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A review of system modeling, assessment and operational optimization for integrated energy systems

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Abstract Building an efficient, safe, and sustainable energy system has been listed as one of the national energy development strategies in China. Through unified management and optimization for the processes of energy generation, transmission, conversion, and distribution, the integrated energy system (IES) can meet the diversified demands on energy with high efficiency and effectiveness, providing the basis to form a low-carbon sustainable social development mode. This research reviews the studies and issues of system modeling, assessment, and operational optimization on the IES. The ongoing problems that need further investigation are also presented. Besides, research of data-driven approaches on the IES will be discussed, based on which the future research directions are suggested here.

Keywords IES, system modeling, assessment, operational optimization, data-driven

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1 Introduction

There are many categories of energy resources for daily life and production, such as electricity, thermal energy, and natural gas. However, the electric power systems, heat supply systems, and natural gas systems are usually managed and operated by different companies or units, resulting in low utilization efficiency. With the shortage of fossil energy resources and the degradation of the natural environment in China, there is an urgent requirement to effectively manage various energy resources to promote their conservation and emission reduction. Thus, the integrated energy system (IES), involving different energy conversion equipment, such as combined heat and power (CHP), electricity to hydrogen device, and heat pump (HP), was developed [1, 2]. The IES refers to an energy system integrating different energy resources, such as electricity, natural gas, thermal energy, and renewable energy. With a smart grid as the core element in a certain region, such a system can realize the coordinated planning and the optimized operation for heterogeneous energy subsystems using the methodologies of advanced information technologies and innovative management.

The IES is of great importance to ensure the safety of energy supply and consumption and to promote sustainable energy development [3]. With the coordinated planning of multiple energy subsystems in an IES, the hierarchical utilization of various energy resources is capable of reducing energy waste [4]. Its coordination mechanism can effectively reduce the disruption risk of energy supply caused by the overload in one of the energy subsystems [5]. Thus, IES is becoming a very attractive research area in the fields, such as electric power systems, natural gas systems, and thermal energy systems. It is worth noting that the United States raised the IES to the national energy strategy in 2007, aiming to develop technologies, such as combined cooling, heating, and power systems [6]. Besides, Germany launched the

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E-Energy project in 2008, aiming to use advanced information technologies and the market mechanism to promote the efficient operation of energy systems [6]. Recently, more than 70 countries and regions, such as Europe and Japan, declared a series of research programs for IES [6]. Similarly, an "energy production and consumption revolution strategy (2016–2030)" was launched in China in 2016, and an action plan to construct "Internet + smart energy" was also released [7].

For IES technologies, it usually exhibits high-level complexity based on the system structure, the dynamics feature, the operational mode, and the equipment categories. It also shows high-level uncertainty when facing a large amount of new renewable energy inputs, such as wind-power electricity, photovoltaic (PV) system, and a large number of battery charger vehicles consumers [8]. Various energy subsystems exhibit different dynamics characteristics, especially based on operational time scales. For instance, the power grid usually responds at a millisecond level, while the heat supply network often requires tens of minutes or several hours to reach its steady-state. Thus, it is a very challenging task to accurately describe an integrated model for such multiple energy subsystems. Besides, many renewable energy suppliers and uncertain electricity charger consumers increase the IES operation uncertainty [9]. It is difficult to approximate the number of renewable energy inputs and their occasions.

Considering the possible and challenging research tasks related to IES design and operation, the IES studies can be summarized as system modeling, assessment, and operational optimization. The modeling of IES aims to estimate the systems states accurately by formulating mathematically steady-state or dynamic characteristics for the entire energy system, which is an essential basis for its subsequent assessment and operational optimization. The system assessment provides dynamic operation evaluation on various time scales when the IES experiences equipment malfunction, large energy flow fluctuations on supply or consumption, and structure variation. It usually consists of a series of studies on system safety margin, vulnerability, stability, and its related dynamic or quantitative criteria. The operational optimization of the IES guarantees a stable and highly efficient utilization of the multiply energy subsystems and their comprehensive scheduling performance. With the rapid advancement of the Internet of Things, big data, and telecommunication technology, a considerable amount of operational data related to the IES are accumulated, and data-driven technologies also exhibit significant development [6, 10]. Given the above considerations, this study summarizes the outcomes of the IES modeling approaches in the literature. It also presents an overview of its assessment and operational optimization. Furthermore, this article surveys the application of the data-driven approaches in the IES field. Finally, some IES future research directions are also explored.

2 Basis of the IES

A typical IES usually integrates multiple energy resources including power, natural gas, heating, and cooling energy, as illustrated in Figure 1. The energy resources interact with each other through energy conversion devices such as CHP units, heat pumps, power to gas (P2G) equipment, electric chillers (EC) and absorption chillers (AC). However, the strong coupling and the multiple-time-scale characteristics of various energy resources lead to a huge challenge for accurate model description of the entire IES [11, 12]. Based on the physical laws of energy resources, such as power and heating, an IES can be described by a number of state variables of nodes and lines within an energy network, as shown in Table 1, which were formulated by the theoretical laws of different energy subsystems [13]:

$$
\begin{cases}
\boldsymbol{y}_e(\boldsymbol{x}_e, \boldsymbol{x}_g, \boldsymbol{x}_h, \boldsymbol{x}_c) = \boldsymbol{0},\\
\boldsymbol{y}_g(\boldsymbol{x}_e, \boldsymbol{x}_g, \boldsymbol{x}_h, \boldsymbol{x}_c) = \boldsymbol{0},\\
\boldsymbol{y}_h(\boldsymbol{x}_e, \boldsymbol{x}_g, \boldsymbol{x}_h, \boldsymbol{x}_c) = \boldsymbol{0},\\
\boldsymbol{y}_c(\boldsymbol{x}_e, \boldsymbol{x}_g, \boldsymbol{x}_h, \boldsymbol{x}_c) = \boldsymbol{0},
\end{cases}
\tag{1}
$$

where $\boldsymbol{y}_e$ denotes the power flow models including power balance equations of nodes and power equations of branches, etc.; $\boldsymbol{y}_g$ denotes the models of natural gas subsystems including the pipe flow equations, formulations of nodes in a gas network, and the energy consumption equations of compressors, etc.; $\boldsymbol{y}_h$ denotes the hydraulic model and thermal model of heating subsystems, and $\boldsymbol{y}_c$ denotes the models of energy conversion devices. The variables $\boldsymbol{x}_e$, $\boldsymbol{x}_g$ and $\boldsymbol{x}_h$ represent the state variables of power, natural gas, and heating subsystems, respectively. $\boldsymbol{x}_c$ represents the state variables of energy conversion devices.

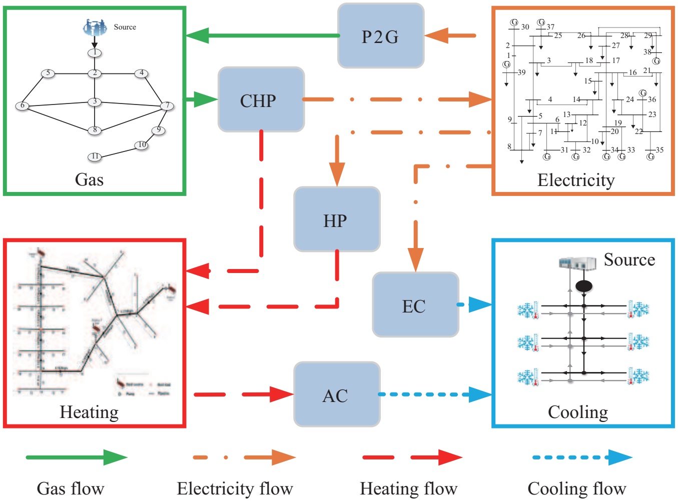

Figure 1 (Color online) A structure of a typical IES.

Table 1 Physical laws and state variables of energy subsystems

Energy subsystem	Physical laws	State variables	
		Nodes	Line/pipeline
Power	Kirchhoff's law Ohm's law	Magnitude of voltage, phase angle, injection power, etc.	Active and reactive power
Natural gas	Law of hydromechanics	Pressure, etc.	Flow in pipeline subsystems
Heating	Law of hydromechanics Law of thermodynamics	Heat power, pressure, supply and return temperature, output temperature, etc.	Flow in pipeline subsystems

3 IES modeling

One can summarize the modeling aim for the IES as the steady-state modeling and the transient-state modeling tasks. The steady-state of the IES refers to a stable working condition, where the values of the state variables operate stably in a certain range or a point. When the IES is disturbed or controlled, it will fall into a transient process, i.e., the transient-state process, where the working states may gradually transfer into another steady state. Here, the studies of the steady-state modeling and the transient-state modeling are reviewed, respectively. In recent years, with the accumulation of the large amount of data reflecting the states of operation processes, the data-driven approaches for the IES steady-state and transient-state modeling are also emphasized in this section. Table 2 [14–48] provides an overview of the IES modeling methods. In the steady-state modeling, the data-driven method is a powerful tool; however, the data accumulated must be of high quality, which should cover all the working conditions of the energy systems. Besides, the transient-state modeling is currently dominated by the mechanism-based methods; thus, in future studies, the data of transient processes can be employed for improving the modeling accuracy.

3.1 Steady-state IES modeling

The traditional steady-state modeling methods of electric power systems, natural gas systems, and heating systems have been studied in [49–51]. They typically involve the modeling of the integrated power and natural gas system (IPGS) [52, 53], the modeling of the integrated power and heating system (IPHS) [54, 55], and the modeling of the integrated power, natural gas, and heating system (IPGHS) [56, 57]. The traditional methods involve the mechanism analysis, which suffer from the high computational load issues, and thus, the data-driven ones are born to tackle these problems.

For the steady-state formulations of energy network, the strong nonlinearity was a significant issue to be addressed, resulting in high computational complexity [58, 59], and thus, local linearization, such as the piecewise linearization [14, 15] and the first-order Taylor expansion [16–18], has become one of the widely-used solutions to cope with the above problem. In the piecewise linearization method, the num-

Table 2 Overview of the IES modeling methods

Category	Issues	Methods	Characteristics
Steady-state IES modeling	Strong nonlinearity modeling	The mechanism-based methods: local linearization, such as the piecewise linearization [14, 15] and the first-order Taylor expansion [16–18].	(1) Easy to implement; (2) strong explainability; (3) difficult to avoid the decrease of the model accuracy in linearization approaches.
		The data-driven methods: the linear regression (LR) [19–21], the support vector regression (SVR) [22–24], and the artificial neural network (ANN) [25–27], etc.	(1) Easy to implement; (2) weak explainability; (3) higher modeling accuracy; (4) requiring the measured data of high quality.
		Combining the mechanism-based and data-driven methods: the serial integration [28], the parallel integration [29], and the embedded [30].	(1) Offering advantages of the former two; (2) the time-variant feature should be further investigated based on real-time data.
	Energy conversion processes	The energy hub methods [31–36].	(1) Characterized by the energy conversion efficiency; (2) constant assumption might be inappropriate.
Transient-state IES modeling (multi-time scale issue)	Considering the transient process of the electric power subsystem	The singular perturbation methods [37–39].	Higher computational burden when considering the transient process of the power systems.
	Ignoring the transient process of the electric power subsystem	For the natural gas subsystem: the implicit finite difference methods [40, 41] and the Wendroff finite difference methods [42–44].	Sensitiveness to the step size in difference methods.
		For the heating subsystem: the quasi-steady methods [45,46] and the quasi-dynamic ones [47, 48].	Compared to the quasi-steady methods, the quasi-dynamic ones could produce more accurate models with a higher computational burden.

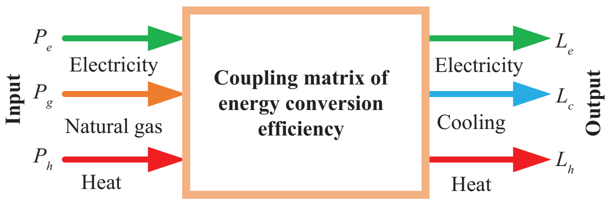

Figure 2 (Color online) An illustration of the EH model.

ber of segments has to be carefully determined to make a tradeoff between the computational accuracy and efficiency for the IES modeling. Although such linearization approaches could reduce the computational cost in some circumstances, they are relatively hard to avoid the decrease of model accuracy or generalization of IES modeling.

It is very important to describe the energy conversion processes between two or more types of energy resources. The energy conversion in an IES consists of the equipment or processes between electricity and natural gas (such as gas turbines (GT) [60], P2G [61] and electric-driven compressors [62]), electricity and heat (such as circulating pumps [54], HP [63] and electric boilers [64]), natural gas and heat (such as gas boilers [65]), and among electricity, natural gas and heat (such as CHP [66]). Particularly, owing to the complexity of energy conversion, an energy hub (EH) method was originally proposed in [31], where the conversion efficiency, expressed as a coupling matrix, was adopted to describe the relationship between the energy supply and demand, as shown in Figure 2. In another study [32], with the constraints of the three-phase power flow and the natural gas flow, an EH model was reported to depict the coupling relationship between the power subsystem and the natural gas subsystem. Besides, an extended EH approach was claimed for the load flow analysis of the highly coupled district energy networks, based on the AC power flow equations and the hydraulic-thermal model of heating subsystems [33]. However, the energy conversion efficiency was assumed to be constant in most of such studies, which might affect the modeling accuracy since it actually exhibited a close relationship with the operational states of the energy conversion equipment or was affected by the external environment variations [34–36].

The above modeling methods are based on mechanism analysis. However, with the development of computers and information technologies, a large amount of data reflecting the operation states of the IES have been accumulated through the wide-area measurement systems (WAMS) and the supervisory control and data acquisition (SCADA) systems [19]. In such a way, a class of data-driven approaches, such as LR [19–21], SVR [22–24], and ANN [25–27], model the complex nonlinear relationships among the system variables in an IES. Typically, in [21], two data-based linear regression models were respectively established for the power subsystem and the heating subsystem, which formed a basis of the power flow calculation in the IPHS. For modeling an IES including cooling and hydrogen energy, an SVR model was investigated for the relationship between the back pressure of a steam turbine and the condenser-related variables [24]. Moreover, based on the operational data, the boilers and steam turbines were modeled by an ANN so as to perform the production planing of CHP in a waste-to-energy plant on a short-term basis [26]. Although these data-driven models could usually achieve high modeling accuracy, they were only treated as the black-box models of the system variables. Thus, they were usually hard to be reasonably explained by employing a mechanism-based principle. Therefore, the data-driven methods applied to industrial practice could be suspected owing to their weak explainability.

For improving the modeling explainability and accuracy simultaneously, a class of hybrid approach combining the mechanism-based method and data-driven one was reported in [67], where three categories were introduced, i.e., the serial integration, the parallel integration, and the embedded. In the serial integration methods, based on a number of key variables selected by the mechanism analysis, the data-driven model was used to correct the mechanism-based one [28]. In the parallel mode, the outputs of the mechanism-based and data-driven models were combined by weighted calculation to help improve the modeling accuracy [29]. Last, in the embedded mode, the data-driven model was embedded into the mechanism-based one as an inner module for complex element substitution or model parameters calibration, for improving the efficiency and flexibility of the model [30]. For instance, in [28], as for the solar power forecasting, the weather features, including the irradiance components and PV cell temperatures, firstly derived from PV analytical modeling, were then used to reformulate the input variables of data-based machine learning models. In [68], a model of district heating system was established in an embedded mode, where the thermal transients and mass flow distributions within the network were described by the conservation equations for mass and energy, with the water circulation process represented by a data-based LR model. However, in the hybrid methods, there is a high requirement of the quality of the accumulated data. The time-variant feature of the system variables needs further investigation based on the historical data in future research.

3.2 Transient-state IES modeling

Since the transient-state modeling involves with multi-energy resources, the multiple-time-scale issue must be addressed. There are huge differences in the transient process time scales among the electric power subsystem, the natural gas subsystem, and the heating subsystem. There exists the extremely short transient process in electric power subsystems, usually during 100–200 ms, while the dynamic processes of natural gas and heating subsystems usually last for a number of minutes or hours. Since the response time in electric power subsystems is so fast, there are currently two ways to deal with this multiple-time-scale issue, i.e., considering the electric transient process and ignoring this transient process.

In some studies, the transient process of electric power subsystems was considered, where multiple-time-scale decomposition was conducted to deal with various response time of the multiple energy resources by using the singular perturbation method [37–39]. For instance, in [37], based on the singular perturbation method, the IPGS was decomposed into a fast subsystem and a slow one. Besides, the singular perturbation method was used for modeling the dynamic processes of the IPGHS in order to obtain the approximated analytical solutions in the three categories of time scales [39].

However, owing to the "instantaneity" of electric power subsystems, in most studies, viewing the electric power subsystems as steady-state processes in the IES, one only considered the transient process of natural gas and heating subsystems, and their impacts on electric power subsystems [69, 70]. For the natural gas subsystem, the values of the pipeline pressure and flows were spatiotemporal-dependent in transient-state models, usually expressed as partial differential equations (PDEs) and algebraic equations [70]. In literature, to solve these transient-state models, the implicit finite difference methods [40, 41] and the Wendroff finite difference methods [42–44] were widely employed for numerical results. Besides, for simplifying the transient-state modeling, the DC power flow and the linearized gas flow equations were employed in [70]. In [71] the natural gas flow model was approximated as a transient matrix. In such a way, the step sizes in these methods lead to great influence on the convergence and accuracy of the algorithms, which should be carefully set up and will suffer from high computational complexity if facing very small step sizes.

As for the heating subsystems in an IPHS, the influence of the dynamic characteristics of temperature on system operation should be taken into account [72]. Its transient modeling methods mainly consist of the quasi-steady one [45, 46] and the quasi-dynamic one [47, 48]. In the former version, according to the multiple-time-scale characteristics of the power subsystems and the heating subsystems, the interaction between them could be divided into a number of quasi-steady stages so as to simplify the transient analysis for the IES [45]. The latter one only considered the dynamics of thermal processes in the heating system, ignoring those of the hydraulic processes. As such, the quasi-dynamic model of the IPHS was established with a steady-state hydraulic part and a dynamic thermal part [73]. Compared to the former method, the latter one could produce more accurate models with a higher computational burden.

However, the existing studies usually concentrate on the multiple-time scale modeling of the IPGS or the IPHS. There are few studies on modeling the more complex IPGHS. Besides, there are few studies on the data-driven methods for the multiple-time scale modeling, and thus, the transient process data help model the IES, providing a good future research direction.

4 Assessments of IES

An IES usually encounters various threats during its operations, e.g., equipment faults, extreme weather, and natural disasters. The assessment of its operation performance becomes an urgent issue, which can be conducted in various perspectives, including the reliability, resilience, and fault degree [74–76]. The reliability measures the disturbance risks of the energy supplies or consumptions when facing device malfunction, energy supplies shortage, immediate load increase, etc. The resilience represents or quantifies the ability of an IES to recover normal operational conditions from major system failures when some unexpected extreme events, such as natural disasters, occur, while the fault degree is utilized to identify and diagnose the causes of the system faults and the laws of fault evolution based on the fault signals and mechanism analysis. Table 3 [77–112] provides an overview of the IES assessment methods, from which one can see that the assessment of electric power systems was more maturely developed than that of the multi-energy IES, and thus, a systematic methodology for the IES assessments remains to be built considering the multi-energy complementation as well as the multiple-time-scale features.

4.1 Reliability assessment

The disturbance of the IES possibly caused by climate hazards, equipment faults, etc., can result in the deviation of designed working conditions, leading to great impact on the stability of multiple energy operations. Therefore, it is crucial to evaluate the reliability of such a system under disturbance. Its computation procedure can be usually summarized as the following [77,78]. First, the reliability evaluation model is established for the operation states of energy systems and its equipment. Then, the operation states are simulated in a short period by using the Monte Carlo or analytical methods, so as to calculate the reliability indices for quantifying the reliability of entire energy system.

(1) Reliability evaluation index. The reliability indices are adopted to quantitatively estimate the reliability level of an IES in multi-energy supply. The indices for the electric power systems mainly consist of the load index and the system index [79], in which the load indices reflect the reliability performance of particular load point in electric power system, i.e., the failure rate of load-point (λ, times/year), the energy interrupting duration of load-point (r, hours/time), and the annual average energy interrupting duration of load-point (U, hours/year). The system indices denote the reliability level of the entire system, i.e., the expected energy not supplied (EENS, MWh/customer/year), the system interruption frequency (SIF, times/customer/year), and the system interruption duration (SID, hours/customer/year). Particularly, the EENS is defined as [79]

$$\mathrm{EENS} = \sum_{s\in\Omega} \Delta I\left(s\right) P\left(s\right), \tag{2}$$

where $P\left(s\right)$ is the probability of system state s, Ω denotes the state set of load curtailments, and ΔI denotes the amount of electricity load curtailment of system state s.

Table 3 Overview of the IES assessment methods

Category	Issues	Methods	Characteristics
Reliability assessment	Reliability evaluation index	For electric power systems: the load index and the system index [77–79]. For multi-energy IES: the indices of energy conversion devices [80–82].	(1) Maturely developed for power systems; (2) remaining to be studied for multi-energy IES.
	Assessment methods	The Monte Carlo (MC) simulation [83–85], the analytical methods [86–88], and the combination of the former two [89–91].	In the IES assessment, the multiple-time-scale behavior of different energy resources should be further considered.
Resilience assessment	Description of the resilience	The resilience triangle [92] and the conceptual resilience trapezoid [93].	The conceptual resilience trapezoid is more informative than the resilience triangle.
	Assessment methods	The power flow-based performance simulation approach [94], the graph-theory-based method [95], etc.	The influence of the multi-energy coupling and conversion on the anti-interference ability of the IES should be further considered.
Fault issues	Fault diagnosis	The model-based methods [96, 97] and the data-based ones [98, 99].	(1) High computational burden and the ability of revealing the nature of failure processes for model-based methods; (2) weak expandability for the data-based ones.
	Cascading failures analysis	For electric power systems: the pattern search theory-based methods [100, 101], the methods based on self-organized criticality theory [102, 103], the complex network theory-based approaches [104, 105], etc. For multi-energy IES: propagation rule of the faults among different energy subnetworks [106], simulation for the heating and power coupling network [107], etc.	(1) Maturely developed for power systems; (2) A systematic methodology remains to be built for the multi-energy IES.
	System restoration	For electric power systems: the intelligent optimization algorithms [108], the dynamic programming [109], the bi-level programming [110], etc. For multi-energy IES: recovery strategy for multi-energy resources [111], sequential operation scheme [112], etc.	(1) Maturely developed for power systems; (2) the multi-energy complementation should be considered for IES system restoration.

As for the reliability indices of the IES with multi-energy resources, most of these indices for electric power systems are considered to be capable of directly applying to the IES since these energy resources can be converted into electricity equivalently, and thus, one could build the reliability indices for each energy subsystems [79, 113]. In [114], the EENS indices for electricity, heat, and natural gas were constructed respectively to indicate the interruption risk of multi-energy supply in an IES. In [115], the loss of energy probability (LOEP) and the expected electricity and gas energy not supplied (EEGNS) were implemented to evaluate the reliability of the IPGS. However, considering the coupling of the multiple energy resources in an IES, in particular, it is very significant to build a reliability index system for the energy conversion devices [80, 81]. In [80], as for the IPGS, the reliability indices in device level were designed for the P2G device, i.e., the P2G device capacity utilization and probability, as well as the contribution of P2G to the EENS. Also, in [82], since the energy conversion devices could be regarded as the bridges between energy subsystems, an importance degree index was reported for evaluating the impact of failure of energy converters on energy supply, based on the concept of "valve level" which was formulated as

$$T\left(e_i\right)=\frac{\psi_{c\max}\left(e_i\right)}{\psi_{c\max}}, \tag{3}$$

where $T\left(e_i\right)$ denotes the valve level of the device e_i, $\psi_{c\max}$ is the maximum energy supply of the IES, and $\psi_{c\max}\left(e_i\right)$ denotes the maximum energy supply of the IES when facing a failure of the component e_i. Nevertheless, although these indices designed for energy conversion devices or integrated systems were developed, they were still not capable of quantifying the reliability level of the IES systematically, which should be further researched.

(2) Assessment methods. The reliability assessment aims to calculate the indices defined above, including the MC simulation methods [83–85], the analytical methods [86–88], and the combination of the former two [89–91].

The MC approach, starting from some initial system states, simulates the operation of the IES for a short period through multiple random samplings, and then one could compute the reliability indices based on these samples [83, 84]. In [83], the distributions of energy flows were simulated by an MC method for evaluating the reliability of a distributed IES, based on which one could assess the impact of the dynamic behavior of the energy load on the heat supply. For improving the computational efficiency, a parallel MC-based reliability evaluation method for distributed power systems was reported in [85]. Moreover, the sequential version of MC (SMC) simulation, owing to its high efficiency, was also widely employed for the IES reliability evaluation. In [81], the reliability evaluation for the IES was performed based on the combination of the SMC simulation and the reconfiguration of smart agent communication systems. Nevertheless, owing to the rare occurrence of the equipment failure, a large number of samples need to be drawn in the MC methods, aggravating the computational burden of the algorithm.

The analytical methods mainly consist of the state space method [86] and the optimization-based method [87, 88]. In [86], with the definition of the matrices of the failure rate and the repair rate based on the EH model, the state space model was utilized to evaluate the energy interruption risk. For improving the reliability of energy supply, an optimal load curtailment problem was solved so as to extend the margin of energy adjustment in the IES [87]. In [88], a hierarchical decoupling optimization framework was reported to calculate the optimal load curtailment. Besides, the MC method and the analytical method were usually combined in some studies, benefiting from the advantages of both. In [89], based on the combination of failure modes analysis and MC simulation, the reliability evaluation was carried out for the microgrids with PV and combined cooling, heating and power (CCHP) systems. Also, considering the multi-energy storage and the integrated demand response, an optimal load curtailment model was solved after the SMC simulation to assess the reliability of the IES [90]. However, in the existing studies on the reliability assessment of IES, the multiple-time-scale dynamic behavior of different energy resources was rarely considered [91, 116].

4.2 Resilience assessment

The resilience events, such as extreme weather or natural disaster, can lead to multiple instantaneous failures of components in an IES. Different from the events considered in the reliability assessment, these can be with the following features: (1) severe consequence with low-probability; (2) multiple simultaneous faults owing to disastrous damages [117]. Thus, the IES resilience refers to the ability of an IES to recover rapidly from extreme external shocks, and to absorb lessons for adapting its operation and structure to be better prepared for similar events in the future [93, 117]. It can usually be described as the resilience triangle [92] and the conceptual resilience trapezoid [93], as shown in Figures 3 and 4, respectively. One can see that there is an apparent advantage of the resilience trapezoid compared to the resilience triangle. The resilience triangle was only capable of assessing the restoration performance following an event. The assumption of an immediate resilience degradation was only applicable to the threat whose duration is momentary, e.g., an earthquake, with the ignorance of the shocks which could last from hours to days, e.g., a typhoon [118, 119]. On the contrary, the conceptual resilience trapezoid of electric power systems provided three phases when encountering extreme events, i.e., the degradation process, the fault stage, and the restoration stage, which was applicable to any type of extreme events [93].

To evaluate the resilience of an IES, the quantitative metrics were usually employed in the existing studies, although there was still no consensus on an appropriate resilience assessment framework. In [120], the $\Phi\Lambda E\Pi$ resilience metric system (see Table 4) was reported to quantify the resilience trapezoid shown in Figure 4, which could capture the performance of the electric power system during different phases. Besides, there are many studies on the IES resilience. In [94], the area under a curve between targeted performance and real performance was treated as a resilience index, calculated by using the power flow-based performance simulation approach. A graph-theory-based method evaluated the resilience of energy systems by considering the interdependency of gas and electricity subnetworks, where the loss of source and sink connectivity was regarded as a resilience index [95]. In [121], the probability that the system performed its intended functions was also employed to form a resilience index. In addition, the power outage data were also utilized to assess the resilience of electrical power distribution systems with the time to restoration following a failure as a quantitative resilience metric [122]. However, the data-driven approaches always suffer from the class imbalance problem since the outage data ought to be the minority

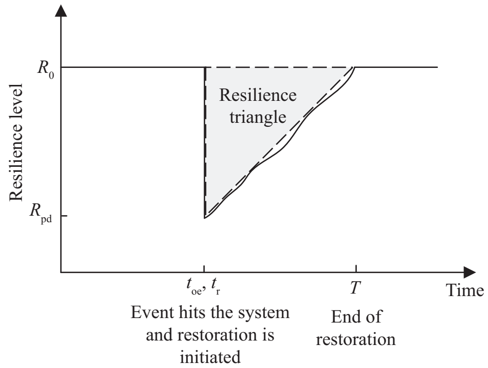

Figure 3 The resilience triangle associated to an event, modified from [92].

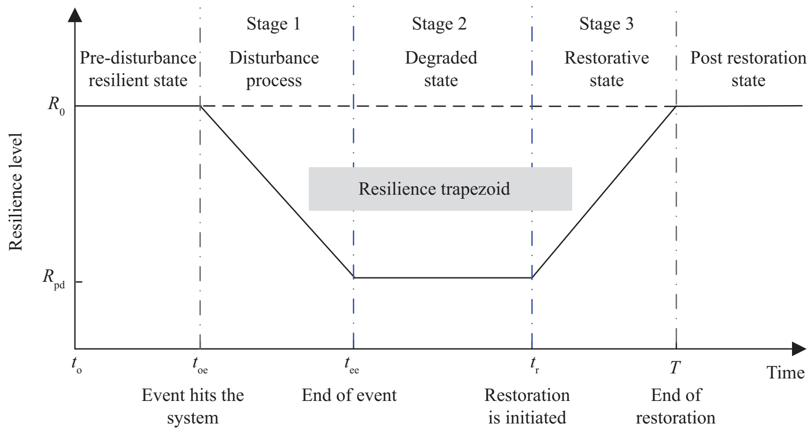

Figure 4 (Color online) Conceptual resilience trapezoid associated to an event, modified from [93].

Table 4 The $\Phi\Lambda E\Pi$ resilience metric system [120]

Stage	State	Resilience metric	Symbol
1	Disturbance progress	How fast resilience drops?	Φ
		How low resilience drops?	Λ
2	Post-disturbance degraded	How extensive is the post-disturbance degraded state?	E
3	Restorative	How promptly dose the system recover?	Π

in the entire dataset. Thus, one has to generate more of them from a simulation framework.

Summarily, owing to the high interdependency and multiple-time-scale dynamics of the energy resources, the vulnerability of the entire energy systems increases. Therefore, the future research direction of resilience evaluation of the IES should focus on investigating the influence of the multi-energy coupling and conversion on the anti-interference ability of the IES.

4.3 Fault issues

The equipment failure and vandalism in an IES can result in the interruption of energy supply. Their occurrence in one of its subsystems may spread throughout the entire IES, i.e., the cascading failures, and cause severe impacts on its stable operation. Hence, the issues of the fault diagnosis, the cascading failures evaluation, and the system restoration for the IES have been widely studied [123, 124].

4.3.1 *Fault diagnosis*

A variety of failure causes may be hidden behind the manifested fault signals of a component in an IES. Based on the fault signals as well as the physical laws of energy systems, to accurately identify these causes can greatly improve the efficiency of fault processing, and can also provide a basis of finding the optimal restoration strategies [125]. One could reveal the causes of faults through analyzing the switching signals and the electrical data of various circuit breakers before and after the occurrence of failures [123].

A great number of studies on it can be found in literature, grouped as the model-based methods [96, 97] and the data-based ones [98, 99]. The former searched for the original fault locations by analyzing the mechanism of energy systems starting from the manifested fault signals. For instance, with a pre-defined threshold, the fault states could be identified when the measured signal exceeded a threshold value [126].

Although the model-based ones could reveal the nature of failure processes, they might suffer from a high computational burden. In the data-based approaches, the relationships between the fault states and the power system variables could be easily built via a large number of historical data, such as the ANNs-based methods [127], the ones based on Bayesian networks [128], and the expert systems [129]. For instance, in [130], a multiple radial basis function (RBF) NN-based fault diagnosis method was proposed for power grids, where the outputs of each RBF NN were combined by using a Choquet fuzzy integral fusion module. A Gaussian mixture regression model combined with the unscented Kalman filter (UKF) was reported in [131] for identifying the non-linear fault features of the heating, ventilation and air-conditioning (HVAC) system. Besides, a data-driven black box fault diagnosis framework was also developed for an HVAC system [132], integrating multiple machine learning methods, such as the support vector machine (SVM) and the partial least squares (PLS) method. Considering the weather conditions, a multi-hidden Markov model (MHM) was reported in [133] to predict the power quality disturbance of smart grids. The high requirement on the quality of training samples contributes to a good performance in the fault detection of the IES; moreover, the class imbalance problem has to be addressed owing to the tiny proportion of the abnormal data in the entire dataset. However, the data-based ones suffer from weak expandability, which may prevent their practical applications.

Particularly, in the data-based approaches, as feature extraction can be regarded as an important prerequisite for accurately identifying the fault states, deep learning (DL)-based methods provide a sound way for the fault diagnosis problems of the IES owing to its ability of extracting potential fault features automatically [134, 135]. A convolutional sequence model was constructed in [134] for a gradual fault early stage diagnosis of the air source heat pump (ASHP) system, where a convolutional NN with an optimized convolution kernel (one-dimensional convolution kernel) was adopted. In [135], a DL model learned the hierarchical features of the data measured by the temperature sensors of exhaust gas, so as to identify the abnormal states of the GTs. Besides, based on the wavelet transform and the deep NN, an intelligent fault detection method was designed for the fault diagnosis of microgrids [136]. Moreover, a long-short term memory (LSTM) network was developed to capture the temporal characteristics of multi-source data coming from the power transmission and distribution processes [137]. A fully closed-loop deep convolutional NN model was reported in [138] for the classification of power quality disturbances. Although these DL-based methods are good at identifying the faults in an IES, they still struggle with weak explainability since one can fail to specific the physical meanings of the extracted fault features.

4.3.2 *Cascading failures analysis*

With the coupling of these energy resources, the fault of one node in a network may widely propagate throughout the energy networks. For instance, in an IPGS, the fault in a natural gas subsystem, affecting the operation of GTs, could subsequently lead to the associated changes of load distribution in the electric power subsystems, which could aggravate the interruption of power supply. Therefore, to evaluate the cascading failures rather than the fault in a single location becomes an urgent need. The cascading failures can be defined as an event sequence in an IES, where an initial disturbance or a group of disturbances trigger one or more associated faults [139]. Currently, the cascading failures evaluation of electric power systems were widely studied, including the pattern search theory-based methods [100, 101], the methods based on self-organized criticality theory [102, 103], and the complex network theory-based approaches [104, 105]. However, the research on the cascading failures of power systems ignores the influence of other forms of energy systems.

To evaluate the cascading failures of the IES, the impact of the multi-energy coupling on fault propagation and evolution should be considered [106, 140]. In [106], the propagation rule of the faults among different energy subnetworks was explored by using a proposed integrated simulation approach. Besides, treating the change of output power of natural gas unit under random faults as a constraint, a cascading failures model was presented in [139] for evaluating the impact of faults in natural gas subsystems on power subsystems. In [107], the fault propagation processes were simulated with initial faults for the heating subnetworks and the power subnetworks, respectively, based on which the cascading failures model was established for these two energy subnetworks. In [141], the influences of initial faults in the natural gas subsystem, the power subsystem, and the heating subsystem on the failure propagation of the entire IES were respectively discussed. The multiple-time-scale dynamics of the energy flows should be considered in the cascading failures of the IES in the future.

4.3.3 *System restoration*

A feasible restoration scheme should be made as soon as possible in the outage area to recover load under a series of operational constraints in an IES, aiming at minimizing the power of outage loads and reducing the number of switching operations [142]. This issue could usually be treated as a mixed integer nonlinear programming (MINP) problem, whose exact solutions were very difficult to be obtained [143, 144]. There are a number of approaches for such similar problems in power grids, such as the intelligent optimization algorithms [108], the dynamic programming [109], and the bi-level programming algorithms [110]. In [145], an improved Viterbi algorithm was reported to make the optimal restoration plan for the distribution networks. In [110], the complex MINP problem was transformed into a bi-level programming problem for power grid recovery, containing the sectionalization problem in the upper level and the restoration problem at the lower level. Besides, considering the operational mode of the distributed generation, a genetic algorithm (GA) based on improved coding strategy was reported to recover distribution networks [145]. The multi-stage optimization approaches were also employed to reduce the complexity of the system restoration problems for power grids [146, 147]. A two-stage recovery model for a power grid was reported in [146], solved by an integer L-shaped algorithm. The restoration procedure was structured into three stages according to the power system status and the goal of the load restoration in [147], taking the influence of renewable energy on the power grid recovery into consideration. Additionally, the multi-agent models [148, 149] and the Petri net methods [150, 151] were also designed in the restoration of smart grids. Although the system recovery problems of power grids have been paid a lot of attention to, there is less research on that when aiming at an IES.

Since there exist numerous energy conversion devices in a multi-energy system, it is crucial to consider the energy conversion processes in restoration planning. In [111], given the advantages of the collaborative multi-energy supply and the thermal inertia characteristics of the cooling and heating storage in an IES, the recovery strategy of multi-energy resources was constructed to deal with the occurrence of faults in energy conversion equipment. Besides, considering that there were various switching devices and energy conversion devices in an IES, a feasible restoration method could be formulated as a sequential operation scheme for each device and the network topology [112]. For the formulation of restoration strategies, the factors such as the coupling of multi-energy and the source-load uncertainties ought to be studied in the future. The multi-energy complementation can be utilized to make the optimal restoration strategy for the IES.

5 Operational optimization of IES

The operational optimization of the IES refers to the unified allocation and management of multi-energy resources considering the difference of their physical characteristics, for the purpose of maximizing economic benefits or minimizing pollutant emission in the operation of the IES [152]. It can be performed from the following perspectives, i.e., the device-level, the system-level, the entity-level and the park-level, as shown in Figure 5. The device-level denotes the energy consumption/generation/conversion equipment, e.g., gas-fired boiler, HP, and wind turbine (WT). The system-level refers to an energy sub-system containing the energy supply, consumption, and storage, e.g., the CCHP, containing a variety of devices. The entity-level is defined as an energy generation-consumption unit embedded in the main energy network, such as office buildings and manufacturing plants, being connected together through the power transmission lines or the gas pipelines. The last one is the park-level, covering multiple entities in a certain region, such as an industrial park or a commercial park. Table 5 [153–182] shows an overview of the IES operational optimization methods. Optimizations at different levels of IES have been studied respectively by many researchers in recent years; however, the coordinative optimization at different levels remains to be an open problem worth studying. Importantly, in the coordinative optimization, the boundary condition at each level should be well investigated in the future.

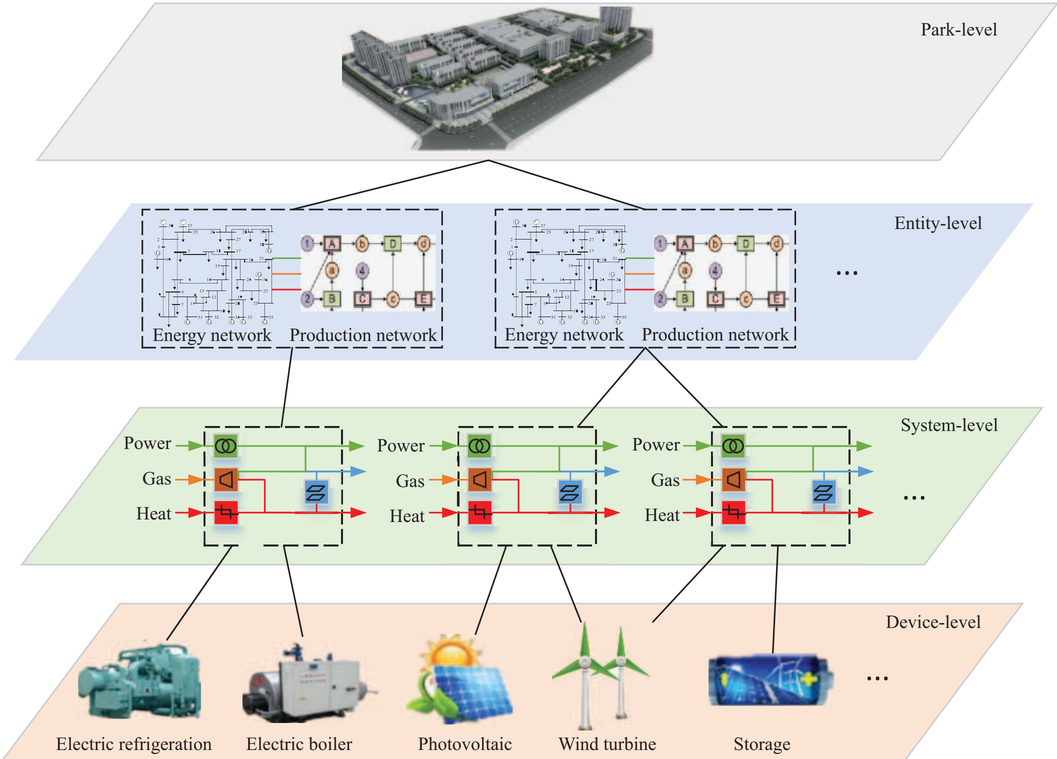

Figure 5 (Color online) Operational optimization of IES in different levels.

Table 5 Overview of the IES operational optimization methods

Category	Issues	Methods	Characteristics
The device-level	Control of renewable energy devices	The fuzzy control [153], the output feedback control [154], the sliding mode control (SMC) [155], etc.	(1) Impacted by environmental conditions greatly; (2) the dynamics of energy devices should be payed more attention to.
The system-level	Considering the multi-energy coupling	For the IPHS: mixture integer linear programming [156], following a hybrid electric-thermal load [157], mixed-integer non-linear programming [158], etc. For the IPGS: the methods with P2G technology [159–161].	Difficult to achieve the optimal allocation for multi-energy resources simultaneously in the IPHS optimization.
	Considering the uncertainties of the source side and the demand side	The stochastic optimization [162], the robust optimization [163, 164], the prediction-based optimization [165, 166], etc.	(1) High computational load in stochastic optimization; (2) lower computational load in robust optimization; (3) requirement of high prediction accuracy in prediction-based ones.
The entity-level	Considering the energy networks	The steady-state constraints: the multi-agent GA [167], the dynamic programming [168], etc. The transient-state constraints: the bi-level programming [169, 170], etc.	High computational complexity in transient-state constraint optimizations.
	Considering the production processes	The industrial demand response (IDR) method [171, 172], the combination of the IDR and the energy storage [173, 174], etc.	(1) Currently focusing on the microgrids; (2) the IDR for multi-energy optimization needs to be further studied in the future.
The park-level	Optimization with multiple entities	The non-interaction methods [175–177], the non-cooperation methods [178, 179], and the cooperation methods [180–182].	(1) Currently focusing on the interaction of microgrids; (2) multiple-time-scale dynamics should be further investigated in multi-energy operational optimization.

5.1 The device-level

Given a large number of distributed energy devices contained in an IES, their optimal control plays an important role in improving the efficiency and the operational stability of an IES, widely studied in literature, e.g., the control problems of the start-up, the turbine speed and the temperature of GT [183], and the control of the closed-cycle GT for power generation [184]. However, in recent years, with the increase of the number of WTs and PV systems in the IES, since the uncertainties of the outputs of these equipment have a great impact on the operation of the IES, the control problems of these renewable energy devices have been paid more attention to [153, 154]. Therefore, this subsection lays stress on the review of control methods of renewable energy devices.

For maximizing the utilization efficiency of renewable energy, it is significant to study the maximum power point tracking (MPPT) problem of WTs and PV systems considering the intermittency of renewable energy [153]. A number of control methods were developed for solving the MPPT in literature, such as the fuzzy control [153], the output feedback control [154], and the SMC [155]. An adaptive fuzzy-PI speed controller extracted the maximal wind power [153], and an output feedback controller was designed for the variable-speed WTs [154]. As for the PV system, a double integral SMC model employed double integral of tracking voltage error terms in its sliding surface so as to eliminate steady-state error apart from providing robust control actions in face of system uncertainties [155]. Most of these were carried out under the assumption of ideal environmental conditions, e.g., uniform illumination. However, the output power of renewable energy devices could be strongly influenced by weather conditions. Typically, the PV systems were extremely susceptible to shadows, resulting in the multi-peak characteristics of the power-voltage that led to bad control performance [185].

Formulated as a multi-extreme value optimization, the intelligent optimization algorithms were widely used to solve the above global optimal MPPT problems [185, 186]. For instance, a simulated annealing-based global MPPT method was designed for the PV systems [185]. An improved particle swarm optimization (PSO) algorithm with dynamic inertia weight coefficient was reported for solving the MPPT [186]. Besides, energy storage devices were also used to address the uncertainties of renewable energy so as to maintain the power balance. In [187], a robust power management strategy with multi-mode control features was reported for an integrated PV and energy storage system, where an automatic switching control strategy was employed to realize a smooth switching. In [188], a lithium-ion battery control method was proposed to mitigate the fluctuations of output power of PV arrays. Summarily, the studies on optimal control have been conducted at device-level, some of which considered the impact of renewable energy resources. However, the dynamics of energy devices have not yet been paid enough attention to, which should be researched in the future.

5.2 The system-level

The system-level operational optimization aims to minimize the operation costs of energy systems through adjusting the output power of controllable devices with the constraints of device capacities and supply-demand balance [156, 157]. Multiple energy resources are converted to each other by the aid of various energy devices. On the other hand, the source-load uncertainties, e.g., the renewable energy generation, often have great impact on the operation efficiency of IES. Thus, in this task, the multi-energy coupling and the source-load uncertainties are regarded as the two main issues at such a level.

(1) Considering the multi-energy coupling. According to the types of energy resources, the IES can fall into the following categories—the IPHS, the IPGS, and the IPGHS, as shown in Section 2. As for the IPHS, the CHP system is an important realization. In a CHP, through the multi-energy complementation, the energy utilization efficiency could be significantly improved, where the waste heat rejected from the power generation unit could be recovered by heat boilers for cooling or heating [156]. Many attempts have been made to perform the operational optimization of CHPs. Typically, an operation strategy of CHP with the following hybrid electricity-thermal load was mentioned in [157], where the reduction of carbon dioxide emission and energy consumption was evaluated with two patterns containing the following electric load (FEL) and the following thermal load (FTL). In [158], an MINP model was developed for the operational optimization of micro-CCHP, where improving the energy saving ratio and the cost saving ratio are both chosen as the objectives. Besides, a multiple-time-scale scheduling strategy was reported in [189] for microgrids considering the differences of the dynamics of electricity and heat. However, it is still difficult to achieve the optimal allocation for multi-energy resources simultaneously owing to their complex coupling constraints.

In the IPGS, with the introduction of P2G technology, the GTs and the P2G were combined to realize the bidirectional conversion of energy flows between the power subsystems and the natural gas ones [159]. A low-carbon economic environmental dispatching method was presented through absorbing the excess renewable energy using the P2G [159]. Similarly, a day-ahead optimal economic dispatching model for microgrids was reported in [160], where the curtailment of wind and solar energy was calculated based on the P2G. Besides, as for the more complex IPGHS, its multi-energy coupling constraints in the operational optimization model were usually formulated as an EH describing the relationship between energy inputs and outputs [161]. Nevertheless, the conversion efficiency in the EH, usually assumed to be constant, actually varied over time owing to the complex external environments, which should be fully considered in the system-level optimization of the IES.

(2) Considering the uncertainties of the source side and the demand side. One of the greatest challenges in the system-level optimization is to deal with the uncertainties of renewable energy resources and the load fluctuation in the demand side [162]. This issue has been widely studied recently, which can be summarized as the stochastic optimization [162], the robust optimization [163, 164], and the prediction-based optimization [165, 166]. The scenario-based method, an important branch of the stochastic optimization, employed the probability density function (PDF) to describe the source side and the load side uncertainties so as to generate a number of scenarios with certain probabilities through sampling technology. In [162], with the uncertainties of WT, PV, and the market price modeled by the Weibull and Gaussian distributions, optimization strategies for renewable-based microgrids were constructed in many scenarios generated with the probabilities. However, it was difficult to determine a suitable PDF for depicting specific uncertain variables, and it often took much more time to perform the stochastic optimization especially with large number of samples. To tackle such a task, the robust optimization employed the confidence intervals to quantify the uncertainty instead of using sampling. A robust optimization-based day-ahead scheduling method was reported to attenuate the disturbance of source-load uncertainties [163]. Besides, in [164], a robust optimization method was provided to accommodate the uncertainties of the cooling, heating, electrical load, and the output power of PV systems.

The former two kinds of methods both addressed the operational optimization problems by depicting the source-load uncertainties, i.e., either by sampling or by confidence intervals. However, predicting the trend of renewable generation and energy consumption also serves as an effective way to tackle this uncertainty issue in the system-level optimization. Usually, the data-driven prediction methods were widely studied in the operational optimization of the IES [190]. As for the microgrids, an ANN ensemble model was developed in [191] to predict the wind power generation and the electrical loads, based on which the optimal scheduling strategy for batteries was formulated. By utilizing the ANNs and the phenomenological models, the power consumption as well as the renewable generation were predicted in [192] to help to provide guidance at each decision step for a renewable-based microgrid. Based on the construction of the prediction intervals for the wind speed, an improved bacterial foraging optimization algorithm was reported in [193]. A demand response energy management method in building and district levels was developed in [194] by using the GA and the ANNs. In [195], they were also used for the operational supply and demand optimization of a multi-vector district energy system. In the above data-driven methods, an optimization model was built based on the prediction results of the source-load uncertainties. However, owing to the time-varying characteristics of energy systems, the prediction models need to be updated real-time according to newly observed data for achieving good prediction performance. In this field, there are also few outcomes presented in current literature. Although this kind of optimization provides good performance on tackling the source-load uncertainties, it requires high prediction accuracy of the forecasting models.

Based on the technologies of the compressed air energy storage (CAES) and the thermal energy storage (TES), the diversified energy storage strategies also became an important way for mitigating the uncertainties of renewable energy [196]. The operational stability of the multi-energy system was guaranteed by optimizing the charging and discharging strategies of the CAES equipment in [197], and a combination of the parameter analysis and simulation was reported in [198] to evaluate the performance of the IES so as to optimize the operation of multi-energy district boilers. The coordination of fuel cells and the hot water energy storage was employed to optimize the operation of the multi-energy systems with electric-vehicles (EVs) integration [199]. However, the multiple-time-scale dynamics of the cooling and heating loads should be fully considered in these studies, remaining to be studied in the future.

5.3 The entity-level

The entity can be divided into the residential entity, the commercial entity and the industrial one. For an entity, multiple energy transmission pathways can be provided to satisfy its demands within an energy network containing many transmission lines of the power subsystems, the pipelines of the natural gas subsystems, etc. [200]. However, diversified energy supply strategies, corresponding to different layouts of energy flows in transmission networks, may result in inefficiency of the system operation. Thus, the entity-level optimization can be defined as optimizing the distributions of multi-energy flows in the networks for economic goals, with the constraints of energy transmission networks. Besides, the industrial production processes, as big users of energy, are closely involved with the energy systems. Therefore, this subsection will review the entity-level operational optimization from two aspects, i.e., considering the energy networks and considering the production processes.

(1) Considering the energy networks. To perform the operational optimization at entity-level, the steady-state constraints and the transient-state ones of the multi-energy transmission networks are considered in the existing studies, respectively. The steady-state constraints are usually expressed as the equations of the AC power flow, the natural gas flow and the balance of EH [167, 168], and thus, the nonlinear characteristics should be addressed. The linearization methods are often used for simplification [201], as introduced in Section 3. For instance, the constraints of the natural gas network were linearized using a piecewise linear approximation (PLA) in a 3-D Euclidean space, based on which a mixed integer linear programming (MILP)-based scheduling model was built [201]. A linear EH model was developed in [202], where a multi-dimensional PLA method was reported for representing the non-convex constraints of the natural gas transmission network. The complex nonlinear constraints in the day-ahead scheduling model for the residential multi-energy systems were reformulated as linear ones by using the PLA to alleviate the computational burden [203]. When the IES was controlled or adjusted, it would fall into a transient-state process, especially for the long-distance natural gas or heating networks. As for the transient-state constraints, since the PDEs were used to describe the transient-state characteristics of the natural gas and heating networks, the operational optimization models for the IES were usually constructed, subject to the PDEs constraints [169], computed by the difference methods, as reviewed in Section 3. For instance, in [170], the Euler finite difference method was adopted to obtain numerical solutions of PDE for the gas network constraints. The transient-state model of the natural gas network and the steady-state power flow were combined to formulate the dynamic constraints in the optimization models [204]. However, in these models, the computational complexity will increase since one has to compute the numerical solutions of the transient-state constraints of energy networks.

(2) Considering the production processes. An industrial entity usually sees the close interaction between the multi-energy systems and a number of complex production processes in demand-side. As a result, the co-optimization between them has become an urgent issue. The IDR, as a powerful tool for the entity-level operational optimization of the IES, reaches the goal of optimal operation by reducing or transferring energy loads of the production processes actively through time-of-use (TOU) pricing or incentive compensation [171]. Currently, the IDR was mostly employed for the management of power grids [172]. For instance, an MILP-based scheduling model was reported in [172] for a multi-stage multi-line production process, considering the constraints of both the production process and the energy network. In [205], a scheduling model based on the resource-task network was proposed, and a state task network (STN)-based IDR energy management scheme was reported in [206] for industrial facilities. However, the adjustment for industrial processes usually made larger changes in energy demand-side, causing that the IDR could not achieve fine-tuning for auxiliary services, e.g., the automatic power generation control and the reactive power adjustment [173]. Therefore, the combination of the IDR and the energy storage for the auxiliary services was created to tackle the above problem [173,174]. A valuable ancillary service was offered through the IDR of cement plants load and energy storage [173]. A two-stage programming model considering power generation and industrial load was reported to provide the load-following reserves under high wind power penetration [174]. Although the demand response of the industrial electrical loads was widely used for entity-level optimization, the integrated demand response with the multi-energy complementation needs to be further studied in the future.

5.4 The park-level

In an industrial park, there are many entities of energy generation and consumption. Each of them has its distinct variables and objectives on energy utilization to improve its own benefit. Given the complex connections of the entities within the main energy network, the coordinated operation among entities plays an important role for considering the operation costs and the safety assurance of the park-level IES [207]. According to the relationships among the entities, one can divide the research on park-level optimization into three categories [207], i.e., the non-interaction, the non-cooperation, and the cooperation ones.

The non-interaction optimization mostly considers the interaction between multiple entities and the external energy suppliers, with the ignorance of the interaction among the entities themselves. The bi-level programming was usually employed in this category, where the bottom layer was an energy consumption cluster composed of multiple entities, and the top layer was a central controller [175]. A model predictive control (MPC)-based distributed economic optimization model was mentioned in [176] for the coordinated energy management of multi-microgrids, where each microgrid was treated as an entity. Also, with multiple EVs being considered as energy consumption entities, a two-stage integrated energy scheduling strategy for multi-microgrid system was presented in [177].

Although the park-level operation efficiency could be improved by clustering multiple entities, the ignorance of interaction among entities could result in energy wastes. With the development of information technology, the co-scheduling in a park could be realized through the real-time interaction among various entities [178]. Therefore, a non-cooperation optimization model, which considered the competitive relationships among entities, could achieve their co-optimization objectives [179]. Typically, a rule of interaction between microgrids and distribution networks was designed in [178], in which the competitive relationship between two microgrids was determined in a bilateral contract. Based on the non-cooperative game theory, a multi-party energy management model for smart building cluster was reported in [179].

Since the individual benefits were excessively emphasized in the competitive models so as to weaken the efficiency of the entire energy systems, the cooperative models for multiple entities were also investigated [180–182]. For instance, a cooperative power dispatching algorithm among multiple microgrids was proposed through a communication infrastructure in power grids [181]. In [208], treating a group of microgrids as one grand coalition with the aim of minimizing the entire operation costs, a cooperative-game-theory-based operational optimization model was designed in the park-level IES. For a multi-energy industrial park, a multi-objective optimization method was provided to maximize the "collective benefits" of a group of microgrids [209]. Besides, the economic and the collaborative operation of the multi-entities park was formulated as a unit commitment problem considering the discrete characteristics of energy transaction [210]. However, the park-level optimization associated with the interaction of microgrids was widely studied, while the multi-energy (e.g., electricity, heat, and gas) operational optimization with multiple-time-scale dynamics should be investigated in the future.

6 Conclusion and future research directions

In this study, the research on modeling, assessment, and operational optimization of the IES is reviewed. There are still issues to be addressed in the current studies. (1) It is difficult to build a unified model of the IES because of the multi-time scale characteristics of different energy resources. (2) Given the coupling of multi-energy resources, it is highly required to establish a more suitable and comprehensive index system of the IES compared to that of the independent energy system, such as the electric power system. (3) The data-driven methods applied in an IES can only realize "computational intelligence", by which the hidden patterns or regularities of the systems can be unearthed based on historical data, without the ability of self-perception of system states, and independent decision-making. Based on the above issues, this study discusses the future research directions of the IES in the following aspects.

For IES modeling, homogenized modeling is a possible future direction. The coordination and interaction between various energy subsystems can be simplified by expressing the operation rules of the energy resources in the same form, e.g., the electrical circuit analogy [211, 212], the gas-electricity analogy [213, 214], and the thermo-electric analogy approaches [215, 216]. However, only the gas-electricity analogy and the thermo-electric analogy were realized in the existing research. The homogenized IES modeling covering electricity, natural gas, and heat has not been investigated and realized. There are still challenges to realize the homogenized modeling of IPGHS owing to the lack of concrete theory in the current studies. Thus, multiple-time-scale coordination should be considered in homogenized modeling owing to the difference in multi-energy resource response time.

The considerable amount of historical data accumulated in the IES operation processes provides a visible future research direction on the IES. Although the data-driven methods are widely used in IES modeling, multiple-time scale modeling of the multiple energy networks integrating the electricity, heat, and gas remains to be addressed. Since the granular computing method [217], as a powerful tool for formulating the energy system states as data segments with different lengths, can effectively describe the correlation between variables with different time scales, this methodology may be an alternative approach to model the multi-scale characteristic between different energy resources in the future.

For the IES assessment, with the accumulation of practical data and the modeling of multi-scale characteristics, a sound, systematic assessment index system of the IES may be established in the future based on energy conversion devices and energy networks.

For the IES operational optimization, the reinforcement learning (RL) method, which is an essential process of learning strategies in the context of "adjusting to the situation", i.e., learning how to act based on the state to achieve maximum expected rewards based on the data, can search the optimal solutions without considering the complex constraints of the problem itself. There are many applications of the RL on IES operational optimization, such as the adaptive dynamic programming for smart grids [218], the multi-battery optimal coordination control problem [219], and the scheduling for microgrids [220]. However, most of these methods are conducted in the optimization scenarios with simple state transition processes of the IES, such as the electric energy storage processes [219]. Given the simple function approximators used in the existing RL methods, it cannot model the complex characteristics of multi-energy systems, and the future direction can focus on the optimization of gas-heat coupled dynamic processes with the characteristics of slow response speed using the RL.

It is worth noting that the knowledge reconstruction, such as transfer learning technology [221], a very active topic in the machine learning field, can provide a promising way for the modeling, assessment, and operational optimization of the IES based on the accumulated practical data. Since the research on electric power systems has gone through significant development, their achievements can be utilized to contribute to the IES with multi-energy coupling and cooperative operations.

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