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Optimal Distributed Generator Placement in Utility-Based Microgrids During a Large-Scale Grid Disturbance

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ABSTRACT Microgrids are localized electric grids that can operate independent of the main grid and help strengthen grid resiliency by working alongside backup generators to maintain electricity supply in the event of a large-scale grid disturbance. This research proposes a single-source capacitated facility location coverage problem (SS-CFLCP) to optimize the location, assignment and number of renewable distributed generators (DGs) within a utility-based microgrid during a large-scale grid disturbance, where the microgrid is operating independent of the main grid. Traditional analytical techniques for DG placement within microgrids tend to focus on minimizing power losses, minimizing electric energy losses, improving voltage profile and maximizing cost savings. To deter from these traditional techniques, the proposed SS-CFLCP combines the facility location and location coverage problems, with an aim to minimize the following: total investment costs, total operation and maintenance cost, the distance traveled for electricity distribution, the power outage levels (unmet electricity demand) experienced due to a large-scale grid disturbance, and the levels of excess renewable penetration, which can cause reverse power flow issues that damage the main grid, within a network. Additionally, the proposed SS-CFLCP is modeled with a budgetary constraint for installing the DGs, making it a more practical and applicable model for a utility company. A case study using solar/photovoltaic-based DGs is used to show the effectiveness of the proposed model.

INDEX TERMS Distributed renewable energy generation, electric grid resilience, facility location, microgrid, optimization.

I. INTRODUCTION

Cities, towns and communities rely on utility-provided electricity to keep essential resources such as hospitals, grocery stores, police and fire stations operational. Grid functionality can be jeopardized by large-scale exogenous disturbances such as storms, earthquakes and cyber-attacks. Backup generators, while extremely beneficial during grid disturbances, have limited capacities and face the difficult challenge of providing electricity during the grid disturbance, which may last from hours to days even weeks depending on the impact of the disruption. Microgrids are localized low voltage grids that can disconnect from the main grid and operate independently. Microgrids contain multiple generation sources that coexist and can operate in parallel [1]. The main elements of microgrids are load/demand nodes, energy storage units, generation sources (renewable and non-renewable), an interconnection switch, a controller and an energy management system [1]. The two operating modes of a microgrid are the ‘‘grid connected mode’’ and ‘‘island mode’’. When in the ‘‘grid connected mode’’, the utility grid is still operational meaning all feeders can be supplied electricity by the utility grid or the renewable sources. When in ‘‘island mode’’ however, the utility grid is no longer supplying electricity thus feeders with connection to renewable sources are supplied electricity by the renewable sources, and feeders that are 100% reliant on utility provided electricity are now inactive [2].

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Electricity customers with large, mission-critical facilities, and customers in areas prone to frequent and/or prolonged power outages are typically the greatest beneficiaries of microgrids. This is primarily due to multiple examples of on-site backup generators failing during prolonged outages [3]. Natural disasters have proven to be extremely threatening to the functionality of the electric grid. Recent examples, such as Hurricane Sandy in 2012, forced a major New York hospital to evacuate 300 patients after the utility provided electricity and backup generators failed [3]. Hurricane Sandy not only affected the electricity supply to essential resources such as hospitals, the hurricane left more than 285,000 customers without electricity for almost two weeks [4], further emphasizing how damaging large-scale grid disturbances can potentially be.

In 2015, Presidential Policy Directive 21 (PPD-21) was implemented. PPD-21 pushed for the strengthening of critical infrastructure security and resilience so that infrastructure, such as the electric grid, can maintain functionality in the event of disturbances [5]. In addition, the US Department of Energy (DoE) launched a microgrid initiative that calls for the development of technical, operational and economic models to demonstrate the value of microgrids to utilities through the use of simulation and case studies [6]. Incorporating microgrids into the main grid system can benefit utilities by providing increased reliability of electricity supply during times of disaster. Microgrids can also add reactive power generation for a utility, reduce demand on the main grid during peak hours of the day, reduce emissions, improve overall energy efficiency by improving voltage regulation for load balancing, and reduce transmission losses due to a closer proximity to end customers. These serve as added benefits for a utility during periods where the main grid is operating without disturbance.

The renewable generation sources within a microgrid can be solar, wind, hydroelectric, etc. based. Solar/photovoltaic (PV) based generation microgrids are typically less challenging to implement within largely populated cities due to the increased availability of rooftop mounting in such locations, but can also be easily implemented in more rural areas. On the other hand, wind based generation microgrids tend to be more likely in more rural areas, where there is sufficient space for large wind turbines to be established and hydroelectric requires a water source to be present. The generation sources proposed in this research are solar/PV-based distributed generators (DGs) due to the ease of installation and geographic flexibility when compared to wind and other generation sources. This research models a scenario where a large-scale disturbance has already occurred and the microgrid is operating in "island mode". The PV-based DG microgrid provides electricity during the day-time hours, while backup generators provide electricity at night when the PV-based DGs can no longer generate electricity. The load/demand nodes are the essential resources - hospitals, large-scale grocery stores, police and fire stations, transportation systems, etc. - within cities, towns and communities. The following section performs a review of literature pertaining this research topic.

II. LITERATURE REVIEW

A literature review is performed to highlight the three main aspects of this research: (1) the potential of microgrids as a solution during a large-scale grid disturbance; (2) the negative impacts high penetration levels of renewable generation can have on an existing electricity network, specifically in the form of reverse power flow (RPF); (3) the general optimization of DGs within a microgrid. This section divides the three aspects and discusses literature pertaining to each aspect separately.

A. MICROGRIDS AS A SOLUTION DURING POWER GRID DISTURBANCE

The authors in [7] present examples from numerous parts of the world where a microgrid was used in the wake of a disaster for reliable electricity supply. For example, in 2011, a microgrid helped restore Japan from the East Japan earthquake. The microgrid contained three different DG types and was kept in operation years after restoration from the earthquake was complete [7]. This example shows the capability of microgrids to accommodate communities when their main grid is affected by some type of large-scale grid disturbance, along with the benefits microgrids can serve during periods where the main grid is fully operational.

Montgomery County, the most populous county in Maryland, installed a 2 megawatt (MW) solar-based microgrid at the Public Safety Headquarters (PSHQ). PSHQ serves as the county's hub for critical public services such as transportation management resources, the County's Office of Emergency Management and Homeland Security, and the police station that serves the central portion of the county [8]. The microgrid was installed as part of a comprehensive effort to ensure resiliency of critical public services during large-scale grid disturbances, and was established in partnership with the Duke Energy utility that serves the area. In addition, the microgrid saves the county $4 million in expenses for aging low-voltage and medium-voltage electrical system upgrades [8]. This microgrid shows how utility involvement can benefit the utility and the area the utility serves, as is suggested by the utility-based microgrid we present in our research.

In 2019, Fremont, California completed the first microgrid system installed at three fire stations within the city [9], [10]. The project demonstrates the islanding of critical infrastructure and increasing the protection of such infrastructure against power outages; currently, fire stations in Fremont can use diesel backup generation for 72 hours before replenishment is necessary. This microgrid system is one of the first examples of DG placement at the site of essential resources. Our research furthers this idea to include more essential resources in total and more essential resource types-hospitals, gas stations, police stations and grocery stores, as opposed to just fire stations.

B. RPF CAUSED BY EXCESS PV-BASED DG PENETRATION

The authors in [11] introduce new methodologies and techniques to determine the impact solar DG systems could have on the main grid. They provide insight to the RPF that can occur through the PV-based DG proliferation [11]. RPF can occur at section, feeder, and substation levels while negatively affecting protection coordination and voltage regulators (VRs). This might offset the feeder load and affect over-current production since most distributed feeders are setup for unidirectional power flow. The study recommends the regulation of VRs to allow for bidirectional power flow to avoid voltage violations, which can prove to be costly due to the expense of installing bidirectional converters within an already designed distribution system. Our research presents a manner to mitigate RPF without having to account for large amounts of bidirectional power flow.

A Renewable System Interconnection study, as part of a larger effort by the DoE, is presented in [12]. The study addresses the challenges of implementing high-penetration levels of distributed renewable technologies such as PV. The goal of the research was to identify the resources needed to compensate high-penetration renewable technologies while enhancing the operation of the main grid [12]. The study acknowledges that penetration of PV could not only offset the load, but also cause RPF in the distribution system. This can further cause over-voltage, increased short circuits, breach of protection coordination, and incorrect operation of control equipment [12]. The study states that one way to contain RPF is through adjustments to the amount of reactive power generated. This can be difficult to execute without some form of system regulation on the PV generation when the sun is available. Our research presents a manner to mitigate excess PV generation without incorporating system regulation.

C. DG OPTIMIZATION IN MICROGRIDS

Optimization of microgrid DG placement through an improved reinitialized social structures particle swarm optimization, known as IRS-PSO, is proposed in [13]. The objective is to minimize real power loss within real and reactive power generation limits and voltage limits. When given a number of DGs, IRS-PSO can perform better than the basic particle swarm optimization, adaptive weight particle swarm optimization, as well as global best, local, and near best particle swarm optimization. However, the model in [13] limits the number of DGs in each microgrid, which can be troublesome when larger demand networks are considered. Our developed model requires at least one DG installed and limitation on how many in total is controlled by the utility's budget.

A novel combined method based on a GA and Intelligent Water Drops (IWD) for the optimization of the location and capacity of DGs within a microgrid is presented in [14]; IWD is described as a swarm-based optimization algorithm developed from observing natural water flow in rivers formed by a swarm of water drops [14]. The objective of the model is to minimize power loss, voltage variation and voltage stability index within the network. The novel GA-IWD method is compared to conventional algorithms such as a general GA, particle swarm optimization and harmony search methods. Results show that the GA-IWD method performs better than the compared methods in terms of quality of answer, number of iterations and run time [14]. Results also showed that the GA-IWD run time increased linearly as the number of DGs installed in the microgrid increased, whereas the other conventional methods increased almost exponentially.

Optimal placement and sizing of DGs in a distribution grid is discussed in [15]. A genetic algorithm (GA), which aims to minimize power loss while maintaining appropriate voltage levels, is employed. The GA is then run on a variety of scenarios and shows that optimal location and size depend heavily on the conditions provided. Configurations, load profiles, and time of year all have an impact on the optimal solutions - number of DGs installed and DG sizes - computed by the algorithm. In terms of seasons, the summer scenario solutions suggested more PV generators be used, while the winter scenarios leaned more towards the combined heat and power units. For a utility, allocating DGs based off of season may not be feasible or desired. In contrast, our developed model allocates microgrid DGs based on annual demand averages, making it more practical for a utility to deploy.

Traditional analytical techniques for the optimization of DG integration within the distribution network usually aim to minimize active/reactive power losses [13]–[15], minimize distribution losses [16], maximize cost savings [16], or improve voltage profiles [14]–[16]. Figure 1, adapted from [16], displays the traditional analytical technique model formulation. To deter from the norm, this research proposes a

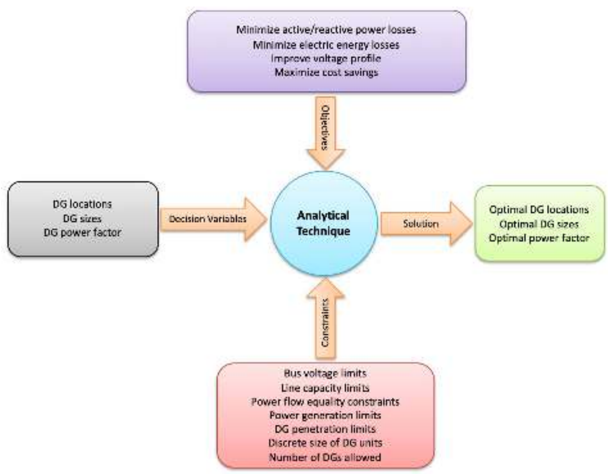

FIGURE 1. Traditional formulation of analytical models that optimize DG integration into the power grid.

single-source capacitated facility location coverage problem (SS-CFLCP) that optimizes the location, size, assignment and number of DGs within a utility-based microgrid with the following objectives: (1) minimize the total cost of installing a microgrid; (2) minimize the total cost of operation and maintenance of microgrid DGs; (3) minimize the distance electricity travels for distribution; (4) minimize the power outage (unmet demand) levels during a large-scale grid disturbance; (5) minimize RPF amounts caused by excess DG penetration. Objective (1) and (2) have been optimized objectives in previous DG integration research. The main contributions of our research are objectives (4) and (5), along with the DGs being established at and providing power to the actual essential resources within the microgrid, and a budget constrained utility perspective of a scenario where a large scale grid disturbance has occurred and the microgrid is operating in island mode. The following section discusses the methodology applied to this research.

III. METHODOLOGY

We propose a SS-CFLCP for the optimization of a utility-based microgrid, under a large-scale grid disturbance scenario. A single-source, as opposed to a multiple-source, forces each demand node/essential resource to be supplied by only a single DG. The single-source problem is generally more challenging because the decision variables are binary, but is considered typical for real life situations where multiple deliveries maybe involved [17]. We use a capacitated problem, as opposed to an uncapacitated problem, due to the generation limitations of the DGs. We incorporate the location coverage problem because the proposed model aims to supply/cover as much demand as possible, given the specified constraints. This section describes the formulation of the SS-CFLCP, which employs a combination of the single-source facility location problem described in [17] and the location coverage problem described in [18], [19]. Furthermore, this section states the assumptions of the developed SS-CFLCP model and describes the model formulation by defining the variables, objectives and constraints. The parameters used within the model are explained in this section and stated in the Nomenclature.

NOMENCLATURE

A. SETS

- i Set of electricity demand nodes $\{1..n\}$.
- j Set of potential DG nodes/locations $\{1..m\}$.

B. VARIABLES

$$D_j = \begin{cases} 1 & \text{if a DG is installed at node } j \\ 0 & \text{otherwise} \end{cases}$$

$$X_{ij} = \begin{cases} 1 & \text{if node } i \text{ is supplied by } j \\ 0 & \text{otherwise} \end{cases}$$

C. PARAMETERS

- a Minimum number of DGs required for microgrid.
- B Budget utility can use to establish the microgrid.
- δ_i Electricity demand for each node i (W).
- α_j Generation power for each DG j (W).
- ω_j Electricity output for each DG j (W).
- ϕ_j Total cost of operation and maintenance for each DG j (\$/W).
- λ_j Penalty cost for excess DG j penetration (\$/W).
- ψ_i Penalty cost for not covering/supplying electricity to demand node i (\$/W); the more important the demand node, the higher the penalty cost.
- γ_j Total cost of installing a utility-based DG j (\$/W); total cost includes the modules, inverter, balance of system structural and electrical components, installation, taxes, land acquisition and permitting, inspection, and interconnection costs.
- c_{ij} An $n \times m$ matrix of the distance costs from demand nodes i to DG location j, where the distances serve as electricity distribution costs.

D. SS-CFLCP MODEL

The SS-CFLCP proposed assumes the following: (1) the maximum number of locatable DGs is known; (2) the candidate nodes for locating DGs are known and assumed to be within an already interconnected distribution network; (3) the generation power and electricity outputs of the DGs are known; (4) the model is deterministic with constant levels of electricity generation and flow within the already assumed interconnected distribution network; (5) the model models a worst-case or large-scale grid disturbance scenario, where the employed microgrid is operating in island mode; (6) the PV-based DG microgrid provides day-time electricity, while backup generators (each demand node/essential resource is assumed to posses a backup generator) provide electricity during night-time; (7) DGs generate and output their full capacity, thus DGs can output more electricity than needed for the annual day-time network demand; (8) the demand for each demand node/essential resource is fully met by only one installed DG [17]; (9) the utility has a pre-determined budget to abide by when establishing the microgrid within the network.

The model contains a given set of demand nodes/essential resources, that also serve as potential DG location sites within the network. Each demand node/essential resource has an electricity demand and a penalty cost suffered if the electricity demand of the node is not met/supplied by the model. Since the demand nodes/essential resources are prioritized, the penalty cost is higher for demand nodes/essential resources with a higher priority. Each potentially installed DG has a generation power and electricity output, a cost for installing the DG, a cost for operation and maintenance and a penalty cost for excess DG penetration that may occur from the DG. For this research, it is desired that at least one DG is installed. Lastly, there is a transportation cost, based on euclidean distance, between each demand node/essential resource and potential DG location site.

For each potential DG location site, a decision must be made to either install or not install a DG. Also, a decision must be made on which demand nodes/essential resources are supplied electricity by which installed DG(s). Given the decision variables, the objective function and constraints of the complete model are described as follows:

$$\text{Min} \quad \left[\sum_{j=1}^{m} \gamma_j \alpha_j D_j\right] + \left[\sum_{i=1}^{n}\sum_{j=1}^{m} \delta_i X_{ij} \phi_j D_j\right] + \left[\sum_{i=1}^{n}\sum_{j=1}^{m} c_{ij} X_{ij}\right] + \left[\sum_{i=1}^{n} \psi_i \delta_i - \sum_{i=1}^{n}\sum_{j=1}^{m} \psi_i \delta_i X_{ij}\right] + \left[\sum_{j=1}^{m} \lambda_j \omega_j D_j - \sum_{i=1}^{n}\sum_{j=1}^{m} \lambda_j \delta_i X_{ij}\right] \tag{1}$$

$$\text{Subject to:} \quad \sum_{j=1}^{m} X_{ij} \leq 1 \quad \forall i \tag{2}$$

$$\sum_{j=1}^{m} D_j \geq a \tag{3}$$

$$\sum_{j=1}^{m} \gamma_j \alpha_j D_j \leq B \tag{4}$$

$$X_{ij} \leq \delta_i \quad \forall i, \ \forall j \tag{5}$$

$$\sum_{i=1}^{n} \delta_i X_{ij} \leq \omega_j D_j \quad \forall j \tag{6}$$

$$D_j \in \{0, 1\} \quad \forall j \tag{7}$$

$$X_{ij} \in \{0, 1\} \quad \forall i, \ \forall j \tag{8}$$

Equation (1) is the objective function and minimizes 5 objectives. The first objective minimizes the total cost of installing DGs:

$$\sum_{j=1}^{m} \gamma_j \alpha_j D_j \tag{9}$$

This objective minimizes the number of DGs installed to meet as much of the demand as possible, and is determined by computing the product of the DG installation costs (γ_j) and the generation power (α_j) of each DG (D_j), summed for all DGs. The second objective minimizes the total cost of operation and maintenance of the DGs:

$$\sum_{i=1}^{n}\sum_{j=1}^{m} \delta_i X_{ij} \phi_j D_j \tag{10}$$

This objective is determined by computing the product of the summed demand (δ_i) met by or assigned to each specific DG (X_{ij}, which is binary) and the operation and maintenance cost (ϕ_j) of each DG (D_j), summed for all DGs. The operation and maintenance costs (ϕ_j) of this second objective are determined as a percentage of the DG installation costs (γ_j) of the first objective [20]. Thus, a decrease in the installation cost objective (first objective) will lead to a decrease in the operation and maintenance cost objective (second objective). Furthermore, an increase in the installation cost objective will lead to an increase in the operation and maintenance cost objective. The third objective minimizes the total electricity distribution costs:

$$\sum_{i=1}^{n}\sum_{j=1}^{m} c_{ij} X_{ij} \tag{11}$$

This objective reduces the distribution losses experienced as electricity travels from DG to demand node/essential resource and is determined by computing the product of the summed distance costs from demand node/essential resource i to DG location j (c_{ij} - electricity distribution costs converted from i to j distances) and the coverage/assignment of demand node/essential resource i to DG location j (X_{ij}, which is binary). The fourth objective, one our main research contributions, minimizes the total network power outage (unmet demand) during a large-scale grid disturbance:

$$\sum_{i=1}^{n} \psi_i \delta_i - \sum_{i=1}^{n}\sum_{j=1}^{m} \psi_i \delta_i X_{ij} \tag{12}$$

Minimizing power outage (unmet demand) levels is not typically an objective of focus in such optimization studies [16] and thus is one of our main research contributions. To incorporate this objective, a penalty cost for not meeting/supplying a demand node/essential resource i (ψ_i) is applied; the more important the demand node/essential resource, the higher the penalty cost. This objective is determined by subtracting the summed demand (δ_i) met by or assigned to a specific DG (X_{ij}, which is binary), from the summed demand (δ_i) of the of the entire network, and then applying the the penalty cost for not covering/supplying electricity to a demand node/essential resource (ψ_i). In other words, the network demand met/supplied is subtracted from the total network demand and that difference is then multiplied by the unmet demand penalty cost. This fourth objective cost function is dependent upon the electricity demand met by each DG ($\delta_i X_{ij}$), which is bounded as described in equation (6), and the demand of each demand node/essential resource (δ_i) which is provided by the data and constrained as described in equation (5); equations (5) and (6) are explained at the end of this section.

The fifth and final objective, another main contribution of our research, deals with excess DG penetration within the network. Distribution systems are designed for radial operation but it has become well known that implementing renewable DGs may cause negative impacts, such as RPF, to the network and thus pre-planning for such impacts is vital [11].

Pre-planning for such impacts becomes even more important when considering utility-scale renewable DG penetration [12], as is considered in this research. Most DG penetration impact studies focus on quantifying the extent of the issues and providing utilities with guidelines, tools, and processes to help manage such issues [11], [12]. The model developed in this research aims to mitigate the potential RPF issue by minimizing the amount of excess renewable penetration (RPF amounts) experienced within the network:

$$\sum_{j=1}^{m} \lambda_j \omega_j D_j - \sum_{i=1}^{n} \sum_{j=1}^{m} \lambda_j \delta_i X_{ij} \tag{13}$$

This objective is determined by subtracting the product of the summed demand (δ_i) met by or assigned to each specific DG (X_{ij}, which is binary) from the summed electricity generation (ω_j) of all DGs (D_js), and then applying the penalty cost for excess DG penetration (λ_j). In other words, the network demand met/supplied is subtracted from the total electricity generated within the network and that difference is then multiplied by the excess penetration cost. This fifth objective cost function is dependent upon the electricity demand met by each DG ($\delta_i X_{ij}$), which is bounded as described in equation (6), and the electricity output of each DG ($\omega_j D_j$) which is provided by the data. The unmet demand cost objective (fourth objective) and this excess penetration cost objective (fifth objective) both depend on how much network demand is met/supplied ($\delta_i X_{ij}$). Thus, an increase in the network demand met/supplied will lead to a decrease in the unmet demand cost objective and in this excess penetration cost objective. Furthermore, a decrease in the network demand met/supplied will lead to an increase in the unmet demand cost objective and can lead to an increase in this excess penetration cost objective depending on what size DG system is installed.

Equation (2) is a demand constraint ensuring that each demand node/essential resource i is assigned to/supplied electricity by at most one DG j. Equation (3) is a constraint ensuring that the total number of installed DGs (D_js) is greater than or equal to the pre-determined number of DGs the utility desires to install (a); this research assumes at least one DG is installed, thus $a \geq 1$. Equation (4) is a budget constraint that ensures the total installation cost ($\gamma_j \alpha_j D_j$) is less than or equal to what the pre-determined utility budget (B) allows. Our problem is modeled from the perspective of a utility attempting to meet network demand during a disturbance. Including a budget that limits the installation costs helps make the cost minimization problem more practical to how a utility would approach establishing a microgrid. An unbounded installation cost would imply that the utility has no limits on how much it is able to spend when establishing the microgrid, which is not realistic due to the business considerations a utility has. Thus, this budget constraint is included as another main contribution of our research because it captures a major business focus of the utility company. Equation (5) is a demand assignment constraint ensuring that a demand node/essential resource is only assigned to a DG if that demand node/essential resource actually has a demand. Equation (6) is a DG constraint ensuring that the total electricity demand met by each DG ($\delta_i X_{ij}$) must be less than or equal to the electricity output of the DG ($\omega_j D_j$), and that demand can only be met/supplied by an installed DG, for all DGs. Equation (7) and (8) ensure that the installing of DGs and the assignment of demand nodes/essential resources to DGs, is binary, for all demand nodes/essential resources and DGs. A case study applying the developed SS-CFLCP model is detailed in the following section.

IV. TENNESSEE CASE STUDY

A network, composed of a 25-node city grid in Tennessee, is used as a case study for this research. The 25 nodes that the network is comprised of are all essential resources that provide essential services. There are 5 hospitals, 5 fire departments, 7 large-scale grocery stores, 4 gas stations and 4 police stations. A distance matrix is developed using the longitude and latitude coordinates of each node [21]. Annual electricity demands for the essential resources are adopted from the U.S. Energy Information Administration (EIA) survey data for commercial buildings within the southern region of the country [22]. Since the electricity generated from the PV-based DG systems in the microgrid is assumed to only provide day-time demand, the annual demands for each building are multiplied by 0.56 to account for the fact that the area of Tennessee the grid encompasses has an annual '%sun' total of 56% [23]; '%sun' is a measure of the percentage of time, between sunrise and sunset, that sunshine reaches the ground [23]. All buildings for each type of essential resource have the same demand (i.e., all hospitals have the same demand and all fire departments have the same demand). The total annual and daytime electricity demands for each building can be viewed in Table 1.

TABLE 1. Electricity demand for the south region of the US.

Building Type	Annual Demand per Bldg (kWh)	Annual Demand per Bldg (W)	Annual Daytime Demand per Bldg (W)
Hospital	7,750,000	884,703	495,434
Fire Station	282,051	32,198	18,031
Grocery Store	271,605	31,005	17,363
Gas Station	65,217	7,445	4,169
Police Station	282,051	32,198	18,031

The generation power and cost of each PV-based DG system is based on data provided by the National Renewable Energy Laboratory (NREL). NREL data is used as opposed to data from public sector integrators such as SolarCity, Sunrun, and Vivint Solar because these integrators account for sold and leased PV-based DG systems. Reported costs for leased systems span the life of the lease rather than the period in which the system is sold, thus making it difficult to accurately determine the true costs at the time of sale [24]. PV-based DG systems of 500 kW, 1 MW and 5 MW are used this research. The electricity output of each system is computed using NREL's PVWatts calculator, which estimates the electricity production of grid-connected PV-based DG systems based on the solar radiation in the specific location (Tennessee) [25]. Each of the 25 nodes within the network can potentially have a PV-based DG system installed through rooftop-mounting or ground-mounting. NREL's benchmark assumptions for the PV sector are that 3 kW - 2 MW PV-based DG systems can be rooftop-mounted and anything greater than 2 MW is a ground-mounted system where land acquisition is required [24]. For our research, a 500 kW system can be installed on gas stations, a 1 MW system on police and fire stations and a 5 MW system on hospitals and large-scale grocery stores. Thus, for hospitals and large-scale grocery stores, land acquisition is included in the cost for locating a PV-based DG system at the site. Electricity outputs for each PV-based DG system, presented by month for the state of Tennessee, can be viewed in Table 2.

TABLE 2. PV-based DG system generation for Tennessee.

PV-based DG system Size	500 kW	1 MW	5 MW
January	40,174	80,347	401,737
February	40,202	80,404	402,020
March	57,646	115,292	576,460
April	60,472	120,944	604,720
May	69,881	139,761	698,806
June	68,626	137,251	686,256
July	65,794	131,589	657,942
August	67,320	134,640	673,202
September	58,242	116,485	582,423
October	53,533	107,066	535,330
November	44,030	88,059	440,295
December	36,949	73,898	369,489
Annual Electricity Production (kWh)	662,869	1,325,736	6,628,680
Annual Electricity Output (W)	135,125	270,250	1,351,248

The costs for each PV-based DG system used for this research include the following: (1) the cost to install a PV-based DG system, expressed in \$/W; (2) the cost of operations and maintenance of each DG, which is set at 3% of the cost to install a system and is expressed in \$/W [20]; (3) the penalty cost applied for excess DG penetration, which is assumed to be half the cost to install a PV-based DG system and is expressed in \$/W; (4) the penalty cost applied for unmet demand, which is higher for more important buildings and is also expressed in \$/W. The unmet demand penalty cost is arbitrarily assigned for each building type based on what we, as the researchers, view as the importance hierarchy of the building types. We view hospitals as the most important during a large-scale grid disturbance and thus assign hospitals the highest unmet demand penalty cost. Grocery stores are viewed as the second most important building type. We assign police stations and fire stations the same level of importance, and thus the same unmet demand penalty cost, because the these two building types have the same electricity demand based on the EIA survey data. Gas stations are viewed as the least important during a large-scale grid disturbance and are thus assigned the lowest unmet demand penalty cost.

We design the unmet demand penalty cost based on an importance hierarchy for practicality purposes. Since the utility-based microgrid we model is under a large-scale grid disturbance scenario, where the microgrid is operating in island mode, decisions would have to be made as to what essential resources are covered, especially since there is a budget constraint that limits the electricity output of the microgrid. As a result, incorporating an importance hierarchy allows for the model to decide what essential resources are covered based on penalization that still leads to the most optimal minimized total cost. The unmet demand penalty costs can be adjusted to the specific desires of the utility and the network the utility serves. The system power and costs for each PV-based DG system can be viewed in Figure 2. The operations and maintenance costs are minor when compared to the other costs, but are included in the model for practicality purposes. A utility establishing a microgrid would have to consider the operation and maintenance costs, thus our developed model accounts for these costs. Even if only in minor amounts, the operation and maintenance costs still add to the overall total cost objective solution of the model. The unmet demand and excess DG penetration penalty costs for each building can be viewed in Figure 3 and Figure 4 respectively. Both penalty costs are displayed as "High", "Medium" and "Low", which signifies the sensitivity levels of the penalty cost. The sensitivity levels help show how sensitive the results are to changes within these two penalty cost parameters. This is later discussed in the sensitivity analysis of the results. The next section provides and discusses the results of the case study.

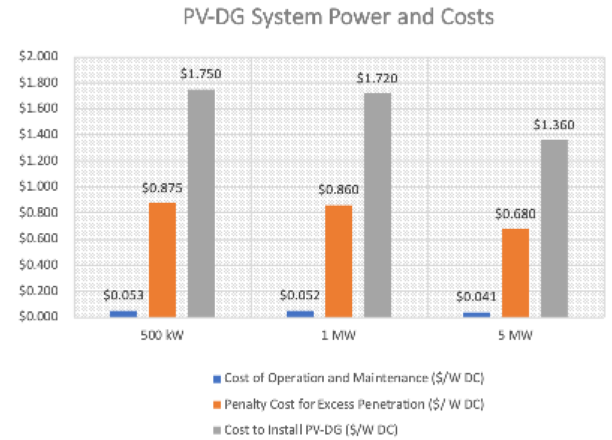

FIGURE 2. Costs for each type of system by rated power.

V. RESULTS OF CASE STUDY

The developed SS-CFLCP model is solved using CPLEX solver 12.8 on a 2.9 GHz Intel Core i7 and the results are presented in Table 3 based on budget (B) amount. Budgets of \$1, \$5, \$10, \$15, \$20 and \$50 million are used. A budget of \$1 million is used as the lowest possible budget amount because the cheapest microgrid possible is one with a single 500 kW system at an investment of \$875,000 as shown in the table; the model requires that the microgrid contain

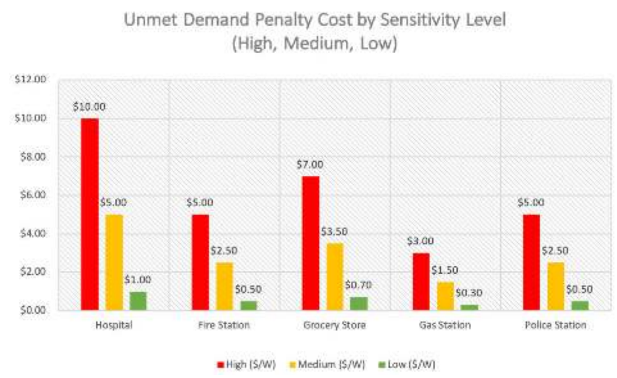

FIGURE 3. Unmet demand penalty cost for each building type at each sensitivity level.

FIGURE 4. Excess penetration penalty cost for each building type at each sensitivity level.

at least one installed DG. The optimal solutions show no improvement for any budget amount greater than $15 million. Even with a budget of $50 million, which would financially allow the utility to install 7 total 5 MW DG systems at a cost of $6.8 million each, the optimal solution at the $50 million budget results in the installation of the same two 5 MW DG systems (DGs 2 and 15) as that of the $15 million budget. This is because the additional installation costs of another PV-based DG system would increase the total cost to a sub-optimal solution. As a result, the total cost minimization objective function finds no improvement for any budget above $15 million, even if the installation cost function was unbounded. Thus, the $20 and $50 million budget results are not presented in Table 3. The optimal solutions for a $5 million budget showed no improvement over $1 million budget and thus the $5 million budget results are also not presented in Table 3. The results display the following information: (1) the investment cost, which is total cost of installing the DG(s); (2) the optimal solution (total cost); (3) the installed DG(s), which are the determined optimal locations within the network to establish DGs upon; (4) total network demand met and unmet for each optimal solution (expressed as a percentage); (5) the demand met for each type of essential resource (expressed as a percentage). Matrices detailing which DG is installed for each solution, and which essential resources are covered by or assigned to each installed DG are provided

TABLE 3. Model solutions with unmet demand sensitivity analysis.

	Unmet Demand Penalty Cost Level	B = $1 million	B = $10 million	B = $15 million
Investment Cost	High	$875,000.00	$6,800,000.00	$13,600,000.00
Optimal Solution (Total Cost)		$26,478,682.65	$21,756,745.17	$18,933,733.59
Installed DG		20	4	2 , 15
Total Network Demand Met		5%	46%	82%
Total Network Demand Unmet		95%	54%	18%
Hospital Demand Met		0%	40%	80%
Fire Station Demand Met		0%	100%	100%
Grocery Store Demand Met		100%	100%	100%
Gas Station Demand Met		75%	100%	100%
Police Station Demand Met		0%	100%	100%
Investment Cost	Medium	$875,000.00	$875,000.00	$875,000.00
Optimal Solution (Total Cost)		$13,680,881.65	$13,680,881.65	$13,680,882.54
Installed DG		20	20	18
Total Network Demand Met		5%	5%	5%
Total Network Demand Unmet		95%	95%	95%
Hospital Demand Met		0%	0%	0%
Fire Station Demand Met		0%	0%	0%
Grocery Store Demand Met		100%	100%	100%
Gas Station Demand Met		75%	75%	75%
Police Station Demand Met		0%	0%	0%
Investment Cost	Low	$875,000.00	$875,000.00	$875,000.00
Optimal Solution (Total Cost)		$3,442,640.85	$3,442,641.74	$3,442,640.85
Installed DG		20	18	20
Total Network Demand Met		5%	5%	5%
Total Network Demand Unmet		95%	95%	95%
Hospital Demand Met		0%	0%	0%
Fire Station Demand Met		0%	0%	0%
Grocery Store Demand Met		100%	100%	100%
Gas Station Demand Met		75%	75%	75%
Police Station Demand Met		0%	0%	0%

at [26]. Installed DGs are denoted with a "1" and highlighted orange, while closed DGs are denoted with a "0". Similarly, essential resources covered by or assigned to an installed DG are denoted with a "1" under that DG and highlighted orange, while non-covered essential resources are denoted with a "0".

A sensitivity analysis is performed on the unmet demand penalty cost, an arbitrarily assigned parameter, that relates to the fourth objective (minimize total network power outage/unmet demand) which is one of our main research contributions. We use three levels for the parameter: high, medium, and low. Figure 3 displays the costs for each essential resource at each sensitivity level of the parameter. The results are similar across all budget options for the "Low" and "Medium" levels. At the "Low" level, the optimal location is either DG 20 or DG 18, both of which are gas stations. The optimal solution is a minimized total cost of $3,442,640.85 for budgets of $1 and $15 million, and $3,442,641.74 for a budget of $10 million. All budget options at the "Low" level cover 100% of the grocery store demand and 75% of the gas station demand, but do not cover any demand for the hospitals, fire stations or police stations. Overall, 5% of the total network demand is met and 95% is unmet. The same situation is witnessed at the "Medium" level except the optimal solution increases to a minimized total cost of $13,680,881.65 for the $1 and $10 million, and $13,680,882.54 for a budget of $15 million. The increase witnessed with the objective solution is caused by the increase in unmet demand penalty cost amount from the "Low" level to "Medium" (see Figure 3).

We begin to see variation within the results at the "High" level of the unmet demand penalty cost. At a budget of $1 million, the results resemble those of the "Low" and "Medium" levels where the optimal solution is a single DG microgrid, with the DG being a 500 kW system (DG 20) installed at a gas station. The investment cost, demand met and demand unmet within the network are exactly the same as well.

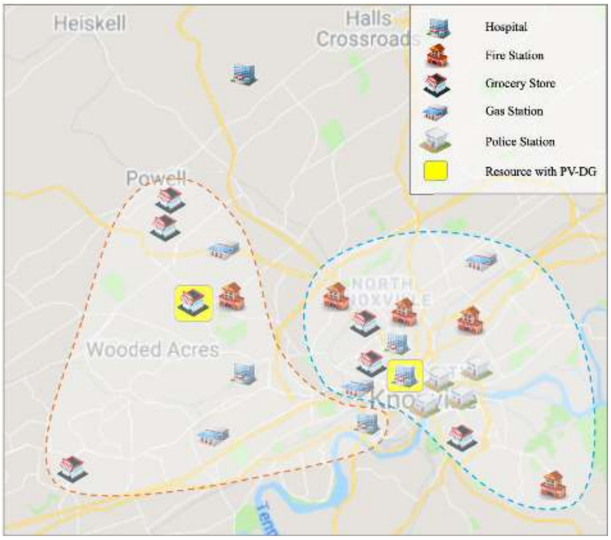

FIGURE 5. **Demand-coverage map for $15 million budget solution under "High" sensitivity level; this is the optimal solution found.**

The optimal solution (total cost) nearly doubles when compared to the $13,680,881.65 of the ''Medium'' level budget options. This is due to the increase in unmet demand penalty cost, which is doubled for the ''High'' level when compared to the ''Medium'' (see Figure 3). When a $10 million budget is used at the ''High'' level, improvements are finally witnessed. The investment cost increases to $6.8 million because the optimal DG selected is a 5 MW system (DG 4), versus the 500 kW systems selected at the ''Low'' and ''Medium'' levels. The total electricity demand met within the network improves from 5% to 46% and we observe that all essential resource buildings are covered except for three of the five hospitals. Most importantly however, we see an improvement in the optimal solution of about $5 million. Improvements continue to be seen when the budget increases to $15 million. The investment cost doubles to $13.6 million because two 5 MW PV-based DG systems (DGs 2 and 15) are selected at optimality now. The total demand met within the network increases to 82% and all essential resource buildings are covered expect for one hospital. The optimal solution also improves by about $3 million over the ''Medium'' level solution.

Figure 5 displays the demand-coverage map for the $15 million budget under the ''High'' level. The yellow highlighted buildings represent the optimal DG locations (ID 2 and 15) within the network. The dotted line shapes represent the essential resources whose demand is met by the PV-based DG highlighted in yellow. The solution only has one essential resource, DG 3, with unmet demand. This same essential resource is not covered in any of the solutions at any of the sensitivity levels. Even with hospitals such as DG 3 having the highest unmet demand penalty cost, the model can opt to leave a hospital uncovered if the other costs involved with covering that hospital (installation, operation and maintenance, distribution and excess penetration (RPF) costs) would increase the total cost to a sub-optimal solution. This is what would happen if essential resource DG 3 were to be covered. The lack of coverage for this essential resource is due to its large demand, which is tied for the highest along with the other four hospitals, and its far distance when compared to other essential resources within the network. Meeting the demand for DG 3 would require installing another 5 MW DG, as the 1 MW and 500 kW sizes would be too small to cover DG 3's annual demand. Installing another 5 MW DG would lead to an increase in excess DG penetration, which in-turn can significantly increase the overall cost due to the excess penetration penalty cost our developed model applies. Increasing the excess DG penetration also weakens the reliability of the grid because it increase RPF amounts within the distribution network. In addition, meeting the electricity demand of DG 3, which is further away in distance from the optimally installed DGs (ID 2 and 15), would increase the total distribution costs within the network in a manner that worsens the optimal solution. As a result, the model accepted the penalty cost of not meeting the electricity demand of DG 3 in order to assure that as much network demand was met with the overall total costs also minimized.

A sensitivity analysis is also performed on the excess DG penetration (i.e., RPF) penalty cost, which is assumed to be half the cost to install a PV-based DG system. This parameter relates to the fifth objective (minimize RPF amounts caused by excess DG penetration) which is another one of our main research contributions. We evaluate how sensitive the results are to an excess DG penetration cost that is equal to the cost of installing a PV-based DG system (''Medium'' level) and greater than the cost of installing a PV-based DG system (''High'' level). At the ''High'' level, the excess DG penetration cost is set at 1.5 times the cost of installing a PV-based DG system. Figure 4 displays the excess DG penetration costs for each essential resource at each sensitivity level of the parameter, where the ''Low'' level represents the assumed cost of excess DG penetration as half of the cost to install a PV-based DG system. The results are displayed in Table 4 with the exclusion of the demand met percentages. The demand met percentages are identical for each installed DG in Table 4 as they are to those in Table 3. For example, demand met percentages for network, hospital, fire station, grocery store, gas station and police station for a solution where the installed DG is DG 20, are identical for Table 4 results as they are for an installed DG 20 solution in Table 3. The results in Table 4 at each ''Low'' level of excess penetration, for each respective unmet demand penalty cost level, are as shown in Table 3. These are the results of the assumed cost for the excess penetration penalty cost (assumed half of the cost to install a PV-based DG system). For the ''Low'' and ''Medium'' levels of the unmet demand penalty cost, there is minimal difference between the optimal solutions at each level of the excess penetration penalty cost and across the budget options. For all budget options at the ''Low'' level of the unmet demand penalty cost, all the solutions are about

TABLE 4. Excess DG penetration sensitivity analysis.

	Excess Penetration Penalty Cost Level	B = $1 million	B = $10 million	B = $15 million
Unmet Demand Penalty Cost Level - High				
Investment Amount	High	$875,000.00	$6,800,000.00	$13,600,000.00
Optimal Solution (Total Cost)		$26,480,567.40	$21,838,187.41	$19,505,292.63
Installed DG		20	4	2 , 15
Investment Amount	Medium	$875,000.00	$6,800,000.00	$13,600,000.00
Optimal Solution (Total Cost)		$26,479,625.02	$21,797,466.29	$19,219,513.11
Installed DG		20	4	2 , 15
Investment Amount	Low	$875,000.00	$6,800,000.00	$13,600,000.00
Optimal Solution (Total Cost)		$26,478,682.65	$21,756,745.17	$18,933,733.59
Installed DG		20	4	2 , 15
Unmet Demand Penalty Cost Level - Medium				
	Excess Penetration Penalty Cost Level	**B = $1 million**	**B = $10 million**	**B = $15 million**
Investment Amount	High	$875,000.00	$875,000.00	$875,000.00
Optimal Solution (Total Cost)		$13,682,766.40	$13,682,766.40	$13,682,766.40
Installed DG		20	20	20
Investment Amount	Medium	$875,000.00	$875,000.00	$875,000.00
Optimal Solution (Total Cost)		$13,681,824.02	$13,681,824.02	$13,681,824.02
Installed DG		20	20	20
Investment Amount	Low	$875,000.00	$875,000.00	$875,000.00
Optimal Solution (Total Cost)		$13,680,881.65	$13,680,881.65	$13,680,882.54
Installed DG		20	20	18
Unmet Demand Penalty Cost Level - Low				
	Excess Penetration Penalty Cost Level	**B = $1 million**	**B = $10 million**	**B = $15 million**
Investment Amount	High	$875,000.00	$875,000.00	$875,000.00
Optimal Solution (Total Cost)		$3,444,525.60	$3,444,526.49	$3,444,525.60
Installed DG		20	18	20
Investment Amount	Medium	$875,000.00	$875,000.00	$875,000.00
Optimal Solution (Total Cost)		$3,443,583.22	$3,443,584.12	$3,443,583.22
Installed DG		20	18	20
Investment Amount	Low	$875,000.00	$875,000.00	$875,000.00
Optimal Solution (Total Cost)		$3,442,640.85	$3,442,641.74	$3,442,640.85
Installed DG		20	18	20

$3.4 million across all excess penetration penalty cost levels. Additionally, for all budget options at the ''Medium'' level of the unmet demand penalty cost, all the solutions are about $13.6 million across all excess penetration penalty cost levels. This means the excess penetration penalty cost level has minimal to no effect on the optimal solution (total cost) at the ''Low'' and ''Medium'' levels of the unmet demand penalty cost. We begin to notice the effect of the excess penetration penalty cost at the ''High'' level of the unmet demand penalty cost. For example, at a budget of $15 million, the optimal solution (total cost) goes from $18.9 million, to $19.2 million, to $19.5 million for the ''Low'', ''Medium'' and ''High'' excess penetration cost levels respectively. A $15 million budget still provides the best solution across all levels of the excess penetration penalty cost as it does across all levels of the unmet demand penalty cost.

The excess penetration amounts and the cost of excess penetration at each level of sensitivity are provided in Table 5 for the each budget solution. With a budget of $15 million, the optimal solution is a microgrid with DGs 2 and 15 installed for a total generation of 2,702,496 W. The optimal solution finds 82% of the total network demand is met/supplied as shown in Table 3. The difference between the total generation of DGs 2 and 15, and the 82% of the network demand met is 420,268 W; this is the excess penetration (RPF) experienced for the optimal solution. The costs of this excess penetration are $285,782.28, $571,564.56 and $857,346.84 at the ''Low'', ''Medium'' and ''High'' levels of the excess penetration penalty cost respectively; these are the costs of the fifth objective for the model. Minimizing the excess penetration is included as one of our main research contributions because it helps strengthen the resilience of the traditional grid. An excess penetration cost

TABLE 5. Excess penetration/RPF amounts and costs by sensitivity level for each budget solution at the ''High'' unmet demand penalty cost level.

	B = $1 million	B = $10 million	B = $15 million
Installed DG	20	4	2 , 15
Total Generation (W)	135,125	1,351,248	2,702,496
Total Network Demand Met (W)	134,048	1,291,360	2,282,228
Excess Penetration/RPF (W)	1,077	59,888	420,268
RPF Cost at "Low" Level	$942.77	$40,723.59	$285,782.28
RPF Cost at "Medium" Level	$1,885.53	$81,447.19	$571,564.56
RPF Cost at "High" Level	$2,828.30	$122,170.78	$857,346.84

of $285,782.28 accounts for about 1.5% of the optimal solution/total cost ($18,933,733.59), meaning the model successfully minimizes the excess penetration amounts (fifth objective) while still meeting 82% of the total network demand (24/25 essential resources covered). Ultimately, this shows the model's ability to address both the unmet demand and excess penetration objectives.

VI. CONCLUSION AND DISCUSSIONS

We have formulated a single-source capacitated facility location coverage problem (SS-CFLCP) model to optimize the location, size, assignment and total number of DGs within a microgrid under a large-scale grid disturbance scenario, where the microgrid is operating in island mode. The SS-CFLCP aims to minimize the total cost of the microgrid, as well as the distance traveled by electricity (distribution costs), network power outage (unmet demand) levels due to a grid disturbance and reverse power flow (RPF) caused by excess DG penetration within the network. The results are presented with the application of a sensitivity analysis on the unmet demand penalty cost parameter and the excess DG penetration cost parameter. The results show no variation at the ''Low'' and ''Medium'' sensitivity levels of the unmet demand parameter. Variation is seen at the ''High'' level of the unmet demand parameter with the best objective solution, and highest percent of network demand met, occurring when a budget of $15 million is provided for the microgrid.

This research helps show the significance of microgrids and how they can be utilized as a way to better secure the functionality of the main grid. As the Presidential Policy Directive 21 (PPD-21) and the Department of Energy microgrid initiative (see introduction) call for, the research performed provides an operational model that demonstrates the value of microgrids for utilities in terms of strengthening the resilience of the traditional grid. This is accomplished with the incorporation of our fourth and fifth objectives, which focus on minimzing the unmet demand and excess DG penetration (RPF) within the network. By applying the model to a case study, this research provides insights towards how beneficial a practical microgrid can be for a city or town that experiences natural disasters, especially when those disasters effect the power distribution system and lead to large-scale blackouts/outages. Food, medical aid and security are prioritized during large-scale power blackouts/outages. By focusing on the essential resources within the city or town that provide food, medical aid and security services, the model developed helps show how to best mitigate the damage a large-scale blackout/outage can have on the city or town. Furthermore, by adding a budget constraint, this research provides utilities a framework for how to feasibly establish the most optimal microgrid for the area the utility serves.

The developed model comes with some limitations. The first limitation pertains to the electricity demand data used, which is surveyed demand data of essential resources [22]. The survey is compiled by census region of the country, but is not depicted by state. Thus, the southern region survey electricity demands are adopted for the state of Tennessee due to its geographical location within the southern region of the country. Ideally, demand data directly from the 25 individual essential resources is preferred. The second limitation pertains to the constraints. The model lacks constraints for the active/reactive power flow equality, line capacity, and voltage balancing at each node within the network. Instead, the model assumes an already interconnected distribution network with static levels of electricity flow. A third limitation of the model pertains to the type of optimization model used. This paper employs a deterministic model, where each parameter is a single value, as opposed to a stochastic model, where the parameters are described by random variables or distributions. A stochastic model allows the modeller to evaluate the natural uncertainty of the modeled system's parameters [27]. The stochastic nature of the parameters used in this model, such as electricity demand and electricity output of a DG, both of which vary over the course of a 24-hour day and over the course of the year, will be addressed in the continuation of this research. A fourth limitation of this model is the lack of energy storage within the microgrid. Energy storage will also be addressed and incorporated into the microgrid framework in the continuation of this research. These limitations will be addressed in our future research.

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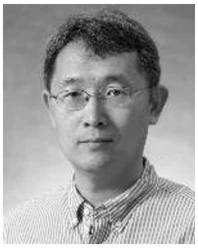

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