

Grid-Aware Tradeoff Analysis for Outage Mitigation Microgrids at Emerging Resilience Hubs

Arnav Gautam¹, Graduate Student Member, IEEE, Destenie Nock²,
and Amritanshu Pandey¹, Senior Member, IEEE

Abstract—Sustained power outages are growing in scale and number primarily due to i) the increasing number and intensity of disasters and ii) decarbonization- and electrification-related grid changes. Outage mitigation technologies (e.g., backup diesel generators, and solar panels) increasingly provide vital electricity access during disasters. However, their adoption is inequitable due to individual- or community-level barriers and historic underinvestment in certain communities. We postulate that community-based Resilience Hubs (RHs), which are being increasingly deployed to provide on-site services during disasters, can be expanded to address this inequity by supplying backup power to vulnerable communities through islanded operations. To that end, we present Grid-Aware Tradeoff Analysis (GATA) framework to identify the best backup power systems for expanded RHs. To include technical, economic, and social facets in the framework, we will use three-phase power flow (TPF) and multi-criteria decision analysis (MCDA). TPF will enforce the electrical feasibility of islanded RH operation, and MCDA will quantify the economic, environmental, and equity-weighted outage mitigation performance. As a use case for GATA, we will evaluate multiple representative RHs in Richmond, California, and highlight the non-dominated systems for the electrically feasible RHs. We show the value of GATA's detailed grid simulation, its ability to quantify tradeoffs across scenarios, and its possible extensions.

Index Terms—Energy equity, MCDA, multi criteria decision analysis, outage mitigation, resilience hubs, three-phase power flow.

NOMENCLATURE

Sets	
G	Distribution network.
$\mathcal{N}$	Nodes in distribution network.
$\mathcal{L}$	Nodes on the distribution network with electrical loads.
$\mathcal{E}$	Edges in distribution network graph.
$\mathcal{P}$	Generic power source.
T	Set of timesteps.
$\mathcal{S}$	Set of backup power systems.
$\mathcal{O}_s$	Set of energy technologies in system s

C_s	Set of criteria values for system s
<i>Indices</i>	
d	Outage duration.
t	Timestep.
RH	Resilience Hub.
o	Energy technology.
s	Backup power system.
<i>Subsets</i>	
G_{RH}	Islanded sub-network.
$\mathcal{N}_{RH}$	Nodes in islanded sub-network.
$\mathcal{L}_{RH}$	Nodes in islanded sub-network with electrical loads.
$\mathcal{E}_{RH}$	Subset of edges within islanded sub-network.
$\mathcal{T}_x$	Transmission lines.
$\mathcal{X}_f$	Transformer.
$\mathcal{S}_f$	Set of feasible backup power systems.
$\mathcal{S}_{ND}$	Set of non-dominated backup power systems.
<i>Parameters</i>	
$\bar{i}_e$	Maximum current allowed through edge.
$\bar{p}_e$	Maximum power allowed through edge.
ϕ	Phase.
v_j	Minimum voltage required at node.
$\bar{v}_j$	Maximum voltage allowed at node.
b	Budget for backup power system purchase.
P_o^u	Per-unit capacity of technology o
c_k	Criteria of type k
α	Social Vulnerability Index hyperparameter.
β	Load priority hyperparameter.
γ	Energy served logarithm hyperparameter.
v_l	Social Vulnerability Index for load l
pr_l	Priority of load l
w_{eq}	Equal Weight Set.
w_{sh}	Expert Survey Weight Set.
w_{ec}	Hand Picked Weight Set.
<i>Variables</i>	
i_e	Current through edge.
p_e	Power through edge.
$v_{j,\phi}$	Voltage at node j on phase ϕ
$\mathcal{T}_p^t$	Power supply needed during outage at time t
$\mathcal{T}_s^t$	Power supply from system s at time t
$\mathcal{T}_{s,o}^t$	Power supply of s contributed by technology o at time t
$\mathcal{T}_l^t$	Load draw by the load l at time t

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Arnav Gautam and Destenie Nock are with the Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, PA 15213 USA (e-mail: ajgautam@andrew.cmu.edu; dnock@andrew.cmu.edu).

Amritanshu Pandey is with the Department of Electrical and Biomedical Engineering, University of Vermont, Burlington, VT 05405 USA (e-mail: amritanshu.pandey@uvm.edu).

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$\mathcal{T}_{RH}^t$	Load draw demanded within islanded sub-network at time t
$\psi_{l,s}^t$	Load draw supplied by system s to load l at time t
c_s^{CNSP}	Customer Not-Supplied Probability of s
c_s^{econ}	Economic production cost of s
c_s^{pol}	Environmental air pollution impact of s
$EWOMP_l$	Equity-Weighted Outage Mitigation Performance for load l
c_s^{EWOMP}	EWOMP of s
s_{dom}	Dominated backup power system.

I. INTRODUCTION

THE resilience of the electric grid is decreasing, as shown by the higher frequency and longer duration of sustained outages [1]. One reason is that our built infrastructure, including the electric grid, is increasingly exposed to natural disasters [2], which are worsening in frequency and magnitude [3]. Another reason is that the grid is rapidly changing due to decarbonization and electrification, which impact its reliability and stability [4]. Sustained outages cause billions of dollars in economic damages and threaten the health and safety of the public [5], so there is a clear need to mitigate these outages. Many outage mitigation technologies have been developed to enable a continued supply of electrical power to consumers in distribution networks facing a regional outage. However, outage mitigation technologies are inequitably distributed [6]. Backup power systems for personal or community use (often diesel generators or solar panels with battery storage) are often unavailable to low-income individuals or communities who cannot afford them. The economic, resilience, and equity implications of widely deploying backup power systems such as home batteries are being explored today by utility companies such as Green Mountain Power [7]. Grid hardening technologies make entire electrical transmission or distribution systems more robust (such as underground electrical cables and switching networks), but utilities have historically underinvested in grid hardening for certain sociodemographic groups. The historic underinvestment in resiliency enhancements in vulnerable communities has been traced back to bureaucratic decisions at utility companies which, although not shown to have institutional bias, nevertheless result in outages that are unequal in the racial or sociodemographic groups they impact [8]. Similarly, the historic underinvestment in post-outage repairs in vulnerable communities can be traced back to utility company policies of enacting repairs in locations based on internal policies which are so-called “colorblind” [9]. This can be seen in the higher rate of power outages faced, for example, by Hispanic and Latino populations [10]. Due to these inequities, there is a lack of backup power systems and grid hardening technologies to help these vulnerable groups during sustained outages.

One opportunity for addressing this problem is by expanding upon an emerging class of disaster-resilience projects known as Resilience Hubs (RHs) [11]. Cities are actively developing RHs as “community-serving facilities augmented to...

coordinate communication, distribute resources, and reduce carbon pollution while enhancing the quality of life” [12], and often specifically site RHs in disadvantaged communities [13]. Many RHs plan to include backup power systems for serving their own critical electrical loads during grid outages [14]. There is some peer-reviewed literature focused on Resilience Hubs [15], and other work which mentions RHs as one approach to achieving equitable resilience [16], but none of this work focuses on the selection of the power system providing backup power to RHs. RHs have been set up in US regions as varied as Minneapolis, Hawai’i Island, Atlanta, and Tallahassee [17]. These settings include full-sized cities, residential areas, and rural settings with different electric grid layouts. The local climate and geography of these settings differ significantly, as do the load profiles and potential stressors on the grid.

We posit that backup power-equipped RHs can surpass just serving their own loads to serve electrical load of its neighbors by islanding the sub-system from the main utility during sustained outages [18]. In doing so, RHs can provide targeted sub-regional outage mitigation for communities vulnerable to the consequences of disaster-induced power outages and for those unable to adopt outage mitigation technologies on their own. But serving backup power to local communities introduces new social and technical considerations for RH planning. What are the societal outcomes of this outage mitigation? Is it electrically feasible – can the distribution grid equipment support this mode of operation? Would using multiple technologies in “hybrid-energy systems” mitigate risk and help reliability as some posit? These questions become central to selecting the RH backup power system. So we ask: how can RH planners evaluate the tradeoffs of backup power systems considering these social facets and technical constraints?

This paper presents a Grid-Aware Tradeoff Analysis framework (GATA) that includes power systems constraints in a decision analysis to help identify the best backup power systems for a RH and highlight their tradeoffs. This sociotechnical analysis is an alternative to the least-cost optimization which is currently performed by RH planners [14]. GATA incorporates the operational, financial, environmental, and social goals RH planners have by combining power systems analysis and decision analysis in a novel way.

There are many decision analysis tools available for choosing a configuration for RH backup power systems, with two main groups of tools being multi-objective optimization and multi-criteria decision analysis (MCDA). Anderson et al. [19] select backup power systems for public buildings by optimizing for a composite objective function incorporating climate and health impacts alongside economics, but this and other multi-objective optimization approaches take away the RH planner’s freedom to decide acceptable tradeoffs between goals. Multi-criteria decision analysis (MCDA) and multi-objective programming (MOP) both serve to find solution(s) to a problem with multiple considerations. MCDA assumes that there is a pre-determined set of options from which to choose a solution. MOP assumes that a solution can be constructed and accepted as long as it adheres to certain constraints as outlined in the MOP itself. The research question of this paper is a case where options for

systems will be limited for multiple reasons, including supplier agreements, available physical space in the Resilience Hub building, and community members' comfort with the installation of particular machines for backup generation purposes. MOP would not reflect the decision-making paradigm of choosing between alternatives. MCDA does not have this dependency, since those constraints are inherently included by selecting the pre-determined set of options (i.e., alternatives). This rests on the fact that the goal of MCDA is not to find a global optimal but rather to allow decisionmakers to uncover their ranking of non-dominated solutions, which may be either local or global. Policymakers solve problems where externally imposed constraints may lead to a set of limited choices, and they must weigh many considerations against each other in order to come to an answer satisfactory to them, which is most suitable for MCDA. The selection of MCDA over classical optimization is based in prior literature, most notably Guitouni and Martel [20] who state that "The perspective of the MCDA may lay in a new paradigm. In fact, there is more than one unique paradigm which are different from one 'school of thought' to another. The idea of the optimal solution is abandoned for the notion of the 'satisfaction of the decision maker'." Furthermore, the decisions being made by RH planners are complex in nature, and formalizing optimization constraints that fully define their decision-making approach would require a level of coordination and effort on their part that would pose a significant burden on the RH planners. MCDA methods have been used for backup power system technology selection [21], but prior work lacks a detailed high-resolution distribution network grid reliability assessment. We will build on this work by developing an MCDA framework capable of distribution grid reliability assessment within existing grid infrastructure.

We use circuit-theoretic current-voltage three-phase power flow (TPF) [22] to evaluate the reliability of the grid for the MCDA, because TPF models AC network constraints and informs us of any voltage or line and transformer violations while supplying backup power. The method we use for evaluating the grid's reliability is built upon established methods of distribution grid analysis [23] and informed by work in circuit simulation [24]. When developing this methodology, we relied on the works referenced above, which cover the underlying concepts and mathematical formulations in great detail. Other power system analyses also exist and can be used instead of TPF. For instance, there are methods for distribution grid and microgrid expansion planning [25] but these don't consider the AC power flow constraints. A more detailed time-domain analysis [26] could also serve as an alternative but these require granular model data (e.g., gain values and circuit time constants as in [27]) that will be very difficult for RH planners to procure. Optimization-based AC optimal power flow (AC-OPF) methods can also model AC constraints for distributed generation placement [28], but we use power system analyses to evaluate system feasibility for various predetermined system configurations, and not to satisfy a certain objective, so the optimization functionality of AC-OPF is not necessary here. In the case of Resilience Hubs, electric grid constraints may be determined by utility company electrical engineers, and passed on to city

planning officials or government employees. Therefore, the two-step approach of TPF + MCDA is designed to more closely resemble the organizational structure of the Resilience Hub development process, in which RH planners may be spread out across organizations and each operate within their own specialty. While MOP can in fact be used as a secondary path to obtain solutions for a problem that is analogous to one formulated in this paper, we have determined that a TPF + MCDA approach would be better suited for easier integration with the workflows of the RH planners, while still providing them with acceptable results.

By merging decision analysis and power system analysis methods, we develop the first high-resolution distribution grid analysis tool which includes social, economic, reliability, and environmental considerations, to evaluate backup power system choices for RHs and network resiliency microgrids. It is also the first tool to include a social impact metric which is an equity-aware valuation for outage mitigation capturing the differing value for electricity provided to loads with different needs. This builds on prior studies in valuing the costs and benefits of outages and outage mitigation, respectively [29], [30]. This literature includes prior work on willingness-to-pay (WTP) for outage mitigation, which is a measure of the monetary value consumers place on the importance of this service. Baik et al. 2018 find that consumers have a higher WTP for electricity which serves critical social services and low-income households in the consumer's neighborhood [31]. Although prior studies placed a value on outage mitigation when quantifying total damages from certain outages [29], or total benefits from mitigating outages [30], these studies have not yet made use of the insight from Baik et al. 2018, that the value placed in electricity differs based on the consumer it goes to.

We will now present how the GATA framework integrates TPF and MCDA to determine the preferred set of backup power systems for RHs. Following this, we describe a case study based on RH projects underway in the city of Richmond, California, which is one of the many opportunities for applying GATA to real-world decision-making situations. We then go over the results of this case study, including the non-dominated options that come out of GATA. We finally have our conclusions and future work.

II. METHODS

An overview of the GATA framework is described in Fig. 1. GATA is designed to take input on the distribution network, energy technology options, economic budget, and expected system performance. It then outputs the best (non-dominated) viable backup power systems options for RH planners to select between. GATA mandates the solution's electrical feasibility while optimizing for critical social facets.

GATA starts by (see Section II-A) using TPF to evaluate the reliability constraints for a generic power source $\mathcal{P}$ at a RH location to serve electricity to a predetermined set of nodes $\mathcal{L}_{RH}$ during outages. The code to run TPF is available publicly at <https://github.com/lucasgodshalk/combined-txds>. The next two steps, discussed in Section II-B, enumerate a set of feasible

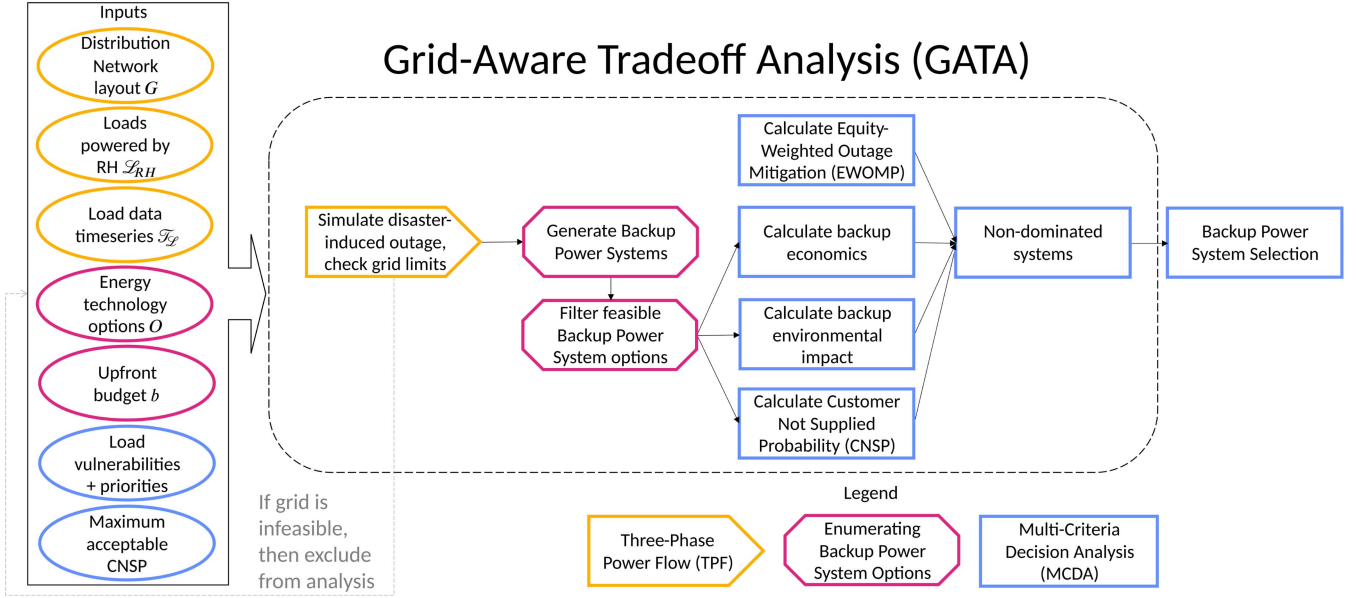


Fig. 1. Grid-Aware Tradeoff Analysis (GATA) Framework. Inputs are the distribution network equipment details, load data, and available energy technology options. Alternative performance across multiple criteria of backup systems determines the non-dominated set.

backup power systems $\mathcal{S}_f$ that could serve as $\mathcal{P}$ during a sustained outage. The remaining steps, discussed in Section II-C, calculate each backup power system's performance along several criteria to run an MCDA and find the non-dominated options $\mathcal{S}_{ND} \subseteq \mathcal{S}_f$. The code to run these steps is available publicly at https://github.com/arnavgautam/resilience_hub_MCDA. These non-dominated options are the output of GATA, and can be used by RH planners for their own backup power system selection.

A. Imposing Distribution Network Constraints Using TPF

In this section, we describe how GATA uses TPF to determine the timeseries $\mathcal{T}_P$ of hourly power supply needed from $\mathcal{P}$ to power $\mathcal{L}_{RH}$ during a sustained outage of duration d . We also determine whether it is electrically feasible to keep $\mathcal{L}_{RH}$ energized during a sustained outage to support its outage-time operations. Section II-B will cover the choice of a mix of energy technologies which will make up $\mathcal{P}$.

1) *Load Selection*: The first input to the TPF simulation is the load nodes $\mathcal{L}_{RH}$ that “island” through distribution automation and draw power from $\mathcal{P}$ during sustained power outages. Each $\mathcal{L}_{RH}$ includes the load of the RH building itself, and optionally can include other load nodes connected via distribution grid equipment to the RH building. RH planners using GATA may select $\mathcal{L}_{RH}$ based on any number of considerations, including population vulnerability [32], perceived importance of load [33], and availability of distribution automation to physically island that subset during an outage [30].

2) *Grid Configuration During Outage Mitigation by RHs*: To simulate the islanding of $\mathcal{L}_{RH}$ during an outage, GATA reconfigures distribution network G in the input file, mimicking actions of distribution automation, to energize only a subnetwork $G_{RH} \subseteq G$, which is supplied by $\mathcal{P}$. G_{RH} electrically connects

nodes $\mathcal{L}_{RH}$ with electrical loads to $\mathcal{P}$ through a combination of graph edges $\mathcal{E}_{RH} \subseteq \mathcal{E}$.

3) *Outage Simulation*: The TPF in GATA simulates the power flow in this sub-network G_{RH} with $\mathcal{P}$, to investigate the system's edge currents and power flow, nodal voltages, and whether the network is feasible [22]. GATA repeatedly performs this outage TPF simulation over the duration d of a sustained power outage, by recursively going through and adjusting load values for $\mathcal{L}_{RH}$ from time-series load values $\mathcal{T}_{RH}^t$ for $t \in T = [1, \dots, d]$. The resulting power output p_t from $\mathcal{P}$ for all timesteps T is collected into $\mathcal{T}_P$.

4) *Grid Feasibility Check*: For each TPF run, GATA checks to see if any grid physics constraints are violated while supplying loads $\mathcal{T}_{RH}^t$ at time t from generic power source $\mathcal{P}$. If the power flow run didn't converge and provide a solution, this is considered a failure. If TPF returns a feasible solution, GATA does three checks for each timestep t .

First, no current i_e through transmission line $e \in \mathcal{T}_x \subseteq \mathcal{E}$ can exceed that line's maximum current capacity $\bar{i}_e$, per (1):

$$i_e^t \leq \bar{i}_e \quad \forall e \in \mathcal{T}_x, \forall t \in T \quad (1)$$

Second, no power p_e flowing through any transformer $e \in \mathcal{X}_f \subseteq \mathcal{E}$ can exceed that transformer's maximum power capacity $\bar{p}_e$, per (2):

$$p_e^t \leq \bar{p}_e \quad \forall e \in \mathcal{X}_f, \forall t \in T \quad (2)$$

Third, all voltages v must remain within specified minimum $\underline{v}_j$ and maximum $\bar{v}_j$ bounds for all nodes $j \in \mathcal{N}_{RH} \subseteq \mathcal{N}$, and all phases ϕ per (3).

$$\underline{v}_j \leq v_{j,\phi}^t \leq \bar{v}_j \quad \{\phi = A, B, C\}, \forall j \in \mathcal{N}_{RH}, \forall t \in T \quad (3)$$

Any failure of these checks for any timestep t would indicate that it is not feasible for the RH to power $\mathcal{L}_{RH}$ for the complete

timeseries T , regardless of what specific equipment is installed at the RH. Therefore, the particular grid configuration G_{RH} with power source $\mathcal{P}$, load locations $\mathcal{L}_{RH}$, and load profiles $\mathcal{T}_{RH}$ is rejected. The GATA user is asked to provide an alternate set of $\mathcal{L}_{RH}$ and RH grid configuration G_{RH} .

B. Finding the Feasible Backup Power System Options

We now discuss how GATA determines a feasible set of backup power systems ($\mathcal{S}_f \subseteq \mathcal{S}$) that can serve as the generic power supply $\mathcal{P}$. $\mathcal{S}_f$ is meant to approximate the range of feasible possibilities for which GATA performs multi-criteria decision analysis (MCDA). We begin with all possible backup power system options, $\mathcal{S}$, given a financial budget, b , set of energy technologies $\mathcal{O}$, and the unit size P_o^u for each energy technology $o \in \mathcal{O}$. We obtain $\mathcal{S}_f$ from $\mathcal{S}$ by filtering out infeasible options based on the steps in the following sections.

1) *Backup Power System Technology Options*: Each backup power system s comprises a set of commercially available energy technologies $o \in \mathcal{O}_s$, with a provided unit capacity P_o^u for each. In the set of technologies $\mathcal{O}_s$, we consider solar panels, battery storage, solid-oxide fuel cells (SOFCs), and diesel generators. These technologies may either be stationary and kept on-site year-round as is considered in previous work [18], or be mobile and brought in just for disaster preparation situations, which is receiving increasing interest [34]. This decision will have an impact when RH planners consider the year-round implications of their backup power sources, as we will briefly explore in Section IV-E. We source information on each technology option's electrical generation profiles, fixed and variable costs, and pollution emission factors from the literature, grey literature, and various outside sources [35], [36], [37], [38], [39], [40], [41].

2) *Enumerating Alternatives for System Configurations*: GATA enumerates all combinations of backup power systems alternatives $\mathcal{S}$ by combining energy technologies listed in Section II-B1, limited only by the total financial budget b and unit capacity of every technology o . GATA therefore deterministically evaluates every single possible alternative at this step.

3) *Filtering Out Infeasible Alternatives*: GATA filters the enumerated alternatives $\mathcal{S}$ to the feasible subset $\mathcal{S}_f$ by checking whether the system can supply sufficient power for the duration d of the simulated outage. For each alternative, $s \in \mathcal{S}$, GATA creates a timeseries $\mathcal{T}_s$ of the power it can supply at each timestamp. To do this, it first calculates the timeseries $\mathcal{T}_o$ of each energy technology for the outage duration d . The calculations assume that the technology is being used to generate the maximum power possible starting from the first hour until the point if and when generation is no longer possible. Each technology's timeseries $\mathcal{T}_{s,o}$ is dependent on the maximum power output $p_o^{\max}$ and the constraints of that technology o , such as solar radiation patterns, battery energy constraints, or diesel fuel requirements. GATA aggregates those $\mathcal{T}_{s,o}$ timeseries values to create a timeseries $\mathcal{T}_s$ of the total power output of the backup power system. $\mathcal{T}_s$ is used to calculate a "customer-not-supplied-probability" (CNSP) metric. The CNSP is a value from 0 to 1, which indicates the proportion of hours in the outage duration that the power output of the backup power system is insufficient to meet the needs of

the network, and customers don't have access to their desired power. GATA evaluates the CNSP of a backup power system in (4).

$$c_s^{CNSP} = \frac{\|\mathcal{T}_s < \mathcal{T}_P\|_0}{\|\mathcal{T}_P\|_0} \quad (4)$$

The set of feasible alternatives $\mathcal{S}_f$ is determined by the acceptable CNSP ($CNSP_{acc}$) input threshold.

C. Evaluating Options to Find the Non-Dominated Set

GATA uses MCDA to evaluate each backup power system in the feasible set $s \in \mathcal{S}_f$. MCDA evaluates the various feasible systems in $\mathcal{S}_f$ based on metrics we describe below, including economic cost, environmental impact, and equity-weighted outage mitigation performance (EWOMP). This analysis focuses on the outage-only operation of these backup power systems. Based on the MCDA evaluation GATA outputs the non-dominated set of systems $\mathcal{S}_{ND}$, which RH planners should finally consider for selection. We further describe the feature space for MCDA.

1) *Economic Cost Evaluation*: GATA evaluates the economic production cost per kWh of a backup power system based on the sum of fixed equipment purchase cost f_o and variable cost v_o of the kWh generated, for all of the $n_{s,o}$ units of each energy technology $o \in \mathcal{O}_s$, as per (5). Electricity generation costs are determined by fuel costs per kWh of energy consumption, which are diesel and natural gas purchase costs for generators and SOFCs, respectively. Solar generation and battery charge/discharge is modeled as having zero variable costs, as it does not require the purchase of any fuel to produce electricity. Both solar and battery storage fixed costs include inverter purchase. The variable costs modeled here are solely short-term operating costs during the outage duration, since longer-term costs and revenue depends on many other factors, as we demonstrate in the results of our case study. Variable costs also don't include labor costs of installation or maintenance or upstream fuel procurement costs.

$$c_s^{econ} = \frac{\sum_{o \in \mathcal{O}_s} (n_{s,o} \times f_o + v_o \times \sum^t \mathcal{T}_{s,o}^t)}{\sum^t \mathcal{T}_s^t} \quad (5)$$

2) *Environmental Impact Evaluation*: GATA evaluates the direct operational environmental impact per kWh of a backup power system using an air pollution assessment in (6).

$$c_s^{pol} = \frac{\sum_{o \in \mathcal{O}} (EF_o^{pol} \times \sum^t \mathcal{T}_{s,o}^t)}{\sum^t \mathcal{T}_s^t} \quad (6)$$

where EF_o^{pol} is the emissions factor of pollutant pol for energy technology o . We evaluate two air pollutants: CO2 and PM10. The emissions per kWh modeled here are only those incurred during outage-time operations. We note that this is a fraction of the emissions that will be incurred over the lifetime of the backup power systems if they are used in normal conditions, but normal condition analysis is outside the scope of this paper.

3) *Equity-Weighted Outage Mitigation Performance (EWOMP) Evaluation*: The equity-weighted outage mitigation performance (EWOMP) is a metric that quantifies the equity-weighted value provided by a backup power system.

Two key insights that contribute to EWOMP's formulation are: 1) the first kWh provided to a consumer is valued more than additional kWh [31], and 2) the value of kWh depends on who is receiving the electricity. EWOMP is designed to lie in the range 0 to 1. An EWOMP of 1 means that s supplies all requested electricity to all high-priority and high-vulnerability loads. If s supplies less than the requested electricity to high-priority and high-vulnerability loads, the EWOMP moves toward the value of zero.

The first insight can be captured with a logarithmic relationship based on electricity supplied, as per (7) and (8). Let us define $\psi_{l,s}^t$ based on the kWh successfully supplied by system s to RH load $l \in \mathcal{L}_{RH}$, assuming an equal demand response by load percentage for all nodes as per (7).

$$\psi_{l,s}^t = \mathcal{T}_l^t \left(\frac{\mathcal{T}_s^t}{\mathcal{T}_p^t} \right), \forall l \in \mathcal{L}_{RH}, \forall t \in T \quad (7)$$

If we sum a log of $\psi_{l,s}^t$ across all timestamps and loads, as per (8), we would obtain a value x_l which represents the benefit of electricity supplied by s to load l during an outage.

$$x_l = \sum_{t=1}^d \log_{10}(\gamma \psi_{l,s}^t + 1) \quad (8)$$

The hyperparameter $\gamma \in (0, 1]$ tunes this value to the appropriate logarithmic relationship reflecting the marginal benefit of additional kWh. A γ approaching 0 indicates a near-linear relationship between value and kWh delivered, while a γ of 1 gives much more value to earlier kWh. However, this formulation doesn't reflect the equity considerations inherent in the RH planning process, so we build further on it.

EWOMP extends this formulation to also capture the second insight, the distributional outcomes of outage mitigation. Calculating EWOMP first compares how the value of the electricity served, as defined in (8), compares to the value of the electricity $\mathcal{T}_l^t$ that would have been provided by the generic power source $\mathcal{P}$ with a CNSP of zero. This is then weighted by two weights described below, v_l and pr_l . EWOMP assigns more value to kWh of energy delivered to load nodes in regions of higher Social Vulnerability index [42], which is an established measure v_l ranging from 0-1 of how vulnerable particular populations are to external stressors like natural disasters [43], with 1 being the most vulnerable. EWOMP also assigns more value to kWh of energy delivered to load nodes of higher priority rank pr_l on a scale of 0-1, with 1 being the highest priority. Priority values must be provided to GATA; these may come from an established index such as for voltage stability, as proposed for utility company load shedding procedures [44], or RH planners could manually assign priority based on an independent assessment of how critical certain loads are to the community. The hyperparameters $\alpha \in [0, 1]$ and $\beta = 1 - \alpha$ reflect how important v_l and pr_l are to RH planners. For example, they may set $\alpha = \frac{1}{3}$ and $\beta = \frac{2}{3}$ if they value priority twice as much as vulnerability, or $\alpha = 1$ and $\beta = 0$ if they only care about vulnerability. This allows RH planners to focus as desired on pursuing either community- or individual-based justice. GATA evaluates the EWOMP of a backup power system as per (9) and

(10). The negative sign in (10) allows the sort in Section II-C4 to prefer lesser values for all criteria.

$$EWOMP_l = (\alpha v_l + \beta pr_l) \times \frac{\sum_{t=1}^d \log_{10}(\gamma \psi_{l,s}^t + 1)}{\sum_{t=1}^d \log_{10}(\gamma \mathcal{T}_l^t + 1)} \quad (9)$$

$$c_s^{EWOMP} = -\frac{1}{\|\mathcal{L}_{RH}\|_0} \times \sum_{l \in \mathcal{L}_{RH}} EWOMP_l \quad (10)$$

The EWOMP metric is dependent on multiple considerations, which include the priority of the loads, the vulnerability of the loads, and the amount of electric demand satisfied at each node. Out of these three considerations, the first two are determined when selecting which nodes to include in the load node set, which is an input to the GATA framework. The amount of electric demand satisfied at each node is a function of the backup power system selected, which is done within the GATA framework. The impact of this is that the range of possible values for EWOMP is determined by the load node selection, with the bounds being the EWOMP of supplying none of the loads in the load node set, and fully supplying the loads in the load node set. And the value of EWOMP within that range will differ for each backup power system evaluated.

CNSP and EWOMP provide multiple dimensions of assessing the ability of a distribution grid section to respond to power outages, which may be useful to grids with different capabilities. CNSP can be a useful metric to evaluate grids that do not have demand response capabilities, since it assesses the sum total of hours for which demand is insufficient. On the other hand, EWOMP will be useful for assessing the extent to which grids should exercise any demand response capabilities they have, and what the equity implications of this action will be.

4) *Identifying Non-Dominated Backup Power Systems:* When all backup power systems are evaluated over the MCDA criteria, GATA identifies $s_{ND} \in \mathcal{S}_{ND}$, the systems that are non-dominated ($s_{ND} \prec s_{dom}$) across all criteria as per (11), and performs a trade-off analysis. The set of non-dominated systems is found by performing an epsilon-nondominated sort as seen in [45]. The epsilon-nondominated sort filters out dominated systems s_{dom} if some dominating system s_{ND} has a vector of criteria performance c which is elementwise less than or equal to the criteria performance of s_{dom} , and the two are not approximately equal along all criteria $C_s = [c_s^{econ}, c_s^{pol}, c_s^{CNSP}, c_s^{EWOMP}]$.

$$s_{ND} \prec s_{dom} \text{ if } \{c_{s_{ND}}^k - \varepsilon_k \leq c_{s_{dom}}^k, c^k \in C\} \text{ and } |C_{s_{dom}} - C_{s_{ND}}| > \varepsilon \quad (11)$$

The value of epsilon ε can be set arbitrarily small, in order for this formula to return a close approximation of the true non-dominated set. This non-dominated set $\mathcal{S}_{ND}$ has the property that no single system outperforms others in the set along all criteria simultaneously as per (12).

$$s_1 \not\prec s_2 \forall s_1, s_2 \in \mathcal{S}_{ND}, s_1 \neq s_2 \quad (12)$$

5) *Selecting a Backup Power System From the Non-Dominated Set:* The final output of GATA is the set of non-dominated backup power systems, from which the user should assess tradeoffs and select the best backup power system for

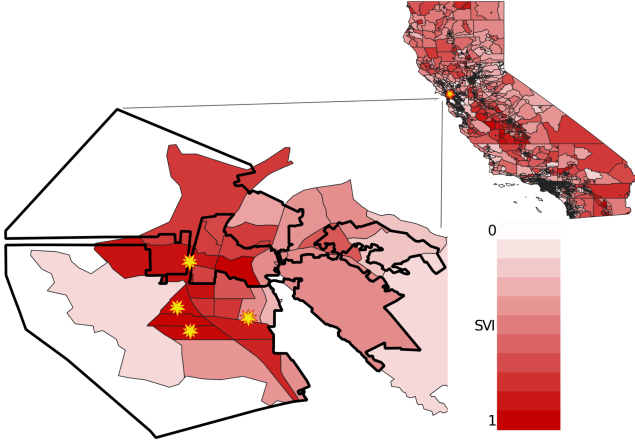


Fig. 2. Map of Richmond, California colored by Social Vulnerability Index (SVI) (light red is less vulnerable, deep red is more vulnerable). The city borders are outlined, and the four planned Resilience Hub locations are starred.

their needs. If the user knows the relative weights w_x that they place on each of the criteria c_s^k calculated for each backup power system, the weighted sum method [46] allows them to calculate a single metric to compare all backup power systems by following the formula in (13). We demonstrate the weighted sum method in the final steps of our case study in Section III to show what the end-to-end use of the GATA framework would look like if the RH planners had certain example weights for the criteria.

$$u(s) = \sum_k w_k \times c_s^k \quad (13)$$

III. CASE STUDY: RICHMOND, CA

In this case study, we apply the GATA framework to a mock-up of ongoing RH implementation in the city of Richmond, CA, as shown in Fig. 2. Richmond has historically faced electricity outages in wildfire season, both when the California utility Pacific Gas & Electric (PG&E) covering Richmond implements Public Safety Shut Offs of transmission lines to prevent wildfires, and when PG&E regions face extreme weather which damages electrical equipment. Richmond is actively putting together 4 RHs [47]. This is a town with areas of high SVI ratings, which corresponds to high levels of vulnerability for the population in those areas. We will evaluate the outage mitigation potential of proposed RH locations on an approximate representation of Richmond's grid, and the best backup power systems for each. In the following sections we describe the inputs we provide for the three sections of the GATA framework.

A. Richmond Case Study Assumptions

In our case study we assume that, during an outage, the RH backup power system is the only power source in the distribution network island G_{RH} , because our TPF solver calculates a single timeseries $\mathcal{T}_P$ of required power output at a specific location on G_{RH} . We assume that other than adding a switch at the backup power system, islanding is done with distribution automation equipment that already exists on this distribution

network, similarly to other examples [48]. We further assume that the RH power system can operate outside of the outage duration according to PG&E's Community Microgrid Enablement Tariff [49], such that SOFCs do not encounter a ramp-up time when an outage begins. We limit our analysis of the operational impacts to the outage duration, although the evaluated equipment could also operate in non-outage situations. Our scenario is set in the year 2024, when we anticipate Richmond's RHs to be operational. We assume the RH planners to be employees of the City of Richmond interested in the operational, financial, environmental, and social goals outlined in [14].

B. Richmond Distribution Network Simulation Inputs

We model a subsection of the Richmond distribution network G using one of the Taxonomy Feeders developed by the Pacific Northwest National Laboratory [50]. These Taxonomy Feeders are representative of classes of distribution grid layouts found in the various regions and settings in the United States. We model the Richmond distribution network using the "R1-12.47-2" Taxonomy Feeder, which is meant to represent a "moderately populated suburban and lightly populated rural area" operating at 12.47 kV on the west coast of the U.S.

The distribution network load timeseries data $\mathcal{T}_G$ for our case study comes from the "Randomized Hourly Load Data for use with Taxonomy Distribution Feeders" dataset developed by the National Renewable Energy Laboratory [51], [52] for each load in many of the Taxonomy Feeders in [50]. The loads in this network average out to around 2% of the average electrical load in the city of Richmond, or around 700 homes, which is comparable to the load serviced by each of Richmond's 16 substations [53]. For our case study we set outage duration to 36 hours, based on the mean duration for weather-related transmission events from 2015-2019 in North America [1]. Our granularity for both load values and power output is hourly, and we use hourly power output and hourly energy output interchangeably in the analysis.

We study four RH locations, independently, to mirror the real-world RH deployment in Richmond. Each RH j has its own $\mathcal{P}$ power source and load nodes $\mathcal{L}_{RH}^j$. The Taxonomy Feeder with RH locations and $\mathcal{L}_{RH}$ sets is shown in Fig. 3.

C. Richmond RH Energy Technology Options Input

The four energy technology options o that we consider in this study are: solar panels, battery storage, solid-oxide fuel cells (SOFCs) powered by natural gas, and diesel generators. Natural gas-powered SOFCs can outperform conventional natural gas combustion generators in multiple settings [54], and can be further improved when provided with hydrogen as fuel. For the fuel-based technologies and storage, which benefit from prior collection of fuel or of prior charging to full capacity, we assume that they begin an outage fully prepared, as they would be if the RH were warned of the outage and recognized that the value of electricity during the outage will be much higher than any costs incurred in such preparations. For each backup power system s , we expect an aggregation of multiple units of these options, limited by the budget and other considerations as described in Section II-B. Our test case values for equipment details come

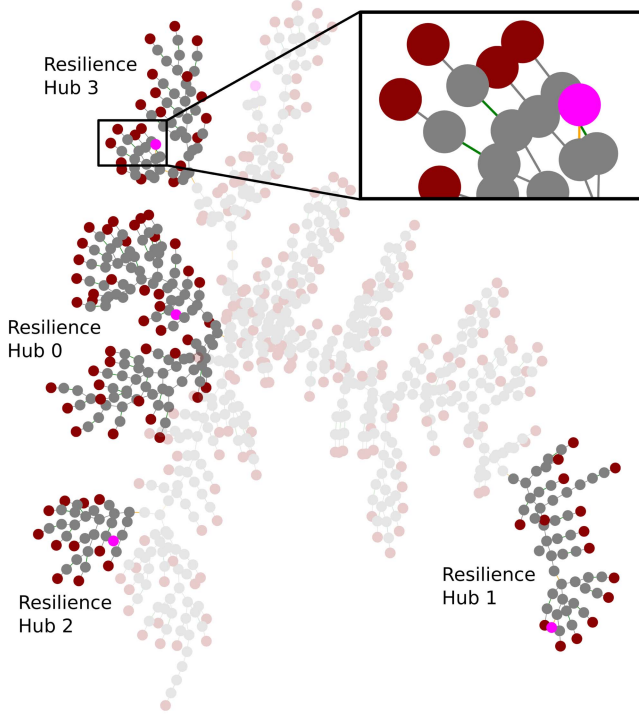


Fig. 3. R1-12.47-2 Taxonomy Feeder, highlighting the RH locations and $\mathcal{L}_{RH}$ load node sets for each RH. Nodes are the RH backup power systems, intermediate nodes power will flow through, and loads that require power. Links are transformers, switches, and transmission lines.

TABLE I
ENERGY TECHNOLOGY DETAILS

Tech	Nominal Output (kW)	Capacity (kWh)	Based On	Sources
Solar	3.8	-	Tesla Solar Panel	[35]
Battery	5	13.5	Tesla Powerwall	[35]
SOFC	10	-	Future SOFC unit	[36]–[38]
Diesel	10	-	Generic generator	[39]–[41]

Dashes indicate a parameter has no value for that energy technology option.

TABLE II
ENERGY TECHNOLOGY EMISSIONS FACTORS AND ECONOMIC COSTS

Tech	CO ₂ Intensity (lb / kWh)	PM ₁₀ Intensity (lb / kWh)	Fixed Cost (USD)	Variable Cost (USD / kWh)
Solar	0	0	12900	0
Battery	0	0	11500	0
SOFC	0.772	0	30000	0.06
Diesel	1.555	0.00007	3900	0.39

Costs are point estimates of uncertain values.

from median or representative industry values during RH development. Data on each technology option’s electrical generation profiles, fixed and variable costs, and pollution emission factors is shown in Tables I and II. We use projected SOFC costs from [37] since 10 kW units are not yet mass-produced. This projected cost is within expectations of previous SOFC cost analyses [55]. For other technologies, we choose costs based on historical trends. We highlight the direct onsite emissions generated due to concerns in local communities, while recognizing (but not considering) that emissions are associated with this equipment’s manufacturing and transportation. The upfront

TABLE III
CRITERIA WEIGHTS UNDER DIFFERENT WEIGHTING SCHEMES

Weighting	Economic	CO ₂	PM ₁₀	CNSP	EWOMP	Source
w_{eq}	0.2	0.2	0.2	0.2	0.2	[57]
w_{sh}	0.29	0.1	0.1	0.23	0.28	[58]
w_{ec}	0.38	0.13	0.1	0.197	0.196	[58], [59]

budget b considered is around \$500,000, which is twice the estimate of currently planned RH backup power systems [11]. In Section IV we allow some margin ($\pm 5\%$) in the value of b and select the minimal value that includes all technologies in the non-dominated set. The purpose of a higher value of b is to evaluate systems with increased investment requirements, but which provide more outage mitigation potential.

D. Richmond MCDA Values

The Social Vulnerability Index v , of the load nodes in G , are set to the measured SVI values of census tracts within Richmond borders. The priority rank of each load node pr_l is randomly assigned from a uniform distribution $[0,1]$ with replacement. The threshold for acceptable CNSP is set at 10%.

The weights that we use for the demonstration of the Weighted Sum method as described in Section II-C5 are selected to be within realistic bounds for RH planners, and to reflect the situation-specific conditions that may impact the decision making process. The weight sets are shown in Table III below. We begin with considering equal weights w_{eq} for each criteria. It is most common to assign equal weights to criteria when using MCDA to make decisions on sustainable energy [56], which has been defended in specific use cases as producing “results nearly as good as optimal weighting methods.” [57] We then construct a representative weight set w_{sh} based on an expert survey [58]. We then hand-select a set of weights w_{ec} as done by Santos et al. 2017 [59] to “observe if any change would occur on the scenario ranking” when assigning higher weights to criteria favoring non-preferred scenarios, which are Economic Cost and CO₂ Pollution.

IV. RESULTS

In the results, we use the GATA framework to investigate the inclusion of RHs in the city of Richmond for outage mitigation. Starting with 4 RH locations in the Richmond distribution network, GATA first determines the locations that can reliably provide outage mitigation to the neighborhood electrical loads. For electrically feasible options, GATA determines the best combinations of energy technologies to serve backup power. The results show how GATA can provide an equivalent comparison of RH backup power systems along multiple criteria. We further show how the RH planners can weigh different criteria to choose a RH energy technology set best suited to their needs.

A. GATA Step 1 - TPF Electrical Feasibility Check

We first investigate the electrical feasibility of each potential RH location j supplying backup power to potential load nodes $\mathcal{L}_{RH}^j$ which may have been pre-set to adhere to planning policy, city-wide decision making processes, or limits in deployed

TABLE IV
THREE PHASE POWER FLOW FEASIBILITY RESULTS PER RESILIENCE HUB AND LOAD NODE GROUP

Resilience Hub	Load Node Set	Status
RH0	40 Load Nodes	Success
RH1	15 Load Nodes	Voltage Deviation Failure
RH2	11 Load Nodes	Success
RH3	20 Load Nodes	Power Flow Convergence Failure

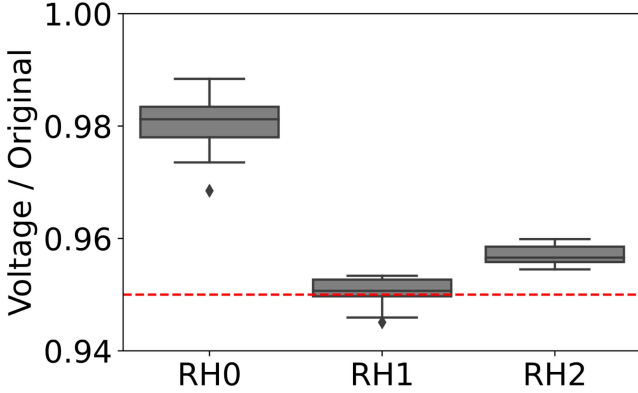


Fig. 4. Voltage deviation during outage mitigation for RH locations and $\mathcal{L}_{RH}$ load node sets which pass the power flow convergence test as part of the grid feasibility analysis.

distribution automation equipment. Table IV indicates how different RH locations perform in the electrical feasibility analysis for an outage.

The power flow solver fails to converge to a solution for RH3. It is deemed infeasible and excluded from further analysis. Fig. 4 shows the voltage deviation for the nodes powered by the remaining three RH locations. We see in Fig. 4 that voltages for $\mathcal{L}_{RH}^0$ and $\mathcal{L}_{RH}^2$ always remain within 5% of their non-outage voltages. However, the $\mathcal{L}_{RH}^1$ voltages violate those boundaries, so RH1 is deemed infeasible. With RH0 and RH2 both feasible, the MCDA can be applied to either location. As an example, we demonstrate determining the choice of backup power system technologies for RH0.

B. GATA Step 2 - MCDA Evaluation

We evaluate various backup power options $\mathcal{S}$ for RH0 during a spring outage at peak load times. All 202,222 economically viable backup power system options are first generated as per Section II-B2 and stored in $\mathcal{S}$, filtered down to 144,274 in $\mathcal{S}_f$ based on CNSP as per Section II-B3, and then to 6 in $\mathcal{S}_{ND}$ based on the epsilon-nondominated sort as per Section II-C. These results are for a budget $b = \$510,000$, which is the tipping point at which solar is included in the non-dominated set. This sensitivity is because to supply $\mathcal{L}_{RH0}$ with budget b requires technologies with low costs, and the cost of solar is high per kW of nominal output. In fact, it is noteworthy that 40 load nodes can be powered during an outage with a budget of \$510,000, only around double of the \$250,000 intended as per [11] for the 1 load node of the RH alone. Fig. 5 shows how the six non-dominated systems perform against each other.

Notably, SOFCs feature heavily in all six non-dominated backup power systems, indicating that an SOFC system with

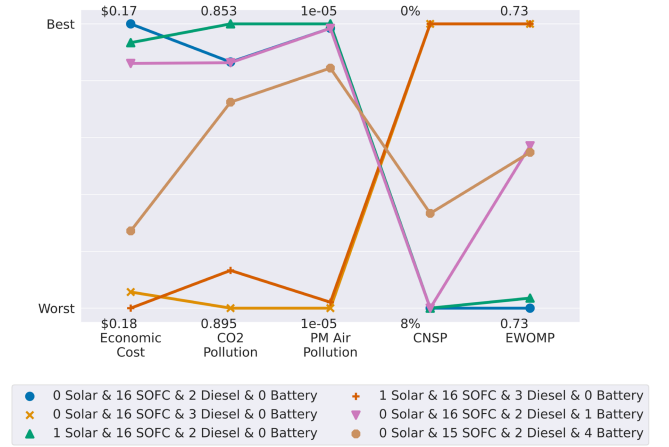


Fig. 5. Non-dominated backup power systems $\mathcal{S}_{ND}$ which can provide outage mitigation during an outage covering the spring peak load for $\mathcal{L}_{RH}^0$ of RH0.

specifications as defined in Tables I and II could be highly desirable for RH backup power. However, the non-dominated options all include at least two separate technologies. Since spending the entire upfront budget b on 17 SOFCs would have been under budget but is not non-dominated, these results indicate that there are benefits of a hybrid energy system. The lowest-capacity systems in Fig. 5 (blue circle and green triangle) perform very well along cost and pollution criteria, but are the worst at CNSP and EWOMP because they have insufficient supply for the most outage hours of the six systems. Two non-dominated systems (blue circle and orange x) have increased production cost but reduced CO2 intensity when they add a single unit of solar (as shown by green triangle and red cross). Adding storage is less expensive than adding diesel despite the higher upfront cost, due to the lower subsequent fuel costs. One option even has a reduction in SOFC to afford significant amounts of battery storage. Systems all have diesel supplementing the SOFC, and adding additional diesel brings improved CNSP and EWOMP by reducing the hours of insufficient power supply, at economic and environmental cost. The performance along PM air pollution and EWOMP metrics do not vary much across non-dominated options; each option has roughly the same amount of diesel generation, and also roughly the same amount of kWh delivered to consumers during the outage.

C. Exploring GATA Output - Trade Offs in Performance

Fig. 6 shows the 6 non-dominated systems for RH0 in spring-time, along EWOMP and Economic Cost performance. Each subplot shades the point corresponding to a system according to its weighted score when EWOMP performance is given a preference between 0 and 1, and the remaining preference is for economic cost performance. Each arrow points from the worst-ranked to the best-ranked system under that set of preference weights. What the figure shows is that the tradeoff between EWOMP and Economic Cost when going from “best” to “worst” changes depending on the preferences, because that changes which systems are considered “best” or “worst” by the decisionmaker. The progression of the arrows as EWOMP

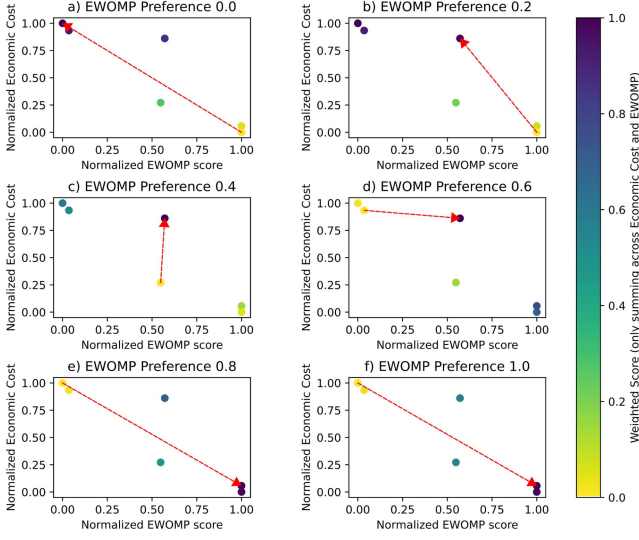


Fig. 6. Systems in $\mathcal{S}_{ND}$ along EWOMP (x-axis) and Economic Cost (y-axis) performance, both normalized across $\mathcal{S}_{ND}$. Each subplot (a)–(f) shades the point corresponding to a system according to its weighted score when EWOMP performance is given a preference between 0 and 1, and the remaining preference is for economic cost performance. Each arrow points from the worst-ranked to the best-ranked system under that set of preference weights.

preference increases, from pointing to the top left to pointing to the bottom right, indicates the trend in how much cost for equity the stakeholders are willing to incur. When preferences are at the extremes, it's acceptable to trade off more of each criteria to achieve better performance in the other. We see this in the fact that the slopes of the best-worst arrow for the subplots (a) and (f) are almost identical, albeit with the arrows going in opposite directions, which shows the largest change along both criteria out of these graphs, and the switch in which one is more highly desired. When preferences are about equal for the two criteria, between (c) and (d), the difference between the “best” and “worst” system changes dramatically. In each of these, the “best” system improves on the “worst” by one criteria substantially, but only a small change in the other criteria.

Fig. 7 shows the ranking of the non-dominated backup power systems (Fig. 5), under the varying economic and EWOMP preference weights (Fig. 6). What we see is that under a wide range of values, we see a few switchover points. A system comprised of 16 SOFCs and 2 diesel units (blue circle) is ranked first for weights less than 0.2, a system with an additional battery (pink triangle) is ranked first for weights between 0.2 and 0.6, and a system instead with an additional diesel unit (orange x) is ranked first for weights greater than 0.6. This indicates the existence of tipping points in this decision making problem, where a continuous change in priorities results in a discontinuous change in what is the most attractive option. We see similar switchover points in which system is ranked second or third, although they are much more frequent.

D. Using GATA Output - Example of Weighted Sum Method

Building on this, we test how a RH could provide outage mitigation multiple times yearly. Fig. 8 shows how non-dominated

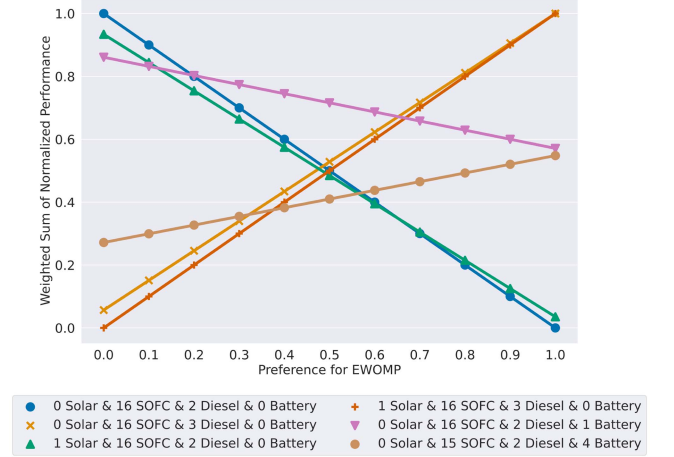


Fig. 7. Weighted sum of normalized scores of systems in $\mathcal{S}_{ND}$, under the varying economic and EWOMP preference weights (Fig. 6) where preference for EWOMP increases from 0 to 1.

systems perform across different outage scenarios, using the weighted sum method with three sets of weights in (a)–(c) of w_{eq} , w_{sh} , and w_{ec} as described in Table III to calculate a comprehensive score for each scenario. Fig. 8 depicts the six non-dominated systems at RH0 selected for a spring peak load outage, and evaluated at peak load outages for each season of the year. The selection of weights changes which of the RH0 options is considered to perform best throughout the year. According to the weights from Shaaban et al. 2018, supplementing SOFC and diesel with battery storage (the pink triangle) is the best choice across all non-dominated systems. However, using the other two weight sets, supplementing with solar instead (the green triangle) is a better choice than it in the spring and summer. This could be attributed to the longer daylight hours and therefore higher potential production of a unit of solar in those seasons. Additionally, w_{eq} values the system with minimal SOFC and diesel (the blue circle) as best in the spring and summer, which is not seen with either of the other weight sets. Fig. 8 indicates that stakeholder preferences must play a key role when deciding on a RH, load node set, and backup power system, since criteria weights can dramatically change what the best system is. Subplot (d) focuses on the most competitive technologies across seasons, and illustrates how the selection of weight set changes what is most desirable for any particular season.

The seasonal features that drive our results are the generation of electricity by backup power systems such as solar PV, and the amount of electric load demanded by load nodes in the network. Both of these are in turn dictated by seasonal shifts in e.g. sunlit hours, and weather conditions such as temperature and precipitation. These changes can be observed in the timeseries of electricity generation for a solar PV plant we obtain from PVWatts, and the timeseries of electric loads.

E. Extension - Estimating Non-Outage Operations

The focus of this paper is on outage mitigation. A fruitful direction for future work would be to investigate how the RH

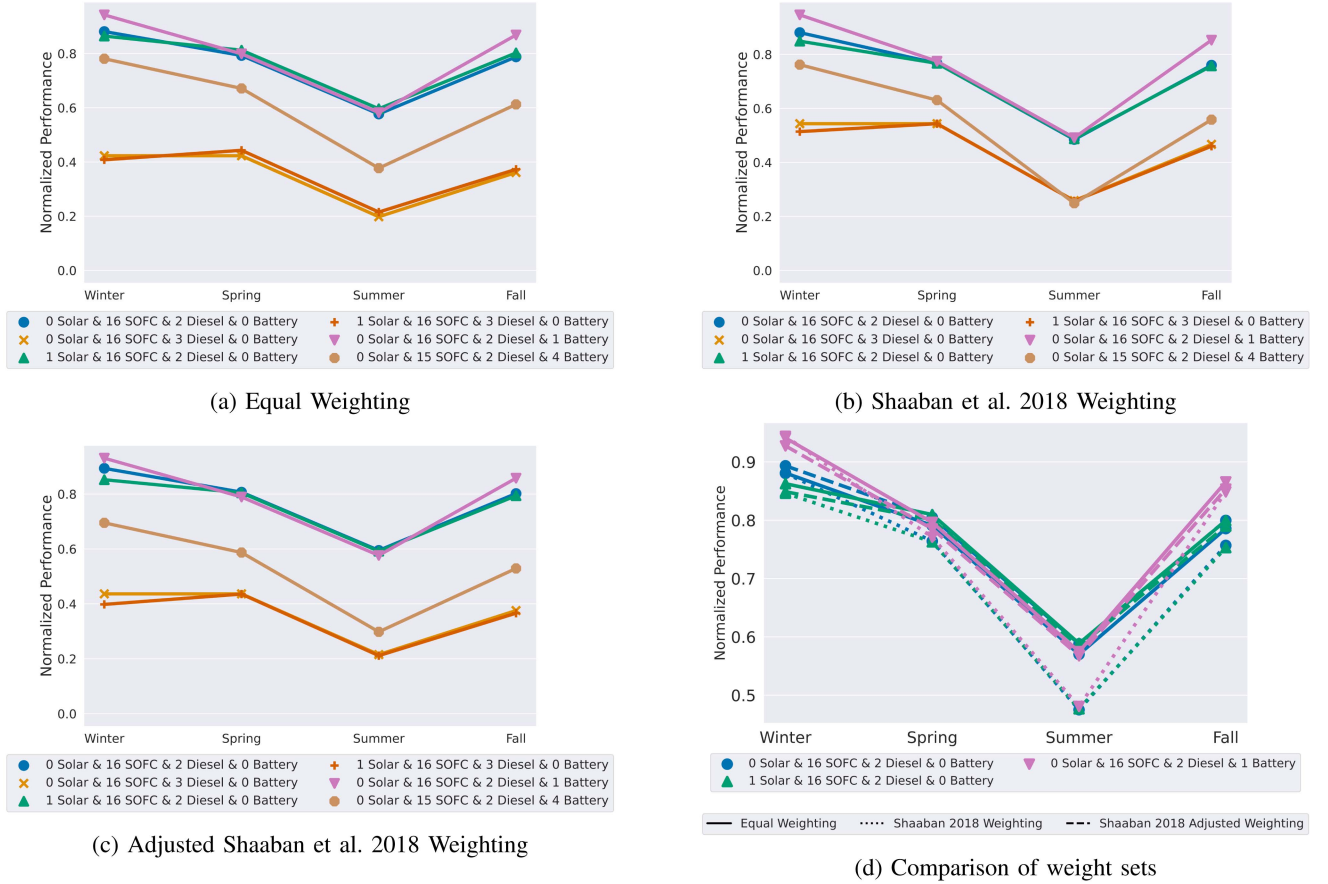


Fig. 8. Performance for systems in S_{ND} , measured across seasonal max peak load periods when (a) criteria are equally weighed, when (b) a realistic weight set is used, and (c) when that realistic weight set is perturbed to alter the importance of criteria. (d) shows a comparison of the three best options across weight sets (a)–(c).

systems would be used in non-outage operation. This could be accomplished by extending the GATA framework to incorporate this, perhaps as additional metrics. While we do not conduct a full analysis of this here, we can approximate the long-term impacts of a backup power system by determining its estimated usage to provide grid services in non-outage times. With Richmond, CA falling under Pacific Gas & Electric's Net Billing Tariff beginning in 2023, after which excess electricity can be sold back to the utility at prices determined by the Avoided Cost Calculator [60], we estimate that operating a natural-gas-powered SOFC system would be economical for around 165 hours in 2024, while operating a diesel system to sell electricity to the market would not break even at any hour in the year. In this scenario, a 16-SOFC-unit system for RH0 could bring in revenue of around \$2,000 over those 165 hours, with an associated production cost of around \$1,500. The environmental impact of this operation would be around 20,300 lbs of CO₂ being emitted. This is one possible outcome, and Table V below shows more scenarios for 2024 when SOFC operating expenses are assumed to vary. These calculations do not incorporate the ramping requirements of the technology or other considerations. Incorporating non-outage operations would require a more detailed analysis of backup power system operations in non-outage times over the equipment lifetime.

TABLE V
2024 NON-OUTAGE OPERATION ESTIMATES FOR RH0 16-SOFC-UNIT SYSTEM, USING EXAMPLE HOURS AND REVENUE BASED ON PG&E ACC

Operating Expenses	Hours	Revenue	Cost	Profit	CO ₂ (lbs)
0.05 \$/kWh	508	\$4,900	\$4,000	\$900	62,700
0.0583 \$/kWh	165	\$2,000	\$1,500	\$500	20,300
0.07 \$/kWh	78	\$1,200	\$900	\$300	9,600

We perform similar estimates for solar PV, and for battery storage. We assume that the solar PV system is operating for all 8760 hours of the year, with no curtailed energy. This simplified calculation does not account for the different behavior during the 36-hour outage duration. For a single solar PV unit, this results in generating 7.5 mWh over 4293 hours, and bringing in revenue of \$223. For simplicity we assume that the battery storage is performing arbitrage with limited foresight, where it knows the average annual price ahead of time, and therefore charges when prices are below average and discharges when prices are above average. This arbitrage is limited by the maximum charging rate, and the maximum capacity of the battery. For a single battery storage unit, this results in charging and discharging a total of 14.7mWh each direction over 2224 hours, and bringing in revenue of \$56. So we find that there is justification for allowing

year-round operations, particularly when assuming no variable costs of operating these technologies unlike for SOFCs.

V. CONCLUSION

As cities and distribution grid operators combat worsening electrical outages, the need arises for better methods of evaluating outage mitigation possibilities such as Resilience Hubs (RHs) with backup power systems. In this paper we present the Grid-Aware Tradeoff Analysis (GATA) framework which integrates Three-Phase Power Flow (TPF) and Multi-Criteria Decision Analysis (MCDA) to determine the feasibility of any particular RH powering a microgrid for outage mitigation, and to ascertain the tradeoffs between the different backup power system options. We exercise the GATA framework on a case study based on the city of Richmond, California, which is in need of outage mitigation and currently putting multiple RHs in place.

GATA identifies the feasible configurations for RH-based outage mitigation in this case study, as well as which particular backup power systems may be considered most suitable depending on the priorities of the stakeholders in Richmond. Our research demonstrates the benefits of detailed distribution grid simulation in evaluating outage mitigation potential. Our results point to SOFCs as playing a large role in future backup power systems, contingent on their exact specifications once SOFCs are more widely commercialized. Finally, our tradeoff analysis indicates that the relative importance of criteria, including equitable outage mitigation as represented by our EWOMP metric, is a key factor when evaluating backup power systems.

The trade-offs between maximizing reliability and cost to the environment are inherent in any resilience hub discussion regardless of where the community is located. This stems from dispatchable technologies used currently in microgrids largely being fossil fuel based. Looking at the equity and justice implications of the application of the GATA framework to Resilience Hub development, we find that a holistic design process for RH backup power directly enables action towards achieving distributional justice in backup power. Since the expanded concept of RHs in this paper are designed to provide backup power to communities already identified as vulnerable by RH planners, this serves to correct the imbalance of backup power availability between groups of different socioeconomic status.

Overall, we demonstrate that GATA could serve as a valuable tool for decision-makers to evaluate RHs, and similar projects which would benefit from GATA's sophisticated power systems analysis paired with holistic evaluation.

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Arnav Gautam (Graduate Student Member, IEEE) received the B.S. in electrical engineering and computer science and the B.A. degree in cognitive science from the University of California, Berkeley, Berkeley, CA, USA. He is currently working toward the Ph.D. degree from the Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, PA, USA. He is also a NSF Graduate Research Fellow with the Department of Engineering and Public Policy, Carnegie Mellon University. He was a Software Engineer with Clean Power Research, and has applied

a variety of computational and analytical tools to address questions in climate change and renewable energy. He is working on the optimization and simulation of microgrids with distributed energy resources, to facilitate natural disaster recoveries. His research interests include equitable decarbonization, infrastructure resilience to climate threats, and improving renewable energy adoption across the globe. He is a student Fellow for the Macro Energy Systems Organization, and a volunteer for the IEEE Power and Energy Society Task Force on Equity and Energy Justice in Power Systems.



Destenie Nock received the two B.S. degrees in electrical engineering and applied mathematics from North Carolina A&T State University, Greensboro, NC, USA, the M.Sc. degree in leadership for sustainable development from the Queen's University of Belfast, Belfast, U.K., and the Ph.D. degree in industrial engineering and operations research from the University of Massachusetts Amherst, Amherst, MA, USA. She is currently an Assistant Professor of civil and environmental engineering, and engineering and public policy. She creates optimization and decision analysis tools which evaluate the sustainability, equity, and reliability of power systems in the US and Sub-Saharan Africa. She has pioneered the development of algorithms to identify energy limiting behavior in households and other hidden forms of energy poverty, which is vital to achieving energy justice. Dr. Nock was the recipient of six NSF grants on energy, resilience, and energy justice. Dr. Nock was an NSF Graduate Research Fellow and an Offshore Wind Energy IGERT Fellow with the University of Massachusetts Amherst.



Amritanshu Pandey (Senior Member, IEEE) is currently an Assistant Professor with the Electrical and Computer Engineering Program, University of Vermont, Burlington, VT, USA with a courtesy appointment in the Electric and Computer Engineering and Engineering and Public Policy Departments, Carnegie Mellon University, Pittsburgh, PA, USA. His overarching research goal is to develop electric energy system technologies to help combat climate change while modernizing the underlying system. In particular, he focuses on developing computational methods that address problems in the space of large-scale grid simulation and optimization, grid cybersecurity, and energy inequity. In the past, he worked on a novel circuit-theoretic simulation and optimization framework for power grids, culminating in a grid analytics tool: Simulation of Unified Grid Analysis and Renewables. He was the recipient of several best paper awards, including two best-of-the-best paper awards at the IEEE PES General Meeting in 2017 and 2021. He actively advises Pearl Street Technology, Inc. (PST) and was with MPR Associates, Inc. and PST.