Policies and Power Systems Resilience Under Time-Based Stochastic Process of Contingencies in Networked Microgrids

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***Abstract*—Given the increasing occurrence of high-impact low-probability (HILP) contingencies in existing power systems, strengthening the resilience of these systems has become of paramount importance. Enhancing the resilience of power systems is not solely a technical issue but also a socio-economic and policy concern. Therefore, improving the performance of power systems greatly relies on the guidance provided by energy policies. While the decarbonization response, supported by these policies to mitigate climate change, influences the adoption of energy technologies, its impact on the resilience of the system remains uncertain. To uncover the interactions between technologies, policies, and economics concerning power systems resilience, this study focuses on constructing resilience-oriented networked microgrid systems. It develops a two-stage stochastic programming model by integrating a method for selecting power outage scenarios identified by users, in the presence of emissions policies. The results confirm the contributions of integrated systems in enhancing resilience, but they also reveal that low-carbon emissions policies play an inhibiting role by increasing the financial costs associated with resilience planning and operations. Nevertheless, a 30% emissions reduction threshold can still be achieved from the integrated network, facilitating the dual benefits of maximizing emissions reduction and minimizing the burden of emissions taxes. The study's contributions are threefold: firstly, it incorporates techno-economic incentives and regulations simultaneously; secondly, it quantifies the unintended consequences of policies on resilience; and thirdly, it provides constructive guidance for future energy policymaking, particularly in maintaining system resilience.**

***Index Terms*—Carbon emissions taxation, energy policies, networked microgrids, power systems resilience, stochastic programming.**

NOMENCLATURE

Acronyms

DERs	Distributed renewable-based generations.
ESSs	Energy storage management systems.
HILP	High-impact low-probability.
MGs	Microgrids.
NC	Number of quasi-scenario cluster.
NS	Number of scenarios for each submicrogrid.
NTS	Number of total scenarios for networked microgrids.
TE	Transactive energy.

Indices & Sets

n	Indices of quasi-scenario case.
t	Indices of time.
∇_t	Indices of time intervals.
T_f	Indices of system fault occurrence time.
∇_{T_f}	Indices of system fault duration time.
i, j	Indices of microgrids.
ω	Indices of scenarios.
Ω^T	Sets of time.
Ω^{MGs}	Sets of microgrids.
$CASE$	Sets of quasi-scenario clusters.
Ω^{ω}	Sets of scenarios.

Parameters

$\overline{\alpha}$	Upper bound of ESSs charging coefficient [-].
$\overline{\beta}$	Upper bound of ESSs discharging coefficient [-].
η	Carbon emissions tax [$\$/lb$].
γ	Carbon emissions abatement coefficient [%].
C_c	Levelized cost of electricity from coal-fired power plant [$\$$/kWh].
C_s	Levelized cost of electricity from utility-scale solar plant [$\$$/kWh].
C_w	Levelized cost of electricity from utility-scale wind plant [$\$$/kWh].
C_{ESS}	Unit cost of installing ESSs [$\$$/kW].
$DE_{i,t}$	Energy demand of microgrid i at time t [kWh].
E_c	Carbon emissions coefficient of coal [lb/kWh].
E_s	Life-cycle carbon footprint of solar [lb/kWh].
E_w	Life-cycle carbon footprint of wind [lb/kWh].
G^c_{loss}	Total loss of coal-fired power generation capacity [kW].
∇G^c_{loss}	User-identified coal-fired power generation capacity loss interval [kW].
$G^{c,opt}_{i,t}$	Optimal coal-fired power generation profile of microgrid i at time t from the base model [kW].
$\overline{G^{c,ini}_{i,t}}$	Capacity of coal-fired power generation of microgrid i at time t without power outage scenario [kW].

Manuscript received 15 September 2022; revised 17 February 2023; accepted 8 October 2023. This work was supported by US National Science Foundation under Grant 1847077. Review of this manuscript was arranged by Department Editor C. Amrit. *(Corresponding author: Ekundayo Shittu.)*

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Color versions of one or more figures in this article are available at https://doi.org/10.1109/TEM.2023.3325188.

Digital Object Identifier 10.1109/TEM.2023.3325188

$\overline{G^c_{i,t,\omega}}$ Capacity of coal-fired power generation of microgrid i in scenario ω at time t [kW].
$\overline{G^s_{i,t}}$ Capacity of solar power generation of microgrid i at time t [kW].
$\overline{G^w_{i,t}}$ Capacity of wind power generation of microgrid i at time t [kW].
P_ω Probability of scenario ω [-].
R_{ESS} Unit reward of storing electrical energy in ESSs [\$/kWh].

Binary Variables

$SOCc_{i,t,\omega}$ State of charging of ESSs of microgrid i in scenario ω at time t [-].
$SOCd_{i,t,\omega}$ State of discharging of ESSs of microgrid i in scenario ω at time t [-].
$SOT_{(ij),t}$ State of transactive energy from microgrid i to microgrid j at time t [-].

Variables

$\alpha_{i,t,\omega}$ Charging coefficient of ESSs of microgrid i in scenario ω at time t [-].
$\beta_{i,t,\omega}$ Discharging coefficient of ESSs of microgrid i in scenario ω at time t [-].
$ESS_{i,t,\omega}$ Amount of energy reserved in ESSs of microgrid i in scenario ω at time t [kWh].
$\overline{ESS_i}$ Capacity of ESSs of microgrid i [kW].
$G^c_{i,t}$ Coal-fired power generation of microgrid i at time t [kW].
$G^s_{i,t}$ Solar power generation of microgrid i at time t [kW].
$G^w_{i,t}$ Wind power generation of microgrid i at time t [kW].
OF_B Expected objective function value of base model [\$].
OF_E Expected objective function value of policy model [\$].
$TE_{(ij),t}$ Amount of transactive energy from microgrid i to microgrid j at time t [kW].

I. Introduction

POWER systems play an essential role in maintaining the uninterrupted functioning of society. As a critical infrastructure system, electricity generation in the U.S. has been diversified with the penetration of more renewable technologies in response to energy policies, and aggregate capacity has increased by 37.5% over the past two decades [1] in response to increasing demand. Unfortunately, correlated with these changes is the increased frequency of sustained outages. For instance, there were fewer than two dozen major disruptions in 2000 in the U.S., but the number surpassed 180 in 2020 [2]. There is no doubt that the existing U.S. electrical system is becoming less dependable given that large and sustained outages have occurred with increasing frequency over the past two decades. Hence, the two objectives of this study are: 1) to explore resilient integrated systems as a hedge against contingencies under sustainability transitions; and 2) to examine the effect of energy policies aimed at alleviating climate change on the resilience of the underlying electricity generating system.

This study is motivated by the severe cascading impacts caused by system disruptions that are characterized as HILP events [3], such as extreme weather or malicious cyberattacks with significant consequences. The failure to restore the system to normalcy when disrupted often leads to cascading consequences with immeasurable economic losses, property damages, and even life safety threats. For instance, the Texas electric power crisis of 2021 led to an estimated property damage of over \$195 billion and 151 deaths [4]. The heatwave in the western U.S. of 2020 triggered a peak demand record of over 162 GW for emergency interconnection [5]. Hurricane Maria of 2017 in Puerto Rico resulted in 3.4 billion customer-hours lost of electricity service and over 3000 deaths [6]. The occurrence of extreme events induced nearly 58% of total power blackouts since 2002 and an average of 18 to 33 billion dollars in economic losses annually.

It is noteworthy that, unlike the reliability metrics that mainly focus on low-impact high-probability events, the resilience metrics are mainly for contingencies of HILP characteristics [3], [7]. Particularly, the concept of resilience is proposed to evaluate the system's performance along the four postdisruption transition stages: deterioration, degradation, restoration, and recovery [7]. Considering the complexity of the evaluation of performance from the dynamic process, there still exist debates on the standardization of resilience in practice [8], but it is widely recognized that resilience is beyond sole technical metrics. Under the context of net-zero carbon power systems, the evaluation of resilience should incorporate the technical, economic recovery, social and institutional resilience, ecological, and infrastructural resilience simultaneously [9].

Yet, improving power systems performance depends on the guidance of energy policies and the support of advanced technologies. On the one hand, the response to climate change has largely focused on adaptation aimed at reducing vulnerability and exposure to climate risks [4], and mitigation or transition to low-carbon technologies. For example, a series of electricity market reforms have been studied to facilitate the process, including the policy incentives to support the customers' accessibility to solar energy [10] and incumbents' adoption of wind energy [11]. Energy policies related to emissions taxation are also implemented to control carbon emissions from production [12]. On the other hand, the development of advanced integration technology and the coordination of multiple energy sources dawn on the improvement of power system operations and protection. For instance, technical components such as distributed generators, supervisory control and data acquisition, phasor measurement unit [13], fault location, isolation, and service restoration technologies [14], and automatic transfer switch for backup energy compensation [15] jointly enhance the operational reliability. Nevertheless, it is unknown to what extent the resilience of the system is being impacted by those zero carbon oriented energy policies.

Although the encouragement of a higher proportion of usage of clean technologies truly facilitates the decarbonization process, it is impossible to turn a blind eye to the downside of the increasing penetration of renewable energy in the existing systems for three reasons. First, the high intermittency of renewable energy sources prohibits system planners from wholly abandoning traditional energy sources such as fossil fuels in terms of the stability of electricity generation [16], [17]. Second, the emerging electricity market and the high price of corresponding production technologies impede both producers and consumers from completely embracing such clean energy technologies [18]. Third, even though the technologies are available, there is still a lack of "smart" policy instructing integrated systems planning and operation, especially in the aftermath of an unexpected system disruption [9], [19]. Admittedly, this dilemma poses a challenge: To what extent do existing energy policies and market influence the resilience of power systems?

Furthermore, the presence of advanced technologies could potentially improve integrated systems operation, but it does not equivalently indicate satisfactory resilience performance for three reasons: First, existing standards prohibit DERs from energizing the main grid during emergencies because of the proportion of their intermittency [20], [21], thus limiting renewable energy in resilience considerations. Second, due to the uncertainties in energy policies regarding emissions tax, the incumbent's investments in large-scale renewable energy projects are still limited [12], which exacerbates the dependency on conventional energy sources. Third, a lack of dominant, reliable, and flexible policy mechanism in guiding the reasonable coordination among subsystems during the postdisruption period hampers the potential energy hub function of integrated systems [22], [23]. Hence, despite the existence of components for systems resilience enhancement, their efficacy is still within the confines of policy and market implications. Consequently, the market and financial considerations for both producers and consumers also play essential roles in influencing the formation of the systems. This combination informs the necessity to examine the construction of integrated power systems on resilience enhancement from a holistic perspective.

Thus, to unveil the interactions between the technologies, policies, and the economics of the system in terms of power systems resilience, this study develops an integrated approach to evaluate the resilience performance with and without the impact of energy policies. This approach incorporates a two-stage stochastic programming model by integrating a user-identified power outage scenario selection method in the presence of emissions policies, i.e., emissions standards (or limits) and emissions taxes. Specifically, this study compares the solutions of two models. The first is a base model without considering the impact of energy policies, where the minimization of the total cost of system planning and operation is the objective. The second is a policy model with the minimization of the total system cost and emissions tax as the objective. Furthermore, the proposed user-identified scenario selection method simulates a stochastic HILP event occurring, and this is used to initiate the preconditions of power outages for resilience optimization.

The results indicate the following.

1) The contributions of renewable energy for resilience enhancement in the integrated power system cannot be underestimated, where solar energy owns greater flexibility in leveraging resilience performance.
2) The implementation of low-carbon emissions taxation policies undoubtedly inhibits resilience performance by increasing the system planning and operation cost, but a critical emissions abatement threshold can be identified where the tradeoff of maximizing emissions abatement and minimizing cost could be reached.
3) The carbon emissions cap and the tax could jointly impact the resilience performance, a sensible decision on the combination of carbon emissions cap and tax benefits system operators most during the sustainability transitions period.
4) The role of ESSs in resilience planning needs to be emphasized, where the battery capacities significantly impact resilience performance.

The contributions are three-fold. First, from the methodological perspective, this study offers an integrated method to demonstrate the value of integrated power systems on resilience enhancement given stochastic scenarios of power outages. Second, from the technology management perspective, the analysis sheds light on the optimal combination of conventional and renewable energy sources for resilience planning in a cost-minimization approach. Third, from the perspective of the energy policies and the electricity market, both emissions standards and tax are evaluated for their optimal thresholds to avoid unintended negative consequences on systems resilience. Overall, this study offers systems planners and policymakers crucial insights for technology planning and the crafting of policies to enhance the resilience of electricity infrastructure systems in sustainability transitions.

II. Literature Review

This review draws from three strands of research: 1) the current decarbonization process and energy policies; 2) the construction of resilience-oriented networked MGs; and 3) the scenario selection method for stochastic programming.

A. Decarbonization Process and Energy Policies

To alleviate the effects of climate change, decarbonization has been deployed in sectors where carbon dioxide emissions are heavily associated. Those sectors involve energy generation and end-user consumption [16]. Electricity generation sector has had a relatively higher penetration of renewable energy than other sectors, but the decarbonization process is still passive due to the following three techno-economic reasons. First, many countries' economic plans and development are still closely coupled with conventional energy sources, and policymakers find it challenging to halt coal and oil expansion immediately [24], [25], [26]. Without an adaptive market mechanism aimed at coordinating global sustainability dispatch, an entire abnegation of the conventional energy industry would bring chaos [27]. Second, given the efficiency limitations of installed renewable-based technologies [28], [29], even though the capacity expansion could improve efficiency, such a long-term decision on investing in sustainability technologies is still subject to further considerations. Decision makers are greatly concerned about the massive capital cost when instructive guidance on designing future energy sectors is missing, and uncertainties about future regulations and market fluctuations exist [18]. Third, other alternative options such as hydroelectricity and nuclear energy are available, but safety concerns, geographical restrictions, and pricey operations and maintenance fail to prioritize those technologies in the decarbonization process [30], [31], [32]. Conversely, fossil-based electricity is flexible and easy to rebalance the power mismatch between supply and demand under the circumstance that higher penetration of renewable energy brings greater intermittency.

Given these challenges, energy policy plays a crucial role in facilitating the decarbonization process. Currently, the emissions trading schedule and carbon emissions taxation are the main strategies for controlling the emissions amount. However, the immaturity and misuse of the mechanisms result in a relatively small proportion of carbon emissions coverage [33], [34], which calls for a sustainability evaluation of the effectiveness of current policies. An emissions tax is a policy instrument used to regulate carbon emissions [12], [35], [36]. The theory of environmental economics posits that the Pigouvian tax helps to internalize the external costs of emissions [37]. The pressure imposed due to tax on emissions influences technology choices by producers and consumers leading to reductions in aggregate emissions [38]. Numerous past research studies have focused on establishing a carbon emissions tax that satisfies both social acceptance and social viability [39], [40], [41].

Policies towards decarbonization influence energy use management and optimization, and they also play a significant role in leveraging both operators' and consumers' selection of energy. This role accelerates the adoption of low-carbon or zero-carbon technologies in sustainability transitions. Given the uncertainties of future carbon emissions tax, different renewable portfolios need to be evaluated to be prepared for risk-averse decision makers. For instance, the renewable portfolios such as solar-only and wind-and-solar outperform other portfolios in terms of the smaller sensitivity to future tax while the carbon emissions abatement maintains at a large level [12].

Nevertheless, optimism towards the net-zero carbon networks underestimates the complexity of the coexistence between renewable energy and conventional energy. First, low-carbon power systems face pressing operational challenges on stability, where cascading outages are more likely to happen due to the increasing fragility of the system [42], [43], [44]. Second, compromise strategies are critical for achieving tradeoffs between economic development and environmental considerations during the sustainability transitions [45]. Under such a scenario, a hasty decision on taxing all carbon emissions not only fails to ensure the smooth adoption of renewable energy and effectiveness on emissions abatement, but also introduces a greater uncertainty to energy structure and brings chaos to the electricity market. Thus, this study takes into account the joint impact of carbon emissions cap and tax on excessive emissions.

Admittedly, discussions on enhancing power systems resilience have largely focused on the technical aspects. However, it is undeniable that power systems resilience requires a holistic approach that also considers energy policies and the market where electricity is traded. It is widely acknowledged that, in the case of power systems being disrupted, the priority is not about the carbon emissions abatement, but the fast restoration of systems back to normalcy [46]. However, under the influence of low-carbon energy policies, the normalcy status itself could be unstable due to the high penetration of intermittent renewable energy. In other words, the restoration of low-carbon power systems from a disruption needs compensation from other power generation sources, such as battery systems, to offset the intermittency of renewable energy.

Likewise, the role of renewable energy in global resilience enhancement is missing from past research. According to the standard, DERs are prohibited from energizing the main grid during emergencies [20], [21], but utility-scale renewable energy owns its potential in maintaining global resilience. For instance, the technical response to disruptions often is to adopt nondispatchable, utility-scale clean technologies such as centralized solar and wind plants to gradually replace the conventional fossil-fueled power plants [9]. As stated before, resilience is a measure beyond sole technical evaluation as it also incorporates the evaluation of its economical and social effectiveness [47], [48]. Even though the capital cost of planning and installing sustainable technologies is relatively high, they outperform conventional fossil-fired power plants in terms of a relatively lower operating and maintenance cost [16]. Under this circumstance, it is worthwhile to examine their contributions to the economic value of power system resilience given the capacities are fixed without generating extra capital costs.

Hence, past studies underestimate the interaction between energy policies and renewable-integrated power system resilience. This study examines portfolios where the impacts of imposing a limit on emissions and setting a price on carbon influence the resilience of the system. The hypothesis is that policies geared at emissions reduction will have impacts on resilience planning, the electricity market, and technological investment with a reinforcing demand for a comprehensive policy framework [19].

B. Construction of Resilience-Oriented Networked MGs

To put it simply, a resilient system is capable to maintain the continuity of supplying electricity to critical loads to a great extent in the aftermath of HILP disruptions [7]. However, as a multiphase and multidimensional measure, the operationalization of resilience is not unitary, as well as the objective of resilience enhancement [8]. Most research regarding power system resilience focuses on the maximization of load restoration, the minimization of operational cost, and the minimization of power mismatch [49]. However, the uniqueness of various system faults results in different resilience performances [3], [50], [51], [52], [53]. For example, the resilience of line faults usually outperforms that of the loss of power generations. This indicates that more attention should be focused on generation-related events such as large-scale power blackouts. For an independent power system with the main power supply being lost, a quick system restoration is not expected to occur; but for an integrated power system, it is promising to obtain a satisfactory resilience performance given the availability of multiple power generation technologies. In this case, MGs with distributed generation resources, especially networked MGs, have been seen as promising platforms for resilience enhancement due to their flexibility for structural reconfiguration, the integration of multiple energy sources, and decentralized control mechanism [49], [54], [55], [56], [57].

The selection of appropriate power generation sources is crucial for the construction of a resilient network. Apart from the conventional fossil fuel power plants, other types of sustainable technologies are also important components in power quality improvement, such as voltage control via inverted-based solar technologies [58]. Furthermore, sustainable technologies can also be utilized to improve resilience. For example, wind energy and solar energy are widely-used generation resources for resilience enhancement with the existence of corresponding battery energy storage systems handling the stochasticity introduced by renewable energy sources [49]. Even so, the exploration of ESSs is still under R & D phase, which would be discussed in the next paragraph. From a technical perspective, the potential of renewable energy in resilience enhancement cannot be ignored; from an economical perspective, as discussed previously, it is promising to see the contributions of sustainability technologies on alleviating stress on resilience cost [26]. However, it is impractical for system planners to wholly rely on sustainability technologies on building systems resilience, given the situation that the entire abnegation of conventional power plants during the sustainability transitions period is unacceptable aforementioned. Hence, a moderate mixture of conventional electricity generation and sustainable technologies serves as a compromise solution, which is also missing from past research, to the best of the author's knowledge.

The contribution of ESSs to resilience enhancement is significant. Research on this aspect has focused on mobile energy storage technologies [56], real-time allocation of mobile emergency generator [59], and lifetime extension of battery devices [60]. Nonetheless, the limited capacity of ESSs worsens the deterioration caused by HILP contingencies. Technically, even if the energy can be stored efficiently, the Quality-of-Service contributions diminish when the energy storage capacity exceeds a certain threshold value [61]. Likewise, the exorbitant purchase and maintenance of battery devices discourage consumers from emphasizing the worthiness of ESSs. There is room to accommodate the effects of ESSs on systems resilience enhancement from a market perspective, where the positive economic incentives in encouraging system operators and energy consumers to store electricity for emergencies become prioritized as conducted in this study.

For networked MGs, the physical structure closely connects with the complexity of energy use and coordination. Theoretical research shows that resilience can be enhanced by both centralization and decentralization, and simultaneously involves the network structures and governance structures [62]. Undoubtedly, system configuration remarkably influences resilience. Pervasive across research literature are instantaneous isolation of deteriorated zones, implementation of islanded operation modes, and prompt adjustment of connection structures [63], [64]. Rather than being static, power systems resilience is dynamic with structural adaptation in a spatiotemporal framework [7]. There are two underlying functions of reconfiguring system structures: 1) the cascading impact is expected to be undermined by isolating fault zones; and 2) power dispatch is to maintain the balance for the rest of the system. Aside from the structural reconfiguration, the TE achieves those two functional purposes. Recent discussions on microgrid transactive energy systems highlight the significance of multiple functional layers for energy management, such that even in a decentralized system structure, interaction among users, system operators, and regulators are preferred [65]. This corresponds to having more centralized governance within a decentralized network for resilience enhancement [62]. The application of structural theory on practical resilience verification is also missing from past research.

It is also necessary to highlight the current status of modeling MGs on resilience impact. There lacks sufficient attention focusing on the resilience modeling based on MGs. For convenience purposes, most existing models are based on two underlying assumptions [49]: 1) the energy supply is unlimited during the system disruption to satisfy the technical constraints; and 2) the time and duration of an outage can be predicated (or even fixed) to ensure the smoothness of all postdisruption phases. Both assumptions would weaken the applicability of research conclusions in practice. The first assumption involves the system planning issue whether generation capacity expansions are required. For the study of MGs on resilience enhancement, the combination of planning and operational strategies is verified to significantly improve the system resilience [66]. Thus, an integrated approach needs to be developed to evaluate the techno-economic performance of system resilience. The second assumption challenges the validity of modeling the stochasticity of HILP events. Stochastic methods [60], [67], [68] and robust optimization [69] have been seen as two mainstream approaches to tackle the uncertainties, but each approach comes with inherent downsides, such as the conservativeness for robust optimization and the computational burden for the stochastic method. Even though there still exist standards to evaluate the validity, these will be further discussed in the following subsection. Thus, this study also develops an integrated model to examine the resilience performance of networked MGs.

C. Scenario Selection for Stochastic Programming

One of the underlying difficulties of studying power systems resilience is the unexpected occurrence of HILP contingencies. Though the available historical data is conducive for prediction, the cascading impact from HILP contingencies is hard to measure [70]. Nevertheless, the literature shows that system management under uncertainties can be enhanced by conducting stochastic optimization, but the computational burden is still the main challenge [71]. For risk assessment, classic methodologies for modeling purposes include continuous time discrete state Markov chain to model the dynamics of system performance under the extreme events [68], and Monte Carlo simulation to simulate postdisaster impact [47]. However, the common drawback of using classic methodologies is the implicit assumption

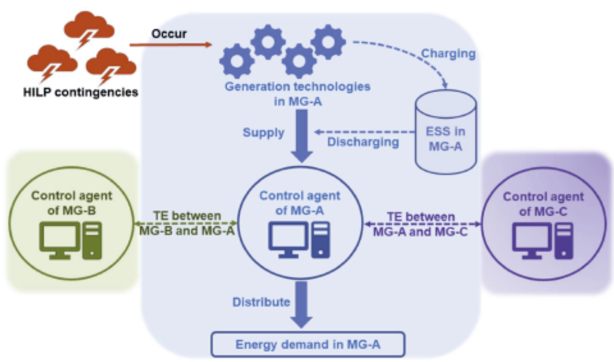

Fig. 1. Conceptual structure of networked MGs.

that the occurrence of system faults follows specific probability distributions that are seldom held in practice. Therefore, scenario generation is more appropriate for evaluating the impact of HILP contingencies [72].

The validity of scenario generation is subject to the stability evaluation, which includes the insample stability and out-of-sample stability [72], [73]. Compared to the true solution, the optimal outcomes from appropriate scenarios must be void of bias—regardless of the differences between the scenarios, the variation of the ultimate optimal solutions should remain stable and converge. Following this principle, increasing the number of scenarios can offer outcome consistency, but with a heavier computational burden. Thus, selecting adequate representative scenarios is a prerequisite to improving computation efficiency. However, scenario selection requires systems parameters and HILP contingencies to be quantifiable, e.g., demand, capacity, and voltage profiles, and categorized into high, medium, and low levels for simplification [67]. For example, the postdisaster impact of stochastic failures can be classified via a multidimensional scenario selection method based on the corresponding amount of lost load and lost generation [71].

While the aforementioned examples offer inspiring insights for scenario generation, understanding that power system resilience is an ongoing process, where the system fault occurrence, duration, and restoration jointly complicate the scenario selection process. Thus, this study offers another methodology to justify the scenario selection process, as well as the probability for each scenario.

In summary, Table I provides a comprehensive snapshot of the most closely related body of work while shedding light on the gaps identified and covered in this article.

III. Methodology

In this section, the proposed conceptual structure of networked MGs and a three-phase methodology are first presented to capture the whole picture of this study. Each phase of the methodology is described in each subsection accordingly.

For reiterate purposes, one objective in this study is to explore the construction of a resilient integrated system to hedge against contingencies under the context of sustainability transitions. From the discussion in the literature review section, the crucial components of a resilience-oriented networked MGs involve the availability of multiple energy sources, the interdependence of the energy sectors, and the flexibility of structure reconfiguration and control mechanisms. Fig. 1 shows the conceptual structure of the system, such that the networked MGs consist of submicrogrids with generators and ESSs independently installed for serving the local region. The layout of the networked MGs is in a decentralized physical structure. However, energy exchange can be realized via TE between neighboring submicrogrids, which is subject to centralized control in governance. In this framework, the cascading impact of HILP contingencies is treated as the loss of power generation capacities from the local power generators.

Another objective of this article is to examine the extent to which the low-carbon policies could impact the resilience-oriented planning and operation of an integrated system. Two models are developed and compared for illustration in this study. The methodology consists of three main phases as presented in Fig. 2. The black arrows indicate the flow of data between phases. The first phase utilizes a user-identified scenario selection method to randomly output power outage profiles with a normalized probability distribution. In the second phase, the base model is developed where a two-stage stochastic programming model is implemented to obtain optimal power generation portfolios with the minimized cost of systems resilience planning in the presence of power outage scenarios. The third phase introduces the policy model where carbon emissions tax with adjustable emissions abatement is added to the base model. The objective function updates power generation portfolios, where the reference level of carbon emissions is derived from the optimal power generation solutions in the second phase. The contributions of carbon emissions reduction policies are evaluated by comparing the objective function value (power systems resilience planning and operation cost) under different emissions abatement levels.

A. User-Identified Scenario Selection

In this research, the occurrence time and the duration of stochastic system faults are jointly identified as uncertainties. For each power generation plant, any unforeseen contingencies could occur at any time with an uncontrolled fault duration period. Table II presents a combination of all power outage possibilities based on the time dimension. The left column indicates all possible fault occurrence times and the top row indicates all possible outage intervals. Each crossing mark indicates the possible existence of a power outage (loss of power generation) at that time spot. For clarification purposes, if a system disruption occurs at 2:00 A.M., there are 23 different fault duration scenarios correspondingly.

Based on the calculation of permutations, the number of all power outage scenarios of a single submicrogrid zone (NS) is 300 for an entire day of a 24-h timescale, as in (1).

$$NS = \sum_{T_f=1}^{24} (25 - T_f) = 300. \quad (1)$$

The total number of power outage scenarios of the entire networked MGs with multiple submicrogrid zones (NTS) is calculated by (2).

$$NTS = (300)^{\text{Count of Sub-microgrids}}. \quad (2)$$

TABLE I
SUMMARY OF GAPS IN RELATED LITERATURE

§§	Research Cluster	Common Objective	Refs.	Research Gap / Issues
A	Carbon Reduction	Focus on the challenges in the decarbonization process & energy market.	[16,17 27]	Gap is the need for adaptive market and the role of energy policies in the decarbonization process.
		Examine the role of decarbonized electricity in economic growth.	[24], [25], [26]	Economic growth is connected to conventional energy sources with no role for renewable technologies.
		Limited efficiency of renewable technologies, economical consideration.	[28,29]	Efficiency improvements limited by economics is contrary to the study in this paper.
		These papers offer overviews of other existing sustainability technologies.	[10, 30, 31, 32]	Premised on technical, safety, and economic concerns limits large-scale sustainability adoption.
		Offer overviews of electricity market and system resilience planning.	[9, 18, 19]	The gap is the absence of resilience-oriented market planning as currently examined in this paper.
	Energy Policies	Focus is on the standards for DERs.	[20,21]	The gap is that DERs are prohibited from energizing the grid in emergencies is contrary to this paper.
		Offer comments on the weakness of the CO2 emissions mechanisms.	[33,34]	Underscores the relatively small proportion of carbon emissions coverage are resulted from existing policies.
		The emphasis is on the establishment of a carbon emissions tax.	[39, 40, 41]	Find uncertainties in CO2 pricing limit economics of generations portfolios contrary to this paper.
		Offer the economics of renewable technologies on resilience planning.	[16,47, 48]	The roles of multiple renewable energy sources for resilience enhancement are underestimated.
		Use partial integrated approaches to evaluate the resilience.	[46]	Resilience evaluation needs to incorporate technical, economic, and social factors.
B	Microgrids Study	Cover the potentials of microgrids for resilience enhancement.	[54,55]	Resilience-oriented networked microgrids needs verification and validation as done in this paper.
		Explore technologies on power quality/resilience enhancement.	[26,49, 58]	The value of sustainable technologies for resilience enhancement cannot be ignored; covered in this paper.
	Energy Storage	Explore mobile energy storage technologies for emergency use.	[56,59]	This paper extends with the integration of energy storage storage systems to meet microgrids needs.
		Explore the lifetime and capacity expansion of battery devices.	[60,61]	Storage capacities play critical role in influencing system planning; addressed in this paper.
	System Architecture	Theoretical study toward de/centralized structure on resilience enhancement.	[62]	The resilience-oriented structure (decentralized in physical and centralized in governance) are covered in this paper.
		Highlight the role of transactive energy in network reconfigurations.	[63, 64, 65]	Transactive energy is integrated into the systems for resilience enhancement as done in this paper.
	Microgrid Modeling	Reviews existing modeling of microgrids' objectives & methodologies.	[49]	Assumptions on unlimited generation capacities and known contingencies weaken its applicability.
		Emphasize the value of planning and operational phases for integrated systems.	[66]	The gap is the absence of an integrated approach for model verification and validation as done in this paper.
		Apply stochastic optimization methods for resilience planning.	[60,67, 68]	There gap is the computational burdens with probability distribution for contingencies; addressed in this paper.
		Apply robust optimization for market price uncertainties.	[69]	The gap is the conservative property of robust optimization; this paper avoids that limitation.
C	Scenario-Selection Method	Use stochastic methods, Markov Chains, & Monte Carlo for generic uncertainties.	[47,68, 71]	The challenge is the computational burden from classic methods for HILP events simulation that this paper avoids.
		Study the theoretical validity of scenario-selection methods for systems modeling.	[72,73]	This paper extends with verification and validation from synthetic modeling of the practical system.
		Apply scenario-selection method is for system modeling without HILP events.	[67,71]	The stochastic nature of HILP events needs to be captured in multi-dimensional scenario generation method.

As stated earlier, the cascading impact from HILP events is simulated as an entire loss of the electricity generation ability of impacted power plant(s). Mathematically, the power generation capacity is null within that period, as in (3).

$$\overline{G^{c}_{i,t}} = 0 \qquad \forall t \in [T_f, T_f + \triangledown T_f]. \tag{3}$$

Clearly, even though all scenarios are displayed, it is impractical and inefficient to handle them on any computation machine. However, though system fault time and fault duration vary for each unique scenario, different scenarios may share the same cascading impact which is represented by the total amount of lost power generation capacities. For instance, the power outage

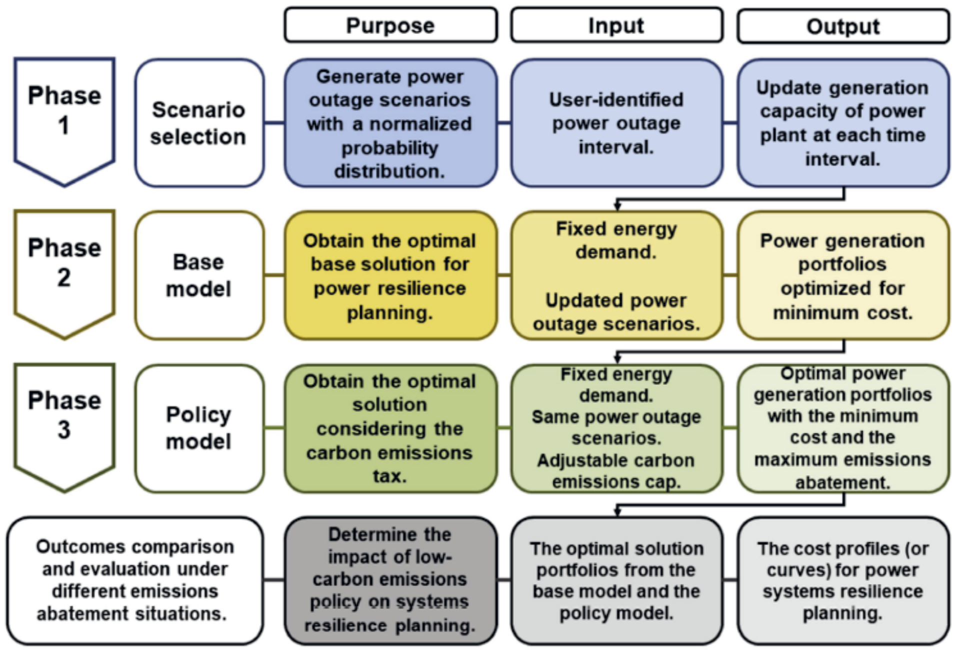

Fig. 2. Methodology flowchart.

TABLE II
TIME-BASED POWER OUTAGES SCENARIO GENERATION

Fault Time	System Fault Duration $\triangledown T_f$						
T_f	$1h$	$2h$	$3h$	...	$22h$	$23h$	$24h$
$1:00$ am	×	×	×	$\cdots$	×	×	×
$2:00$ am	×	×	×	$\cdots$	×	×	
$3:00$ am	×	×	×	$\cdots$	×		
$4:00$ am	×	×	×	$\cdots$			
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$			
$10:00$ pm	×	×	×				
$11:00$ pm	×	×					
$12:00$ am	×						

scenario occurring at 2:00 A.M. with a duration of five hours may result in the same amount of lost power generation as the power outage scenario occurring at 6:00 A.M. with a duration of only two hours. Thus, a user-identified scenario selection methodology is proposed to alleviate the computational burden of the program while simultaneously maintaining the validity of the scenario selection procedure and avoiding any selection bias. The specific process is visualized on the left side of Fig. 3.

Equation (4) presents the sum of lost power generation capacities from all power outage scenarios. This magnitude serves as the fundamental for conducting the subsequent scenario classification.

$$G^c_{loss} = \sum_{i\in\Omega^{MG}} \left(\sum_{t=T_f}^{T_f+\triangledown T_f} \overline{G^{c,ini}_{i,t}} \right). \tag{4}$$

It is notable that $\overline{G^{c,ini}_{i,t}}$ is different from $\overline{G^c_{i,t}}$, where the former stands for the initial power generation capacity without power outage situation and the latter stands for the actual power generation capacity under the power outage impact. The user can customize a power outage amount interval $\triangledown G^c_{loss}$ as the benchmark to classify scenarios into each corresponding quasi-scenario cluster Ω^ω. The quasi-scenario cluster is identified as the set of all scenarios whose lost power generation capacity lies within the same interval. Equation (5) presents the calculation of the number of quasi-scenario clusters (NC), and (6) is the quasi-scenario cluster categorization process

$$NC = \left\lceil \frac{G^c_{\text{loss}}}{\triangledown G^c_{\text{loss}}} \right\rceil \tag{5}$$

$$\Omega^\omega_n \in [(n-1)\cdot \triangledown G^c_{\text{loss}} \;,\; n\cdot \triangledown G^c_{\text{loss}}] \qquad n = 1, 2, \ldots NC. \tag{6}$$

By updating the customized power outage interval, another different set of quasi-scenario clusters can be obtained. The set of quasi-scenario clusters under the same power outage interval is labeled as $CASE$ in this study. For clarification purposes, the affiliation relation between scenario, quasi-scenario cluster, and $CASE$ is clarified in (7).

$$\omega \in \Omega^\omega \in CASE. \tag{7}$$

Every single scenario, randomly chosen from the quasi-scenario cluster, can be seen as a standard representative of the corresponding quasi-scenario cluster. Thus, they share the same probability. The probability is calculated by the ratio of the total number of scenarios from each cluster to the total number of scenarios of this $CASE$, as in (8).

$$P_\omega = P_{\Omega^\omega} = \frac{Number\ \ of\ \ scenarios\ \ per\ \ cluster}{NTS}. \tag{8}$$

The power outage scenarios are treated as the input for stochastic optimization. For each $CASE$, the algorithm randomly selects

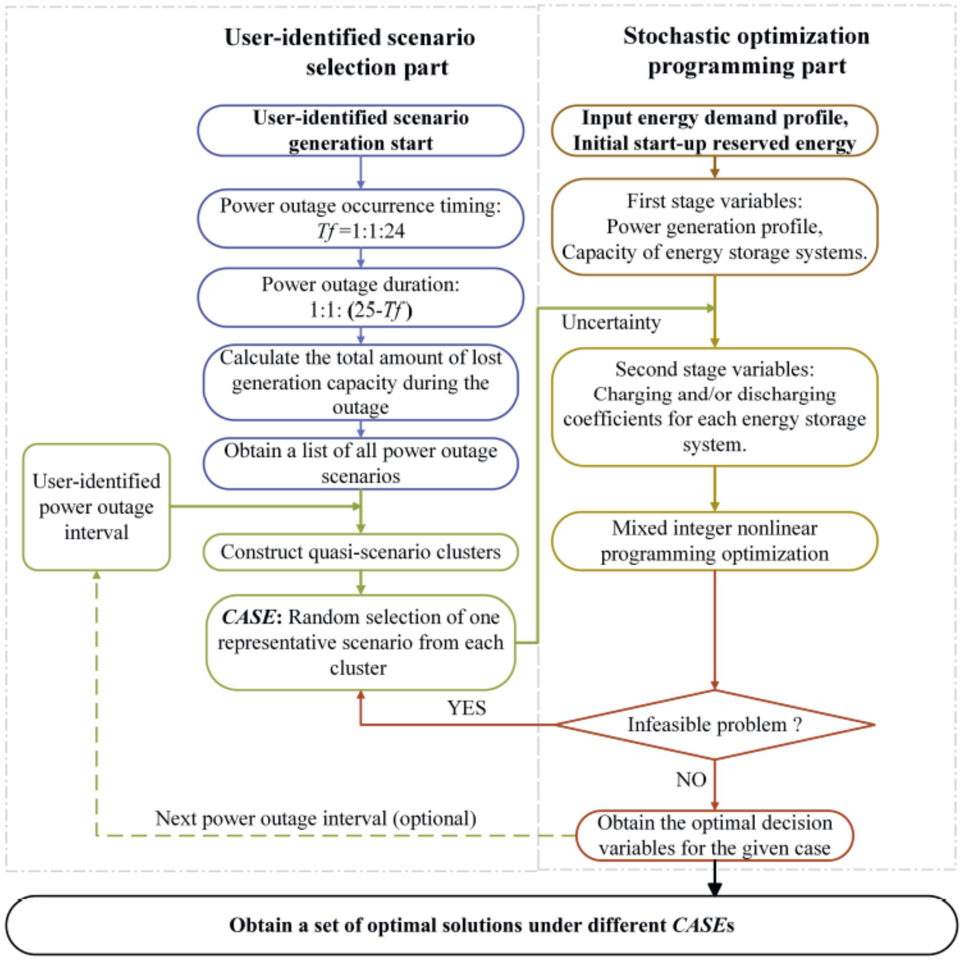

Fig. 3. Framework of the proposed stochastic two-stage programming.

one scenario from its corresponding quasi-scenario cluster to form the data for the test. By implementing stochastic programming repeatedly based on different $CASE$s, a unified, convergent trend of solution profiles is expected to be obtained. The modeling outcomes displayed in the results section illustrate the feasibility of the proposed methodology.

B. Base Model

The objective of developing a base model is to examine system resilience planning in the presence of system disruptions but without considering any influence from existing energy policies. The base model is formulated as a two-stage stochastic programming, which corresponds to the planning and operation phase of networked MGs in practice. The first stage (planning phase) involves the capacity decision of ESSs and the electricity profiles including power generation from each plant and TE schedule. The second stage (operation phase) involves the specific operation of ESSs including discharging status and disconnection status under the uncertainties of power outages. The uncertainties are introduced from the implementation of the user-identified scenario selection method aforementioned. A complete optimization flowchart is presented on the right side of Fig. 3.

To justify the determination of first-/second-stage variables, there are two underlying assumptions. First, the capacities of power generators and ESSs are supposed to be fixed in the planning phase, which indicates the unlimited energy supply is avoided in this model. Second, ESSs have been installed locally within corresponding submicrogrid zones. When a system disruption occurs, local ESSs take actions for system restoration. Though TE also plays a role in restoring power balance, it is not generated from a single energy source and is subject to multi-faceted coordination such as the remaining availability of power generation capacities, the demand from local users, the operation status of ESSs, and the system disconnection structures. Hence, it is more appropriate to assign the TE portfolios as first-stage variables.

It is also necessary to mention that there exists the possibility the optimization process ends up with an infeasible problem due to the numerical infeasibility of parameters. This situation also results from the random selection of power outage scenarios. The issue can be solved by running the scenario selection algorithm again to generate another set of scenarios under the same power outage interval.

The implementation of the proposed optimization model outputs the optimal resilience planning under the circumstance of minimized financial cost, which includes the power generation portfolios, TE scheduling, and ESSs status. The detailed explanations of the objective function and technical constraints are as follows.

1) Objective Function: In the proposed base model, the total cost of systems resilience planning and operation without the impact of energy policies is the objective function. Equations (9) and (10) define the proposed system cost to be minimized physically and mathematically, respectively.

$$\begin{aligned}\min \quad Objective_{(base)} = &\ \textit{Cost of power generation}\\ &+ \textit{Cost of ESSs installation}\\ &- \textit{Expected finanical rewards from}\\ &\ \textit{energy storage}\end{aligned} \tag{9}$$

$$\begin{aligned}\min \quad OF_B = \sum_{i\in\Omega^{MG}} \Bigg[&\sum_{t\in\Omega^T} \nabla_t \cdot (C_c \cdot G^c_{i,t} + C_s \cdot G^s_{i,t}\\ &+ C_w \cdot G^w_{i,t}) + C_{ESS} \cdot \overline{ESS}_i\\ &- \sum_{t\in\Omega^T}\sum_{\omega\in\Omega^\omega} P_\omega \cdot \nabla_t \cdot R_{ESS} \cdot ESS_{i,t,\omega}\Bigg].\end{aligned} \tag{10}$$

There are three parts to the objective function. The first term is the total cost of generating power from available power plants. The second term is the cost of installing ESSs with the installed capacity in the corresponding microgrid zone. The third term is the hourly financial rewards mechanism for encouraging the storage of electrical energy in ESSs for emergency use.

It should be noted that only the second-stage terms take stochastic scenario indices. In the proposed model, the second-stage variables are the amount of energy stored in the ESSs that varies by different scenarios. The power generation and ESSs capacity, which are presented as first-stage variables without scenario indices, are also influenced by the ultimate second-stage decision variables.

2) ESSs Constraints: ESSs are locally installed within the corresponding submicrogrid for self-supply use purposes. In the event of HILP contingencies, ESSs are relatively efficient measures to supply electricity. With the aid of advanced development of power electronic technologies, ESSs can realize the smart charging and discharging commands delivered from online sensors or control agents [74]. In this study, the charging and discharging states are treated as two independent binary variables but with mutual exclusive coexistence constraints, as in (11).

$$SOCc_{i,t,\omega} + SOCd_{i,t,\omega} \le 1 \qquad \forall i,t,\omega. \tag{11}$$

The variable of 1 means this state works at the time, while the variable of 0 means this state is disabled at the time. The constraint ensures that at most only one of two states works at the time. There is a possibility that both charging and discharging states are determined as 0 simultaneously, which means the ESSs are disconnected from the main system.

From the perspective of physical operations, the operation of ESSs at each time step depends on its discharging states from the last time step. The stored energy at (t) time point equals charged energy added to the remaining energy at $(t-\nabla t)$ time point or discharged energy subtracted from the remaining energy at $(t-\nabla t)$ time point. Equations (12)–(15) mathematically present the constraints for the real-time amount of energy stored inside ESSs.

$$0 \le ESS_{i,t,\omega} \qquad \forall i,t,\omega \tag{12}$$

$$\begin{aligned}ESS_{i,t,\omega} \le &\ ESS_{i,t-\nabla t,\omega} + SOCc_{i,t,\omega}\cdot\alpha_{i,t,\omega}\cdot G^c_{i,t}\\ &- SOCd_{i,t,\omega}\cdot\beta_{i,t,\omega}\cdot ESS_{i,t-\nabla t,\omega} \quad \forall i,t,\omega\end{aligned} \tag{13}$$

$$0 \le \alpha_{i,t,\omega} \le \overline{\alpha} \le 1 \qquad \forall i,t,\omega \tag{14}$$

$$0 \le \beta_{i,t,\omega} \le \overline{\beta} \le 1 \qquad \forall i,t,\omega. \tag{15}$$

First, the numerical value of stored energy in ESSs should be nonnegative at any time point, as stated in (12). Second, the charging and discharging states can be integrated into a unique equation based on the mutual exclusiveness of the state of discharging variables. As presented in (13), when the charging state is ON, a certain amount of the external electricity generated from the power plant is stored in ESSs, which depends on a charging coefficient $\alpha_{i,t,\omega}$. When the discharging state is ON, a certain amount of the internal reserved electricity based on the last period $(t-\nabla t)$ is released to the main system, which depends on a discharging coefficient $\beta_{i,t,\omega}$. Third, both charging and discharging coefficients is less than a positive upper bound value, restricted to less than 1, as in (14) and (15), respectively.

Equation (16) is the amount of real-time stored energy that is limited by the capacity of ESSs.

$$0 \le ESS_{i,t,\omega} \le \overline{ESS}_i. \tag{16}$$

For each scenario, the real-time stored energy inside ESSs cannot exceed its capacity where the ESSs capacities $(\overline{ESS_i})$ are decision variables in the first-stage planning phase.

Equation (17) describes a day-ahead planning condition that the stored energy in the ESSs at the last timescale is expected to be no less than that at the initial timescale, which prepares the ESSs for use at the beginning of the next day.

$$ESS_{i,t=0,\omega} \le ESS_{i,t=24,\omega}. \tag{17}$$

3) TE Dispatch Constraints: The contributions to the energy balance from TE between neighboring submicrogrids need to be emphasized for the operations of networked MGs. Though the TE between two neighboring submicrogrid zones is a bidirectional variable, the mutual exclusiveness of energy flow directions is the underlying assumption. The state of TE from microgrid i to microgrid j is labeled as $SOT_{(ij),t}$ in (18).

$$SOT_{(ij),t} + SOT_{(ji),t} \le 1 \qquad \forall i,j,t,i\neq j. \tag{18}$$

It should be noted that $SOT_{(ij),t}$ and $SOT_{(ji),t}$ are two independent binary variables. The value of 1 indicates the existence of energy flow from the start point to the destination, and vice versa.

There are circumstances in that no energy exchange happens between two neighboring submicrogrid zones, given the value of 0 for both SOT variables.

Similar to the ESSs, it needs to highlight the assumptions of the operations of TE. First, the value of TE should be nonnegative at all time points. Second, TE is outputted to other submicrogrids under the circumstance that local energy demand has been satisfied. Equations (19) and (20) show that TE outputted from microgrid i under the assumptions mentioned.

$$0 \leq TE_{(ij),t} \tag{19}$$

$$TE_{(ij),t} \leq SOT_{(ij),t} \cdot (G^c_{i,t} + G^s_{i,t} + G^w_{i,t} - DE_{i,t}) \quad \forall i,j,t,i \neq j. \tag{20}$$

In this model, we only treat TE from its power injection node to other neighboring nodes to safeguard the uniqueness of the direction of TE. A bidirectional energy exchange at the same time between two submicrogrids is strictly forbidden.

4) Energy Balance Constraints: The complexity in evaluating the operations of networked MGs lies in the interdependence among multiple sectors. To put it in a simple way, each submicrogrid can be seen as a main energy sector. Once the energy balance of all submicrogrids can be maintained with the aid of TE, the global stability of the energy supply over the whole networked MGs can be secured accordingly. From the perspective of physical operation, the energy balance of each submicrogrid can be measured by the relationship between supplied energy and consumed energy. Equations (21) and (22) present the energy balance constraint by considering all contributions in the system physically and mathematically, respectively.

$$\begin{aligned} &\textit{Generated energy} + \textit{Injected transactive energy} \\ &\quad + \textit{Discharged energy from ESSs} \\ &\geq \textit{Demanded energy} + \textit{Outputted transactive energy} \\ &\quad + \textit{Charged energy into ESSs} \end{aligned} \tag{21}$$

$$\begin{aligned} &G^c_{i,t} + G^s_{i,t} + G^w_{i,t} + \sum_{j \in \Omega^{MG}, i \neq j} SOT_{(ji),t} \cdot TE_{(ji),t} \\ &\quad + \sum_{\omega \in \Omega^\omega} P_\omega \cdot SOCd_{i,t,\omega} \cdot \beta_{i,t,\omega} \cdot ESS_{i,t-\nabla t,\omega} \\ &\geq DE_{i,t} + \sum_{j \in \Omega^{MG}, i \neq j} SOT_{(ij),t} \cdot TE_{(ij),t} \\ &\quad + \sum_{\omega \in \Omega^\omega} P_\omega \cdot SOCc_{i,t,\omega} \cdot \alpha_{i,t,\omega} \cdot G^c_{i,t} \quad \forall i,t. \end{aligned} \tag{22}$$

The left side of the inequality represents the supplied energy, which encompasses energy generated by power plants, the TE injected into this submicrogrid, and the energy discharged from ESSs to compensate for the energy balance. The right side is the consumed energy that includes the energy demand within the submicrogrid, the TE exported to serve other neighboring submicrogrids, and the energy charged into the ESSs.

5) Generation Capacity Constraints Under Uncertainties: As stated in literature review section, the roles of renewable energy in resilience enhancement are unclear, especially when sustainability technologies become indispensable components of integrated energy systems with a higher penetration of renewable energy. Thus, we are particularly interested in examining the resilience performance of those sustainability technologies in this study. The power systems resilience performance is to be evaluated under the circumstance that the plant of larger capacity goes offline during the postdisruption period. Correspondingly, even though there are multiple energy sources available in integrated power systems, only the coal-fired power plants are simulated to be impacted by HILP contingencies. Equation (23) constraints the coal-fired power generation by considering the average expected value of generation capacity at each time point

$$0 \leq G^c_{i,t} \leq \sum_{\omega \in \Omega^\omega} P_\omega \cdot \overline{G^c_{i,t,\omega}} \quad \forall i,t. \tag{23}$$

For other energy sources, such as utility-scale solar and wind power plants, the power generated is subject to real-time generation limitation that is related to the corresponding installation capacities, as in (24) and (25), respectively.

$$0 \leq G^s_{i,t} \leq \overline{G^s_{i,t}} \quad \forall i,t \tag{24}$$

$$0 \leq G^w_{i,t} \leq \overline{G^w_{i,t}} \quad \forall i,t. \tag{25}$$

C. Policy Model

The policy model is proposed to examine the influence of energy policies on systems resilience performance. The outcomes from the base model recommend optimal power generation portfolios where the cost of resilience is minimized. Based on the outcomes, an emissions tax serves to influence the system planner's decision. As stated in literature review section, a reasonable combination of emissions cap and tax on excessive carbon emissions are more appropriate for the current sustainability transitions period than a hasty implementation of tax on all carbon emissions. In this study, the carbon tax and the emissions cap are integrated as control variables and added to the original objective function, as in (26) and (27). All constraints are kept the same as the base model.

$$\min \quad OF_E = OF_B + \textit{Excessive carbon emissions tax} \tag{26}$$

$$\begin{aligned} &\textit{Excessive emissions tax} \\ &= \eta \cdot \max\Bigg[\sum_{i \in \Omega^{MG}} \sum_{t \in \Omega^T} \nabla t (Gc_{i,t}E_c + Gs_{i,t}E_s + Gw_{i,t}E_w) \\ &\quad - \gamma \cdot \sum_{i \in \Omega^{MG}} \sum_{t \in \Omega^T} \nabla t (Gc^{opt}_{i,t}E_c + Gs^{opt}_{i,t}E_s + Gw^{opt}_{i,t}E_w), 0\Bigg]. \end{aligned} \tag{27}$$

Three points need to be highlighted regarding the policy model. First, only excess carbon emissions are taxed. As in (27), the first term is the ultimate carbon emissions, and the second term is an adjustable emissions cap. If the ultimate emissions amount is below the emissions cap, no emissions are taxed. The unit charge is labeled, η, i.e., a constant parameter determined by the regulator or policymaker. Second, the reference emissions cap is dependent on the optimal power generation portfolios from

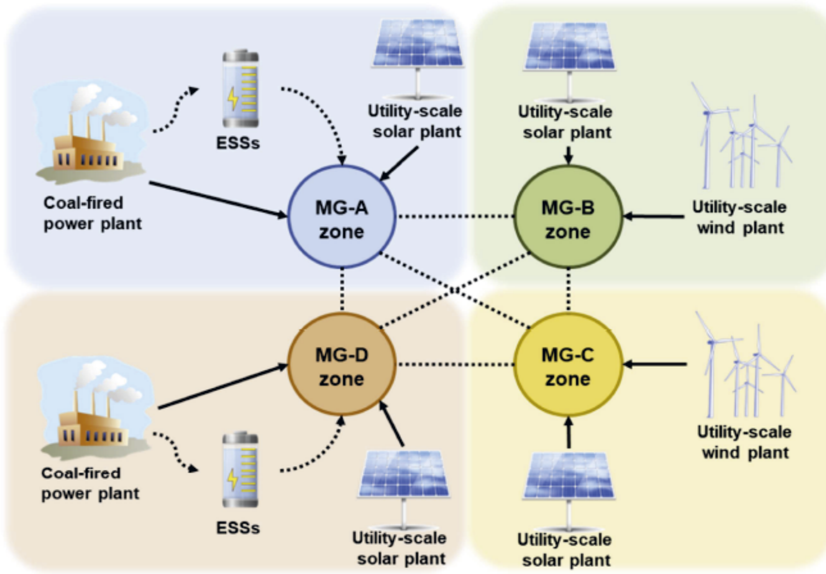

Fig. 4. Physical structure of the tested networked MGs.

TABLE III
ENERGY SOURCES OF EACH SUBMICROGRID WITH INSTALLED CAPACITY [75]

Microgrid Index	Coal-fired Power Plant Connection (Capacity MW)	Solar Power (PV) Connection (Capacity MW)	Wind Power (WT) Connection (Capacity MW)
MG-A	YES (20)	YES (12.8)	NO
MG-B	NO	YES (11.2)	YES (2.6)
MG-C	NO	YES (11.2)	YES (3.4)
MG-D	YES (20)	YES (11.2)	NO

the base model. In other words, the purpose of implementing the policy model is to scrutinize whether and to what extent low-carbon emissions policies would impact optimal resilience planning. Third, the emissions cap is adjustable, and γ serves as the emissions abatement coefficient. For clarification purposes, if $\gamma = 1$, the emissions abatement cap is 0%, i.e., all emissions are permissible based on the optimal power generations of the base model. If $\gamma = 0$, the emissions abatement cap is 100%, i.e., no emission is permissible and all emissions are taxed.

IV. Data and Modeling Platform

The following analysis is based on a modified benchmark networked MGs test system. The original test system has been developed and evaluated for reliability in the previous research study [75]. The physical topology of the modified test system is displayed in Fig. 4.

The modified networked MGs system consists of four submicrogrid zones. Within each zone, there are multiple but independent power plants. ESSs are only connected to coal-fired power plants where higher power generation capacities are available. The solid line indicates the necessary power dispatch path, and the dotted line indicates that the power dispatch (path connection) is subject to specific commands.

Table III presents the specific types of power plants connected to each submicrogrid with corresponding installed capacities. For coal-fired power plants, the actual hourly power generation amount is at most the installed capacity. For solar and wind energy, the actual power generation amount is subject to the weather and time. The reference values of those system parameters are also provided in the previous study on the original test system [75], including the hourly power demand in each submicrogrid and hourly availability of renewable energy in the percentage of the installed capacity, which are presented in Tables IV and V, respectively.

It is noteworthy that, compared to the reference value, the installed capacities of solar and wind plants are doubled to obtain more evident numerical results for further analysis.

Table VI shows the value of cost-related parameters. The levelized cost of electricity (LCOE) from technologies including coal, solar, wind, and battery purchase is derived from the 2020 power generation costs data [76]. This analysis assigns a 10% reward of LCOE for coal-fired energy that is stored in ESSs.

As stated in the methodology section, the impact of energy policies on system resilience planning is reflected by a joint implementation of carbon emissions cap and tax. Both factors are adjustable parameters in the policy model. Here, the average

TABLE IV
HOURLY ENERGY DEMAND IN EACH SUBMICROGRID (KWH) [75]

Time	MG-A	MG-B	MG-C	MG-D
1:00 am	7951.77	6279.72	6390.40	4556.00
2:00 am	7559.09	6279.72	6470.28	4271.25
3:00 am	7853.60	6133.68	6550.16	4442.10
4:00 am	7755.43	6060.66	6709.92	4556.00
5:00 am	7755.43	6133.68	6869.68	4726.85
6:00 am	8049.94	6133.68	6869.68	4897.70
7:00 am	8246.28	6352.74	7109.32	5068.55
8:00 am	8540.79	6571.80	7189.20	5125.50
9:00 am	8835.29	6936.90	7348.96	5239.39
10:00 am	9227.98	7155.96	7508.72	5410.25
11:00 am	9326.15	7228.98	7668.48	5353.30
12:00 pm	9227.98	7155.96	7588.60	5467.20
1:00 pm	9129.81	7009.92	7508.72	5467.20
2:00 pm	8933.46	6717.84	7348.96	5353.30
3:00 pm	8638.95	6498.78	7189.20	5125.50
4:00 pm	8540.79	6352.74	7189.20	5125.50
5:00 pm	8933.46	6571.80	7348.96	5296.35
6:00 pm	9326.15	6936.90	7988.00	5467.20
7:00 pm	9620.66	7228.98	7988.00	5695.00
8:00 pm	9817.00	7302.00	7988.00	5695.00
9:00 pm	9522.49	7228.98	7748.36	5638.05
10:00 pm	9227.98	7082.94	7428.84	5353.30
11:00 pm	8246.28	6571.80	6630.04	4783.80
12:00 am	8638.95	6790.86	6630.04	5296.35

TABLE V
HOURLY AVAILABILITY OF RENEWABLE ENERGY IN PERCENTAGE OF THE INSTALLED CAPACITY (%) [75]

	Solar Energy				Wind Energy	
Time	MG-A	MG-B	MG-C	MG-D	MG-B	MG-C
1:00 am	0	0	0	0	0	19
2:00 am	0	0	0	0	0	19
3:00 am	0	0	0	0	17	24
4:00 am	0	0	0	0	17	24
5:00 am	0	0	0	0	34	37
6:00 am	0	0	0	0	34	37
7:00 am	11	17	19	23	28	40
8:00 am	20	35	38	39	28	40
9:00 am	40	45	46	50	21	52
10:00 am	60	64	68	73	21	52
11:00 am	86	87	93	100	18	56
12:00 pm	100	100	100	100	18	56
1:00 pm	100	100	100	100	16	57
2:00 pm	100	100	100	100	16	57
3:00 pm	83	83	89	91	32	46
4:00 pm	56	56	65	69	32	46
5:00 pm	32	32	41	50	33	43
6:00 pm	23	23	31	35	33	43
7:00 pm	0	0	0	0	26	24
8:00 pm	0	0	0	0	26	24
9:00 pm	0	0	0	0	19	21
10:00 pm	0	0	0	0	19	21
11:00 pm	0	0	0	0	0	18
12:00 am	0	0	0	0	0	18

TABLE VI
VALUE OF COST-RELATED PARAMETERS [76]

Parameter	C_c $\$/kWh$	C_s $\$/kWh$	C_w $\$/kWh$	C_{ESS} $\$/kW$	R_{ESS} $\$/kWh$
Value	0.017	0.057	0.039	635	0.0017

reference emissions tax η is selected as $0.02723\$/lb$, which is sourced from the Organization for Economic Co-operation and Development (OECD) [77].

In this study, it is noteworthy that the life-cycle carbon footprint is adopted instead of the direct carbon emissions per unit. Although there is no direct carbon emitted into the atmosphere during the electricity generation process from wind-powered and solar-powered technologies, the life-cycle carbon footprint has been treated as a more holistic and practical assessment index for system planning purposes [78], [79]. The unit value for carbon emissions from coal-fired generation E_c is $2.23lb$/kWh, which is referred from the Energy Information Administration (EIA) [80]. The value of the life-cycle carbon emissions footprints of solar energy E_s and wind energy E_w are $0.110231lb$/kWh and $0.02425lb$/kWh, respectively, which are sourced from the Cool Effect Organization [81] and the Office of Energy Efficiency & Renewable Energy [82], correspondingly. Notably, the carbon emissions coefficient of coal-fired energy is numerically more than 20 times that of renewable energy sources, which indicates that the ultimate optimization results are not impacted if the carbon emissions of renewable energy sources are adjusted to null.

Considering the increasing computational burden of the proposed mixed-integer nonlinear programming as more stochastic scenarios add up when the power outage interval is smaller, the time interval $\bigtriangledown_t$ is selected as three hours to accelerate the optimization process; intervals lower than three hours offer no discernible differences in numerical results.

For clarification purposes, the computation time of 20 $CASE$s under different models are recorded and visualized in Fig. 5.

For both the base model and policy model with different emissions abatement levels, the computation time increases as the user-identified power outage interval decreases. The specific power outage interval and corresponding scenario numbers are presented in the results section.

Regarding the specific modeling platforms, the user-identified power-outage scenario selection method (Phase 1) is conducted in MATLAB (R2022a version). The proposed base model (Phase 2) and policy model (Phase 3) are implemented in A Mathematical Programming Language (AMPL) software with the Couenne nonlinear solver. The processor of the machine for simulation is Inter(R) core i5-5300 U CPU at 2.30 GHZ and 8 GB of RAM.

V. RESULTS

The results are presented following the tripartite methodology structure. The first part is the results from the user-identified scenario selection process. The second part is the comparison of

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

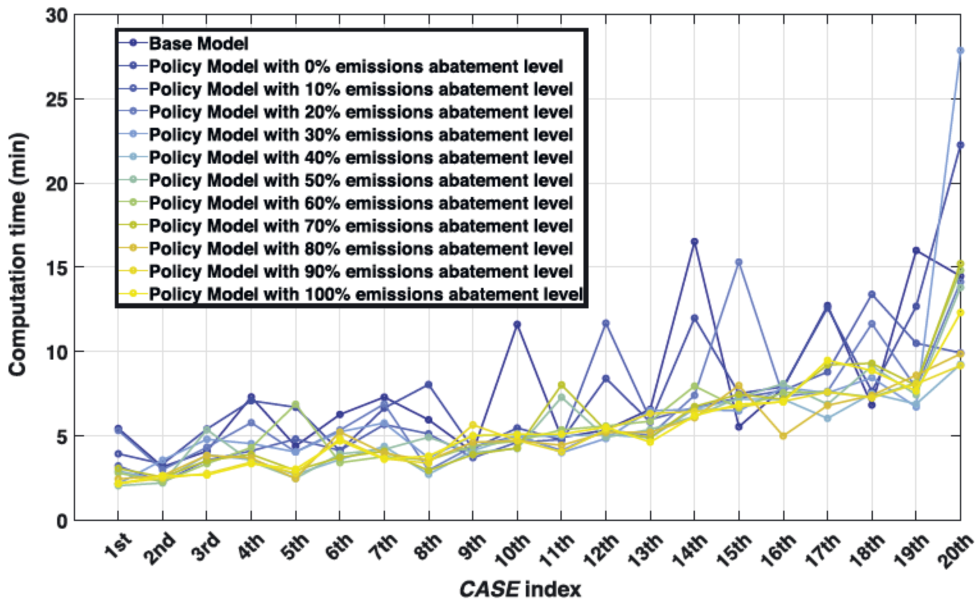

Fig. 5. Computation time for $CASE$s under each model.

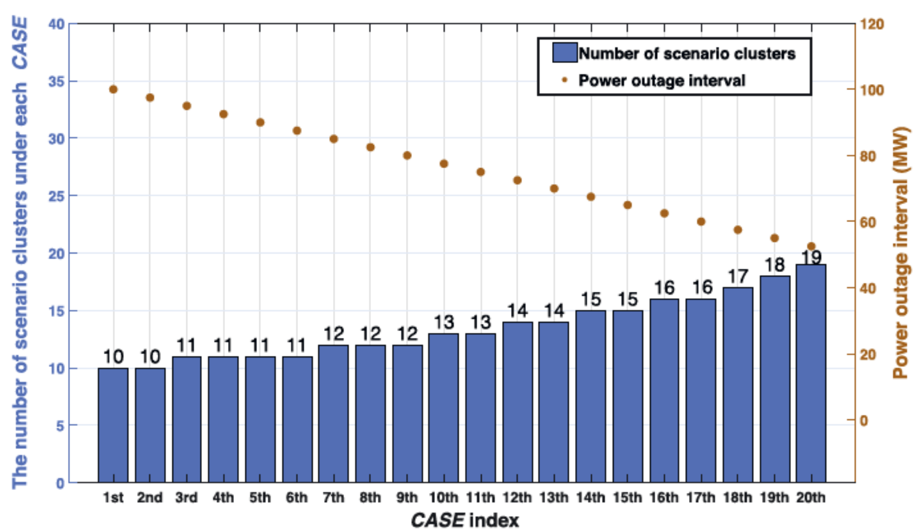

Fig. 6. Number of scenarios and the power outage interval of each $CASE$.

power systems resilience planning with different energy sources under different emissions abatement levels. The third part is a detailed presentation of optimal power generation portfolios under the optimal emissions abatement case. The last segment discusses the results.

A. Outcomes of Scenario Selection

As stated in the methodology section, the power outage scenarios are simulated to only occur within MG-A and MG-D where the coal-fired power plants are connected. The number of scenarios for corresponding power outage interval is presented in Fig. 6.

As seen in Fig. 6, the orange dotted plot indicates the specific user-identified power outage interval amount for each $CASE$, and the blue bar stands for the number of quasi-scenario clusters within each $CASE$. The initial power outage interval is selected as 100 MW for $CASE$-1. There is a constant 2.5 MW reduction from the power outage interval as the $CASE$ is updated (97.5 MW for $CASE$-2, 95 MW for $CASE$-3, etc). With the power outage interval becoming smaller, more scenario clusters are correspondingly generated. In total, there are 20 $CASE$s and 270 scenarios selected for verification.

The probability distribution of scenarios for each $CASE$ is presented in Fig. 7. With the $CASE$ index being updated (a smaller power outage interval is selected), the overall probability distribution presents a smoother trend, which indicates a smaller probability for each power outage scenario cluster. However, no matter how power outage interval varies, the probability distribution for each $CASE$ is always normalized; the probability density always sums to 1 for each $CASE$, which confirms the validity of the proposed scenario selection method.

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

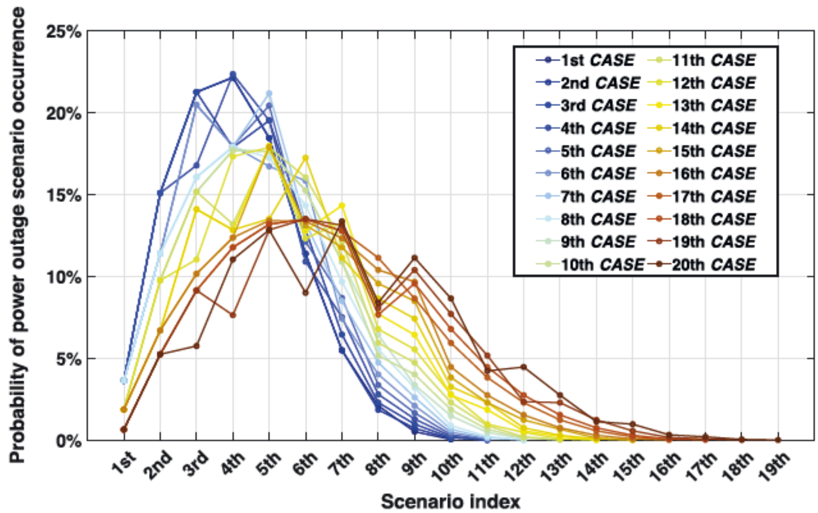

Fig. 7. Probability distribution of scenarios of each $CASE$.

From a practical perspective, it is also plausible to explain the probability distribution is visually skewed toward the left side. First, the underlying assumption of this study is the inevitable occurrence of HILP events, and the cascading impact is measured by the total amount of lost power generation capacity. Second, the user-identified power outage interval is used to generate various ranges for the lost generation capacities. Among all scenarios, only one scenario can represent the worst case that two power plants simultaneously experience an entire 24-h blackout without ontime restoration, which results in a relatively smaller probability of scenarios within the same power outage range (right-side tail). Likewise, the situation of only a one-hour power outage with ontime restoration likely deviates from the definition of severe influence from HILP events, but there are 24 scenarios representing this situation for each power plant, which indicates the probability (left-side tail) is larger than that of the worst case (right-side tail) numerically.

B. Comparison of Optimization Outcomes

Following the user-identified power outage scenario selection phase, the optimization results can be obtained by implementing the base model and the policy model, respectively.

First of all, the accomplishment of the proposed stochastic programming indicates all technical constraints are satisfied. Under this circumstance, the system resilience performance is secured where the main concern for the energy mismatch is resolved in the presence of power outage scenarios. The joint contributions of sustainability technologies, ESSs, and TE in networked MGs are successfully validated for resilience enhancement. The following analysis is based on the feasibility of networked MGs being resilient systems.

To obtain a complete profile of integrated power systems resilience planning costs under different policy regimes, the carbon emissions abatement coefficient varies from 0% to 100%, and the emissions tax increases to four times the reference level. The comparison of results is presented in Fig. 8.

As seen in Fig. 8, the power system resilience planning cost profile (optimal value of the objective function) is the red curve, and the blue curve indicates the change of taxation amount on excessive carbon emissions. Three interesting points can be observed from this result. First, for the average resilience planning cost profile, an overall upward trend is observed as the emissions abatement increases. However, the uptrend below 30% emissions abatement is less pronounced than that above 30% emissions abatement. Furthermore, the cost profiles are impacted to a greater extent by a larger emissions tax when the emissions abatement is above 30%. Second, the emissions tax profile also shows an overall upward trend when the emissions abatement exceeds 30%. However, no carbon tax is generated when the emissions abatement is below 30% because carbon emissions are below the emissions cap. Third, combining those two result profiles, it can be seen that applying low-carbon emissions policies undeniably increases the financial cost of systems resilience planning. Nevertheless, a strategic blend of carbon emissions caps and taxes can prove advantageous for all stakeholders. System operators would be able to invest minimally in the system, thereby facilitating more robust system management, while energy policymakers could make substantial progress in achieving their emissions abatement goals. This would be the appropriate identification of the critical point at 30% emissions abatement.

Even though, it is conceivable that the critical emissions threshold greatly depends on the power generation capacities of the system, particularly the capacities of sustainability technologies. As stated in the literature review section, it is impractical to wholly abnegate conventional fossil-fired power generation during the sustainability transitions period. Hence, a larger capacity from sustainability technologies indicates a larger replacement of electricity generated from fossil-fired power plants, as well as a larger emissions abatement. The capacity expansion of clean technologies is undoubtedly the future research direction.

The comparison of usage proportion of different energy sources is presented in Fig. 9.

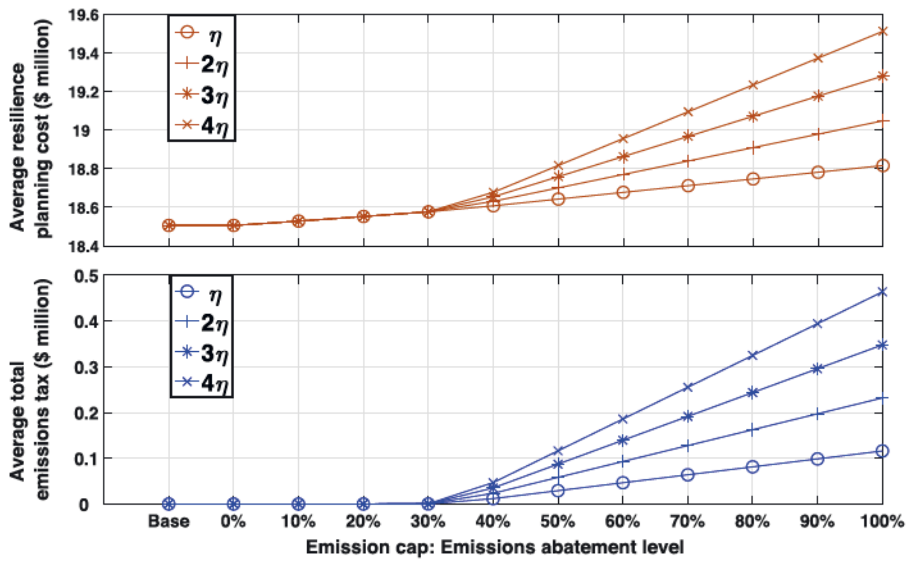

Fig. 8. Comparison of cost for power systems resilience planning and emissions taxation.

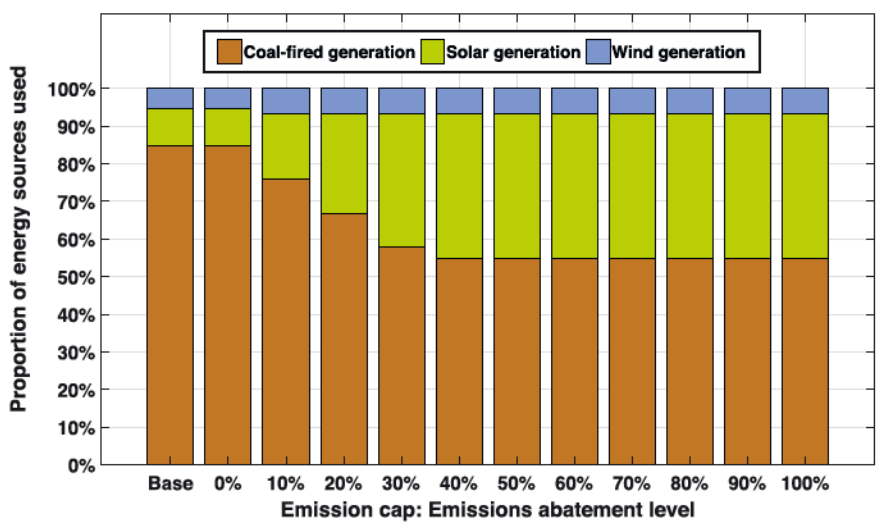

Fig. 9. Comparison of energy sources usage under different emissions taxation caps.

As can be seen in Fig. 9, at a higher level of emissions abatement, the usage proportion of clean energy sources increases. However, due to the limitations of the power generation capacities, the increase of usage proportion of clean energy stops at its maximum capacity. An interesting finding is that the threshold point is also located between 30% and 40% emissions abatement. This is due to the maxed-out generation from clean energy sources when the emissions abatement is greater than 40%.

Combining both results in Figs. 8 and 9, a salient observation emerges—the implementation of a low-carbon emissions policy undoubtedly increases the optimal power systems resilience planning cost. However, the reasons behind the cost increase are subject to further analysis depending on the critical emissions abatement point. When emissions abatement is below the critical point, though no emissions are taxed, the financial cost increases due to higher usage of clean technologies, which are more expensive than conventional coal-fired power generation. When emissions abatement is above the critical point, the utilization of clean technologies reaches its maximum capacity, causing emissions tax to dominate the financial cost. Hence, for policymakers who are interested in establishing a tax on excessive carbon emissions, it is of great essence to evaluate the energy usage situations for the entire system in order to determine an appropriate carbon emissions cap prior to establishing the tax level. An appropriate carbon emissions cap brings about dual benefits: 1) an acceptable threshold of carbon emissions abatement; and 2) a minimized emissions tax burden for system operators.

C. Analysis of Power Generation Profiles

With the identification of the critical emissions abatement point, a closer examination of power generation portfolios is of importance to systems planners of resilient systems. The power generation portfolios of coal, wind, and solar under 30%

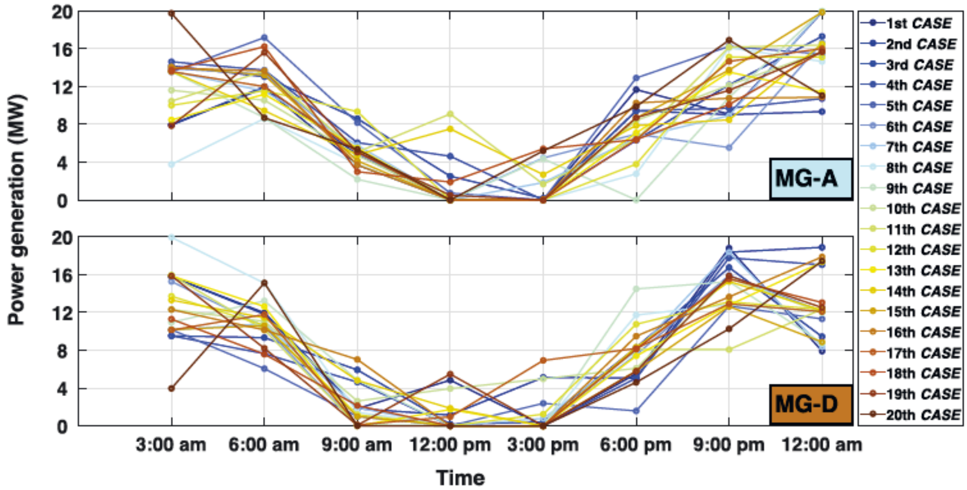

Fig. 10. Power generation profiles from coal-fired power plants under 30% emissions abatement.

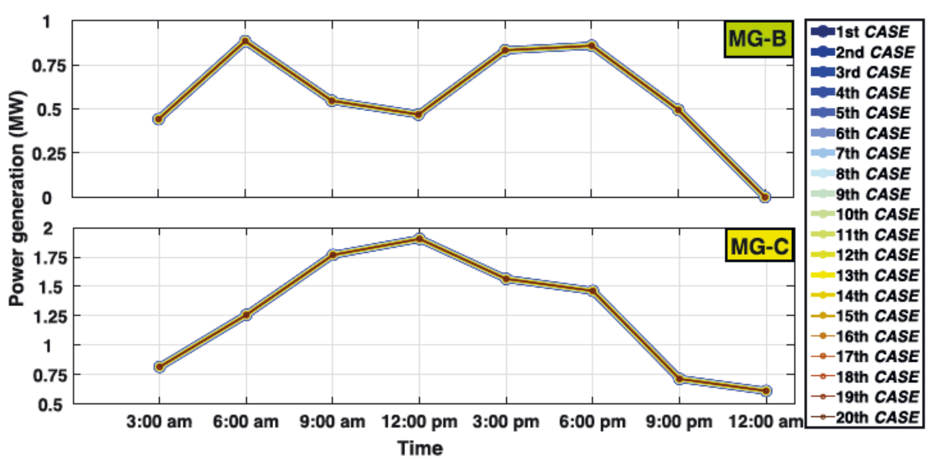

Fig. 11. Power generation profiles from wind power plants under 30% emissions abatement.

emissions abatement are shown in Figs. 10–12, respectively. The power generation profile under each $CASE$ circumstance is represented by a unique color on the figures.

In Fig. 10, though all 20 $CASEs$ are generated independently, a clear convergent trend of power generations can be observed, and this is expected from the outcomes of the stochastic optimization routines. The two implications of this result are: 1) given the high energy demand during the day and the impact of power outage scenarios, the availability of renewable energy greatly alleviates the stress of generating power from conventional coal-fired power plants; 2) the incentives from the energy policies lead to a more evident tendency in using renewable energy whenever it is available.

In Fig. 11, the results from all $CASEs$ overlap for the power generation portfolios from wind technology. This result follows from the cheaper price and the lower life-cycle carbon footprint of wind energy than solar energy.

Unlike wind energy with an overlapping profile, the power generations from solar technology show a more nonuniform profile in Fig. 12. This result exactly illustrates the potentials of solar energy for resilience enhancement in the presence of energy policies. On the one hand, wind energy would run out immediately for its cheaper cost and lower life-cycle carbon footprint, which leaves no space to prepare for any further possible occurrence of power outage situations. The cost of solar energy is more expensive, but the availability of remaining energy could be used for emergency use. On the other hand, utility-scale solar power plants are introduced in this study, but solar energy is more flexible in its forms of accessibility such as rooftop solar panels at customers' houses, which could be used as a short-term strategy for meeting local demand. Hence, compared to wind energy, solar energy owns greater flexibility in enhancing systems resilience.

D. Analysis of ESSs Status

In this study, another incentive to enhance power system resilience is the energy reserve rewards mechanism. By financially encouraging utilities to reserve energy, the robustness of the energy supply is enhanced. Notably, the charging and discharging status of ESSs are second-stage decision variables in the model, thus the reserved energy profiles in ESSs vary by each power outage scenario. In Fig. 13, the change

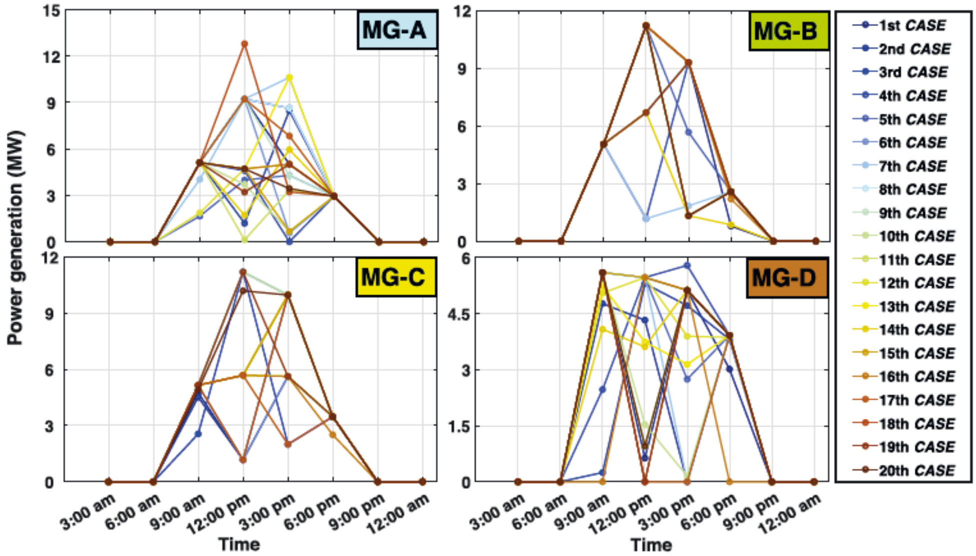

Fig. 12. Power generation profiles from solar power plants under 30% emissions abatement.

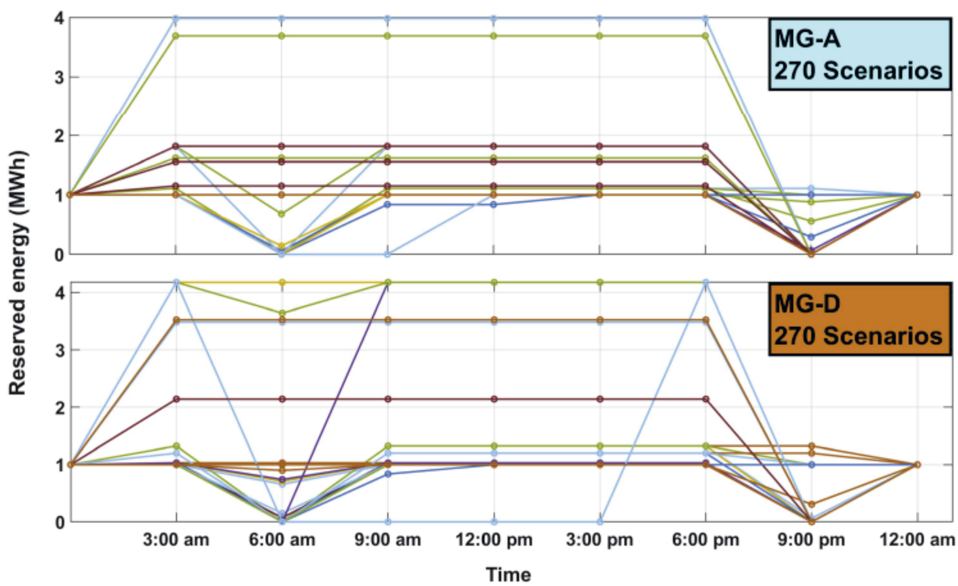

Fig. 13. Reserved energy in ESSs under 30% emissions abatement circumstance.

profiles of reserved energy in ESSs for all 270 scenarios are presented.

As can be seen in Fig. 13, the line with a positive slope indicates the operation of charging status and a negative slope is the discharging status. As expected, most of the time, the energy can be maintained at its maximum capacity to ensure enough energy is reserved for contingencies. It is also worthwhile to mention that the reserved energy at the last timescale $t = 24$ converges to the initial stored energy value at $t = 0$; resetting the ESSs preparatory for use the next day.

This is a very interesting finding from this study. From past research on ESSs, batteries are usually used to alleviate power generation stress during the peak hours of a day. However, in this study, the operations of ESSs mostly occur during the evening when the energy demand is relatively small. This situation could be explained by the following two points. First, the objectives of the proposed models are to minimize the total cost for a 24-h time scale. Under the financial incentives from the energy reserve rewards mechanism, a full capacity means the maximum revenue. Hence, during the day, solar and wind energy are prioritized for use in response to the low-carbon emissions requirement. Second, at night, it is still more profitable to use energy stored in ESSs than to generate electricity from conventional coal-fired power plants.

E. Discussion

The proposed methodology offers an avenue for system planners to determine the optimal portfolios of generation technologies from different energy sources to hedge against the impact of HILP contingencies. Policymakers may estimate an appropriate carbon emissions abatement level for the objective of maximizing carbon emissions abatement while simultaneously minimizing the burden of emissions tax. This core observation sheds more light on four important implications.

First, in the presence of low-carbon energy policies, the contributions of networked MGs for resilience enhancement are validated in this study. The multiple energy sources, the flexible decentralized system structures, the centralized governance control, the advanced energy storage technologies, and the reasonable energy incentives programs are all indispensable components. However, the practical construction of such highly integrated systems is much beyond the technical considerations, which also calls for operational regulations and management policies.

Second, an optimal power generation portfolio does not mean that the proposed resilient system can fully hedge against HILP contingencies. One of the prerequisites for utilizing the optimization model is treating power outage scenarios as input parameters, considering all postdisruption phases, including occurrence time and duration. However, the scenario-based optimal solutions can mitigate the cascading impact to the greatest extent because the worst scenario (power outage of 24 hours in each $CASE$) has already been considered in the computation process.

Third, from the financial perspective, taking into account low-carbon emissions in systems planning indeed inhibits resilience enhancement by introducing more intermittent renewable energy and increasing the total planning cost. However, the contributions of renewable energy cannot be underestimated in the process of decarbonization. The occurrence of high-impact contingencies indeed is of small probability, and the advantages of higher utilization of clean technologies outweigh the consequences of climate change from a long-term perspective.

Fourth, from the perspective of energy policies, though the critical emissions abatement point is determined to be at 30% in this study, this recommendation is subject to specific system parameters. The entire methodology can be replicated, i.e., the critical emissions abatement point varies depending on the system configuration and energy source capacities. Additionally, the implementation of energy policies impacts system operation, while the system planning follows the stipulation of the policies.

VI. Conclusion

In sustainability transitions aimed at responding to climate change, enacted energy policies and disruptions jointly challenge system resilience performance. The difficulty in studying this problem goes beyond only technical consideration because policies and economics are also of equivalent significance in influencing decision-making. In this study, an integrated approach is developed and implemented to demonstrate the effectiveness of constructing networked MGs for resilience enhancement, and to explore the influence of low-carbon emissions policies on resilience performance. The proposed approach is developed as a two-stage stochastic optimization model that captures both the system planning and operation phases in the presence of HILP contingencies.

The outcomes shed light on the potentials of integrated systems at enhancing power resilience with large-scale adoption of sustainable technologies. The comparison of results from the base model and the policy model offers insights into the establishment of low-carbon emissions policies where a reasonable combination of emissions cap and tax can achieve the tradeoffs between the expectations of larger carbon emissions abatement and the strengthening of system stability in the presence of power outage circumstances. The results also imply the beneficial contributions from policy incentives and demand response programs where both system operators and energy consumers could cooperatively behave in stabilizing the operation of the systems.

To summarize, several practical and managerial implications can be derived from this study for both policymakers and system planners. For policymakers who are charged with establishing energy policies, it is of significance to realize the existence of a critical emissions abatement threshold. To reach this threshold, system planners are expected to invest in clean technologies to reduce carbon emissions. However, beyond this threshold, system planners face the burden of emissions tax. Though this critical point is not significantly impacted by the emissions tax, appropriately setting the level of the carbon tax is a prerequisite to stabilizing the planning and operation of the entire system. For system planners who are contributing to the resilience enhancement, it is imperative for them to be cognizant of the trends in future energy policies. This is crucial because resilience is not only a technical performance metric, it is a multidimensional metric including the joint contributions from policies and economics.

The opportunities for the directions this work could be extended to in the future include the focus on the transmission capacity expansion within integrated systems, the consideration of the heterogeneity of service purposes of different infrastructure subsystems, and the application of the model into different regions where energy policies vary.

Acknowledgment

The authors would like to thank the editor, the associate editor, and anonymous reviewers for their comments and suggestions that significantly helped to improve the quality of the manuscript.

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