Controllable Structure Planning for Energy Internet

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***Abstract*—Secure system operations rely on reliable network structures. The loss of controllability may be the main reason to cause cascaded failures for complex network, e.g., Energy Internet (EI). However, the existing studies do not consider the network controllability to guide the system reconfiguration. To address this issue, the paper proposes a new structuring planning method for EI with consideration of controllability and economy. Firstly, the structure planning problem is modeled as a dynamic optimization problem with the tradeoff objectives of maximum social welfare and minimum driven nodes for long-term period. Then, a mixed maximum matching and deep deterministic policy gradient method is presented to obtain the approximate optimal planning solution with strong adaptability. Finally, simulation results demonstrate the effectiveness of the proposed method.**

***Index Terms*—controllability, structure planning, energy internet, cascading failure**

I. Introduction

A further innovation of smart grid, Energy Internet (EI) is required to accommodate all types of distributed energy nodes with great flexibility in energy sharing [1], [2]. The rapidly increasing distributed energy resources and intelligent participators lead to a series of impacts on the security and quality in the energy trading, control and operation in view of coordination, intermittence, communication and physical topology variabilities, and randomness, etc. As a promising solution, the concept of energy router (ER) is proposed, which is seen as an intelligent power electronics-based equipment that can flexibly manage the energy flows in a similar fashion as the information flows in Internet [3], [4].

EI and ER aim to accommodate all distributed energy resources to increase the energy transmission efficiency and optimize energy dispatch. ERs will serve as an essential building block in the envisioned EI. Indicated by the name, the ER is a technological combination of energy and information exchanges. It has two major capabilities, namely, dynamic adjustment of energy flows and real-time communications among energy nodes, which also interact with each other within the context of a complex cyber-physical system. When a large number of ERs are integrated into EI, it is needed to develop new network architecture to achieve the cooperated energy management of multi-ER and enhance the stability of the entire EI system. In EI system composed of multiple ERs, the stability and resilience of each multi-energy microgrid is not only related to its own infrastructures but also affected by the other multi-energy microgrids as well as the entire EI communication and physical networks. The overall structure planning along with analysis and integrated operations of different energy resources and ERs contribute to enhanced system hardening and resilience, and decrease the risk of a system failure. Several planning methods with diversified evaluation indices are established to guide the system structure reconfiguration. For instance, the plant configuration for co-generation systems was investigated in [5], where the annual demands are used as the indices to construct the scale and number of equipments. Considering the uncertainties of energy loads, the expansion of coplanning of multiple energy systems was studied in [6], [7], where the stochastic programming method is employed to find the optimal operations. From the perspective of low carbon, a bi-level expansion planning model was proposed in [8], which is further solved by a decentralized approach. Recently, literature [9] proposed an entropy-based weighted approach to plan the energy allocation to support the development of Beijing towards 2035.

Although the existing planning methods above have achieved some satisfactory results, they mainly consider the economy and low-carbon features, leading to limited scope. Note that one common consequence in a blackout may be the loss of the controllability, which could happen in any kind of energy resources as well as converters and then spread to other multi-energy microgrids, resulting in large-scale cascading failure and huge economic losses. On the contrary, if the system is controllable, we can add external control inputs on some critical nodes to make the system states be restricted into tolerant ranges, thus being able to decrease the risk of fault. Thus, whether the system is controllable or

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not contributes to an important effect on the security of the whole EI system, which opens up a new way to guide the EI system reconfiguration with better resilience. Related specific challenges are as follows: (1) There exist strong heterogeneity and interaction among different multi-energy microgrids. This implies that the controllability of different multi-energy microgrids is interdependent. No existing research takes the overall controllability of the EI into account. (2) Caused by the network fault, the interconnected multi-energy microgrids may be partitioned into several islands. Effective network structure planning to protect the controllability of each multi-energy microgrid and even the controllability of the whole EI system is not addressed.

To tackle those challenges, this paper proposes a structure planning method for EI from the perspective of controllability together with economy. The major contributions are as follows:

1) We propose a new structure planning model that takes the network controllability and economic operation into account, simultaneously. To our best knowledge, it is the first time to introduce the controllability index to guide the structure planning for EI.

2) We propose a mixed maximum matching and deep deterministic policy gradient method to solve the studied problem. It is capable of obtaining the approximate optimal planning solutions to protect tradeoff controllability and economy under dynamically cascaded faults.

The rest of this paper is organized as follows. Section II models the structure planning problem for EI, which is further formulated as a dynamic optimization problem. Section III proposes the mixed maximum matching and deep deterministic policy gradient method. Section IV provides an illustrative example to demonstrate the effectiveness of the proposed method. Section V concludes this paper.

II. Problem Formulation

In this paper, we jointly consider the controllability and economy to guide the structure planning. The studied EI is composed of multi-energy microgrids. For each multi-energy microgrid, it integrates diversified energy generation and conversion devices, including renewable generators (RGs), renewable heating devices (RHDs), fuel generators (FGs), fuel heating devices (FHDs), combined heat and power (CHP) devices, electricity storages (ESs), heat storages (HSs), gas producers (GPs). Meanwhile, the energy loads (ELs) in each multi-energy microgrid contain power loads, heat loads and gas loads, each of which contains a must-run load and a schedulable load. Each multi-energy microgrid is equipped with a local energy router (ER) which is employed to exchange information with the cloud computing center and control the energy exchange between the inside and the outside of the multi-energy microgrid. The planning problem is formulated as a dynamic optimization problem over period $[0, T]$ that is divided into m time steps with time interval $\triangle t = T/m$.

A. Stochastic model of multi-energy microgrid

The EI is in stochastic environment because of the intermittency and uncertain nature of the RGs, RHDs and must-run loads. In practice, they are always regarded as undispatchable units. It is very difficult to establish their explicit mathematical models and forecast the exact generations as well as demands. In order to take the stochastic characteristics into account, the uncertainty variables at time t are modeled as

$$p_i^{re}(t) = p_i^{re,\dagger}(t) + \delta_{i,p}^{re}(t), \delta_{i,p}^{re}(t) \in [\underline{\delta}_{i,p}^{re}(t), \overline{\delta}_{i,p}^{re}(t)], \quad (1)$$

$$h_i^{re}(t) = h_i^{re,\dagger}(t) + \delta_{i,h}^{re}(t), \delta_{i,h}^{re}(t) \in [\underline{\delta}_{i,h}^{re}(t), \overline{\delta}_{i,h}^{re}(t)], \quad (2)$$

$$l_{i,\phi}^{mt}(t) = l_{i,\phi}^{mt,\dagger}(t) + \delta_{i,\phi}^{mt}(t), \delta_{i,\phi}^{mt}(t) \in [\underline{\delta}_{i,\phi}^{mt}(t), \overline{\delta}_{i,\phi}^{mt}(t)], \quad (3)$$

where t denotes the time step; p_i^{re} and h_i^{re} represent the power and heat generations of RG and RHD, respectively; $l_{i,\phi}^{mt}$ represents the must-run energy loads, in which $\phi = p, h, g$ refers to power, heat and gas, respectively; $p_i^{re,\dagger}$, $h_i^{re,\dagger}$ and $l_{i,\varphi}^{mt,\dagger}$ represent the corresponding forecast values; $\delta_{i,p}^{re}$, $\delta_{i,h}^{re}$ and $\delta_{i,\varphi}^{mt}$ represent the forecast error, which can vary randomly within the corresponding lower bounders (i.e., $\underline{\delta}_{i,p}^{re}$, $\underline{\delta}_{i,h}^{re}$, $\underline{\delta}_{i,\varphi}^{mt}$) and upper bounders (i.e., $\overline{\delta}_{i,p}^{re}$, $\overline{\delta}_{i,h}^{re}$, $\overline{\delta}_{i,\varphi}^{mt}$) to embody the stochastic characteristics. Moreover, we assume the forecast error obey Gaussian distribution with confidence level $100(1-\vartheta)\%$ to reasonably determine the bounders.

B. Control model of multi-energy microgrid

Except for RGs, RHDs and must-run loads, the other devices are considered to be schedulable, whose control model, cost function and operation limits are discussed as follows.

1) FG, FHD model: At each time step, we denote p_i^{fu} and h_i^{fu} as the energy outputs of the FG and FHD in ith multi-energy microgrid, respectively. As schedulable energy components, the operations of FG and FHD are driven by the corresponding control commands denoted as $u_{i,p}^{fu}$ and $u_{i,h}^{fu}$, respectively. To simply notations, φ is used to represent p or h. Then, the dynamics of the energy outputs for FG and FHD between two adjacent time steps can be modeled as

$$\varphi_i^{fu}(t+1) = \varphi_i^{fu}(t) + k_{i,\varphi}^{fu} u_{i,\varphi}^{fu}(t), \quad \varphi \in p, h \quad (4)$$

where $k_{i,p}^{fu}$ is the control gain. In addition, the corresponding cost functions as well as the capability constraints, which are employed to guide the optimal control behavior, are often modeled as the following non-quadratic form

$$\begin{aligned} C(\varphi_i^{fu}(t)) = a_{i,\varphi}^{fu}\big(\varphi_i^{fu}(t)\big)^2 + b_{i,\varphi}^{fu}\varphi_i^{fu}(t) + c_{i,\varphi}^{fu} \\ + \mu_{i,\varphi}^{fu}\exp\big(\varepsilon_{i,\varphi}^{fu}\varphi_i^{fu}(t)\big), \end{aligned} \quad (5)$$

$$\underline{\varphi}_i^{fu} \le \varphi_i^{fu} \le \overline{\varphi}_i^{fu}, \ \ \varphi \in p, h \quad (6)$$

where $a_{i,\varphi}^{fu}$, $b_{i,\varphi}^{fu}$, $c_{i,\varphi}^{fu}$, $\mu_{i,\varphi}^{fu}$ and $\varepsilon_{i,\varphi}$ are nonnegative cost coefficients; $\underline{\varphi}_i^{fu}$ and $\overline{\varphi}_i^{fu}$ are the lower and upper bounds of φ_i^{fu}, respectively.

2) CHP model: The CHP, generating power and heat simultaneously, is one of important device to link the power and heat systems. We denote p_i^{chp} and h_i^{chp} as the power and heat output of the CHP in i multi-energy microgrid. Meanwhile, the corresponding control commands are defined as $u_{i,p}^{chp}$ and $u_{i,h}^{chp}$, respectively. Then, it control model is defined as

$$\varphi_i^{chp}(t+1) = \varphi_i^{chp}(t) + k_{i,\varphi}^{chp} u_{i,\varphi}^{chp}(t), \ \ \varphi \in p, h \quad (7)$$

where $k_{i,\varphi}^{chp}$ is the control gain. Furthermore, the cost function and the local restrictions are often modeled as

$$C(p_i^{chp}(t), h_i^{chp}(t)) = a_i^{chp}\big(p_i^{chp}(t)\big)^2 + b_i^{chp}p_i^{chp}(t) + c_i^{chp} + \alpha_i^{chp}\big(h_i^{chp}(t)\big)^2 + \beta_i^{chp}h_i^{chp}(t) + \varepsilon_i^{chp}p_i^{chp}(t)h_i^{chp}(t), \quad (8)$$

$$e_{i,\eta}p_i^{chp} + f_{i,\eta}h_i^{chp} + z_{i,\eta} \geq 0, \quad \eta = 1, 2, 3, 4 \quad (9)$$

where a_i^{chp}, b_i^{chp}, c_i^{chp}, α_i^{chp}, β_i^{chp} and ε_i^{chp} are nonnegative cost coefficients; $e_{i,\eta}$, $f_{i,\eta}$ and $z_{i,\eta}$ are the coefficients of the ηth linear inequality constraint determined by the feasible operation region.

3) GS model: By using similarity method, the control model for GS is formulated as

$$g_i^{gs}(t+1) = g_i^{gas}(t) + k_{i,g}^{gas}u_{i,g}^{gas}(t), \quad (10)$$

where g_i^{gas} is the gas output of the GS in ith multi-energy microgrid; $u_{i,g}^{gas}$ is the control command; $k_{i,g}^{gas}$ is the control gain. The corresponding cost function and operation limits are given by

$$C(g_i^{gas}(t)) = a_i^{gas}\big(g_i^{gas}(t)\big)^3 + b_i^{gas}\big(g_i^{gas}(t)\big)^2 + c_i^{gas}g_i^{gas}(t) + d_i^{gas}, \quad (11)$$

$$0 \leq \underline{g}_i^{gas} \leq g_i^{gas} \leq \overline{g}_i^{gas}, \quad (12)$$

where a_i^{gas}, b_i^{gas}, c_i^{gas} and d_i^{gas} are nonnegative cost coefficients; $\underline{g}_i^{gas}$ and $\overline{g}_i^{gas}$ are the lower and upper bounds of g_i^{gas}, respectively. It should be pointed out that (11) is a convex function within the region (12).

4) ES, HS model: The ES and HS, which can conduce to energy supplies or demands in each multi-energy microgrid, play an important role in maintaining supply-demand balance, and reducing peak as well as filling valley for long-term planning. We denote p_i^s (or h_i^s) and $SOC_{i,p}^s$ (or $SOC_{i,h}^s$) as the exchanged power and stored energy of ES (or HS) in multi-energy microgrid i, respectively. Therein, it is defined that p_i^s (or h_i^s) is positive for discharging and negative for charging. The received control commands for ES and HS in EB i is denoted as $u_{i,\varphi}^s$. Then, the control model for energy storage devices is given by,

$$\varphi_i^s(t+1) = \varphi_i^s(t) + k_{i,\varphi}^s u_{i,\varphi}(t), \quad \varphi \in p, h \quad (13)$$

where $k_{i,\varphi}^s$ is the control gain. Since the utilization life of storage devices can be reduced by the frequent changing/discharging operations, the operation penalty is taken into account, which is formulated as

$$C(\varphi_i^s(t)) = a_i^s\big(\varphi_i^s(t)\big)^2, \quad \varphi \in p, h \quad (14)$$

where a_i^s is positive plenty coefficient. Moreover, for each storage device, its charging and discharging rates are restricted; meanwhile, the stored energy should also be maintained within a proper range to avoid deep charing and discharging. The mathematical expressions are as follows

$$-\varphi_i^{s,ch} \leq \varphi_i^s \leq \varphi_i^{s,ds}, \quad \varphi \in p, h \quad (15)$$

$$SOC_{i,\varphi}^s(t+1) = SOC_{i,\varphi}^s(t) - \Big(\varrho_{i,\varphi}^{ch}\sigma_{i,\varphi}^{ch}(t) + \frac{1}{\varrho_{i,\varphi}^{ds}}\sigma_{i,\varphi}^{ds}(t)\Big)\varphi_i^s(t)\triangle t, \quad \varphi \in p, h \quad (16)$$

$$\underline{SOC}_{i,\varphi}^s \leq SOC_{i,\varphi}^s \leq \overline{SOC}_{i,\varphi}^s, \quad \varphi \in p, h \quad (17)$$

$$\sigma_{i,\varphi}^{ch}(t) + \sigma_{i,\varphi}^{ds}(t) \leq 1, \quad \varphi \in p, h \quad (18)$$

where $\varphi_i^{s,ch}$ and $\varphi_i^{s,ds}$ are the maximum charging and discharging rates; $\varrho_{i,\varphi}^{ch}$ and $\varrho_{i,\varphi}^{ds}$ are the charging and discharging coefficients; $\sigma_{i,\varphi}^{ch}, \sigma_{i,\varphi}^{ch} \in \{0, 1\}$ represent the operation state, where $\sigma_{i,\varphi}^{ch} = 1$ and $\sigma_{i,\varphi}^{ch} = 1$ refer to charging and discharging state, respectively; $\underline{SOC}_{i,\varphi}^s$ and $\overline{SOC}_{i,\varphi}^s$ are the allowed lower and upper bounds of $SOC_{i,\varphi}^s$. In practice, we often set $\underline{SOC}_{i,\varphi}^s = 0.2SOC_{i,\varphi}^{s,cap}$ and $\underline{SOC}_{i,\varphi}^s = 0.8SOC_{i,\varphi}^{s,cap}$. Therein, $SOC_{i,\varphi}^{s,cap}$ is the maximum capability of the corresponding storage device.

5) Schedulable load models: The demand response can provide the function of virtual storage which is further taken into consideration to enhance the flexibility of the EI system. $l_{i,p}^{sl}$, $l_{i,h}^{sl}$ and $l_{i,g}^{sl}$ are denoted as the schedulable power, heat and gas loads of ith EB with control commands $u_{i,p}^{sl}$, $u_{i,h}^{sl}$ and $u_{i,g}^{sl}$. Then, the dynamics of the schedulable load demands are given by

$$l_{i,\phi}^{sl}(t+1) = l_{i,\phi}^{sl}(t) + k_{i,\phi}^{sl}u_{i,\phi}^{sl}(t), \quad \phi \in p, h, g \quad (19)$$

where $k_{i,\phi}^{sl}$ is the control gain. Driven by profit, it can create sufficient incentives to increase the consumer participation, which is determined by utility function shown as follows

$$U(l_{i,\phi}^{sl}(t)) = \sum_{\phi \in p,h,g}\bigg(-a_{i,\phi}^{sl}\big(l_{i,\phi}^{sl}(t) + l_{i,\phi}^{mt}(t)\big)^2 + b_{i,\phi}^{sl}\big(l_{i,\phi}^{sl}(t) + l_{i,\phi}^{mt}(t)\big)\bigg), \quad (20)$$

$$0 \leq l_{i,\phi}^{sl}(t) \leq l_{i,\phi}^{max}(t) - l_{i,\phi}^{mt}(t), \quad \phi \in p, h, g \quad (21)$$

where $a_{i,\phi}^{sl}$ and $b_{i,\phi}^{sl}$ are utility coefficients; $l_{i,\phi}^{max}(t)$ are the upper bound of the corresponding energy load.

In the considered EI system, there are some alternative energy loads which can be afforded by different kinds of supplier. That also means the power, heat and gas loads may be transformed into each other with diversified energy demand mix, which can be formulated as

$$\overline{\Upsilon}_i^{g\to p} \leq l_{i,p}^{sl}/(l_{i,p}^{sl} + \Psi l_{i,g}^{sl}) \leq \underline{\Upsilon}_i^{g\to p}, \quad (22)$$

$$\overline{\Upsilon}_i^{g\to h} \leq l_{i,h}^{sl}/(l_{i,h}^{sl} + \Psi l_{i,g}^{sl}) \leq \underline{\Upsilon}_i^{g\to h}, \quad (23)$$

$$\overline{\Upsilon}_i^{p\to h} \leq l_{i,p}^{sl}/(l_{i,p}^{sl} + l_{i,h}^{sl}) \leq \underline{\Upsilon}_i^{p\to h}, \quad (24)$$

where $\overline{\Upsilon}_i^{g\to p}$, $\overline{\Upsilon}_i^{g\to h}$ and $\overline{\Upsilon}_i^{p\to h}$ are the lower bound of the conversion percentages; $\underline{\Upsilon}_i^{g\to p}$, $\underline{\Upsilon}_i^{g\to h}$ and $\underline{\Upsilon}_i^{p\to h}$ are the upper bound of the conversion percentages; Ψ represents the transformation ratio from SCM/h to MW. In practice, Ψ is often set to $1/84$.

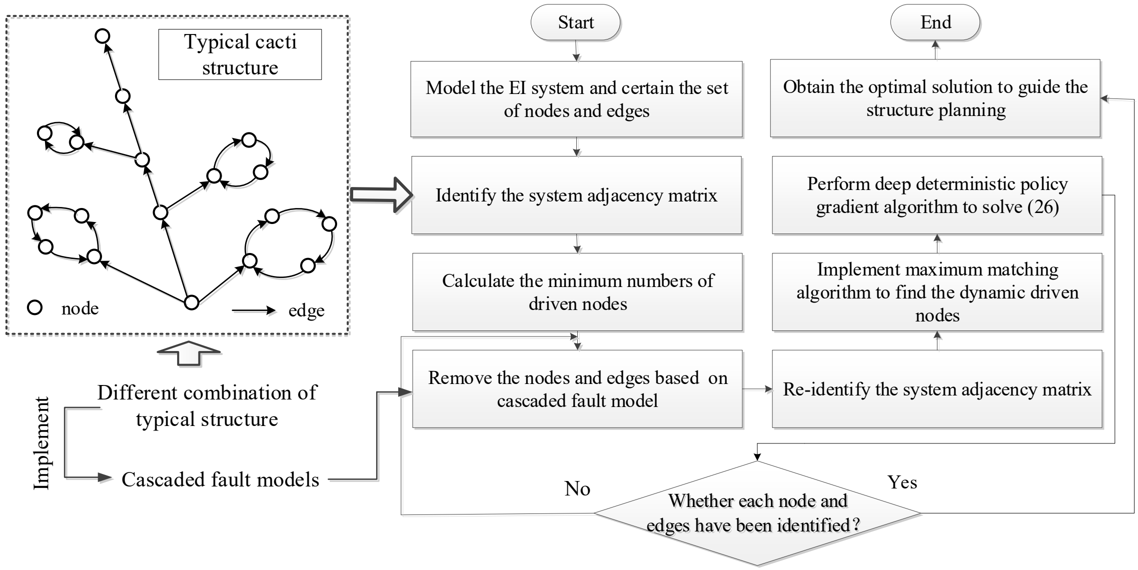

Fig. 1. Flowchart of mixed maximum matching and deterministic policy gradient algorithm.

C. Network controllability model

We can make use of graph to model the EI system, where the energy devices/loads and the interconnected lines are seen as the nodes edges, respectively. According to [10], a physical system is able to be viewed as controllable if it has structural controllability. Thus, we make the EI be spanned by cacti with no inaccessible node and dilation, such that the whole system possesses structural controllability. We can add additional control inputs on some nodes to restore the structural controllability for a system. In a given set of faults, the following critical objectives are designed to guide the planning of system structure, 1) adding minimum control inputs for driven nodes to maintain the structural controllability in each microgid when it operates in islanded mode under time-and space-varying scenarios; 2) identifying the minimum numbers of driven nodes for EBs when they operate in interconnected mode under time-and space-varying scenarios. The cascaded fault models are used to simulate evolutions of the system structure in both time and space domains. The computation for dynamic driven nodes can be designed as

$$\mathrm{N}_{t,dr}=\sum_{t=0}^{m}\gamma_t \max\{N_t-M_t,1\}, \tag{25}$$

where $\mathrm{N}_{t,dr}$ represents cumulative future driven nodes; γ_t is the discount factor; N_t and M represents the total number of nodes and the size of the maximum matching.

D. Structure planning model for EI

Based on the models of multi-energy microgrid and network controllability, we consider two trade-off objectives to guide the structure planning i.e., maximizing the total social welfare and minimizing the total driven nodes for long time $[0,T]$. Meanwhile, a set of global supply-demand balance constraints and operation constrains in each time step are considered to evaluate and limit the planning operation. The mathematical expressions are given by

$$\max \quad Obj = \jmath_W \sum_{t=1}^{m} W(t) - \jmath_N N_{t,dr}, \tag{26}$$

subject to

$$\begin{aligned} p^{ma}(t) = &\sum_{i=1}^{n}\left(p_i^{re}(t)+p_i^{fu}(t)+p_i^{chp}(t)+p_i^{s}(t)\right) \\ &-\sum_{i=1}^{n}\left(l_{i,p}^{mt}(t)+l_{i,p}^{sl}(t)\right), \end{aligned} \tag{27}$$

$$\begin{aligned} h^{ma}(t) = &\sum_{i=1}^{n}\left(h_i^{re}(t)+h_i^{fu}(t)+h_i^{chp}(t)+h_i^{s}(t)\right) \\ &-\sum_{i=1}^{n}\left(l_{i,h}^{mt}(t)+l_{i,h}^{sl}(t)\right), \end{aligned} \tag{28}$$

$$h^{ma}(t) = \sum_{i=1}^{n} g_i^{gas}(t) - \sum_{i=1}^{n}\left(l_{i,g}^{mt}(t)+l_{i,g}^{sl}(t)\right), \tag{29}$$

and (1-4), (6-7), (9-10), (12-13), (15-19) and (21-25). Therein,

$$\begin{aligned} W(t) = &\sum_{i=1}^{n}\Bigg(U(l_{i,\phi}^{sl}(t)) - C(p_i^{chp}(t),h_i^{chp}(t)) \\ &-\sum_{\varphi\in p,h}\left(C(\varphi_i^{fu}(t))+C(\varphi_i^{s}(t))-C(g_i^{gas}(t))\right) \\ &-\sum_{\phi\in p,h,g}\varpi Pr_\phi(t)\phi^{ma}(t)\Bigg), \end{aligned} \tag{30}$$

is the total social welfare at time t; Pr_ϕ is the energy price of the main energy networks; ϖ is the price ratio; ϕ^{ma} expresses the exchanged energy between the main networks and multi-energy microgrids; $\jmath_W$ and $\jmath_N$ are positive constants. Since the main networks tend to sell the energy with higher prices

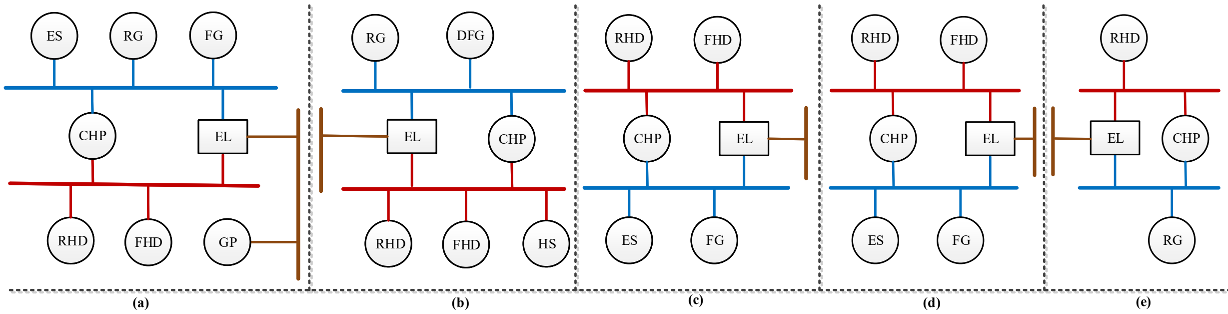

Fig. 2. Basis structures: (a) multi-energy microgrid 1. (b) multi-energy microgrid 2. (c) multi-energy microgrid 3. (d) multi-energy microgrid 4. (e) multi-energy microgrid 5.

to multi-energy microgrids and buy enough cheaper energy from multi-energy microgrids. To express the concept, we let ϕ^{ma} be positive for selling energy to multi-energy microgrids with $\varpi = 1$ and negative for buying energy from multi-energy microgrids $\varpi = 0.8$.

In addition, to unify the control operation, we set the operation space of each control variable as $\{-1, -(\tau - 1)/k, \cdots, 0, \cdots, (\tau - 1)/\tau, 1\}$ with $2\tau + 1$ elements. In this case, the corresponding control gains are endowed with important practice significance which represents the maximum adjustment value between two adjacent time steps.

III. Solution Method

The studied problem belongs to a kind of complex dynamic optimization problem that involves strong stochastic, non-convex, and nonlinear. To obtain the approximate optimal solution, we propose a mixed maximum matching and deep deterministic policy gradient method. The flowchart of the proposed method is reported in Fig. 1. During the planning process, the cascaded fault model [13] is employed to generate different network structures. The proposed method is employed to evaluate its feasibility and find the optimal solution from the perspective of long-term planning. The major procedures of the proposed method are illustrated as follows:

Step 1: Input the current network structure of EI system and obtain the node set and edge set.

Step 2: Identify the system adjacency matrix based on the physical structure.

Step 3: Calculate the minimum numbers of driven node of EI system in time-and space-varying scenario based on (25).

Step 4: Remove the selected nodes and edges based on the cascaded fault model [13] to obtain diversified network structures for further simulations.

Step 5: Re-identify the system adjacency matrix after performing cascaded fault.

Step 6: Implement the maximum matching algorithm [11] to find the dynamic driven nodes.

Step 7: Performance deep deterministic policy gradient algorithm [12] to solve problem (26) with a set of operation constraints.

Step 8: If all nodes and edges have been identified, then go to Step 9. Otherwise, go back to Step 4.

Step 9: Compare with the different solutions after cascaded faults to obtain the optimal solution and provide reference information to guide the structure planning.

IV. Illustrative Example

To evaluate the proposed method, we follow [14] to set five basis multi-energy microgrids as shown in Figs. 2(a-e). The parameters of the cost/utilizty functions and constraints can be found in [14].

A. System reconfiguration

In this section, we focus on reconfiguring the five basis structures and combing them to form an EI system with the balance of controllability and economy. We set $T = 24$ and $m = 24$. It implies that we consider one day structure planning problem. By performing the propose method, the newly built EI system is shown in Fig. 3. It can be observed that the structure of each multi-energy microgrid tends to be reconfigured as multiple circle components. This further enables to form cacti structure for the whole EI system with enhanced controllability. For example, the ES, RG, FG and CHP in multi-energy microgrid 1 are reconstituted as a circle structure that is also called as a bud. As a controllable unit, the bud is a part of cacti structure. Although one of the interconnected line is disconnected caused by the cascaded faults, we do not need to add extra control input to maintain the controllability. This result implies that the planning structure possesses strong controllability and robustness to defend cascaded faults, which verifies the effectiveness of the proposed method.

B. Comparison analysis

In this section, we focus on texting the performance of the planned structure by comparing with the one before planning [14]. By using the same cascaded fault model [13], the variations of the normalized objection function during $[0, T]$ for the two structures are reported in Fig. 4. It can be observed that the value of the normalized objection function under the structure after planning is higher than the one before planning. In addition, the rate of descent for the value of normalized objection function under the structure after planning is less than the one before planning. Those results imply that the planned structure is capable of maintaining high economy and controllability against cascaded faults.

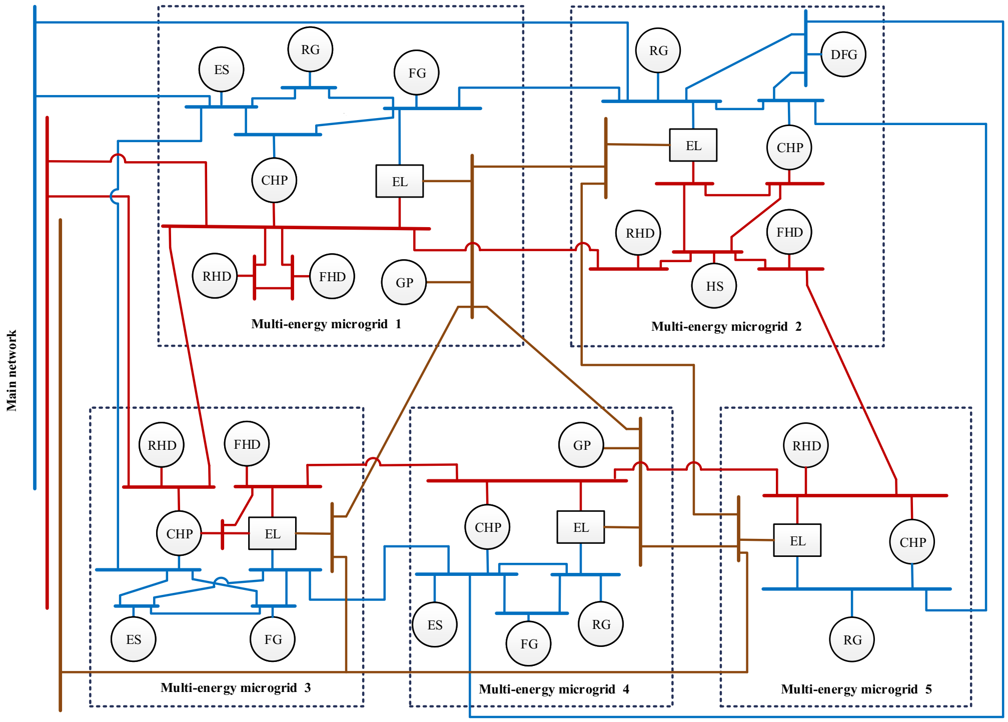

Fig. 3. Planning results of EI system with five multi-energy microgrids.

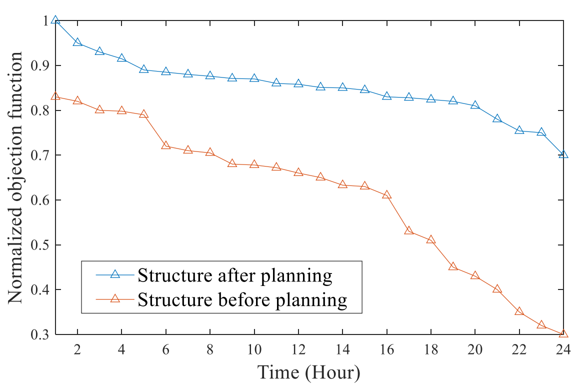

Fig. 4. Normalized objection function after cascaded fault.

CONCLUSION

This paper investigates the structure planning problem for the EI. The controllability and economy have been proposed to jointly build the model of the structure planning problem that is further formulated as a complex dynamic optimization problem. Then, a mixed maximum matching and deep deterministic policy gradient method has been presented to find approximate optimal solution that enables to defend the cascaded faults from the perspective of long-term planning. In the future, we will consider the influences of stability on network planning.

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