Resilient Distribution Networks Considering Mobile Marine Microgrids: A Synergistic Network Approach

Morteza Dabbaghjamanesh, Senior Member, IEEE, Soroush Senemmar, Student Member, IEEE, and Jie Zhang, Senior Member, IEEE

Abstract—This paper proposes a resilient and secure configuration for coastal distribution grids by integrating the security constraint unit commitment (SCUC) and mobile marine microgrids (MMMGs). In the proposed configuration, MMMGs can be connected to the coastal distribution grids in both normal and post-disaster operations. It is assumed that both MMMGs and SCUC networks include both dispatchable (e.g., gas turbines and diesel generators) and nondispatchable generators (e.g., photovoltaics and wind turbines). The proposed problem consists of realistic formulations that seek to minimize the total MMMGs and SCUC operation costs, while maximizing distribution grid resiliency. A heuristic technique, known as the collective decision optimization algorithm, is employed to address the complexity and nonlinearity of the formulated problem. Moreover, the unscented transform technique is adopted to model the uncertainties associated with renewable energy sources output and load demand. To show the effectiveness and merits of the proposed configuration, the IEEE 69-bus distribution network is selected and tested for both normal and post-disaster operations.

Index Terms—Grid reliability, mobile microgrids, resiliency, security configuration, uncertainty.

NOMENCLATURE

\[ D/d \] Set/index of load.
\[ \Omega^{N}/n,m,l \] Set/index of bus nodes.
\[ \Omega^{S}/s \] Set/index of MMMG.
\[ \Omega^{T}/t \] Set/index of time.
\[ \Omega^{DG}/k \] Set/index of DGs in MMMGs.
\[ \Omega^{U}/u \] Set/index of uncertain variables.

\[ C_{ks} \] Generation cost of the \( k \)th unit in the \( s \)th MMMG.
\[ C_{t} \] Generation cost of the \( t \)th unit.
\[ C_{snt}^{E}/C_{snt}^{D} \] Entrance/departure cost of \( s \)th MMMG to node \( n \) at time \( t \).
\[ C_{snt}^{M} \] Sailing cost of \( s \)th MMMG from node \( m \) to node \( n \) at time \( t \).
\[ F_{nmt} \] Power flow in line \( nm \) at time \( t \).
\[ I_{it} \] Status of unit \( i \) at time \( t \). 1 if unit is on; otherwise, it is 0.
\[ L_{snt}^{E}/L_{snt}^{D} \] Entrance/departure status of the \( s \)th MMMG at time \( t \). 1 if MMMG is connected to node \( n \); otherwise, 0.
\[ L_{snt}^{M} \] Sailing status of the \( s \)th MMMG at time \( t \). 1 if MMMG is moving from node \( m \) to node \( n \); otherwise, 0.
\[ f_{sh} \] Load shedding of bus \( m \) at time \( t \).
\[ I_{snt} \] Status of the \( s \)th MMMG in bus \( n \) at time \( t \). 1 if it is located at bus \( n \); otherwise, it is 0.
\[ L_{lm} \] Current of line \( lm \) at time \( t \).
\[ N_{h}/N_{T} \] Total number of customers interrupted/served. Number of interruptions.
\[ O_{snt} \] The \( s \)th MMMG operating status at time \( t \). 1 if it is operating in bus \( n \); otherwise, it is 0.
\[ P_{D} \] Power of the \( i \)th unit at time \( t \).
\[ P_{kst} \] Power of the \( k \)th unit in the \( s \)th MMMG at time \( t \).
\[ P_{lm} \] Transmitted active power from line \( lm \) at time \( t \).
\[ Q_{lm} \] Transmitted reactive power from line \( lm \) at time \( t \).
\[ P_{Dn} \] Load demand at bus \( n \).
\[ R_{U}, R_{D} \] Ramp up/down rate of units.
\[ r_{t} \] The percentage of load for spinning reserve.
\[ S_{U}, S_{D} \] Startup and shutdown costs.
\[ T_{s} \] Moving time of the \( s \)th MMMG from node \( m \) to node \( n \).
\[ T_{CL}^{n,t} \] Service time of the load in post-disaster restoration at time \( t \).
\[ T_{on}, T_{off} \] Number of successive ON/OFF hours for units at time \( t \).
\[ Z, X, R \] Impedance, reactance, and resistance of lines.
\[ V_{mt} \] Voltage of node \( m \) at time \( t \).
\[ UT, DT \] Minimum up/down time of units.
\[ W_{n} \] Load importance (weight) at bus \( n \).
\[ W_{ant} \] The \( s \)th MMMG waiting status at time \( t \). 1 if it is waiting in bus \( n \); otherwise, it is 0.
\( \gamma \) Energy to money conversion coefficient.
\( \theta_{nm} \) Phase of impedance between bus \( n \) and \( m \).
\( \delta, \delta_{n} \) Bus voltage angle and voltage angle of bus \( n \).
\( \delta_{kt} \) Status of the \( k \)th unit in the \( s \)th MMMG at time \( t \).
\( 1 \) if unit is on; otherwise it is 0.
\( \Upsilon_{h} \) Restoration time (min).
\( \omega_{E,t} \) Charging/discharging index of energy storage.
\( E_{E,t} \) Charging/discharging power of energy storage.
\( \text{SOC}_{E,t} \) State of charge of energy storage at time \( t \).

I. INTRODUCTION

Modern power grids have been undergoing a rapid increase in size and complexity due to the growth in demand and grid modernization. In addition, the loads and generation units are disproportionately increasing, which makes the grid more vulnerable to power outages [1]. On the other hand, grid contingencies, natural disasters, and cyber/physical attacks are highly unpredictable and costly preventable [2], which require fast and reliable energy resources for service restoration [3], [4].

Leaving millions of customers without power for weeks, natural disasters could result in severe and widespread damages to power grids. For example, approximately 2.2 million people were reported without power after Hurricane Sandy struck the East Coast of the USA in 2012 [5]. The development of more resilient power grids is motivated by weather-related power outages that cause significant life risks and tremendous economic losses, especially in the coastlines [6]. One of the most critical requirements for a resilient power grid is an effective and rapid response for the electric service restoration, where most recovery activities greatly depend on reliable power supply [7].

In recent years, mobile generation units have gained a lot of attention to enhance the power system resiliency due to their technical and strategical benefits for the grid [8]. For instance, the resiliency of distribution lines was improved in [9], where the authors considered mobile emergency generation units in the presence of natural disasters. Lei et al. [10] used mobile power sources, e.g., electric vehicle and truck-mounted mobile energy storage systems, to enhance the resiliency of a distribution power grid. The resiliency of distribution power grids was investigated in [11]–[13] by considering the mobile energy storage and also decomposing the grid into interconnected microgrids. Dabbaghjamanesh et al. [14] explored how power grid intentional islanding and mobile renewable energy plants could increase the resiliency of power grids. A resilient scheme for disaster recovery was investigated in [15], where the authors developed a co-optimization framework for both mobile power sources and repair crews. In [16], mobile distributed energy resources were considered to enhance the resiliency of a distribution network. Resiliency enhancement of power grids by considering mobile storage and the dynamic line rating constraint was investigated in [17]–[20]. Although different types of mobile energy plants have been proposed for increasing the resiliency of the power grid, large capacity mobile energy platforms that can move and recover a large amount of loads after disasters have not been explored in the literature.

Mobile marine microgrids (MMMGs), as one of the largest mobile energy resources, can quickly move and connect to local transmission/distribution lines [21]. A single MMMG can generate up to 500 MW power, which is enough to provide electricity for 250,000 people [22]. Such large generation capacities could lead to significant advantages to the grid, e.g., assist power grid operations, enhance power system resiliency (by supplying energy rapidly to areas affected by natural disasters), and prevent large investments on power transmission infrastructure [23]. MMMGs’ large upfront capital investment cost has also motivated them to be used for multiple purposes. On the other hand, countries with large island territories often struggle to deliver power to island regions because connecting disparate islands with subsea cables are costly and complex [24], [25]. Therefore, island power lines are often separate from mainland grids. Moreover, building local power plants for serving a small size of the population is usually economically undesirable. Thus, using MMMGs that include diesel and gas generators as well as offshore renewable power sources (e.g., wind and wave energy) is becoming increasingly popular in the normal operation of the island power grid. However, they are only practicable when islands can easily be connected up.

The advantages of utilizing MMMGs in power systems operation and planning are twofold: 1) enhance the reliability of power grids in normal operations, and 2) enhance the resiliency of power grids in the presence of natural disasters or contingencies. However, the coordination of MMMGs and security constraint unit commitment (SCUC) could be challenging to solve [26], [27]. The impacts of MMMGs on power systems reliability and economic efficiency were investigated under normal operations, and those on power grid resiliency in the post-disaster period in [26]. To better characterize the uncertainties in the renewable generation (on MMMGs) and electric loads, gated recurrent units were adopted in this article to forecast MMMGs photovoltaics (PVs) power generation. The main contributions of this article are summarized as follows:

1) Develop a coordination framework of MMMGs and SCUC in power system operations by taking into account the impacts on the base station and the transportation cost of MMMGs;

2) Develop a new synergistic approach for distribution grids by integrating MMMGs in power system operations to enhance the power grid resiliency in the presence of natural disaster or contingency.

The rest of the paper is organized as follows. In Section II, the overall MMMGs and SCUC coordination framework is formulated. In Section III, the adopted deep learning technique for renewable and load forecasting is described. In Section IV, simulation results on the IEEE 69-bus distribution network are discussed. Finally, Section V concludes this article.

II. MODELS AND MATHEMATICAL FORMULATIONS

A. Objective Function of the Synergistic Configuration

As mentioned, the proposed configuration is a multiobjective optimization problem \( F(x) = F_{2}(x) - F_{1}(x) \) that seeks to minimize the total operation cost of the SCUC and MMMGs, as
shown in (1), while maximizing the distribution grid resiliency, as shown in (2). It is worth noting that the first and second terms of (1) are the SCUC and MMMGs operation costs, respectively. Also, the first term of (2) is the system performance, which can be evaluated by the total electrical energy supplied to consumers based on their weighting priority. The variable $T^b_{n,t}$ is determined based on the travel time of MMMGs to the load center. Finally, the second term of (2) is the power generation cost of both SCUC and MMMGs. It is worth noting that the grid resiliency can be enhanced either by maximizing the system performance or minimizing the generation cost [12].

1) Minimizing the Operation Cost:

$$\min \ F_1(X) = \sum_{n,m \in \Omega^N} \sum_{s \in \Omega^B} \sum_{t \in \Omega^T} [C^E_{snt} I_{snt}^E + C^D_{snt} I_{snt}^D] + C^M_{smt} I_{smt}^M] + \sum_{k \in \Omega^{DG}} \sum_{t \in \Omega^T} [C_{kst} P_{kst} I_{kst}^D + \delta_{kst}]
+ SU_{kst} + SD_{kst} + \sum_{i \in \Omega^{DG}} \sum_{t \in \Omega^T} [C^i_{kst} I_{it} + SU_{it} + SD_{it}]$$

2) Maximizing the Resiliency [12]:

$$\max \ F_2(X) = \gamma \times \sum_{n \in \Omega^N} W_n F_n^D T_{n,t}^{CL}$$

$$- \sum_{t \in \Omega^T} \sum_{s \in \Omega^B} \sum_{i \in \Omega^{DG}} \sum_{k \in \Omega^{DG}} [P_{kst} I_{kst}^E + P_{kst} I_{kst}^D]$$

Eq. (1) depicts a common power grid resilience curve during a natural disaster event. The power grid performance includes the following five states [12], [28]:

1) natural disaster progress state, which is $[t_e, t_{pe}]$;
2) post-event degraded state, which is $[t_{pe}, t_r]$;
3) restoring state, which is $[t_r, t_{pr}]$;
4) post-restoration state, which is $[t_{pr}, t_{pi}]$;
5) infrastructure recovery state, which is $[t_{pi}, t_{ps}]$.

The main focus of this article is in the post-disaster period, i.e., the restoring and post-restoration stages, as highlighted in Fig. 1. Indeed, during this time period, MMMGs are employed and will be sailed to the affected area to compensate for the power shortage.

B. Constraints of the Synergistic Configuration

The proposed synergistic configuration problem is the integration of MMMGs and SCUC. To this end, two types of limitations exist as follows.

1) SCUC Limitations: Constraints related to the day-ahead SCUC are presented in (3)–(16).

Power generation constraints: Equations (3) and (4) show that the active and reactive power of each generator should be within its minimum and maximum rates

$$I_{it} P_{it}^G \leq P_{it}^G \leq I_{it} P_{it}^G \forall t \in \Omega^T, \forall i \in \Omega^{DG}$$

(3)

$$I_{it} Q_{it}^G \leq Q_{it}^G \leq I_{it} Q_{it}^G \forall t \in \Omega^T, \forall i \in \Omega^{DG}$$

(4)

Ramp up and ramp down constraints: The changes in output power of each generator at each hour is limited by its ramp up/down rates, which are mathematically formulated as follows:

$$P_{it}^G - P_{i(t-1)}^G \leq RU \forall t \in \Omega^T, \forall i \in \Omega^{DG}$$

(5)

$$P_{i(t-1)}^G - P_{it}^G \leq RD \forall t \in \Omega^T, \forall i \in \Omega^{DG}$$

(6)

Minimum on/off time constraints: Each generator is constrained by its minimum on/off time limits as follows:

$$T_{on}^i \geq UT_i(I_{it} - I_{i(t-1)}) \forall t \in \Omega^T, \forall i \in \Omega^{DG}$$

(7)

$$T_{off}^i \geq DT_i(I_{i(t-1)} - I_{it}) \forall t \in \Omega^T, \forall i \in \Omega^{DG}$$

(8)

Spinning reserve constraint: Equation (9) shows that the maximum rates of all distributed generators (DGs) at each hour should meet the spinning reserve constraint as

$$\sum_{i \in \Omega^{DG}} I_{it} P_{it}^G \geq P^D_{it} (1 + r_i \%) \forall t \in \Omega^T$$

(9)

Power flow constraints: Equations (10)–(16) present the constraints on network power flow as

$$\sum_{l \in \Omega^{DL}} \left[P_{lm,t}^L - R_{lm}(I_{lm,t}^L)^2\right] - \sum_{m \in \Omega^{DL}} P_{mn,t}^L + P_{i,t}^G
+ P_{k,t}^G = P_{i,t}^D - P_{i,t}^sh \forall t \in \Omega^T, \forall i \in \Omega^{DG}, \forall k \in \Omega^{DG}$$

(10)

$$\sum_{l \in \Omega^{DL}} \left[Q_{lm,t}^L - X_{lm}(I_{lm,t}^L)^2\right] - \sum_{m \in \Omega^{DL}} Q_{mn,t}^L + Q_{i,t}^G
+ Q_{k,t}^G = Q_{i,t}^D - Q_{i,t}^sh \forall t \in \Omega^T, \forall i \in \Omega^{DG}, \forall k \in \Omega^{DG}$$

(11)

$$(V_{i,n,t})^2 - (V_{i,n,t})^2 = 2(R_{mn} P_{mn,t}^L + X_{mn} Q_{mn,t}^L)$$

(12)

$$- (Z_{mn})^2(I_{mn,t}^L)^2 + \Delta V_{mn,t} \forall t \in \Omega^T, \forall m \in \Omega^{DL}$$

(13)

$$\Delta V_{mn,t} \leq (V - |V|(1 - w_{mn,t}^L))$$

(14)

$$\forall t \in \Omega^T, \forall m \in \Omega^{DL}$$

$$0 \leq I_{mn,t}^L \leq T_{w_{mn,t}}^L \forall t \in \Omega^T, \forall m \in \Omega^{DL}$$

(15)
Equations (10)-(13) present the network power flow formulations. The minimum and maximum limits for voltage values are shown in (14). Equation (15) shows the maximum allowable voltage difference in each line. Lines currents are constrained by their nominal rates in (16).

Energy storage constraints: The output power of the storage unit is constrained as
\[
\begin{align*}
E_{E,t} - E_{\text{dch}, \text{min}} & \geq E_{E,t} - E_{\text{dch}, \text{max}} + \omega_{E,t}, & \forall t \in \Omega^T, \\
E_{E,t} & \leq E_{E,t} + E_{\text{dch}, \text{min}} + \omega_{E,t}, & \forall t \in \Omega^T. 
\end{align*}
\]
(17)

It should be noted that the storage unit cannot be in the charging and discharging mode at the same time. That means
\[
\omega_{E,t} + \omega_{E,t} \leq 1. 
\]
(18)

Finally, the state of charge (SOC) of the energy storage is calculated based on the value of charged/discharged power as shown in (19). SOC is constrained by its maximum capacity as shown in (20).
\[
\begin{align*}
\text{SOC}_{E,t} &= \text{SOC}_{E,(t-1)} - E_{E,t}, & \forall t \in \Omega^T, \\
0 & \leq \text{SOC}_{E,t} \leq \text{SOC}_{E,\text{max}}, & \forall t \in \Omega^T. 
\end{align*}
\]
(19)
(20)

2) MMMGs Limitations: Equations (21)-(34) formulate the MMMGs constraints.

MMMGs moving constraints: Equations (21) and (22) show that each MMMG is moving or connecting to a node at each hour. In addition, (23) and (24) present the entering/departing status of each MMMG, respectively. Equation (25) prevents from entering and departing simultaneously
\[
\sum L_{snt} + \sum L_{snt}^M = 1; \forall s \in \Omega^S, \forall n \in \Omega^N, \forall t \in \Omega^T 
\]
(21)
\[
\begin{align*}
W_{snt} + O_{snt} & \geq L_{snt}^M - L_{snt}^M, & \forall s \in \Omega^S, \forall n \in \Omega^N, \forall t \in \Omega^T 
\end{align*}
\]
(22)
\[
\begin{align*}
L_{snt}^M & \geq L_{snt}^M - L_{snt}^M, & \forall s \in \Omega^S, \forall n \in \Omega^N, \forall t \in \Omega^T 
\end{align*}
\]
(23)
\[
\begin{align*}
L_{snt}^E & \geq L_{snt}^E - L_{snt}^E, & \forall s \in \Omega^S, \forall n \in \Omega^N, \forall t \in \Omega^T 
\end{align*}
\]
(24)

MMMGs operational status constraints: MMMGs are limited to operate and wait as well as operate and sail simultaneously based on the following equations, respectively:
\[
L_{snt} = W_{snt} + O_{snt}, & \forall s \in \Omega^S, \forall n \in \Omega^N, \forall t \in \Omega^T 
\]
(26)
\[
O_{snt} \leq L_{snt}^{(t-1)}; & \forall s \in \Omega^S, \forall n \in \Omega^N, \forall t \in \Omega^T. 
\]
(27)

MMMGs sailing time constraints: The MMMGs are constrained by the moving time between two nodes given by the following equations as
\[
\begin{align*}
\sum L_{snt}^m & \leq T_{s}^{(t-1)} - (1 - L_{snt}^{D}) M, & \forall s \in \Omega^S, \forall n \in \Omega^N, \forall t \in \Omega^T 
\end{align*}
\]
(28)
\[
\begin{align*}
\sum L_{snt}^m & \geq T_{s}^{(t-1)} - (1 - L_{snt}^{D}) M, & \forall s \in \Omega^S, \forall n \in \Omega^N, \forall t \in \Omega^T. 
\end{align*}
\]
(29)

MMMGs operation constraints: MMMGs operation constraints that consist of allowable generation interval, ramp up and ramp down time limits, and minimum ON/OFF time limits are presented in the following equations:
\[
\begin{align*}
\text{DABBAGHJAMANESH et al.} & 
\end{align*}
\]
\[
\begin{align*}
\delta_{kst} P_{G_k}^G & \leq P_{G_k}^G \leq \delta_{kst} P_{G_k}^G, & \forall t \in \Omega^T, \forall k \in \Omega_D 
\end{align*}
\]
(30)
\[
\begin{align*}
P_{sk}^G - P_{sk}^G(t-1) & \leq R_{sk} \forall t \in \Omega^T, \forall k \in \Omega_D 
\end{align*}
\]
(31)
\[
\begin{align*}
P_{sk}^G(t-1) - P_{sk}^G & \leq R_{sk} \forall t \in \Omega^T, \forall k \in \Omega_D 
\end{align*}
\]
(32)
\[
\begin{align*}
T_{snst}^m & \geq U_{sk}(\delta_{sk} - \delta_{sk-1}) \forall t \in \Omega^T, \forall k \in \Omega_D 
\end{align*}
\]
(33)
\[
\begin{align*}
T_{snst}^m & \geq U_{sk}(\delta_{sk} - \delta_{sk-1}) \forall t \in \Omega^T, \forall k \in \Omega_D. 
\end{align*}
\]
(34)

III. A STOCHASTIC FRAMEWORK BASED ON UNSCENTED TRANSFORM

A. UT Technique to Model Uncertain Parameters

As mentioned above, the integration of SCUC and MMMG is associated with uncertainties resulted from renewable power output and load demand. Different techniques exist to model uncertainties such as 1) Monte Carlo simulations that require a large number of runs to converge, 2) analytical techniques that suffer from simplification or linearization, and 3) estimation techniques that balance the former two. To this end, in this article, an estimation technique, known as the unscented transform (UT) is adopted to model the uncertainties, which are briefly described as follows.

For a stochastic nonlinear problem \( y = f(x) \), where \( y \) is the uncertain output vector and \( x \) is the random input vector. Assuming that there are \( q \) uncertain parameters, \( x \) is a vector of length \( q \) with a mean value \( \mu \) and a covariance \( \sigma_x \). The symmetrical elements of the matrix \( \sigma_x \) are the variance of the uncertain variables, while the nonsymmetrical elements are the covariance among different uncertain parameters. Based on these assumptions, the UT technique can find the mean \( \mu_y \) and covariance \( \sigma_y \) of variable \( y \) as follows.

**Step 1:** Use the following equations to reach \( 2q + 1 \) samples from the input uncertain data
\[
x_0 = \mu 
\]
(35)
\[
x_\omega = \mu \pm (\sqrt{\frac{q}{1-W^0\sigma_x}}) \omega; \omega = 1, 2, \ldots, q
\]
(36)
where \( (\sqrt{\frac{q}{1-W^0\sigma_x}}) \omega \) is the \( \omega \)-th row or column of the square root of \( (\frac{1}{W^0\sigma_x}) \) and \( W^0 \) is the weight of the mean value \( \mu \).

**Step 2:** Calculate the weight of each \( x \) by using (37) and (38).

\[
W_\omega = \frac{1-W^0}{2q}; \omega = 1, 2, \ldots, q
\]
(37)
\[
W_{\omega+q} = \frac{1-W^0}{2q}; \omega = q+1, q+2, \ldots, 2q
\]
(38)
\[
\sum_{\omega=0}^{2q} W_\omega = 1. 
\]
(39)
Step 3: Render $2q + 1$ sample points to the nonlinear function $y = f(x)$ to gain the output samples points as the following equation:

$$y_{\omega} = f(X_{\omega}). \quad (40)$$

Here, the nonlinear function can be considered as a black box. Therefore, no simplification or linearization is needed.

Step 4: Finally, the covariance $\sigma_y$ and the mean $\mu_y$ of the output variable $Y$ are calculated based on the following equations, respectively:

$$\mu_y = \sum_{\omega} W_{\omega} Y_{\omega} \quad (41)$$

$$\sigma_y = \sum_{\omega} W_{\omega} (Y_{\omega} - \mu_y)(Y_{\omega} - \mu_y)^T. \quad (42)$$

B. CDOA Optimization Technique

As mentioned, the proposed problem is a nonlinear and non-convex problem due to ac power flow nonlinear constraints. Thus, to overcome the complexity and nonlinearity of the problem, a heuristic technique, known as the collective decision optimization algorithm (CDOA), is utilized.

CDOA is a population-based heuristic technique, which uses the decision-making pattern of humans to obtain the global optimum [19]. Compared to other well-known heuristic techniques, CDOA has shown higher flexibility and accuracy, and fast convergence. In the CDOA technique, it is assumed that a group of people seek to develop the best plan in a meeting, which consists of the following main steps.

1) Population generation: CDOA is based on an initial population, defined as follows:

$$Z_u(t) = (Z_u^1(t), Z_u^2(t), \ldots, Z_u^D(t)) \quad \forall u \in \Omega^H \quad (43)$$

$$Z_u^l(t) = LB^l + \text{rand}(UB^l - LB^l) \quad \forall l \in \Omega^D \quad (44)$$

where rand is in the range of [0,1], which means that each individual in the population represents a control vector that can potentially determine the optimal ON or OFF status of the generation units.

2) Individual’s experience-based step: After generating the initial population, an individual decider proposes the best plan based on his personal knowledge and experience. This step is known as the best position of the individual, given by

$$Z_{u_0}^{new}(t) = Z_u(t) + \tau_1 \times \text{step}_{size}(t) \times \Phi_0 \quad \forall t \in \Omega^T. \quad (45)$$

3) Others’ experience-based step: In the next step, the individual decider interacts with others, randomly, to receive something helpful and new to update the decisions. The mathematical model of this step is formulated as follows:

$$Z_{u_1}^{new}(t) = Z_{u_0}^{new}(t) + \tau_1 \times \text{step}_{size}(t) \times \Phi_1; \forall t \in \Omega^T. \quad (46)$$

4) Group thinking-based step: In this step, deciders present their suggestions, which may affect each other. Thus, a new position can be defined as follows:

$$Z_{u_2}^{new}(t) = Z_{u_1}^{new}(t) + \tau_2 \times \text{step}_{size}(t) \times \Phi_2; \forall t \in \Omega^T. \quad (47)$$

5) Leader-based step: In the CDOA algorithm, the best individual of the population is defined as the leader, which plays an important role in the group. This step is formulated as follows:

$$Z_{u_3}^{new}(t) = Z_{u_2}^{new}(t) + \tau_3 \times \text{step}_{size}(t) \times \Phi_3; \forall t \in \Omega^T. \quad (48)$$

6) Innovation-based step: In CDOA, the mutation operator is the innovation-based step, which creates a small change among variables as follows:

$$\text{rand}_1 \leq MF \times Z_{u_4}^{new}(t) = Z_{u_3}^{new}(t) \times Z_{u_4}^{L,new} \quad (49)$$

where $MF$ is a large number to improve the population diversity and also prevent premature convergence [4]. Furthermore, $L$ is a random number in the range of $[1, \Omega^D]$. The step size of the algorithm is calculated as follows:

$$\text{step}_{size}(t) = \Gamma_1 - \Gamma_2 \left( \frac{t - 1}{IN - 1} \right). \quad (50)$$

IV. Case Study

In this section, a modified IEEE 69-bus test system is selected and tested, as shown in Fig. 2. The proposed distribution network contains two MMMGs, two wind turbines (WTs), one PV, and one energy storage unit. Also, each MMMG, as an independent network, contains a PV system, a fuel cell, and a microturbine. In the normal condition, the MMMGs are coordinated with the SCUC to improve the reliability and security of the network, while minimizing the cost. However, in the emergency condition, MMMGs can sail and connected to distribution grids to prevent the severe blackout and also enhance the resiliency of the network.

Tables I and II show the DGs (total capacity) and energy storage characteristics, respectively. Also, Figs. 3 and 4 show the day-ahead forecasted values of WTs and PVs output power,
respectively. The forecasted values of the total load demand, as well as the load demand of each damaged area, are depicted in Fig. 5.

To show the effectiveness and merit of the proposed synergistic model, three cases are investigated as follows.

A. Case 1: Normal Condition

In this case, the MMMGs are integrated into the main distribution grids, where their first objective is to satisfy their load demand. MMMGs will also be integrated into the distribution grids due to economic consideration as well as providing higher reliability and security for the grids. The main challenge of this case is to find out the best possible integration for both grids, the main grid and the MMMGs, so that the total cost reduce, while the system converges as well. To this end, based on the simulation results, the best synergistic approach for the normal condition (among possible connection busses) is to connect the MMMG 1 and MMMG 2 to bus 46 and bus 27, respectively [29].

Fig. 6 shows the output power of the main DG of the grid as well as the MMMG DGs. Based on this figure, the cheapest units are more committed than others; that means the output power of DGs is only based on economic consideration.

Fig. 7 depicts the purchasing power from the MMMGs by the main grid. Based on the figure, MMMG 1 is more committed than MMMG 2, which is due to its lower operation cost (refer to Table I). It should be noted that in both normal and extreme conditions, each MMMG should satisfy its demand before selling any power to the main distribution grid.

B. Case 2: Area 1 Damaged

In this case, a small part of the grid (depicted as Area 1 in Fig. 2) is affected by a natural disaster and is disconnected from the main grid. To compensate for the shortage of power, MMMG 2, which is closer to Area 1 and also has cheaper sailing cost, is sailed to connect to Area 1 to compensate for the shortage of power.
power. In the extreme condition case, the most important factor is to select a MMMG that has enough capacity for the damaged area. Also, it is important to connect the sailed MMMG to an available bus, which can lead to higher resiliency as well as lower operation costs. However, the main priority is given to resiliency improvement. To this end, to provide a synergistic grid, MMMG 2 has been connected to bus 32 of Area 1. Fig. 8 shows the output power of DGs within the grid and MMMGs. Based on the figure, the main grid DG is more committed than its commitment in case 1, which is due to disconnecting MMMG 2 from the main grid (refer to Figs. 6 and 8).

Fig. 9 shows the purchasing power of the main grid from the MMMGs. Same as Case 1, MMMG 1 is more committed than MMMG 2 due to its lower cost. Also, based on Fig. 9, MMMG 2 is OFF for the first 3 hours. This is because it is in the sailing mode and cannot be connected to the main grid. However, based on Fig. 8, MMMG 2 still produces power in the first 3 hours. This amount of power is used for the MMMG demand, which should be satisfied even in the sailing mode.

C. Case 3: Area 2 Damaged

In this case, a larger part of the network is affected so that one MMMG capacity is not enough to compensate for the shortage power of the damaged area. Thus, both MMMGs should be sailed to compensate for the power shortage. Based on the simulation results, unlike Case 2, the best synergistic approach for this case is to connect MMMG 2 and MMMG 1 to bus 34 and bus 62, respectively. Fig. 10 shows the output power of DGs within both the main grid and MMMGs. Based on this figure, the total load demand of the main grid demand has been satisfied by the main DG, while the MMMGs power is only used for the marine demand and damaged area.

Fig. 11 depicts the purchasing power from the MMMGs by the damaged area. Based on the figure, both MMMGs provided power with almost their maximum capacities. However, MMMG 1 and MMMG 2 are OFF for the first 3 and 6 hours, respectively; this is because they are in sailing modes. Similar to the Case 2, based on Fig. 10, the DGs within MMMGs have still provided power, which is used for their load demand. That means, even during the sailing mode, they still need to produce power to satisfy their demand.

Fig. 12 depicts the SOC status of the energy storage unit for all cases. It shows that energy storage has more participation in energy management under extreme conditions. For example, at hour 5, in Case 1, the storage SOC is 85%, while in Cases 2 and 3, the SOC is 30% and 50%, respectively.

Fig. 13 shows the resiliency curves (refer to Fig. 1) of all cases. Based on the figure, using the MMMGs in the distribution.
grid can significantly improve the resiliency of the distribution network under extreme conditions. For instance, by using the MMMGs, the post-disaster worst resiliency curves of Case 2 and Case 3 are increased to 97% and 79%, respectively, which shows the capability and effectiveness of the proposed technique.

Fig. 14 shows the total stochastic and deterministic operation costs for all cases. It is seen that stochastic simulations when quantifying the uncertainties have increased the costs in all cases. The reduced economic efficiency will be compensated with the enhanced system resiliency and reliability.

Using MMMGs in coastline distribution networks can lead to significant benefits for the grids, such as 1) higher reliability and lower operation cost: The reliability and economic efficiency of the system can be improved when using MMMGs in normal conditions; 2) higher resiliency: using MMMGs can lead to higher resiliency and less load shedding of the network in post-disaster conditions due to their moving flexibility and high capacities. However, along with these advantages, there exist some significant challenges for MMMGs, e.g., uncertainty in the MMMGs route under abnormal conditions and extreme weather. Thus, more economic and technical investigations are needed before the formal use of MMMGs in coastline distribution grids.

V. CONCLUSION

In this article, a new synergistic approach was developed to enhance the resiliency and reliability of the coastline distribution grids, by integrating MMMGs into distribution networks. The developed model was examined on a modified IEEE 69-bus test system. Simulation results show that, by using the MMMGs in extreme conditions, the resiliency of the system could be increased significantly. Indeed, employing MMMGs in the distribution network could compensate for a large amount of power in post-disaster conditions. This is mainly due to the large capacities of MMMGs, compared with other mobile energy sources, e.g., mobile battery storage units. Also, in the normal condition, integrating the MMMG can enhance the reliability of the network. Overall, the proposed technique can be utilized in both normal conditions (to increase the reliability of the network) and post-disaster conditions (to increase the resiliency of the network). However, more investigation is still needed before the formal adoption of MMMG in distribution grids.

REFERENCES


Morteza Dabbaghjamanesh (Senior Member, IEEE) received the M.Sc. degree in electrical engineering from Northern Illinois University, DeKalb, IL, USA, in 2014, and the Ph.D. degree in electrical and computer engineering from Louisiana State University, Baton Rouge, LA, USA, in 2019. Currently, he is a Research Associate with the Design and Optimization of Energy Systems (DOES) Laboratory, The University of Texas at Dallas, Richardson, TX, USA. His current research interests include power system operation and planning, smart grids, operation and planning of multicarrier energy systems, and energy management.

Soroush Senemmar (Student Member, IEEE) received the B.Sc. and M.Sc. degrees in electrical engineering from Shiraz University, Shiraz, Iran, in 2015 and 2019, respectively. He is currently working towards the Ph.D. degree in electrical engineering at the Department of Electrical and Computer Engineering, The University of Texas at Dallas, Richardson, TX, USA. His current research interests include power systems operation and planning, smart grids, operation and planning of multicroier energy systems, and energy management.

Jie Zhang (Senior Member, IEEE) received the B.S. and M.S. degrees in mechanical engineering from the Huazhong University of Science and Technology, Wuhan, China, in 2006 and 2008, respectively, and the Ph.D. degree in mechanical engineering from Rensselaer Polytechnic Institute, Troy, NY, USA, in 2012. He is currently an Assistant Professor with the Department of Mechanical Engineering, The University of Texas at Dallas, Richardson, TX, USA. His current research interests include multidisciplinary design optimization, complex engineered systems, big data analytics, wind and solar forecasting, renewable integration, and energy systems modeling and simulation.