

Multi-Criteria Decision-Making and Robust Optimization Methodology for Generator Sizing of a Microgrid

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ABSTRACT Microgrids provide multiple benefits to end-use customers and electric utilities, including enhanced reliability and resilience, reduced operational costs, streamlined renewable generation integration, and improved energy efficiency. However, the microgrid technology's large capital cost remains a major barrier to establishing its economic viability. This paper addresses this challenge by proposing a practical methodology for microgrid generation sizing. The proposed methodology uses the concept of robust optimization and a multi-criteria decision-making process, taking overall cost, emission reduction, and demand response into account as important factors in optimal generation sizing. The objective is to minimize the supply gap throughout the year, which is defined as the unmet load or required load curtailment under various load and solar generation scenarios. Numerical simulations on a real-world microgrid, ComEd's Bronzeville Community Microgrid (BCM) on Chicago's South Side, exhibit the practicality of the proposed method and its applications for electric utilities. The study proposes an optimal size of 4.8 MW considering the commercially available generator sizes for the BCM, which has a total peak load of 7 MW, 0.75 MW of PV and 0.5MW/2MWh of Battery energy storage installed.

INDEX TERMS Microgrid, distributed energy resource (DER), generator sizing, robust optimization, multi-criteria decision-making (MCDM).

NOMENCLATURE

A. INDICES

- g Thermal units $g = 1, \dots, N_g$.
 b BESS units $b = 1, \dots, N_b$.
 t Hourly time slots $t = 1, \dots, N_T$.
 dis Discharging modes of BESS units.
 c Charging modes of BESS units.

B. PARAMETERS

- N_G Number of thermal units.
 N_b Number of BESS units.
 T Number of time slots in the whole dispatchable period.

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P_g^{max}	Maximum power output of thermal unit g .
P_g^{min}	Minimum power output of thermal unit g .
RU_g	Maximum upward ramp of thermal unit g .
RD_g	Maximum downward ramp of thermal unit g .
\mathcal{L}'_g	Minimum ON time of thermal unit g .
\mathcal{H}_g	Minimum OFF time of thermal unit g .
$\eta_{b,c}$	Charging efficiency of BESS unit b .
$\eta_{b,dis}$	Discharging efficiency of BESS unit b .
$P_{b,max}^c$	Maximum charging power output of BESS unit b .
$P_{b,max}^{dis}$	Maximum discharging power output of BESS unit b .
E_b^{min}	Minimum energy stored in BESS unit b .
E_b^{max}	Maximum energy stored in BESS unit b .
$Load_t$	Total load at time t .

- $LD_{VIP,t}$ Very important load at time t .
 I_{ex} Operation mode of the microgrid (grid-connected mode if $I_{ex} = 1$ and islanded mode if $I_{ex} = 0$).

C. VARIABLES

- $C_g^P(.)$ Cost function of dispatched power of thermal unit g .
 $C_b^P(.)$ Cost functions of charging and discharging power of BESS unit b .
 $P_{g,t}$ Power output of thermal unit g at time t .
 $I_{g,t}$ On/off status of thermal unit g at time t .
 $y_{g,t}$ Startup indicator of thermal unit g at time t .
 $z_{g,t}$ Shutdown indicator of thermal unit g at time t .
 $P_{pv,t}$ Power output of solar PV unit pv at time t .
 $P_{b,t}^{dis}$ Discharging power output of BESS unit b at time t .
 $P_{b,t}^c$ Charging power output of BESS unit b at time t .
 LC_t The value of load curtailment in islanded mode at time t .
 $I_{b,t}^{dis}$ Discharging status of BESS unit b at time t .
 $I_{b,t}^c$ Charging status of BESS unit b at time t .
 $E_{b,t}$ Stored energy of BESS unit b at time t .

I. INTRODUCTION

The frequency and impact of threats to power grids, including natural disasters, extreme weather events, and cyber-attacks, are rising [1]. Recent events that caused unprecedented damage to the grid include Hurricanes Sandy [2], Katrina [3], Irma and Maria [4], and a cyber-attack in 2016 that targeted Ukraine [5]. As a further example, a summer 2020 derecho in the US Midwest is considered the costliest thunderstorm in US history with estimated damages reaching \$7.5 Billion [6]. In the past, research aimed to enhance the resilience of the distribution grid by optimizing generation resources prior to high-impact events [7] or by pre-event reconfiguration [8].

Microgrids (MGs) are emerging as a viable defense against these increasing threats due to their distinctive islanding capabilities [9]. MGs help ensure maximum DER utilization and support grid stability [10]. Further, a properly designed MG can overcome operational challenges and effectively increase the participation of DERs [11]. However, it is crucial to analyze the economic viability of a MG before investing in these technologies. It is anticipated that MGs connected to the existing distribution network will operate in grid-connected mode for the majority of the time to allow for the economic operation of the MG by leveraging resources from the main grid whenever possible. Clean energy resources, such as solar integration and energy storage, will support the

grid while promoting sustainability. During grid-connected operation the relatively more expensive natural gas and diesel generators connected to the MG could either remain idle or participate in a wholesale market, such as an ancillary services market, until they are required to support islanding. As a result, it is critical to analyze the MG generation mix prior to investment and implementation.

The MG will seamlessly transition from grid-connected to islanding mode and vice-versa as necessary to offer resilience benefits. The MG controller manages available resources to ensure an optimal, secure, and stable operation in both modes. Further, it can host more renewable resources by addressing uncertainties in availability [12] while also providing the voltage regulation required to mitigate any over/under voltage issues. Dispatchable resources, including natural gas generators, provide the required inertia and mechanisms for load balance in the islanding mode of operation. Accordingly, the MG controller seamlessly manages renewable resources and inertia-based generation to provide stability to the MG within the islanded mode.

Although the MG's optimal operation and control has been extensively studied, research is limited on the optimal sizing of DERs in a MG with the objective to minimize the supply gap and adhere to the criteria of utility stakeholders. The study in [13] proposes a model to determine optimal combinations of renewable and conventional energy resources in a MG and further analyzes the effect of emission taxes on distributed system planning results. The study in [14] investigates the application of DERs in a MG in lieu of conventional generation and transmission planning. It is shown in the study that a coordinated and market-based approach to the deployment of a MG would make the most out of emerging MG planning alternatives. The study in [15] investigates the optimal design and planning of a hybrid MG by considering emission caps and the life cycle costs of renewable energy resources. The study concludes that a mix of diesel and renewable sources in a MG offers the lowest net present cost and a small carbon footprint, as compared to a stand-alone, diesel-based MG. The study further suggests that additional analyses are required to address mixed options based on renewable generation, because of high initial capital costs. The study in [16] proposes a two-stage multi-objective MG planning model for identifying the optimal region for MG installations and determining the locations and sizes of a specified number of distributed generation units within the MG. The study in [17] presents a method for optimally siting and sizing distributed generation units in a MG which is based on stipulated reliability criteria. However, all the mentioned studies do not provide a methodology to size DERs for MG a considering existing resources. It also fails to incorporate stakeholder criterion and produce a robust result. The study in [18] explores new applications of agent-based simulations for exploiting renewable energy resources in a MG. A bi-layer multi-agent MG planning model is proposed to maximize MG payoffs and to alleviate environmental obligations in energy markets.

This paper presents a practical approach to optimizing the generation mix for a test case of a real-world MG operated by Commonwealth Edison Company (ComEd), an electric utility serving more than 4 million customers in northern Illinois including the city of Chicago. Feasibility studies conducted in Bronzeville on Chicago's South Side showed that a MG would offer significantly improved reliability and resiliency to a number of critical customers in the community. In February 2018, the Illinois Commerce Commission (ICC) authorized ComEd to build the Bronzeville Community Microgrid (BCM). The BCM will serve approximately 7 MW of customer load utilizing a 0.5 MW/2 MWh battery energy storage system (BESS), 0.75 MW of solar PV, demand response, and a natural gas generator. In addition, a MG master controller developed in partnership with the US Department of Energy (DOE) will optimally dispatch MG resources and ensure stable operation in both the grid-connected and islanded modes. However, the utility must also select and add an optimally sized controllable generator to the existing generation mix to ensure uninterrupted power to customers should the main grid suffer a significant outage.

Analysis of historical Advanced Metering Infrastructure (AMI) data for the BCM from 2017 to 2019 was performed to ensure the robustness of the MG design related to DER sizing. As a worst-case scenario, the analysis considered microgrid operation in islanded mode throughout the year to determine the supply gap and optimize resources to minimize the supply gap with varying generator sizes. The total installed and projected solar outputs were also considered. With the identified resources and three years of load profile obtained from AMI data, a study is performed to determine the optimal DER size for the MG.

Authors in [19] apply the l_1 norm of load curtailment in the objective function to the model in [20] to efficiently schedule available resources and reduce the supply gap. Research has been conducted to solve these problems. The first area of research focused on designing a strategy to curtail loads safely and expeditiously. Some researchers design the load shedding controller for MGs to improve frequency stability. A distribution state estimator is integrated into the controller, which can estimate the load demand in [21]. Some researchers design control strategies in hierarchical operation, such as using voltage and frequency as indicators in secondary control [22], estimating droop coefficient in load shedding to support reliability [23], and a fast, hierarchical regionalized approach to mitigate MG's voltage and frequency deviations simultaneously [24]. However, this research is limited to curtailment strategies and does not address calculating load amount.

The second area of research supports efforts to design an energy management strategy that determines the amount of load to be curtailed. Work done in [25] presents an optimization model to minimize total load curtailment by relaxing constraints on voltage and active power flows. Reference [26] provides three-stage load priorities to minimize total load curtailment of the AC-DC MG. These research initiatives are

designed to minimize the total load curtailment but do not consider minimization of the maximum load curtailment in one day. Maximum load curtailment is very important for MG future planning, demand response design, and frequency stability. Therefore, how best to reduce total load curtailment and maximum load curtailment at the same time is an issue that needs to be solved for the islanded MG. While these proposed methods have utility, they are time-consuming and present complications that prevent an optimal solution. This study uses a multi-objective optimization model to minimize the supply gap and the cost of generation scheduling. The model presented utilizes mixed-integer linear programming, which offers a comparatively time-efficient solution. It is capable of economically optimizing all resources, guarantees the eventual minimization of the supply gap, and adjusts BESS outputs according to the load.

Demand Response (DR) is another potential resource to further bridge the supply gap. DR programs are typically coordinated with anticipated peak loads. However, localizing these programs within the MG can promote increased compliance, particularly where proactive customers can connect the benefits of program participation with visible energy efficiency and grid modernization efforts.

After the analysis is performed to ensure the load is always served with different sizes of natural gas generation, researchers must conduct a multi-criteria decision-making process. To determine the generator size, a scoring method measures islanding capabilities by assigning different weights to the cost of the natural gas generator, utilization of full DR potential, emission reductions potential, and maximizing solar integration and battery storage. These factors are considered as part of this case study. The factors and their weights are determined by extensive involvement of utility stakeholders. However, there can be other decision-making criterion (factors) such as considering protection studies, behind the meter solar availability, the percentage islanding capability and acceptable noise level that may be considered. If these additional factors are also considered, the optimal DER size as a result of the MCDM process may be different.

The paper contributes the following toward solving the issue of DER sizing within a microgrid:

- 1) We propose a methodology that aims at solving for DER sizing by fully utilizing existing resources.
 - are approaches available to propose different generation resources for a given load curve within a confined microgrid boundary. Our method factors in the practical limitations of microgrids by considering existing resources (Solar, BESS, AMI) and proposes the optimal new resource (controllable generation) required to meet the load demand.
 - We demonstrate methods to utilize AMI data, solar data and BESS output and optimize an 8760-generation schedule with the objective to minimize both total supply gap and maximum supply gap. This study is a dynamic simulation that

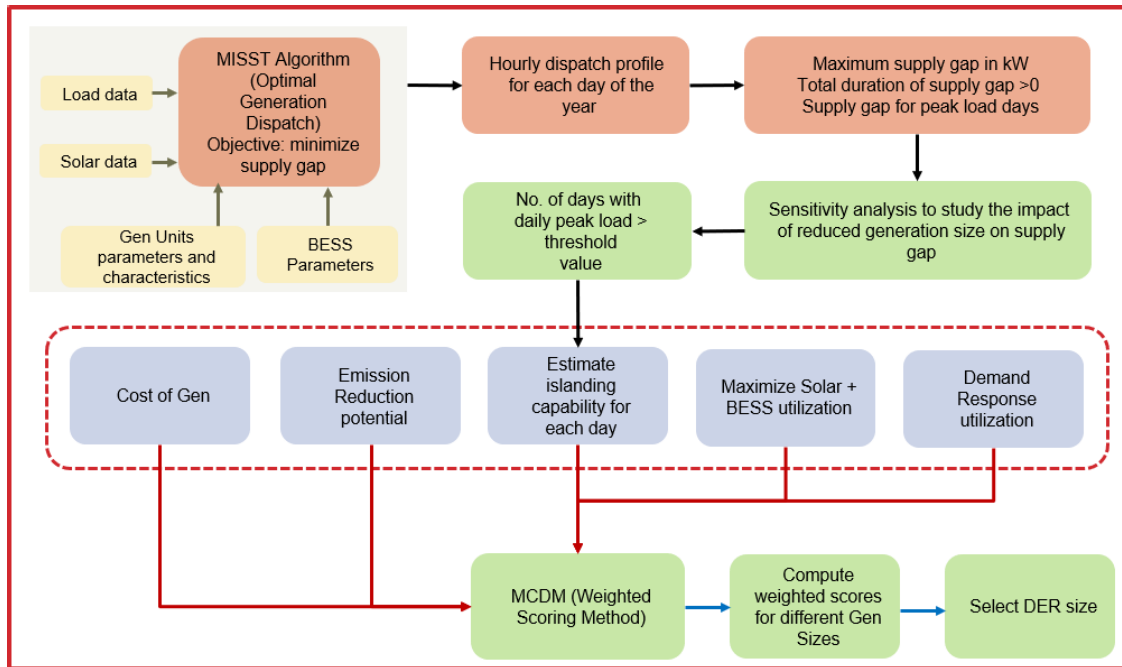


FIGURE 1. Generator sizing process.

considers all the possible scenarios at every hour in a three-year study period in the microgrid rather than a static simulation that optimizes instances occurring just once or few times.

- 2) We propose a robust optimization approach to dispatch DERs under uncertain loads and renewable generation and consider varying commercially available generator sizes.
 - The robust optimization will find the worst-case optimal solution as uncertain parameters vary within their associated uncertainty intervals.
- 3) We propose to use a weighted scoring methodology to factor in several stakeholders' criteria to determine the final generator size for decision making.
 - We have provided a framework to use the weighted scoring methodology that helps to factor in criteria such as the cost of generators, utilization of Solar, battery, and demand response capabilities. It also takes considers the possibility of minimizing emissions produced by the microgrid.
 - The proposed method can aid similar studies seeking to include their stakeholders' assessment into the decision-making process.
- 4) The results demonstrate the actual sizing of the DER for ComEd's Bronzeville Community Microgrid.
 - The results point out that for a microgrid of about 7 MW with the identified load curve, existing solar, battery and demand response capabilities with a size of 4.8 MW of controllable generation can help meet the load demand 99.6 % of the time.

The rest of the paper is organized as follows: Section II discusses the optimization objective and constraints for generator sizing, followed by load and solar data analysis, robust optimization, emissions reduction, and a multi-criteria decision-making methodology in Section III. Section IV presents analysis results outlining how the supply gap is computed and the use of the multi-criteria decision-making process in determining the generator size. Section V concludes the paper.

II. GENERATOR SIZING STUDY

The optimal generator sizing process is explained by the flowchart in Fig. 1. The input parameters to the dispatch model are three years of AMI data from the MG, solar output data, BESS parameters and controllable generator sizes. The process incorporates BESS (0.5 MW/ 2 MWh) and solar PV (0.75 MW) that have already been installed as an input. However, the framework provides flexibility for adding any size and number of BESS or solar for the analysis. The optimal scheduling algorithm retrieves the hourly dispatch results with varying generator sizes. The study considers the actual load of the BCM measured using the AMI from 2017 to 2019. It considers the estimated output of 750 kW of solar PV along with a 500 kW and 2000 kWh of BESS. The analysis is carried out for each day over the three-year period assuming an islanded condition. Analysis is run with two conservative assumptions: a 10 % solar uncertainty, i.e., reduction in solar output, and a state of charge (SOC) of 25 % for the BESS at the start and end of the day. The objective function and constraints are designed to maintain or achieve a 25 % SOC at the end of each day. Further, a sensitivity analysis is carried

out to estimate the number of days and hours with supply gaps given different generator sizes. Once the robust optimization, i.e., 8760 analysis with different generation and supply gap is obtained, a multi-criteria decision making (MCDM) problem is set up. The factors that are considered for this decision-making process are:

- 1) Cost of different generation sizes.
- 2) The increase in emission reduction potential obtained by reducing the generation size.
- 3) Ability to island more than 99 % of the time.
- 4) Ensuring the maximum utilization of solar and BESS coordination.
- 5) Ability to utilize and encourage demand response within the microgrid footprint.

There are different weights assigned to these factors and the highest score generator size is selected as the optimal and adequate generation for the microgrid.

A. MISST FOR OPTIMAL GENERATION SCHEDULING AND SUPPLY GAP MINIMIZATION

When facing inherent uncertainty of renewables in the MG, the Microgrid Integrated Solar Storage Technology (MISST) is a good solution [12]. In this section, a day-ahead, multi-objective, robust unit commitment (RUC) model is discussed to minimize the total generation scheduling cost as well as both the total supply gap (MWh) and the maximum supply gap (MW) in one day. The MG is considered to be operating in islanded mode. The detailed model is as follows:

$$\min_{P, LC} \left(\sum_{t=1}^T \left(\sum_{g=1}^{N_G} C_g^P(P_{g,t}) + c_1 LC_t + \sum_{b=1}^{N_b} C_b^P(P_{b,t}^{dis} - P_{b,t}^c) \right) \right) + (c_2 \max LC_t) \quad (1)$$

$$\text{subject to: } P_g^{min} I_{g,t} \leq P_{g,t} \leq P_g^{max} I_{g,t}, \quad \forall g, t, \quad (2)$$

$$P_{g,t} - P_{g,t-1} \leq RU_g(1 - Y_{g,t}) + P_g^{min} Y_{g,t}, \quad \forall g, t, \quad (3)$$

$$P_{g,t-1} - P_{g,t} \leq RD_g(1 - Z_{g,t}) + P_g^{min} Z_{g,t}, \quad \forall g, t, \quad (4)$$

$$Y_{g,t} + Z_{g,t} \leq 1, \quad \forall g, t, \quad (5)$$

$$Y_{g,t} - Z_{g,t} = I_{g,t} - I_{g,t-1}, \quad \forall g, t, \quad (6)$$

$$\sum_{\tau=t}^{t+L'_g-1} I_{g,\tau} \geq L'_g Y_{g,t}, \quad \forall g, t, \quad (7)$$

$$\sum_{\tau=t}^{t+H'_g-1} I_{g,\tau} \leq H'_g(1 - Z_{g,t}), \quad \forall g, t, \quad (8)$$

$$0 \leq P_{b,t}^{dis} \leq P_{b,max}^{dis} I_{b,t}^{dis}, \quad \forall b, t, \quad (9)$$

$$0 \leq P_{b,t}^c \leq P_{b,max}^c I_{b,t}^c, \quad \forall b, t, \quad (10)$$

$$I_{b,t}^c + I_{b,t}^{dis} \leq 1, \quad \forall b, t, \quad (11)$$

$$E_{b,t} = E_{b,t-1} + \eta_{b,c} P_{b,t}^c - P_{b,t}^{dis} / \eta_{b,dis}, \quad \forall b, t, \quad (12)$$

$$E_b^{min} \leq E_{b,t} \leq E_b^{max}, \quad \forall b, t, \quad (13)$$

$$E_{b,T} = E_{b,0}, \quad \forall b, \quad (14)$$

$$0 \leq LC_t \leq (Load_t - Ld_{VIP,t})(1 - I_{ex}), \quad \forall t, \quad (15)$$

$$\sum_g P_{g,t} + \sum_b (P_{b,t}^{dis} - P_{b,t}^c) = Load_t - LC_t - \sum_{pv} P_{pv,t}, \quad \forall t, \quad (16)$$

Eq. (1) is the objective function comprised of three terms. The cost formulation of a thermal unit is $C_g^P(P_{g,t})$, where: $C_g^P(P_{g,t}) = c_g P_{g,t}^2 + b_g P_{g,t} + a_g$, and c_g, b_g, a_g are the coefficients of the quadratic cost function for thermal unit g . The second and fourth terms represent the cost of the supply gap. c_1 is the penalty coefficient or price of the supply gap and is considered larger than the marginal generation cost. c_2 is the penalty coefficient or price to maximum load curtailment of one day. The third term adjusts the battery's output so that when the load is high, the battery can discharge more power, and when the load is low, the battery can discharge less power or switch to charging. The cost formulation of a BESS unit is $C_b^P(P_{b,t}^{dis} - P_{b,t}^c)$, where: $C_b^P(P_{b,t}^{dis} - P_{b,t}^c) = c_b P_{b,t}^{dis} - c_b P_{b,t}^c$, and c_b is the cost of BESS unit b .

Constraint (2) is the range of output power of thermal units and constraints (3)-(4) represent ramping up and ramping down constraints of thermal units, respectively. Constraints (5)-(6) represent the relationships of start-up indicator $Y_{g,t}$, shutdown indicator $Z_{g,t}$, and ON/OFF status $I_{g,t}$ of thermal unit g at time t . At any time, generators can only be in one status, ON or OFF. Constraints (7)-(8) are minimum ON/OFF time constraints respectively. (7) is the minimum ON time constraint. L'_g is the minimum ON time of thermal unit g . This equation means that if unit g is turned ON at time t , it must remain ON at time $t + 1, t + 2, \dots, t + L'_g - 1$. (8) is the minimum OFF time constraint. H'_g is the minimum OFF time of thermal unit g . This equation means that if unit g is turned OFF at time t , it must remain OFF at time $t + 1, t + 2, \dots, t + H'_g - 1$. Constraints (9) and (10) limit the range of discharging power and charging power, respectively. At any given time, the BESS can only work in one mode: discharging or charging, as defined in (11). The constraints of energy in BESS are (12)-(14), which calculate the energy stored in BESS at time t , define the range of energy in BESS and relationship of energy at the beginning of the scheduling horizon ($t = 0$) and at the end of the scheduling horizon ($t = T$), respectively. Constraint (15) limits the amount of load curtailment or supply gap. I_{ex} is the MG operation mode. When $I_{ex} = 1$, the MG is in grid-connected mode. When $I_{ex} = 0$, the MG is in islanded mode. Here, we only consider the islanded mode, so I_{ex} is considered 0. Constraint (11) is the power constraint equation of the MG. To guarantee secure operation of the MG, the total output power of all generators should be equal to total load minus load curtailment.

Objective (1) is non-linear because of the term $\min(c_2 \max LC_t)$. In order to linearize (1), LC' , an auxiliary variable, is used to represent $\max LC_t$. Furthermore,

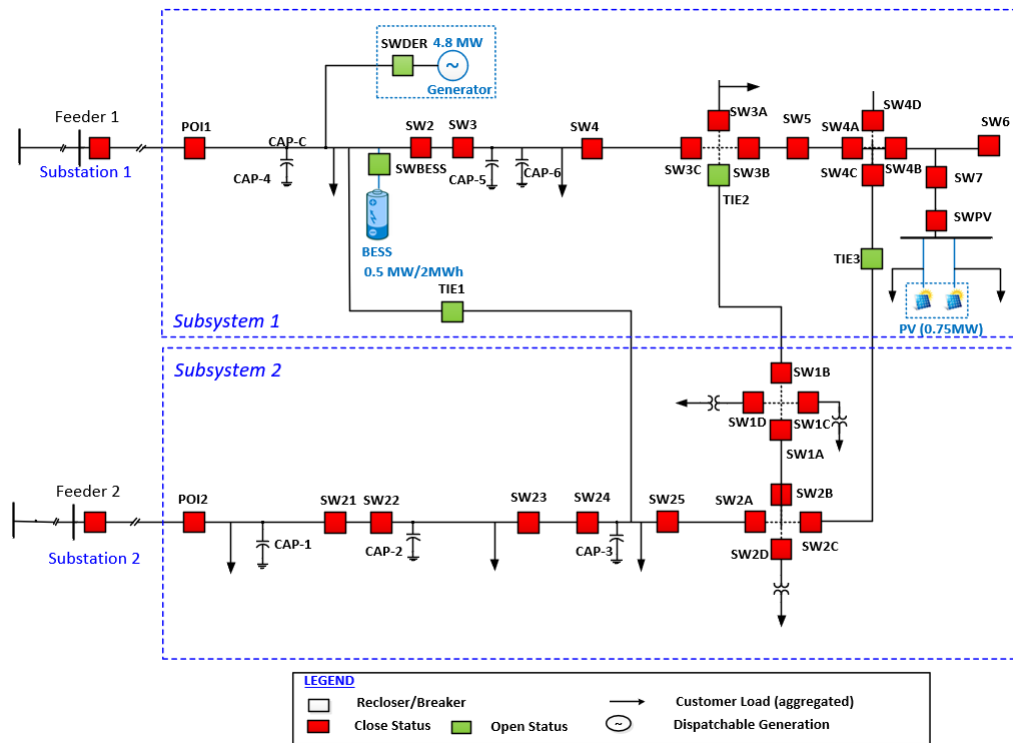


FIGURE 2. One-line diagram of the bronzeville community microgrid.

a new constraint (18) about LC' is added to make sure the new problem and the original problem are equivalent and have the same solution. The new model is shown as follows:

$$\min_{P, LC} \sum_{t=1}^T \left(\sum_{g=1}^{N_G} C_g^P(P_{g,t}) + c_1 LC_t + \sum_{b=1}^{N_b} C_b^P(P_{b,t}^{dis} - P_{b,t}^c) + c_2 LC' \right) \quad (17)$$

subject to : (2) – (16)

$$LC' \geq LC_t \quad (18)$$

This new model is a mixed-integer programming problem and it is convenient to use Cplex or Gurobi to obtain the optimal results.

III. MULTI-CRITERIA DECISION-MAKING FOR GENERATOR SIZING IN BRONZEVILLE COMMUNITY MICROGRID

ComEd chose the BCM's location strategically as it includes critical infrastructures such as the Chicago Police Department headquarters as well as approximately 1,000 residences, businesses, and institutions. The BCM leverages a cutting-edge microgrid master controller, on-site generation, and storage, enabling it to operate connected to ComEd's grid or disconnect to keep locally generated power flowing in the event of a major interruption to the main grid. A schematic of the BCM is shown in Fig. 2. The MG area when grid-connected has two feeders being fed from two upstream substations. During

islanded mode one of the three tie-switches is closed and the grid is formed by the MMC that coordinates the generation set point of DERs according to the load.

With its defined set of customers, the BCM is completely observable using AMI data. The data for each customer has been logged since 2017. The analysis carried out in the MG design bases its peak and average load on the three years of AMI data (2017, 2018, and 2019). Furthermore, the BCM has 750 kW generation of solar power distributed among multiple buildings and ground arrays. The solar PV system installation, finalized in 2019, is divided into two groups of inverters, North and South. The solar PV operation is coupled with BESS operation. The MG controller provides a schedule for BESS to enable solar dispatchability by mitigating variability when the MG is grid-connected. In islanded mode, BESS can be dispatched to supply power that can mitigate the variability of solar and minimize the supply gap. Historical PV output estimates are calculated using the PV system site specifications, such as the number and size of inverters, the number of PV panels per inverter, and model and orientation. Current forecasting tools include features that allow consideration of shading and its seasonal variability. This further enables the model to be more robust and accurate and better represents the installation characteristics. This analysis uses the solar forecasting tool for estimating PV output data from 2017 to 2019. As the 750kW solar PV units were not operational until 2019, the forecasting tool was used to estimate the PV output profile from 2017 to 2019.

A. AMI DATA ANALYSIS

Fig. 3 shows a cumulative plot with the percentage of load variability. The system’s average load remains around 3.75 MW whereas the peak load recorded was 6.87 MW in 2018. The load in the MG footprint is less than 4.8 MW 90 % of the time. It is more than 6 MW for only 1 % of the time.

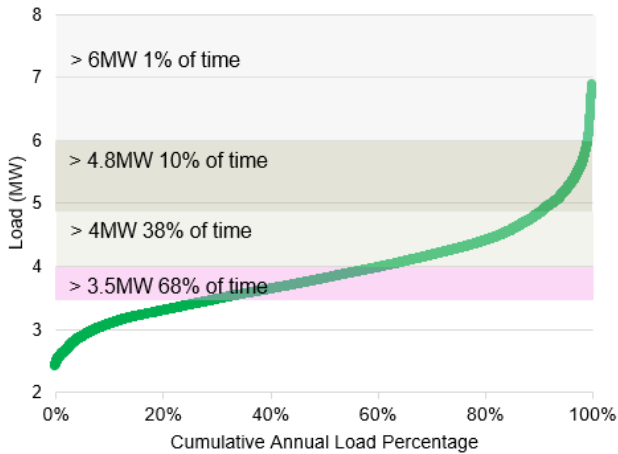


FIGURE 3. AMI load data of MG for past 3 years.

B. ROBUST OPTIMIZATION

The robust optimization will find the worst-case optimal solution as uncertain parameters vary within their associated uncertainty intervals. This is obtained by maximizing the minimum value of the objective function over uncertainty sets. In conventional robust optimization, the obtained complex max-min problem is commonly converted to a tractable problem using the duality theory. In this paper the same approach is followed, given that the objective function is minimized over the primary variables (i.e., generator sizes) while being maximized over the uncertain parameters (i.e., load demand). As expected, the worst-case solution is obtained at the peak load, further proving the suitability of this approach.

To size the natural gas generator to support the formation and stable operation of the MG, we have considered different sizes of generators. The generator units are assumed to be available in fixed sizes of 3.9 MW, 4.4 MW, 4.8 MW, and 5.2 MW. The maximum load recorded was 6.56 MW in 2019 and 6.87 MW in 2018, whereas 2017 saw a peak load of 6.48 MW. The optimal scheduling of DERs was performed to assess the supply gap hours using different generator sizes. The idea is to size the generator optimally. To build a successful and reliable Islanding capability for a MG any under-sizing should be avoided to allow for a seamless transition from grid-connected to islanded mode and stable operation of the MG to supply uninterrupted power to customers in islanded mode. This recognizes the fact that a MG can be called upon to form an island due to planned or unplanned outages. After determining that 2018 had the highest loading, we further analyzed how generators of different

sizes, along with other dispatchable resources, serve the load to minimize the supply gap. The BCM has the potential of utilizing customer-owned generating resources that can be leveraged in a worst-case loading scenario. Each possibility and resource is considered in designing the MG generation mix.

C. MCDM: WEIGHTED SCORING METHOD

Multi-Criteria Decision-Making or MCDM, provides a mathematical approach for choosing one alternative among several. It is based on the scores of alternative factors against a set of structured and weighted criteria as shown in the decision Table 1. Consider the MCDM problem with n criteria and k alternatives. Let C_1, C_2, \dots, C_n and A_1, A_2, \dots, A_k denote the criteria and alternatives, respectively. The generic decision matrix for solving the MCDM problem is shown in Table 1. Each column in the table represents a criterion and each row describes the performance of an alternative. The score S_{ij} describes the performance of alternative A_i against criterion C_j . As shown in the decision table, weights W_1, W_2, \dots, W_n reflect the relative importance of criteria C_j in the decision making. In this paper we use Weighted Scoring Method (WSM) as an MCDM technique [27]. The best alternative is the one with the highest score. In WSM the final score for alternative A_i is calculated using the following formula.

$$S(A_i) = \sum W_j S_{ij} \tag{19}$$

where sum is over $j = 1, 2, \dots, n$; W_j is relative importance of j th criterion; S_{ij} is score that measures how well alternative A_i performs on criterion C_j .

TABLE 1. MCDM table.

Alternatives	Criteria 1	Criteria 2	Criteria 3	Criteria N
	W_1	W_2	W_3	W_n
A_1	S_{11}	S_{12}	S_{13}	S_{1n}
A_2	S_{21}	S_{22}	S_{23}	S_{2n}
-	-	-	-	-
A_k	S_{k1}	S_{k2}	S_{k3}	S_{kn}

D. EMISSIONS REDUCTION

One reason to choose a natural gas generator is its low level of emissions as compared to diesel generators. When designing the generation mix with a fixed budget, planners should consider given towards the emissions aspect of generation. Moreover, these community MGs are in residential areas and high emissions could have severe short-term or long-term health effects on the community. In this work we have considered two scenarios:

- 1) Emission reduction when the grid is islanded all year long
- 2) Emission reduction during peak a loading day

In this analysis CO_2 emissions [28], [29] and NO_x emissions are considered [30]. Carbon equivalent of NO_x is determined to estimate total carbon equivalent emission. The intent

TABLE 2. Greenhouse gas emissions.

Emission Gas	Diesel (kG/MWH)	Natural Gas (kG/MWH)
CO_2	733.44	658.19
NO_x	13.15	0.061

is to replace the supply gap by reducing the size of the DER with a cleaner energy option such as demand response.

Table 2 shows that the natural gas generators have lower greenhouse emissions when compared with the diesel generators. The total value for savings in emission reduction is tracked based on the amount of renewable energy generated within the MG as well as the load reduction due to behavioral economic programs such as energy efficiency and demand response. Consumer awareness and education are heightened within the MG; thus, increased uptake of participation is projected as the MG installation and construction nears completion. The reduction of generation and load is converted into component emissions (kg per MWh) avoided. Each type of emission (CO_2 , NO_x) is scaled by the associated costs of carbon (note: that nitrogen oxides (NO_x) include nitric oxide (NO) and nitrogen dioxide as well as the greenhouse gas, nitrous oxide N_2O).

IV. RESULTS AND DISCUSSIONS

A. SUPPLY GAP ANALYSIS

In this section, the results of a traditional dispatch model that considers load curtailment is compared with the proposed model. As opposed to the proposed model, a traditional dispatch model only considers minimizing total load curtailment while the proposed model considers minimizing both total load curtailment and maximum load curtailment [31]. Note that load curtailment reflects the supply gap. Table 3 shows the results from a traditional dispatch model and Table 4 shows the results from the proposed model. The maximum supply gap from the traditional dispatch model is larger than that of the proposed model. For example, the maximum supply gap in 2018 from the traditional dispatch model is 2.1 MW with a 4.8 MW DER, while that of the proposed dispatch model is 1.49 MW. This means that to fill the gap,

TABLE 3. Three years SG analysis with traditional dispatch model.

Year	Gen. Size (MW)	Maximum Supply Gap (MW)	Total Hours of Supply Gap	Total % of hours with Supply Gap
2019	5.7	0.55	13	0.15
	5.2	0.91	78	0.89
	4.8	1.35	248	2.83
	4.4	1.80	747	8.53
	3.9	2.23	2394	27.33
2018	5.7	1.15	74	0.85
	5.2	1.51	195	2.23
	4.8	2.10	540	6.16
	4.4	2.54	1291	14.74
	3.9	2.98	2700	30.82
2017	5.7	0.46	8	0.09
	5.2	0.84	37	0.42
	4.8	1.28	230	2.63
	4.4	1.78	645	7.36
	3.9	2.25	1848	21.1

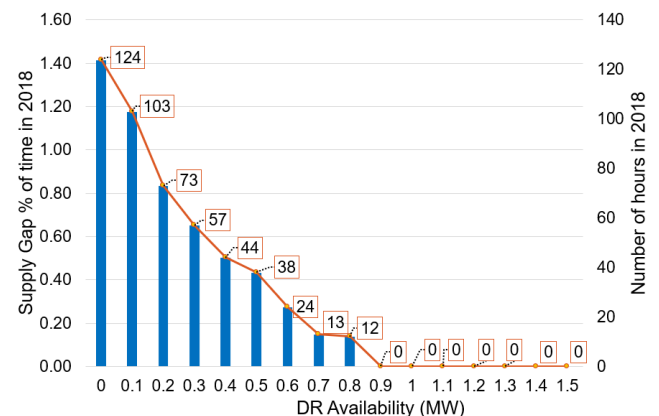
TABLE 4. Three years SG analysis with proposed dispatch model.

Year	Gen. Size (MW)	Maximum Supply Gap (MW)	Total Hours of Supply Gap	Total % of hours with Supply Gap
2019	5.7	0.23	20	0.2
	5.2	0.64	110	1.3
	4.8	1.27	267	3.1
	4.4	1.80	897	10.2
	3.9	2.23	2649	30.2
2018	5.7	0.5	92	1.1
	5.2	0.88	220	2.5
	4.8	1.49	585	6.7
	4.4	2.18	1398	16.0
	3.9	2.66	2972	33.9
2017	5.7	0.13	15	0.2
	5.2	0.49	44	0.5
	4.8	0.98	276	3.2
	4.4	1.55	755	8.6
	3.9	2.22	2103	24

more resources (e.g., DR) are required for the traditional model than the proposed model, which costs more and is not economical. However, the total hours of supply gap from the proposed model are longer than that of the traditional dispatch model. In short, the proposed model can save money at the expense of longer total hours of supply gap.

B. 2018 SUPPLY GAP ANALYSIS WITH VARYING DEMAND RESPONSE CAPABILITY

The BCM footprint has an additional capacity of customer-owned generators that can be potentially leveraged to invoke the demand response if required. This estimated capacity is around 1 MW. With a 5.2 MW generation capacity, the BCM would be covered 100 % of the time; however, the DR capability would be underutilized as seen in Fig. 4. With a 5.7 MW generator the DR is further underutilized as the peak supply gap with this generator is observed to be 0.5 MW. When we consider a 4.4 MW generation capacity as our natural gas generator with a 1 MW of DR capacity the supply gap remains 1.18 MW. Moreover, the supply gap with 1 MW demand response is over 112 hours out of 8760 hours, as shown in Fig. 5. This results in an islanding capability below 99 %.

**FIGURE 4.** Supply gap analysis with 5.2 MW generation.

When using a 4.8 MW generator, there would be a supply gap for only 36 hours in the entire year of 2018, as shown

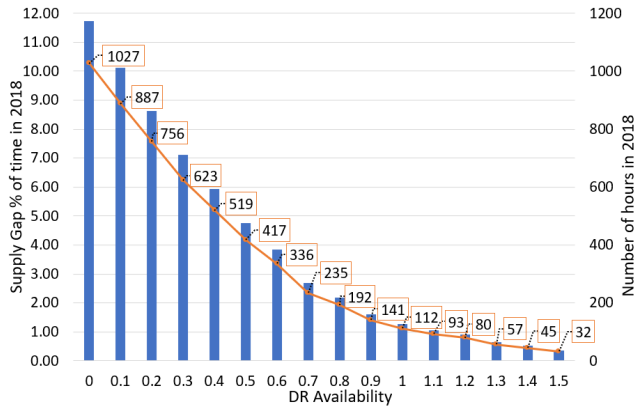


FIGURE 5. Supply gap analysis with 4.4 MW generation.

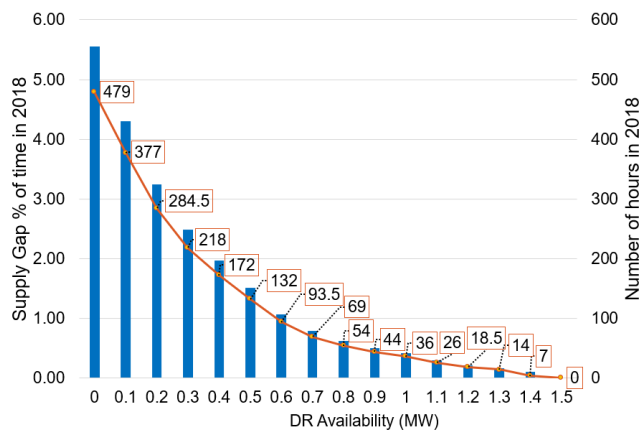


FIGURE 6. Supply gap analysis with 4.8 MW generation.

in Fig. 6. It must be noted that we have used a solar uncertainty factor and accounted for conservative battery use. We also anticipate that the MG will experience Voluntary Load Reduction (VLR) to further reduce the peak load and bridge the supply gap. In summary, the MG would have zero supply gap for 99.6 % of the time in 2018 by utilizing a 4.8 MW generator in coordination with other existing resources and 1 MW demand response.

C. PEAK DAY ANALYSIS

The BCM is expected to provide uninterrupted power to all customers even during grid outages without shedding any customer loads. Hence, an analysis and a zoomed-in view in the worst loading day is required. It may be fair to say that we may not experience a need to island on the worst loading day. However, it is important to assess what additional resources (and for what duration) may be required if that case arises.

Here we analyze a day in August 2018 when the load peaked at 6.8 MW. The DER dispatch schedule was run to minimize the supply gap. With a 4.8 MW natural gas generator, the supply gap is highlighted in yellow in Fig. 7. Throughout the analysis, we have made two conservative assumptions: a 10 % solar uncertainty, i.e., reduction in solar

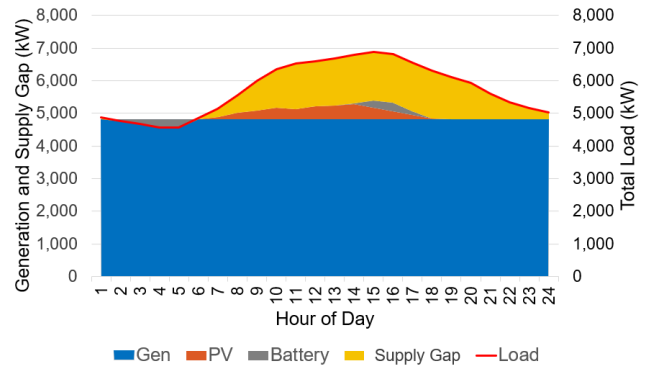


FIGURE 7. Peak day analysis.

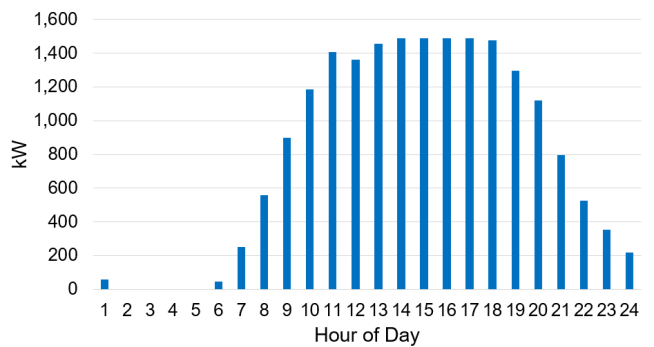


FIGURE 8. Peak day supply gap.

output, and a state of charge (SOC) of 25 % for the BESS at the start and end of the day. The output of BESS depends on the load. If the load is higher than the dispatchable generator and the solar output, the BESS will not be charged; however, if the load is less, the BESS can be charged to be used at higher loading hours. During an actual islanding scenario, it may be the case that the BESS is at 100 % state of charge at the start of the day and is allowed to discharge completely by the end of the day. This could bridge the supply gap further.

Fig. 8 shows the supply gap for each hour of the day. The maximum supply gap is 1.49 MW (1490 kW). Therefore, an additional demand response coupled with a mobile generator (if required) can cover the MG’s total load for the worst loading day. The objective is to minimize the maximum supply gap so that the additional resources required to fill the gap are of a lower MW capacity.

D. EMISSION REDUCTION

The existing supply gap with varying generator size is considered to be bridged by clean energy such as solar, demand response, or energy efficiency. However, reducing generator size eventually saturates the percentage increase in potential emission reduction. Fig. 9 shows the potential reduction in emission if the MG was islanded the entire year. This assumes that the demand response and other resources will be invoked only when the total MG generation is unable to meet the

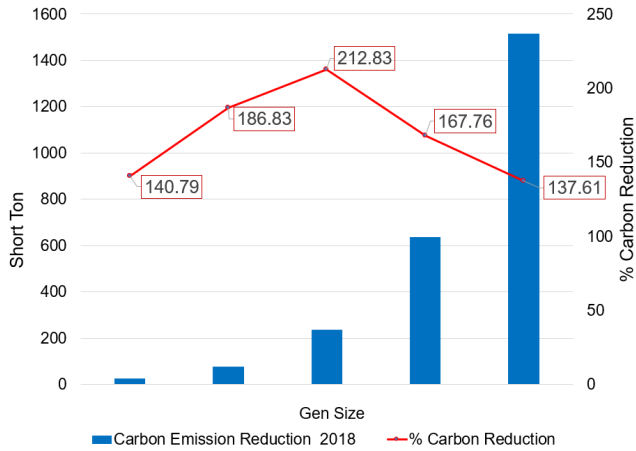


FIGURE 9. Emission reduction 2018.

demand. It can be seen that a reduction from 4.8 MW to 4.4 MW generation precipitates a decline in carbon reduction percentage.

Fig. 10 shows the potential emission reduction with varying generator sizes. This shows a similar trend with the potential in reduction increasing along with reduction in size; however, the percent increase decreases at 4.8 MW.

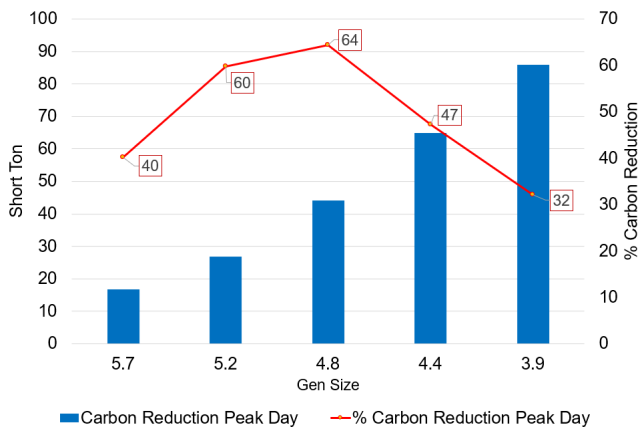


FIGURE 10. Emission reduction peak day.

E. WEIGHTED SCORING METHOD (WSM)

This analysis focused on several criteria referenced in Table 5. The most important factor is, always supporting the islanding of the MG and it is assigned a binary value – given as high if the chosen generator size along with all other resources such as solar, battery and demand response can cover the load for more than 99 % during the entire year. With a 4.8 MW generator the supply cap will be zero for over 99.4 % of the time; whereas with a 4.4 MW generator the islanding support will be met for only 98.6 % of the time. Reducing the size of the generator further reduces the islanding capability of the MG.

From the perspective of deriving the maximum utilization from the installed and cleaner photo-voltaic (solar) and battery energy storage it is important to study if, with a given generator size, there is maximum utilization of these cleaner resources. As mentioned, it is assumed that the BESS will start at 25 % SOC in the beginning of the day and end at the same 25 % SOC at the end of the day. The demand response utilization and solar & BESS utilization is given as follows for the peak day analysis. Having a 5.7 MW generator allows the BESS to charge in the early hours and during the peak hour. Here, the maximum utilization of solar & BESS is 0.92 MW whereas the maximum utilization of demand response is 0.5 MW. For the 4.4 MW generator the maximum supply gap during the peak day is as high as 2.2 MW and the utilization of Solar & BESS is only 0.5 MW. Moreover, a generator size of 4.4 MW or below cannot support islanding for over 1 % of the time. The inputs to WSM is given in Table 6. Given the weights in Table 5 the final scores are shown in Table 7.

Based on the score obtained from the analysis, a 4.8 MW generator with score 80 % was recommended, whereas the second best score i.e., 76 % was obtained by the generator

TABLE 5. Criteria and weight.

Criteria	Weights (%)
Cost	5
Emission Reduction	20
Demand Response Utilization	15
Solar+BESS utilization	20
Islanding Support	40

TABLE 6. Inputs to WSM.

Gen Size (MW)	Cost (Number)	Incremental Emission Reduction (%)	Demand Response Utilization (MW)	Solar+BESS utilization (MW)	Islanding Support (Binary)
5.7	1	140	0.50	0.92	1
5.2	2	186	0.90	0.90	1
4.8	3	212	1.50	0.72	1
4.4	4	167	2.20	0.50	0
3.9	5	137	2.70	0.50	0

TABLE 7. Final score.

Gen Size (MW)	Score (%)
5.7	60
5.2	76
4.8	80
4.4	23
3.9	20

TABLE 8. Score with equal weights.

Gen Size (MW)	Score (%)
5.7	40
5.2	61
4.8	70
4.4	38
3.9	40

size of 5.2 MW. One may argue the logic behind the weights given to the criteria. The weights were given with focus on certain factors that are important to the utility, such as high support of islanding and high reliability and resiliency of customers within the MG. Emissions reduction and utilization of solar & BESS is important to derive the maximum learning out of this operation for future deployments. It is also important to have a flexible grid that can make up for any brief shortage in generation or a supply gap. Furthermore, the weighted scores for different generator sizes were also computed by giving all criteria equal weights, i.e. a weight of 0.2. Table 8 shows that the 4.8 MW generator still received the highest score, 70 %.

V. CONCLUSION

This paper presents a framework to optimally size the controllable DER required to obtain a generation mix for a MG that ensures economical operation in grid-connected mode while also operates in a secure and stable manner in islanded mode when called upon for reliability needs. It considers different inputs such as historical load and solar irradiance data, energy storage, solar generation and varying natural gas generation to minimize the amount and duration of supply gap. Mixed integer linear programming (MILP) based optimal scheduling algorithm retrieved the hourly dispatch results with varying generator sizes. A sensitivity analysis was carried out to estimate the number of days and hours with supply gaps with different generators. Additional resources such as the potential demand response capability within the MG footprint were considered to minimize supply gap. Decision-making criteria such as cost, incremental emissions reduction, demand response utilization, utilization of renewable and islanding capability were weighted. The methodology recommended a natural gas generator of 4.8 MW capacity as an optimal option for the MG that could cover the islanding scenario for 99.6 % of the time by utilizing all the resources at its disposal. Other factors such as protection study, noise, and generator size can be considered along with different levels of islanding confidence to achieve optimal sizing using the proposed methodology.

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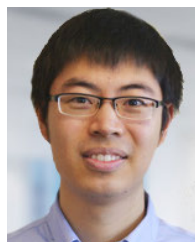


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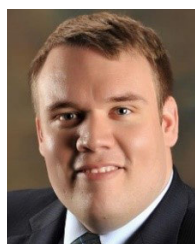


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