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Optimal Sizing, Location, and Assignment of Photovoltaic Distributed Generators with an Energy Storage System for Islanded Microgrids

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Abstract: Disruptive events, such as the winter storm of 2021 that left 40 million people in the U.S. without power, have revealed the potential danger of societal dependence on centralized energy sources. Localized energy grids (called microgrids (MGs)) can help add energy reliability and independence by using distributed generators (DGs) with photovoltaic (PV) energy sources and energy storage systems (ESSs). Such MGs can independently energize critical energy demand nodes (DNs) when isolated from the primary grid with renewable energy. The optimal sizes and assignments of PVDG/ESS units to the DNs during outages are crucial to increasing energy reliability. However, finding an optimal configuration–energy management strategy is difficult due to the investment costs, complexity of assignments, potential capacities, and uncertainties in the PV system output. In this research, we developed a simulation framework, augmented by genetic algorithms (GAs), to optimize costs and fulfill energy demands by selecting the appropriate MG configuration and ESS management strategy for an islanded MG for emergency power during an extended disruption. The simulation model was based on historical data, referencing Knoxville, TN, models, and changing the output and load conditions due to the time of day and weather for PVDG/ESS MGs to help quantify some stochastic attributes. The solutions were evaluated under given investment budgets with minimal costs and maximal average hourly energy demands met. Solutions also provide an appropriate energy management strategy and prioritization of specific DNs during load shedding.

Keywords: resilient power grid; distributed generation; renewable energy; genetic algorithm; ESS; microgrid; energy storage management; ESS charging strategy

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1. Introduction

There are various modern examples where unforeseen disruptive events deprive people of access to electrical power. These events can cause anything from minor inconveniences to situations (leading to mortal danger). Since the 2000s, there has been a drastic increase in weather-related power outages (affecting more than 50,000 customers [1,2]). One recent example is the winter storm that hit the lower 48 U.S. states in 2021, leaving 4 million people without electricity. A distributed generation microgrid (MG) can help make energy access more reliable and resilient to unforeseen disruptions while increasing energy independence. A properly configured MG can be run as the only energy source (island mode) or as extra energy to power all or some of an area's critical energy demand nodes (DNs). DNs, such as hospitals, fire stations, and grocery stores, can be prioritized during disruptions to maintain safety and comfort. MGs, in these situations, must fully or partially power all necessary DNs with minimal investments, operations, and maintenance costs. MGs with PVDG sources are promising but require additional considerations and equipment to utilize their potential fully. In an island mode situation where the MG is expected to provide emergency power, which is the focus of the work, these issues are critical to optimal solutions.

According to a report by the National Renewable Energy Laboratory [1], photovoltaic distributed generation (PVDG) systems could supply electricity during grid outages resulting from extreme weather or other emergencies. In order to take advantage of this capability, the systems must be designed with energy uncertainties in mind and combined with other technologies, such as energy storage systems (ESSs). DGs that utilize renewable energy sources (RESs) can help provide environmentally friendly energy sources but cause unique problems. First, PVDG energy output ties directly to environmental conditions, such as the amount of solar radiation an area receives and the area's current sky conditions (cloudiness). Thus, energy output from the PVDG is intermittent, so there is a need to regulate the power received by DNs to see a consistent voltage profile even when solar resources are low. Second, high energy output from the PVDG can pose issues. Excess unused energy can cause reverse power flow (RPF) in systems with renewable energy sources. If the system generates more power than the DN requires, issues in the primary energy grid, such as loss of voltage control, increased dangers from short circuits, and degradation of the reliability of protective systems, can occur [3–5]. Thus the appropriate sizes or capacities of PVDG systems are crucial to help minimize these issues.

ESSs can help control voltage fluctuations and the RPF that RESs can cause by storing and discharging energy as needed. The appropriately chosen ESS capacity is key to ensuring that the ESS is optimally utilized. Too large of a capacity leads to wasted monetary resources due to unused capacity; too small, and there may not be enough storage to help mitigate potential RPF or provide enough backup energy. However, adding the appropriately sized ESS will only improve conditions with appropriate charging strategies. A good charging strategy must respond with power when the system is at low output, be reactive to the intermittent production of RESs, and be able to store excess energy at the appropriate times [6]. Charging unnecessarily when the system is at a low output or discharging when the system is at a high output will only amplify RES-related problems. As more renewable sources become a part of the energy grid, assignments, sizing, and storage management strategies become increasingly important.

Due to the varied capacity sizes, possible locations, and different charging strategies of DGPV/ESS systems finding optimal solutions can be problematic and computationally expensive. In addition, a feasible solution must consider the uncertain nature of the environmental conditions upon which the RESs depend on. Therefore, researchers are active in the optimal DG/ESS placement and sizing (ODGSP) problems, as well as ESS energy management. Many have sought to solve these problems using various techniques, including purely numeric, heuristic, machine learning [7], and simulation [8].

This work seeks to tackle the ODGSP and energy management using a genetic algorithm (GA) and simulation-based approach for a system in an island mode situation. The selected MG configuration must be the sole source of energy during the sunlight hours over the course of an extended disruption in service to act as emergency power. GA-based heuristics search for optimal solutions based on the results of simulations of each purposed configuration of the MG. The simulation provides insight into how a proposed solution will perform in a real-world environment based on historical data to gauge solution feasibility realistically.

In this work, we used a test set of twenty-five DNs and co-located PVDG/ESS units to test the optimization capabilities of the algorithm. The goal was to evaluate the algorithm's ability to find solutions with minimal costs, maximal energy demand fulfillment, and minimized RPF MG configurations, to provide an appropriate energy management strategy that allows DN-type prioritization for load shedding. The results show that the method can achieve these desired goals. The following section will describe previous research on ODGSP, distributed energy storage sizing, placement, and management, and distributed generation in island mode microgrids.

The method's objective is to optimize several factors (at a high-level model of a MG) from the perspective of operations research for critical strategic decision-making. First, the investment and operating costs for a set of PVDG/ESS units can be high, so this work seeks to minimize the sizes of these constraints below a predefined start-up budget while minimizing average operational costs. Second, meeting the demands of the critical DN is the emergency MG's primary goal; thus, the solutions must fulfill maximal average hourly demands. Third, specific types of DNs may be deemed more critical than others in extreme situations. A heuristic was employed based on adjustable node priorities to aid load shedding decisions. Therefore, the described algorithm allowed the specified facility or DN types to prioritize their energy demands. Fourth, the PVDG requires an appropriate energy management strategy, and the method provides hourly ESS management strategies that exhibit peak shaving and voltage regulatory characteristics. Lastly, the potential RPF must be minimized for the MG to be suitable as an auxiliary power source in normal non-isolated conditions. In comparison to other works, this study sought to tackle these five problems simultaneously with one unified methodology. To make the model tractable, the proposed MG model does not include factors such as power quality, temperature-based performance considerations, equipment degradation, fluctuating energy costs, and low-level electronics of charging and discharging the ESS units.

2. Literature Review

2.1. Optimal Sizing and Distributed Generation Placement

There has been a lot of research on ODGSP. Analytical, numerical, and heuristic methods, such as GAs, are the most common [7]. A review of the methods used to find optimal solutions to the ODGSP, conducted by [7], found that heuristic methods are usually robust and provide near-optimal solutions for significantly complex ODGSP problems. For example, [9] utilized GAs and particle swarm optimization (PSO) algorithms to obtain the optimal allocation and size of a PVDG system. Their goal was to reduce the total power losses and enhance voltage and frequency profiles using an objective to minimize these factors. The simulation results indicate that the PSO algorithm performs better than GA in terms of speed of convergence, power loss reduction, and grid quality improvement for the chosen objective. They also show that variable load consumption curves and changing weather conditions can affect the determination of the PVDG optimal position, capacity, and grid security, indicating the importance of modeling weather conditions to gain feasible solutions. Similarly, the works by Hengsritawat et al. [8] used the Monte Carlo simulation and statistical data to quantify the stochastic and probabilistic nature of PVDG energy production. Hengsritawat et al. showed that when finding optimal solutions to the ODGSP in a test case in Thailand, the inclusion of factors, such as background harmonic distortion, change the optimal solution and, thus, are essential considerations when designing an optimal PVDG MG. The authors of the book *Artificial Intelligence and Renewables* [10] used GA-derived ODGSP solutions to improve the live voltage stability index (LVSI). Other GA-based hybrid algorithms, such as the GA-GSF (genetic algorithm with generating scaling factor), have been employed to optimize DG sizing and placement. GA-GSF-based optimization of line capacities in systems (to minimize locational marginal prices (LMPs) by finding optimal sizing and placements) has been successful. It allows for identifying a network's weaknesses to help avoid line congestion that increases LMP [11,12]. The work by [13] utilizes the manta ray foraging optimization (MRFO) to optimize the ODGSP using a multi-objective function. These works show that GAs and other heuristic methods are commonly utilized to solve the ODGSP problem, with varying optimization goals. Results indicate that various heuristic algorithms are robust and reliable tools for these optimization problems.

2.2. Distributed Energy Storage Placement (DEP) and Management

Similarly, research has been conducted on the optimal sizing and placement of ESSs. Reference [14] performed a critical review on ESS planning covering ESS sizing and modeling algorithms. Their work provided a critical one-stop overview of one hundred and four methods in six categories of optimization techniques. The study presented various pros and cons of the different methods, including analytical, heuristic, and hybrid approaches. They concluded that while all have their strengths and weaknesses, the most promising strategies are found through hybrids of individual methods. In [15], the authors presented an algorithm to determine the optimal installation placement and sizing of an ESS for a virtual multi-slack (VMS) operation based on a power sensitivity analysis in a stand-alone successful microgrid. In [16], the authors looked at problems associated with deploying an intermittent, unpredictable, and uncontrollable solar photovoltaic PVDG that could be feasibly solved with a battery ESS (BESS) by optimizing the available capacity, increasing reliability, and reducing system losses. The mentioned research projects show that the common understanding of the importance of ESS to distributed generation is still being explored, and various analytical, heuristic, and hybrid tools have proven successful. As mentioned, proper utilization requires an appropriate charging strategy when using ESS with PV systems, and the next section looks at research related to this subject.

2.3. ESS: Storage Management and Optimal Charging Strategies

Much of the research on energy management methodologies for ESSs focus on using EVs (electric vehicles) as a part of the system. The possible economic, ecological, and social benefits support the rapid diffusion of grid-connected MGs; however, economic feasibility still stands as the primary goal of commercial MGs [17]. In [18], the authors shows that—similar to the conclusion found by [14]—hybrid optimization methods for energy storage and management of a DG/ESS system where EVs are present can minimize costs. They found optimal configurations by utilizing real-time electricity prices, real-time calculation of PV power based on solar radiance, and an extensive system simulation. However, in [17], the authors found that the bidirectional charging strategy (using BESS to charge EVs and using EVs to store and supply energy at peak demand times) may not pay off in the long run. Researchers are also looking into the optimal management of ESSs to buffer charging infrastructures for smart cities. In [19], the authors focused on maximizing demand with increased EV presence at a minimal cost. They modeled the charging station network and energy storage system, showing potential savings of 20–36% for energy storage development. These research examples show that the ESS management aspect of the DG/ESS system is essential to utilizing PVDG systems and is expanding to include the growing number of EVs in today's market. The mentioned studies discuss standard capabilities that the addition of ESS to PVDG can impart, such as providing power during peak demand times and maximizing demand met. These factors are essential when attempting to run a PVDG/ESS system in island mode, which is the focus of this work.

2.4. Island Mode Mg Analysis

The capability of a DG/ESS system to provide power in island mode is also a hot topic of research. According to Georgilakis and Hatziargyriou [7], the intentional islanding of DG MGs increases the economic competitiveness of DGs and improves reliability across the board. The authors of Satheesh Kumar and Immanuel Selvakumar [20] looked into the analysis and optimization for islanded DG and ESS systems intending to maximize power point tracking and power flow management. In Abdelgawad [21], the authors utilized a random forest hybrid technique with an embedded system and a numerical/analytic approach to maximize the efficiency of solar energy harvesting systems, supplying an MG. In Dhundhara and Verma [22], the authors researched utilizing other ESS technologies, such as hydro energy storage for reliable microgrid systems. In Wang et al. [23], the authors formulated the ODGSP as a mixed-integer program (MIP) considering the probabilistic nature of DG outputs and load consumption, wherein the costs were minimized. In an islanded situation, profits were maximized for MG. Other researchers have also sought to minimize the costs of an islanded ESS-based MG. In Hesaroor and Das [24], the authors sought for solutions to minimize the running cost of a BESS MG by a heuristic method that exploited the price difference in time of a usage tariff scenario. The researchers utilized incremental cost data to find optimal sizing solutions for the ESSs among five different cases.

The studies mentioned above show that optimizing MG utilizing DG/ESS systems in island mode is essential as the penetration of renewable energy increases and the need for more resilient energy systems rises. The mentioned works take varying resolution levels when modeling the MG and focus on various objectives from minimizing costs to controlling power quality and providing energy management strategies and combinations of the former. This work takes a high-level approach to model the MG, excluding discussions of the power system factors related to power quality control and the degradation of the PV/ESS units as an initial step in building a more physically accurate model of an island mode MG. The current model is meant to explore the optimization performance, ability for DN prioritization, and feasibility of the energy management strategies produced by the methods described. This work seeks to utilize simulation and heuristics-based optimization, considering uncertainties from the intermittent nature and changing load demands of renewable energy generation to find solutions based on the environmental conditions of specific areas. Through the use of historical data about a region's average PV outputs throughout the day and statistics about the sky conditions of the area, and realistic approximations of a set of DG/ESS units can be simulated. The algorithm can then compare the performance of each proposed solution according to a predefined set of constraints and metrics. This description describes the perfect framework for a GA-based solution. The simulation allows for quantifying the stochastic environmental conditions and, subsequently, stochastic PV output. The GA allows for a directed search through the solution space with our defined objective of maximizing the energy demands met while minimizing costs under a set budget. The simulation and GA methods of finding optimal solutions involve performing tasks in a manner that more mathematical methods may find intractable over "larger" horizons. The following section will provide a formal description of this work's problem, a mathematical description of the objective that the GA solution seeks to optimize, and the constraints of the simulated system.

3. Model Formulation

The problem to be modeled can be described using the sets, variables, and parameters found in Tables 1–3 as follows. A utility seeks to purchase and install a PVDG/ESS MG capable of providing, at most, a month's worth of emergency power. There is a set $\mathcal{I}$ of critical DNs that must have a maximal amount of their energy demands met using a set of PVDG/ESS units during the sunlight hours of the day $\mathcal{H}$ in an islanded MG. A monetary budget $\mathcal{B}$ is available for the purchase and installation of the units that must be honored. Energy system management seeks the optimal MG configuration of PVDG/ESS units and an appropriate hourly charging strategy feasible for the specific location and environmental conditions that maximize demands fulfilled while minimizing RPF, startup, and operational costs. In addition, the utility seeks solutions that prioritize specific DN energy demands over others.

Table 1. Sets used for MG model and optimization.

Sets	Description
$\mathcal{I}$	Set of critical demand nodes {1, 2, . . . , n} $i \in \mathcal{I}$
$\mathcal{J}$	Set of potential PVDG/ESS units {1,2, . . . , m} $j \in \mathcal{J}$
$\mathcal{I}_j$	$\subseteq \mathcal{I}$ assigned to DG/ESS unit j
$\mathcal{J}_{g,j}$	Set of binary values, 1 if PDG/ESSj is open for assignment for solution $g \in \mathcal{G}$, 0 otherwise
$\mathcal{R}$	Set of possible ESS states {0(discharge), 1(charge), 2(idle)} for an hour h
μ_g	$\mathcal{H}$ sized vector where entry h is a value $\in \mathcal{R}$ that dictates the ESS charging strategy over hour h for a solution g
$\mathcal{G}$	Set of form $\{\{J_1, \mu_1\}, \ldots, \{J_k, \mu_k\}\}$, each tuple represents a solution g
$\mathcal{W}$	Set of sky conditions {sunny, cloudy, overcast} for an hour h, $w \in \mathcal{W}$
$\mathcal{H}$	Sunlight hours (6 a.m.–6 p.m.) {1, . . . , 13} a solution g will be simulated $h \in \mathcal{H}$ daily
$\mathcal{D}$	Set of days {1, . . . , N} a solution g will be simulated over $\mathcal{H}$ hours to measure fitness

Table 2. Parameters used for MG model and optimization.

Parameters	Description
$\mathcal{B}$	Budget (\$) for the purchase & installation of some DG/ESS units $\mathcal{J}_g$
α_j	Rated power capacity (kw) for a PVDG unit j
ε_j	Rated energy capacity (kwh) for an ESS unit j
b_j	Proportion of output needed to charge ESS unit j for one hour of output
ρ_j	Dollar per kW investment rate for a PV unit j
ψ_j	Dollar per kWh investment rate for an ESS unit j
$\mathcal{C}_j$	Investment and installation cost for a PVDG/ESS unit j
ν_j	Dollar per kw operation and maintenance rate for a PV unit j
o_j	Dollar per kw operation and maintenance rate for an ESS unit j
λ_j	Excess energy penalty for a PVDG/ESS unit j
τ_t	Unmet demand penalty for DN type t
ϕ	Unmet demand weight
Γ	Number of generations of solutions to test
ζ	Number of solutions in each generation of solutions
$d_{i,j}$	Distance between DN i and a PVDG/ESS unit j
χ_j	Rated number of hours of output from full charge until depletion
Y	Set of priority values where entry y_t corresponds to priority for type t where the greater the values $\implies$ higher priority

Table 3. Variables used for the MG model and optimization.

Variables	Description
$\mathcal{E}_{j,h}$	Energy output (kW) for ESS j over hour h
$q_{j,h}$	consecutive charge hours ESS unit j requires to be fully charged at the start of hour h
$\mathcal{P}_{j,h,w}$	Energy output (kW) for PV j over hour h under weather w
$\mathcal{V}_{j,h}$	Summation of energy output over hour h for a PVDG/ESS unit j
$\Xi_{j,h}$	$-b_j$ if j has excess energy in charge mode and $q_{j,h} > 0$, 1 if j has insufficient energy in discharge mode and $q_{j,h} \leq \chi_j$, 0 otherwise
$\gamma_{g,h}$	Energy generated over hour h $\forall$ PVDG/ESS units of solution g
$\Delta_{i,h}$	Energy demand over hour h for the DN i
$\omega_{i,j,h}$	Energy supplied to DN i from a PVDG/ESS unit j over hour h
$\Omega_{j,h}$	Total energy supplied over hour h for some DGs j to all of its assigned nodes I_j
$\mathcal{S}_h$	Total energy supplied over hour h from all DNs
$\mathcal{T}_{g,h}$	Total transmission costs for solution g
$\mathcal{M}_{j,h}$	Operation and maintenance costs for PVDG/ESS unit j over hour h
$\pi_{j,h}$	Excess energy produced by PVDG/ESS unit j over hour h
Π_h	Total excess energy produced by a $\mathcal{J}_g$ over hour h
$\mathcal{U}_h$	Total unmet demand for all DNs over hour h
$\mathcal{A}_{i,j}$	Binary, 1 if DG j assigned DN i, 0 otherwise
$\mathcal{C}_g$	Total investment cost for all selected units $j \in \mathcal{J}_g$ for solution g
$\mathcal{K}_g$	Average transmission, operation, and maintenance costs for solution g
Υ_g	Average unmet demand for solution g
υ_g	Average reverse power flow potential for solution g
$\mathcal{F}_g$	Total monetary, unmet demand, potential reverse power flow, cost for a solution g
Λ_g	Score used to score a given solution g and rank for selection of breeding pairs

Three tasks can describe the problem. The first task is the selection of the locations and sizes of a set of co-located AC-coupled utility-scale (MW) PVDG/ESS units or DGs $\mathcal{J}_{g,j}$ from the set of possible units $\mathcal{J}$. The selected units will energize the DN set $\mathcal{I}$. The second task involves the assignment of each of the selected PVDG/ESS units j to an independent subset of the DN $\mathcal{I}_{g,j}$ from $\mathcal{I}$. The assignment allows each DG unit j to be assigned to multiple DNs, and each DN i to only be assigned to one DG unit (see Equation (11)). A given assignment $\mathcal{A}_{i,j}$ is represented as a binary value where if the unit j is assigned to the DN i the value is 1 and 0 otherwise. An example assignment can be seen in Figure 1 below.

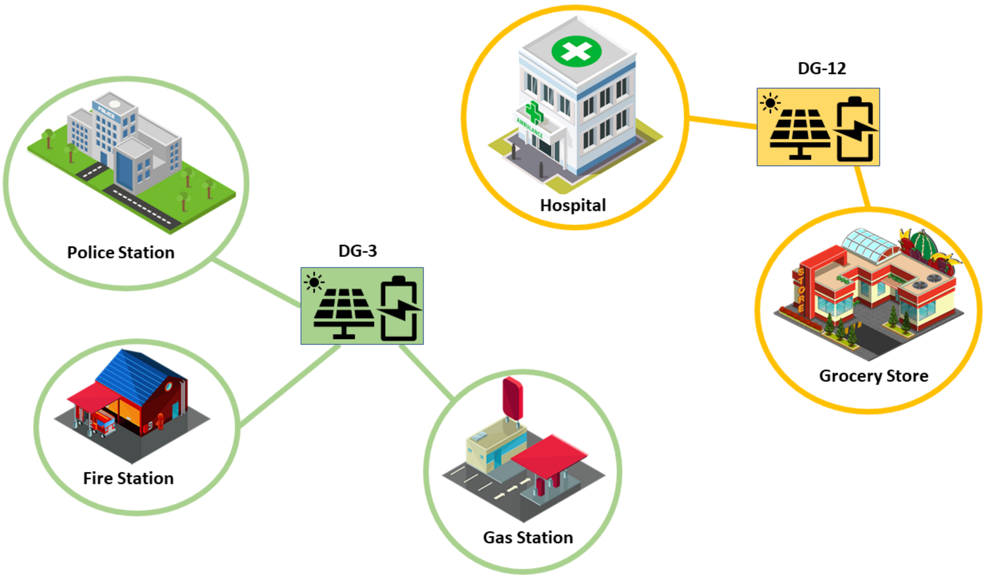

Figure 1. Example assignment using 2 DGs to supply 5 DNs. DG unit 3 is assigned, with the DNs representing police, fire, and gas stations. DG unit 12 is assigned, with DNs representing the hospital and grocery store.

The third task is to provide an appropriate energy management/charging strategy $\mu_{g,h}$ for each operation hour. For each of the sunlight hours, a general directive is to be given for all ESS units currently assigned from the set of possible directives $\mathcal{R}$ that will help dictate if the units will charge, discharge, or remain idle over the hour.

The objective is to minimize the initial startup cost $\mathcal{C}_g$, average hourly operational costs $\mathcal{K}_g$, average excess unused energy or potential RPF v_g, and the average amount of unmet energy demands Υ_g. The sum of these factors $\mathcal{F}_g$ (see Equation (21)) represents the optimization objective. The available budget $\mathcal{B}$ constrains the total startup costs for the selected PVDG/ESS units $\mathcal{C}_g$ for any potential solution g (see Equation (1)). It is assumed that other measures will be taken outside sunlight to energize the DN.

A desire to prioritize different DN energy demands over others and minimize potential RPF is also desired. When energy resources are scarce, decisions may need to be made on which of the critical DNs are more important. For example, a grocery store may be spotlighted over a gas station by setting the priority of the grocery store $\mathcal{K}_t$ higher than that of the gas station so that its energy demands are prioritized. The value of $\mathcal{K}_t$ is adjustable, so different types of DNs can be prioritized. Minimizing potential RPF is also a goal, so the system may be suitable for connecting to the primary grid.

In the following paragraphs, the mathematical models and expressions representing costs of investment and operation and the energy output for the units $\mathcal{J}_{g,j}$ are given. Next, the energy demands and transmission costs for the DN $\mathcal{I}$ and the expressions used to model their energy supply and demand dynamics are described. Finally, the GA and other heuristics applied to find an optimal solution to the three tasks are detailed.

The set of selected units $\mathcal{J}_{g,j}$ are expected to power the DN $\mathcal{I}$ throughout the sunlight (6 a.m.–6 p.m.) hours $\mathcal{H}$. Each unit j in the selected set $\mathcal{J}_{g,j}$ is located at various positions around the energy demand nodes and comes in different capacity parameter combinations for the PVDG and ESS units. The parameters (Table 2), time of day (h), and current sky condition govern each unit $j's$ behavior. Each unit j consists of a DG component modeled as a mono-crystal single-axis PV energy generation unit and an ESS modeled as BESS based on Li-ion batteries. The PV and ESS units have investment costs based on the product of the nameplate power and energy rating of the component (α_j and ϵ_j respectively) and an investment rate, which comes in the form of dollars per kW rate for the PV unit (ρ_j) and dollars per kWh for the ESS component (ψ_j). The total investment cost for a given unit j is then the summation of the investment cost for the PV and ESS units, labeled $\mathbf{C}_j$ in Equation (1).

$$\mathcal{C}_j = (\alpha_j \cdot \rho_j) + (\varepsilon_j \cdot \psi_j) \tag{1}$$

For a selected subset $\mathcal{J}_{g,j}$ of DG units representing a potential solution, the total investment cost $\mathcal{C}_g$ is then the summation of all units currently selected for assignment (Equation (2)) for that given solution g. The investment cost represents purchasing the units, necessary equipment, and installation.

$$\mathcal{C}_g = \sum_{j=1}^{m} \mathcal{C}_j \cdot \mathcal{J}_{g,j} \tag{2}$$

This investment cost for a given solution g corresponding to selection $\mathcal{J}_{g,j}$ represents the monetary investment that must be less than the set investment budget $\mathcal{B}$ (Equation (3)).

$$\mathcal{B} \leq \mathcal{C}_g, \forall\, g \in \mathcal{G} \tag{3}$$

Along with individual investment rates, each PV and ESS component has individual operation and maintenance (O&M) rates, ν_j and o_j, respectively. These rates represent the dollars per kW costs of maintaining and utilizing DG unit j at a level of energy output over an hour. For the PV component, the energy output over hour h under the sky condition w is represented by $\mathcal{P}_{j,h,w}$. The maximum expected energy output for a given PV component is twenty percent of its rated capacity α_j (Equation (4)). This efficiency factor is based on the average efficiency of mono-crystal PV units according to the most conservative modeling of utility-scale PV systems (as per [25]). The product of the energy output over the hour and its O&M rate ν_j is the monetary cost of operating the PV unit for the hour.

The fluctuating energy represented by $\mathcal{P}_{j,h,w}$ values simulates the intermittent nature of PV energy production due to uncertain weather conditions and the dependence on the amount of sunlight. The magnitude of energy output $\mathcal{P}_{j,h,w}$ is lowest in the early morning (low sun) and overcast conditions, with the highest occurring when the sun is at its apex, and the sky condition is sunny.

$$\mathcal{P}_{j,h,w} \leq \alpha_j \cdot 20\% \tag{4}$$

The probability of sunny, cloudy, and overcast are 0.266, 0.293, and 0.441, respectively, and are based on historical sky condition data [26]. Similarly, the ESS component has output over an hour $\mathcal{E}_{j,h}$, and the product of this and the O&M rate o_j is its O&M cost in dollars over the hour h. For the ESS of unit j, the energy output is based on its rated energy capacity ε_j, the level of charge $q_{j,h}$ at the time h, the current energy demand and supply conditions, and the current energy management directive $\mu_{g,h}$. The nature of the ESS output is discussed in more detail in the next paragraph. Thus, the overall O&M costs $\mathcal{M}_{j,h}$ for unit j is the summation of the O&M costs for its PV and ESS components over the hour h at the output capacity in kW (Equation (5)). The expression indicates that if the ESS unit is charging, thus producing a negative energy value, or when it is idle, there is no operation and maintenance charge for that hour for the ESS unit. Otherwise, its O&M costs are based on the energy output over the hour h and its rated costs.

$$\mathcal{M}_{j,h} = \nu_j \cdot \mathcal{P}_{j,h,w} + o_j \cdot max(\mathcal{E}_{j,h}, 0) \tag{5}$$

The charging commands $\mathcal{R}$ indicate the suggested charging/discharging behaviors for all ESS units currently in operation. A given charging strategy $\mu_{g,h}$ provides hourly charging directives for maximizing the demands met and minimizing excess unused energy over the sunlight hours $\mathcal{H}$ for each hour h. Each ESS will follow the command based on the charge left in the ESS $q_{j,h}$ and the difference between the energy produced by its corresponding PV unit and their assigned DNs $\mathcal{I}_{g,j}$ represented by $\Xi_{j,h}$ (Table 3). ESS system commands consist of discharge (0), meaning to supply stored energy if available and required, charge (1), meaning to store energy from the corresponding PV unit, and remain idle (2), meaning to neither discharge nor charge. The amount of charge left $q_{j,h}$

represents the amount of discharging hours a given ESS has experienced without an hour of charge. When the unit experiences an hour in discharge mode, its $q_{j,h}$ value is incremented, and each hour in the charge mode decrements the value to a minimum of 0, meaning the unit is fully charged. When the value equals the rated hourly energy rating for the unit represented by χ_j, the ESS unit j is considered fully discharged and can provide no power until it has received at least an hour of charge. Each hour a given ESS unit can output $\frac{\epsilon_j}{\chi_j}$ kW until fully discharged, and it receives b_j% of its possible output from its given PV unit j during charging, reducing the available output from the PV unit. When the system is set to idle mode, no energy is output from the ESS unit, nor does it draw any from the PV unit. This logic is represented by Equations (6) and (7). This behavior is intended to model the discharging and charging behaviors of an ESS without considering the more complex thermal behaviors of ESS systems or the static discharge they exhibit.

$$\mathcal{E}_{j,h} = \Xi_{j,h} \cdot \frac{\epsilon_j}{\chi_j} \tag{6}$$

$$\mathcal{E}_{j,h} > 0, \iff 0 \leq q_{j,h} < \chi_j, \forall\, j \tag{7}$$

Equation (8) represents the initial state of all ESS units at the start of a given simulation run, indicating that each is "fully" charged at the start. Each hour, the $q_{j,h}$ value for a given ESS unit is updated using Equation (9). These expressions ensure that the maximum discharge hours that a given ESS unit can provide are limited to its specified amount.

$$h = 1, d = 1 \implies q_{j,h} = 0 \tag{8}$$

$$q_{j,h+1} = \begin{cases} \min(0, q_{j,h} - 1), \text{iff} & \mu_{g,h} = 1 \\ \max(\chi_j, q_{j,h} + 1), \text{iff} & \mu_{g,h} = 0 \\ q_{j,h}, \text{otherwise} \end{cases} \tag{9}$$

The overall energy output for a given unit j for hour h $\mathcal{V}_{j,h}$ is expressed in Equation (10), detailing it as the sum of the energy output of its PV and ESS components. These expressions are intended to model the energy production of PV units with varying sunlight and sky conditions, the energy output of an ESS unit based on its ratings, charge level, and simple heuristics based on the need for extra energy based on supply and demand. The following paragraphs will describe the expressions used to model the demand nodes $\mathcal{I}$ and the energy exchange dynamics between the DG and DN.

$$\mathcal{V}_{j,h} = \mathcal{P}_{j,h,w} + \mathcal{E}_{j,h} \tag{10}$$

There are five types of possible demand nodes, including hospitals, grocery stores, fire stations, gas stations, and police stations, each having varying hourly demands to simulate time-varying loads. The different types can have their demands prioritized using the type priority variables represented by $\mathcal{K}_t$. Each of the selected possible DG units j from the selected set $\mathcal{J}_{g,j}$ are assigned a disjoint subset of the DN $\mathcal{I}_j$ from the set $\mathcal{I}$. Each i in the set $\mathcal{I}_j$ can only be assigned to one unit j for a given solution (Equation (11)). Each DN i will require varying energy over a given hour $\Delta_{i,h}$ based on historical data for the type of building during the sunlight hours, and must be supplied solely from its assigned PVDG/ESS unit j.

$$0 \leq \sum_{j=1}^{m} \mathcal{A}_{i,j} \leq 1\,, \forall\, i \tag{11}$$

$$0 \leq \omega_{i,j,h} \leq \Delta_{i,h} \tag{12}$$

Due to Equation (12), there may be some amount of unmet demands for the demand nodes, and this value is the difference between what is demanded over the hour $\Delta_{i,h}$ and what its assigned DG unit j could supply $\omega_{i,j,h}$. The total unmet demand for a given hour $\mathcal{U}_h$ is then the summation of all unmet demand for all DNs $\mathcal{I}$ as seen in Equation (13). Each different type of DN has its unmet demand weighted by the priority value $\mathcal{K}_t$. There is also an adjustable overall unmet demand weight ϕ to control the optimization's sensitivity to unmet demands and control for the potential difference in magnitude in costs and unmet demands.

$$\mathcal{U}_h = \phi \cdot \sum_{i=1}^{n}\sum_{j=1}^{m}(\Delta_{i,h} - \omega_{i,j,h}) \cdot \mathcal{K}_t \tag{13}$$

To energize each DN, a transmission cost is incurred. The transmission cost for a given DN is the product of the energy supplied to it at hour h $\omega_{i,j,h}$, and the distance between the energy source and the DN $d_{i,j}$. The total transmission cost over an hour h is the summation of all transmission costs for the DN, as seen in Equation (14).

$$\mathcal{T}_{g,h} = \sum_{i=1}^{n}\sum_{j=1}^{m}(\mathcal{A}_{i,j} \cdot d_{i,j} \cdot \omega_{i,j,h}) \tag{14}$$

For each GA-generated solution $\mathcal{G}$, there are DG selection and hourly charging variables (for each chromosome). The selection gene represented by $\mathcal{J}_{g,j}$ determines the investment cost by selecting a specific subset of the potential PVDG/ESS units from the set $\mathcal{J}$. The selection of $\mathcal{J}_{g,j}$, as well as the charging strategy gene $\mu_{g,h}$, will determine the average transmission, operation, and maintenance costs, along with the energy dynamics of the MG. Each solution $\mathcal{G}$ is given $\mathcal{D}$ day of $\mathcal{H}$ hour runs. After the simulated time, the average transmission, operation, and maintenance costs are calculated with Equation (15) representing the average hourly monetary cost of operating for a given solution.

$$\mathcal{K}_g = \frac{\sum_{d=1}^{D}\sum_{h=1}^{\mathcal{H}}\sum_{j=1}^{m}(\mathcal{M}_{j,h} \cdot \mathcal{J}_{g,j}) + \sum_{d=1}^{D}\sum_{h=1}^{H}(\mathcal{T}_{g,h})}{\mathcal{H} \cdot \mathcal{D}} \tag{15}$$

Along with the costs, the potential RPF for the selected units $\mathcal{J}_{g,j}$ labeled $\pi_{j,h}$ are calculated each hour with Equation (16). There is an adjustable weight λ to control how sensitive the "most fit" solution G is to potential excess unused energy. For each DG, Equation (17) demonstrates the calculation of a given DG's total energy supplied to its assigned DN. The total potential RPF for an hour h is then the summation of each unit in $\mathcal{J}_{g,j}$'s potential RPF with Equation (18).

$$\pi_{j,h} = (\mathcal{V}_{j,h} - \Omega_{j,h}) \cdot \lambda \tag{16}$$

$$\Omega_{j,h} = \sum_{i=1}^{m}(\omega_{i,j,h})\mathcal{A}_{i,j} \tag{17}$$

$$\Pi_h = \sum_{j=1}^{m}\pi_{j,h} \cdot J_{g,j} \tag{18}$$

The average potential RPF v_g for a solution g (Equation (19)) is used in the objective function to determine fitness. The solution with the lower v_g is more fit.

$$v_g = \frac{\sum_{d=1}^{\mathcal{D}}\sum_{h=1}^{\mathcal{H}}\Pi_h}{\mathcal{H} \cdot \mathcal{D}} \tag{19}$$

To quantify solution $\mathcal{G}$'s ability to meet the energy demands of the demand node $\mathcal{I}$, the average unmet demand over the run is calculated as seen in Equation (20), which is another metric for solution $g's$ fitness.

$$\Upsilon_g = \frac{\sum_{d=1}^{\mathcal{D}}\sum_{h=1}^{\mathcal{H}}\mathcal{U}_h}{\mathcal{H} \cdot \mathcal{D}}. \tag{20}$$

For each possible solution, its fitness is calculated by summing the investment cost for the selected DG units $\mathcal{J}_{g,j}$, the average monetary costs $\mathcal{K}_g$, average potential RPF v_g , and the average unmet demand Υ_g with Equation (21).

$$\mathcal{F}_g = \mathcal{C}_g + \mathcal{K}_g + \Upsilon_g + v_g \tag{21}$$

For each generation of solutions ζ their, fitness scores $\mathcal{F}_g$ are converted into what are termed here residual fitness scores Λ_g to perform the minimization task. All fitness scores are summed, and then the difference between each and the sum is used for the survival of the fittest pair selection process with Equation (22). This step ensures that the solution g with the highest residual Λ_g is the solution with the lowest fitness $\mathcal{F}_g$. The fittest or optimal solution is the solution g, such that it achieves the minimum $\mathcal{F}_g$ score, i.e., the maximum residual score Λ_g as indicated with Expression (23). This way, the solution with the highest residual is the fittest of a given generation ζ for a given set of solutions. Equation (23) is the metric used to compare the solution's fitness. The following section will briefly describe the data used for the simulation, how the simulation uses heuristics to adjust the behavior of the ESS units, and the assignment to ensure feasible and accurate solutions. Following this, we present a description of the model and simulation logic along with the application of the GA.

$$\Lambda_g = (\sum_{g=1}^{\zeta} \mathcal{F}_g) - \mathcal{F}_g \tag{22}$$

$$g \text{ such that } \min(\mathcal{F}_g) \implies \max(\Lambda_g) \; \forall \; g \in \mathcal{G} \tag{23}$$

4. Modeling and Simulation: Data, Model Structure, and Optimization Methodology

4.1. Data Sources

The DG and DN are represented in the simulation as a set of agents using data to model their various attributes stored in an AnyLogic database. The data come from information from the National Renewable Energy Laboratory [27] (PV outputs), Energy Information Administration [28] (costs and capacities), and Open Energy Information [29] (DN energy demands). The DG data contain various co-located PV and ESS unit capacities at various locations. The DN data consist of different hourly energy demands based on the DN type at different locations in the examined region. The historical sky condition data are sourced from the National Centers for Environmental Information [26] and are used to define the probability of different sky conditions. Each agent has a geographic location based on the area from which the weather data are sourced (Knoxville, TN, USA).

4.2. Simulation Framework and Model Structure

The model used for simulation of the MG and optimization tasks treats the PVDG, ESS, and DN as agents that interact through exchanging an amount of energy over the hour h. Each agent has specifications and parameters (Table 2). The GA optimization tool is also treated as an agent interacting with the MG by providing PVDG/ESS selections and hourly charging strategies, ranking the solutions by their fitness scores, and performing the GA crossover and mutation operations. Once all solutions have had their simulations, the GA process is used to generate the next set of solutions. The process continues until the set number of generations has been simulated. At the end of the process, the solution that achieved the lowest investment, average operational costs, RPF, and the highest average demands met are reported.

Each solution has a selection gene and an hourly charging strategy gene. At the beginning of each solution's simulation, the selection gene/variable is used to determine which of the available PVDG/ESS units are to be assigned with 1 s in a given position j, indicating the PVDG/ESS unit j is open for assignment and 0 otherwise. Each DN will be assigned to a given PVDG/ESS unit as shown in Algorithm 1. Iterating through the DN from highest to lowest priority, all open DGs will be tested to see if they can supply energy to a given DN i based on what the DG has been assigned to apply. All DGs begin supplying zero energy, and as they are assigned, the supply is increased by either the amount of energy the DN demands at hour 1 or whatever the DG has left to supply based on its current assignments. The earliest hour and sunny conditions are chosen as the output metric to ensure the given DG can supply the DN under the lowest output time. The DG will only be assigned if it has energy left to supply, and adding this DG to the set will not exceed the set budget $\mathcal{B}$. This algorithm means that if there are no open DGs that meet the criteria, the DN will go unassigned. DNs are assigned, the open DG will be iterated through, and any that are not assigned will be used to adjust the selection gene to match the actual assignment. This method ensures that the solution scored matches to solution implemented.

Algorithm 1 Algorithm for assigning a DG to a DN

B is the investment budget for the MG
DG is a list of all open units
DN is the list of DNs sorted by priority in descending order
$\mathcal{C}_j$ investment cost for the DG j
$\mathcal{C}_g$ investment cost for currently assigned DG
S_j currently supplied energy from DG j based on the currently assigned DN, initially 0
$PV_{j,1,1}$ capacity of DG i at hour 1 with sunny weather
$\Delta_i, 1$ energy demanded by node i at hour 1
$\omega_i, j, 1$ energy supplied by DG j to DN i over hour 1
for i < ∣DN∣ **do**
for $j < |DG|$ **do**
# If the addition of the DG unit does not go over budget
# and it has an amount of energy left to supply a DN with . . .
if $C_j + C_g \leq$ B & $PV_{j,1,1} - S_j > 0$ **then**
$C_g = C_g + C_j$
# If the DG has more than enough for this DN demand
# assign DG$_j$ to DN$_i$, increase the current DG supplied amount by
# what was demanded and set the DN as supplied what it desired
if $PV_{j,1,1} - S_j > \Delta_{i,1}$ **then**
S_j += $\Delta_{i,1}$
DN$_i$ supplied = $\Delta_{i,1}$
# If the DG has less energy than this DN demands left to supply,
# set the DG to be supplying all that it can so it can no longer be assigned to another DG,
# and supply the DN with what was left
else
DG$_j$ supply = $PV_{j,1,1}$
DN$_i$ supplied = $PV_{j,1,1} - S_j$
end if
end if
end for
end for
# Adjust selection gene to match actual assignments
for j < ∣DG∣ **do**
# If the DG was not assigned any DN, then make sure it is a 0 in the solution gene
if DG$_j$ is not assigned any DN **then**
$\mathcal{J}_{g,j} = 0$
end if
end for

Each hour of the simulation for a given solution g, the outputs for the PV units are adjusted based on the hour h and sky condition w. Once this is done, the current hour's demands are calculated for each given unit $j's$ assigned DN. Next, the energy contribution of the ESS unit is determined based on the amount of energy demanded by the assigned DN; the ESS remaining stored energy is based on its $q_{j,h}$ value and the charging command for the hour. The simulation only allows the ESS units to charge if they are not fully charged, the PV units produce more than is demanded from the assigned DN, and the system command is to charge. Similarly, the simulation only allows the ESS units to discharge stored energy if they are not fully discharged, the PV unit produces less than what is demanded by the assigned DN, and the system command is to discharge. If the ESS has not had more than the specified hours of discharge without an hour of charge, they can discharge; otherwise, they cannot. When the system conditions are correct for the ESS to discharge, its specified hourly energy rate adds to the supply used to energize the DN. Suppose the system conditions are correct for the charging operation. In that case, the overall energy supply is reduced by the specified proportion of its hourly energy rate to “charge” the ESS reducing the energy supply. The pseudo-code for this operation is seen in Algorithm 2. Similar to how the selection gene is adjusted to match the valid assignment of selected PVDG/ESS units, the charging strategy is adjusted based on what most ESS units do over the simulation for that hour. If most ESS units are in charge for a given hour, the charging gene is adjusted accordingly, and so on.

Algorithm 2 Algorithm for adjusting available energy supply each hour

```
P is the output for the current hour and weather condition for a PV
S is the total energy available for a given hour
E is the output for the current hour and weather condition for an ESS
h is the current hour
b_j is the specified proportion of the potential energy output
D is the total demands for the DG units assigned Nodes
q_j is the number of discharge hours without charging the ESS unit has experienced
X is the number of discharge hours without charging the ESS can experience before depletion
R is the current charging strategy for the hour
R_max
idle_count
charging_count
discharging_count
for j < |DG| do
    # If the unit is not fully discharged and the PV unit is producing less than is demanded
    # and the current charge directive is to discharge
    if q_j < X and P < D and R = 0 then
        # add the ESS unit energy output to the total supply
        S = P + E
        # update the ESS unit charge variable with a discharge
        q_j = max(q_j + 1, X)
        discharging_count++
        # If the unit is not fully charged and the PV unit is producing more than is demanded
        # and the current charge directive is to charge
    else if q_j > 0 and P > D and R = 1 then
        S = P − (ε_j / X) · b_j
        q = min(q−1, 0)
        charging_count++
        # otherwise the ESS is idle
    else
        S = P
        idle_count++
    end if
end for
# calculate the majority behavior
if charging_count > idle_count and charging_count > discharging_count then
    R_max = 1
else if discharging_count > idle_count and discharging_count > charging_count then
    R_max = 0
else
    R_max = 2
end if
# adjust the current hours charging strategy based on what the majority does
# set the directive for this hour to the majority behavior
μ_{g,h} = R_max
```

After the output for the PVDG/ESS unit is determined, the simulation will simulate the process of energizing the DN over the hour using the process demonstrated in Algorithm 3. From the highest priority DN assigned to the given PVDG/ESS unit j, to the lowest, the algorithm will attempt to supply what each DN demands for the current hour. If the DG has more than enough energy left to supply a DN, it will be allotted what it demands for the hour. In contrast, if it has some energy supply left but less than what is demanded by a given node, the node will be supplied with whatever energy was remaining, and the DG supply is set to zero left over. This algorithm allows some DNs to go 'unsupplied' with energy if there is not enough energy to supply all of them. Therefore, it prioritizes the DN with the higher priority values first.

Algorithm 3 Algorithm supplying the DN from a given PVDG/ESS unit j

S is the total output for the PVDG/ESS unit j at hour h available for supplying the DN
DN is the list of DNs sorted by priority in descending order assigned to the PVDG/ESS unit j
Δ_i, h is the demand for DN i at hour h
for i < |DN| **do**
    if S > 0 **then**
        if S > $\Delta_{i,h}$ **then**
            S = S $-$ $\Delta_{i,h}$
            DN [i] supply = $\Delta_{i,h}$
        else
            DN [i] supply = S
            S = 0
        end if
    end if
end for

The above-described algorithms are the heuristic approaches taken to assign the DN to DG, adjust energy supplies for the PVDG/ESS units each hour and supply the assigned DN as possible. The following section explains the GA operations used to perform the survival of the fittest selection for a given population of solutions, what crossover techniques are utilized, and how the mutation process is handled. Following this, descriptions of the test problems and results are discussed.

4.3. Ga Optimization Application and Methodology

As aforementioned, each solution has a selection and hourly charging variables or genes and will receive a residual score. Each selection gene of a solution is a binary string, the size of the number of potential DG units. The charging genes are vectors with values of 0 (discharge), 1 (charge), or 2 (idle), the length of the number of hours the MG will rely on the DG units. The scores are converted into the probability of selection scores by dividing them by the total sum of all residual scores. The higher residual score solutions will have a more significant selection probability when selecting breeding pairs. To ensure that the more optimal solutions are selected with even more substantial probability, a top **N** value and weight can be set that will add a small amount of the probability of the selection to the top **N** solutions. The larger the weight, the higher the probability that the top **N** will be selected for breeding. A smaller top **N** value and larger weight converge faster. In comparison, a larger **N** value allows for a more exhaustive search of the solution space by allowing more varied solutions to participate in the breeding process.

When the breeding process occurs, two breeding pair solutions are chosen and used to generate two child solutions until the original population of solutions is replaced. Then, the breeding pair solutions will either experience crossover or be copied into the next generation at a set probability. The GA crossover method is the variable-to-variable single-point crossover technique. Each chromosome or variable is crossed over separately with different random crossover points. When two breeding pairs are selected, they are decomposed into the individual selection and charging scheme portions. Each has a different random crossover point chosen. The resulting child genes from a crossover have a combination of attributes from the two corresponding pairs of solutions (see Figure 2). Each separate child gene will have a mutation occur at a set probability for each of its corresponding values. When a mutation occurs, two of a chromosome's values are switched for each gene.

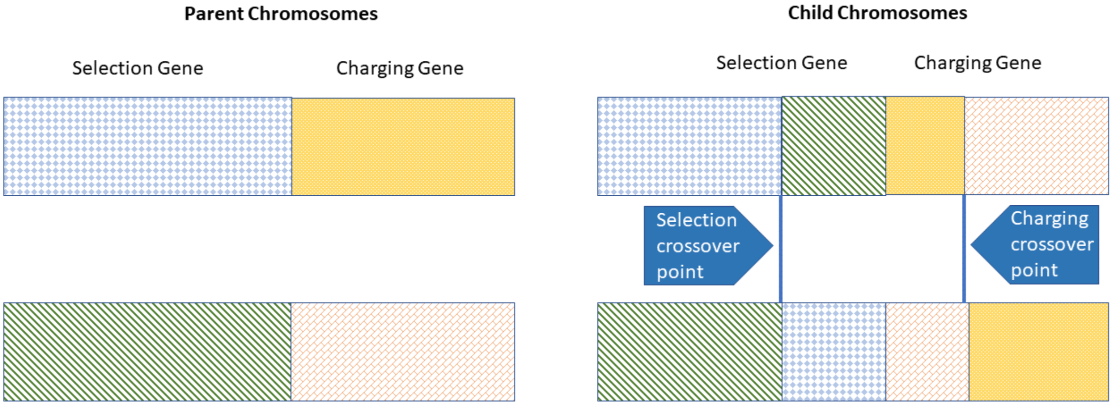

Figure 2. Visualization of the variable-to-variable crossover operation with random crossover points for the selection variable/gene and the charging strategy variable/gene.

4.4. Ga and Simulation Parameter Optimization

Several test runs were performed to obtain the optimal parameters for the GA operations. The tests varied in population size, probability of mutation (PM) and crossover (PC), top **N** value and weight (N_{weight}), and the number of generations Γ. After repeated testing, a population of 25, PC of 0.65, PM of 0.02, and 90 generations achieved the most consistent results with reasonable computation times.

The simulations use thirty days to produce the tightest 95% confidence intervals for the average costs and energy demands met. Each "day" of the simulation consisted of a thirteen-hour simulation of the sunlight hours.

5. Analytical Methods

Test Problems

The authors used three cases of synthetic problems to explore and evaluate the algorithm's performance, each using the same set of twenty-five possible PVDG/ESS units and different numbers of DNs of various types. The first problem is termed the "small problem" or "best case" and optimizes a DN set with one hospital, fire station, police station, grocery store, and gas station. The small or five DN problems intend to evaluate the algorithm's ability to find a small subset of DG/ESS units from a set of twenty-five that will provide maximal energy demands met at a minimal cost where there are many options. For this and all problems, the various types of nodes will have varying geographic locations, as seen in Figure 1. The second problem, labeled the "large" problem or "intermediate case", expands the number of DNs to twenty-five. It tests the algorithm's ability to optimize a problem where it is more difficult to find a solution that will meet maximal demands at minimal investment cost. When there is five times the number of DNs, the algorithm must find solutions that meet a higher amount of required demand while minimizing costs and coming under the investment budget. The final test case scales down the energy outputs of the PVDG units to KW levels to make the optimization task more difficult due to there being smaller power capacities overall to power the small (5 total) DN set. This problem is termed the "hard" problem or "worst case" and is intended to test how well the algorithm performs when the task of meeting maximal demands when the energy available is less than what the DNs require. This problem will explore how the algorithm performs when it is difficult to meet demands with any possible solution. The solutions for this problem must find a middle ground between meeting the demands and coming in under the budget. Thus, the algorithm must thoroughly search the solution space to find an optimal one. For each test case, budgets of USD 10, USD 100, and USD 900 hundred million were tested. Each test case ran using 30 days of simulation to score each solution.

Sensitivity tests were also employed for the overall unmet demand penalty, RPF penalty, and the algorithm's ability to prioritize the different demand nodes based on the set DN priority values. Finally, an analysis of the fittest charging strategies produced by the algorithm is detailed to examine their feasibility and characteristics. The analysis explored if the strategies follow a peak shaving-like or a more voltage regulatory approach. The energy demands of the system peaked around hours 8 (11 a.m.) through 10 (1 p.m.), and the energy output peaks around hours 7 (10 a.m.) to 9 (12 p.m.) (Figure 3). Suppose the system utilizes a more peak-shaving style. The BESS systems will be utilized when there is the highest demand, helping shave some of the burdens. If the system instead uses a more voltage regulation approach, the BESS system is intermittently discharged when energy output is low such as in the early and later hours.

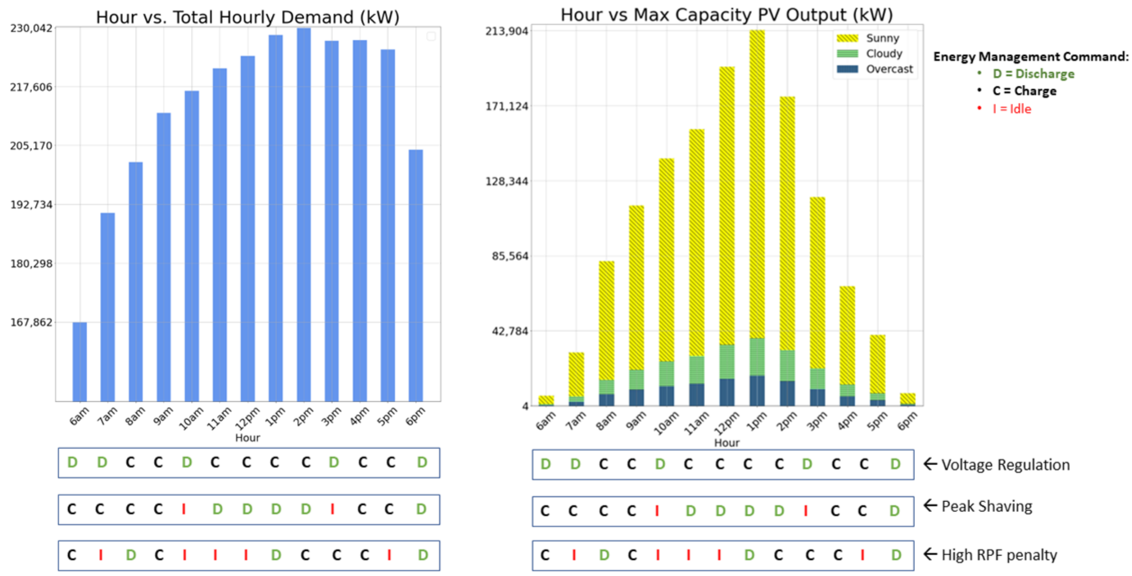

Figure 3. Example charging strategies (**bottom**) produced compared to total hourly demand (**left**) and example PV output (**right**) for the maximum capacity PVDG.

A feasible charging strategy will not see the ESS units discharging for longer than their specified discharge hour limit and being charged for more consecutive hours than this limit indicates. The idle stage should be utilized when the MG will not need to charge or discharge the unit. For example, when they have all been charged but the PV units can provide sufficient energy for the DN, the ESS units should remain idle. There is a four-hour consecutive discharge limit for all ESS modeling, meaning the unit will be fully depleted after four hours of continuous discharge without an hour of charge. Each hour of charge will provide an hour of energy to discharge up the four hours. The results of the tests are discussed in the next section.

6. Results and Discussion

6.1. Large vs. Small vs. Hard Cases

6.1.1. Optimization Cost and Demand Fulfillment vs. Budget

Table 4 displays the testing results for three problems described in Section 5 with investment budgets of USD 10, USD 100, and USD 900 million for each. The results show that the provided algorithm can find minimal investment cost, maximal demand met solutions that provide an assignment, and a charging strategy at a cost below a set budget for all three cases. The solutions for the "small" and "large" problems at the maximum budget achieved as high as 96% and 90% respectively for average demands met. At the highest budget, the "hard" problem can meet 69% of the hourly demands on average. The "hard" problem at the highest budget results shows that even when the available DG has a much lower capacity than is required, the algorithm can find maximal energy demand, meeting solutions that do not violate the investment budget constraints. With the budget set to the lowest values, the "large" problem has a more challenging time meeting demands than small and hard problems. At the lowest budget, the small problem can achieve an average hourly percentage of demands met of around 34%, and the hard problem can meet 27% on average. In contrast, the "large" problem can only meet around 7% on average at the lowest budget. These results indicate that the budget constraint restricts the selection of DG units while showing the algorithm's ability to seek a solution to meet maximal energy demands under these constraints.

Table 4. Small (best case), large (intermediate case), and hard (worst case) problem results.

Problem Type	Budget	Investment Cost	Avg Hourly Demand %	RPF	Charge Behavior
Small Problem	\$10 M	\$6 M	33.97 ± 3.33	279.41 ± 102.27	Voltage Regulation
	\$100 M	\$65 M	85.55 ± 4.32	2247.64 ± 453.98	Voltage Regulation
	\$900 M	\$306 M	96.42 ± 1.29	7175.33 ± 1017.28	Peak Shaving
Large Problem	\$10 M	\$4 M	7.29 ± 1.20	79.31 ± 50.27	Voltage Regulation
	\$100M	\$67 M	55.94 ± 5.56	850 ± 250.59	Peak Shaving
	\$900 M	\$440 M	90.18 ± 1.73	5032.93 ± 534.97	Peak Shaving
Hard Problem	\$10 M	\$4 M	27.25 ± 3.59	134.51 ± 44.55	Voltage Regulation
	\$100 M	\$8 M	43.13 ± 4.33	197.13 ± 60.02	Voltage Regulation
	\$900 M	\$78 M	69.39 ± 5.58	2018.29 ± 329.35	Voltage Regulation

As the budget increases, all problem cases show solutions that achieve higher average energy demands met at higher investment costs. The results also show that higher demand meeting solutions incur higher potential RPF due to selecting higher numbers and capacities of DG. The "large" problem exhibits the lowest average RPF at the lowest budget and a smaller average RPF at the middle and highest budgets than the "small" problem. This result comes from MG meeting more energy demand each hour in the "large" problem compared to the other two problems. This configuration leaves less room for unused energy leading to lower RPF values on average. With this specific set of potential DG units, solutions can find well-matched capacities to the energy demand needs. For the "small" problem, there are DG units of higher capacity that may be chosen that exceed the energy capacity needs of the smaller MG. This condition leads to increased amounts of potential RPF. The "hard" problem has much lower RPF values, which is to be expected since the capacities for the DGs are lowered to kW levels leading to a much lower potential for excess unused energy. Through observing the RPF results, it seems that this particular set of DG units with essentially equal numbers of large, medium, and small capacity PVDG and ESS units are well suited for the "large" problem. With a more extensive, more diverse set of DGs the "small" and "hard" problems may also be able to find solutions that lead to smaller RPF values when smaller capacity units are included.

6.1.2. Optimized Charging Strategies

Table 4 also gives examples of the different charging strategy behavior exhibited by the solutions in the far right column. Examples of these can be seen in Figure 3 below. The total hourly energy demand graph (left) demonstrates the total energy demand for all DNs for each of the thirteen hours the MG will be expected to power them. Similarly, the right graph shows an example of the typical DG power outputs across the sunlight hours under the three possible weather conditions. The energy demand rises to its peak between 11 a.m. and 2 p.m., while the peak output of the PV is between the hours of 11 a.m. to 2 p.m. Below each graph are examples of voltage regulatory, peak-shaving, and high RPF penalty charging strategies produced by the algorithm. One can notice there are never more than four consecutive charging (C) and discharging (D) intervals as specified in the model description. Thus, the algorithm produces feasible charging strategies based on the specifications of the modeled ESS. The following paragraphs detail the characteristics of the charging strategy solutions produced for the "small" and "large" problems and the result of setting a high RPF penalty.

The "hard", "small", and "large" problems favored different charging strategies depending on the budget. The "large" problem primarily utilized the peak shaving management scheme, only utilizing the voltage regulation behavior at the lowest budget. The small problem utilized the voltage regulation method at the low and mid-tier budget levels, only utilizing the peak shaving behavior at the highest budget. The hard problems exclusively utilized voltage regulation strategies. The voltage regulation management style is shown below each graph in the first row of charging strategies in Figure 3. This strategy suggests a solution focused on meeting demands during lower output times using the ESS units and storing any excess energy when peaks in PV output occur. The peak-shaving method in the second row suggests a solution whose charging strategy focuses on providing auxiliary power when demand is highest while storing energy at lower demand and higher PV output times. With a larger budget, the "large" problem solutions sought to provide auxiliary power during peak demand times, often charging when the PV output exceeded what was demanded during the non-peak hours. At the lowest budget, all cases tended toward voltage regulation providing energy throughout the day.

The bottom row of examples seen below the graphs in Figure 3 shows the charging strategies produced with the "small" problem, with a very high RPF penalty (1k). When setting the RPF penalty to a very high value, the charging strategies utilize the idle stage much more, reducing the overall use of the ESS units. This behavior reduces potential RPF by reducing the potential total energy output by primarily utilizing the PV units alone. This result shows that the RPF penalty does cause the algorithm to select solutions that attempt to reduce excess unused energy. For the "small" problem, there is enough energy produced by the PV units alone to power the DN during most hours of the day. Thus, when forcing the algorithm to find ways to reduce excess energy, it will select solutions that utilize the ESS output as little as possible and utilize them more for energy storage to reduce potential excess energy.

These results indicate that when forced to provide solutions with lower investment costs and thus lower overall capacities, the charging strategies produced use the ESS units more during low PV output throughout the day. On the other hand, when the MG has a high number of higher capacity DG, as with the "large" problem at mid and high budgets or the "small" problem at the highest budget, the charging strategies tend toward peak-shaving. The following section discusses the conflicting nature of the optimization for this problem and how it can be seen in visualizations of the algorithm as it runs.

6.2. Dueling Objectives: Maximizing Energy Demands Met While Minimizing Costs

The algorithm needs to find a middle ground between finding minimal cost solutions while meeting maximal demands, and these two goals can be somewhat at odds. Increased numbers and capacities of DGs may meet higher average demand but cost more. Using less DG capacity will decrease costs and potentially increase unfulfilled energy demands. The algorithm can perform this task, and a visualization of this process reveals the dueling nature of minimizing cost and unmet energy demands. The algorithm will often find minimal-cost solutions first, leading to a spike in the unmet demand. However, as the algorithm continues, it will eventually produce higher average energy demand-met solutions. This behavior can be seen in Figure 4 where the average and best current demands met (left) and investment and operating costs (right) of solutions for each generation can be seen. In the initial generations, the average costs of the solutions reduce while the average demands met drop. However, they eventually settle into solutions that seem to meet somewhere in the middle by maintaining low-cost solutions and finding solutions that meet more energy demands on average.

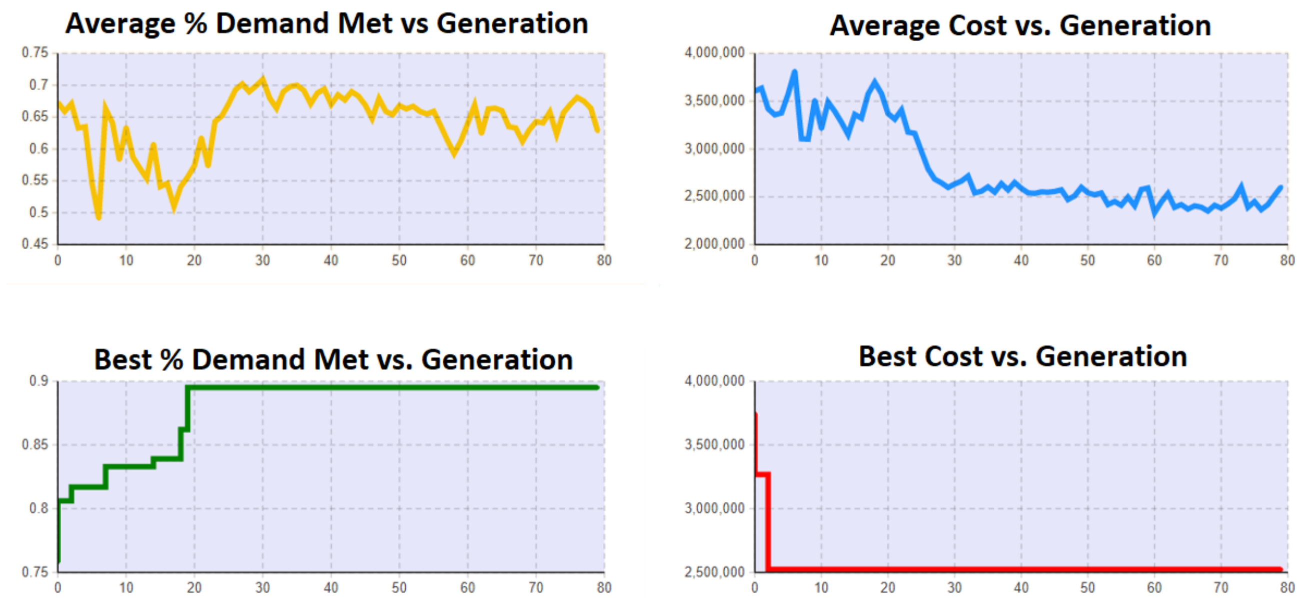

Figure 4. The large problem's minimal cost and maximal demand met progress by generation.

The weighting of the unmet demand aided in driving the algorithm toward higher average demand met solutions. When the cost goes down, the energy demands met will often only decrease if there is not enough weight given to meeting the energy demands due to the different magnitudes of costs and energy demands met. The experiments with the unmet demand weight showed that if it is too low, the algorithm will be driven by the greater magnitude of investment and operating costs only to minimize costs. The experiments also revealed that if the weight of unmet demand is too high, it becomes tough for the algorithm to find better solutions for either task thus, there needs to be a balance between the cost and unmet demand portions of the objective Equation (21) so that both can be optimized. Next, a discussion of the algorithm's ability to prioritize specific types of DNs over others is given.

6.3. Demand Node Prioritization

The prioritization of specific demand nodes over others functions as intended when tested with the "large" problem (Table 5). From experimentation with the "large" problem, the highest prioritized node will, on average, have a higher hourly percentage of their demands met. This result is seemingly harder to accomplish with the higher energy-demanding nodes, which are harder to energize consistently. For example, the DN with the highest peak demand, hospitals, while still receiving higher average demands met when prioritized over the others, only achieved around 85.3% compared to the lowest peak demand node, gas stations, with their 98.7% average hourly demands met (Table 5). Observing Table 5, it can be seen that when one DN is prioritized one hundred times more than the rest, its average percentage of hourly demand met is higher using the average of four simulations for each. This result shows that the prioritization of different nodes can be achieved by weighting their unmet demands differently.

Table 5. Sensitivity to prioritization of one node type above all others. The results in bold indicate the effectiveness of prioritization with higher percentage of average demand met.

Type	Priority	Peak	Average % Demand Met
Hospital	200	1024	**85.3**
Grocery Store	20	155	80.3
Fire Station	20	158	71.3
Police Station	20	158	83.7
Gas Station	20	36	76.3
Hospital	20	1024	85.0
Grocery Store	200	155	**97.3**
Fire Station	20	158	90.7
Police Station	20	158	91.0
Gas Station	20	36	87.3
Hospital	20	1024	76.1
Grocery Store	20	155	78.8
Fire Station	200	158	**84.0**
Police Station	20	158	78.3
Gas Station	20	36	80.4
Hospital	20	1024	82.3
Grocery Store	20	155	83.7
Fire Station	20	158	82.7
Police Station	200	158	**94.3**
Gas Station	20	36	82.7
Hospital	20	1024	82.3
Grocery Store	20	155	86.0
Fire Station	20	158	85.3
Police Station	20	158	84.0
Gas Station	200	36	**98.7**

7. Conclusions, Limitations, and Future Research

This work sought to develop an optimization via a simulation framework to find optimal PVDG sizing, locations, and assignments, and an hourly ESS charging strategy that minimizes costs and unmet energy demand while allowing for the prioritization of specific types of DNs for a MG in the island mode. The results show that the algorithm can find solutions for these problems under a given budget. The algorithm is also shown to have the ability to prioritize specific demand nodes. The obtained charging strategies exhibit peak shaving and voltage regulatory behaviors as detailed in Section 6.1. Different computational test cases show that the charging strategies produced in different situations will utilize the ESS units effectively.

There are some limitations and potential expansions to the current model. First, the current model is an approximate high-level model of a PVDG/ESS MG process in operation. The model does not consider the power quality or other specifications required to meet system standards. Works, such as Hengsritawat et al. [8], on the effects of background harmonics, can have an impact on the optimal PVDG sizing. Moreover, the authors of Yazdi et al. [30] focused on over-voltage regulation. Their work showed the importance of other power quality factors when selecting an optimal MG configuration. The current model also excludes factors, such as the relationship between thermal conditions PV energy, ESS charging behavior, and static discharge of ESS. There are studies [31–33] that explore methods of mathematically modeling this complex system; future work will utilize such models and alike to update and advance the model. Second, the current model uses generalized approximations of the PV and ESS unit costs, and future efforts will include actual unit specifications for a localized case study. Third, the hourly energy demands are based on aggregated averages for the specified type of building; works, such as [8], discuss the importance of accurately modeling the stochastic nature of energy demands.

Fourth, the current method uses only one charging strategy for all selected ESS units and weather conditions.

Future research directions include making the simulation more physically accurate to incorporate the crucial considerations discussed above. It would be of interest to modify the MG model to have more advanced component modeling capabilities allowing for factors such as the degradation of the PV/ESS components and power factor concerns. The expansion of the ESS model is needed to achieve a more accurate simulation of the charging and discharging behaviors. The current model can also be extended by implementing stochastic energy demands based on historical data to accurately capture demand uncertainties. An evaluation of the model under a grid-connected post-disruption configuration may be of significance to justify the investment costs in the long run. Future work may extend the charging strategies to test weather condition-specific and ESS unit-specific charging schemes. In addition, many models now explore the inclusion of electric vehicles (EVs) as potential storage devices, and future work will explore these additional energy resources. Lastly, the current solution utilizes a GA-based method. One may pursue a comparative study with other meta-heuristics and deep reinforcement learning methods.

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Abbreviations

DN	energy demand nodes or facilities
DG	distributed generators
ESS	energy storage system
PV	photovoltaic
PVDG	photovoltaic distributed generator
PVDG/ESS	co-located PVDG and ESS
MG	microgrid
ODGSP	optimal distributed generation sizing and placement
RPF	reverse power flow
RES	renewable energy source

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