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Abstract—In this paper, a new configuration security framework is developed for reliability and resiliency improvement of distribution networks by the coordination of the security-constraint unit commitment (SCUC) and mobile marine power sources (MMPSs) under both post-disaster and normal restoration operations. It is assumed that a MMPS contains non-dispatchable distributed generators (DGs), e.g., photovoltaics (PV), as well as dispatchable DGs, e.g., gas turbines and diesel generators. A mixed-integer linear programming model is formulated for coordinating MMPSs and SCUC under both normal and extreme conditions (e.g., natural disasters, cyber and physical attacks). To better characterize the uncertainties in renewable generation and electric load, a deep learning gated recurrent unit model is adopted to forecast the PV power output. The proposed model is tested on the IEEE 69-bus distribution network to validate the effectiveness and merits of MMPSs. Results show that the reliability and resiliency could be enhanced by using MMPSs within the network.

Index Terms—Configuration security, deep learning, resiliency and reliability, mobile marine power sources, security driven configuration management.

NOMENCLATURE

Sets/Indices

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
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<tbody>
<tr>
<td>( l_m, m_n )</td>
<td>Indices of distribution lines</td>
</tr>
<tr>
<td>( D/d )</td>
<td>Set/index of load</td>
</tr>
<tr>
<td>( \Omega^N/n, m, l )</td>
<td>Set/index of bus nodes</td>
</tr>
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<td>( \Omega^S/s )</td>
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<tr>
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<td>Set/index of time</td>
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<td>( \Omega^DG/s /k )</td>
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<td>( \Omega^U/u )</td>
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<td>( \Omega^{DL} )</td>
<td>Set of distribution lines</td>
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Parameters and variables

<table>
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<td>( C_{ks} )</td>
<td>Generation cost of the ( k )th unit in the ( s )th MMPS.</td>
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<tr>
<td>( C_i )</td>
<td>Generation cost of the ( i )th unit.</td>
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<tr>
<td>( C^{E_{snt}}/C^{D_{snt}} )</td>
<td>Entrance/departure cost of ( s )th MMPS to node ( n ) at time ( t ).</td>
</tr>
<tr>
<td>( C^{M_{snt}} )</td>
<td>Sailing cost of ( s )th MMPSs to node ( n ) at time ( t ).</td>
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</table>

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\( F_{mnt} \) | 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. |
| \( I^{L}_{lm} \) | Current of line \( lm \) at time \( t \). |
| \( L^{E}_{snt}/L^{D}_{snt} \) | Entrance/departure status of the \( s \)th MMPS at time \( t \): 1 if MMPSs is connects to node \( n \); otherwise, 0. |
| \( L^{M}_{st} \) | Sailing status of the \( s \)th MMPS at time \( t \): 1 if MMPSs is connects to node \( n \); otherwise, 0. |
| \( L^{sh}_{nt} \) | Load shedding of bus \( n \) at time \( t \). |
| \( L^{mt}_{nt} \) | Status of the \( s \)th MMPS in bus \( n \) at time \( t \): 1 if it is located at bus \( n \); otherwise, it is 0. |
| \( N_h/N_T \) | Total number of customers interrupted/served. |
| \( O_{snt} \) | Number of interruptions. |
| \( P^{G}_{it} \) | Power of the \( i \)th unit at time \( t \). |
| \( P^{L}_{snt} \) | Power of the \( k \)th unit in the \( s \)th MMPS at time \( t \). |
| \( P^{D}_{nt} \) | Load demand at bus \( n \) at time \( t \). |
| \( Q^{L}_{snt} \) | Transmitted reactive power from line \( lm \) at time \( t \). |
| \( R_{i} \) | Ramp up/down rate of units. |
| \( r_{i} \) | The percentage of load for spinning reserve |
| \( S_U, S_D \) | Startup and shutdown costs |
| \( T_s \) | Moving time of the \( s \)th MMPS from mode \( n \) to node \( m \). |
| \( T^{CL}_{nt} \) | Service time of the load in post-disaster restoration at time \( t \). |
| \( T^{on}_{it}, T^{off}_{it} \) | Number of successive on/off hours for unit \( i \) at time \( t \). |
| \( U_T, D_T \) | Minimum up/down time of units |
| \( V_{nt} \) | Voltage of node \( n \) at time \( t \). |
| \( W_{n} \) | Load importance (weight) at bus \( n \). |
| \( W^{snt} \) | The \( s \)th MMPSs waiting status at time \( t \): 1 if it is waiting in bus \( n \); otherwise, it is 0. |
| \( Z, X, R \) | Impedance, Reactance, Resistance |
| \( \gamma \) | Energy to money conversion coefficient |
| \( \theta_{nm} \) | Phase of impedance between bus \( n \) and \( m \). |
| \( \delta_{snt} \) | Bus voltage angle, voltage angle of bus \( n \) at time \( t \). |
| \( \delta_{kst} \) | Status of the \( k \)th unit in the \( s \)th MMPS at time \( t \): 1 if unit is on; otherwise it is 0. |
| \( \Upsilon_{h} \) | Restoration time (minutes) |
I. INTRODUCTION

GRID modernization and demand growth have been increasing the size and complexity of modern power grids. In addition, power outages make the grid more vulnerable to the disproportionately increasing generation units and loads [1]. On the other hand, natural disasters, cyber/physical attacks, and grid contingencies are costly, hardly preventable, and unpredictable, which increases the need of service restoration from reliable and fast energy resources [2].

Natural disasters can cause widespread and severe damages to power grids. Thus, millions of people leave without power for weeks or months. For instance, approximately 2.2 million customers were reported without power, when in 2012 hurricane Sandy hit the USA East Coast [3]. Weather-related power outages occur more frequently in recent years, especially in the coastlines, which cause tremendous economic loss and significant life risks [4]. One of the key requirements for a resilient power grid is the rapid and effective response of electric service restoration, where reliable power supply is greatly dependent on the most recovery activities [5].

Recently, a significant amount of research has been performed to enhance the power system resiliency by using mobile generation units due to their strategic and technical benefits for the grid. For instance, in [6], mobile emergency generation units in the presence of natural disasters were proposed to improve the resiliency of distribution lines. In [7], mobile truck-mounted energy storage systems, as well as electric vehicles, were employed to improve the resiliency of a distribution power grid. The resiliency of distribution power grids was investigated in [8] and [5] by decomposing the power grid into interconnected microgrids and using mobile energy storage systems. Dabbaghjamanesh et al. [9] investigated a technique for mobile renewable energy plants and power grid intentional islanding to increase the power grid resiliency. Lei et al. [10] investigated a resilient scheme for disaster recovery to develop a co-optimization framework for both repair crews and mobile power sources. In [11], mobile distributed energy resources were considered to improve the distribution network resiliency. Power grid resiliency enhancements by considering dynamic line rating constraint and mobile storage were investigated in [12]–[15]. Although different mobile energy plant types were introduced for enhancing the power grid resiliency after disasters, platforms with large capacity mobile energy that can recover and move large loads have not been investigated in the literature.

As one of the key benefits of mobile energy sources, mobile marine power sources (MMPSs) can move quickly to the affected area and connect to the local distribution/transmission lines. In addition, a single MMPS can generate up to 500 MW, which is sufficient to bring electricity for 250,000 people [16]. This large power source could lead to a significant benefit to the grid, such as assisting operations of power grid, enhancing the resiliency of power systems (by rapidly supplying power to areas that are affected by natural disasters), and preventing investments on the infrastructure of power transmission. The capital investment cost of MMPSs’ large upfront has also motivated to be used for several purposes.

Moreover, countries with large islands often have difficulties to deliver power to island regions, because connecting different islands with cables of sub-sea are complex and costly [17]. Furthermore, power lines of islands are separated from grids of the mainland. Furthermore, serving a small size of population is undesirable economically by building local power plants.

The benefits of using MMPSs in operation and planning of power systems are twofold: i) improve the power grid resiliency in the presence of contingencies and natural disasters, and ii) improve the power grid reliability in normal operation. It should be noted that the model has been investigated for the transmission network reliability and resiliency in [18]. Also, a synergistic network approach is developed in [19], where each ships is modeled as a microgrid. It is important to note that the coordination of MMPSs and security-constraint unit commitment (SCUC) is challenging [20]–[22]. This study investigates the effects of MMPSs on power systems economic efficiency, reliability, and resiliency in the period of post-disaster. To better characterize the uncertainties (on MMPSs) in electric loads and renewable generation, an algorithm of deep learning gated recurrent unit (DLGRU) is adopted to predict the power generation of photovoltaic (PV) plants on MMPSs. The main contributions of this paper are summarized as:

- Develop a coordination framework of MMPSs and SCUC in power system operations, by taking into account of the impacts on base station and the transportation cost of MMPSs.
- Integrate MMPSs in power system operations to enhance the power grid reliability and resiliency in the presence of natural disaster or contingency.

The rest of the paper is organized as follows. The overall MMPSs and SCUC coordination framework is formulated in Section II. The adopted deep learning technique for renewable and load forecasting is described in Section III. Simulation results on the IEEE 69-bus distribution network are discussed in Section IV, followed by the conclusion in Section V.

II. MODELS AND MATHEMATICAL FORMULATIONS

A. Objective function

In this study, MMPSs are adopted for (i) improving the resiliency of power grids, in the presence of natural disaster or other contingencies, and (ii) increasing the reliability and economic efficiency of power system operations. Hence, the coordination of MMPSs and SCUC is a multi-objective problem, which seeks to minimize the operation cost, while maximizing the resiliency of the network, as $F(x) = F_2(x) - F_1(x)$.

1) Minimizing the operation cost:

$$
\min F_1(X) = \sum_{n,m \in \Omega^N} \sum_{s \in \Omega^S} \sum_{t \in \Omega^T} [C_{snt}^E I_{snt}^E + C_{snt}^D L_{snt}^D]
+ C_{st}^M L_{st}^M + \sum_{k \in \Omega^{DGM}} \sum_{s \in \Omega^S} \sum_{t \in \Omega^T} [C_{ks}^G P_{kst}^G \delta_{kst}]
+ SU_{kst} + SD_{kst}] + \sum_{i \in \Omega^{DOC}} \sum_{t \in \Omega^T} [C_i F_{it}^G I_{it} + SU_{it} + SD_{it}]
$$

(1)
2) Maximizing the resiliency [5]:

\[
\max F_2(X) = \gamma \times \sum_{n \in N} W_n P_n^{D} r^{CL}_{n,t} \\
- \sum_{t \in T^f} \sum_{i \in \Omega^S} \sum_{k \in \Omega^{DGM}} [P_{it}^G + P_{kt}^G]
\]

(2)

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. Here, the variable \(T^{CL}_{n,t}\) is determined based on the travel time of MMPSs to the load center. The second term in (2) specifies the power generation cost of the network, which includes both DGs and MMPSs. It should be noted that the resiliency of the network can be constrained by the ramp-up and ramp-down rates limits as estimated by (3)-(6), respectively.

\[
P_{it}^{G} \leq \bar{P}_{it}^{G} \leq \bar{P}_{it}^{G} \forall t \in \Omega^T, \forall i \in \Omega^{DG}
\]

(6)

Min up and down time constraints: The generation units are constrained by the minimum up and down time limits given by (7) and (8), respectively.

\[
T_{it}^{ou} \geq UT_t \left( I_{it} - I_{it(t-1)} \right) \forall t \in \Omega^T, \forall i \in \Omega^{DG}
\]

(7)

\[
T_{it}^{uf} \geq DT_t \left( I_{it} - I_{it(t-1)} \right) \forall t \in \Omega^T, \forall i \in \Omega^{DG}
\]

(8)

Spinning reserve constraint: Equation (9) represents the spinning reserve constraint, which is to supply the load demand in case of unexpected load rise or generation fall.

\[
\sum_{i \in \Omega^{DG}} I_{it} \bar{P}_{it}^{G} \geq \bar{P}_t^{D} (1 + r_{\%}) \forall t \in \Omega^T
\]

(9)

Network constraints: The grid operational network limitations are considered as follows.

\[
\sum_{t \in \Omega^T} \left[ P_{mnt}^{L} - R_{mnt} \left( I_{mnt}^{L} \right)^{2} \right] = \sum_{m \in \Omega^{DGM}} P_{mnt}^{L} + P_{it}^{G}
\]

(10)

\[
P_{kt}^{G} = P_{t}^{D} - P_{t}^{sh} \forall t \in \Omega^T, \forall i \in \Omega^{DG}, \forall k \in \Omega^{DGM}
\]

(11)

\[
\sum_{t \in \Omega^T} \left[ Q_{mnt}^{L} - X_{mnt} \left( I_{mnt}^{L} \right)^{2} \right] = \sum_{m \in \Omega^{DGM}} Q_{mnt}^{L} + Q_{it}^{G}
\]

(12)

\[
\sum_{t \in \Omega^T} \left( V_{mnt}^{L} \right)^{2} = \left( P_{mnt}^{L} \right)^{2} + Q_{mnt}^{L} \forall t \in \Omega^T, \forall m \in \Omega^{DL}
\]

(13)

\[
0 \leq I_{mnt}^{L} \leq \frac{1}{2} \left( V_{mnt}^{L} \right)^{2} \forall t \in \Omega^T, \forall m \in \Omega^{DL}
\]

(14)

2) MMPSs constraints: Equations (17)-(30) formulate the MMPSs constraints.

MMPSs moving (sailing) constraints: Equations (17) and (18) ensure that the MMPSs are moving (sailing) or connecting to a node (operating) at any time.

\[
\sum_{s \in \Omega^S} L_{snt}^{M} = 1; \forall s \in \Omega^S, \forall n \in \Omega^N, \forall t \in \Omega^T
\]

(17)

\[
W_{snt} + O_{snt} \geq L_{mnt}^{M} - L_{mnt}^{M} \forall s \in \Omega^S, \forall m \in \Omega^N, \forall t \in \Omega^T
\]

(18)

MMPSs entering/departing constraints: MMPSs entering and depart constraints are defined in (19) and (20), respectively. Furthermore, Equation (21) ensures that the MMPSs can not enter and depart at the same time.

\[
L_{snt}^{D} \geq L_{snt}^{U} \forall s \in \Omega^S, \forall t \in \Omega^T
\]

(19)

\[
L_{snt}^{E} \geq L_{snt}^{U} - L_{snt}^{U} \forall s \in \Omega^S, \forall t \in \Omega^T
\]

(20)

\[
L_{snt}^{E} + L_{snt}^{D} \leq 1 \forall s \in \Omega^S, \forall t \in \Omega^T
\]

(21)
**SAIDI** is the total duration of an interruption for the average post-disaster restoration are defined as follows [26], [27].

\[
L_{snt} = W_{snt} + O_{snt} \quad \forall s \in \Omega^S, \forall n \in \Omega^N, \forall t \in \Omega^T
\]

(22)

\[
O_{snt} \leq L_{snt(t-1)} \quad \forall s \in \Omega^S, \forall n \in \Omega^N, \forall t \in \Omega^T
\]

(23)

**MMPSs sailing time limitations:** MMPSs moving time between two nodes are constrained by (24) and (25).

\[
\sum L_{snt} \leq T_{nm} + (1 - L_{snt})M \\
\quad \forall s \in \Omega^S, \forall mn \in \Omega^N, \forall t \in \Omega^T
\]

(24)

\[
\sum L_{snt} \geq T_{nm} - (1 - L_{snt})M \\
\quad \forall s \in \Omega^S, \forall mn \in \Omega^N, \forall t \in \Omega^T
\]

(25)

3) **MMPSs operation constraints:** MMPSs operation constraints include power generation, ramp up and down, and minimum up and down times, as expressed in (26)-(30).

\[
d_{skt}P_{G_k}^G \leq P_{G_k}^G \leq d_{skt}P_{G_k}^G \quad \forall t \in \Omega^T, \forall k \in \Omega^{DGM}
\]

(26)

\[
P_{skt}^G - P_{sk(t-1)}^G \leq RU_{sk} \quad \forall t \in \Omega^T, \forall k \in \Omega^{DGM}
\]

(27)

\[
P_{skt}^G - P_{sk(t-1)}^G \leq RD_{sk} \quad \forall t \in \Omega^T, \forall k \in \Omega^{DGM}
\]

(28)

\[
T_{skt}^m \geq UT_{sk}(d_{skt} - d_{sk(t-1)}) \quad \forall t \in \Omega^T, \forall k \in \Omega^{DGM}
\]

(29)

\[
T_{skt}^{off} \geq DT_{sk}(d_{sk(t-1)} - d_{skt}) \quad \forall t \in \Omega^T, \forall k \in \Omega^{DGM}
\]

(30)

**C. Reliability Evaluation**

The main reliability indices that are evaluated during the post-disaster restoration are defined as follows [26], [27].

**System Average Interruption Duration Index (SAIDI):** SAIDI is the total duration of an interruption for the average customer during the restoration, which is calculated as:

\[
SAIDI = \frac{\sum \tau_{h}N_{h}}{N_{T}} \quad \forall h \in [t_r, t_{ir}]
\]

(31)

**Customer Average Interruption Duration Index (CAIDI):** CAIDI is the average time to restore service, which is calculated as:

\[
CAIDI = \frac{\sum \tau_{h}N_{h}}{\sum N_{h}} \quad \forall h \in [t_r, t_{ir}]
\]

(32)

**Average Service Availability Index (ASAI):** ASAI is the ratio of the total number of customer hours that service was available during the restoration to the total customer hours demanded, which is calculated as

\[
ASAI = 100 \times \left[1 - \frac{\sum \tau_{h}N_{h}}{N_{T} \times T}\right] \quad \forall h \in [t_r, t_{ir}]
\]

(33)

It should be noted that only one blackout is considered in this study. Hence, other reliability indices, e.g., customer interrupted per interruption index and system average interruption frequency index, are not affected during the post-disaster. The proposed optimization problem is solved by using a heuristic method, known as the collective decision based optimization algorithm (CDOA), which is adopted from [14].

**III. DEEP LEARNING GRU TECHNIQUE**

A number of solar power forecasting methods have been investigated in the literature, and one of the most popular techniques is the recurrent neural network (RNN). The main benefit of RNN over other machine learning techniques is its ability to predict the future of the system based on the past and present information of the system. However, the main issue of the RNN technique is the vanishing or exploding gradient during the training of the network [28]. To solve this issue, several different techniques have been proposed in the literature [29]. Two of the most popular techniques are the long short-term memory (LSTM) and the gated recurrent units (GRU) [29]–[31]. These two techniques can prevent the exploding/vanishing gradient of the RNN by controlling the weights and biases between two cells. Between these two techniques, GRU has shown better performance due to its lower complexity and higher speed of training [32], [33]. To this end, in this paper, we have adopted GRU to generate solar power forecasts (for PV plants on MMPSs) to assist the scheduling of MMPSs.

**A. Gated Recurrent Unit**

GRU was proposed by Cho et al. in 2014 [32]. The data flow in GRU is controlled by several gates, and a block diagram of GRU is presented in Fig. 2.

\[
h_t = (1 - z_t)h_{t-1} + z_t \tilde{h}_t
\]

(34)

where \(z_t\) is an update gate that stores the information of updates of each unit, which is given by,

\[
z_t = \sigma(U_z h_{t-1} + W_z x_t + b_z)
\]

(35)

where \(\sigma\) is a differentiable and smooth activation function. \(U_z, b_z\) and \(W_z\) are the previous activation constant, the bias, and input constants of the update gate (z), respectively. The candidate activation in (34) and Fig. 2 is updated as shown below.

\[
\tilde{h}_t = \tanh(U_r (r_t \odot h_{t-1}) W x_t)
\]

(36)

where \(r_t\) is the reset gate, and \(\odot\) is an element-wise multiplication. Fig. 3 shows the block diagram of the proposed deep learning model.

\[
r_t = \sigma(U_r h_{t-1} + W_r x_t + b_r)
\]

(37)
The solution procedure of the coordination framework of MMPSs and SCUC is explained in Algorithm 1.

**Algorithm 1 Solution procedure**

**Data Definition:** Define the number of MMPSs, number of generators, generator characteristics, MMPSs features, and parameter settings for the optimization problem.

**for time = 1:24 do**

1. Update gate $Z_t$ based on the weights and biases to decide the ratio of input data that can be passed.
2. The reset gate $r_t$ is updated to forget some range of input data.
3. A memory unit $\tilde{h}_t$ is obtained based on the amount of data that is forgotten.
4. From the memory unit $\tilde{h}_t$, update gate $Z_t$, and previous cell output $h_{t-1}$, the next output $h_t$ is selected and applied to the next GRU unit based on the derived equations.

**end**

Solve the MILP optimization problem (1)-(27).

if there is a contingency, physical attacks, or natural disaster then

1. Calculate the total required power for the damaged area
2. Check the status of MMPSs and calculate the distance to the damaged area
3. Sail MMPSs that have available capacity to compensate for the power shortage of the damaged area
4. Solve the optimization problem (1)-(27)
5. Evaluate the index of (2)
6. Go to next step

else

1. Go to next step

end

Calculated the DGs output power, cost functions (1) and (2), and the energy not supplied

**IV. Simulation Results**

In this section, a modified IEEE 69-bus distributed test system is selected to evaluate the benefits of MMPSs. Fig. 4 shows the single line diagram of the modified IEEE 69-bus test system, and it is assumed that four areas are affected by a natural disaster. For instance, Area 1 contains red bus, while Area 4 contains red, blue, green, and pink buses. The total load demand in each affected area is shown in Fig. 5. Fig. 6 depicts the load demand at each affected bus individually (red, blue, green, and pink). Furthermore, the characteristics of dispatchable generation (DG) units and MMPSs are summarized in Table I. Table II shows power forecasts of the PV system which is located on MMPS, by using the GRU model. The forecasting mean square error (MSE) is 0.0027 [p.u.], indicating the high-performance of the GRU technique.

It is assumed that the four areas are affected by a natural disaster, as small (Area 1), medium (Area 2), and large (Areas 3 and 4) portions of the grid. Five different cases (i.e., normal operation case and Areas 1-4 damaged cases) are investigated and compared as follows.
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is $124,684.15.

The total operation cost of this case are committed with their maximum capacity; that means, the grid. It is shown that the cheapest units (MMPSs 1 and 2) power of the DG and MMPSs under the normal condition of the network has been enhanced by using MMPSs.

<table>
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<tr>
<th>Type</th>
<th>$\delta_i^{\text{U}}/P^{\text{UT}_i}$ (KW)</th>
<th>$U_{\text{T}<em>i}/D</em>{\text{T}_i}$ (h)</th>
<th>$C_{\text{H}/C_{\text{SH}}}$ ($)</th>
<th>$C_{\text{SM}}$ ($)</th>
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<td>3/3</td>
<td>-</td>
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<td>1/1</td>
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<td>MMPS2</td>
<td>2.72</td>
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TABLE II

**HOURLY PV POWER FORECASTING**

<table>
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<tr>
<th>Time (hour)</th>
<th>Actual Data (kW)</th>
<th>Forecasted Data (kW)</th>
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<tr>
<td>1-8</td>
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**Case 1 - Normal Operation Case:** In this case, the network operates under the normal condition, i.e., the network is within the time interval $[0, t_e]$ (refer to Fig. 1). Fig. 7 shows the output power of the DG and MMPSs under the normal condition of the grid. It is shown that the cheapest units (MMPSs 1 and 2) are committed with their maximum capacity; that means, the output power of the generation units is purely based on the economic consideration. The total operation cost of this case is $124,684.15.

**Fig. 7. Generation units output power in normal condition**

**Case 2 - Area 1 Damaged:** In this case, only Area 1 of the grid is affected and disconnected from the main grid due to the natural disaster, which is shown in Fig. 4 as the red bus/area. In this case, MMPS 1, the closest MMPS to the affected area, is sailed to compensate for the shortage of power. Fig. 8 shows the output power of the generation units for this case. It is shown that the MMPS 1 is OFF for the first three hours, when it is sailing to the affected area; and it is ON after sailing and entering the affected area. Moreover, MMPS 2 is committed with its maximum capacity for the entire horizon. The total operation cost of the grid in Case 2 is $151,646.22, which is increased in comparison to Case 1 due to sailing, entering, and departing costs of the MMPS 1. It should be noted that all of the loads have been satisfied after 3 hours, and the resilience of the grid has been enhanced by using MMPSs.

**Fig. 8. Generation units output power in Area 1**

**Case 3 - Area 2 Damaged:** In this case, more buses/branches of the grid are affected when Area 2 is damaged by the natural disaster as shown in Fig. 4. According to Figs. 6 and 7, both MMPSs 1 and 2 should sail to Area 2 to compensate for the shortage of power. Fig. 9 depicts the generation units output power of this case. It is shown that MMPSs 1 and 2 are connected to Area 2 after three and four hours, respectively. It should be noted that MMPS 1 is connected sooner than MMPS 2 due to its faster speed and shorter distance to the damaged grid. Though both MMPSs 1 and 2 are connected to the area with their maximum capacity to help the service restoration, the two MMPSs’ total capacity is still not enough to compensate for the load demand of Area 2. The total operational cost of Case 3 is $151,646.22.

**Fig. 9. Generation units output power in Area 2**

**Case 4 - Area 3 Damaged:** When Area 3 is damaged, the affected area is not fully connected. Based on the load demand in Fig. 6, the load of the left part of the affected area (green bus) is smaller than that of the right part (red plus blue buses). Hence, the larger capacity MMPSs, i.e., MMPSs 1 and 2, are sailed and connected to the higher demand area to compensate for more power shortage. Also, MMPS 1 is sailed and connected to the smaller grid (green bus). Fig. 10 displays the optimal output power of the generation units. In comparison with the previous Area 2 case, the output power of the main DG has significantly been reduced, due to less demand in the main grid. Also, similar to the Area 2 case, MMPS 2 is committed with its maximum capacity once connected. However, unlike the previous case, MMPS 1 is only committed with approximately
increased. However, the total cost has been decreased as less load is satisfied. The loss of load is quantified by the energy not supplied (ENS) reliability index, which is presented in Table III. It is observed that by increasing the size of the damaged area, the ENS value is increased. Also, according to the results of Table III, compared to the normal condition and Area 1 damaged case, the Area 2 damaged case has a higher generation cost, due to sailing both MMPSs 1 and 2 to compensate for the shortage of power, which can increase the total operation cost. Also, compared to Area 3 and Area 4 damaged cases, the Area 2 damaged case has a higher operation cost, as well as less load shedding; that means higher generation units participate in the network.

Fig. 12 depicts the energy supplied percentage in the post-disaster period \([t_r, t_{r'}]\). It is observed that the ENS of the system is increased, by expanding the damage. However, the system can still supply a significant portion of the loads by utilizing high-capacity MMPSs.

Table IV shows the daily reliability indices of the network in the post-disaster restoration period with and without considering MMPSs. Based on this table, by using the high-capacity MMPSs in the post-disaster period, the power grid reliability has been significantly improved. For instance, in Area 1, by using the proposed MMPS model, the SAIDI reliability index has been improved by 87%. However, by increasing the size of the affected area, this improvement has been decreased due to the lack of efficient power sources.

**TABLE IV**

<table>
<thead>
<tr>
<th>Considering MMPSs</th>
<th>Area</th>
<th>SAIDI (minutes)</th>
<th>CAIDI (# of customers)</th>
<th>ASAI (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>Area 1</td>
<td>17.3</td>
<td>180</td>
<td>98.7</td>
</tr>
<tr>
<td>No</td>
<td>Area 1</td>
<td>138.8</td>
<td>1440</td>
<td>90.3</td>
</tr>
<tr>
<td>Yes</td>
<td>Area 2</td>
<td>51</td>
<td>268</td>
<td>96.4</td>
</tr>
<tr>
<td>No</td>
<td>Area 2</td>
<td>273.4</td>
<td>1440</td>
<td>81.01</td>
</tr>
<tr>
<td>Yes</td>
<td>Area 3</td>
<td>84.2</td>
<td>302</td>
<td>94.14</td>
</tr>
<tr>
<td>No</td>
<td>Area 3</td>
<td>400.5</td>
<td>1440</td>
<td>72.18</td>
</tr>
<tr>
<td>Yes</td>
<td>Area 4</td>
<td>122.3</td>
<td>281</td>
<td>91.50</td>
</tr>
<tr>
<td>No</td>
<td>Area 4</td>
<td>626.2</td>
<td>1440</td>
<td>56.51</td>
</tr>
</tbody>
</table>

One of the main objectives in the post-disaster network resiliency is to increase the system performance in the interval of \([t_r, t_{r'}]\) of the resiliency curve. Fig. 13 shows the system performance of all areas during the normal and post-disaster periods. Based on the figure, the resiliency of the network has been increased significantly by considering MMPSs. For
instance, in the Area 1 damaged case, the system is returned almost to the normal operation after 3 hours.

V. CONCLUSION

This paper proposed a new approach for utilizing large capacity mobile marine power sources to enhance the reliability and resiliency of distribution power grids in the occurrence of incidents such as natural disasters, contingencies, and cyber/physical attacks. The proposed method was examined on a modified IEEE 69-bus test system. Simulation results indicated that a close cooperation between MMPSs and the distribution grid can significantly enhance the reliability of the power system under both normal and extreme conditions. Utilizing the MMPSs in power grids could compensate for a large amount of loss of power and enhance the resiliency of the network. Comparing with other mobile energy sources such as mobile battery storage units, MMPSs have larger capacities and can be sailed and connected to the grid more quickly. This benefit can mitigate the energy not supplied. Also, using MMPSs in the post-disaster restoration would be more interesting from the national level perspective, since oceans cover more than 70% of the Earth’s surface and are connected. However, potential impacts of regulations and public policy on the development of the integrated MMPSs should be investigated before formal adoption. Potential future work will (i) consider MMPS as a microgrid instead of a single generator, (ii) optimize the path schedule of MMPSs, and (iii) optimize the connection points of MMPSs to the affected grid.

REFERENCES

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