability, and resilience) of μMEHs, which the authors are currently doing.

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.

Data availability

Data will be made available on request.

Appendix

Table A1
Review papers in the field of multi-carrier EH-based IESs.

Ref.	Highlight	Published year
[3]	Presenting a critical discussion of models and assessment approaches of multi-carrier IESs from different perspectives as well as various criteria for their TE&E evaluation	2014
[6]	Categorizing various modeling and optimization frameworks of optimal operation related to multi-carrier EH-based IESs in uncertain environments	2017
[7]	Classifying multi-carrier EH-based IESs in terms of their structure (e.g., inputs, outputs, converters, and storage systems)	2017
[8]	Examining main aspects and potential research topics on demand side management programs in multi-carrier EH-based IESs	2017
[9]	Providing a thorough study of concepts and applications of multi-carrier EH-based IESs in various energy sectors	2018
[10]	Arranging multi-carrier EH-based IESs according to modeling methods, applications, and TE&E considerations	2019
[5]	Overviewing multi-carrier EH-based IESs with an emphasis on the operation and expansion planning problems of such systems	2019
[11]	Evaluating demand side management programs in multi-carrier EH-based IESs from different perspectives	2020
[12]	Investigating the design and operation process of multi-carrier EH-based IESs in terms of optimization problems features (e.g., models, objectives, algorithms)	2020
[13]	Scrutinizing different models developed for the operation and performance evaluation of multi-carrier IESs	2020
[14]	Assessing the economics and reliability indices related to the performance of multi-carrier EH-based IESs and energy storage systems	2021
[15]	Labeling multi-carrier EH-based IESs according to design methods, topologies, input-output energy carriers, and elements	2021
[1]	Organizing the prominent problems and solutions related to multi-carrier EH-based IESs	*2022*
[16]	Studying multi-carrier IESs in terms of time and space, uncertainty, energy behavior, and energy transition	2022
[17]	Analyzing smart multi-carrier EH-based IESs in terms of uncertainty modeling, optimization challenges, and performance	2022

Table A2
The classification of μMEH's studies regarding analysis methods.

Analysis method	Definition	Reference
Design	Finding the optimal combination and size of various components of the μMEH from TE&E perspectives to satisfy multi-carrier energy demands	[25,27,30,38,41,45,52,53,55,61,62,64,65,73–75,77,78,80, 85,89,92,96,99,101,103,104,107,115,121]
Planning	Finding the optimal decision(s) to invest in the expansion of the μMEH's structure from TE&E perspectives to meet future multi-carrier energy demands	Static [29,42,43,86,87,90,102,105,111]: Pseudo-dynamic [32,71,83,108,110,116]:
Operation	Seeking to find an optimal schedule(s) for existing components in the μMEH to generate, convert, transfer, and distribute different energy carriers to minimize/maximize TE&E objectives under predetermined limitations, if any	[26,28,31,33–37,40,44,46–51,54,56–60,63,66–70,79,81,82, 84,88,93,94,97,106,109,112–114], [117–119]
Dynamic	Investigating dynamic aspects of different components of the μMEH that couple multiple energy carriers under normal and abnormal operating conditions	[39]
Control	Using various strategies to determine and coordinate the actions of different components in the μMEH or a cluster of μMEHs to manage the multi-carrier energy flow in their structures	[72,120]
Reliability	Examining the existence of sufficient facilities to produce, convert, transfer, and distribute different carriers to meet multi-carrier energy demands as well as the ability to respond to local and widespread dynamic and transient disturbances to which the μMEH is exposed	[122,123]
Resilience	Evaluating the ability of the μMEH to i) anticipate, withstand, and minimize impacts of natural and/or man-made low-frequency high-impact disasters and/or faults, ii) bounce back to the pre-disrupting condition in the shortest possible time, and iii) adapt to respond to newly emerging threats more effectively	[76,91,95,98,100]

Table A5
A classification of the solution methods, including the solution approaches, solvers, and software used to solve optimization problems related to μMEHs' studies.

Class	Solution	Ref.	Class	Solution	Ref.

(continued on next page)

Table A3
The uncertainty matrix for UIPs in μMEHs' studies.

The UIP	Ref.	Dimension of the UIP											
		Nature		Level			Location						
		Epistemic uncertainty	Variability uncertainty	Statistical uncertainty	Scenario uncertainty	Recognized ignorance	Context	Model uncertainty		Inputs		Parameter uncertainty	Model outcomes
								Model structure	Model technical	External driving forces	System data		
Energy price	EL: [28,32,40,61,63,68,69,73,84,90,94,104,108], GA: [28,32,61,63,69,90,97,104,108,118], HE: [28], FF: [40], BI: [61,104], WA [90]:		*	*							*		
Energy demand	EL: [32,40,46,61,63,68–70,73,87,90,93,95,97,101,108, 112,115,118,119], HE: [32,40,61,68,69,73,75,90,93,95, 101,104,108,109,112,115,118,119], CO: [32,68,75,97, 101,112,115,118,119], WA: [90], HY [118]:		*		*						*		
Production capacity of RERs	PV: [46,51,61,68–70,73,75,76,81,83,90,91,93,94,97,101, 106,112,115,118,119], WT: [69,73,75,81,90,97,118,119], TI [90]:		*		*						*		
Cost	IN: [32,61,108,110], O&M: [32,108], CO2 emission [32]:		*		*							*	
Energy charged to and energy discharged from the storage	HE [40,61]:		*	*						*			
Energy imported to and energy produced from the converter	HE [40]:		*	*						*			
Efficiency of converters	[61]	*				*				*			
Charge/ discharged rate of the storage	HE [61]:		*		*						*		
Loss of the storage	EL: [61], HE [61]:		*	*							*		
Emission factor	CO_2 emission [61]:	*			*					*			
The efficiency of the upstream network	DHN [61]:	*				*				*			
Electrical load curtailment	[73]		*		*							*	
Network outage	EN, NGN [76,91]:		*	*							*		
Charging load of EVs	[84,118]		*		*						*		
Cost per PV module	[92]		*		*							*	
Initial resource of hydrogen	[95]	*		*							*		

(*continued on next page*)

Table A3 (*continued*)

The UIP	Ref.	Dimension of the UIP: Nature – Epistemic uncertainty	Nature – Variability uncertainty	Level – Statistical uncertainty	Level – Scenario uncertainty	Level – Recognized ignorance	Location – Context	Location – Model uncertainty – Model structure	Location – Model uncertainty – Model technical	Location – Inputs – External driving forces	Location – Inputs – System data	Location – Parameter uncertainty	Location – Model outcomes
The output power of CHP	[95]	*		*								*	
Boiler efficiency	[95]	*				*				*			
Building form	[98]	*		*						*			
Urban density	[98]	*		*						*			
Climate variations	[98]		*		*						*		
Price of electricity generated by PV	[104]		*	*							*		
Power obtained from regenerative braking	[106]		*		*						*		
Comfort level relative to illumination, temperature, and the charge level of EVs	[109]	*				*	*						
Interest rate	[110]		*	*							*		
The charging rate of EVs	[110]		*	*							*		
Mobility demand factor	[110]		*		*						*		
Carbon intensity of the electricity grid	[110]	*				*				*			
Electricity supply	[116]		*		*						*		

In this table: EL, electricity; GA, gas; HE, heating; FF, fossil fuel; BI, biomass; WA, water; CO, cooling; HY, hydrogen; IN, investment; O&M, operational and maintenance; CO_2 emission, carbon dioxide emission; PV, photovoltaic panel; WT, wind turbine; TI, tidal unit; DHN, district heating network; EN, electricity network; NGN, natural gas network; SOC, state of charge; EV, electric vehicle.

Table A4
Different techniques to model uncertain parameters in μMEHs' studies.

Technique	Sub-technique	Method	The key idea for modeling UIPs	Well-known example	Strength	Weakness	Ref.
Probabilistic	Numerical approaches	–	Using statistical distributions to simulate real states	MCE	High accuracy; simple to implement; suitable performance on large and complicated problems; can simulate actual conditions; can consider the correlation between UIPs	Time-consuming process; high computational burden; needs the accurate information of UIPs	MCE: [28,61,63,68,76,83,84,87,90,91,93,94,106,109], Gaussian mixture model [93]:
	Analytical approaches	Linearization-based	Using linearization concept	Gram Charlier	Simple to implement; fast	Low accuracy in calculating high order moments; needs the accurate information of UIPs	
		PDF approximation-based	Dividing realization space into different scenarios with a certain probability for each scenario	SDM method	Simple to implement; fast; can consider the correlation between UIPs; can convert the continuous uncertain space to different discrete scenarios with various probability; appropriate accuracy if the correct number of scenarios are selected	Needs accurate information on UIPs; cannot give the PDF of the output variable and only gives its expected value; computational burden increases sharply with the increase of scenarios; gives an approximate response	SDM method [40,69,70,73,75,81,106,108,118]:
			Using PDF approximation	2PE method	Straightforward to implement; fast; suitable accuracy; can consider the correlation between UIPs; has no converge problem	Cannot give the PDF of the output variable; can only give the mean and standard deviation of the output variable; needs the accurate information of UIPs; computational burden and runtime depend on the number of UIPs	2PE method [51,94,97]:
Possibilistic			Using fuzzy MFs	α-cut method	Straightforward to implement; can give the MF of the output variable	Time-consuming process; high computational burden; needs the accurate information of UIPs; cannot consider the correlation between UIPs	
Hybrid probabilistic-possibilistic			Using both probabilistic and possibilistic concepts	α-cut-MCE	High accuracy; can simulate actual conditions; can consider the correlation between UIPs; can model both possibilistic and probabilistic uncertainties	Time-consuming process; complex to implement; needs the accurate information of UIPs	
Interval arithmetic			Using interval bounds	Interval arithmetic	Effective for conditions that there is only an interval bound for each UIP	Complex to implement, especially in nonlinear problems; cannot consider the correlation between intervals	
RO			Using intervals and sets	RO	Effective for conditions that there is only an interval bound for each UIP	Complex to implement, especially in nonlinear problems; cannot consider the correlation between intervals and sets	[32,84,112,119]
IGDT			Using a variable set around the predicted value	IGDT	Effective for decision-making under severe uncertainties; there is no need for any initial information related to UIPs	Complex to implement (inherently is a bi-level optimization problem)	[97,118]
Not specified							[101,110,115]

Table A5 (*continued*)

Class	Solution			Ref.	Class	Solution			Ref.
	Approach	Solver	Software			Approach	Solver	Software	
	Approach	Solver	Software			Approach	Solver	Software	
Deterministic	MILP	CPLEX	GAMS	[34,35,43,63,67,68,71,75,81,82,90,95,97,106,119]	Deterministic	MINLP	DICOPT	GAMS	[48,49,56,112,118]
			MATLAB	[38,65,87,111]			BONMIN	GAMS	[50]
			IBM ILOG	[80,84,103,121]			BARON	GAMS	[97]
			AIMMS	[52,55]		MIQP	CPLEX	GAMS	[56]
			AMPL	[93,104]					[72]
		GUROBI	MATLAB	[70,113]			GUROBI	MATLAB	[120]
			Python	[107,110,116]		DP		MATLAB	[108]
		YALMIP	MATLAB	[77,87]		CO	ADMM		[66]
		Intlinprog	MATLAB	[57]		NCO	NC&CG	MATLAB	[69]
			GAMS	[105]			BMIBNB	MATLAB	[44]
				[42,45,62]	Stochastic	GA		MATLAB	[65,94,99,109,114]
	LP	CPLEX	MATLAB	[47]		PSO		MATLAB	[58,60,74,114]
			GAMS	[32]		EB		–	[64,73,85,96,98]
		GUROBI	Python	[89]		NSGA-II		MATLAB	[38,80,101]
			MATLAB	[102]		FPA		MATLAB	[60,76,91]
		YALMIP	MATLAB	[102]		TS		–	[59]
			MATLAB	[41]		ABC		–	[79]
				[100,114]		GWO		MATLAB	[109]
	MIP	CPLEX	GAMS	[78,118]		SFLA		MATLAB	[109]
		GUROBI	Python	[92]		TLBO		MATLAB	[109]
			GAMS	[37]		GRFO-SPO		MATLAB	[115]
	NLP	GRGA		[25,27,30,53]	Stochastic learning	RL		MATLAB	[33]
		BARON	GAMS	[46]	Not specified			–	[28,31,36,40,61]
		CONOPT	GAMS	[83]				MATLAB	[26,39,88,117]
		CIP	MATLAB	[54]				GAMS	[39,51]
		SNOPT		[86]					
			GAMS	[29]					

In this table: MILP, mixed-integer linear programming; LP, linear programming; NLP, non-linear programming; GRGA, generalized reduced gradient algorithm; CIP, constraint integer program; MIP, mixed-integer programming; MIQP, mixed-integer quadratic programming; DP, dynamic programming; CO, convex optimization; ADMM, alternating direction method of multipliers; NCO, nonconvex optimization; NC&CG, nested column-and-constraint generation; B&B, branch and bound; NSGA-II, non-dominated sorting genetic algorithm II; GA, genetic algorithm; PSO, particle swarm optimization; EB, evolutionary-based algorithms; FPA, flower pollination algorithm; TS, tabu search; ABC, artificial bee colony; GWO, grey wolf optimizer; SFLA, shuffled frog-leaping algorithm; TLBO, teaching-learning-based optimization; GRFO-SPO, joint Garra rufa fish optimization and student psychology optimization; RL, reinforcement learning.

Table A6
A classification of μMEHs' studies from the perspective of the scheme used for decision-making analysis.

Decision-making analysis		Ref.
Single objective		[25–33,36,37,39–41,43–51,53–63,65–70,72,74–79,82–84,86–95,97,99,100,102,103,105,107–110,112–114,117–121]
Multi-objective	Bi objective	[34,35,38,42,52,64,71,80,81,85,96,98,104,106,115,116]
	Tri-objective	[73,101,111]

Table A7
A classification of μMEHs' studies from the perspective of multi-objective optimization techniques to find the Pareto-optimal solution set.

Technique	Category	Key idea	Main advantage	Main disadvantage	Familiar example	Ref.
Non-interactive	Basic	These techniques transform the multi-objective problem into a single-objective one using weights or constraints. The aggregated objective function represents a compromise solution that balances the conflicting objectives.	• Simplicity: They are easy to understand and implement. • Efficiency: They are computationally efficient and suitable for solving large-scale optimization problems. • Flexibility: They can handle multiple objectives and constraints.	• Lack of sensitivity analysis: They cannot provide information on the sensitivity of the solution to changes in the weights or constraints. •Limited decision support: They cannot provide decision support to the decision-maker. •Risk of overlooking important trade-offs: They do not explicitly account for trade-offs between objectives.	• Weighting method •ε-constraint method	Weighting method [35,71,104,111]: ε-constraint method [34,42,52,80,81,106,116]:
	No preference	These techniques find some compromise solution typically 'in the middle' of the Pareto optimal set because there is no preference information available to direct the solution process otherwise.	• Pareto optimality: They represent the best possible trade-offs between conflicting objectives. • Non-dominance: They avoid explicit trade-offs or preferences by identifying non-dominated solutions. • Wide range of solutions: They identify a wide range of Pareto-optimal solutions.	• Computationally intensive: They are computationally intensive, especially for large-scale problems. •Limited decision support: They do not provide explicit decision support to the decision-maker, as they do not involve the decision-maker in the decision-making process or provide feedback on the trade-offs between objectives. •Risk of overfitting: They can overfit the optimization problem if the algorithm is not calibrated correctly or the objective function is not appropriately defined.	• Method of global criterion •Neutral compromise solution	–
	A prior	These techniques obtain a solution that satisfies predefined constraints and objectives without explicitly considering trade-offs between conflicting objectives.	•Simplicity: They are relatively simple and easy to understand. •Single solution: They provide a solution that meets the decision-makers' predefined criteria. •Handles soft constraints: They handle soft constraints that allow for some deviations from the targets.	•Ignores trade-offs: They do not consider the trade-offs between conflicting objectives. •Arbitrary weights: The choice of weights or priorities in a priori techniques is subjective and arbitrary and can significantly affect the resulting solution. •Limited flexibility: They are inflexible and cannot handle changes in the problem formulation or the decision-maker's preferences.	•Value function method •Lexicographic ordering •Goal programming	–
	A posterior	These techniques generate and represent the Pareto optimal set to the decision-maker, who selects the most satisfactory solution as the final one.	• Identifies Pareto-optimal solutions: They identify a set of Pareto-optimal solutions representing the best possible trade-offs between conflicting objectives. • Flexibility: They handle changes in the problem formulation or the decision-maker's preferences. • Handles hard constraints: They handle hard constraints that must be satisfied strictly.	• Computationally intensive: They are computationally intensive, requiring the optimization technique to be run multiple times to generate a set of solutions. • A large number of solutions: They result in many solutions that can be difficult for the decision-maker to analyze and interpret.	• Method of weighted metrics • Achievement scalarizing function approach • Approximation methods	–
Interactive		These techniques identify optimal solutions that best meet the decision-maker's preferences and requirements by providing	• Customization: They allow for the customization of solutions based on the decision-maker's preferences, which can	• Time-consuming: They are time-consuming, involving multiple iterations and evaluations, which may not be feasible in time-critical situations.	• Trade-off based methods	–

(*continued on next page*)

Table A7 (*continued*)

Technique	Category	Key idea	Main advantage	Main disadvantage	Familiar example	Ref.
		more control and flexibility for the decision-maker in the decision-making process.	lead to more personalized and satisfactory outcomes. • Flexibility: The iterative nature of these techniques allows for greater flexibility in the decision-making process, as the decision-maker can adjust their preferences and priorities as they go along.	•Expertise: They may require expertise in using and interpreting the results, which can be a barrier for some decision-makers. • Improved decision-making: They give the decision-maker various alternatives with trade-offs and benefits.	•Reference point methods •Cost: Implementing an interactive technique may require significant resources, such as software, hardware, and personnel, which can be costly.	
• Reduced complexity: They help reduce the complexity of decision-making by breaking it down into smaller, more manageable steps.	•Limited scope: They may be limited and cannot consider all possible factors and variables that can impact the decision.			•Classification-based methods		
Evolutionary multi-objective		These techniques simultaneously optimize multiple conflicting objectives to provide a range of trade-off solutions to help decision-makers make informed choices.	•Flexibility: They require no prior knowledge about the problem or the objectives to be optimized. •Wide range of solutions: They generate diverse Pareto-optimal solutions, allowing the decision-maker to choose a solution that best suits their preferences. •Adaptability: They handle multiple conflicting objective functions having complex, nonlinear, and non-convex, nature.	• Time-consuming: They are computationally expensive and time-consuming, especially for high-dimensional problems. • Converge problem: They suffer from premature convergence, which converges to a suboptimal solution before finding the true Pareto-optimal front. • Dependence on parameters setting: They require carefully selecting parameters and settings to perform well. • A large number of solutions: They generate too many solutions, making it difficult for the decision-maker to choose the best one.	• Non-dominated sorting genetic algorithm-II (NSGA-II) •Strength Pareto evolutionary algorithm-2 (SPEA2) •Multi-objective particle swarm optimization (MOPSO)	Joint Garra rufa fish optimization and student psychology optimization [115]: NSGA-II [101]: Multi-objective genetic algorithm [38]: Co-operative co-evolutionary algorithm [85,98]: Evolutionary algorithm [73,96]: Steady-state epsilon dominance method [64]:

References

[1] Shabanpour-Haghighi A, Karimaghaei M. An overview on multi-carrier energy networks: from a concept to future trends and challenges. Int J Hydrogen Energy 2022;47:6164–86. https://doi.org/10.1016/J.IJHYDENE.2021.11.257.
[2] Nazari-Heris M, Asadi S, Mohammadi-Ivatloo B, editors. Planning and operation of multi-carrier energy networks; 2021. https://doi.org/10.1007/978-3-030-60086-0.
[3] Mancarella P. MES (multi-energy systems): an overview of concepts and evaluation models. Energy 2014;65:1–17. https://doi.org/10.1016/J.ENERGY.2013.10.041.
[4] Favre-Perrod P, Geidl M, Klöckl B, Koeppel G. A vision of future energy networks. In: Proceedings of the inaugural IEEE PES 2005 conference and exposition in africa. 2005; 2005. p. 13–7. https://doi.org/10.1109/PESAFR.2005.1611778.
[5] Sadeghi H, Rashidinejad M, Moeini-Aghtaie M, Abdollahi A. The energy hub: an extensive survey on the state-of-the-art. Appl Therm Eng 2019;161:114071. https://doi.org/10.1016/J.APPLTHERMALENG.2019.114071.
[6] Mohammadi M, Noorollahi Y, Mohammadi-ivatloo B, Yousefi H, Jalilinasrabady S. Optimal scheduling of energy hubs in the presence of uncertainty-A review. Journal of Energy Management and Technology 2017;1:1–17. https://doi.org/10.22109/JEMT.2017.49432.
[7] Mohammadi M, Noorollahi Y, Mohammadi-ivatloo B, Yousefi H. Energy hub: from a model to a concept – a review. Renew Sustain Energy Rev 2017;80:1512–27. https://doi.org/10.1016/J.RSER.2017.07.030.
[8] Wang J, Zhong H, Ma Z, Xia Q, Kang C. Review and prospect of integrated demand response in the multi-energy system. Appl Energy 2017;202:772–82. https://doi.org/10.1016/J.APENERGY.2017.05.150.
[9] Mohammadi M, Noorollahi Y, Mohammadi-ivatloo B, Hosseinzadeh M, Yousefi H, Khorasani ST. Optimal management of energy hubs and smart energy hubs – a review. Renew Sustain Energy Rev 2018;89:33–50. https://doi.org/10.1016/J.RSER.2018.02.035.
[10] Maroufmashat A, Taqvi ST, Miragha A, Fowler M, Elkamel A. Modeling and optimization of energy hubs: a comprehensive review. Inventions 2019;4:50. https://doi.org/10.3390/INVENTIONS4030050. 50. 4 (2019).
[11] Vahid-Ghavidel M, Sadegh Javadi M, Gough M, Santos SF, Shafie-Khah M, Catalão JPS. Demand response programs in multi-energy systems: a review. Energies 2020;13:4332. https://doi.org/10.3390/EN13174332. 13 (2020) 4332.
[12] Xu Y, Yan C, Liu H, Wang J, Yang Z, Jiang Y. Smart energy systems: a critical review on design and operation optimization. Sustain Cities Soc 2020;62:102369. https://doi.org/10.1016/J.SCS.2020.102369.
[13] Nazari-heris M, Jabari F, Mohammadi-ivatloo B, Asadi S, Habibnezhad M. An updated review on multi-carrier energy systems with electricity, gas, and water energy sources. J Clean Prod 2020;275:123136. https://doi.org/10.1016/J.JCLEPRO.2020.123136.
[14] Son YG, Oh BC, Acquah MA, Fan R, Kim DM, Kim SY. Multi energy system with an associated energy hub: a review. IEEE Access 2021;9:127753–66. https://doi.org/10.1109/ACCESS.2021.3108142.
[15] Aljabery AAM, Mehrjerdi H, Mahdavi S, Hemmati R. Multi carrier energy systems and energy hubs: comprehensive review, survey and recommendations. Int J Hydrogen Energy 2021;46:23795–814. https://doi.org/10.1016/J.IJHYDENE.2021.04.178.
[16] Fodstad M, Crespo del Granado P, Hellemo L, Knudsen BR, Pisciella P, Silvast A, Bordin C, Schmidt S, Straus J. Next frontiers in energy system modelling: a review on challenges and the state of the art. Renew Sustain Energy Rev 2022;160:112246. https://doi.org/10.1016/J.RSER.2022.112246.
[17] Lasemi MA, Arabkoohsar A, Hajizadeh A, Mohammadi-ivatloo B. A comprehensive review on optimization challenges of smart energy hubs under uncertainty factors. Renew Sustain Energy Rev 2022;160:112320. https://doi.org/10.1016/J.RSER.2022.112320.
[18] Kalua A. Urban residential building energy consumption by end-use in Malawi. Buildings 2020;10:31. https://doi.org/10.3390/BUILDINGS10020031. 31. 10 (2020).
[19] Schweiger G, Eckerstorfer Lv, Hafner I, Fleischhacker A, Radl J, Glock B, Wastian M, Rößler M, Lettner G, Popper N, Corcoran K. Active consumer participation in smart energy systems. Energy Build 2020;227:110359. https://doi.org/10.1016/J.ENBUILD.2020.110359.
[20] Bulut MB, Odlare M, Stigson P, Wallin F, Vassileva I. Active buildings in smart grids - exploring the views of the Swedish energy and buildings sectors. Energy Build 2016;117:185–98. https://doi.org/10.1016/J.ENBUILD.2016.02.017.
[21] Behavioural insights for demand-side energy policy and programmes report published – UsersTCP, (n.d.). https://userstcp.org/news/behavioural-insights-for-demand-side-energy-policy-and-programmes-report-published/(accessed April 7, 2022).
[22] Fan H, Wang C, Liu L, Li X. Review of uncertainty modeling for optimal operation of integrated energy system. Front Energy Res 2022;9:947. https://doi.org/10.3389/FENRG.2021.641337/BIBTEX.
[23] Kiani-Moghaddam M, Shivaie M, Weinsier PD. Modern music-inspired optimization algorithms for electric power systems. 2019. https://doi.org/10.1007/978-3-030-12044-3.
[24] Kiani-Moghaddam M, Shivaie M, Weinsier PD. Power Systems Planning 2019. https://doi.org/10.1007/978-3-030-12044-3_6.
[25] Fabrizio E, Filippi M, Virgone J. An hourly modelling framework for the assessment of energy sources exploitation and energy converters selection and sizing in buildings. Energy Build 2009;41:1037–50. https://doi.org/10.1016/J.ENBUILD.2009.05.005.
[26] Syed F, Fowler M, Wan D, Maniyali Y. An energy demand model for a fleet of plug-in fuel cell vehicles and commercial building interfaced with a clean energy hub. Int J Hydrogen Energy 2010;35:5154–63. https://doi.org/10.1016/J.IJHYDENE.2009.08.089.
[27] Fabrizio E, Corrado V, Filippi M. A model to design and optimize multi-energy systems in buildings at the design concept stage. Renew Energy 2010;35:644–55. https://doi.org/10.1016/J.RENENE.2009.08.012.
[28] Kienzle F, Ahčin P, Andersson G. Valuing investments in multi-energy conversion, storage, and demand-side management systems under uncertainty. IEEE Trans Sustain Energy 2011;2:194–202. https://doi.org/10.1109/TSTE.2011.2106228.
[29] Sheikhi A, Ranjbar AM, Oraee H. Financial analysis and optimal size and operation for a multicarrier energy system. Energy Build 2012;48:71–8. https://doi.org/10.1016/J.ENBUILD.2012.01.011.
[30] Bayraktar M, Fabrizio E, Perino M. The extended building energy hub: a new method for the simultaneous optimization of energy demand and energy supply in buildings. HVAC R Res 2012;18:67–87. https://doi.org/10.1080/10789669.2011.588300.
[31] Orehounig K, Mavromatidis G, Evins R, Dorer V, Carmeliet J. Towards an energy sustainable community: an energy system analysis for a village in Switzerland. Energy Build 2014;84:277–86. https://doi.org/10.1016/J.ENBUILD.2014.08.012.
[32] Akbari K, Nasiri MM, Jolai F, Ghaderi SF. Optimal investment and unit sizing of distributed energy systems under uncertainty: a robust optimization approach. Energy Build 2014;85:275–86. https://doi.org/10.1016/J.ENBUILD.2014.09.009.
[33] Rayati M, Sheikhi A, Ranjbar AM. Optimising operational cost of a smart energy hub, the reinforcement learning approach, vol. 30; 2014. p. 325–41. https://doi.org/10.1080/17445760.2014.974600. Http://Dx.Doi.Org/10.1080/17445760.2014.974600.
[34] Brahman F, Honarmand M, Jadid S. Optimal electrical and thermal energy management of a residential energy hub, integrating demand response and energy storage system. Energy Build 2015;90:65–75. https://doi.org/10.1016/J.ENBUILD.2014.12.039.
[35] Maroufmashat A, Elkamel A, Fowler M, Sattari S, Roshandel R, Hajimiragha A, Walker S, Entchev E. Modeling and optimization of a network of energy hubs to improve economic and emission considerations. Energy 2015;93:2546–58. https://doi.org/10.1016/J.ENERGY.2015.10.079.
[36] Rastegar M, Fotuhi-Firuzabad M. Load management in a residential energy hub with renewable distributed energy resources. Energy Build 2015;107:234–42. https://doi.org/10.1016/J.ENBUILD.2015.07.028.
[37] Rastegar M, Fotuhi-Firuzabad M, Lehtonen M. Home load management in a residential energy hub. Elec Power Syst Res 2015;119:322–8. https://doi.org/10.1016/J.EPSR.2014.10.011.
[38] Evins R. Multi-level optimization of building design, energy system sizing and operation. Energy 2015;90:1775–89. https://doi.org/10.1016/J.ENERGY.2015.07.007.
[39] Xu X, Jia H, Wang D, Yu DC, Chiang HD. Hierarchical energy management system for multi-source multi-product microgrids. Renew Energy 2015;78:621–30. https://doi.org/10.1016/J.RENENE.2015.01.039.
[40] Ottesen SO, Tomasgard A. A stochastic model for scheduling energy flexibility in buildings. Energy 2015;88:364–76. https://doi.org/10.1016/J.ENERGY.2015.05.049.
[41] Orehounig K, Evins R, Dorer V. Integration of decentralized energy systems in neighbourhoods using the energy hub approach. Appl Energy 2015;154:277–89. https://doi.org/10.1016/J.APENERGY.2015.04.114.
[42] Mavromatidis G, Orehounig K, Carmeliet J. Evaluation of photovoltaic integration potential in a village. Sol Energy 2015;121:152–68. https://doi.org/10.1016/J.SOLENER.2015.03.044.
[43] Maroufmashat A, Fowler M, Sattari Khavas S, Elkamel A, Roshandel R, Hajimiragha A. Mixed integer linear programing based approach for optimal planning and operation of a smart urban energy network to support the hydrogen economy. Int J Hydrogen Energy 2016;41:7700–16. https://doi.org/10.1016/J.IJHYDENE.2015.08.038.
[44] Yang H, Xiong T, Qiu J, Qiu D, Dong ZY. Optimal operation of DES/CCHP based regional multi-energy prosumer with demand response. Appl Energy 2016;167:353–65. https://doi.org/10.1016/J.APENERGY.2015.11.022.
[45] Morvaj B, Knezović K, Evins R, Marinelli M. Integrating multi-domain distributed energy systems with electric vehicle PQ flexibility: optimal design and operation scheduling for sustainable low-voltage distribution grids. Sustainable Energy, Grids and Networks 2016;8:51–61. https://doi.org/10.1016/J.SEGAN.2016.10.001.
[46] Barmayoon MH, Fotuhi-Firuzabad M, Rajabi-Ghahnavieh A, Moeini-Aghtaie M. Energy storage in renewable-based residential energy hubs, IET Generation. Transm Distrib 2016;10:3127–34. https://doi.org/10.1049/IET-GTD.2015.0957.
[47] Batić M, Tomašević N, Beccuti G, Demiray T, Vraneš S. Combined energy hub optimisation and demand side management for buildings. Energy Build 2016;127:229–41. https://doi.org/10.1016/J.ENBUILD.2016.05.087.
[48] Gerami Moghaddam I, Saniei M, Mashhour E. Improvement of energy performance employing electrical heat pump in scheduling a residential energy hub. International Transactions on Electrical Energy Systems 2016;26:2618–42. https://doi.org/10.1002/ETEP.2224.
[49] Moghaddam IG, Saniei M, Mashhour E. A comprehensive model for self-scheduling an energy hub to supply cooling, heating and electrical demands of a building. Energy 2016;94:157–70. https://doi.org/10.1016/J.ENERGY.2015.10.137.

[50] Ha T, Zhang Y, Thang Vv, Huang J. Energy hub modeling to minimize residential energy costs considering solar energy and BESS. Journal of Modern Power Systems and Clean Energy 2017;5:389–99. https://doi.org/10.1007/S40565-017-0281-4/FIGURES/11.
[51] Rastegar M, Fotuhi-Firuzabad M, Zareipour H, Moeini-Aghtaieh M. A probabilistic energy management scheme for renewable-based residential energy hubs. IEEE Trans Smart Grid 2017;8:2217–27. https://doi.org/10.1109/TSG.2016.2518920.
[52] Wu R, Mavromatidis G, Orehounig K, Carmeliet J. Multiobjective optimisation of energy systems and building envelope retrofit in a residential community. Appl Energy 2017;190:634–49. https://doi.org/10.1016/J.APENERGY.2016.12.161.
[53] Biglia A, Caredda Fv, Fabrizio E, Filippi M, Mandas N. Technical-economic feasibility of CHP systems in large hospitals through the Energy Hub method: the case of Cagliari AOB. Energy Build 2017;147:101–12. https://doi.org/10.1016/J.ENBUILD.2017.04.047.
[54] Setlhaolo D, Sichilalu S, Zhang J. Residential load management in an energy hub with heat pump water heater. Appl Energy 2017;208:551–60. https://doi.org/10.1016/J.APENERGY.2017.09.099.
[55] Marquant JF, Evins R, Bollinger LA, Carmeliet J. A holarchic approach for multi-scale distributed energy system optimisation. Appl Energy 2017;208:935–53. https://doi.org/10.1016/J.APENERGY.2017.09.057.
[56] Jafari F, Samet H, Seifi AR, Rastegar M. Developing a two-step method to implement residential demand response programmes in multi-carrier energy systems, IET Generation. Transm Distrib 2018;12:2614–23. https://doi.org/10.1049/IET-GTD.2017.1557.
[57] Ramos-Teodoro J, Rodríguez F, Berenguel M, Torres JL. Heterogeneous resource management in energy hubs with self-consumption: contributions and application example. Appl Energy 2018;229:537–50. https://doi.org/10.1016/J.APENERGY.2018.08.007.
[58] Huo D, Le Blond S, Gu C, Wei W, Yu D. Optimal operation of interconnected energy hubs by using decomposed hybrid particle swarm and interior-point approach. Int J Electr Power Energy Syst 2018;95:36–46. https://doi.org/10.1016/J.IJEPES.2017.08.004.
[59] Lin H, Liu Y, Sun Q, Xiong R, Li H, Wennersten R. The impact of electric vehicle penetration and charging patterns on the management of energy hub – a multi-agent system simulation. Appl Energy 2018;230:189–206. https://doi.org/10.1016/J.APENERGY.2018.08.083.
[60] Raza A, Malik TN. Biogas supported bi-level macro energy hub management system for residential customers. J Renew Sustain Energy 2018;10:025501. https://doi.org/10.1063/1.4996271.
[61] Mavromatidis G, Orehounig K, Carmeliet J. Uncertainty and global sensitivity analysis for the optimal design of distributed energy systems. Appl Energy 2018;214:219–38. https://doi.org/10.1016/J.APENERGY.2018.01.062.
[62] Atănăsoae P, Pentiuc RD. Choosing the energy sources needed for utilities in the design and refurbishment of buildings. Buildings 2018;8:54. https://doi.org/10.3390/BUILDINGS8040054. 8 (2018) 54.
[63] Roustai M, Rayati M, Sheikhi A, Ranjbar AM. A scenario-based optimization of Smart Energy Hub operation in a stochastic environment using conditional-value-at-risk. Sustain Cities Soc 2018;39:309–16. https://doi.org/10.1016/J.SCS.2018.01.045.
[64] Perera ATD, Coccolo S, Scartezzini JL, Mauree D. Quantifying the impact of urban climate by extending the boundaries of urban energy system modeling. Appl Energy 2018;222:847–60. https://doi.org/10.1016/J.APENERGY.2018.04.004.
[65] Marquant JF, Bollinger LA, Evins R, Carmeliet J. A new combined clustering method to Analyse the potential of district heating networks at large-scale. Energy 2018;156:73–83. https://doi.org/10.1016/J.ENERGY.2018.05.027.
[66] Zhong W, Yang C, Xie K, Xie S, Zhang Y. ADMM-based distributed auction mechanism for energy hub scheduling in smart buildings. IEEE Access 2018;6:45635–45. https://doi.org/10.1109/ACCESS.2018.2865625.
[67] Eshraghi A, Salehi G, Heibati S, Lari K. An enhanced operation model for energy storage system of a typical combined cool, heat and power based on demand response program: the application of mixed integer linear programming, vol. 40; 2018. p. 47–74. https://doi.org/10.1177/0143624418792475. Https://Doi.Org/10.1177/0143624418792475.
[68] Jadidbonab M, Dolatabadi A, Mohammadi-Ivatloo B, Abapour M, Asadi S. Risk-constrained energy management of PV integrated smart energy hub in the presence of demand response program and compressed air energy storage. IET Renew Power Gener 2019;13:998–1008. https://doi.org/10.1049/IET-RPG.2018.6018/CITE/REFWORKS.
[69] Yan M, Zhang N, Ai X, Shahidehpour M, Kang C, Wen J. Robust two-stage regional-district scheduling of multi-carrier energy systems with a large penetration of wind power. IEEE Trans Sustain Energy 2019;10:1227–39. https://doi.org/10.1109/TSTE.2018.2864296.
[70] Ma L, Liu N, Zhang J, Wang L. Real-time rolling horizon energy management for the energy-hub-coordinated prosumer community from a cooperative perspective. IEEE Trans Power Syst 2019;34:1227–42. https://doi.org/10.1109/TPWRS.2018.2877236.
[71] Olsen DJ, Zhang N, Kang C, Ortega-Vazquez MA, Kirschen DS. Planning low-carbon campus energy hubs. IEEE Trans Power Syst 2019;34:1895–907. https://doi.org/10.1109/TPWRS.2018.2879792.
[72] Long S, Marjanovic O, Parisio A. Generalised control-oriented modelling framework for multi-energy systems. Appl Energy 2019;235:320–31. https://doi.org/10.1016/J.APENERGY.2018.10.074.
[73] Perera ATD, Nik VM, Wickramasinghe PU, Scartezzini JL. Redefining energy system flexibility for distributed energy system design. Appl Energy 2019;253:113572. https://doi.org/10.1016/J.APENERGY.2019.113572.
[74] Ayele GT, Mabrouk MT, Haurant P, Laumert B, Lacarrière B. Optimal placement and sizing of heat pumps and heat only boilers in a coupled electricity and heating networks. Energy 2019;182:122–34. https://doi.org/10.1016/J.ENERGY.2019.06.018.
[75] Jing R, Wang M, Zhang Z, Wang X, Li N, Shah N, Zhao Y. Distributed or centralized? Designing district-level urban energy systems by a hierarchical approach considering demand uncertainties. Appl Energy 2019;252:113424. https://doi.org/10.1016/J.APENERGY.2019.113424.
[76] Raza A, Malik TN. Energy management in commercial building microgrids. J Renew Sustain Energy 2019;11:015502. https://doi.org/10.1063/1.5034352.
[77] Yuan Y, Bayod-Rújula AA, Chen H, Martínez-Gracia A, Wang J, Pinnarelli A. An advanced multicarrier residential energy hub system based on mixed integer linear programming. Int J Photoenergy 2019;2019. https://doi.org/10.1155/2019/1384985.
[78] Ghorab M. Energy hubs optimization for smart energy network system to minimize economic and environmental impact at Canadian community. Appl Therm Eng 2019;151:214–30. https://doi.org/10.1016/J.APPLTHERMALENG.2019.01.107.
[79] Jabarullah NH, Shabbir MS, Abbas M, Siddiqi AF, Berti S. Using random inquiry optimization method for provision of heat and cooling demand in hub systems for smart buildings. Sustain Cities Soc 2019;47:101475. https://doi.org/10.1016/J.SCS.2019.101475.
[80] Waibel C, Evins R, Carmeliet J. Co-simulation and optimization of building geometry and multi-energy systems: interdependencies in energy supply, energy demand and solar potentials. Appl Energy 2019;242:1661–82. https://doi.org/10.1016/J.APENERGY.2019.03.177.
[81] Salehi J, Namvar A, Gazijahani FS. Scenario-based Co-Optimization of neighboring multi carrier smart buildings under demand response exchange. J Clean Prod 2019;235:1483–98. https://doi.org/10.1016/J.JCLEPRO.2019.07.068.
[82] Eshraghi A, Salehi G, Heibati S, Lari K. Developing operation of combined cooling, heat, and power system based on energy hub in a micro-energy grid: the application of energy storages, vol. 30; 2019. p. 1356–79. https://doi.org/10.1177/0958305X19846577. Https://Doi.Org/10.1177/0958305X19846577.
[83] Senemar S, Rastegar M, Dabbaghjamanesh M, Hatziargyriou N. Dynamic structural sizing of residential energy hubs. IEEE Trans Sustain Energy 2020;11:1236–46. https://doi.org/10.1109/TSTE.2019.2921110.
[84] Lu X, Liu Z, Ma L, Wang L, Zhou K, Feng N. A robust optimization approach for optimal load dispatch of community energy hub. Appl Energy 2020;259:114195. https://doi.org/10.1016/J.APENERGY.2019.114195.
[85] Perera ATD, Wickramasinghe PU, Nik VM, Scartezzini JL. Introducing reinforcement learning to the energy system design process. Appl Energy 2020;262:114580. https://doi.org/10.1016/J.APENERGY.2020.114580.
[86] Mu Y, Chen W, Yu X, Jia H, Hou K, Wang C, Meng X. A double-layer planning method for integrated community energy systems with varying energy conversion efficiencies. Appl Energy 2020;279:115700. https://doi.org/10.1016/J.APENERGY.2020.115700.
[87] Song T, Li Y, Zhang XP, Wu C, Li J, Guo Y, Gu H. Integrated port energy system considering integrated demand response and energy interconnection. Int J Electr Power Energy Syst 2020;117:105654. https://doi.org/10.1016/J.IJEPES.2019.105654.
[88] Gholinejad HR, Loni A, Adabi J, Marzband M. A hierarchical energy management system for multiple home energy hubs in neighborhood grids. J Build Eng 2020;28:101028. https://doi.org/10.1016/J.JOBE.2019.101028.
[89] Wirtz M, Kivilip L, Remmen P, Müller D. 5th Generation District Heating: a novel design approach based on mathematical optimization. Appl Energy 2020;260:114158. https://doi.org/10.1016/J.APENERGY.2019.114158.
[90] Roustaei M, Niknam T, Salari S, Chabok H, Sheikh M, Kavousi-Fard A, Aghaei J. A scenario-based approach for the design of smart energy and water hub. Energy 2020;195:116931. https://doi.org/10.1016/J.ENERGY.2020.116931.
[91] Raza A, Malik TN, Khan MFN, Ali S. Energy management in residential buildings using energy hub approach. Build Simulat 2020;13:2. https://doi.org/10.1007/S12273-019-0590-9. 13 (2020) 363–386.
[92] Rech S, Casarin S, Silva CS, Lazzaretto A. University campus and surrounding residential complexes as energy-hub: a MILP optimization approach for a smart exchange of solar energy. Energies 2020;13:2919. https://doi.org/10.3390/EN13112919. 13 (2020) 2919.
[93] Shafiullah DS, Vergara PP, Haque ANMM, Nguyen PH, Pemen AJM. Gaussian mixture based uncertainty modeling to optimize energy management of heterogeneous building neighborhoods: a case study of a Dutch university medical campus. Energy Build 2020;224:110150. https://doi.org/10.1016/J.ENBUILD.2020.110150.
[94] Emrani-Rahaghi P, Hashemi-Dezaki H. Optimal scenario-based operation and scheduling of residential energy hubs including plug-in hybrid electric vehicle and heat storage system considering the uncertainties of electricity price and renewable distributed generations. J Energy Storage 2021;33:102038. https://doi.org/10.1016/J.EST.2020.102038.
[95] Mehrjerdi H, Hemmati R, Shafie-Khah M, Catalao JPS. Zero energy building by multicarrier energy systems including hydro, wind, solar, and hydrogen. IEEE Trans Ind Inf 2021;17:5474–84. https://doi.org/10.1109/TII.2020.3034346.
[96] Perera ATD, Wang Z, Nik VM, Scartezzini JL. Towards realization of an Energy Internet: designing distributed energy systems using game-theoretic approach. Appl Energy 2021;283:116349. https://doi.org/10.1016/J.APENERGY.2020.116349.
[97] Kafaei M, Sedighizadeh D, Sedighizadeh M, Sheikhi Fini A. A two-stage IGDT/TPEM model for optimal operation of a smart building: a case study of Gheshm

Island, Iran. Therm Sci Eng Prog 2021;24:100955. https://doi.org/10.1016/J.TSEP.2021.100955.
[98] Perera ATD, Javanroodi K, Nik VM. Climate resilient interconnected infrastructure: Co-optimization of energy systems and urban morphology. Appl Energy 2021;285:116430. https://doi.org/10.1016/J.APENERGY.2020.116430.
[99] Talebjedi B, Behbahaninia A. Availability analysis of an Energy Hub with CCHP system for economical design in terms of Energy Hub operator. J Build Eng 2021;33:101564. https://doi.org/10.1016/J.JOBE.2020.101564.
[100] Huang W, Zhang X, Li K, Zhang N, Strbac G, Kang C. Resilience oriented planning of urban multi-energy systems with generalized energy storage sources. IEEE Trans Power Syst 2021. https://doi.org/10.1109/TPWRS.2021.3123074.
[101] Wang J, Qi X, Ren F, Zhang G, Wang J. Optimal design of hybrid combined cooling, heating and power systems considering the uncertainties of load demands and renewable energy sources. J Clean Prod 2021;281:125357. https://doi.org/10.1016/J.JCLEPRO.2020.125357.
[102] Garavaso P, Bignucolo F, Vivian J, Alessio G, de Carli M. Optimal planning and operation of a residential energy community under shared electricity incentives. Energies 2021;14:2045. https://doi.org/10.3390/EN14082045. 14 (2021) 2045.
[103] Rahimzadeh A, Christiaanse TV, Evins R. Optimal storage systems for residential energy systems in British Columbia. Sustain Energy Technol Assessments 2021;45:101108. https://doi.org/10.1016/J.SETA.2021.101108.
[104] Tonellato G, Heidari A, Pereira J, Carnieletto L, Flourentzou F, De Carli M, Khovalyg D. Optimal design and operation of a building energy hub: a comparison of exergy-based and energy-based optimization in Swiss and Italian case studies. Energy Convers Manag 2021;242:114316. https://doi.org/10.1016/J.ENCONMAN.2021.114316.
[105] Pazouki S, Haghifam MR. Optimal planning and scheduling of smart homes' energy hubs. International Transactions on Electrical Energy Systems 2021;31:e12986. https://doi.org/10.1002/2050-7038.12986.
[106] Akbari S, Fazel SS, Jadid S. Optimal operation of a smart railway station based on a multi-energy hub structure considering environmental perspective and regenerative braking utilization. Energy Sci Eng 2021;9:1614–31. https://doi.org/10.1002/ESE3.937.
[107] Christiaanse Tv, Loonen RCGM, Evins R. Techno-economic optimization for grid-friendly rooftop PV systems – a case study of commercial buildings in British Columbia. Sustain Energy Technol Assessments 2021;47:101320. https://doi.org/10.1016/J.SETA.2021.101320.
[108] Lei Y, Wang D, Jia H, Li J, Chen J, Li J, Yang Z. Multi-stage stochastic planning of regional integrated energy system based on scenario tree path optimization under long-term multiple uncertainties. Appl Energy 2021;300:117224. https://doi.org/10.1016/J.APENERGY.2021.117224.
[109] Imanloozadeh A, Nazififard M, Sadat SA. A new stochastic optimal smart residential energy hub management system for desert environment. Int J Energy Res 2021;45:18957–80. https://doi.org/10.1002/ER.6991.
[110] Mittelviefhaus M, Pareschi G, Allan J, Georges G, Boulouchos K. Optimal investment and scheduling of residential multi-energy systems including electric mobility: a cost-effective approach to climate change mitigation. Appl Energy 2021;301:117445. https://doi.org/10.1016/J.APENERGY.2021.117445.
[111] Jelić M, Batić M, Tomašević N. Demand-side flexibility impact on prosumer energy system planning. Energies 2021;14:7076. https://doi.org/10.3390/EN14217076. 14 (2021) 7076.
[112] Honarmand HA, Ghaderi Shamim A, Meyar-Naimi H. A robust optimization framework for energy hub operation considering different time resolutions: a real case study. Sustainable Energy, Grids and Networks 2021;28:100526. https://doi.org/10.1016/J.SEGAN.2021.100526.
[113] Zhang N, Yang L, Sun Qiuye, Li Y. IET energy systems integration. In: Matrix modelling and optimisation calculation method for large-scale integrated We-Energy; 2022. p. 2–3. https://doi.org/10.1049/ESI2.12069.
[114] Li J, Li D, Zheng Y, Yao Y, Tang Y. Unified modeling of regionally integrated energy system and application to optimization. Int J Electr Power Energy Syst 2022;134:107377. https://doi.org/10.1016/J.IJEPES.2021.107377.
[115] Elango K, Prakash A, Umasankar L. Multiobjective optimization model for renewable energy sources and load demands uncertainty consideration for optimal design of hybrid combined cooling, heating, and power systems. Int J Energy Res 2022. https://doi.org/10.1002/ER.7684.
[116] Mittelviefhaus M, Georges G, Boulouchos K. Electrification of multi-energy hubs under limited electricity supply: de-/centralized investment and operation for cost-effective greenhouse gas mitigation. Advances in Applied Energy 2022;5:100083. https://doi.org/10.1016/J.ADAPEN.2022.100083.
[117] Quirosa G, Torres M, Chacartegui R. Analysis of the integration of photovoltaic excess into a 5th generation district heating and cooling system for network energy storage. Energy 2022;239:122202. https://doi.org/10.1016/J.ENERGY.2021.122202.
[118] Kafaei M, Sedighizadeh D, Sedighizadeh M, Fini AS. An IGDT/Scenario based stochastic model for an energy hub considering hydrogen energy and electric vehicles: a case study of Qeshm Island, Iran. Int J Electr Power Energy Syst 2022;135:107477. https://doi.org/10.1016/J.IJEPES.2021.107477.
[119] Doosti R, Sedighizadeh M, Sedighizadeh D, Sheikhi Fini A. Robust stochastic optimal operation of an industrial building including plug in electric vehicle, solar-powered compressed air energy storage and ice storage conditioner: a case study in the city of Kaveh, Iran. IET Smart Cities 2022;4:56–77. https://doi.org/10.1049/SMC2.12025.
[120] Lefebure N, Khosravi M, Hudobade Badyn M, Bünning F, Lygeros J, Jones C, Smith RS. Distributed model predictive control of buildings and energy hubs. Energy Build 2022;259:111806. https://doi.org/10.1016/J.ENBUILD.2021.111806.
[121] Wang W, Yang D, Huang N, Lyu C, Zhang G, Han X. Irradiance-to-power conversion based on physical model chain: an application on the optimal configuration of multi-energy microgrid in cold climate. Renew Sustain Energy Rev 2022;161. https://doi.org/10.1016/J.RSER.2022.112356.
[122] Shariatkhah MH, Haghifam MR, Parsa-Moghaddam M, Siano P. Modeling the reliability of multi-carrier energy systems considering dynamic behavior of thermal loads. Energy Build 2015;103:375–83. https://doi.org/10.1016/J.ENBUILD.2015.06.001.
[123] Shariatkhah MH, Haghifam MR, Parsa-Moghaddam M, Siano P. Evaluating the reliability of multi-energy source buildings: a new analytical method for considering the dynamic behavior of thermal loads. Energy Build 2016;126:477–84. https://doi.org/10.1016/J.ENBUILD.2016.05.043.
[124] Walker WE, Harremoës P, Rotmans J, van der Sluijs JP, van Asselt MBA, Janssen P, von Krauss MPK. Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support, vol. 4; 2010. p. 5–17. https://doi.org/10.1076/IAIJ.4.1.5.16466. Http://Dx.Doi.Org/10.1076/Iaij.4.1.5.16466.
[125] Evaluation of Sensitivity and Uncertainty Analysis Methods in a Quality Assessment Framework with Application to Environmental and Business Statistics Lot 14 of EUROSTAT SUP COM 1997 JRC reference: Administrative Arrangement 13592-1998-01 A1CA ISP LU, (n.d.).1–56.
[126] Cacuci DG, Ionescu-Bujor M, Navon IM. Sensitivity and uncertainty analysis, volume II : applications to large-scale systems, sensitivity and uncertainty analysis, ume II; 2005. https://doi.org/10.1201/9780203483572.
[127] Wei T. A review of sensitivity analysis methods in building energy analysis. Renew Sustain Energy Rev 2013;20:411–9. https://doi.org/10.1016/J.RSER.2012.12.014.
[128] Evaluation of sensitivity and uncertainty analysis methods in a quality assessment framework with application to environmental and business statistics lot 14 of EUROSTAT SUP COM 1997 JRC reference: administrative arrangement. 1999.
[129] Saltelli A, Aleksankina K, Becker W, Fennell P, Ferretti F, Holst N, Li S, Wu Q. Why so many published sensitivity analyses are false: a systematic review of sensitivity analysis practices. Environ Model Software 2019;114:29–39. https://doi.org/10.1016/J.ENVSOFT.2019.01.012.
[130] Aien M, Hajebrahimi A, Fotuhi-Firuzabad M. A comprehensive review on uncertainty modeling techniques in power system studies. Renew Sustain Energy Rev 2016;57:1077–89. https://doi.org/10.1016/J.RSER.2015.12.070.
[131] Thomopoulos NT. Essentials of Monte Carlo simulation: statistical methods for building simulation models. Essentials of Monte Carlo Simulation: Statistical Methods for Building Simulation Models 2013;9781461460220:1–171. https://doi.org/10.1007/978-1-4614-6022-0/COVER.
[132] Rosenblueth E. Two-point estimates in probabilities. Appl Math Model 1981;5:329–35. https://doi.org/10.1016/S0307-904X(81)80054-6.
[133] Hong HP. An efficient point estimate method for probabilistic analysis. Reliab Eng Syst Saf 1998;59:261–7. https://doi.org/10.1016/S0951-8320(97)00071-9.
[134] Zadeh LA. Fuzzy sets as a basis for a theory of possibility. Fuzzy Set Syst 1999;100:9–34. https://doi.org/10.1016/S0165-0114(99)80004-9.
[135] G.J. Klir, B.O. Yuan, H. Jtwww, Fuzzy sets and fuzzy logic theory and applications, (n.d.). www.prenhall.com (accessed April 21, 2023). 1–551.
[136] H. Dawood, Interval Mathematics as a Potential Weapon against Uncertainty, https://Services.Igi-Global.Com/Resolvedoi/Resolve.Aspx?Doi=10.4018/978-1-4666-4991-0.Ch001. (1AD) 1–38. https://doi.org/10.4018/978-1-4666-4991-0.CH001.
[137] Van Kampen E. Global optimization using interval analysis: interval optimization for aerospace applications. 2010. https://repository.tudelft.nl/islandora/object/uuid%3Afdc2dbda-b419-450f-a305-64825a43a0c8. [Accessed 21 April 2023].
[138] Alefeld G, Mayer G. Interval analysis: theory and applications. J Comput Appl Math 2000;121:421–64. https://doi.org/10.1016/S0377-0427(00)00342-3.
[139] Gorissen BL, Yanikoğlu I, den Hertog D. A practical guide to robust optimization. Omega (Westport) 2015;53:124–37. https://doi.org/10.1016/J.OMEGA.2014.12.006.
[140] Sun L, Xu Q, Yang Y, Ji Y. Game-theoretic robust optimization for a small-scale integrated power system. Elec Power Syst Res 2021;192:106852. https://doi.org/10.1016/J.EPSR.2020.106852.
[141] Zhang Y, Liu F, Su Y, Chen Y, Wang Z, Catalao JPS. Two-stage robust optimization under decision dependent uncertainty. IEEE/CAA Journal of Automatica Sinica. 2022;9:1295–306. https://doi.org/10.1109/JAS.2022.105512.
[142] K. Yang, J. Huang, Y. Wu, · Xiaodong Wang, · Mung Chiang, Distributed robust optimization (DRO) Part I: framework and example, ([n.d.]).
[143] Ben-Haim Y. Info-gap decision theory: decisions under severe uncertainty, info-gap decision theory: decisions under severe uncertainty. 2006. p. 1–368. https://doi.org/10.1016/B978-0-12-373552-2.X5000-0.
[144] Kiani-Moghaddam M, Shivaie M, Weinsier PD. Introduction to meta-heuristic optimization algorithms. 2019. https://doi.org/10.1007/978-3-030-12044-3_1.
[145] Kiani-Moghaddam M, Shivaie M, Weinsier PD. Introduction to multi-objective optimization and decision-making analysis. 2019. https://doi.org/10.1007/978-3-030-12044-3_2.

[146] Deb K. Introduction to evolutionary multiobjective optimization. Lect Notes Comput Sci 2008;5252:59–96. https://doi.org/10.1007/978-3-540-88908-3_3. LNCS.
[147] Miettinen K, Ruiz F, Wierzbicki AP. Introduction to multiobjective optimization: interactive approaches. Lect Notes Comput Sci 2008;5252:27–57. https://doi.org/10.1007/978-3-540-88908-3_2. LNCS.
[148] Miettinen K. Introduction to multiobjective optimization: noninteractive approaches. Lect Notes Comput Sci 2008:1–26. https://doi.org/10.1007/978-3-540-88908-3_1. 5252 LNCS.