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Reliability Modeling and Evaluation of Urban Multi-Energy Systems: A Review of the State of the Art and Future Challenges

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ABSTRACT Urban multi-energy systems (UMESs) are integrated energy systems (IESs) which can alleviate the current energy crisis, improve energy utilization and realize multi-energy complementarity of modern. Various subsystems involved in the coupling of UMESs, including power grids, gas pipeline networks, cold/heat networks, transportation networks, and energy cyber-physical system, exhibit coupling characteristics such as multi-energy source modeling, complex uncertainty factor modeling, mutual influence of information and physical coupling. At present, the modeling and reliability assessments of UMESs are the most urgent tasks. In this paper, the latest research results on the reliability modeling and evaluation of UMESs are analyzed by considering their coupling components. In addition, the reliability modeling methods and the evaluation indexes of UMESs, including power-gas systems, power-thermal systems, power-traffic systems, and energy cyber-physical systems, are presented in this paper, with specific UMES modeling methods divided into model-driven modeling and data-driven modeling. Finally, future challenges for the reliability modeling and evaluation of UMESs are proposed, such as the dispatch strategy of the coupling components needs to be developed and continuously optimized to improve the reliability of UMESs, and the resilience of UMESs under the extreme scenarios needs to be further studied.

INDEX TERMS Urban multi-energy system, reliability indexes, reliability modeling, coupling components, resilience.

I. INTRODUCTION

The impacts of the global energy crisis and environmental deterioration are forcing humanity to use various forms of energy to take development in a diversified and low-carbon direction [1]. Integrated energy systems (IESs) have emerged as a response, and major countries around the world have issued corresponding energy policies for the development of IESs [2]. The national smart grid strategy proposed by the United States calls for building a comprehensive energy network with high efficiency, low investment, safety, reliability, intelligence and flexibility. According to the energy internet construction target proposed by China, an energy internet industry system will be built by 2025. European countries have conducted a wide range of research on IESs; for exam-

ple, the UK Engineering and Physics Research Institute has funded a large number of research projects in this area involving renewable energy access, synergy among different energy sources, the interaction of energy and transportation systems and infrastructure, the improvement of building energy efficiency, etc.

A UMES can connect a plurality of heterogeneous energy subsystems through different coupling elements that integrate power, natural gas, cooling and heating, internet information and transportation systems according to different application scenarios to promote the production, transmission, distribution, conversion, storage and consumption of all kinds of energy. Due to the complementary and coupling characteristics of different types of energy in a space-time form, the randomness and volatility of renewable energy can be compensated for by IESs, thus promoting the utilization of renewable energy. In addition, by reasonable planning, taking

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the power system as a core and coupling the power grid with gas, cooling and heating, and traffic and information systems, the risk caused by an outage of a single energy supply system can be reduced. Because of rapid economic and societal development, people have increasingly higher requirements for the reliability of their energy supply, so the reliability research of IESs is very important. However, when different energy systems are coupled, the reliability evaluation methods of traditional single-energy supply systems will change. In [3], it was noted that in two or more coupling systems, the coupling characteristics of coupling elements and the whole system should be considered when designing the reliability of set systems. Coupling elements will lead to cascading failures and may even cause the complete isolation of two independent networks. The more distributed components are attached, the more prone the system will be to failure. Effectively modeling and evaluating the reliability of IESs is an urgent problem to be solved [4].

Taking the reliability research of individual power systems and individual natural gas systems as examples, the reliability modeling and evaluation of single energy supply systems have been extensively studied [5] and constantly updated in pace with technological developments. In a reliability study of independent power systems, three probabilistic transient stability indexes were proposed in [6] to study the influence of dynamic emergencies on power system reliability to evaluate the robustness of the system and calculate its reliability index. In [7], the cold load pickup condition was considered and a reliability assessment method was studied in a distribution network. In [8], the energy management strategy of a microgrid outage was considered and its influence on the reliability of the microgrid was studied. In research on the reliability of an individual natural gas system, [9] introduced maximum flow reliability in graph theory and a unit importance degree based on the threshold level in an analysis of the reliability of a tree-shaped gas transmission pipe network, obtaining a system reliability index. In [10], a natural gas pipeline network and a three-tier reliability evaluation index system was proposed that included a reliability class, maintenance class and robustness class. In [11], the corrosion of a natural gas pipeline was assessed using the limit state function and a burst of internal pressure to evaluate the time-dependent probability of a fault; a heuristic search algorithm was applied to advance a method for evaluating the reliability of a natural gas transmission system.

In terms of the reliability modeling and evaluation of UMESs, a large number of scholars have conducted research from multiple perspectives in recent years, most of which were concentrated on single coupling systems with specific application scenarios. In [12], an optimal load reduction problem in an IES was assessed, including power and natural gas subsystems, and an event enumeration method and a reduced-order method of high-order accidental events were used to evaluate the reliability, which reduced the computing time. In [13], a power-gas-heat load reduction optimization model using wind and electricity with a power-gas-heat cou-

pling system was considered to establish reliability indexes of power-gas-heat deficiency expectations, abandoned wind expectations and a capacity utilization ratio of a power to gas (P2G) device from the perspective of both system and equipment. Based on the result, a reliability evaluation method of a power-gas interconnection system with P2G was proposed. In [14], a power-heat system was considered using the thermal inertia of a thermal system and the multi-energy mutual economic characteristics of coupling elements. By taking into account the complementary benefits, a reliability evaluation method of a power-heat system considering the operation strategy of the coupling elements was obtained. In [15], the coupling characteristics of power a system and an information system were assessed by analyzing the influence of the fault mode of the power information system on the power physical system, decoupling the information network from the physical network. In [16], a power information-physical coupling system in a state space with different dependence relation equipment was sampled by a non-sequential Monte Carlo simulation method, and the reliability of the power information and the physical coupling system was analyzed. In [17], a reliability simulation of an energy information-physical coupling system was carried out based on a software defined network (SDN). In [18], the impact of vehicle to grid (V2G) information interactions of power line communications on the reliability of a traffic network was analyzed for a V2G coupling. In [19], a hierarchical optimization method was adopted to optimize the location and capacity of distributed power generation and electric vehicle charging stations, which improved the reliability of the distribution network, including electric vehicle charging stations. In [20], a power-vehicle grid system adopted a distribution feeder reconstruction (DFR) strategy and a symbiotic organism search (SOS) to improve the overall reliability of a vehicle-power grid system.

Generally, the range of a UMES is large, and the subsystems involved in coupling and interconnection cover many aspects. In terms of energy circulation, integrated energy subsystems can include power flow, natural gas, heating and cooling, traffic, information flow, etc., all of which involve multi-disciplinary knowledge. With the further development of UMESs, subsystems will interconnect in the future, and multiple energy subsystems will participate in this coupling and interconnection. In terms of studying the reliability of UMESs, although research on IESs has become more popular in recent years, it has not been well verified, and many scholars continue to conduct research in this area. Although multi-energy flow systems promote the consumption and utilization of various energy sources, the constraints associated with internal energy networks (e.g., power, heat and natural gas) and operational uncertainties (e.g., in energy demand) are often ignored due to the nonlinearity and modeling complexity of a multi-energy flow system [21]; in addition, the operational strategy of coupling elements also has a large impact on the overall reliability assessment of multi-energy flow systems [22]. While multi-energy flow subsystems can

provide complementary benefits, assessing the potential for collaborative optimization between systems and the impact of constraints on overall reliability remains a challenge. In addition, how to enhance the resilience of UMESs presents future challenges.

This paper assesses the overall research and the latest results of UMESs terms of reliability, including coupling components, reliability modeling methods, and corresponding evaluation indexes of UMESs, with specific UMES modeling methods divided into model-driven modeling and data-driven modeling. It provides a reference for future research on reliability modeling methods of UMESs, facilitates the establishment of reliability evaluation indexes of UMESs in the future. Finally, it puts forward that the reliability research of UMESs can be studied in depth on dispatch strategy of the coupling components, and the interactions between multi-systems needs to be further studied, and the resilience of UMESs under the extreme scenarios is also a new challenge for future research.

The rest of this paper is organized as follows: section II describes UMES definitions and coupling models; the reliability modeling method of a UMES is summarized in section III; section IV describes a common framework for a reliability index evaluation of a UMES; section V discusses the challenges in UMES reliability research; and section VI summarizes the conclusions and prospects for future work. The paper's main study structure as shown in FIGURE 1.

II. DEFINITION AND COUPLING MODEL OF A MULTI-ENERGY FLOW SYSTEM

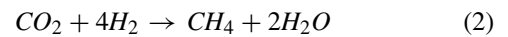
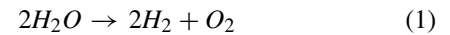
A. DEFINITION OF AN URBAN MULTI-ENERGY FLOW SYSTEM

An urban multi-energy system is also called an urban integrated energy system (UIES), in reference to the IES in which the main energy elements are distributed in a city. Unlike an island-type integrated energy system, a UMES has larger energy coupling intersections. Power, heating, air-conditioning, transportation, natural gas and communication requirements are ubiquitous in a city, and their energy sources are converted and connected by various coupling devices. UMESs exhibit three characteristics: multi-energy flow couplings, multi-time scales and multi-management agents. There are several coupling relationships in UMESs, listed as follows:

1) POWER-GAS COUPLING SYSTEM

A power-gas coupling system includes a power conversion process and a gas conversion process. The power-gas process passes through a power-gas device to decompose water and produce combustible gas. The power used in power-gas process passes can be generated by wind, hydro, solar and other renewable energy sources, and according to the needs of the system, the combustible gas can be hydrogen or methane. This involves two kinds of power-gas processes. The first is a power conversion to hydrogen, which decomposes water

into oxygen and hydrogen through an electrolytic reaction, and the second is a power conversion to methane, which electrolyzes hydrogen with carbon dioxide to produce methane on the basis of producing hydrogen [23]; the chemical expression is as follows:



Since methane is converted using hydrogen, the efficiency is lower than power conversion to hydrogen; however, hydrogen cannot be injected into a natural gas pipeline on a large scale because it will lead to hydrogen embrittlement and penetration of the pipeline. Methane can be directly injected into a natural gas pipeline as the gas source to participate in the operation of the gas network [24]. The power-gas equipment provides a load for the power system that can be used as a standby power supply for peak regulation and can reduce congested backup power, as the natural gas system is a gas source that can be converted into natural gas for transmission. The gas-to-power process is realized through a gas turbine; the gas turbine is supplied with gas from the natural gas network as gas-to-power equipment, which supplies the load of the gas network as well as the power supply of the power grid. At present, the two hydrogen production methods of steam methane reforming (SMR) and electrolysis can be combined with the operation optimization of an electric power and natural gas system to form a flexible energy use mechanism [25].

In a power-gas system, P2G technology has obvious advantages in capacity [26], which can realize long-term and large-capacity power storage, and because natural gas infrastructure is more economical than power infrastructure, natural gas pipelines can realize long-distance transportation when the power network is insufficient. Reference [27] studied the power system and natural gas system from the point of view of a power-gas integrated energy system (PGIES). As an extension and integration of optimal power flow (OPF) and optimal gas flow (OGF), optimal energy flow (OEF) is regarded as the cornerstone of a PGIES, which is seen as the basis for further study of the operation and analysis of PGIESs for random conditions and strain states.

2) COMBINED COOLING, HEATING AND POWER (CCHP) COUPLING SYSTEM

In a traditional energy system, a single source such as natural gas or electricity cannot give full play to the complementary advantages and synergistic benefits of energy, resulting in energy waste. CCHP is a cooling-heating-power triple supply system that realizes the energy conversion of power, gas, cooling and heating on the basis of the power-gas system [28]. The system includes a power grid, a heating network, a natural gas network and a cooling network. Different energy networks are connected by energy hubs that contain different energy conversion equipment. According to their conversion

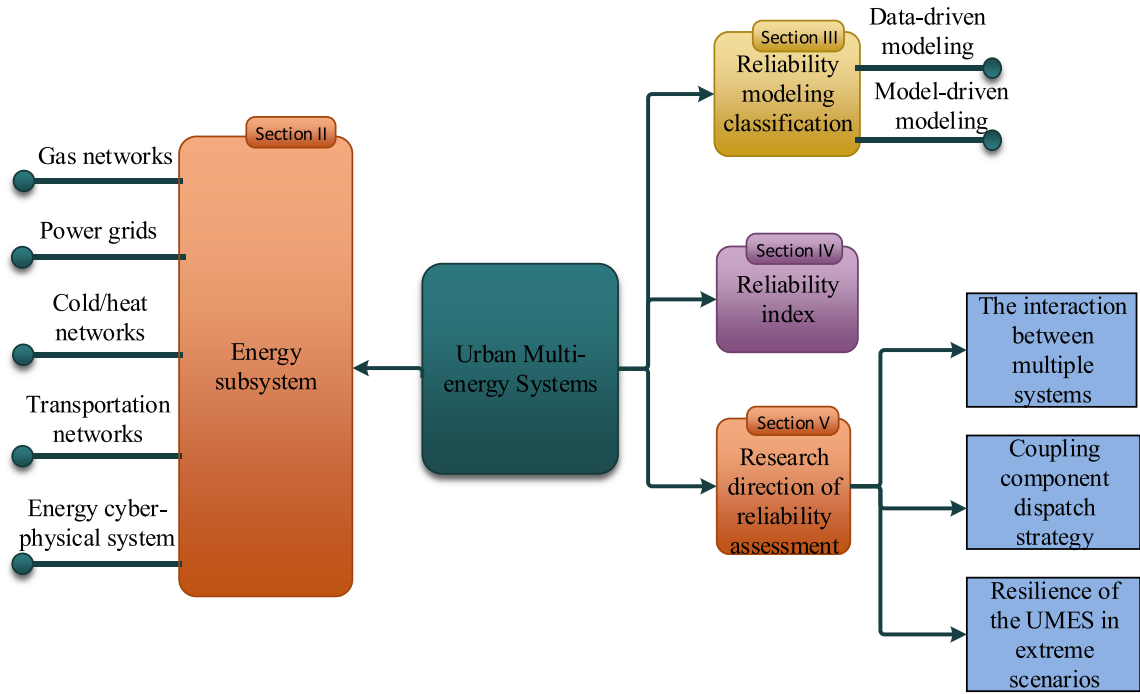


FIGURE 1. The structure of the study.

requirements, energy conversion equipment can be divided into four categories.

- (1)
 - 1) power-heating conversion equipment such as electric boilers and air conditioners;
 - 2) power-heating-gas conversion equipment such as gas turbines and waste heat boilers;
 - 3) power-cooling conversion equipment such as electric refrigerators;
 - 4) heating-cooling conversion equipment such as absorption chillers.

Additionally, energy collection and distribution are realized by power busses, natural gas pipelines, heat distribution pipelines and cooling pipelines, so the energy flows are balanced at all times. In addition, using electric storage (ES), gas storage (GS), heating storage (HS) and cooling storage (CS) equipment can realize the real-time utilization and storage of energy.

Due to the diversity of energy forms, it is necessary to consider the structure of different networks and how to realize the reasonable retrieval and optimization of various energies. Reference [29] pointed out that power, heating, refrigeration and natural gas supply systems were an important part of Russian infrastructure in thane actual context. The general framework and conceptual elements of IESs were put forward. The integrated control of power and thermal networks involves the combination of operating conditions of electrical and thermal networks integrated in intelligent energy supply systems that can be mathematically described. In addition, the results of two exemplary case studies were

also explained. The first case represents the study of super grid-level emergencies in the energy system layer when a pipeline accident occurs in a natural gas transport network. The second case uses a city as an example to study the interdependence between power and heating microgrids during an emergency. Reference [30] integrated refrigeration, heating and power systems into a single community energy system by aggregating various distributed energy sources, and a day-to-day dispatch strategy of the community energy system based on integrated energy and ancillary service markets was proposed to provide a method for the rational dispatch of multiple energy sources. However, research on the modeling of each energy network is still incomplete at present, and methods of energy source dispatching that consider economic and environmental impacts need further study.

3) POWER-GAS-TRAFFIC NETWORK COUPLING RELATIONSHIP

New-energy vehicles driven by electricity or hydrogen have great advantages and application prospects in addressing the greenhouse effect caused by urban carbon dioxide emissions and changing energy structures [31]. Electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs) are used as the power system load to access the power system through a city’s charging network—the connection between the vehicle, the power grid and the mobile electricity storage device through which energy is sold to the grid operator. The bidirectional flow of the electric power is realized under the V2G mode [19]. Hydrogen energy vehicles can realize the coupling of a vehicle-to-gas network through urban filling stations. At

the same time, the transportation paths of traffic networks, mobile power storage devices and mobile gas source travel modes depend on the road capacity of urban traffic networks, the power supply capacity of urban distribution networks and the gas supply capacity of gas networks, which affect and restrict each other and strengthen the coupling relationships between traffic, power or gas networks [32]. In V2G mode, the spatial transfer of EVs will cause charging load uncertainties in a power system. Most of the current research can be divided into two fields of study: one considers the behavioral characteristics of EVs, studies the orderly charging and optimal control of EVs and realizes the optimal operation of power grids [18], [33]; The second considers the characteristics of traffic networks and studies the specific locations and planned capacities of charging stations [19], [34].

4) ENERGY CYBER-PHYSICAL SYSTEM (ECPS)

At present, there is no uniform and clear definition of the of energy cyber-physical system (ECPS), but it mainly refers to the highly integrated system of the physical level and the information level. In the UMESs, the physical level mainly refers to various energy or transport subsystems, including power systems, natural gas systems, cooling/heating systems, traffic systems. In the ECPS, the physical environment and information processing have deeper interaction, the physical equipment will embed computing, communication ability, and through the processing of information will react to the physical environment, and finally form a networked physical equipment system.

All in all, the whole ECPS system is a real-time perception and dynamic control of large Multidimensional complex systems based on the physical environment, which utilizes the organic fusion and deep cooperation of computing, communication and control means.

The introduction of the energy internet has provided new directions for the interconnection, interworking and complementarity of a variety of energy sources (such as natural gas, heat, power, oil, etc.) [35]. Electric energy, as the power source for communication infrastructure, has a direct coupling relationship; the communication network connects the energy router [35] of a local area network to the power network via information and communications technology, automatic control technology, and power electronics technology to achieve physical level power coupling. Internet, big data, cloud computing and other cutting-edge information and communication technologies achieve communication coupling at the information level. The realization of an information network circumvents the traditional “power production-power consumption” system and integrates the power system with other energy systems to realize the coordinated optimization and control of multi-energy systems.

At present, the construction of information networks is still in the stage of information physical fusion where the integration of information communication infrastructure and energy and power infrastructure construction is manifested in the development stage of an energy internet based on

physical information fusion. Related research, such as [36], takes into account the coupling relationship between different energy systems, energy networks and information networks, as well as the impact of multiple uncertainties on IESs. It was proposed in [37] that the information and physical integration mechanisms of a wind energy conversion system and the safety optimization of EV charging can be realized by using blockchain in intelligent communities. The coupling of the complex physical elements and communication networks can make a system more vulnerable, and [38] pointed out that the safety optimization of EV charging can be realized by using blockchain in intelligent communities.

FIGURE 2 illustrates a UMES that integrates a power network, natural gas network, heating network, cooling network, traffic network and information network to realize real-time management and monitoring of the utilization and distribution of multiple energy flows through an information network. The energy hub realizes the conversion between different energy sources and closely couples each system.

B. UMES COUPLING COMPONENT MODEL

To outline the latest UMES research results, the coupling elements in different coupling scenarios are arranged in TABLE 1, and the models of each coupling component are summarized, including power-gas systems, power-thermal-gas systems, power-traffic systems and power-communication systems.

1) P2G COUPLING COMPONENT MODEL

The input and output vectors of P2G and coupling coefficients were used to describe the energy conversion process in [24], and a power-gas P2G coupling mathematical model was established. The conversion coefficient is determined by P2G internal converter efficiency, connection modes and dispatch coefficients. The coupling model can be described as follows:

$$\begin{bmatrix} G_{SNG} \\ G_{H2} \\ L_{P2G} \end{bmatrix} = \begin{bmatrix} G_{SNG} \\ G_{H2} \\ C_{P2G} \end{bmatrix} \times P_{P2G} \quad (3)$$

where L is the energy output vector of the P2G hub; P_{P2G} is the input power, and the matrix C is the conversion coefficient matrix between the power input and different energy outputs. According to the model, the internal P2G operational mode can be represented flexibly.

2) POWER-THERMAL COUPLING COMPONENT MODEL [41]

$$Q_{MT}(t) = \frac{P_{MT}(t)(1 - \eta_{MT}(t) - \eta_L)}{\eta_{MT}(t)} \quad (4)$$

$$Q_{he-MT}(t) = Q_{MT-he}(t) \times \eta_{he} = Q_{MT}(t) \times C_{he} \times \eta_{he} \quad (5)$$

$$V_{GT} = \frac{\sum P_{MT} \Delta t}{\eta_{MT}(t) \times F_{LH-ng}} \quad (6)$$

where $P_{MT}(t)$ and $Q_{MT}(t)$ are the generation power and the flue gas residual heat of a micro-gas turbine in period t ; $\eta_{MT}(t)$

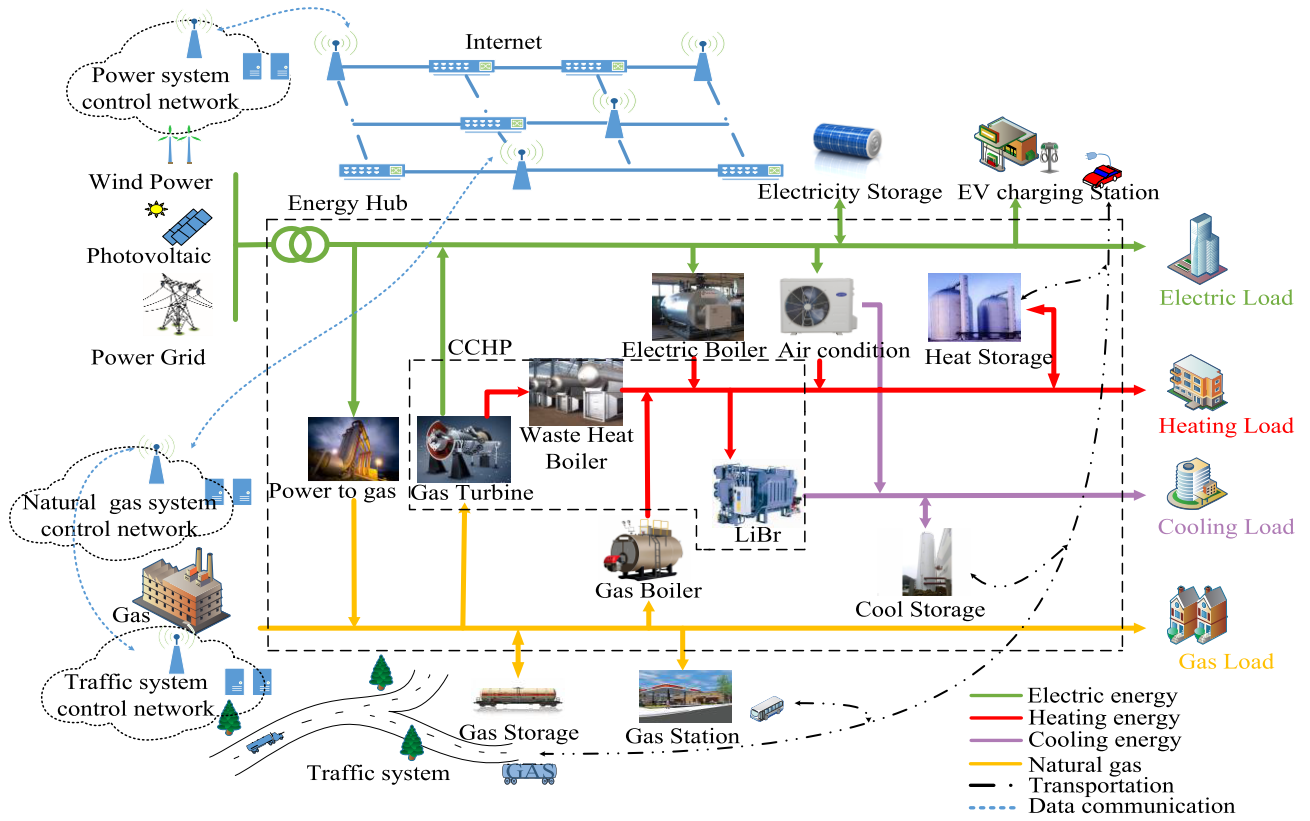


FIGURE 2. UMES coupling.

is the efficiency of a micro-gas turbine in period t ; η_{he} is the waste heat recovery efficiency of a waste heat boiler; C_{he} is the heating coefficient of a heat exchanger; η_L is the heat loss coefficient of exhaust smoke from a micro-gas turbine; $Q_{he-MT}(t)$ is the amount of heat that can be supplied by the residual heat from the flue gas of a micro-gas turbine; $Q_{MT-he}(t)$ is the amount of waste heat from the flue gas of a micro-gas turbine entering a waste heat boiler; V_{GT} is the amount of natural gas consumed by a gas turbine while running; Δt is the running time of a gas turbine; and F_{LH-ng} is the low calorific value of natural gas.

3) CCHP COUPLING COMPONENT MODEL

A CCHP system is typically composed of a gas turbine, an absorption chiller, a waste heat boiler, an electric refrigerator and an auxiliary boiler. The gas turbine is powered by natural gas and produces electric energy as well as waste heat. The released waste heat is cooled by the absorption chiller and can also be produced by the waste heat boiler. The electric refrigerator is cooled by electricity consumption, and the auxiliary boiler produces heat by consuming natural gas [46]. Therefore, CCHP couples a power grid and a gas network to achieve an integrated energy supply.

a.

1) The gas consumption of a gas turbine and energy generation data are fitted to obtain a quadratic function

relationship between them, as follows:

$$w_{i,t}^{pgu} = a_1(P_{i,t}^{pgu})^2 + b_1P_{i,t}^{pgu} + c_1I_{i,t}^{pgu} \quad (7)$$

where $w_{i,t}^{pgu}$ and $P_{i,t}^{pgu}$ are the gas consumption and generated energy for the gas turbines, respectively; $I_{i,t}^{pgu}$ is the operating state of gas turbine, where $I_{i,t}^{pgu} = 1$ means that the gas turbine is turned on and $I_{i,t}^{pgu} = 0$ means that the gas turbine is turn off; and a_1 , b_1 and c_1 are the quadratic function coefficients obtained for fitting the gas consumption of the gas turbine and the power generation data.

2) The cooling capacity of the absorption chiller and the generated energy of the gas turbine meet the cubic function, as follows:

$$U_{i,t}^{ac} = a_2(P_{i,t}^{pgu})^3 + b_2(P_{i,t}^{pgu})^2 + c_2P_{i,t}^{pgu} + d_2I_{i,t}^{pgu} \quad (8)$$

where $U_{i,t}^{ac}$ is the cooling capacity of the absorption chiller at time t ; a_2 , b_2 , c_2 and d_2 are the coefficients of cubic function obtained by fitting the cooling capacity of the absorption chiller and the energy generation data of the gas turbine.

3) The heat generated by the waste heat boiler and the energy generated by the gas turbine meet the quadratic function, as follows:

$$H_{i,t}^{boiler} = a_3(P_{i,t}^{pgu})^2 + b_3P_{i,t}^{pgu} + c_3I_{i,t}^{pgu} \quad (9)$$

TABLE 1. Coupling component models.

Coupling components	Coupling scenarios	References	Main features
P2G facilities	power-gas	[24] [25] [39] [40]	P2G facilities use electricity to decompose water to produce gas. Hydrogen is generated in the first process, and methane gas is generated in the second process; both are transported into the natural gas system.
CHP facilities	power-thermal	[41]	This cogeneration system, based on micro-gas turbines, realizes the step utilization of the energy source and high temperature as well as the waste heat from flue gases discharged by the micro-gas turbine; energy can be supplied to the heat load when the power generation is run by the micro-gas turbine.
CCHP facilities	power-thermal/cooling-gas	[42] [43] [44] [45] [46]	Gas turbines or internal combustion engines generate electricity; heat exchangers provide thermal transfer; absorption chillers provide cooling; the combined operation efficiency can exceed 80%.
Charging stations and gas filled stations	power-traffic	[47] [48] [49]	The coupling of a transportation network with a distribution network and natural gas network is realized through electric vehicle (EV) charging and gas vehicle (GV) charging.
IT infrastructure	energy cyber-physical system	[50]	Providing fault protection and almost instant two-way communication, ranging from a single load to a grid-wide control center, including all important devices at the distribution and transmission levels and involving the processing of a large number of data transactions for analysis and automation
Microgrid assemblies	Multi-microgrid	[51]	A MG can be operated in grid or islanding modes and can also switch between the two modes.

where $H_{i,t}^{boiler}$ is the heat produced by the waste heat boiler at time t ; a_3 , b_3 and c_3 are the coefficients of cubic function obtained by fitting the heat of the waste heat boiler and the energy generated by the gas turbine.

4) The electric refrigerators and auxiliary boilers:

$$U_{i,t}^{cc} = \delta_{cc,i} P_{i,t}^{cc} \tag{10}$$

$$H_{i,t}^{aux} = \eta_{aux,i} w_{i,t}^{aux} \tag{11}$$

where $U_{i,t}^{cc}$ and $P_{i,t}^{cc}$ are the cooling capacity and power consumption of electric refrigeration, respectively; $\delta_{cc,i}$ is the efficiency of electric refrigerators; $H_{i,t}^{aux}$ and $w_{i,t}^{aux}$ are the heat and gas consumption of the auxiliary boiler, respectively; and $\eta_{aux,i}$ is the thermal efficiency of the auxiliary boiler.

4) COUPLING COMPONENT OF ENERGY CYBER-PHYSICAL SYSTEM

Energy cyber-physical system is a typical cyber-physical system (CPS) [52], and its coupling is mainly composed of a large number of switching devices in which a sensor can provide the power system with a real-time operational state of its power equipment or the state of its surrounding environment, such as voltage measurement units, current measurement units, etc. In addition, this state can be converted into the desired form of physical information output to allow the communication system to transmit physical information to the corresponding controller of the communication network. The reference signal of the actuator in the corre-

sponding power equipment is obtained through the relevant controlling or optimization algorithm in the controller, and the running state of the equipment is ultimately changed to realize the interconnection of the power-communication system. A typical system includes a supervisory control and data acquisition (SCADA) system, a wide-area protection (WAP) system, an automatic voltage control (AVC) system, an automatic generation control (AGC) system, etc.

5) POWER-GAS-TRAFFIC COUPLING COMPONENT MODEL

The key coupling components between a traffic network and a power-gas system are charging stations and gas filling stations. According to the aggregation effect of energy demands of a traffic network, there is an increasing relationship between energy demand and vehicle flow [53]. Therefore, if an EV is charged during idle time, the EV is charged normally, and the loads of GV charging stations are approximately expressed by a linear relationship:

$$P_{i,t+12}^{d,TN,UN} = \sum_{l \in C(i)} a_i^{d,TN} x_{l,t} \tag{12}$$

$$P_i^{d,TN,N} = \sum_{l \in C(i)} a_i^{d,TN} x_l \tag{13}$$

$$g_m^{d,TN} = \sum_{l \in G(m)} b_i^{d,TN} x_l \tag{14}$$

where $P_i^{d,TN,UN}$ is the charging amount when the EV is idle at the i station; $P_i^{d,TN,N}$ is the charging amount when the EV is at normal rest at the i station; $a_i^{d,TN}$ is the charging efficiency

coefficient of the i charging station; and $C(i)$ is the collection of charging substations of the i charging station.

The gas station stores liquefied natural gas (LNG), so it is also necessary to carry out pressurization and liquefaction after natural gas is supplied by the pipeline. The loss of natural gas generated by the pressure at a node m is $g_{m,loss}^{TN}$:

$$g_{m,loss}^{TN} = a_{m,loss}^{TN} H_m^2 + b_{m,loss}^{TN} H_m + c_{m,loss}^{TN} \quad (15)$$

where $a_{m,loss}^{TN}$, $b_{m,loss}^{TN}$ and $c_{m,loss}^{TN}$ are the loss coefficients, and H_m is the pressure parameter of the pressurizer at node m that can be adjusted. It has a maximum and minimum limit, as follows:

$$H_{m,min} \leq H_m \leq H_{m,max} \quad (16)$$

In summary, the influence of traffic network coupling on the load of a power-gas network is as follows:

$$p_i^d = p_i^{d0} + P_{i,t}^{d,TN,UN} + P_i^{d,TN,N} \quad (17)$$

$$g_m^d = g_m^{d0} + g_m^{d,TN} + g_{m,loss}^{TN} \quad (18)$$

where p_i^{d0} and p_m^{d0} are original the power load and gas load, respectively [47]–[49].

III. UMES RELIABILITY MODELING METHOD

A. UMES CLASSIFICATION OF RELIABILITY MODELING METHODS

In the reliability modeling of UMESs with multiple kinds of coupled energy subsystems, the current research carried out by scholars can be categorized as either model-driven modeling and data-driven modeling.

1) *Model-Driven Modeling*: the interaction between systems is analyzed and accurate mathematical models is established to calculate system reliability. The Monte Carlo simulation method is often used in the reliability evaluation model, and random sampling is generated; the multi-energy flow analysis of each system state, to solve the optimal energy flow problem; the model-driven reliability modeling method needs to solve plenty of system state energy flow calculation and optimization problems, resulting in long and low efficiency of reliability evaluation.

2) *Data-Driven Modeling*: By analyzing a large amount of energy data to acquire knowledge automatically or semi-automatically, knowledge here is defined as a quantitative description of the relationship between data. Using methods such as machine learning, mining the relationship between reliability parameters and their influencing factors, or through other statistical means of data, summing up the classification and induction of scene sets after reliability failure, so as to evaluate the reliability of the system. The data-driven modeling replaces the model-driven modeling method that requires the establishment of accurate mathematical models.

B. MODEL-DRIVEN METHOD FOR UMES RELIABILITY MODELING

The model-driven method of reliability modeling primarily uses state modeling and state assessments for each subsystem,

which also includes an analytical evaluation of the interaction between the system and a system based on a theoretical mathematical model. Finally, the reliability probability degree and the risk probability degree of the system are calculated according to the reliability risk index between the systems.

Energy flow models in different energy networks are considered in the state analysis of reliability modeling. In the linking of state evaluations, it is necessary to analyze the multi-energy flow of each system state, and the optimal energy flow modeling and solution of multi-energy coupling is the core of system state assessment. To address the optimal load curtailment (OLC) in a CHP system, [12] solved the optimal scheduling and the optimal power flow problems of an energy hub by using a hierarchical decoupling optimization framework that made the calculations more accurate and efficient. An evaluation algorithm was proposed for the impact-increment-based state enumeration (ISE) method that further improves the calculation efficiency under the influence of the higher order state by transforming the effect of the higher order contingency state into a corresponding lower order contingency state. A comprehensive reliability assessment framework for integrated energy cyber physical systems using the Monte Carlo simulation method to generate the system state was proposed in [22], and an energy flow model in the different energy networks was considered in state analysis, for example, by considering the real-time electricity balance of a power grid and the flow balance of a natural gas transmission network. For risk assessment, a power-thermal power flow calculation model was established, and a corresponding power flow calculation algorithm was proposed in [58] according to the characteristics of pipeline flow loss and heat generation via condensation in a heat network. Then, the key index system of IES risk assessment was put forward based on the different needs of operational and user sides of a regional IES, and the calculation process of total operational risk for the IES was designed on the basis of power-thermal power flow calculations.

A UMES coupling model is the key component of reliability modeling and evaluation. Reference [59] proposed a generic framework for multi-energy system modeling that includes multiple-energy carriers such as electricity, heat, gas, etc. In addition, the cores of the energy hub were defined as a transition matrix, which can describe the interactions of multiple energy sources among production, trading and consumption, as well as a failure rate matrix representing the risk of the system, which is based on mathematical expressions of energy hub and repair rate matrices using a state-space method for a risk assessment system. Reference [36] pointed out the necessity of carrying out reliability analyses and research on comprehensive energy systems under the background of cyber-physical systems by analyzing the influencing factors of multiple uncertainties and the coupling relationship between systems and proposed a reliability assessment framework for an integrated energy cyber-physical system based on the analysis of a reliability model of

TABLE 2. Classification of UMES reliability modeling methods.

Classification	Based on reliability assessment method	References	Main features	Application scenarios
Model-driven modeling	Based on a first-order reliability method (FORM), and established the FORM optimization model.	[54]	The FORM estimates the probability of failure and introduces the Hasofer Lind and Rackwitz Fiessler (HLRF) algorithm to solve the FOM optimization model while considering the random behavior and dependence of a variety of energy sources.	power-gas system
	An optimum quantile method based on the Wasserstein distance metric. The IES model under study consists of a correlation model, coupled multiple energy model, and probabilistic energy-flow calculation model based on the Newton Raphson theory.	[55]	A typical scheme set in IES is generated by considering the correlation of energy based on weather conditions and the use of discrete variables.	power-thermal system
	Based on a second-order reliability method (SORM), and analyzed the uncertainty of IESs to establish gas, heat, and power networks model.	[56]	In contrast to classic Monte Carlo methods, the SORM does not require robust sampling but exhibits good stability and a low computation time. Compared to the FORM, the SORM better addresses nonlinear problems.	power-thermal system
	Based on a hierarchical decoupling optimization framework and impact-increment-based state enumeration (IISE), and the incorporating interactions among different energy systems in the energy centers were modeled.	[12]	The traditionally independent OPF problem is hierarchically coupled with the integrated optimization process of an IES, and the state enumeration method is used to obtain a high-precision solution and reduce the calculation burden.	power-thermal system
	Based on an analytic method, and studied the operation mode of the coupling system and established the power supply reliability model of the power-gas coupling system.	[57]	Models the load, wind turbine and coupling equipment.	power-gas system
	Based on an energy flow model.	[13] [22] [58] [59]	Considering the uncertainty of supply and demand under fault, the state analysis of an energy flow model in an energy network is carried out, and the coupled power flow is calculated. Finally, it is used for reliability evaluation.	power-thermal system
	Based on the equivalent multi-state time-varying reliability models for energy physical components and demand-side energy consumption.	[36] [37]	Analyzes a reliability model of energy physical elements and the equivalent reliability model of energy consumption behavior on the demand side.	energy cyber-physical systems
Data-driven modeling	Based on smart agent communication with sequential Monte Carlo simulation, and the model considered the operating characteristics for different sub-systems and interaction effects between them.	[66]	Evaluates the status and reconfiguring a system autonomously.	CCHP system
	Based on an energy supply and demand uncertainty method, and relevant energy data were used.	[60]	Estimates the gas supply fault probability based on wind power, load, gas data and in-station gas supply data.	power-gas system
	Based on the central moment method, the data of correlated power, loads, and gas supply deliverability have been considered.	[61]	Calculates the central moment of statistical heat load and the gas supply to estimate the gas supply.	micro IES
	Based on a multi-temporal simulation model and an integrated analysis method of the power, thermal and gas distribution networks.	[42]	Uses electricity network parameters, heat network parameters, and gas network parameters to obtain the relevant load time series data at specific locations; showing the change of energy flow through a Sankey diagram.	power-thermal system

TABLE 2. (Continued.) Classification of UMES reliability modeling methods.

Based on City Fast Fluid Dynamics (City FFD) and City Building Energy Model (City BEM).	[62] [63]	Uses microclimate data to predict the thermal response and load of buildings.	CCHP system
Based on a basic operational strategy of thermal inertia and multi-energy economy of thermal subsystems, and used the data considered time dependence.	[14] [64] [65]	Models system state probability considering time dependence.	power-thermal system

energy physical elements and an equivalent reliability model of demand-side energy consumption.

The time-varying characteristics of the system-state probability and the uncertainty modeling of energy supply and demand are the intrinsic needs of operational reliability evaluation and the characteristics that distinguish it from conventional reliability evaluations. Under the consideration of the probability of energy supply failures, the first-order reliability method (FORM) was used in [54] to estimate the failure probability of an IES and consider the problems of insufficient gas supply, limited grid capacity, and the random behaviors, dependencies and limitations of various energy sources. The failure probabilities and absorption limits of a power grid were solved by the HLRF theory. Different from the Monte Carlo method, the probability of failure can help evaluate the reliability of the system and ultimately improve reliability by modifying the relevant schemes. Reference [56] considered the limits of wind power generation and the correlation between thermal load and natural gas supply faults in an IES. The second-order reliability estimation method (SORM) was adopted to address the nonlinearity caused by network constraints, and 3.5 s was required to obtain a failure probability. Compared with the first-order reliability method (FORM), the proposed method improves accuracy by at least 10 times.

To address the insufficient consideration of system abandonment and operating characteristics of P2G units in current state analysis models of multi-energy flow systems, [13] proposed an energy flow model based on a P2G unit, a gas unit and an optimization model of power/gas/heat load reduction considering wind power abandonment. A reliability evaluation method of a power-gas interconnection system containing a P2G unit was put forward to address the reliability index.

To fully considered the impact of external environmental changes and weather factors on multi-energy flow systems, [55] proposed an optimum quantile method based on the Wasserstein distance metric to generate a scenario set in an IES, which took into account energy correlations based on weather conditions. Compared to continuous variables based on sampling techniques, such as Monte Carlo simulations, the use of discrete variables sets this study apart from other studies. An analytic method for the power supply reliability evaluation of a power-gas coupled system was proposed in [57], which focused on the power supply reliability of a

power-gas coupled system. A Belgian 20-node natural gas system and an IEEE-RBTS Bus-6 system were used to analyze the calculation examples. The proposed model and algorithm were verified through simulations, and the impact of the coupling system on the reliability of the power supply system was analyzed in detail by comparing calculation results in different scenarios.

C. DATA-DRIVEN METHODS FOR UMES RELIABILITY MODELING

A UMES is a multi-physical field coupling system in which a power system is at the center, and gas, thermal, cooling, traffic and information systems can be coupled [67]. The primary problem of UMES reliability modeling is that it is difficult to establish an accurate mathematical model. However, artificial intelligence technology based on big data has incomparable advantages in terms of energy prediction (including intermittent power forecasting and energy load forecasting of renewable energy), fault diagnosis, and operational optimization and control [68]. At present, preliminary research results have been obtained in the reliability modeling of multi-energy flow systems by using data-driven methods and making full use of energy big data.

Considering the influence of reliability caused by uncertainties in energy supply and demand, a data-driven model was established in [60] based on wind power, load, gas consumption and in-station gas supply data in an IES to estimate the failure probability of a gas supply in a reliability analysis of a natural gas supply system. The proposed data-driven IES model was simple and took advantage of the uncertainty and the relationship between the limit state function based on plentiful real data to guarantee the accuracy of the proposed method through three case analyses of the traditional method based on a physical model that included the Iman and Stein method, a first-order reliability method and a hybrid Monte Carlo algorithm. By calculating the available transmission capacity (ATC) under an uncertain energy supply, [69] established a probability available transfer capacity (PATC) model of an IES considering static security constraints and uncertainties. Because of the error among the traditional complex modeling, the actual engineering and the physical model can only obtain a numerical solution of the function gradient and Hessian matrix, the proposed data-driven model was more practical. The central moment method was first applied to a fault probability estimation of a gas supply in [61]; the

difference between the proposed method and the traditional calculation of failure probability, which is based on an actual probability distribution, is that the proposed method, based on the statistical data of heat load and gas supply, calculated the central moment to estimate the gas supply. Compared with traditional methods, including the Iman and Stein method, the first-order reliability method, the hybrid algorithm based on Latin hypercube sampling, the Cholesky decomposition, the Nataf transformation and the maximum entropy method, the proposed method was faster and more authentic, providing a practical solution for the fault probability estimation of a gas supply.

Heating and refrigeration in a UMES are affected by climate, as interruptions of heating or refrigeration in extreme weather can cause damage to urban buildings and infrastructure, such as the freezing of water pipes. Reference [62] proposed a new urban scale model that integrated City Fast Fluid Dynamics (CityFFD) and a City Building Energy Model (CityBEM) by considering the survivability of buildings subjected to local climate factors in cities. Taking more than 1500 buildings on an island near Montreal, Canada, as an example, a simulation study of the 1971 Montreal blizzard was carried out to investigate the ability to withstand three days of blackouts caused by the storm and further advance a building reconstruction strategy.

To address the multi-energy flow reliability assessment of a CCHP system in an energy distribution network and the interaction of electrical, gas, cooling and heating systems, [63] evaluated the performance of buildings by assessing energy flexibility, as buildings typically only use a single form of energy for power transfer capability, energy transfer efficiency, economic benefit and comfort, and proposed a method that used the energy storage function of buildings to realize a flexible dispatch of multi-energy flows. [66] proposed a k-1 algorithm based on smart agent communication, which can autonomously realize a reconstructed system, and a system state evaluation process was carried out together with a reconstruction process to improve the reliability evaluation efficiency. To focus on the influence of current thermal system research regarding the thermal inertia of a thermal subsystem [14] set up a basic strategy of system operations according to the differences of energy grade when modeling a metastable model. A multiple time scale Monte Carlo simulation method was applied to realize a dynamic simulation while considering the time sequence correlation of each device [64]. [65] analyzed the influence of the reliability of multi-energy flow systems in detail, which were caused by photovoltaic power supply and CHP unit permeability, combined them with the Monte Carlo simulation method and provided a scheme for practical future planning. The detailed parameters of electric, heat and gas networks were used to model the three networks in an integrated way in [42] using a MATLAB-excel VBA tool, and the network energy flow was demonstrated with a Sankey diagram, thus providing a basis for reliability assessment and planning research.

An analysis indicated that the reliability modeling of a multi-energy flow system based on a data-driven method offered a preliminary development that can excavate energy-related big data and solve the problems of existing energy fields by using machine learning, which has become the focus in present academic circles [70]; however, this approach still faces many scientific challenges and technical problems [68] such as fault diagnosis and abnormal energy-use behavior detection in energy application scenarios, and the data obtained during a specific period of time still belongs to a small sample set, which does not qualify for big data criteria. In addition, there are upper accuracy limits, overfitting and underfitting risks in data-driven methods [71].

IV. UMES RELIABILITY EVALUATION INDEX

Reliability theory is based on the concept of chains, and the strength of any chain is represented by its weakest link [72]. The reliability of a UMES is represented by the reliability of each subsystem and the coupled elements. Therefore, the reliability of a coupled subsystem must be evaluated in detail. The reliability indexes of independent energy subsystems and the power-gas, power-traffic and power-communication coupled systems are summarized as follows.

A. RELIABILITY INDEX OF INDEPENDENT SUBSYSTEMS

1) RELIABILITY INDEX OF URBAN DISTRIBUTION NETWORK SYSTEMS

The reliability of a distribution system refers to the measurement of the entire distribution system from the power supply point to the user, as well as the ability of equipment to meet the power and electricity requirements of users according to acceptable standards and expected quantities, including the adequacy and security of the system [73].

Conventional reliability evaluation is mainly used in system planning and design to measure the reliability level of the system under long-term operating conditions, and the time interval is often months or even years. The main indexes are the load point index and the system index, depending on the hierarchy. The system index is usually divided into an energy index and probability index. Specifically, the load point index includes the average failure rate of the load point, the average annual power outage time of the load point and the average power outage duration of each fault. The system index includes the average power outage frequency and average power outage duration of the system, the average power outage frequency and average outage duration of the users, the average power supply availability index, the system total power shortage index and the system average power shortage index [74]. The reliability of the system can be effectively evaluated by the combined probability reliability index [75].

A conventional reliability assessment should not only reflect the load loss of the system but also reflect the load margin of the system, which can reflect the line overload, node voltage overrun and other operating constraints as well as the voltage safety margin, power flow safety margin, etc.

One must be able to comprehensively describe the overall reliability of the system and reveal the reliability of key elements, key nodes, key areas and key links to reflect short-term reliability and evaluate long-term reliability [76].

System reliability can be measured from three angles [77]: the reliability of structural elements, the connection reliability between node pairs, and system performance reliability, which means ensuring that the infrastructure equipment is not loaded or keeping a minimum water head (pressure) to meet maintenance requirements. For this reason, a power system must establish a relatively perfect four-dimensional index system, including a state dimension, degree dimension, hierarchical dimension and time dimension [76].

The state dimension index describes the overall operational reliability of the system; the distribution network operational state can be divided into a health state, critical state and risk state.

The degree dimension index is a quantification of operational reliability that is used to reflect the operating safety margin of a system or area under a critical state or the consequence severity under a risk state. It is divided into three sections: a safety zone, an over-limit zone and a load-cutting zone, and each section corresponds to a margin index, over-limit index and load-cutting index.

The hierarchical dimension index includes four levels: a system layer, area layer, node layer and component layer. The component layer index includes the power flow safety probability and margin, the overload probability and expected value, the load cutting probability and the expected value caused by the overload. The node layer includes the voltage safety probability and margin, the voltage overrun probability and expected value, and sub-indexes of all load-cutting indexes. The system layer and area layer include all sub-indicators of degree dimensions. The time dimension index reflects the reliability of different evaluation time limits, including the minute level, hour level, sky grade, monthly grade, grade, etc. The corresponding time dimension index can be obtained by calculating the index based on different prediction times.

2) RELIABILITY INDEX OF NATURAL GAS PIPELINE NETWORKS

The reliability of a natural gas network depends on three main factors:

- 1) Structural reliability of the main supply pipeline in the network. Thus, a probability certainty and structural integrity assessment of a pipeline failure are highly relevant.
- 2) The reliability of a pump (gas compressor) station, valves and other equipment and the structure of the main supply pipe of the network. Failure of these components may result in heat loss, loss of natural gas supply, and insufficient pressure or flow in the pipeline.
- 3) The reliability of the source of supply. During a hot water or gas failure, the rest of the network should

also perform its functions, even if the supply of these resources can be interrupted for all users in the network.

- 4) A fault data analysis is performed, the reliability evaluation criteria are defined, and the criteria describing the fault characteristics of the main components are selected to define the reliability index, including failure rate (not considered affected by the failure); average maintenance time (not affected by failure); System Average Interrupt Duration Index (SAIDI); System Average Interrupt Frequency Index (SAIFI).

3) RELIABILITY INDEX OF HEATING AND COOLING NETWORKS

[78] pointed out that equipment or component failures will lead to the failure of a subsystem or the whole system, so the reliability index of a heating/cooling network is defined from the component level, including the failure rate λ , repair rate μ , reliability R and availability A . The failure rate λ is the fault frequency of a component or system over a period of time. The repair rate μ is the recovery frequency of a fault component or system.

When the failure rate and repair rate are constant, the reliability function of the component or system can be expressed as follows:

$$R(t) = e^{-\lambda t} \quad (19)$$

Availability is defined as the probability that a component or system can run over a period of time:

$$A = \frac{\mu}{\lambda + \mu} \quad (20)$$

[79] pointed out that probability of the above state was related to the structure of the heating network, and the failure rate was related to the repair rate of the components, which reflects the structural properties of the heating networks. However, this assessment cannot reveal the heating capacity under a fault condition and the influence of the fault on the indoor conditions of consumers. Therefore, the functional reliability index of a heating network is put forward to evaluate heating quality in a comprehensive manner.

Taking into account the inadequate heating capacity caused by a failure, the failure-free working index (Rf) is defined as the ratio of the actual thermal power to the ordered thermal power:

$$R_f = \frac{E(Q)}{Q'} \quad (21)$$

where Q is the actual thermal power during heating, Q' is the ordered thermal power, and $E(Q)$ is expected value of actual heating.

Considering that some components fail, relevant users will not be able to obtain enough heat from the network, which will affect the internal state of a building, especially the indoor temperature. t_{ink} is defined as the indoor temperature under variable external conditions to assess the impact of failures on consumers.

- When there is no backup heat network,

$$t_{ink} = t_{ok} + (t'_{in} - t_{ok})e^{-\tau_r/\chi} \quad (22)$$

where t_{ok} is the outdoor temperature during the heating season, τ_r is the fault correction time, χ is the thermal storage capacity, and t'_{in} is the calculated indoor temperature.

- When there is a backup heat network,

$$t_{ink} = t_{ok} + (t'_{in} - t'_o)e^{-\tau_r/\chi} + \beta_k(t'_{in} - t_{ok})(1 - e^{-\tau_r/\chi}) \quad (23)$$

where t'_o is the calculation of the outdoor temperature, and β_k is heat gain ratio in the case of failure.

A synthesis of the above indexes not only reflects the structural attributes of the system but also reflects the heating capacity and the influence of failure on the indoor conditions of consumers.

4) RELIABILITY INDEX OF TRAFFIC NETWORKS

The reliability of a traffic network can be defined as the ability of transportation operational states to meet the prescribed functional degree under established conditions and within a given time, and the corresponding probability measure is the reliability of the road network [80]. Traffic congestion and road failures will reduce the reliability of the traffic network and make transport and travel difficult. Most reliability assessments of traffic networks are analyzed from three aspects: traffic network topology, traffic network capacity and travel time, which have corresponding definitions of connectivity such as a terminal reliability index, road network capacity reliability index, travel time reliability index [81], etc.

Specifically, considering the cascade failure caused by accidental failures or sudden disasters in traffic network nodes (such as bus stations, railway stations, ports), [82] defined network efficiency as a reliability measure of the cascading failure of transportation networks and described the effect of cascading failure on the overall connectivity of an urban agglomeration transportation network. The formula is as follows:

$$E = \frac{1}{n(n-1)} \sum_{i,j \in \Omega(i \neq j)} \frac{1}{d_{ij}} \Omega \quad (24)$$

where d_{ij} is the distance between nodes, n is the number of nodes in the network, and Ω represents the collection of all nodes in the network.

For the reliability of travel time, [83] defined a travel time reliability model of a traffic network based on risk as t_a .

$$t_a = t_0 \left[1 + \alpha \left(\frac{Q_a}{C_a} \right)^\beta \right] \quad (25)$$

where t_a is the travel time of section a at time t , t_0 is the travel time of section a under the condition of free flow, Q_a is the traffic volume of motor vehicles at time t of the section,

C_a is the actual capacity of the section a at time t , and α, β are parameters with recommended assignments of 0.15 and 4, respectively.

The probability of reliable travel is defined for the travel time, and the connectivity reliability of a traffic network is defined by the product of probability in [80]. Reference [84] considered the traffic flow and the speed of the vehicle and defined a comprehensive connectivity index y of the section as

$$y = vq = kv^2 = \begin{cases} kv_f^2 \left(e^{-ek/k_j} \right)^2, & k \leq k_m \\ k \frac{v_f^2}{e^2} \left(\ln \frac{k_j}{k} \right)^2, & k > k_m \end{cases} \quad (26)$$

where q is the traffic volume of this section, v is the average speed, v_f is the free flow velocity, k is the average vehicle density, k_m is the density corresponding to the maximum flow rate, and k_j is the jamming density.

At present, the emergence of new energy vehicles such as EVs has greatly increased the uncertainty risk of traffic networks, filling stations, charging stations, etc. As new considerations affect the reliability of traffic networks, the reliability index needs further improvements.

5) RELIABILITY INDEX OF COMMUNICATIONS NETWORKS

The reliability of a communications network must consider the connectivity and transmission capacity of communications networks to predict effectively the failure of each node in a communications network and the influence of link failures on network performance.

[85] introduced the concept of a normalized capacity weighted reliability index and examined networks as a whole from a macro perspective. The reliability index is defined as follows:

- A weighted reliability index PI_{ij} of normalized capacity between two nodes.

$$PI_{ij} = \sum_{s_{ij}(z) \in S_{ij}} \alpha_{ij}(S_{ij}(z)) \times P_{S_{ij}}(z) \quad (27)$$

$$\alpha_{ij}(S_{ij}(z)) = \begin{cases} 1, & C_{ij}(S_{ij}(z)) \geq C_{ij}(1) \\ \frac{C_{ij}(S_{ij}(z))}{C_{ij}(1)}, & C_{ij}(S_{ij}(z)) < C_{ij}(1) \end{cases} \quad (28)$$

where S_{ij} is a set of topological states of disjointed networks between nodes i and j ; $S_{ij}(z)$ is a disjointed network state in the set; $\alpha_{ij}(S_{ij}(z))$ is the normalized capacity weighting factor when the network state is $S_{ij}(z)$ when the connection routing condition exists between the nodes i and j ; $P_{S_{ij}}(z)$ is the probability of $S_{ij}(z)$ occurrence; $C_{ij}(S_{ij}(z))$ is the maximum capacity that can theoretically be utilized between nodes i and j under the condition that the topological state of the disjointed network is $S_{ij}(z)$; and $C_{ij}(1)$ is the maximum expected capacity between nodes i and j .

- A weighted total reliability index PI of normalized capacity of the whole network.

$$PI = \sum_{\substack{i,j=1 \\ (i \neq j)}}^n \beta_{ij} \times PI_{ij} \quad (29)$$

$$\beta_{ij} = \frac{C_{ij}(1)}{\sum_{\substack{i,j=1 \\ (i \neq j)}}^n C_{ij}(1)} i \quad (30)$$

Suppose a network has n nodes and is numbered continuously from 1 to n , where β_{ij} is the weight coefficient of the capacity between nodes i and j in the entire network.

The reliability index definition above describes the influence on the reliability index between each node and the total reliability index of the whole network when the availability probability and capacity change at each node and each link in detail.

B. RELIABILITY INDEX OF POWER-GAS COUPLING SYSTEMS

The reliability index of a power-gas coupled energy flow system with P2G devices can be divided into a system level and an equipment level.

1) SYSTEM LEVEL RELIABILITY INDEX

The values of expected electric demand not supplied (EEDNS), expected gas demand not supplied (EGDNS), expected gas demand not supplied (EHDNS) and expected wind power abandoned (EWPA) are used to reflect the supply level of the power load, gas load, and heating load and the severity of abandoned wind in the system; the expressions are as follows:

$$EEDNS = \sum_{x \in G_1} P(x) C_e(x) \quad (31)$$

$$EGDNS = \sum_{x \in G_2} P(x) C_g(x) \quad (32)$$

$$EHDNS = \sum_{x \in G_3} P(x) C_h(x) \quad (33)$$

$$EWPA = \sum_{x \in G_4} P(x) \Delta P_w(x) \quad (34)$$

where $P(x)$ is the probability of system state x , and G_1, G_2, G_3 and G_4 are the state sets of power load, gas load, heating load reduction and wind abandonment phenomenon, respectively. $C_e(x), C_g(x), C_h(x)$ and $\Delta P_w(x)$ are the power load, gas load, heating load reduction and abandoned air volume of system state x , respectively.

$$C_e(x) = \sum_{i=1}^{N_d} C_{e,i} \quad (35)$$

$$C_g(x) = \sum_{m=1}^{N_g} C_{g,m} \quad (36)$$

$$C_h(x) = \sum_{k=1}^{N_b} C_{h,k} \quad (37)$$

$$\Delta P_w(x) = \sum_{i=1}^{N_w} \Delta P_{w,i} \quad (38)$$

2) EQUIPMENT LEVEL RELIABILITY INDEX OF P2G DEVICE

The P2G utilization probability (PUP) is used to reflect the possibility of opening the P2G device and the probability of the wind abandoning phenomenon occurring in the system. The expression is as follows:

$$PUP_k = \sum_{x \in G_{5,k}} P(x) \quad (39)$$

where PUP_k and $G_{5,k}$ are the utilization probability of P2G device k and the set of states in the open state, respectively.

The P2G capacity utilization (PCU) is used to reflect the utilization of P2G device capacity. The expression is as follows:

$$PCU_k = \sum_{x \in G_{5,k}} P(x) \left(\frac{P_{P2G,k}}{C_{P2G,k}} \right) \quad (40)$$

where PCU_k and $C_{P2G,k}$ are the capacity utilization ratio and device capacity of P2G device k , respectively.

The contribution of P2G to EEDNS/EGDNS/EHDNS (CPED/CPGD/CPHD) and the contribution of P2G to EWPA (CPEW) are used to reflect the contribution of P2G devices in per unit capacity to the reliability index of the system. These contributions are equal to the ratio of the change of the EEDNS/EGDNS/EHDNS/EWPA and the capacity of P2G devices before and after the access of P2G devices; the expressions are as follows:

$$CPED_k = (EEDNS_0 - EEDNS_1) / C_{P2G,k} \quad (41)$$

$$CPGD_k = (EGDNS_0 - EGDNS_1) / C_{P2G,k} \quad (42)$$

$$CPHD_k = (EHDNS_0 - EHDNS_1) / C_{P2G,k} \quad (43)$$

$$CPEW_k = (EWPA_0 - EWPA_1) / C_{P2G,k} \quad (44)$$

where $CPED_k, CPGD_k, CPHD_k$ and $CPEW_k$ are CPED/CPGD/CPHD/CPEW for the P2G device k , respectively. The subscripts 0 and 1 of each system level index represent the P2G device k before and after access, respectively.

In a specific case, [86] developed a robust dispatching model that considered an unexpected scenario of a natural gas pipeline and an N-1 power transmission. A new topology simplification method was proposed to calculate the reliability index of a natural gas system in [39], and the reliability of the distribution system was evaluated based on the shortest path method. In particular, a reliability model of the coupling device was established to quantify the interdependence between the distribution system and the gas distribution system. The reliability of the two subsystems was evaluated by considering the difference in the operating characteristics of the two subsystems. To solve the uncertainty of energy services provided by wind power output and a P2G plan,

an effective probability method was proposed to obtain the reliability models of these energy sources in [47]. When considering the fluctuations of energy demands in a multiple-state analysis model, the load distribution map model and the probability model of energy hub resources can become convoluted. The possible operational strategy of an energy hub can also be considered when calculating different reliability indexes.

C. RELIABILITY INDEX OF POWER-THERMAL-COOLING COUPLING SYSTEMS

Regarding the importance of key system components, the problem of energy supply interruptions caused by component failure was considered in [64]. The “valve level” [1] concept of a component was introduced to quantify the influence of a component failure on the energy supply in an IES.

The reliability index of a power-heating-cooling system is thus defined. $T(e_i)$ (valve level of energy conversion equipment) and $I_{prob}(e_i)$ (importance of equipment e_i) reflect the reliability level of a system. The definition is as follows:

$$T(e_i) = \frac{\psi_{c \max}(e_i)}{\psi_{c \max}} \tag{45}$$

$$\psi_{c \max} = L_E + L_H + L_C \tag{46}$$

where $\psi_{c \max}$ is the maximum energy supply when the system is running without failure, L_E is the maximum power supply, L_H is the maximum heat supply, L_C is the maximum cool supply, and $\psi_{c \max}(e_i)$ is the maximum power supply for the system after the failure of device e_i .

$$I_{prob}(e_i) = \frac{1 - T(e_i)}{\sum_{i=1}^M (1 - T(e_i))} \tag{47}$$

where M is a collection of all energy conversion devices.

The indexes above characterize the influence of the power-gas-heating system coupling elements on the system and the importance of the corresponding components, which can provide a reference for the identification of weak links in a system and guide the formulation of corresponding strengthening measures. According to the operational reliability definition index of the system, a multi-energy flow system is divided into a load point reliability index and a system level reliability index, based on the hierarchy, to evaluate the reliability of the system [87].

For a cogeneration system, the reliability index of the load point includes the failure rate of the load point λ year (times/year), the load point energy outage duration r (hours/times) and the average annual interruption time of load point U (hours/year). The relationship is defined as follows:

$$r = \frac{U}{\lambda} \tag{48}$$

The concept of a corresponding index is introduced, and the annual failure rates of power and heating load points are defined as λ^e and λ^h , respectively. The durations of power

and heating interruptions at the load points are defined as r^e and r^h , respectively. The average annual interruption times of power and heating load points are defined as U^e and U^h , respectively.

In a system level reliability index reference power system, the system interruption frequency SIF_{IES} (times/customer/year), the system interruption duration SID_{IES} (hours/customer/year), the system energy not supplied $SENS_{IES}$ (MWh/customer/year) and the system service availability SSA_{IES} (%) are defined. Based on the reliability index of a load point, the reliability index of the system level can be obtained, and the calculation formula is as follows:

$$SIF_{IES} = \frac{\sum_{i \in E} \lambda_i^e N_i^e + \sum_{i \in H} \lambda_i^h N_i^h}{\sum_{i \in E} N_i^e + \sum_{i \in H} N_i^h} \tag{49}$$

$$SID_{IES} = \frac{\sum_{i \in E} U_i^e N_i^e + \sum_{i \in H} U_i^h N_i^h}{\sum_{i \in E} N_i^e + \sum_{i \in H} N_i^h} \tag{50}$$

$$SENS_{IES} = \sum_{i \in E} L_i^e U_i^e + \sum_{i \in H} L_i^h U_i^h \tag{51}$$

$$SSA_{IES} = 1 - \frac{\sum_{i \in E} U_i^e N_i^e + \sum_{i \in H} U_i^h N_i^h}{8760 \left(\sum_{i \in E} N_i^e + \sum_{i \in H} N_i^h \right)} \tag{52}$$

where E is the power load point set, H is the heating load point set, N_i^e and N_i^h are the number of users at the i load point in the power grid and heat network, respectively, and L_i^e , L_i^h are the demand for power and heat at the i load point in the power grid and heating network, respectively.

D. RELIABILITY INDEX OF POWER-TRAFFIC COUPLING SYSTEMS

EVs represent a new source of large electric load; because of environmental and economic concerns [88], they have become new members of the current traffic network, and a new coupling system of power grids and vehicle networks has appeared. If a large number of EVs are charged during a peak load period, this will further aggravate the load peak and valley differences of a power grid and increase the burden on the power system, thus affecting the power supply quality of the power system and reducing the reliability of the coupling system.

[89] and [90] considered the access of EVs by increasing the capacity of substations to increase power grid reliability, thus improving the charging behavior of EVs by reasonably planning substation positions and subsequently improving the reliability of the vehicle network. References [91], [92] and [93] evaluated the reliability of the system by considering the reliability index of power quality under the condition of connecting to EVs.

Therefore, based on the reliability index of a power system, the reliability of the system is evaluated and considered after an EV is connected to the distribution network.

The average service availability index (ASAI) and the energy not supplied (ENS) are selected as the reliability indexes of the system. Active power loss (PLOSS) is selected as an economic index [94].

1) AVERAGE POWER AVAILABILITY

The ASAI directly reflects the impact of failure on production and use. In the actual operating process of a distribution network, the ASAI value cannot reach the level of 1.00, usually peaking at 0.99, and it can characterize obvious improvements [95]. Considering the characteristics of the ASAI, the satisfaction evaluation function f_A of the ASAI is constructed as follows:

$$f_A = \begin{cases} 0 & A_S < A_S^0 \\ a_A A_S^2 + b_A A_S + c_A & A_S^0 \leq A_S \end{cases} \quad (53)$$

where A_S is the ASAI value, A_S^0 is set as the lowest ASAI value, and a_A , b_A and c_A are setting parameters.

2) INSUFFICIENT SYSTEM POWER SUPPLY

The ENS directly reflects the scale and range of fault influence on the whole distribution network system. If the power supply of the system is insufficient, it is necessary to remove unimportant loads to maintain power balance. The ENS is also an important index used to reflect economic losses. The ENS value in a general distribution system is approximately 5 ~ 10 times the total average active power of the system [96]. Considering the characteristics of the ENS, the satisfaction evaluation function f_E of the ENS is constructed as follows:

$$f_E = \begin{cases} 1 & E_N \leq E_N^1 \\ \frac{E_N^0 - E_N}{E_N^0 - E_N^1} & E_N^1 \leq E_N \leq E_N^0 \\ 0 & E_N^0 \leq E_N \end{cases} \quad (54)$$

where E_N is the ENS value, E_N^0 is the ENS value in the initial network state, and E_N^1 is the minimum ENS value of the distribution system in theory.

3) ACTIVE POWER NETWORK LOSS

The economic operational level of the system is reflected through the loss of active power networks in the system. The important basis for judging the merits and demerits of a reconfiguration scheme is the size of the active power network loss. By constructing the satisfaction evaluation function f_p of active power network loss P_L , different distribution network reconfiguration schemes can be evaluated.

$$f_p = \begin{cases} 1 & P_L \leq P_L^{\min} \\ a_L P_L^2 + b_L P_L + c_L & P_L^{\min} \leq P_L \leq P_L^0 \\ 0 & P_L^0 \leq P_L \end{cases} \quad (55)$$

where P_L^{\min} is the theoretical minimum network loss value of the distribution network system, P_L^0 is the value of PLOSS in the initial network state, and a_L , b_L and c_L are setting parameters. The smaller P_L is, the closer the value of the satisfaction evaluation function is to 1.

E. RELIABILITY INDEX OF ENERGY CYBER-PHYSICAL SYSTEM

Communications networks are widely used in power systems and are often referred to as critical infrastructure (CI) [97]; their reliability has a great impact on the normal supply of power. Examples include the application of supervisory controls, data acquisition systems, and WIDE-AREA protection systems.

To assess network connection reliability, [98] introduced three indexes—cumulative failure probability, steady-state availability and component probability importance—for communication systems in wide-area protection (CSWAP) to realize the analysis of system failures, component failures and their effects on CSWAP to provide a quantitative analysis basis. The specific definitions are as follows:

- The cumulative failure probability:

$$CFP(t) = \Pr(T \leq t), \quad T > 0, \quad CFP(0) = 0 \quad (56)$$

where $CFP(t)$ is the cumulative fault probability of the system in a $(0, t)$ time period, and T is the system failure time.

- The steady-state availability A:

$$A = \frac{MTBF}{MTBF + MTTR} \quad (57)$$

where MTBF is the mean time between failure, MTTR is the mean time to repair, and A is the reliability of CSWAP when running for a long time.

The component probability importance index $I_i^{pr}(t)$ is used to analyze the influence of the change of component failure rate on the system failure rate. The component probability importance index is introduced to identify the components that have a significant impact on the reliability of CSWAP. The index is defined as a partial derivative of the failure probability of the system to the failure probability of the component, and the formula is as follows:

$$I_i^{pr}(t) = \frac{\partial F(t)}{\partial F_i(t)} = P_r \{g_{yk} = 1\} - P_r \{g_{yk} = 0\} \quad (58)$$

where $F_i(t)$ is the probability of failure of element i at time t , $F(t)$ is the failure probability of the system at a time t , and g is the system structure function. $P_r \{g_{yk} = 1\}$ indicates system unreliability due to the failure of component i , and $P_r \{g_{yk} = 0\}$ indicates system unreliability under component i operation.

To measure the reliability of the network from the perspective of connectivity, based on [99] and working from the node, set p and $q = 1 - p$ be the probability of successful and unsuccessful communications between the two nodes of a network G . When the corresponding node and connection link are working properly, set $p = 1$ and the other $p < 1$. Thus, p can be understood as the reliability of the node and the link of the connecting node, and the whole end reliability is defined as:

$$R_{ALL}(G, p) = pR(G * e) + qR(G - e) \quad (59)$$

where $G * e$ is a network formed by merging two nodes connected to e in network G , and $G - e$ is a network formed by removing e from network G .

F. RELIABILITY INDEX OF OTHER UMESs

Other UMESs were considered in terms of renewable energy access in [100], and the overall reliability evaluation indicators are as follows:

1) RELIABLE ENERGY SUPPLY RATE OF THE SYSTEM

Taking the energy receive rate of a power load and natural gas load as the index of reliable energy supply rate of the system, the reliability of the energy supply of the combined system is evaluated.

$$S_p = 1 - \sum_{t=1}^M \frac{P_{S(t)}}{P_{L(t)}} \quad (60)$$

where $P_{S(t)}$ is the load shortage, $P_{L(t)}$ is the total load, and M is the evaluation time.

2) NATURAL GAS SYSTEM ABSORPTION RATE

Renewable energy can be used to supply a natural gas load through P2G equipment conversion. The gas load supplied by synthetic natural gas (SNG) can be used to evaluate the level of wind power absorption in a natural gas system.

$$S_{gas} = \sum_{t=1}^M \frac{Q_{SNG(t)}}{Q_{GASL(t)}} \quad (61)$$

where $Q_{SNG(t)}$ is the natural gas load supplied by SNG produced by P2G, and $Q_{GASL(t)}$ is the natural gas load.

3) RATE OF PEAK CUTTING AND VALLEY FILLING IN A GRID

Using wind power as an example, P2G equipment and batteries can store and utilize wind power when wind power is in excess at night; at this point, these two types of equipment are considered to be power loads. At the peak of daytime power consumption, the batteries feed the stored power energy into the power grid to reduce the total load demand of the power grid, and the batteries are regarded as the power supply at this time. Therefore, the application of any kind of equipment is beneficial to reduce the peak and valley differences in a power grid.

$$S_{ep} = \left| \sum_{t=1}^M \frac{P_1^{\max}(t) - P_2^{\max}(t)}{P_1^{\max}(t)} \right| \quad (62)$$

where $P_1^{\max}(t)$ is the system load when P2G equipment and batteries are not used, and $P_2^{\max}(t)$ is the system load of P2G equipment and batteries after being placed into use.

4) EXCESS CAPACITY OF RENEWABLE ENERGY

The fluctuation of new energy power generation is large; using wind power as an example, the wind speed at night is generally higher; at this time, the level of wind power generation is larger, but the demand for night power load is smaller,

which can lead to abandoned wind power. By calculating the excess capacity of renewable energy, the abandoned wind level can be reflected.

$$S_{ex} = \sum_{t=1}^M \frac{P_{total}(t) - P_{use}(t)}{P_{use}(t)} \quad (63)$$

where $P_{total}(t)$ is the total renewable energy generation power; $P_{use}(t)$ is the renewable energy power for power load utilization, including P2G equipment, general power load and batteries.

V. CHALLENGES IN UMES RELIABILITY RESEARCH

Through the above research in this paper, it can be seen that the reliability modeling and evaluation of multi-energy flow systems focus on the modeling of the systems, but due to the diverse couplings of the subsystems, research on the relationships between these subsystems remains insufficient, so it is difficult to establish an accurate system model. At the same time, in order to realize multi-energy complementarity of the UMES and improve the reliability, the dispatch strategy of the coupling components should be fully considered.

In view of the above problems, this paper puts forward the following three research challenges.

A. THE COUPLING COMPONENT DISPATCH STRATEGY OF UMES TO BE CONSIDERED URGENTLY

Coupling component dispatch strategy is rarely applied to IESs, which contain a variety of energy requirements such as cooling, heating, and electricity [101]. Existing studies have focused on coupling component dispatch strategy in microgrids and multi-energy complementary systems with CCHP units but have not considered the coupling component dispatch strategy of natural gas and thermal. With the expansion of China's power market reforms, IES coupling component dispatch strategy has become an inevitable trend [102].

[103] summarized the value of coupling component dispatch strategy in improving the reliability of power systems under extreme cases. Reference [104] proposed coupling component dispatch strategy, and due to the complementary nature of multi-energy systems, the interactive capability of coupling component dispatch resources can be fully utilized while maintaining the comfort level of consumers. Further, in [105], to address the integrated community energy system (ICES) configuration issue, the randomness of resources and renewable generation in ICESs was analyzed in depth; a resilience-oriented stochastic ICES configuration framework considering energy dispatch influence was proposed, and a generalized energy dispatch model based on energy price fluctuation was established to improve the overall economy and system resiliency. In terms of corresponding evaluation indicators, vulnerability indicators of ICES tie lines and converting equipment were summarized to demonstrate occasional interruptions under normal operation and power failures during emergencies. In [72], an optimized energy

solution was proposed to accurately estimate the power and heating demands of a certain area, and a CCHP system was established to achieve reliability and economic service while satisfying the power supply of a multi-energy system in a residential environment. The study noted that reliability should be ensured without the interruption of service, redundancy of the system should be assessed, and installation costs should also be taken into account. This study serves as a guide to make the right choices in energy systems.

There is an interdependence between heating and power supply, which limits the operational flexibility of a CHP system, especially during cold seasons, and the coupling of a CHP system usually leads to a large power reduction of renewable energy because of the random heat demands. [44] established an energy-storage-like (ESL) model based on the dynamic temperature change and time-delay effect of the medium in a pipeline system, which represented the heat storage capacity of a regional heat network. The modeling of the ESL model was not complicated because it was described by two state variables (charging/discharging rate and storage capacity).

Because of the nonlinearity and modeling complexity of UMESs, some constraints associated with internal energy networks and operational uncertainties are often ignored. Reference [21] established a model that considered both constraints and uncertainties, which was critical for assessing flexibility under stress conditions. Considering the uncertainty of wind generators and coupling components, a robust security region (RSE) model of a power-gas system was established in [106]. [107] defined the security region (SR) of an IES by referencing the definition of the SR of the power grid, including a pressure security region (PSR) and a transmission security region (TSR). In addition, a general nonlinear optimization energy flow model was established to form the SR, PSR and TSR of a natural gas network in an IES, and a framework for constructing the SR of a natural gas network in a multidimensional space was proposed. More reliable operational plans will be required when the gas network is integrated into the power grid because of the increased uncertainty of the whole system. Reference [108] proposed a three-stage robust optimization model for the flexible operation of an energy system. The model integrated a power grid and a natural gas transmission network to minimize load reduction from attacks. In addition, the proposed three-stage problem was reformulated into a two-stage mixed-integer linear program (MILP) that could be solved using a Benders decomposition algorithm.

B. A NEW METHOD FOR ANALYZING THE INTERACTIONS BETWEEN SYSTEMS NEEDS TO BE CONSIDERED URGENTLY

The analytical evaluations of system-to-system interactions and probabilistic risk evaluations between systems are also considered studies of system reliability.

To assess the controllability of a power grid, [109] proposed that the co-optimization of a generator and transmis-

sion topology can improve the controllability of the network. In addition, a common optimization scheme for optimizing power generation unit commitment and a transmission switching problem was proposed while ensuring the N-1 reliability. The results indicated that the best topology of the network may change every hour. When a cascading failure triggered by a random attack was encountered, the optimal interconnection design of the interdependent network systems was considered, and the in-layer node degree information was used to design interdependent structures to maximize their robustness against the cascading faults triggered by random attacks. By using a system equation based on seepage theory, the robustness of the network was correlated with its degree sequence; [110] described the optimal design of a one-to-one structure with complete interdependence and partial interdependence under random attacks.

In addition, regarding probabilistic risk assessment (PRA), the complexity of modern systems and their dynamic behavior abilities continue to improve. The classic PRA technology has difficulty in accurately analyzing these systems.

To analyze these complex systems in a comprehensive and accurate manner, different characteristics need to be used, such as functional dependencies between components, system time behaviors, and multiple failure modes/components/system states, which need to consider the system behaviors and the uncertainties of fault data. However, the classic methods cannot address these aspects.

Bayesian networks (BNs) are popular in risk assessment applications because of their flexible structure and their ability to process analysis considering the above aspects. BNs have the ability to performing diagnostic analysis, and Petri nets are also used as formalized graphics and mathematical tools. In [111], BNs and Petri nets were used to model and analyze the dynamic behavior of systems and assess system reliability and safety risks. In addition, PRA methods include, but are not limited to, fault tree analysis (FTA), failure mode and effects analysis (FMEA), and event tree analysis (ETA).

C. THE RESILIENCE OF UMESs IN EXTREME SCENARIOS NEEDS TO BE CONSIDERED

There have many studies on the resilience of power systems in extreme scenarios and their corresponding recovery strategies.

The daily operation of a power system is closely related to changing weather patterns. In a data-driven approach, [112] used real-time weather data based on weather forecast data to realize an accurate time-space power generation prediction, evaluate asset health, assess reliability, predict the probabilistic load, and simulate the power market, eventually realizing the load interruption recovery. To effectively estimate the dynamic failure probability with multiple space-time parameters and analyze the overall reliability sensitivity of dynamic problems, a moment estimation method for the extreme value of the dynamic limit state function was proposed in [113]. However, the uncertainty of weather forecasts and abnormal peak loads will lead to the misalignment of probabilistic load

forecasting. In [114], a data-driven artificial neural network was used to realize probabilistic normal load forecasting and probabilistic uncertain peak load prediction. In extreme weather, a fault-like disconnection or pole/tower failure in a transmission network is likely to occur, which will lead to a power outage, so it is necessary to evaluate the reliability of the line by considering weather factors. In [115], a power line outage rate model considering weather conditions and conductor temperatures was established by analyzing several data sources, including operational data, weather data, land cover, altitude data, and asset management data. The analysis from the line outage probability was obtained, and then the risk assessment was carried out based on a Markov tree search method. To assess the cascade fault of a transmission line, [116] established a recovery model, and a simulation analysis was carried out with a sequential Monte Carlo scheme in order to quantify the influence of extreme weather events on the reliability/availability performance of a power system transmission network. Reference [117] proposed adding links to the underlying network structure to assess the network robustness against cascade failures, including a random linking strategy (RLS), a high-betweenness linking strategy (HBS) and a low-polarization linking strategy (LPS).

However, studies on the resilience of multi-energy flow systems remain scarce. Reference [118] noted that cyber-physical systems (CPS) are vulnerable to random failures or intentional attacks, and a reliability analysis model was modeled based on network science theory. The influence of the cascade fault effect was studied based on seepage theory, revealing a detailed mathematical analysis of fault propagation in CPSs. The proposed reliability analysis model can be effectively used for attack prevention and protection purposes in CPS systems. Considering the coordination of district multi-energy systems (DMES), a hierarchical management strategy was proposed in [119] to enhance the resilience of integrated energy distribution systems (IEDS). Energy storage devices and network communication facilities in DMES were fully utilized to achieve flexible energy dispatch, and the reliability and resilience of the system were guaranteed under the three modes mentioned in the strategy, including a normal operation mode, a preventive operation mode and a resilient operation mode. Reference [120] proposed the regional coordinated operation of an IES to enhance its resilience under extreme conditions, and a bidirectional flow model for a regional IES was established by using power gas technology; a three-level two-stage robust model was established to adapt to the random interruptions caused by natural disasters in natural gas, power generation and transmission systems. A two-level algorithm based on a Benders decomposition and column constraint generation algorithm was proposed to solve the robust IES problem.

Because of the situational complexity when a UMES is attacked in extreme scenarios, a quick evaluation is difficult. The linkage failure mechanisms of UMESs also need to be studied in the future.

VI. CONCLUSION

UMES involves many different forms of energy, covering a variety of energy subsystems. The coupling components and models of energy hubs in UMESs are summarized in this paper, including power grids, gas networks, cooling/heating networks, traffic networks and energy cyber-physical system. Therefore, the reliability modeling and evaluation of UMESs are the primary tasks to promote the deep coupling of UMESs, improve energy utilization and realize the multi-energy complementary. Firstly, the background and significance of UMESs are introduced. Then, the coupling relationships between different energy systems were introduced, including power-gas system, power-gas-heating/cooling system, power/gas-traffic system and energy cyber-physical system. The coupling components and models of energy hubs in UMESs are summarized in this paper. The reliability modeling method of UMES and the reliability evaluation index of an independent energy subsystem are summarized, and then, with the power system as the core, the reliability evaluation indexes of a power-gas coupling system, a power-thermal/cold coupling system, a power-traffic coupling system and energy cyber-physical system are summarized.

The latest reliability modeling methods were divided into model-driven methods and data-driven methods, and classifications and summaries are provided in this paper.

The advantage of model-driven modeling is that it reflects the interrelations and influences of each subsystem, but more complex coupling systems cannot be accurately modeled, and there are errors compared with actual systems sometimes. Data-driven models can make full use of energy big data and use specific actual scene data as samples to realize more accurate assessments of system reliability, but they cannot reflect the correlation structure between subsystems.

The reliability evaluation index was mainly defined based on the following aspects: 1) defining the energy index according to the shortages of energy supply and demand in each energy subsystem, such as an insufficient gas supply or a shortage of heating; 2) defining a probability index, such as the failure rate and the repair rate, for the component failure in each energy subsystem; and 3) in a practical application scenario, defining the environmental factors and user influencing factors, such as indoor temperature, etc.

Because of the complexity of UMESs, the present study focused on two- or three-energy coupled systems (such as CHP, CCHP), and the study of the specific modeling and reliability evaluations was insufficient. In this paper, a summary of the work provides references and advice at the same time for the establishment of comprehensive reliability assessment models and evaluation indexes. Because the present research is inadequate and the actual fault scenarios still lack effective evaluation methods, future research challenges are proposed:

- 1) The multi-energy complementarity is the advantage of UMESs. The dispatch strategy of the coupling components, and reliability of the UMESs should be developed and continuously optimized. The multi-energy

is optimized by hierarchical and orderly steps in the links of source-network-storage-load and to improve the efficiency of energy utilization.

- 2) The variety of energy subsystems are growing, which makes new analysis methods of the interactions between the system and subsystems should be studied. It needs to consider the system behaviors and the uncertainties of fault data including functional dependencies between components, system time behaviors, and multiple failure modes/components/system states.
- 3) The multi-energy complementarity of UMES endows it with strong resilience. Under the extreme conditions, making full use of and evaluating the resilience of UMESs should be a new research challenge. It includes establishing a set of effective evaluation indexes and proposing recovery strategies in extreme conditions.

REFERENCES

- [1] G. F. Li, Z. H. Bie, and Z. H. Wang, "Research status and prospects on reliability evaluation of integrated energy system," *Gaodiyanya Jishu/High Voltage Eng.*, vol. 43, no. 01, pp. 114–121, 2017.
- [2] P. Kankanala, S. Das, and A. Pahwa, "AdaBoost⁺: An ensemble learning approach for estimating weather-related outages in distribution systems," *IEEE Trans. Power Syst.*, vol. 29, no. 1, pp. 359–367, Jan. 2014.
- [3] S. V. Buldyrev, R. Parshani, G. Paul, H. E. Stanley, and S. Havlin, "Catastrophic cascade of failures in interdependent networks," *Nature*, vol. 464, no. 7291, pp. 1025–1028, Apr. 2010.
- [4] S. Sheikh, M. Komaki, and B. Malakooti, "Integrated risk and multi-objective optimization of energy systems," *Comput. Ind. Eng.*, vol. 90, pp. 1–11, Dec. 2015.
- [5] S. Huai, Z. Jinjun, and Y. Nan, "Research on reliability assessment methods for large gas pipeline network," *Oil Gas Storage Transp.*, vol. 35, no. 01, pp. 7–15, 2016.
- [6] M. Benidris, J. Mitra, and C. Singh, "Integrated evaluation of reliability and stability of power systems," *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 4131–4139, Sep. 2017.
- [7] A. Al-Nujaimi, M. A. Abido, and M. Al-Muhaini, "Distribution power system reliability assessment considering cold load pickup events," *IEEE Trans. Power Syst.*, vol. 33, no. 4, pp. 4197–4206, Jul. 2018.
- [8] H. Farzin, M. Fotuhi-Firuzabad, and M. Moeini-Aghtaie, "Role of outage management strategy in reliability performance of multi-microgrid distribution systems," *IEEE Trans. Power Syst.*, vol. 33, no. 3, pp. 2359–2369, May 2018.
- [9] C. Siding, L. Zhongjian, and C. Lipeng, "Reliability evaluation of dendritic gas pipeline network," *Oil Gas Storage Transp.*, vol. 31, no. 5, pp. 335–339 and 408, 2012.
- [10] M. Li, X. Xue, J. Ma, Y. Zheng, L. Xue, H. Zheng, M. Ai, and L. Duan, "A reliability evaluation system of complex gas pipeline network system in the operation period," *Oil Gas Storage Transp.*, vol. 38, no. 7, pp. 738–744, 2019.
- [11] K. F. Tee and K. Pesinis, "Reliability prediction for corroding natural gas pipelines," *Tunnelling Underground Space Technol.*, vol. 65, pp. 91–105, May 2017.
- [12] Y. Lei, K. Hou, Y. Wang, H. Jia, P. Zhang, Y. Mu, X. Jin, and B. Sui, "A new reliability assessment approach for integrated energy systems: Using hierarchical decoupling optimization framework and impact-increment based state enumeration method," *Appl. Energy*, vol. 210, pp. 1237–1250, Jan. 2018.
- [13] Y. Juan, M. Mengnan, and G. Lin, "Reliability evaluation of integrated electrical and natural-gas system with power-to-gas," *Proc. CSEE*, vol. 38, no. 3, pp. 708–715, 2018.
- [14] L. Jiawei, Z. Shenxi, and C. Haozhong, "Reliability evaluation of integrated energy system consider thermal inertia and operation strategy," *Autom. Electr. Power Syst.*, vol. 42, no. 20, pp. 9–18, 2018.
- [15] H. Lei, C. Singh, and A. Sprintson, "Reliability modeling and analysis of IEC 61850 based substation protection systems," *IEEE Trans. Smart Grid*, vol. 5, no. 5, pp. 2194–2202, Sep. 2014.
- [16] H. Lei and C. Singh, "Non-sequential Monte Carlo simulation for cyber-induced dependent failures in composite power system reliability evaluation," *IEEE Trans. Power Syst.*, vol. 32, no. 2, pp. 1064–1072, Mar. 2017.
- [17] L. Jianqi, S. Wenhao, and Z. Dexiang, "Research on information communication network of user side in energy interconnection," *Electr. Power Inf. Commun. Technol.*, vol. 14, no. 4, pp. 13–17, 2016.
- [18] Y. Sun, H. Yue, J. Zhang, and C. Booth, "Minimization of residential energy cost considering energy storage system and EV with driving usage probabilities," *IEEE Trans. Sustain. Energy*, vol. 10, no. 4, pp. 1752–1763, Oct. 2019.
- [19] A.-M. Hariri, M. A. Hejazi, and H. Hashemi-Dezaki, "Reliability optimization of smart grid based on optimal allocation of protective devices, distributed energy resources, and electric vehicle/plug-in hybrid electric vehicle charging stations," *J. Power Sources*, vol. 436, Oct. 2019, Art. no. 226824.
- [20] A. Kavousi-Fard, M. A. Rostami, and T. Niknam, "Reliability-oriented reconfiguration of vehicle-to-grid networks," *IEEE Trans. Ind. Informat.*, vol. 11, no. 3, pp. 682–691, Jun. 2015.
- [21] E. A. M. Cesena and P. Mancarella, "Energy systems integration in smart districts: Robust optimisation of multi-energy flows in integrated electricity, heat and gas networks," *IEEE Trans. Smart Grid*, vol. 10, no. 1, pp. 1122–1131, Jan. 2019.
- [22] S. Chen, Z. Wei, G. Sun, D. Wang, Y. H. Sun, H. X. Zang, and Y. Zhu, "Probabilistic energy flow analysis in integrated electricity and natural-gas energy systems," *Proc. CSEE*, vol. 35, no. 24, pp. 6331–6340, Dec. 2015.
- [23] S. Clegg and P. Mancarella, "Integrated modeling and assessment of the operational impact of power-to-gas (P2G) on electrical and gas transmission networks," *IEEE Trans. Sustain. Energy*, vol. 6, no. 4, pp. 1234–1244, Oct. 2015.
- [24] D. Xun, Z. Wenhao, and L. Yizhi, "A review of operation of natural gas-electricity coupling system considering power-to-gas technology," *Power Syst. Technol.*, vol. 43, no. 1, pp. 165–173, 2019.
- [25] Z. Yang, C. Gao, and M. Zhao, "Coordination of integrated natural gas and electrical systems in day-ahead scheduling considering a novel flexible energy-use mechanism," *Energy Convers. Manage.*, vol. 196, pp. 117–126, Sep. 2019.
- [26] W. Yanan, X. Xiaoyuan, and Y. Zheng, "Optimizing operation of integrated electrical and gas network with power-to-gas process," *Modern Electr. Power*, vol. 34, no. 4, pp. 1–7, 2017.
- [27] Y. Tan, X. Wang, and Y. Zheng, "A new modeling and solution method for optimal energy flow in electricity-gas integrated energy system," *Int. J. Energy Res.*, vol. 43, no. 9, pp. 4322–4343, Jul. 2019.
- [28] Y. Wang, Y. Wang, Y. Huang, J. Yang, Y. Ma, H. Yu, M. Zeng, F. Zhang, and Y. Zhang, "Operation optimization of regional integrated energy system based on the modeling of electricity-thermal-natural gas network," *Appl. Energy*, vol. 251, Oct. 2019, Art. no. 113410.
- [29] N. Voropai, V. Stennikov, S. Senderov, E. Barakhtenko, O. Voitov, and A. Ustinov, "Modeling of integrated energy supply systems: Main principles, model, and applications," *J. Energy Eng.*, vol. 143, no. 5, Oct. 2017, Art. no. 04017011.
- [30] Y. Zhou, Z. Wei, G. Sun, K. W. Cheung, H. Zang, and S. Chen, "A robust optimization approach for integrated community energy system in energy and ancillary service markets," *Energy*, vol. 148, pp. 1–15, Apr. 2018.
- [31] J. Kester, G. Zarazua de Rubens, B. K. Sovacool, and L. Noel, "Public perceptions of electric vehicles and vehicle-to-grid (V2G): Insights from a nordic focus group study," *Transp. Res. D, Transp. Environ.*, vol. 74, pp. 277–293, Sep. 2019.
- [32] Y. Xinran, L. Lin, and X. Yue, "Degradation charging scenarios and impacts on voltage stability of urban distribution network under 'EV-road-grid' coupling," *Electr. Power Autom. Equip.*, vol. 39, no. 10, pp. 102–108 and 122, 2019.
- [33] L. Jian, Y. Zheng, X. Xiao, and C. C. Chan, "Optimal scheduling for vehicle-to-grid operation with stochastic connection of plug-in electric vehicles to smart grid," *Appl. Energy*, vol. 146, pp. 150–161, May 2015.
- [34] F. Varshosaz, M. Moazzami, B. Fani, and P. Siano, "Day-ahead capacity estimation and power management of a charging station based on queuing theory," *IEEE Trans. Ind. Informat.*, vol. 15, no. 10, pp. 5561–5574, Oct. 2019.
- [35] M. Zhao, Z. Xiaoxin, and S. Yuwei, "Exploring the concept, key technologies and development model of energy Internet," *Power Syst. Technol.*, vol. 39, no. 11, pp. 3014–3022, 2015.

- [36] J. Heping, D. Yi, and S. Yonghua, "Review of reliability analysis for integrated energy systems with integration of cyber physical systems," *Power Syst. Technol.*, vol. 43, no. 1, pp. 1–11, 2019.
- [37] M. Moness and A. M. Moustafa, "A survey of cyber-physical advances and challenges of wind energy conversion systems: Prospects for Internet of energy," *IEEE Internet Things J.*, vol. 3, no. 2, pp. 134–145, Apr. 2016.
- [38] Z. Su, Y. Wang, Q. Xu, M. Fei, Y.-C. Tian, and N. Zhang, "A secure charging scheme for electric vehicles with smart communities in energy blockchain," *IEEE Internet Things J.*, vol. 6, no. 3, pp. 4601–4613, Jun. 2019.
- [39] C. Juanwei, Y. Tao, X. Yue, C. Xiaohua, Y. Bo, and Z. Baomin, "Fast analytical method for reliability evaluation of electricity-gas integrated energy system considering dispatch strategies," *Appl. Energy*, vol. 242, pp. 260–272, May 2019.
- [40] Y. Zijuan, G. Ciwei, and Z. Ming, "Review of coupled system between power and natural gas network," *Autom. Electr. Power Syst.*, vol. 42, no. 16, pp. 21–31 and 56, 2018.
- [41] W. Renbo, X. Wen, and G. Yang, "Hierarchical control strategy of regional energy network considering electrical-thermal coupling characteristics," *Southern Power Syst. Technol.*, vol. 12, no. 3, pp. 85–90, 2018.
- [42] X. Liu and P. Mancarella, "Modelling, assessment and Sankey diagrams of integrated electricity-heat-gas networks in multi-vector district energy systems," *Appl. Energy*, vol. 167, pp. 336–352, Apr. 2016.
- [43] X. Xu, K. Li, X. Yu, H. Jia, and Y. Guo, "Implications of gas infrastructure in integrated community energy systems," *J. Energy Eng.*, vol. 143, no. 5, Oct. 2017, Art. no. 04017053.
- [44] J. Yu, X. Shen, and H. Sun, "Economic dispatch for regional integrated energy system with district heating network under stochastic demand," *IEEE Access*, vol. 7, pp. 46659–46667, 2019.
- [45] F. Fang, Q. H. Wang, and Y. Shi, "A novel optimal operational strategy for the CCHP system based on two operating modes," *IEEE Trans. Power Syst.*, vol. 27, no. 2, pp. 1032–1041, May 2012.
- [46] W. Jing, X. Jian, and L. Siyang, "Coordinated optimization of integrated electricity-gas energy system considering uncertainty of renewable energy output," *Autom. Electr. Power Syst.*, vol. 43, no. 15, pp. 2–15, 2019.
- [47] M. Moeini-Aghtaie, H. Farzin, M. Fotuhi-Firuzabad, and R. Amrollahi, "Generalized analytical approach to assess reliability of renewable-based energy hubs," *IEEE Trans. Power Syst.*, vol. 32, no. 1, pp. 368–377, Jan. 2017.
- [48] N. Z. Xu and C. Y. Chung, "Reliability evaluation of distribution systems including vehicle-to-home and vehicle-to-grid," *IEEE Trans. Power Syst.*, vol. 31, no. 1, pp. 759–768, Jan. 2016.
- [49] Z. Jinhui, W. Xu, and J. Chuanwen, "Optimal scheduling method of multi-network regional integrated energy system based on traffic flow uncertainty," *Power Syst. Technol.*, vol. 43, no. 9, pp. 3081–3093, 2019.
- [50] K. Moslehi and R. Kumar, "A reliability perspective of the smart grid," *IEEE Trans. Smart Grid*, vol. 1, no. 1, pp. 57–64, Jun. 2010.
- [51] N. Nikmehr and S. N. Ravadanegh, "Reliability evaluation of multi-microgrids considering optimal operation of small scale energy zones under load-generation uncertainties," *Int. J. Electr. Power Energy Syst.*, vol. 78, pp. 80–87, Jun. 2016.
- [52] G. Qinglai, X. Shujun, S. Hongbin, and W. Jianhui, "Power system cyber-physical modelling and security assessment: Motivation and ideas," *Proc. CSEE*, vol. 36, no. 6, pp. 1481–1489, 2016.
- [53] X. Wang, M. Shahidehpour, C. Jiang, and Z. Li, "Resilience enhancement strategies for power distribution network coupled with urban transportation system," *IEEE Trans. Smart Grid*, vol. 10, no. 4, pp. 4068–4079, Jul. 2019.
- [54] X. Fu, Q. Guo, H. Sun, X. Zhang, and L. Wang, "Estimation of the failure probability of an integrated energy system based on the first order reliability method," *Energy*, vol. 134, pp. 1068–1078, Sep. 2017.
- [55] X. Fu, Q. Guo, H. Sun, Z. Pan, W. Xiong, and L. Wang, "Typical scenario set generation algorithm for an integrated energy system based on the wasserstein distance metric," *Energy*, vol. 135, pp. 153–170, Sep. 2017.
- [56] X. Fu, G. Li, and H. Wang, "Use of a second-order reliability method to estimate the failure probability of an integrated energy system," *Energy*, vol. 161, pp. 425–434, Oct. 2018.
- [57] C. Juanwei, Y. Tao, X. Yue, and C. Xiaohua, "Analytic method for power supply reliability assessment of electricity-gas coupled energy system," *Autom. Electr. Power Syst.*, vol. 42, no. 24, pp. 59–69, 2018.
- [58] H. Wang, X. Wang, Z. Ren, X. Wang, and Z. He, "Risk assessment of integrated energy system based on electrical-thermal energy flow," *Electr. Power Construct.*, vol. 39, no. 12, pp. 102–108, 2018.
- [59] T. Krause, G. Andersson, K. Fröhlich, and A. Vaccaro, "Multiple-energy carriers: Modeling of production, delivery, and consumption," *Proc. IEEE*, vol. 99, no. 1, pp. 15–27, Jan. 2011.
- [60] X. Fu, G. Li, X. Zhang, and Z. Qiao, "Failure probability estimation of the gas supply using a data-driven model in an integrated energy system," *Appl. Energy*, vol. 232, pp. 704–714, Dec. 2018.
- [61] X. Fu and X. Zhang, "Failure probability estimation of gas supply using the central moment method in an integrated energy system," *Appl. Energy*, vol. 219, pp. 1–10, Jun. 2018.
- [62] A. Katal, M. Mortezaadeh, and L. Wang, "Modeling building resilience against extreme weather by integrated CityFFD and CityBEM simulations," *Appl. Energy*, vol. 250, pp. 1402–1417, Sep. 2019.
- [63] M. Liu and P. Heiselberg, "Energy flexibility of a nearly zero-energy building with weather predictive control on a convective building energy system and evaluated with different metrics," *Appl. Energy*, vols. 233–234, pp. 764–775, Jan. 2019.
- [64] W. Ni, L. Lv, Y. Xiang, J. Liu, Y. Huang, and P. Wang, "Reliability evaluation of integrated energy system based on Markov process Monte Carlo method," *Power Syst. Technol.*, pp. 1–9, Nov. 2019.
- [65] Z. Chi, T. Qinghua, Y. Wei, W. Jufang, and H. Zhe, "Reliability evaluation of integrated community energy system based on particle-swarm-interior-point hybrid optimization algorithm," *Electr. Power Construct.*, vol. 38, no. 12, pp. 104–111, 2017.
- [66] G. Li, Z. Bie, Y. Kou, J. Jiang, and M. Bettinelli, "Reliability evaluation of integrated energy systems based on smart agent communication," *Appl. Energy*, vol. 167, pp. 397–406, Apr. 2016.
- [67] L. Cheng and T. Yu, "Smart dispatching for energy Internet with complex cyber-physical-social systems: A parallel dispatch perspective," *Int. J. Energy Res.*, vol. 43, no. 8, pp. 3080–3133, Jun. 2019.
- [68] Y. Ting, Z. Liyuan, and W. Chengshan, "Review on application of artificial intelligence in power system and integrated energy system," *Automat. Electr. Power Syst.*, vol. 43, no. 1, pp. 2–14, 2019.
- [69] Z. Wei, S. Chen, G. Sun, D. Wang, Y. Sun, and H. Zang, "Probabilistic available transfer capability calculation considering static security constraints and uncertainties of electricity-gas integrated energy systems," *Appl. Energy*, vol. 167, pp. 305–316, Apr. 2016.
- [70] T.-E. Huang, Q. Guo, H. Sun, C.-W. Tan, and T. Hu, "A deep spatial-temporal data-driven approach considering microclimates for power system security assessment," *Appl. Energy*, vol. 237, pp. 36–48, Mar. 2019.
- [71] H. Tianen, "Hybrid model and data driven concepts for power system security features election and knowledge discovery: Key technologies and engineering application," *Autom. Electr. Power Syst.*, vol. 43, no. 1, pp. 95–101, 208, and 102–104, 2019.
- [72] F. Salata, A. de Lieto Vollaro, R. de Lieto Vollaro, and L. Mancieri, "Method for energy optimization with reliability analysis of a trigeneration and teleheating system on urban scale: A case study," *Energy Buildings*, vol. 86, pp. 118–136, Jan. 2015.
- [73] S. Yu, W. Xiu-Li, W. Jian-Xue, and X. Shao-Yu, "An overview of the short-term reliability evaluation of power system," *Power Syst. Protection Control*, vol. 39, no. 8, pp. 143–154, 2011.
- [74] B. Zhaohong, W. Xiuli, and W. Xifan, "Reliability evaluation of complicated distribution systems," *J. Xi'an Jiaotong Univ.*, vol. 34, no. 8, pp. 9–13, 2000.
- [75] S. A. Arefifar and Y. A.-R.-I. Mohamed, "DG mix, reactive sources and energy storage units for optimizing microgrid reliability and supply security," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1835–1844, Jul. 2014.
- [76] L. Hu, Y. Diao, K. Liu, W. Luan, and W. Sheng, "Operational reliability analysis of distribution network based on big data technology," *Power Syst. Technol.*, vol. 41, no. 1, pp. 265–271, 2017.
- [77] L. Chang and Z. Wu, "Performance and reliability of electrical power grids under cascading failures," *Int. J. Electr. Power Energy Syst.*, vol. 33, no. 8, pp. 1410–1419, Oct. 2011.
- [78] J. Jiang, W. Gao, X. Wei, Y. Li, and S. Kuroki, "Reliability and cost analysis of the redundant design of a combined cooling, heating and power (CCHP) system," *Energy Convers. Manage.*, vol. 199, Nov. 2019, Art. no. 111988.
- [79] X. Shan, P. Wang, and W. Lu, "The reliability and availability evaluation of repairable district heating networks under changeable external conditions," *Appl. Energy*, vol. 203, pp. 686–695, Oct. 2017.
- [80] Z. Tianxing, Z. Ke, and L. Lan, "Multimodal transport channels and network reliability of urban agglomeration," *China Transp. Rev.*, vol. 41, no. 3, pp. 59–65, 2019.

- [81] C. Jianjun, Y. Lei, C. Xumei, and C. Kun, "General description of evaluation techniques of road network reliability," *Urban Transp. China*, vol. 6, no. 1, pp. 67–70 and 64, 2008.
- [82] L. Cheng-Bing, H. Yu-Cheng, G. Wei, and L. Feng-Xiao, "Modelling of cascading failure and reliability simulation of urban agglomeration traffic network," *J. Highway Transp. Res. Develop.*, vol. 35, no. 05, pp. 135–141, 2018.
- [83] Y. Rao, L. Guangquan, C. Peng, and W. Yunpeng, "An improved transportation network reliability model under a certain level of risk," in *Proc. 11th Annu. China Intell. Transp. Conf.*, Chongqing, China, 2016, p. 10.
- [84] P. Yulong, W. Yu, and P. Ting, "Connection reliability analysis of road network based on the speed-density model," *Urban Transp. China*, vol. 11, no. 4, pp. 66–69 and 12, 2013.
- [85] D. Fu-sheng, "New definition of reliability index and algorithm for a communication network," *Syst. Eng. Electron.*, vol. 28, no. 11, pp. 1641–1647 and 1651, 2006.
- [86] L. Bai, F. Li, T. Jiang, and H. Jia, "Robust scheduling for wind integrated energy systems considering gas pipeline and power transmission N-1 contingencies," *IEEE Trans. Power Syst.*, vol. 32, no. 2, pp. 1582–1584, Mar. 2017.
- [87] S. X. Zhang, M. Wen, H. Z. Cheng, X. Hu, and G. D. Xu, "Reliability evaluation of electricity-heat integrated energy system with heat pump," *CSEE J. Power Energy Syst.*, vol. 4, no. 4, pp. 425–433, Dec. 2018.
- [88] X. Chen, "Reconfiguration strategy for active distribution network considering spatial-temporal electrical vehicle load model," *High Voltage Eng.*, vol. 43, no. 3, pp. 1049–1056, 2017.
- [89] C. Feng, B. Zhou, N. Lin, Y. Li, and Y. Xia, "Application of comprehensive evaluation method integrating Delphi and GAHP in optimal siting of electric vehicle charging station," *Electr. Power Autom. Equip.*, vol. 32, no. 9, pp. 25–29, 2012.
- [90] Y. N. Wu, M. Yang, H. B. Zhang, K. F. Chen, and Y. Wang, "Optimal site selection of electric vehicle charging stations based on a cloud model and the PROMETHEE method," *Energies*, vol. 9, no. 3, p. 20, Mar. 2016.
- [91] Y. Long, "Research on site selection for electric vehicle charging stations based on AHP and fuzzy evaluation method," *Heilongjiang Electr. Power*, vol. 37, no. 4, pp. 313–317, 2015.
- [92] W. Meng, L. Kai, and N. Liyong, "Study on decision-making and evaluation of location of electrical vehicle charging stations," *Logistics Technol.*, vol. 34, no. 18, pp. 117–120 and 144, 2015.
- [93] L. Liu, Y. Zhou, W. Zhou, Q. Jing, Y. Luo, and Q. Qiu, "Research on sitingplanning evaluation system of electric vehicle charging station," *Elect. Meas. Instrum.*, vol. 53, no. 18, pp. 1–5, 2016.
- [94] D. Cunlu and J. Shuqin, "Reliability consideration of distribution network reconfiguration with electric vehicles," *Process Autom. Instrum.*, vol. 40, no. 2, pp. 48–52 and 57, 2019.
- [95] H. Yuqing, L. Dingguo, Z. Chao, and W. Ming, "Novel model and multistage algorithm for distribution network reconfiguration considering system reliability," *Autom. Electr. Power Syst.*, vol. 35, no. 17, pp. 56–60, 2011.
- [96] H. Yuqing, "Fast reliability evaluation and reconfiguration of distribution network," M.S. thesis, Dept. Elect. Inf. Eng., Hunan Univ., Hunan, China, 2011.
- [97] A. Bobbio, G. Bonanni, E. Ciancamerla, R. Clemente, A. Iacomini, M. Minichino, A. Scarlatti, R. Terruggia, and E. Zendri, "Unavailability of critical SCADA communication links interconnecting a power grid and a Telco network," *Rel. Eng. Syst. Saf.*, vol. 95, no. 12, pp. 1345–1357, Dec. 2010.
- [98] Z.-H. Dai, Z.-P. Wang, and Y.-J. Jiao, "Reliability evaluation of the communication network in wide-area protection," *IEEE Trans. Power Del.*, vol. 26, no. 4, pp. 2523–2530, Oct. 2011.
- [99] L. Zhang, X. S. Liu, J. W. Pang, D. G. Xu, and V. C. M. Leung, "Reliability and survivability analysis of artificial cobWeb network model used in the low-voltage power-line communication system," *IEEE Trans. Power Del.*, vol. 31, no. 5, pp. 1980–1988, Oct. 2016.
- [100] D. Lin, S. Liang, and C. Houhe, "Multi-index evaluation of integrated energy system with P2G planning," *Electr. Power Autom. Equip.*, vol. 37, no. 6, pp. 110–116, 2017.
- [101] Y. Wang, Y. Wang, Y. Huang, H. Yu, R. Du, F. Zhang, F. Zhang, and J. Zhu, "Optimal scheduling of the regional integrated energy system considering economy and environment," *IEEE Trans. Sustain. Energy*, vol. 10, no. 4, pp. 1939–1949, Oct. 2019.
- [102] Y. Sui, R. Ding, and H. Wang, "An integrated management system for occupational health and safety and environment in an operating nuclear power plant in east China and its management information system," *J. Cleaner Prod.*, vol. 183, pp. 261–271, May 2018.
- [103] F. Wang, H. Xu, T. Xu, K. Li, M. Shafie-Khah, and J. P. S. Catalão, "The values of market-based demand response on improving power system reliability under extreme circumstances," *Appl. Energy*, vol. 193, pp. 220–231, May 2017.
- [104] J. Wang, H. Zhong, Z. Ma, Q. Xia, and C. Kang, "Review and prospect of integrated demand response in the multi-energy system," *Appl. Energy*, vol. 202, pp. 772–782, Sep. 2017.
- [105] Z. Guo, G. Li, M. Zhou, and W. Feng, "Resilient configuration approach of integrated community energy system considering integrated demand response under uncertainty," *IEEE Access*, vol. 7, pp. 87513–87533, 2019.
- [106] S. Chen, Z. Wei, G. Sun, W. Wei, and D. Wang, "Convex hull based robust security region for electricity-gas integrated energy systems," *IEEE Trans. Power Syst.*, vol. 34, no. 3, pp. 1740–1748, May 2019.
- [107] X. Li, G. Tian, Q. Shi, T. Jiang, F. Li, and H. Jia, "Security region of natural gas network in electricity-gas integrated energy system," *Int. J. Electr. Power Energy Syst.*, vol. 117, May 2020, Art. no. 105601.
- [108] H. Cong, Y. He, X. Wang, and C. Jiang, "Robust optimization for improving resilience of integrated energy systems with electricity and natural gas infrastructures," *J. Modern Power Syst. Clean Energy*, vol. 6, no. 5, pp. 1066–1078, Sep. 2018.
- [109] K. W. Hedman, M. C. Ferris, R. P. O'Neill, E. B. Fisher, and S. S. Oren, "Co-optimization of generation unit commitment and transmission switching with N-1 reliability," *IEEE Trans. Power Syst.*, vol. 25, no. 2, pp. 1052–1063, May 2010.
- [110] S. Chattopadhyay, H. Dai, D. Y. Eun, and S. Hosseinalipour, "Designing optimal interlink patterns to maximize robustness of interdependent networks against cascading failures," *IEEE Trans. Commun.*, vol. 65, no. 9, pp. 3847–3862, Sep. 2017.
- [111] S. Kabir and Y. Papadopoulos, "Applications of Bayesian networks and Petri nets in safety, reliability, and risk assessments: A review," *Saf. Sci.*, vol. 115, pp. 154–175, Jun. 2019.
- [112] P. Dehghanian, B. Zhang, T. Dokic, and M. Kezunovic, "Predictive risk analytics for weather-resilient operation of electric power systems," *IEEE Trans. Sustain. Energy*, vol. 10, no. 1, pp. 3–15, Jan. 2019.
- [113] Y. Shi, Z. Lu, K. Cheng, and Y. Zhou, "Temporal and spatial multi-parameter dynamic reliability and global reliability sensitivity analysis based on the extreme value moments," *Struct. Multidisciplinary Optim.*, vol. 56, no. 1, pp. 117–129, Jul. 2017.
- [114] L. Xu, S. Wang, and R. Tang, "Probabilistic load forecasting for buildings considering weather forecasting uncertainty and uncertain peak load," *Appl. Energy*, vol. 237, pp. 180–195, Mar. 2019.
- [115] R. Yao and K. Sun, "Toward simulation and risk assessment of weather-related outages," *IEEE Trans. Smart Grid*, vol. 10, no. 4, pp. 4391–4400, Jul. 2019.
- [116] F. Cadini, G. L. Agliardi, and E. Zio, "A modeling and simulation framework for the reliability/availability assessment of a power transmission grid subject to cascading failures under extreme weather conditions," *Appl. Energy*, vol. 185, pp. 267–279, Jan. 2017.
- [117] X.-B. Cao, C. Hong, W.-B. Du, and J. Zhang, "Improving the network robustness against cascading failures by adding links," *Chaos, Solitons Fractals*, vol. 57, pp. 35–40, Dec. 2013.
- [118] H. Peng, C. Liu, D. D. Zhao, and J. M. Han, "Reliability analysis of CPS systems under different edge repairing strategies," *Phys. A-Stat. Mech. Appl.*, vol. 532, p. 13, Oct. 2019, Art. no. 121865.
- [119] S. Qi, X. Wang, X. Li, T. Qian, and Q. Zhang, "Enhancing integrated energy distribution system resilience through a hierarchical management strategy in district multi-energy systems," *Sustainability*, vol. 11, no. 15, p. 4048, Jul. 2019.
- [120] M. Yan, Y. He, M. Shahidehpour, X. Ai, Z. Li, and J. Wen, "Coordinated regional-district operation of integrated energy systems for resilience enhancement in natural disasters," *IEEE Trans. Smart Grid*, vol. 10, no. 5, pp. 4881–4892, Sep. 2019.



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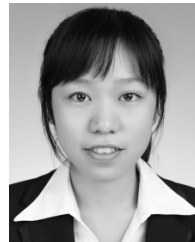
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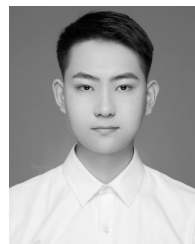
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