ABSTRACT  Military bases, communities, and university-scale microgrids are being implemented to serve critical loads of high priority. Remote switch scheduling and distributed energy resources (DERs) operation strategies for post-disaster service restoration have been explored in previous literature. Flexible buildings offer the central microgrid management system an opportunity to ensure available energy is directed to critical loads. This work presents a novel bi-level optimal sequence of operations for managing the controllable devices in small-scale microgrids to serve loads based on a priority scheme in campus-scale microgrids. This study introduces a technique for step-by-step restoration of customers’ granular loads. After and during an outage scenario, the facilities’ internal loads are energized in sequence according to their customer and local criticality levels, as well as the amount of energy available from the bulk system and DERs. The proposed methodology is formulated as a mixed-integer linear programming (MILP) model and adapts to various operating conditions. The proposed method is validated by performing controller hardware-in-the-loop (CHIL) case studies on the Banshee microgrid benchmark model on a real-time simulator.

INDEX TERMS  Building management systems, demand side management, hardware-in-the-loop simulation, microgrids, power system restoration.
I. INTRODUCTION

Every year the number of disaster events increases globally, primarily attributed to climate change. Natural disasters can be in several forms, such as landslides, hurricanes, tornados, wildfires, etc. [1], [2]. In general, natural disasters can be a potential threat to the electrical power system. However, hurricanes are the major cause of damage and interruption of electrical energy supply for long durations, which affect economic prosperity, national security, public health, and safety [3]. Most disaster outages result from power delivery support structures damage and failure, which relates to distribution towers and poles [4]. Hence, the resilience of power systems against hurricanes is critical to ensure their rapid recovery.

Electrical power systems have been traditionally designed to be reliable during typical contingencies. However, they are now strictly required to be resilient against the high-impact and low-probable events caused by extreme weather and cyber-physical events [5]. After a natural disaster, the objective of the system operators is to restore the critical loads as a priority and reduce the total number of de-energized customers if it is not possible to restore all the loads. During the outage period, consumers rely on backup systems to maintain the power supply to the critical loads. Although, most of these backup systems present a limited time/power capacity and high operational cost.

The general concept of resiliency is the ability of a system to anticipate and withstand external shocks, bounce back to its pre-shock state as quickly as possible, and adapt to be better prepared for future scenarios. These concepts become more critical from the power systems scope under catastrophic events [6], [7], [8]. Power systems resilience modeling must consider the fragility of individual components and the whole system interaction based on the lack of available resources. Each device has a failure probability that relies on its historical data and real-time usage level.

Critical consumers are not entirely composed of critical loads but a mix of critical and non-critical devices. A grid-friendly demand response (DR) controller can efficiently manage the building level loads based on their criticality rank and the available power generation during the outage period [9]. Advanced Building Energy Management Systems (BEMS) technics allow a power consumption reduction without compromising comfort [10], as well as support and ensure the grid operation stability and safety as an ancillary service [11], [12]. Residential facilities are compounded by binary and flexible controllable loads, which both can be optimally managed to achieve the facility’s electrical goal based on weather, grid, and consumer constraints [13], [14]. Furthermore, once their communication with the distribution network operator (DNO) is reliably and coordinately established, these distributed resources can strongly contribute to grid resiliency [15], [16].

The exponentially increasing number of Distributed Generation (DG) and Distributed Energy Resources (DERs)
integrated into the distribution systems have led to a decentralized power system. DERs can improve the consumers’ energy supply resiliency [17, 18]. With hierarchical optimization energy management methods, microgrid communities can be a solution to restore critical loads on distribution feeders after a major disaster [19]. Medium and low voltage level DERs can operate as temporary power resources for critical loads located in different regions on the feeder. To make this feasible, the microgrids’ stability limits (frequency and voltage), along with DG dynamic and steady-state constraints, must be satisfied during the critical load restoration process [20].

A. LITERATURE REVIEW
The advancement of microgrid controls has enabled efficient solutions to coordinate distributed generation and demand response. Energy storage systems (ESS) integrated with renewable energy resources, such as PV, wind, and hydrogen can improve customer reliability of active distribution systems [21]. Microgrids have shown their selves as useful capabilities in modern distribution systems. In [22], a stochastic bi-level problem is proposed to enable the DNO coordination of networked microgrids. Microgrids are considered distinct entities with their individual objectives and both dispatchable and non-dispatchable generations. The results show that coordination between multiple microgrids can be beneficial to the DNO and reduce their operating costs. Besides that, integrating microgrids into the distribution system can improve the levels of ancillary service on the grid. Research studies have shown that microgrids have the potential to provide ancillary services and support the regulation of voltage and frequency levels in grid-connected mode. On islanded mode, besides controlling voltage and frequency, the system can still ensure reliable supply to its critical loads [23].

Most of the challenges related to microgrid integration into distribution systems are related to DR management [24]. Demand response is a useful tool to support the grid operation under outage scenarios, as well as provide financial benefits to the customers. However, DR is a crucial technique to make the operation of the microgrid feasible [25]. An efficient must be able to manage customer loads to respect and respect the customers’ constraints according to their criticality [26]. The objectives of this paper are to (1) develop a framework to identify the appropriate decentralized energy options for demand and supply matching within a community and (2) determine which of these options can suitably plug the existing demand and supply gap at varying levels of grid unavailability.

B. RESEARCH GAP
Several microgrid controllers have been discussed in the literature that works with the main grid and benefits both customers and DNO. In addition, numerous papers have also discussed the possibility of BEMS solutions that can minimize the customers’ impact under DR periods, but there is still a research gap on networked microgrids to meet resiliency objectives.

There is a current lack of integrated MGMS and BEMS solution for high-critically facilities that considers buildings’ flexibility for load shedding. Most research has approached demand response without considering the physical limitations of real buildings. Critical facilities have a high level of non-controllable loads, which are even more essential for site operation.

C. CONTRIBUTION AND PAPER ORGANIZATION
The current study proposes a complete integrated MGMS and BEMS solution. The novel operation strategy focuses on controlling DERs, flexible building loads, and remote switches to maintain or drop the power supply to critical loads based on a priority scheme. With a multi-time step optimization technique in a hierarchical scheme, the strategy enables the entire or partial restoration of the distribution system loads. All levels work interactively in real-time to make decisions based on measurements and grid conditions. The proposed service restoration approach seeks to restore the system’s loads by evaluating the available power consumption range. Upper control levels observe the network state to improve its reliability and resiliency, as lower levels control optimized loads and DERs to respect higher-hierarchical commands. Each consumer can optimally manage which devices are critical for its current operation with this range.

The main contribution of this work is to address the current research gaps related to the lack of integrated microgrids and building solutions to meet resiliency objectives.

The primary contribution of the paper is:

- The implementation of the granular load controls and their integration with other agents inside the multiagent platform.
- Networking building DERs allow for flexible coordination among distributed devices for networked microgrids. The proposed integrated solution will include BMS using VOLTTRON to enable priority control of loads.
- Networked buildings’ load management will enable serving more critical loads.
- Using several distributed control and sensing platforms, VOLTTRON for integrating buildings will solve solves communication bottlenecks.
- VOLTTRON enables high-resolution aggregated sensing at the building levels.
- Interoperability issue mitigated by using several building-level protocols/drivers supported in VOLTTRON.

The remaining sections of this paper are organized as follows. Section II clarifies the resilient-oriented building operations. Section III presents some of the problem formulations for emergency mode operation. Section IV describes the Bansee Microgrid testbed network. In section V, the case scenarios are discussed, and the results are presented. Finally, Section VI provides the conclusion of the present study.
II. RESILIENT-ORIENTED BUILDING OPERATIONS

Network reconfiguration is a well-established technique to minimize losses, manage congestion, mitigate voltage violations, increase DER hosting capacity in distribution networks, and redirect power flow from one feeder to the other during atypical operational scenarios. Circuit breakers, line switches, and tie switches at different locations in a distribution system enable the system’s reconfiguration to new topologies [27], [28].

The novelty of this paper is the disintegrated control of distributed DERs and flexible building loads, categorized into several priority groups. Based on the service’s criticality, each building has a priority rank. The flexible building concept enables an internal management system to control the facility's loads and efficiently prioritize consumption during outage scenarios. According to the load type, the internal load consumption can be completely or partially reduced by the building management system (BEMS)/home management system (HMS) after receiving an external command from the microgrid management system (MGMS). The test setup includes the CHIL connection between Generic Algebraic Modeling System (GAMS) based optimization platform, the python-based open-source VOLTTRON platform, and the real-time simulator. The GAMS solver running on the industry-hardened PC allows the high-level modeling of generic mathematical optimization problems at the base microgrid level. The VOLTTRON platform, running on Raspberry Pi, deploys two-level BEMS control architecture. The secondary level BEMS provides centralized control decisions, while the primary level BEMS implements the localized control commands. The exchange of data between the GAMS and the secondary level BEMS is facilitated using an intermediate MODBUS server, and the communication between the BEMS is possible using the in-built intercommunication feature of the VOLTTRON platform. Figure 1 shows the general control hierarchy and how the BEMS/HMS interacts with the internal loads based on an MGMS requirement to have a grid-level response.

The MGMS central management system is located at a tertiary level and is responsible for managing the dispersed generation and controlling the switches at the same level. The overall objective of the primary and secondary level BEMS/HMS is to coordinate and control the power consumption of flexible internal loads to provide demand response capability. The granular level building optimization algorithm deployed on the GAMS platform provides the dispatch command that prioritizes always serving the critical loads. Based on the dispatch signal, the two-level BEMS controller will schedule/operate different granular loads within the building model to ensure the resiliency of the dispersed critical loads. During regular operation, the BEMS/HMS is based on price signals and time of the day periods; however, during outage moments, the management system prioritizes the flexible loads based on the available power collectively. The proposed building structure considers six different groups of flexible and controllable loads:

- Group 1: Electric vehicle charging equipment (5%).
- Group 2: Plug & process loads, including servers, controllers, and other non-critical loads (20%).
- Group 3: Thermostat-controlled HVAC systems (40%).
- Group 4: Smart lighting loads (20%).
- Group 5: Miscellaneous critical HVAC systems (10%).
- Group 6: Most critical and essential devices (5%).

Demand response approaches rely on reliable and stable bi-directional communication between BEMS and electrical sensors and controllers. The Internet of Things (IoT) has been widely applied to energy systems like the Internet of Energy (IoE), which encompasses the communication network responsible for linking central controllers and intelligent, flexible devices for data flow, commands, and cloud storage [29]. With stable communication, building flexible loads can be commanded by a high-level controller capable of receiving and compiling information from a granular level to define the best group scenario [30]. The granular level operation is based on the assigned weighting factor of each device, which is defined in each BEMS/HMS priority control algorithm and can vary during the operation period. Each building has its composition of loads and the weighting factor for each type. Different facilities can have other priority ranks, such as a lumped load, and the load within each building can be grouped based on their criticality.

III. MGMS PROBLEM FORMULATION

A multi-stage controller that the MGMS dictate at the central level and BEMS at the building level is formulated in this paper to schedule/operate the various devices in the Banshee microgrid system to ensure the resiliency of the dispersed critical loads.

A. OBJECTIVE FUNCTIONS

The optimization is performed to minimize the load shedding by scheduling the various generation sources and switching operations available in the microgrid system. When a general blackout or partial power outage occurs in a microgrid, the most critical concern is maintaining service to the priority loads and the remaining customers affected. The objective...
function is defined for the entire considered time horizon. The optimization problem can be formulated by either (1) or (2), subject to constraints in (5)-(39).

\[
\min \sum_{t \in \Omega_T} \sum_{i \in \Omega_L} \left( \phi_{i,t}^L \cdot p_{i,t}^L - u_{i,t}^G \cdot p_{i,t}^G - u_{i,t}^{ESS} \cdot p_{i,t}^{ESS} \right) \quad (1)
\]

\[
\min \sum_{t \in \Omega_T} \sum_{i \in \Omega_L} \sum_{h \in \Omega_B} \sum_{l \in \Omega_P} \left( \phi_{i,h,l,t}^L \cdot p_{i,h,l,t}^L - u_{i,h,l,t}^G \cdot p_{i,h,l,t}^G - u_{i,h,l,t}^{ESS} \cdot p_{i,h,l,t}^{ESS} \right) \quad (2)
\]

In (1), the buildings are lumped as aggregated loads, with priorities given to the building loads as a whole. A relay-operated circuit breaker is capable of disconnecting the building in the microgrid. The additional power generation factors will ensure that the maximum generation is available for each step, which is done by multiplying the power generation output variable with a time-varying fuel-generator and battery weight factors (\(I_{i,t}^G\) and \(I_{i,t}^{ESS}\)), where the weight for the current time step will be higher than the next time step. This will ensure that the power output is maximized for each step until the generator runs out of fuel or a battery completely discharges. If the goal is to conserve the generation and battery, the weight factors \(I_{i,t}^G\) and \(I_{i,t}^{ESS}\), will be set to zero, while the optimization problem will minimize as much load shedding as possible for the estimated outage time frame. The conservation of energy is critical during long-term outages due to natural disasters with limited fuel availability.

In (2), the buildings are considered to be disintegrated into several load groups with different criticality levels. These loads could be homogeneous or heterogeneous. Assigning weights to the load groups will be performed through an Intelligent Load Control (ILC) algorithm using an analytic hierarchy process as presented in [11]. AHP is a popular and widely used method for the multi-criteria decision-making process, executed in two steps:

1. Step 1: Determine the relative weights of the decision criteria.
2. Step 2: Determine the relative priorities of alternatives (end-use loads to curtail).

The AHP process prioritizes the load groups for curtailment by prioritizing load groups based on a priority vector. The AHP consists of four steps:

1. Step 1: Pairwise comparison of selected criteria.
2. Step 2: Formulation of a priority criteria vector.
3. Step 3: Consistency checking.
4. Step 4: Aggregation of final priorities.

The AHP calculates the eigenvector, \(\vec{v}\), between two criteria under evaluation. The judgment matrix, \(A\) (\(\vec{v}\)) can be calculated by multiplying the eigenvalue, \(\lambda\), corresponding to the eigenvector as shown in Eq. (3).

\[
A(\vec{v}) = \lambda \cdot \vec{v} \quad (3)
\]

In pairwise comparison, the building load groups are compared to each other based on relative importance. An eigenvector created a scale of (1-9), which is assigned for the pairwise building comparison. For example, if \(\lambda_\alpha\) (building \(\alpha\)) is more important than \(\lambda_\beta\) (building \(\beta\)), it is assigned a value of 9, and \(\lambda_\beta\) must be less important than \(\lambda_\alpha\) assigning a value of 1. From the eigenvectors a \(N_L \times N_L\) matrix \(A\) is formed. The judgment matrix, \(A\) is normalized by multiplying the inverse of each column summation (W). The normalized judgment matrix \((A_{\text{normal}})\) identifies the weights of each criterion. After normalizing, the principal eigenvector \((A_p)\) can be calculated by averaging across the rows, which determines the building priority as ratios. \(A_p\) is a \(1 \times N_L\) matrix. The alternative decision matrix, \(B\), is an \(N_L \times N_B\) real matrix where numerical values (1-9) are assigned to the relative importance of load groups in each building. As an example, if the server group loads, \(x\) in building \(a\) (\(b_{ax}\)) is more critical than the server group loads, \(x\) in building \(b\) (\(b_{bx}\)), then \(b_{ax} > b_{bx}\). The matrix \(B\) is normalized by multiplying the inverse of each row summation of \(B\). The decision priority matrix, \(\vartheta\), can be calculated by multiplying each element of the normalized alternative decision matrix \((B_{\text{normal}})\).

\[
\vartheta = A_p \cdot B_{\text{normal}} \quad (4)
\]

where, \(\vartheta\) is a \(N_L \times N_B\) matrix, used to determine the weight factors for the different load groups in the buildings. \(\phi_{i,h,l,t}^L\) is the element in \(i^{th}\) row and \(h^{th}\) column of the matrix \(\vartheta\). \(\phi_{i,h,l,t}^L\) determines the weight factor for the \(h^{th}\) load group in the building connected to \(i^{th}\) bus. Based on the normalized matrix, \(\vartheta\) the sum of all elements in the matrix should equal 1, otherwise represented as \(\sum_{i,h,l} \phi_{i,h,l,t}^L = 1\) [31].

The problem is formulated as a MILP model that can be effectively solved by commercial solvers. To restore a system from a local outage state, the initial condition constraints should be adequately configured to incorporate the information on the energization status and availability of each component.

B. INEQUALITY AND EQUALITY CONSTRAINTS

In this sub-section, the equality and inequality constraints for optimizing the microgrid are discussed. The main control variables which contribute to the operation performance are tie-switches and DERs.

1) MICROGRID SYSTEM MODEL

The power-flow equations are inherently nonlinear due to the loads modeled as constant P-Q, which requires several iterations to find the solution. By modifying the load models, the power-flow problem equations for a microgrid system can be transformed into a linear system model. Simplified DistFlow equations have been widely used for radial distribution systems based on the assumption that the nonlinear terms in the DistFlow equations are much smaller than the linear terms and can be ignored [32]. The following equations extend the linear DistFlow equations using binary variables:

\[
V_{j,t} - V_{i,t} + \frac{R_{ij}^l \cdot P_{ij,t}^l + X_{ij}^l \cdot Q_{ij,t}^l}{V_0} \leq \left(1 - u_{ij,t}\right) \cdot M \quad (5)
\]

\[\forall (i,j) \in \Omega_N, t \in \Omega_T\]
inverter as given by (12) and (13). The active power is limited by the apparent power limit of the
voltages and achieve better performance. With some modifications, these power flow models can be used in the proposed method to handle different system topologies and achieve better performance.

2) VOLTAGE CONSTRAINT
Voltage measurements must be estimated during each optimization run to check for voltage violations whenever they occur. The voltages must be maintained within the limits \(V_{min} \leq V_{i,t} \leq V_{max}\). Typically, \(V_{min}\) is 0.95 p.u. and \(V_{max}\) is 1.05 p.u.

\[
V_{min} < V_{i,t} < V_{max}, \quad \forall i \in \Omega_N, t \in \Omega_T
\]  

(11)

3) INTERMITTENT ACTIVE AND REACTIVE POWER CONTROL
The active power is limited by the apparent power limit of the inverter as given by (12) and (13).

\[
P^e_i = P_{MPPT} - P_{cart} \quad \forall i \in \Omega_v
\]

(12)

\[
0 < P^e_i < S_{Invmax} \quad \forall i \in \Omega_v
\]

(13)

The reactive power capability is determined by the present active power and the power factor limit at each bus given by (14) and (15).III-B4.

\[
-Q_{Invcap} < Q^e_i < Q_{Invcap} \quad \forall i \in \Omega_v
\]

(14)

\[
Q_{Invcap}^r = \min \left\{ \sqrt{(S_{Invmax}^r)^2 - (P_{MPPT,v})^2} \right\} \quad \forall i \in \Omega_v
\]

(15)

4) BATTERY CONSTRAINTS
The \(P_{ESS}\) could either be a discharging or charging process controlled by the decisions \(u_{i,t}^{ESSD}\) for discharging or \(u_{i,t}^{ESSC}\) for charging, as represented by (16)(6) and (17)(6).

\[
P_{i,t}^{ESS} = \left( u_{i,t}^{ESSD} \cdot P_{ESSD}^{max} \right) / \left( 60 \cdot ESS \right) - u_{i,t}^{ESSC} \cdot P_{ESSC}^{max} / 60 \quad \forall i \in \Omega_e, t \in \Omega_T
\]

(16)

\[
0 < u_{i,t}^{ESSD} + u_{i,t}^{ESSC} \leq 1 \quad \forall i \in \Omega_e, t \in \Omega_T
\]

(17)

The state of charge (SoC) of each battery connected to a bus at any time \(t\), depends on its SoC at the previous time step and its discharging/charging rate given by (18).

\[
SoC_{i,t}^{ESS} = SoC_{i,t-\Delta t}^{ESS} - \frac{E_{act}^{Bat,i}}{E_{Bat,i}^{max}} \quad \forall i \in \Omega_e, t \in \Omega_T
\]

(18)

The \(SoC_{i,t}^{ESS} = SoC_{i,t-\Delta t}^{ESS}\) and \(SoC_{i,t}^{ESS}\) are the previous step and current SoCs of the ESS \(e\) at time \(t - \Delta t\) and \(t\), respectively. \(SoC_{i,t}^{ESS}\) is limited by \(SoC_{i,t}^{min}\) and \(SoC_{i,t}^{max}\) as presented in (19).

\[
SoC_{i,t}^{min} < SoC_{i,t}^{ESS} < SoC_{i,t}^{max} \quad \forall i \in \Omega_e, t \in \Omega_T
\]

(19)

ESS can deliver exceptional flexibility for DSR because of its capability of generating and absorbing power strategically. A critical concern for ESS operation is to maintain the residual energy, or SoC, during the charging and discharging process. In this paper, it is assumed that both active and reactive power can be dispatched for an ESS and that the SoC is not affected by dispatching reactive power. For each ESS \(i \in \Omega_e\) at each bus, \(i\) step \(t \in \Omega_T\), the operational constraints can be formulated by (20)-(22).

\[
\begin{align*}
\begin{cases}
ESSD \cdot P_{i,t}^{min} & < P_{i,t}^{ESSD} < ESSD \cdot P_{i,t}^{max} \\
ESSC \cdot P_{i,t}^{min} & < P_{i,t}^{ESSC} < ESSC \cdot P_{i,t}^{max}
\end{cases}
\forall i \in \Omega_e, t \in \Omega_T
\end{align*}
\]

(20)

\[
\begin{align*}
\begin{cases}
ESSD \cdot E_{i,t}^{Bat,i} & < E_{i,t}^{ESSD} < ESSD \cdot E_{i,t}^{max} \\
ESSC \cdot E_{i,t}^{Bat,i} & < E_{i,t}^{ESSC} < ESSC \cdot E_{i,t}^{max}
\end{cases}
\forall i \in \Omega_e, t \in \Omega_T
\end{align*}
\]

(21)

\[
E_{i,t}^{Bat,i} = E_{i,t}^{act} < E_{i,t}^{max} \quad \forall i \in \Omega_e, t \in \Omega_T
\]

(22)

5) GENERATION-RESOURCE CONSTRAINT
The amount of energy that DDGs can provide in an isolated microgrid is limited by the available fuel reserves given by (23).

\[
\sum_{i \in \Omega_d} \sum_{i \in \Omega_d} \Delta t \cdot P_{DDG,i,t} \leq E_{DDG,i}^{act}
\]

(23)

The left-hand side of (21) is the total amount of energy served by the DDG from the start of the emergency condition. On the right-hand side, \(E_{DDG,i}^{act}\) is the upper limit on the amount of energy that DDGs can provide during emergency conditions. For convenience, these energy terms are all measured by equivalent electric energy in kWh.
The conversion rate from the amount of fuel to electric energy varies with machines and should be determined case by case. As an example, the diesel generator generating 1-kWh electric energy consumes about 0.086 gallons of diesel [20].

6) CONNECTIVITY AND SEQUENCING CONSTRAINTS

The connectivity constraints are defined to ensure connectivity among energized components at each time step. For example, an energized network at a particular time step should satisfy \( s^N_{i,t} = 1 \) for all the energized nodes and \( s^N_{i,t} = 0 \) for all the de-energized nodes. Similar constraints apply to the binary variables for branches, loads, and DGs. Connectivity constraints among the binary variables should be satisfied based on the rules presented by (24)-(28).

\[
\begin{align*}
    u^l_{i,j,t} &\leq s^N_{i,t} \in \Omega_N, \quad (i,j) \in \Omega_l, \ t \in \Omega_T \quad (24) \\
    u^l_{i,j,t} &\leq s^N_{i,t} \in \Omega_N, \quad (i,j) \in \Omega_l, \ t \in \Omega_T \quad (25) \\
    u^G_{i,j,t} &= s^N_{i,t} = s^N_{j,t} \in \Omega_N, \quad (i,j) \in \Omega_l, \ t \in \Omega_T \quad (26) \\
    u^l_{i,j,t} &= s^N_{i,t}, \quad \forall i \in \Omega_N, \ t \in \Omega_T \quad (27) \\
    u^l_{i,j,t} &= s^N_{i,t}, \quad \forall i \in \Omega_N, \ t \in \Omega_T \quad (28)
\end{align*}
\]

Equations (25)-(28) satisfy the condition that the switchable line can only be energized when both end nodes are energized, a non-switchable line and both its end nodes will be energized simultaneously, and a node will be energized if it connects to a black-start DG or a substation node, a switchable load can only be energized when it connects to an energized node, and a non-switchable load will be energized immediately, when it connects to an energized node, respectively.

7) TOPOLOGICAL CONSTRAINTS

To ensure that the energized system is operated in the tree topology during the restoration process, the energized system at each time step should be a connected graph and satisfy (29).

\[
\sum_{i \in \Omega_N} s^N_{i} - \sum_{(i,j) \in \Omega_l} u^l_{i,j} = \sum_{i \in \Omega_N} u^G_{i}, \forall t \in \Omega_T \quad (29)
\]

In this paper, there is one substation node, and several black-start DERs are assumed to exist in the system. Constraint (27) can be used for systems with multiple substation nodes and black-start DERs to form multiple isolated sub-systems. Note the connectivity and sequencing constraints guarantee that the energized network at each time step is a connected graph.

8) LOAD CONTROL CONSTRAINTS

The building load shedding control is made hierarchically on the two levels, the MGMS, and the BEMS layers. At a base microgrid level, the MGMS is responsible for balancing the available generation resources with the building loads according to their priority rankings. In the proposed work, at the building level, either the entire building can be shut down by opening one circuit breaker, or the buildings can be partially shed by assigning loads into different groups of priorities, which are categorized according to the criticality levels. The building demand response is responsible for managing and maintaining energized as many groups of loads as possible according to the power consumption limit set by the MGMS. The load shedding is made according to the amount of energy consumption that the building is required to reduce. The \( h \) group of loads is dropped from the less to the most critical one, and their drop is made until the requested power consumption reduction is achieved. If the entire building load is shed, then the constraint in (30) must be respected.

\[
\begin{align*}
0 &\leq PLS^L_{i,t} \leq u^f_i \cdot P^f_{i,t} \quad \forall i \in \Omega_L \\
0 &\leq QLS^L_{i,t} \leq u^f_i \cdot Q^f_{i,t} \quad \forall i \in \Omega_L \quad (30)
\end{align*}
\]

Considering the disintegration of loads into different groups, the load groups can be shed by (31):

\[
\begin{align*}
&PLS^L_{i,h,t} = \sum_{h \in \Omega_h} PLS_{i,h,t} \quad \forall i \in \Omega_L, \ h \in \Omega_h, \ t \in \Omega_T \\
&QLS^L_{i,h,t} = \sum_{h \in \Omega_h} QLS_{i,h,t} \quad \forall i \in \Omega_L, \ h \in \Omega_h, \ t \in \Omega_T \\
0 &\leq PLS^L_{i,h,t} \leq x^L_{i,h,t} \cdot P_{i,t} \quad \forall i \in \Omega_L, \ h \in \Omega_h, \ t \in \Omega_T \\
0 &\leq QLS^L_{i,h,t} \leq x^L_{i,h,t} \cdot Q_{i,t} \quad \forall i \in \Omega_L, \ h \in \Omega_h, \ t \in \Omega_T \\
\sum_{h \in \Omega_h} u^f_i \cdot h < 1 &\quad \forall i \in \Omega_L, \ h \in \Omega_h, \ t \in \Omega_T
\end{align*}
\]

where \( x^L_{i,h,t} \) is the controllable factor of the \( h \)th group load as a percentage of the entire building, and the sum is less than 1, signifying that the entire building cannot have controllable loads. Once all buildings maintain their power consumption less or equal to the limit set by the MGMS, the microgrid’s stable and safe operation is ensured.

- **EV Load Model**: The power demand of EV charging stations tied to buildings is based on the estimated charging demand of the EVs. Charging stations can be controlled through programmable circuit breakers with ON/OFF positions. The power demand of EV charging stations is shown in (32).

\[
\begin{align*}
P^EV_{i,y,t} &= P^CP_{i,y,t} \cdot u^CP_{i,y,t} \quad \forall i \in \Omega_L, \ t \in \Omega_T
\end{align*}
\]

where \( u^CP_{i,y,t} = \{0,1\} \), represents the circuit breaker off and on status of the EV charging station for one interval. \( P^CP_{i,y,t} \) is the estimated charging power demand of the \( y \)th EV in the next interval. It is obtained by using the current SOC of the EV, the time period of the next interval, and the predicted charging profile of the EV. Data mapping with current SOC as the identification parameter is used to determine the starting point in the predicted charging profile. The number of data points equal to the number of minutes in the next interval (30 min in this case) is extracted to calculate the value of the power conditioning system (PCS). The load model for predicting the charging profile of the EV using initial SOC, final SOC, and previous charging profile is described in [21]. The entire building’s EV power demand is then given by (33).

\[
\begin{align*}
P^EV_B = \sum_{y \in \Omega_y} P^EV_{i,y,t} \quad \forall i \in \Omega_L, \ t \in \Omega_T
\end{align*}
\]
where \( N_{ev} \) is the total number of EV charging stations installed in the building.

- **AC System Load Model:** The power demand of one AC system load is based on its motor power rating, circuit breaker ON/OFF status, and motor operating speed concerning the VSD frequency as presented in (34).

\[
p_{i,k,t}^{HVAC} = p_{i,k}^{Motor} \cdot B_{i,k,t}^{Motor} \cdot f_{i,k}^{VSD, supply} \cdot u_{i,k,t}^{HVAC} \tag{34}
\]

where \( k \) is the HVAC system unit number, \( p_{i,k}^{HVAC} \) is the AC system power demand of the \( k \)th unit, \( p_{i,k}^{Motor} \), is the AC system motor rated power of the \( k \)th unit, \( B_{i,k}^{Motor} \), represents the circuit breaker ON/OFF status of the \( k \)th unit, \( f_{i,k}^{VSD} \), \( k \) is the variable speed driver (VSD) operating frequency, which varies depending upon the outside temperature and human occupancy factors, \( f_{i,k}^{supply} \) is the supply frequency, and \( u_{i,k,t}^{HVAC} \) represents the ON/OFF status of the \( k \)th unit. The entire building’s AC system power demand is then obtained by (35).

\[
p_{i,t}^{HVACB} = \sum_{k \in \Omega_i} p_{i,k,t}^{HVAC} \quad \forall i \in \Omega_L, \ t \in \Omega_T \tag{35}
\]

where \( N_i \) is the total number of AC system loads installed in the building, as presented in [34].

- **Interruptible Load Model:** Interruptible loads (IL) can be categorized as loads that can be disconnected instantaneously without any dynamics involved. The power demand of other ILs is based on the load-rated power, and the load control module (LCM) ON/OFF status is represented by (37).

\[
p_{i,w,t}^{IL} = p_{i,w,t}^{LCM} \cdot u_{i,w,t}^{LCM} \quad \forall i \in \Omega_L, \ t \in \Omega_T \tag{36}
\]

where \( w \) is the IL unit number, \( p_{i,h,t}^{IL} \) is the IL power demand of the \( w \)th unit, \( p_{i,w,t}^{LCM} \) is the estimated power demand of the \( w \)th IL in the next interval, and \( u_{i,w}^{LCM} \) represents the ON/OFF status of the \( w \)th unit. The total building’s IL power demand takes the form of (37).

\[
p_{i,t}^{ILB} = \sum_{w \in \Omega_w} p_{i,w,t}^{IL} \quad \forall i \in \Omega_L, \ t \in \Omega_T \tag{37}
\]

where \( N_w \) is the total number of ILs in the building. ILs can be sub-categorized into the non-critical interruptible load (NCIL), lighting load (light), miscellaneous interruptible loads (misc), and critical interruptible loads (CIL). The building current load demand \( P_{i,t}^l \) can then be obtained by summing the total EV, AC system, and IL power demands along with the un-controllable loads (UCL). The building current load demand is given by (38).

\[
P_{i,t}^l = P_{i,t}^{EV} + P_{i,t}^{HVAC} + P_{i,t}^{NCIL} + P_{i,t}^{light} + P_{i,t}^{misc} + P_{i,t}^{IL} + P_{i,t}^{UCL} \quad \forall i \in \Omega_L, \ t \in \Omega_T \tag{38}
\]

**IV. BEMS PROBLEM FORMULATION**

A central BEMS coordinates with the MMS to schedule the loads for real-time adjustment. The BEMS receives the scheduled power, \( P_{i,t}^l \) determined by the optimization solution described in Section III, which is provided to the pending BEMS solution as thresholds, \( \Gamma_{i,t}^l \) for each building. The optimization is performed one time step ahead of the scheduling time interval. In real-time, the forecasted schedule of the buildings could be different from the actual power consumption. The BEMS receives the thresholds from the optimization solution and adjusts the group loads by switching on/off in real-time to respect the threshold limits.

The group loads are scheduled in real-time according to Algorithm 1. Based on the current group load measurements (\( P_{meas}^{l_1,1}, ..., P_{meas}^{l_n,N_o} \)), current group load on/off status (\( x_{i,1,t}^{L}, ..., x_{i,N_o,t}^{L} \)), and priority list information (\( \theta_{i,1}^{L}, ..., \theta_{i,N_o}^{L} \)), maximum group load demands (\( P_{max}^{l_1}, ..., P_{max}^{l_n} \)), new sets are created. The load switch on/off status of the electric vehicles (\( x_{i,w}^{EV} \)), load control module (\( x_{i,w,t}^{LCM} \)), and HVAC system unit (\( x_{i,k,t}^{HVAC} \)) are relabeled as a standard variable, \( x_{i,k,t} \).

The group priority weight sets for each building, \( \theta_{i}^{L} \) is extracted from the decision priority matrix, \( \theta \). A structure, \( D_{i}^{f} \) is created with the decision priority sets, \( \theta_{i}^{L} \), measured group load values set, \( s_{i}^{L} \) and the current on/off status sets, \( x_{i}^{L} \). The elements in the decision priority sets, \( \theta_{i}^{L} \) is arranged in descending order based on the values, along with the measured group load value sets, \( s_{i}^{L} \) and the on/off status sets, \( x_{i}^{L} \) by applying the process indicated in step 8. The \( zip \) function creates an iterator that will aggregate elements from the sets stored in \( D_{i}^{f} \). The \( sort \) function sorts the items in the iterator in descending order based on the \( \theta_{i}^{L} \) element values. The \( zip(*) \) function will disaggregate the iterator into individual sorted sets.

Next, the loads at each building level are measured in real-time, \( P_{meas}^{l_1,1}, ..., P_{meas}^{l_n,N_o} \), and compared with the building threshold, \( \Gamma_{i,t}^l \). If the building measurement is above the threshold, the loads are curtailed to be under the threshold. This iterative curtailment process is repeated until measured building loads become less than the threshold powers determined in the scheduling period, with a gap of \( \delta_{i}^{L} \).

It may be the case that more power becomes available in different time slots due to solar PV increase, which could allow for turning on more loads. In such a scenario, the next set of priority loads are scheduled in these time slots until the threshold and maximum power gap are reduced. When the building measurement is below the threshold, then a load increment is performed to narrow the gap between the threshold and maximum power capacities of the next set of priority loads until the gap is narrowed to \( \delta_{i}^{L} \). The reason for considering the maximum loads is due to the unknown power consumption of the groups until they are switched on, which will also ensure scheduling without any chattering issues. For each time step, \( t \), the scheduled group loads are finalized as \( x_{i,1,t}^{L}, ..., x_{i,N_o,t}^{L} \).
Algorithm 1 for Scheduling Loads Based on Real-Time Measurement

Input: $\delta P_{1,1}, \ldots, \delta P_{N,1}, \delta P_{1,2}, \ldots, \delta P_{N,2}, \delta P_{1,3}, \ldots, \delta P_{N,3}, \delta P_{1,4}, \ldots, \delta P_{N,4}$

1. Start procedure
2. Create sets for load group weight factors in building $i$, $w_{L,i} = \{w_{L,1,i}, \ldots, w_{L,N,i}\}$
3. Create sets for load group weight factors in building $i$, $s_{PmaxL,i} = \{s_{PmaxL,1,i}, \ldots, s_{PmaxL,N,i}\}$
4. Create sets for load group weight factors in building $i$, $s_{PmaxL,i} = \{s_{PmaxL,1,i}, \ldots, s_{PmaxL,N,i}\}$
5. Create sets for load group weight factors in building $i$, $w_{L,i} = \{w_{L,1,i}, \ldots, w_{L,N,i}\}$
6. Create structure $D_t^{i,j}$ containing $s_{PmaxL,i}$, $s\delta P_{C1,1}$, $s\delta P_{C1,2}$
7. Sort $D_t^{i,j}$ in descending order according to value of $s_{PmaxL,i}$
8. $D_t^{i,j} = \text{zip}(s_{PmaxL,i}, s\delta P_{C1,1}, s\delta P_{C1,2}, s\delta P_{L,i})$

9. end procedure
10. for $i = 1: N_B$
11. for $t = 1: T$
12. $s_{L,z,1,1} = \{s_{L,z,1,1}, \ldots, s_{L,z,1,1}\}$
13. $s_{L,z,1,2} = \{s_{L,z,1,2}, \ldots, s_{L,z,1,2}\}$
14. $s_{L,z,1,3} = \{s_{L,z,1,3}, \ldots, s_{L,z,1,3}\}$
15. $s_{L,z,1,4} = \{s_{L,z,1,4}, \ldots, s_{L,z,1,4}\}$
16. $s_{L,z,1,5} = \{s_{L,z,1,5}, \ldots, s_{L,z,1,5}\}$
17. end
18. end
19. for $i = 1: N_B$
20. if $s\delta P_{C1,1} > s\delta P_{C1,1}$
21. for $t = 1: T$
22. while $\Gamma_{L,i}^{t} = \{s_{L,z,1,1}, \ldots, s_{L,z,1,1}\}$
23. $s_{L,z,1,1} = \{s_{L,z,1,1}, \ldots, s_{L,z,1,1}\}$
24. for $h = 1: length(s_{L,z,1,1})$
25. $s_{L,z,1,1} = 0$
26. end
27. for $h = 1: length(s_{L,z,1,1})+1: N_B$
28. $s_{L,z,1,1} = 1$
29. end
30. end
31. end
32. else $s\delta P_{C1,1} < s\delta P_{C1,1}$ and $s\delta P_{C1,1} = s\delta P_{C1,1}$
33. for $t = 1: T$
34. while $\Gamma_{L,i}^{t} = \{s_{L,z,1,2}, \ldots, s_{L,z,1,2}\}$
35. $s_{L,z,1,2} = \{s_{L,z,1,2}, \ldots, s_{L,z,1,2}\}$
36. $s_{L,z,1,2} = \{s_{L,z,1,2}, \ldots, s_{L,z,1,2}\}$
37. for $h = 1: length(s_{L,z,1,1})$
38. $s_{L,z,1,1} = 1$
39. end
40. for $h = 1: length(s_{L,z,1,1})+1: N_B$
41. $s_{L,z,1,1} = 1$
42. end
43. end
44. end
45. else
46. for $h = 1: N_B$
47. $s_{L,z,1,1} = s_{L,z,1,1}$
48. end
49. end
50. return $\delta L_{1,1}, \ldots, \delta L_{N,1}$

V. BANSHEE DISTRIBUTION NETWORK

The Banshee microgrid system is a real-world, reconfigurable military base facility served by three utility radial feeders. Figure 2 shows the Banshee network topology. The system can also be operated as one unique or several small islanded microgrids. The Banshee network is balanced with 18 building loads, totaling 13 MW of load in the system, along with two inductive motors. These loads have dynamic consumption behavior with a limited power factor range from 1 to 0.9 lagging. The system’s voltage and frequency must be maintained within the standard limits, 0.95 and 1.05 p.u., and 59.5 and 60.5 Hz, respectively. The network hosts four DERs, a diesel generator, a CHP generator, a PV plant, and an ESS, which are sufficient to supply the total load system load. All DERs are considered to have black-start capabilities and are always assumed to be connected during a disaster event.

The problem was formulated for a generic approach in Eq. (1)-(38). Considering the Banshee network, the problem is formulated with 98 nodes in $\Omega_N$, and 22 lines in $\Omega$. The Banshee building loads are categorized in three different priority ranges, critical, priority, and interruptible, as shown in Table 1, [35]. The critical buildings are considered the most important ones, which are mission-critical facilities and strongly rely on power supply continuity. Priority buildings are ranked after the critical ones and do not have a large impact when de-energized. Finally, the interruptible buildings can be de-energized for short periods without a considerable impact.

Based on the original Banshee buildings’ configuration, the present paper proposes a breakdown structure that splits the building’s aggregated loads into five different desegregated groups of loads that compound $\Omega$. Each building can be disintegrated into load groups with different priorities. For example, even though building $P1$ is less critical than $C1$, $P1$ may have more important loads than some loads in building $C1$. By having a granular structure, non-critical loads in $C1$ can be disconnected and enable supply to $P1$ critical loads. Each building can be restored in small load steps according to the DER available capacity and the buildings and group loads’ rank position. Different weight factors are

| ID     | Priority | Category | Nominal Power [kVA] |
|--------|----------|----------|---------------------|
| C1-C6  | 1-6      | Critical | 6500                |
| P1-P6  | 7-12     | Priority | 5500                |
| H1-H6  | 13-18    | Interruptible | 2450            |
TABLE 2. Banshee microgrid loads grouping based on dropout priority.

| Load Type    | Building ID | Priority List | Cluster Weight | Weighted Group Priority | Dropout Priority |
|--------------|-------------|---------------|----------------|-------------------------|-----------------|
| EVSE Charging| 16          | 0.0531        |                | 0.00265                 | 1               |
|              | 15          | 0.0534        | 0.05           | 0.00267                 | 2               |
| Non-Critical | C1          | 0.0580        |                | 0.00290                 | 18              |
| Critical     | 16          | 0.0531        |                | 0.00796                 | 19              |
| Plug         | 15          | 0.0534        |                | 0.00801                 | 20              |
| Loads        | C1          | 0.0580        |                | 0.00870                 | 36              |
| Sum          | 1 \times \sum N_i | 1            |                | 1                       |                 |

assigned for each group of loads according to their criticality. Larger weight factors are given to critical loads to ensure they are not curtailed. Table 2 shows the weight factors for each group of loads.

VI. TESTBED AND CASE STUDIES

A. CONTROLLER-HARDWARE-IN-THE-LOOP

The validation testbed is based on a Controller-Hardware-In-the-Loop (C-HIL) topology, which is broken down into four levels. The primary, secondary, and tertiary levels are control layers, while the last layer is the electrical network model.

1) TESTBED TOPOLOGY

Figure 3 illustrates the C-HIL testbed topology. All the different elements are tied to a common Ethernet switch. The communication between each component is made by the standard MODBUS TCP IP communication protocol. At the tertiary level, the proposed MGMS solution is computed, which has been carried out on a computer with Intel Xeon @ 3.5-GHz CPU, 32-GB memory, and Windows 10 as the operating system. The MGMS runs the GAMS optimization solution which utilizes CPLEX solver for solving the MILP problem. The input to the MGMS is the distribution system parameter and constraints and provides the hourly optimal solution for the system based on real-time measurements, including DERs dispatch and groups shedding commands. At the secondary level, the central BEMS is deployed on a DELL central server at the control station. The central BEMS is responsible for monitoring the entire grid operation, collecting data, and forwarding hourly dispatch to the local controller at the primary level. The grid operation includes control of breakers, active and reactive power setpoints for DERs, voltage and frequency regulation, and hourly consumption of the building. The primary BEMS uses raspberry pi to implement the primary load control algorithm at the building level. The output of the algorithm is the dispatch commands to the building loads. The load control algorithm is written in python programming language and is deployed using the open-source agent-based VOLTTRON platform. The VOLTTRON pub/sub message framework handles data flow in the system. Each Raspberry Pi hosts two VOLTTRON instances, one for each building control. The local controller receives the building dispatch command from the central BEMS and provides a granular dispatch signal to the virtual building models in OPAL-RT. The OPAL-RT OP5700 Real-time Digital Simulator compounds the base layer. OPAL-RT is well known for its high capability to host large electrical systems. The entire Banshee Network, its DERs, and buildings were modeled using RT-Lab software. The building model followed the proposed granular structure presented in section IV, and each model has a unique virtual IP address to exchange data with external controllers.

2) CONTROL TOPOLOGY

The hierarchical control topology and its implementation is presented in Figure 4. The tertiary level is responsible...
for calculating the optimization requirements for the entire grid, as explained in section III. Based on these optimization requirements, secondary level BEMS manages the DERs and loads within the grid. The primary level BEMS manages the building assets depending on the building threshold values assigned by the MGMS, as explained in section IV. The local priority load control (PLC) algorithm at the primary level manages the granular building loads grouped based on different priority assignments. Figure 5 shows the control sequence diagram utilized for the case studies. At the beginning of a control cycle (hourly time interval), the secondary controller requests the forecasted data on a rolling-horizon basis for the next hour. The secondary controller passes the request to the primary level. The primary controller acquires the requested data via the master driver agent and forwards the data back to the secondary level and then to the tertiary level. After receiving the data, the MGMS, performs optimization to schedule the hour ahead DERs setpoints and building thresholds. The central BEMS dispatches the received DERs setpoint and the building thresholds to the respective building controller. Based on the received threshold values, the local BEMS uses local priority load control logic and publishes the granular loads’ status on the building simulation model. If the building consumption exceeds the threshold imposed by the optimization results, the local BEMS agent publishes the priority load shedding command. If the building consumption is less than the threshold, the MMS agent publishes the priority load increment command to re-energize critical loads and minimize the difference between the threshold value and the actual power consumption.

B. EMERGENCY OPERATIONS CASES

The present paper proposes different case studies to evaluate the MGMS and BEMS solutions in managing building and generation assets after different outage events. The major disturbances that can be considered are outages due to weather events or cyberattacks. In grid disturbances, the validation aims to MGMS operation independent from the grid for long durations, supplying a minimum of 3 MW critical. To ensure the system’s stability, the BEMS might be required to shed non-essential loads. For example, the MGMS could generate a signal to curtail 20% of loads in one of the buildings. The BEMS controller will then be responsible for dropping the non-essential building loads based on the priority-grouping algorithm weights. The scenarios are divided into four cases, which consider two outage conditions. The first considers an unconstrained outage, and the second considers a one-week outage. The first two cases assume buildings as aggregated loads under these two outage conditions. The last two cases intend to compare the buildings with disintegrated loads capable of granular level control, and the same two outage conditions are considered. Figure 6 illustrates the case studies.

1) CASE 1
In this case, the buildings are considered aggregated lumped loads, and the outage is unconstrained. The buildings will follow the priority order for emergency load shedding to meet the power balance [34]. While considering the generation schedule, the end time of the outage is not considered, which forces the fuel generator and battery to produce their maximum outputs at each time step. The generators operate at their total capacity until their fuel is out, tripping the device. Similarly, the battery runs until its discharges completely.

2) CASE 2
In this case, the buildings are again considered aggregated lumped loads but under a one-week outage. While considering the generation schedule, the end time of the outage is now taken into consideration which will enable the fuel generator to produce outputs conservatively for each time step. The fuel generators and the battery will operate at optimal outputs. This approach ensures that critical building loads are supplied at the end of the predicated outage duration. This type of outage duration estimation can be predicted based on past events.

3) CASE 3
In this case, the buildings are disintegrated with granular group loads. The outage is unconstrained, and the generation scheduling aims to supply as many loads as possible, similar to Case 1.

4) CASE 4
In this case, the buildings are considered disintegrated group loads under a one-week outage. Emergency operations will be like Case 2. The time constraint will ensure that the DERs’ energy is dispersed over the estimated outage duration to ensure energy supply for critical loads, while non-critical are shed first.
VII. C-HIL RESULTS AND DISCUSSION

As presented, Cases 1 and 3 consider the same aggregated building control. However, Case 1 is time-unconstrained, while Case 2 is time-constrained for the one-week outage scenario. Similarly, Cases 3 and 4 consider the same load group disaggregated building control. But Case 3 is time-unconstrained while Case 4 is time-constrained for the one-week outage scenario. Figure 7 presents performance profiles for each case under a 1-week outage. Each graph shows the overall microgrid active power profiles for DERs generation, actual served, actual demand, and demand shed. The served demand is computed according to the DERs’ availability, which is often less than the actual demand, creating shed demand defined by the difference between the actual demand and actual served.

Figure 8 shows the results obtained for each group of loads under Case 3. The graphs display the actual served and actual demand and shed overall active power profiles for each group of loads in the microgrid. The disintegrated aspect of the loads enables a more flexible and precise shed command, where groups of loads are turned off instead of entire buildings being shut down. Case 3 does not consider priority weights for the groups, which causes all load groups to be reduced by approximately the same amount. Figure 9 shows a similar analysis but for Case 4, which considers granular control following groups’ priority under different levels of criticality. The graphs display the actual served and actual demand and shed overall active power profiles for each group of loads. As the priority rank increases from group 1 to 6, under shed commands, the optimization algorithm aims to ensure that group 6 followed by group 5 remain supplied by shedding other non-critical load groups.

The Total Connected Load (TCL) factor is computed to measure the levels of supplied loads during the period of study. The TCL formulation for the overall building and group load buildings is shown in (39) and (40), respectively.

\[ TCL = \sum_{t \in T} \sum_{i \in \Omega_L} p_{L,i}^L u_{i,t} U_{i,t} \]  

\[ TCL = \sum_{i \in \Omega_L} \sum_{h \in \Omega_h} \sum_{t \in T} u_{i,h,t} p_{L,i}^L L_{i,h,t} \]  

The Total Actual Load (TAL) factor measures the total actual load connected, \( u_{L,i}^L = 1 \), and the %shed calculates the percentage of disconnected loads over the study period, as shown in (41) and (42), respectively.

\[ TAL = \sum_{t \in T} \sum_{i \in \Omega_L} p_{L,i}^L u_{L,i,t} \]  

\[ \%Shed = \left(1 - \frac{TCL}{TAL}\right) \cdot 100 \]  

Table 3 summarizes the shedding results for all four test-case scenarios. To demonstrate the effectiveness of the proposed BEMS strategy, the results are computed based on the output from the GAMS software. From the table, it is possible to see that there are no load groups shed in Cases 1 and 2, as the loads are considered to be aggregated. For Case 3, the overall group load shedding is between 59-74%. While, for Case 4, there are no loads shedding for the critical groups 5 and 6, and group 4 has 30% of load shed.

These results validate the proposed solution’s capability to ensure service continuity for critical loads by shedding a large percentage of non-critical loads on each microgrid’s...
building. For the daily load analysis, from Table 3, it is possible to observe that there was no considerable shedding in Cases 1 and 3 on the first day. Loads start to be shed as the number of outage days increases and microgrid generation capabilities are reduced. The fuel-based generator and battery energy levels decrease as the loads are supplied over the outage period. The grid-forming PV plant has become the unique resource available in the last few days. Due to the time constraint, the power was conserved for the 1-week outage scenario in Cases 2 and 4. This energy was optimally planned and scheduled to ensure service continuity for the most critical loads in the microgrid.

The primary advantage of the disaggregated control of loads is shown in Fig. 10. Most of the usual microgrid controls aim to use as much power available as possible to meet the load demands at the beginning of an outage. Considering this approach, Case 1 from Fig. 10 shows that the battery, diesel, and natural gas generators are all exhausted after the 13th hour. By this, after the 13th hour, almost all loads are disconnected, and only a small percentage of the microgrid demand can be supplied by the grid-forming PV plant generation whenever it is available. In contrast, when the proposed generation conservation algorithm is considered, interruptible and priority buildings loads are shed to ensure the critical buildings loads’ service continuity during the entire 1-week outage period, as shown in Case 3 from Fig. 10. When the microgrid’s buildings are categorized based on the same groups of loads, the MGMS receives additional flexibility to curtail non-critical load groups from all the buildings.

Similar to Case 1, in Case 2, all the generation is used to meet the current load since the start of an outage. The percentage of aggregated buildings shed for the outage period is comparable to the percentage of group loads shed after the 13th hour, as shown in Fig. 10. For Case 4, the interruptible load groups are shed first to ensure the critical load groups’ service continuity during the outage period. In this scenario, groups 4 and 5 remain in service, as shown in Fig. 10.

A. RESULTS DISCUSSION

While in an aggregate scenario, buildings must be completely de-energized to respect the power balance constraints, a granular capability of control enables a higher level of flexibility and precision for demand response shedding. Smaller amounts of loads can be disconnected to respect the available levels of energy. Buildings’ group loads are turned off
based on their criticality factor before compromising critical groups. The proposed methodology not only covers the management of granular building loads under outage scenarios but also proposes a solution to optimize the load consumption on long-duration outages. As presented, most of the current microgrids management algorithms aim to entirely supply load demand at the start of an outage period. If all fuel and storage energy is used at the beginning to supply critical and non-critical loads, the system’s reliability may be compromised as the outage perpetuates. However, the outage duration can be predicted based on previous events. This information can be essential to scheduling the load and generation to supply critical loads over the outage period.

VIII. CONCLUSION

This paper has proposed a resilience-oriented optimization strategy for networked microgrids focusing on building-level management during emergency conditions. The main contributions of this research are to integrate the microgrid operations at the tertiary level with the BEMS, the central BEMS at the secondary level, and the individual building controllers at the primary level. This type of integrated solution is currently not available in the market but is highly required for critical facilities operation with reliable conditions during outage periods. All proposed control levels work interactively in real-time to make decisions based on measurements and grid conditions. High-level controls take decisions on the grid benefit, and low-level controls optimize loads and DERs, respecting higher-hierarchical commands. The proposed solution has been implemented on real-time prototype platforms and validated with a real-time simulator. With increasing building flexibilities which include HVAC, lighting, plug-load controllers, EV chargers, water heaters, etc., its integration to BEMS platforms will give microgrid operations the much-needed flexibility to curtail several non-critical loads distributed in different buildings. Pre-disaster, each

| Categories   | Case 1 | Case 2 | Case 3 | Case 4 |
|--------------|--------|--------|--------|--------|
| Overall Building Load % Shed | | | | |
| Interruptible | 72     | 100    | 57     | 79     |
| Priority      | 66     | 99     | 57     | 57     |
| Critical      | 71     | 22     | 64     | 49     |
| Group Load % Shed | | | | |
| Group 1      | -      | -      | 59     | 100    |
| Group 2      | -      | -      | 74     | 100    |
| Group 3      | -      | -      | 72     | 99     |
| Group 4      | -      | -      | 67     | 30     |
| Group 5      | -      | -      | 68     | 0      |
| Group 6      | -      | -      | 68     | 0      |
| Daily Load % Shed | | | | |
| Day 1        | 23     | 64     | 0      | 59     |
| Day 2        | 81     | 70     | 48     | 60     |
| Day 3        | 91     | 68     | 91     | 60     |
| Day 4        | 86     | 68     | 86     | 59     |
| Day 5        | 59     | 61     | 58     | 45     |
| Day 6        | 59     | 61     | 59     | 57     |
| Day 7        | 77     | 67     | 77     | 64     |
| Total        | 69     | 66     | 59     | 59     |
building load has been evaluated for the possibility of control via a priority index and the abilities of DERs to operate during the disaster event. Without increasing the operating cost, the proposed solution can assure service continuity to critical loads during emergencies. During emergency operations, the proposed scheme has reduced the load shedding of critical loads from 71% for case 1 to 22% for case 2. However, if each building is considered to have some critical loads at the granular level, it was observed that the critical load groups 5 and 6 shedding reduced from 68% to 0%. This reduction in load shedding amount implies that at least the most critical loads are survived during emergency operations. The reduction in load shedding increases the service reliability on the one hand, and it saves the penalty cost on the other hand. It can be concluded that the proposed resilience-oriented optimization strategy can reduce load shedding considerably at the cost of a minute increase in the operation cost.

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