Looking Beyond Bill Savings to Equity in Renewable Energy Microgrid Deployment

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Abstract

Microgrids powered by renewable energy can provide backup power to critical infrastructure during grid outages. These systems can also play an important role in advancing energy justice by providing economic, environmental, health, and resilience benefits for underserved communities. The value of microgrids is often measured by the economic savings and resilience provided, but there are other energy justice factors that should be considered. This paper describes a methodology for quantifying broader costs and benefits including utility bill savings, value of resilience, social cost of carbon, public health costs, and jobs associated with the construction and operation of microgrids. We evaluate these factors at three case study sites and find that including energy justice values in the cost-benefit analysis of microgrids can change investment decisions. When climate, health, resilience, and job creation are considered, cost-optimal microgrids include more renewable generation, leading to a 52-82% reduction in emissions and diesel fuel use. The net present values of the microgrids grow from negative $626,000-843,000 in the diesel only case to $10-16 million in the hybrid microgrid case and $12-19 million in the renewable microgrid case, indicating potential for greater microgrid deployment if energy justice values are incorporated in decision making. However, we also see large increases in capital expenses, which could limit deployment unless accompanied by innovative financing measures. These findings may be useful to communities as they seek to strengthen resilience to natural disasters while also improving public health, meeting climate goals, and providing economic opportunity for residents.

Keywords *— Microgrid, resilience, equity, energy justice, environmental justice, energy decision-making*

1. Introduction

Renewable energy-powered microgrids are increasingly being used to provide backup power to critical infrastructure during grid outages [1]. While diesel generators are a common emergency power source, generator limitations including low reliability, high emissions, and dependence on fuel re-supply are prompting facility managers to seek alternatives such as hybrid microgrids that include a renewable source of power and storage [2]. Reliable backup power is particularly important as large outages, caused by climate-related events, are occuring more frequently [3]. Typically, microgrid investments are assessed based on cost and ability to power critical loads during outages [4]. However, these systems can also provide increased energy autonomy, promote cleaner electricity sources, and help retain economic benefits in the community [5]. They may also play an important role in advancing energy justice by providing economic, environmental, health, and resilience benefits for underserved communities [6].

The literature does not yet offer a single definition of energy justice within the context of the clean energy transition. However, three components of energy justice are commonly discussed [7] [8]. Recognition

justice addresses which segments of the population are ignored or underrepresented, acknowledging that energy infrastructure decisions are often made without including those being affected [9]. Procedural justice considers how various communities are engaged and how engagement with each stakeholder is weighted or prioritized. This type of justice calls for equitable processes that engage affected stakeholder in non-discriminatory ways. Distributional justice refers to the allocation of the costs and benefits of energy investments and considers whether the decisions being made disproportionately affect historically marginalized communities [10]. This aspect of energy justice concerns the siting of energy infrastructure and access to energy services [11] [12]. Our work focuses on distributional justice and attempts to quantify the benefits and costs of a particular type of energy infrastructure, namely microgrids. We seek to augment a techno-economic design model to consider the broader costs and potential benefits of increased system resilience, a social cost of carbon, public health costs, and jobs associated with the construction and operation of microgrids. By quantifying and explicitly considering these factors, we develop a methodology that considers distributional justice concepts that can inform microgrid investments and the operation of these distributed energy resources.

Techno-economic models are commonly used to evaluate the costs and benefits of microgrids to support design and financing decisions. These tools can help decision makers understand technical and economic feasibility as well as sustainability benefits of potential systems. Many microgrid tools optimize systems to sustain the critical load at lowest lifecycle cost of energy. For example, the REopt model identifies the microgrid system design and dispatch strategy that minimizes lifecycle cost of energy to the site, considering both the capital costs of microgrid technologies as well as the cost savings they can provide by reducing utility bills [13]. Similarly, the Distributed Energy Resources- Customer Adoption Model (DER-CAM) finds optimal distributed energy resource investments for microgrids while co-optimizing multiple stacked value streams including load shifting, peak shaving, power export agreements, and ancillary service markets [14]. The HOMER microgrid design software uses analytical methods to simulate all possible combinations of user-specified technology types and sizes, and sorts them according to the optimization variable of choice, including cost metrics such as lifecycle cost or levelized cost of energy [15].

These tools inform investment decisions, but often omit enegy justice considerations. Sovacool et al. [7] explore how justice concepts can inform energy decision-making and assist energy planners and consumers in making more informed energy choices. This requires understanding how justice costs and benefits might be measured, and how externalities might be considered in the techno-economic anlaysis. When microgrid system designs are optimized to minimize lifecycle cost of energy, they consider only the costs of generation assets and potential economic savings or loses; they do not include the potential value of resilience, emissions reductions, or job creation.

Other models measure community energy justice indices such as pollution burden and vulnerability to the effects of pollution, with the goal of identifying communities most in need of investment. Tools including the Environmental Justice Screening and Mapping Tool (EJSCREEN) [16] and CalEnviroScreen [17] are used to identify communities at higher risk. They incorporate environmental indicators such as air pollution and proximity to hazardous waste as well as demographic indicators such as income, race, education, linguistic isolation and age. These models can be used to identify and target investments in disadvantaged communities [18].

While we have tools for evaluating the technical and economic feasibility of specific microgrid projects, and tools for identifying communities in which to target investment for energy justice, a gap remains in combining these two. To fully consider energy justice in project decision making, we need to identify and quantify energy justice values and incorporate them into economic modeling and investment decision making. Some initial work has been done in this area. For example, Nock et al. [19] explore how capacity

expansion models can be adapted to maximize social benefit, rather than to minimize cost, in electricity planning. Laws et al. [20] and Anderson et al. [21] develop methods to include the value of resilience in solar and storage system sizing. Farthing [22] adds social cost of carbon and avoided public health costs as additional values for renewable energy only microgrids.

This research builds on prior work by proposing a methodology for expanding microgrid cost-benefit analysis to include five energy justice values: 1) bill savings, 2) social cost of carbon, 3) avoided public health costs, 4) avoided outage costs, and 5) job creation. The following section outlines a methodology for quantifying these values and including them in the objective function and lifecycle cost calculations of an existing microgrid design optimization model. We then adapt the REopt model and demonstrate the method on three case study sites to show how investment decisions may change when environmental justice factors are included in microgrid cost-benefit analysis.

2. Methods

This work adapts the REopt software to consider lifecycle cost of energy, value of resilience, social cost of carbon, public health costs, and the economic output from job creation in the model. REopt is a mixed-integer program that evaluates the economic viability of grid-connected solar PV, energy storage, wind turbines, combined heat and power, and geothermal heat pumps for a building or campus. The model minimizes discounted cashflow associated with cost and savings over the analysis period (typically 25 years) while adhering to constraints on fuel use, system operations, system capacities, and load balancing. The model recommends an optimally sized mix of renewable energy, conventional generation, and storage technologies while simultaneously optimizing the corresponding operating strategy. By comparing the optimized case to the "business-as-usual" case, where there is no microgrid, we estimate the net present value of potential savings. Figure 1 shows the model inputs and outputs.

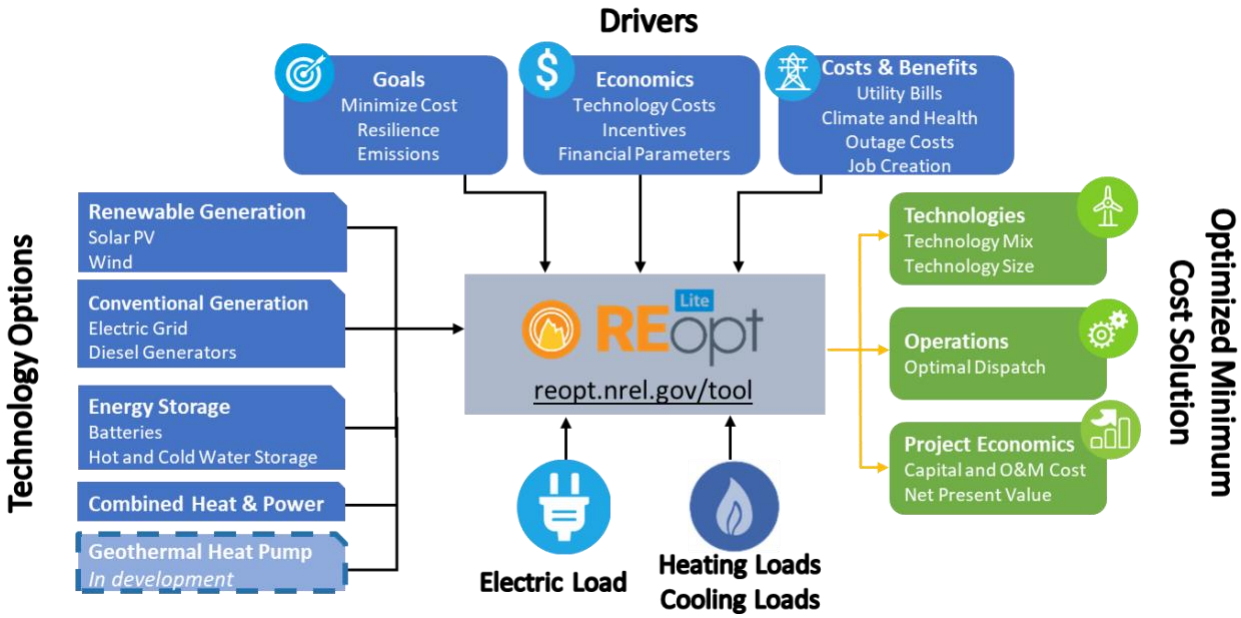


Figure 1: REopt model, with inputs shown in blue and outputs in green

2.1 Modeling Energy Justice Values

The current REopt model objective function minimizes lifecycle cost of energy, including technology capital costs, operations and maintenance costs, and utility costs. We modify the objective of REopt as shown in Ogunmodede et al. [23] to add two costs to the objective: a) social cost of carbon; and b) public health costs; additionally, we calculate the impact of c) value of resilience; and d) job creation on lifecycle cost of energy. Each of these is explained in more detail below.

Energy costs: We quantify energy cost savings by calculating reductions in grid-purchased electricity resulting from the distributed generation technologies in the microgrid. We use the existing methodology in REopt Lite which calculates the lifecycle cost of energy as the sum of the present value of technology capital costs, operation and maintenance costs, fuel charges, and utility costs, less incentives [23].

Value of Resilience: During power outages, individuals, businesses, and communities experience an array of losses that may include business interruption, lost productivity, lost data, damage to machinery, damage or spoilage of perishable stock such as food or manufacturing materials, and even loss of life [24]. These damages can be quantified using the "value of lost load," expressed as dollars lost per kilowatt-hours of energy unserved. Installing a microgrid avoids some or all of these costs. We quantify the avoided outage costs by multiplying the total load served by the microgrid during grid outage hours by the value of lost load ($/kWh), as described in [21].

Social Cost of Carbon: We quantify the climate benefits of the microgrid based on reduced CO_2 emissions from grid-purchased electricity and on-site diesel consumption resulting from the renewable energy generation technologies that power the microgrid. We value these reduced social damages caused by CO_2 emissions using the social cost of carbon from the U.S. Environmental Protection Agency (EPA) [25]. We adapt the method described in Fathing [22] by including climate impacts of on-site fuel consumption, using a present worth factor and escalating the social cost of carbon over time at the rate estimated by the U.S. EPA [25]. As described in Anderson et al. [26], we use EPA data for the diesel CO_2 emissions factor and the EPA's AVoided Emissions and geneRation Tool (AVERT) to generate hourly regional marginal emissions factors for grid-purchased electricity [27]. We choose the marginal rather than average emissions factors because these better represent impacts of distributed energy projects [28]. Grid marginal emissions factors are assumed to remain constant throughout a project's financial lifetime.

Public Health Costs: We quantify the health benefits of the microgrid based on reduced emissions from grid-purchased electricity and on-site diesel consumption resulting from renewable energy generation. We adapt the method described in Farthing [22] by including health impacts of on-site fuel consumption, using a present worth factor and escalating the marginal health costs over time at the same rate as the social cost of carbon (see the Appendix for more details). We estimate the hourly costs (or damages) of sulfur dioxide (SO_2), nitrous oxides (NO_x), and fine particulate matter (PM2.5) as the product of each pollutant's marginal emissions rate, marginal damage cost, and net load. We use the EPA's AVERT to generate hourly regional marginal emissions factors for grid-purchased electricity [27]. We calculate emissions rates for diesel fuel consumption by averaging emissions rates for commerical diesel fuelburn from the EPA's WebFIRE database [29]. We use marginal health damage costs for grid emissions from Estimating Air pollution Social Impact Using Regression (EASIUR) [30], using the methods described in Farthing [22]. For on-site diesel consumption, emissions are assumed to be released from ground-level at the site location.

Job Creation: We quantify the economic impact of jobs created from the construction and operation of the microgrid using the Jobs & Economic Development Impact Models (JEDI) [31]. JEDI estimates the economic impacts associated with the construction and operation of distributed generation power plants. JEDI represents the entire economy, including cross-industry or cross-company impacts. For example, JEDI estimates the impact that the installation of a distributed generation facility would have not only on

the manufacturers of PV modules and inverters, but also on the associated construction materials, metal fabrication industry, project management support, transportation, and other industries that are required to enable the procurement and installation of the complete system. JEDI does not predict or incorporate displacement of related economic activity or alternative jobs due to the implementation of the proposed project. As such, the JEDI results are considered gross estimates as opposed to net estimates. This study uses capital payments and operations and maintainence (O&M) payments to estimate job-related economic output resulting from building and operating microgrids. In JEDI, "output" is a measure of overall economic activity. At the business level, this can be thought of as revenue. It is not a measure of profitability, but it does show the scale of dollars moving within an economy. We incorporate this output value into the microgrid life cycle cost and net present value calculations.

2.2 Mathematical formulation

The objective of the REopt model is to minimize the life cycle cost of energy, from the perspective of the microgrid owner. The model finds the optimal technology sizes and optimal dispatch strategy to minimize the life cycle cost of energy subject to design, operating, and policy constraints. For microgrid analysis, these include constraints requiring that the load can be met without the utility grid during the grid outage period. For brevity, we do not detail the entire formulation in this document. For the full formulation, refer to Ogunmodede et al. [23]. Rather, we describe the objective function and the additions to model energy justice values. The notation we employ for the math that follows in this document, which we summarize in Table 1, uses lowercase or Greek letters for parameters and capital letters for decision variables; superscripts denote descriptors, while subscripts denote indices on sets.

Table 1. Notation supporting the mathematical formulation of REopt

Sets		
$b \in B$	Storage systems	
$d \in D$	Time-of-use demand periods	
$e \in E$	Electrical time-of-use demand tiers	
$f \in F$	Fuel types	
$h \in H$	Time steps	
$m \in M$	Months of the year	
$n \in N$	Monthly peak demand tiers	
$t \in T$	Technologies	
$p \in P$	Health-related pollutants (NO_x, SO_2, PM2.5)	
Subsets and indexed sets		
$H^g \in H$	Time steps in which grid purchasing is available	
$K^c \in K$	Capital cost subdivisions	
$S_{tk} \in S$	Power rating segments from subdivision k applied to technology t	
$T_f \in T$	Technologies that burn fuel type f	
$T^f \in T$	Fuel-burning, electricity-producing technologies	
$U^p \in U$	Electrical energy purchase pricing tiers	
$U_t^s \in U$	Electrical energy sales pricing tiers accessible by technology t	
$U^{sb} \in U$	Electrical energy sales pricing tiers accessible by storage	
Parameters		**[units]**
Δ	Time step scaling	[h]
c^{afc}	Utility annual fixed charge	[$]
c_{ts}^{cb}	y-intercept of capital cost curve for technology t in segment s	[$]
c_{ts}^{cm}	Slope of capital cost curve for technology t in segment s	[$/kW]
c_{uh}^{e}	Export rate for energy in energy demand tier u in time step h	[$/kW]
c_{uh}^{g}	Grid energy cost in energy demand tier u in time step h	[$/kW]
c_b^{kW}	Capital cost of power capacity for storage system b	[$/kW]
c_b^{kWh}	Capital cost of energy capacity for storage system b	[$/kWh]
c_b^{omb}	Operation and maintenance cost of storage system b per unit of energy rating	[$/kWh]

c_t^{omp}	Operation and maintenance cost of technology t per unit of production	[$/kWh]
$c_t^{om\sigma}$	Operation and maintenance cost of technology t per unit of power rating	[$/kW]
c_{de}^{r}	Cost per unit peak demand in time-of-use demand period d and tier e	[$/kW]
c_{mn}^{rm}	Cost per unit peak demand in tier n during month m	[$/kW]
c_f^u	Unit cost of fuel type f	[$/MMBTU]
c^{CO2}	Marginal damage cost of CO_2 (social cost of CO_2)	[$/t CO_2]
c_p^g	Marginal damage cost of health-related pollutant *p* from grid-purchased electricity	[$/t]
c_p^o	Marginal damage cost of health-related pollutant *p* from on-site fuel burn	[$/t]
f_t^{pf}	Present worth factor for fuel for technology t	[unitless]
f^e	Energy present worth factor	[unitless]
f^{em}	Emissions present worth factor	[unitless]
f^{om}	Operations and maintenance present worth factor	[unitless]
f^{tot}	Tax rate factor for off-taker	[fraction]
f^{tow}	Tax rate factor for owner	[fraction]
u_t^{oCO2}	CO_2 emissions factor for on-site technology *t* (based on fuel type used)	[t CO_2 / kWh fuel]
u_h^{gCO2}	CO_2 marginal emissions factor for grid-purchased electricity in period *h*	[t CO_2 / kWh]
u_{tp}^o	Emissions factor for on-site technology t (based on fuel type used) and health-related pollutant *p*	[t CO_2 / kWh fuel]
u_{hp}^g	Marginal emissions factor for grid-purchased electricity in period *h* for health-related pollutant *p*	[t CO_2 / kWh]
Variables		
X_b^{bkW}	Power rating for storage system b	[kW]
X_b^{bkWh}	Energy rating for storage system b	[kWh]
X_{de}^{de}	Peak electrical power demand allocated to tier e and time-of-use demand period d	[kW]
X_{mn}^{dn}	Peak electrical power demand allocated to tier n during month m	[kW]
X_{th}^{f}	Fuel burned by technology t in time step h	[MMBTU/h]
X_{uh}^{g}	Power purchased from the grid for electrical load in demand tier u during time step h	[kW]
X^{mc}	Annual utility minimum charge adder	[$]
X_t^{pi}	Production incentive collected for technology t	[$]
X_{tuh}^{ptg}	Exports from production to the grid by technology t in demand tier u during time step h	[kW]
X_{th}^{rp}	Rated production of technology t during time step h	[kW]
X_t^{σ}	Power rating of technology t	[kW]
$X_{tks}^{\sigma s}$	Power rating of technology t allocated to subdivision k, segment s	[kW]
X_{uh}^{stg}	Exports from storage to the grid in demand tier u during time step h	[kW]
$Z_{tks}^{\sigma s}$	1 if technology t in subdivision k, segment s is chosen; 0 otherwise	[unitless]

The objective function of REopt seeks to minimize the net present value of the sum of (i) lifecycle costs for purchased assets, i.e., capital, fuel, and operations and maintenance costs, (ii) utility costs, and (iii) emissions costs including climate and public health impacts. The terms added for this work are the last two associated with climate and health, respectively:

$$\min_{\boldsymbol{X},\boldsymbol{Z}} \underbrace{\sum_{t\in T,k\in K^C,s\in S_{tk}} \left(c_{ts}^{cm}\cdot X_{tks}^{\sigma s} + c_{ts}^{cb}\cdot Z_{tks}^{\sigma s}\right)}_{\text{Generating Technology Capital Costs}} + \underbrace{\sum_{b\in B}\left(c_b^{kW}\cdot X_b^{bkW} + (c_b^{kWh}+c_b^{omb})\cdot X_b^{bkWh}\right)}_{\text{Storage Capital Costs}} +$$

$$(1-f^{tow})\cdot f^{om}\cdot\left(\underbrace{\sum_{t\in T} c_t^{om\sigma}\cdot X_t^{\sigma}}_{\text{Fixed O\&M Costs}} + \underbrace{\sum_{t\in T^f,h\in H} c_t^{omp}\cdot X_{th}^{rp}}_{\text{Variable O\&M Costs}}\right) + (1-f^{tot})\cdot\Delta\cdot\underbrace{\sum_{f\in F} c_f^u\cdot\sum_{t\in T_f,h\in H} f_t^{pf}\cdot X_{th}^{f}}_{\text{Fuel Charges}}$$

$$+$$

$$(1-f^{tot})\cdot f^{e}\cdot\Bigg(\underbrace{\Delta\cdot\sum_{u\in U^{p},h\in H^{g}}c^{g}_{uh}\cdot X^{g}_{uh}}_{\text{Grid Energy Charges}}+\underbrace{\sum_{d\in D,e\in E}c^{r}_{de}\cdot X^{de}_{de}}_{\text{Time-of-Use Demand Charges}}+\underbrace{\sum_{m\in M,n\in N}c^{rm}_{mn}\cdot X^{dn}_{mn}}_{\text{Monthly Demand Charges}}+$$

$$\underbrace{c^{afc}+X^{mc}}_{\text{Fixed Charges}}+\underbrace{\Delta\cdot\Bigg(\sum_{h\in H^{g}}\Bigg(\sum_{u\in U^{sb}}c^{e}_{uh}\cdot X^{stg}_{uh}+\sum_{t\in T,u\in U^{S}_{t}}c^{e}_{uh}\cdot X^{ptg}_{tuh}\Bigg)\Bigg)}_{\text{Energy Export Payments}}\Bigg)-(1-f^{tow})\cdot\underbrace{\sum_{t\in T}X^{pi}_{t}}_{\text{Production Incentives}}$$

$$+$$

$$f^{em}\cdot\Delta\cdot c^{CO2}\cdot\Bigg(\underbrace{\sum_{t\in T^{f},h\in H}u^{oCO2}_{t}\cdot X^{f}_{th}}_{\text{Fuel Burn Climate Emissions}}+\underbrace{\sum_{h\in H,u\in U}u^{gCO2}_{h}\cdot X^{g}_{uh}}_{\text{Grid Climate Emissions}}\Bigg)+$$

$$f^{em}\cdot\Delta\cdot\sum_{p\in P}\Bigg(c^{o}_{p}\cdot\underbrace{\sum_{t\in T^{f},h\in H}u^{o}_{tp}\cdot X^{f}_{th}}_{\text{Fuel Burn Health Emissions}}+c^{g}_{p}\cdot\underbrace{\sum_{h\in H,u\in U}u^{g}_{hp}\cdot X^{g}_{uh}}_{\text{Grid Health Emissions}}\Bigg)$$

To calculate climate costs, we consider the CO_2 emissions associated with both fuels burned on-site in the microgrid and grid-purchased electricity. Fuel burned is multiplied by an emissions factor that depends on fuel type (diesel, in our case studies), and grid purchases are multiplied by an hourly regional marginal emissions factor, and then summed over all fuel types, electric pricing tiers, and hours. Emissions are then multiplied by the social cost of carbon c^{CO2} and an annuity factor to calculate the present value of climate costs. Health costs are calculated similarly, using emissions factors for each fuel type and grid-purchased electricity, and for each health-related pollutant (SO_2, NOx, and PM2.5). We multiply these emissions by the associated marginal damage costs for fuel and grid-purchased electricity, sum over all pollutants, and multiply by an annuity factor to calculate the present value of health costs. While not included in the objective function, we calculate the impact of value of resilience and job creation on the lifecycle cost of energy.

Lifecycle cost of energy is minimized with several constraints in mind. Fuel constraints restrict fuel consumption to the amount of fuel available. Switch constraints restrict the rate of production from a technology to an operating window between the system's minimum turn down and its maximum size. Storage constraints ensure that the stored energy does not exceed the battery energy capacity, the charge and discharge in each timestep does not exceed the power capacity, and they provide inventory balance for the state of charge. Power rating constraints impose lower and upper limits on the power rating of a technology and ensure only selected technologies and subdivisions in a technology class are nonzero. Load balancing and grid sales constraints account for all generation, from renewable energy, storage, and the grid, and ensure that it is equal to demand from site load, battery charging, and energy exports across all time steps. Rate tariff constraints enforce net metering limits, the order of pricing tiers in utility rate tariffs, and demand ratchets. Minimum utility charge constraints enforce a minimum payment to the utility provider. Finally, non-negativity and integrality constraints ensure all variables assume non-

negative values and establish integrality of appropriate variables. Refer to [23] for a complete description of modeling constraints; no constraints were added for this work.

2.3 Case Study Sites

We select three case study sites to demonstrate the method in geographically diverse locations with different utility rates, grid emissions, renewable resources, and natural hazards. These locations are chosen based on recent climate-related grid outages, coupled with high scores in the EPA EJScreen Energy Justice Index, indicating increased susceptibility to the negative impacts of pollution.

- *California:* The first site is located in Petaluma, California where wildfires have led to public safety power shutoffs (PSPS) in which power is turned off to help prevent wildfires. PSPS events have affected 3.2 million customers in California from 2013-2020, with an average outage duration of 41.0 hours and a maximum outage duration of 162.8 hours [32]. Petaluma scores in the 82nd percentile for demographic index and 88th percentile for Energy Justice Index PM2.5 in EJScreen, an environmental justice mapping and screening tool that evaluates environmental and demographic indicators [16]. This indicates relatively high levels of ambient air pollution combined with relatively high low-income and/or minority populations compared to the national average, resulting in more individuals susceptible to the negative impacts of pollution.
- *Texas:* The second site is located in Austin, Texas where winter storms and hurricanes have caused power outages, including a freeze in February 2021 that resulted in 4.5 million customers (more than 10 million people) losing electricity for as much as seven days [33] and Hurricane Harvey in 2017 that caused 1.67 million customer outages for up to 14 days in Houston [34]. The Montopolis neighborhood of Austin scores in the 94th percentile for demographic index and 95th percentile for Energy Justice Index PM2.5 in EJScreen [16]. This indicates high levels of ambient air pollution combined with high low-income and/or minority populations, resulting in increased susceptibility to pollution.
- *Louisiana*: The third site is located in Baton Rouge, Louisiana. In 2005, Hurricane Katrina caused 2.6 million customers to lose power across Louisiana, Mississippi, Alabama, Florida, and Georgia [35], some for up to three weeks [36]. The Zion City neighborhood of Baton Rouge scores in the 99th percentile for demographic index and 96th percentile for Energy Justice Index PM2.5 in EJScreen [16]. This indicates very high levels of ambient air pollution combined with very high low-income and/or minority populations, resulting in high susceptibility to pollution.

Schools are commonly used as shelters during natural disasters [37], and thus serve as critical infrastructure that must have backup power during a grid outage. Therefore, in each location, we design a microgrid to sustain the load of a school serving as a shelter during a one-week outage, starting on the peak load hour of the year to conservatively size the system for a worst-case outage occurring during the building's maximum load period. We model the typical hourly load for one year using the DOE Commercial Reference Building secondary school load profile for the location's climate zone [38]. The load during the outage period is modeled using the DOE Commercial Reference Building large hotel load profile to reflect the adjusted usage pattern when the school is being used as a shelter. We assume each site would have enough diesel fuel stored on site to sustain the load for one week.

The data inputs and assumptions for each case study, including applicable utility rates, technology cost and performance assumptions, and economic, climate, and health parameters are summarized in the appendix. We assume the technologies are purchased by the city or county government, and, as tax exempt entities, they are not eligible for federal tax incentives or accelerated depreciation. We include only the costs of microgrid generation assets; additional microgrid costs, such as critical load panels, are highly site-specific and are not included here. Energy costs are calculated based on the applicable utility rate in each location, which include time-of-use energy and demand charges. Grid emissions are

calculated for each location based on hourly factors from the AVERT database. For on-site diesel consumption, emissions are assumed to be released from ground-level at the site location, and thus have higher marginal health costs than equivalent emissions from the grid. We assume a value of lost load, or avoided outage cost, of $4/kWh for each location based on [24], and assume the 7-day outage occurs every year in the 25-year analysis period. To quantify the economic impact of job creation, we estimate the total regional gross output (equivalent to domestic supply or sales revenue) based on the microgrid capital cost and O&M costs using the JEDI suite of models [31]. Case study site characteristics are summarized in Table 1, and more details are available in the appendix.

Table 1: Site Characteristics

	California	**Texas**	**Louisiana**
City	Petaluma	Austin	Baton Rouge
Average annual load (kW)	265	388	388
Annual energy consumption (kWh)	2,318,927	3,400,954	3,400,954
Energy consumption during outage (kWh)	47,332	69,771	69,771
Average energy charge ($/kWh)	0.11	0.054	0.061
Average demand charge ($/kW/month)	12.38	14.64	2.85
Outage period	Sep. 28, 3pm-Oct. 5, 3pm	Sep. 15, 3pm-Sep. 22, 3pm	Sept 15, 3pm-Sep. 22, 3pm

2.4 Scenarios

For each of the case study sites, we consider three microgrid technology options: diesel only; hybrid (solar PV+storage+diesel); and renewable only (solar PV+storage). These are compared to the "business-as-usual" case, where there is no microgrid. We then consider a range of potential value streams, and evaluate how the economics of the microgrid change under the following value combinations:

- *Bill savings only (B):* Microgrid assets are sized to minimize lifecycle cost of energy, considering only utility bill savings.
- *Bill savings + climate (BC):* Microgrid assets are sized to minimize lifecycle cost of energy, considering utility bill savings and social cost of carbon.
- *Bill savings + health (BH):* Microgrid assets are sized to minimize lifecycle cost of energy, considering utility bill savings and public health costs.
- *Bill savings + climate + health (BCH)*: Microgrid assets are sized to minimize lifecycle cost of energy, considering utility bill savings, social cost of carbon, and public health costs.
- *Bill savings + climate + health + resilience (BCHR)*: Microgrid assets are sized to minimize lifecycle cost of energy, considering utility bill savings, social cost of carbon, and public health costs. Value of resilience is added to the lifecycle cost.
- *Bill savings + climate + health + resilience + jobs (BCHRJ)*: Microgrid assets are sized to minimize lifecycle cost of energy, considering utility bill savings, social cost of carbon, and public health costs. Value of resilience and economic output due to jobs are added to the lifecycle cost.

2.5 Limitations

This analysis attempts to expand consideration of equity values when making microgrid design and investment decisions, but the factors captured in this analysis represent only a small portion of the broader energy justice space. For example, we do not address recognition and procedural justice concepts of whether all groups are involved in the decision making process around microgrid implementation. If we

were to evaluate actual sites, it would be important to elicit feedback from diverse community members and incorporate their feedback in implementation plans.

Additionally, we do not address barriers of financing in low-income communities. We assume city or county governments would directly purchase the microgrid for the shelter, but funding may not be available, especially for solar+storage or hybrid microgrids which have a higher capital cost. Furthermore, values such as social cost of carbon, public health and value of lost load, while very important, are not necessarily monetizable. Therefore, it may be difficult to include these when seeking financing, absent government policies like carbon taxes or cap and trade programs that monetize these. Details of policy and program implementation are beyond the scope of this study, but will be important to energy justice outcomes.

Our analysis also assumes that the benefits of a microgrid will accrue to disadvantaged residents in a community if a microgrid is installed there. Ensuring this will require thoughtful site selection and implementation. For example, for disadvantaged community members to realize the resilience benefits of a microgrid at the shelter, they must be able to access it during an emergency. Ensuring prioritization of disadvantaged neighborhoods when installing microgrids requires intentional decision making and policies that prioritize these communities.

3. Results

In this section, we summarize the impact of including energy justice values on 1) microgrid system sizes; 2) economics; 3) emissions; and 4) resilience. We focus on the results for diesel only and hybrid microgrids; results for renewable energy microgrids are included in the appendix.

3.1 Microgrid system sizes: Including energy justice values results in microgrids with more renewable generation, but not 100% renewable

As energy justice values are added, PV and storage sizes increase, while diesel generator sizes decrease, as shown in Figure 2. Health and climate values lead to larger PV and storage systems in all locations, but the relative increase varies by location. In California, large solar and storage systems are economically viable when considering utility bill savings only, due to higher utility rates. Adding public health and climate costs increase PV and storage system sizes by up to 8%, and decrease diesel generator size up to 6%, compared to bill savings only. In Texas, by comparison, only smaller solar and storage systems are economically viable when just bill savings are considered. Adding public health and climate values has a larger impact, increasing PV system size up to 124%, storage size up to 233%, and decreasing diesel generator size by 29%. In Louisiana, neither PV nor storage are cost-effective with bill savings alone. In this location, adding health and climate values changes the economics for PV and storage size from negative to positive, and decreases diesel generator size by 46%.

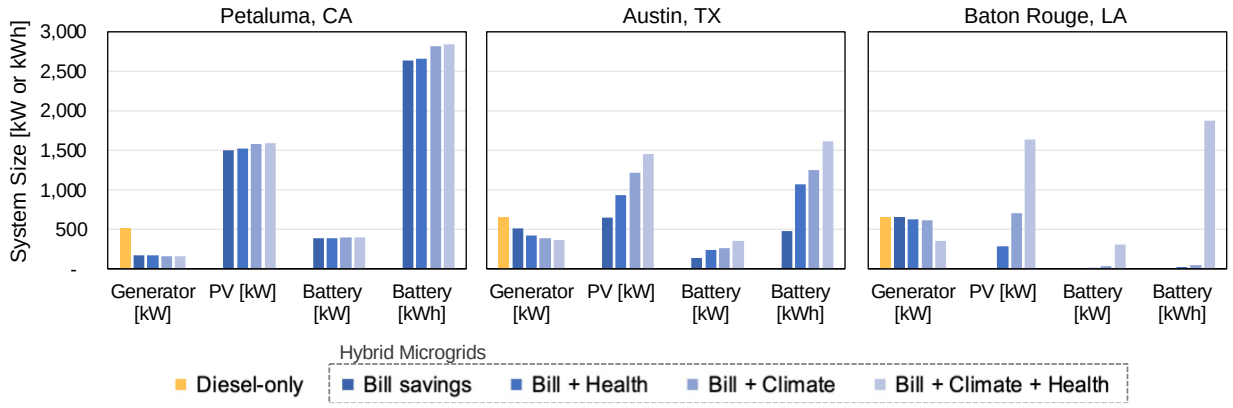


Figure 2: Cost-optimal system sizes across locations and optimization scenarios. Smaller diesel generators and larger PV and storage systems become cost optimal as health and climate costs are incrementally included within the lifecycle cost calculation.

Table 1 compares the net present value (NPV) and system sizes of diesel only, hybrid, and renewable only microgrids across the three locations. While adding energy justice values results in microgrids with more renewable generation, it does not necessarily lead to fully renewable microgrids. In all locations, hybrid microgrids that consist of solar, storage, and diesel are more economical than solar and storage configurations without diesel, when bill savings, climate, health, and resilience values are considered. Without diesel generation, solar and storage system sizes must increase significantly to meet the load during nighttime or cloudy periods, and this requires substantial additional capital investment. When the economic output associated with job creation is considered, fully renewable microgrids become more economical than hybrid microgrids due to the increased economic output associated with higher capital investments. The system size and configuration of the hybrid microgrids do not change when adding resilience and jobs values because those are not included in the objective function.

Table 1: Net Present Value and System Size of Diesel, Hybrid, and Renewable Energy Microgrids including various energy justice values

	NPV ($)			System Size		
	California	**Texas**	**Louisiana**	**California**	**Texas**	**Louisiana**
Diesel	-625,799	-842,524	-842,524	516 kW	650 kW	650 kW
Hybrid				1591 kW PV	1455 kW PV	1641 kW PV
BCH	5,247,393	934,640	-784,356	407 kW; 2836 kWh	355 kW; 1609 kWh	307 kW; 1874 kWh
BCHR	8,544,189	5,794,371	4,075,375	storage	storage	storage
BCHRJ	16,082,769	12,570,379	10,098,920	161 kW diesel	367 kW diesel	352 kW diesel
Renewable						
BCH	4,266,164	-2,012,179	-5,097,941	1863 kW PV	3013 kW PV	3107 kW PV
BCHR	7,562,960	2,847,552	-238,210	713 kW; 6185 kWh	1152 kW; 8340 kWh	1047 kW; 8182 kWh
BCHRJ	19,445,114	21,757,058	12,952,414	storage	storage	storage

B= Bill Savings; C= Climate; H= Health; R=Resilience; J=Jobs

3.2 Economics: Including energy justice values results in microgrids with higher net present values, but also higher capital costs

As energy justice values are added, the net present value of microgrid investments increase, as shown in Figure 3, indicating growing benefits. The life cycle cost of both the business-as-usual case and the microgrid case increase as social cost of carbon and public health costs are accounted for, but it increases more for the business-as-usual case, which has higher emissions and provides no resilience nor job creation value.

While microgrid net present values improve across all locations when adding energy justice values, the relative improvement varies by location. In California, a microgrid has a positive net present value when considering only bill savings. Adding energy justice values further increases the positive net present value. In Texas, on the other hand, a microgrid has a negative net present value when only bill savings are considered. The addition of any single energy justice value shifts the net present value from negative to positive, indicating a potential change in investment decisions. In Louisiana, the net present value remains negative until the economic output associated with resilience or job creation is added.

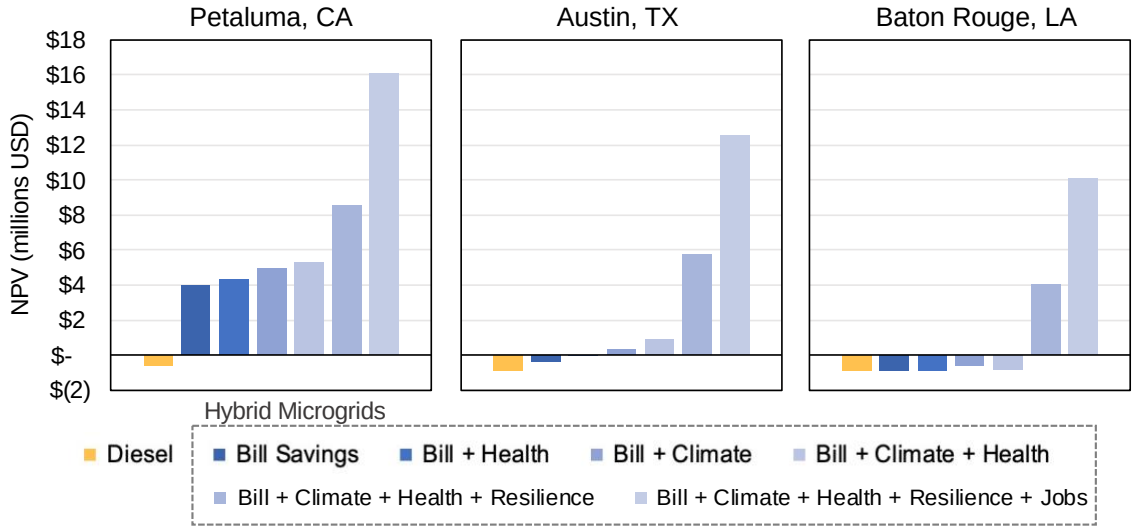


Figure 3: Net present value (NPV) of microgrid investment. The NPV is calculated as the LCC in the optimized case minus the LCC in the "business-as-usual" case, with no outage and no on-site distributed energy resources.

Microgrid lifecycle cost components are shown in Figure 4. Adding energy justice values increases microgrid capital costs, due to the higher investment cost of solar and storage compared to diesel generators. These higher initial costs are recovered through reduced annual utility bills, resulting in a reduction in energy burden, reduced emissions costs and avoided outage costs, and increased economic output associated with job creation. Note that climate and health costs are calculated in all cases but are only included in the objective function in the scenarios noted with "Climate" and/or "Health." The relative cost of climate and health emissions varies by location. For the case study sites evaluated here, climate costs are higher than health costs.

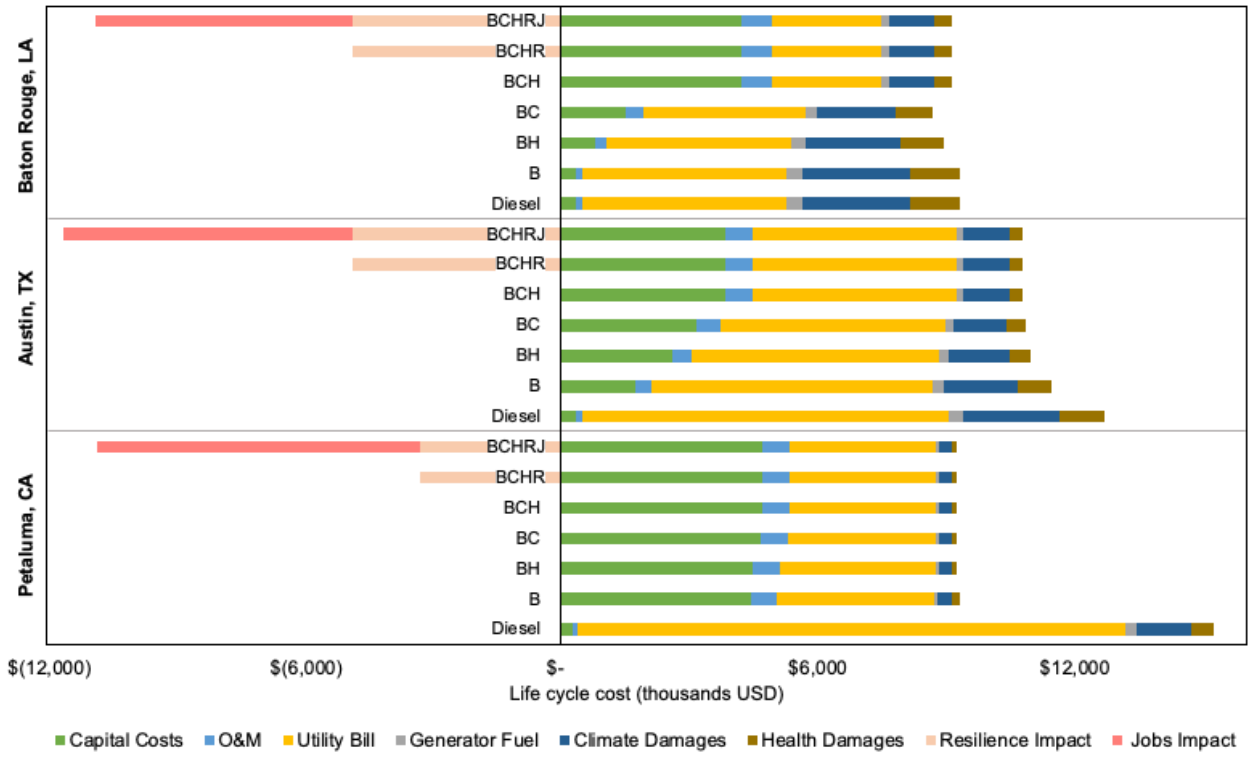


Figure 4: Categorizing the components of lifecycle cost shows that capital costs increase, while utility costs and emissions costs decrease, as energy justice values are added.

3.3 Emissions: Including energy justice values results in microgrids with lower emissions

As energy justice values are included, and microgrids include more renewable generation, emissions decrease in every location, as shown in Figure 5. This is primarily due to reductions in grid-purchased electricity. The PV and storage systems in the microgrid operate throughout the year, not only during grid outages, enabling a significant reduction in emissions associated with grid-purchased electricity. Reductions in diesel fuel use during outages also leads to reduced emissions, but the impact is much smaller than the impact of reducing grid-purchased electricity. This is because the diesel generator is only run during the one-week outage, whereas electricity is purchased from the grid for 51 weeks out of the year.

In California, the cost-optimal microgrid includes substantial renewable generation even when only bill savings are considered, reducing emissions by 70-73% across each pollutant (CO_2, SO_2, NO_X, PM2.5) compared to a diesel backup power system. When climate and health costs are added, there is only a small additional decrease in emissions, for a total reduction of 73-82% compared to the diesel-only system. In Texas, on the other hand, when only bill savings are included, the cost-optimal microgrid includes a smaller PV system and reduces emissions by only 24% compared to the diesel system. Adding climate and health costs results in a substantial additional decrease, for a total reduction of 52-57% compared to the diesel-only system. In Louisiana, when only bill savings are included, the cost-optimal microgrid includes no renewable generation, and therefore offers no emissions reduction. Adding climate and health costs leads to a reduction of 55-61% compared to the diesel system.

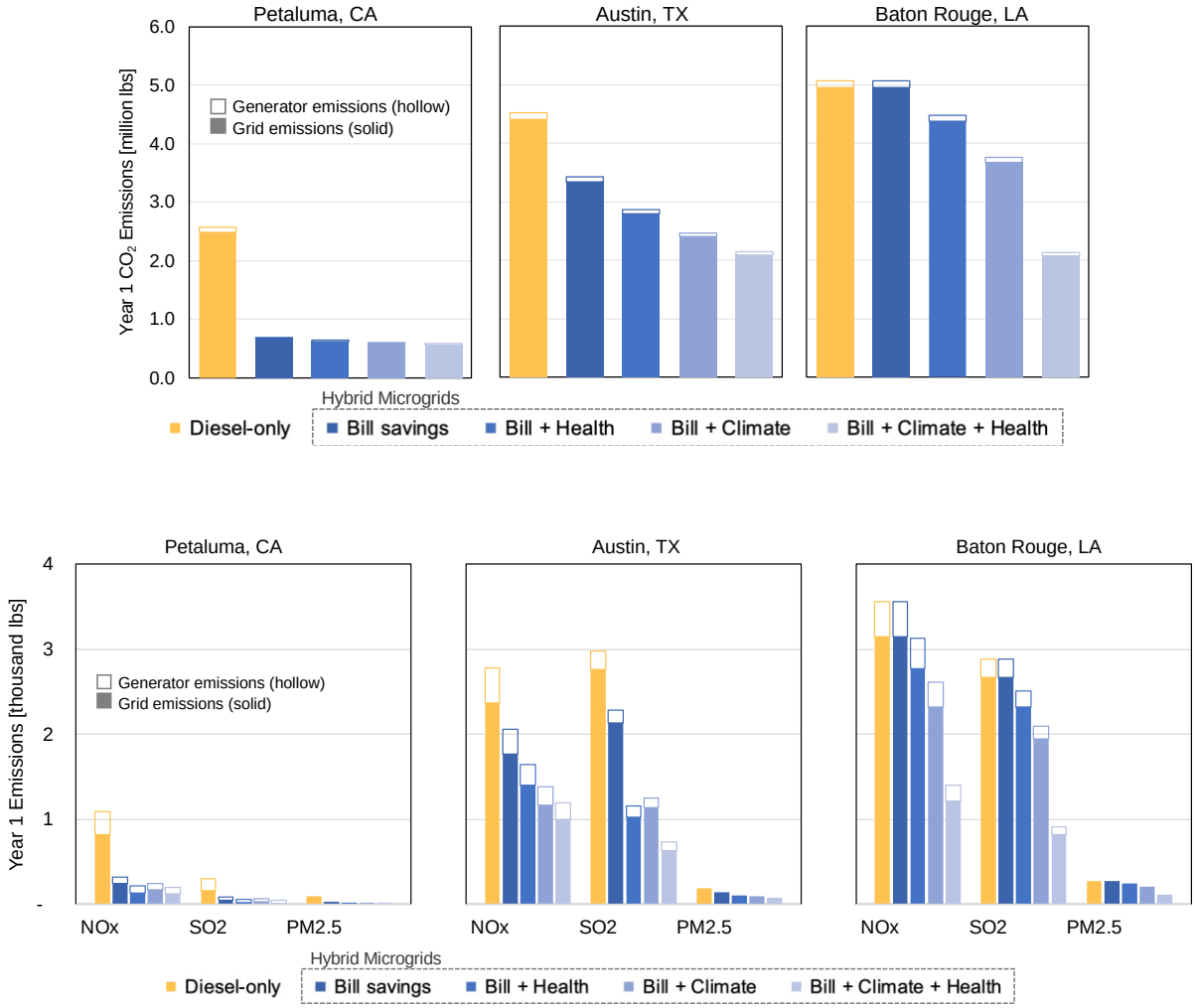


Figure 5: Emissions decrease as the value of climate and health impacts are added.

3.4 Resilience: Including energy justice values results in microgrids with lower diesel dependency but higher variability in resilience

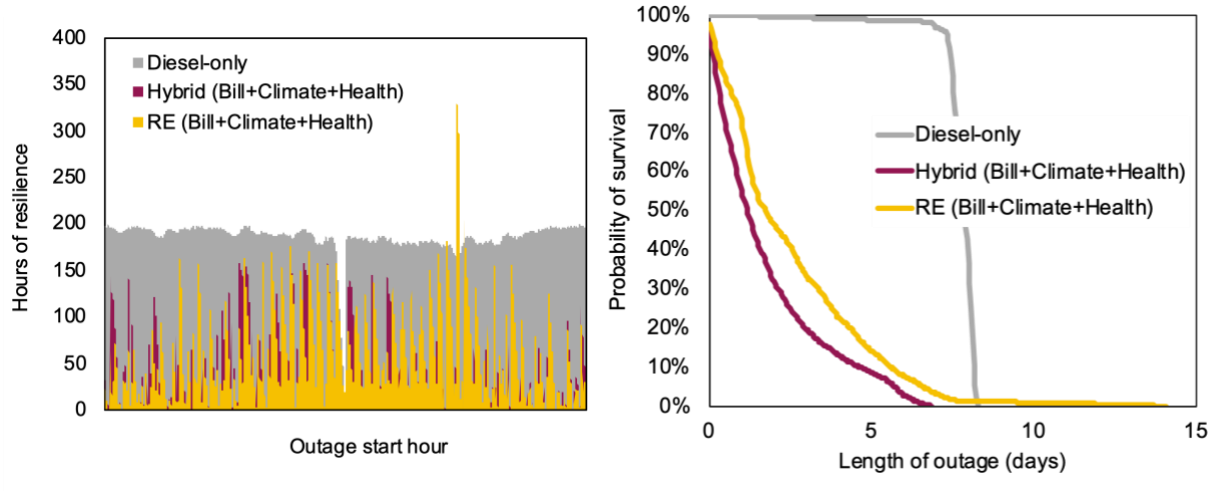
As energy justice values are included, solar and storage system sizes increase, and diesel generator sizes decrease. This reduces diesel fuel consumption of the microgrid, which can be important during natural disasters when diesel fuel re-supply may be interrupted, or fuel may be prioritized for only the most critical infrastructure. In California, diesel fuel consumption falls by 82% from the diesel-only microgrid to the hybrid microgrid sized for bill savings, health, and climate. In Texas, diesel fuel use falls by 53%, and in Louisiana by 55% (see Table 2) for the same microgrid scenarios.

Table 2: Diesel Fuel Consumption in Diesel, Hybrid, and Renewable Energy Microgrids including bill savings, climate, and health costs for a one-week outage

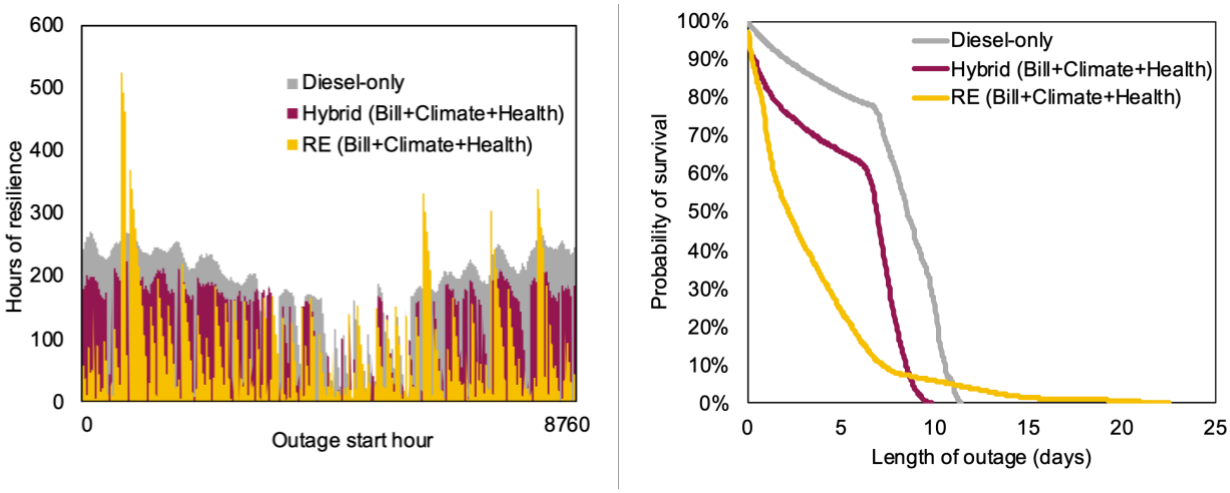
	California (gallons diesel)	Texas (gallons diesel)	Louisiana (gallons diesel)
Diesel-only	3,592	5,305	5,305
Hybrid BCH	957	2,499	2,402
RE	0	0	0

The increased solar and storage generation resulting from energy justice values also causes more variability in the amount of resilience provided by the microgrid, measured as hours of load sustained during an outage. The microgrids in this analysis were designed to sustain a 7-day outage period starting on the hour of peak load for the modeled secondary schools. We selected the peak load hour to provide a conservative estimate of system sizes, but the actual outage start date is uncertain. To evaluate the performance of the microgrid at other times, we simulated outages starting every hour of the year (8,760 simulations) and evaluated how many hours the microgrid could sustain the full critical load in each hour, using the methodology described in [39].

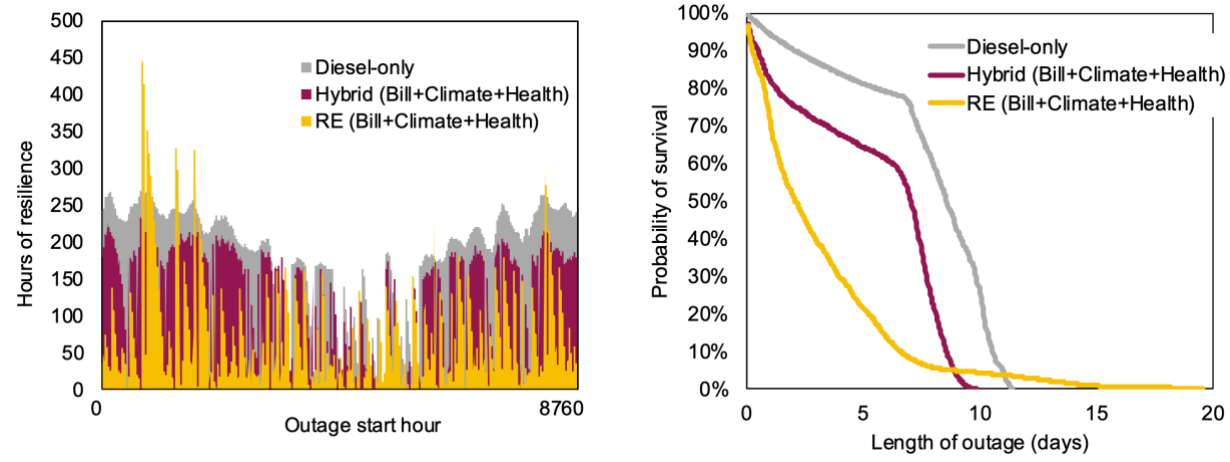
As shown in the left-hand graphs of Figure 6, the number of hours of resilience the microgrid can provide varies depending on the outage start hour. This is due to variations in load and solar resource throughout the year. The load is consistent year-round in California but increases during the summer in Texas and Louisiana due to air conditioning loads. Therefore, the microgrids tend to provide fewer hours of resilience in the summer in Texas and Louisiana, when loads are higher in each hour. Diesel-based microgrids provide the most consistent or predictable power, while hybrid microgrids have more variability, and renewable microgrids are the most variable. Occasionally, the renewable microgrids sustain critical loads longer than diesel or hybrid systems, but for the most part they provide fewer hours of resilience or lower probability of surviving outages, as shown in the right-hand graphs of Figure 6. This is in part due to the assumptions used in our simulations, where we assume resilience or survivability ends in the first hour that there are not enough resources to meet the full critical load. While the microgrid may still be able to sustain load in a future hour (for example, when the sun rises and PV starts to generate energy again), this is not considered in our model; this is an area for future work. Additionally, this analysis does not consider the reliability of the renewable microgrids, which may be significantly higher than diesel generators. A recent study by Marqusee et al. [40] found poorly maintained diesel generators have only a 50% probability of operating 48 hours or longer.



Petaluma, CA



Austin, TX



Baton Rouge, LA

Figure 6: Hours of resilience by outage start hour and probability of survival by length of outage, for diesel-only, hybrid, and renewable-only microgrids. System sizes are shown in Table A.5.

The 7-day outage modeled in this analysis is based on the peak load of the secondary school. However, for the hybrid and renewable-only microgrids, the solar resource and battery state of charge are also important drivers in sizing the microgrid. In Table 3, we show the increase in system sizes and capital cost required for systems that can sustain the critical load for any 7-day outage regardless of when it begins, when optimizing for bill savings, climate, and health (scenario BCH). System sizes were determined by modeling a year-long outage. In the hybrid and renewable only cases, larger PV and storage systems would be required to sustain any 7-day outage as compared to the 7-day outage that begins at the hour of peak load for the secondary school. While the capital costs for hybrid and renewable microgrids are significantly higher than those of diesel-only microgrids, these systems can provide energy bill savings during grid-connected operations, and incur less fuel costs than diesel-only systems.

Table 3: Percentage increase in microgrid system sizes and upfront capital costs for systems that can survive any 7-day outage as compared to the specified 7-day outage.

Scenario	Metric	California	Texas	Louisiana
Diesel Only	Generator kW	0.6%	7.8%	7.8%
	Capital Cost	0.6%	7.7%	7.7%
Hybrid	Generator kW	20%	-47%	-36%
	PV kW	11%	84%	68%
	Storage kW	71%	163%	195%
	Storage kWh	76%	344%	266%
	Capital Cost	35%	134%	112%
Renewable Only	PV kW	147%	63%	25%
	Storage kW	-12%	-19%	13%
	Storage kWh	664%	134%	174%
	Capital Cost	349%	81%	79%

4. Discussion & Conclusions

This analysis demonstrates that including energy justice values in the techno-economic analysis of microgrids can change investment decisions. When climate, health, resilience, and job creation costs and benefits are considered, cost-optimal microgrids include more renewable generation, leading to reduced emissions and diesel fuel use. The net present values of the microgrids increase, indicating that renewable microgrid deployment may increase if energy justice values are incorporated in decision making. However, we also see large increases in the initial capital costs, which could limit deployment unless accompanied by innovative financing measures, incentives, or other means to value externalities. Furthermore, renewable microgrids lead to more variability in resilience provided, due to larger dependence on a variable solar resource, and must therefore be carefully designed. While trends are consistent across the three locations evaluated (with the size of renewable energy systems increasing as more energy justice related values are incorporated), results vary significantly, highlighting the importance of site-specific analysis to determine the microgrid system configuration that best meets a site's goals. There likely will not be a one-size-fits-all solution.

These findings may be useful to cities and states as they seek to increase resilience to natural disasters while also improving public health, meeting climate goals, and providing economic opportunity for residents. For policymakers considering measures such as carbon pricing, this work provides an understanding of how monetizing an energy system's impact on climate, health, resilience, and jobs can alter investments. Fully accounting for these impacts, which disproportionately burden low- and moderate-income communites, can support a transition to a more just energy system. Quantifying these impacts does not necessarily improve distributive justice on its own, but it provides the information needed to understand the broader costs and benefits of energy investments, and evalute whether they are fairly allocated in a community.

While this analysis provides a starting point to incorporating energy justice values in microgrid design and investment decisions, there are many opportunities for future work. Modeling can be improved by integrating the value of resilience and job creation directly in the optimization objective function, where it may influence system size recommendations. Adding other missing value streams, and refining the values used in these case studies (particularly value of resilience, which is highly site-specific) or conducting sensitivity analysis around parameters, will improve our understanding of the impact of energy justice values on microgrid design.

Quantifying value is only the first step; to realize a more just energy system, we must develop ways to monetize these values so they can be financed. Funding is likely to be a significant barrier to renewable microgrids, especially in underserved communities, and innovative financing mechanisms that require no upfront capital investment like Pay as You Save (PAYS) will be important to equitable deployment. Finally, recognition and procedural justice concepts of who is involved in the decision making process are also critical to addressing injustices. The benefits of a microgrid do not automatically accrue to disadvantaged residents. As communities build microgrids, thoughtful site selection and program implementation will be needed to ensure microgrids are built in locations that benefit disadvantaged community members.

Acknowledgments
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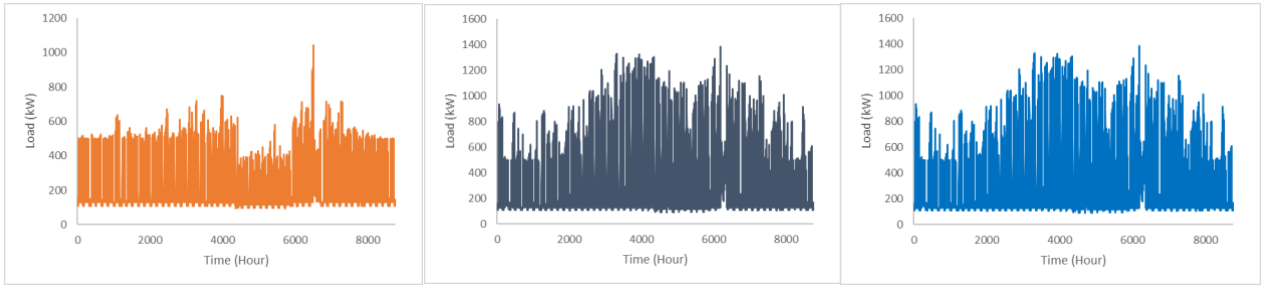
Appendix

A.1 Load Profiles

We model hourly data for one year for each location (see Figures A.1 and A.2). The typical load is simulated based on the DOE Commercial Reference Building Secondary School model for each location's climate zone [38]. The load during the outage period is modeled using the DOE Commercial Reference Building Large Hotel load profile to reflect the adjusted usage pattern when the school is being used as a shelter.



Petaluma, California Austin, Texas Baton Rouge, Louisiana

Figure A.1: Electric demand for one year for each location

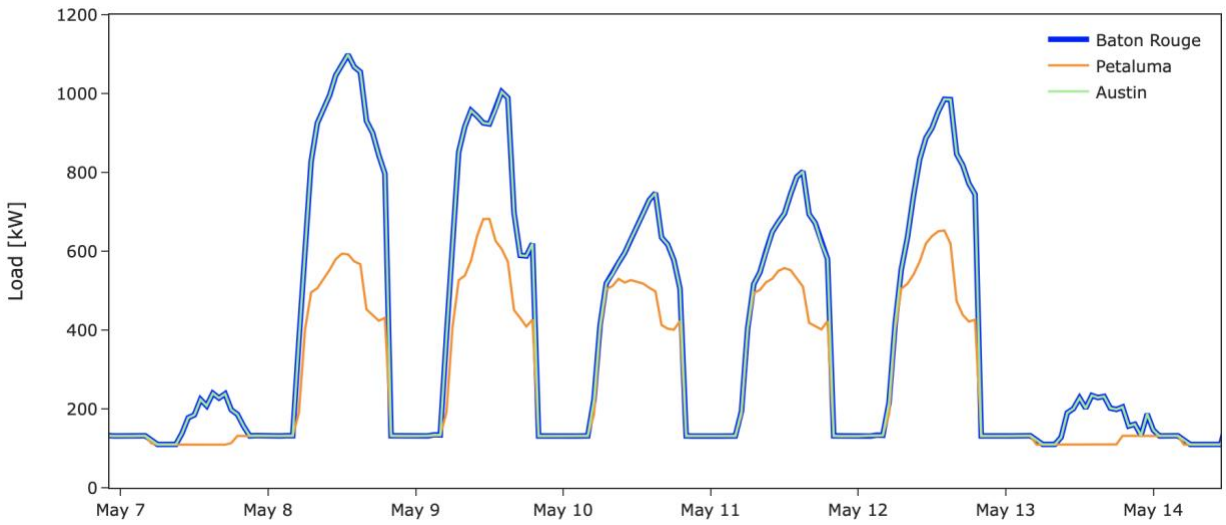


Figure A.2. Electric demand for one week (May 7-14) for each location. Note that Baton Rouge, LA and Austin, TX are in the same DOE Commercial Reference Building climate zone, and thus the modeled buildings in these locations have identical load profiles.

A.2 Utility Rate Tariffs

We model actual rate tariffs based on the selected locations and building loads. Rates are made of energy, demand, and fixed charges that may be constant (Texas); or vary by season, weekday versus weekend,

and time of day (California); or usage (Louisiana). The tariffs modeled in each location are described in Tables A.1 through A.3.

Table A.1: California rate tariff: Pacific Gas & Electric E-19 Medium General Demand TOU (Secondary)

Period	Rate	Schedule
Energy Charge		
1	$0.10397/kWh	See [41]
2	$0.10468/kWh	
3	$0.10727/kWh	
4	$0.11325/kWh	
5	$0.11325/kWh	
Seasonal/Monthly Demand Charge		
1	$24.93/kW	All months
Time of Use Demand Charge		
1	0	See [41]
2	0	
3	$11.12/kW	
4	$13.63/kW	
Fixed Charge		
N/A	$27.58/day	All days

Table A.2: Texas rate tariff: Austin Energy Commercial Secondary Voltage Greater than 300 kW-Inside

Rate	Schedule
Energy Charge	
$0.05367/kWh	All hours
Demand Charge	
$14.64/kW	All hours
Fixed Charge	
$71.50/month	All months

Table A.3: Louisiana rate tariff: Entergy Large General Service (LGS-L)

Tier	Rate	Usage
Energy Charge		
1	$0.0655/kWh	0- 30,000 kWh
2	$0.0559/kWh	30,000-70,000 kWh
3	$0.0465/kWh	>70,000 kWh
Demand Charge		
1	0	0-60 kW
2	$2.85/kW	>60 kW
Fixed Charge		
N/A	$277.61/month	All months

A.3 Technical and Economic Parameters

We assume a standard set of technology cost, economic, health, and climate parameters for each case study site, as shown in Table A.4. Both the social cost of carbon and the marginal costs of health-related pollutants are estimated to increase over time. The EPA has estimated the social cost of carbon to increase nearly linearly over the years. The year-over-year escalation rate for the social cost of carbon is used in the calculation of a present worth factor within REopt, which accounts for both the off-taker's discount rate and the escalation rate of the social cost of carbon. The rate of escalation of the marginal health damage costs is location-dependent, given that it depends on the local population increase and meteorological factors. In this analysis, we estimate that the marginal damage costs of PM2.5, SO_2, and NOx escalate at the same rate as that of the social cost of carbon.

A.5 Results

Complete results for all scenarios evaluated are shown below, including system sizes (Table A.5), economics (Table A.6), and emissions (Table A.7).

Table A.4: Technology cost and performance assumptions

PV parameters	**Value**	**Reference**
Array type	Rooftop, fixed	[42]
Array azimuth	180°	[42]
Array tilt	Latitude of each site	
DC-to-AC size ratio	1.2	[42]
System losses	14%	[42]
Capital cost	$1,600/kW-DC	[42]
O&M cost	$16/kW/year	[43]
Incentives	None	-
Battery parameters	**Value**	**Reference**
Rectifier efficiency	96%	[44]
Round-trip efficiency	97.5%	[44]
Inverter efficiency	96%	[44]
Minimum state of charge	20%	[44]
Initial state of charge	50%	-
Battery life	10 years	[45]
Energy capacity cost	$420/kWh	[46]
Energy replacement cost	$200/kWh	[46]
Power capacity cost	$840/kW	[46]
Power replacement cost	$410/kW	[46]
O&M cost	$0/kW	-
Incentives	None	-
Diesel generator parameters	**Value**	**Reference**
Capital cost	$500/kW	[47]
O&M cost	$10/kW/year	[47]
Federal incentive	None	-
Diesel cost	$3/gallon	[48]
Diesel availability	7 days of critical load	-
Fuel burn rate	0.076 gallons/kWh	[49]
General economic parameters	**Value**	**Reference**
Analysis period	25 years	[43]
Ownership model	Direct ownership	-
Host discount rate (nominal)	3.0%	[43]
Host effective tax rate	0%	[43]
Electricity cost escalation rate (nominal)	2.3%	[50]
O&M cost escalation rate	2.5%	[43]
Net metering limit and wholesale rate	0	-
Resilience parameters		
Outage length	7 days	-
Value of Lost Load	$4/kWh	[24]
Health and climate parameters	**Value**	**Reference**
Social cost of CO_2 in first year	$51/ton	[51]
Annual escalation of social cost of CO_2	1.78%	[51]
Grid marginal emissions factors	Region-specific, hourly [lb/kWh]	[27]
Health costs (NOx, SO_2, PM2.5)	City-specific, annual average [$/lb]	[30]
Diesel CO_2 emissions rate	22.51 lb / gal	[29]
Diesel NOx emissions rate	0.078 lb / gal	[29]
Diesel SO_2 emissions rate	0.040 lb / gal	[29]
Diesel PM2.5 emissions rate	0.0 lb / gal	[29]

Table A.5: System Sizes

Location	Scenario	Objective*	PV (kW)	Battery (kW)	Battery (kWh)	Generator (kW)
Austin	Diesel	B	-	-	-	650
Austin	Hybrid	B	651	136	483	515
Austin	Hybrid	BC	1,215	269	1,250	392
Austin	Hybrid	BH	932	241	1,075	419
Austin	Hybrid	BCH	1,455	355	1,609	367
Austin	Hybrid	BCHR	1,455	355	1,609	367
Austin	Hybrid	BCHRJ	1,455	355	1,609	367
Austin	Renewable	B	3,013	1,152	8,340	-
Austin	Renewable	BC	3,013	1,152	8,340	-
Austin	Renewable	BCH	3,013	1,152	8,340	-
Austin	Renewable	BCHR	3,013	1,152	8,340	-
Austin	Renewable	BCHRJ	3,013	1,152	8,340	-
Petaluma	Diesel	B	-	-	-	516
Petaluma	Hybrid	B	1,499	394	2,633	172
Petaluma	Hybrid	BC	1,575	405	2,810	163
Petaluma	Hybrid	BH	1,519	396	2,658	170
Petaluma	Hybrid	BCH	1,591	407	2,836	161
Petaluma	Hybrid	BCHR	1,591	407	2,836	161
Petaluma	Hybrid	BCHRJ	1,591	407	2,836	161
Petaluma	Renewable	B	1,828	719	6,194	-
Petaluma	Renewable	BC	1,854	715	6,187	-
Petaluma	Renewable	BCH	1,863	713	6,185	-
Petaluma	Renewable	BCHR	1,863	713	6,185	-
Petaluma	Renewable	BCHRJ	1,863	713	6,185	-
Baton Rouge	Diesel	B	-	-	-	650
Baton Rouge	Hybrid	B	-	0	0	650
Baton Rouge	Hybrid	BC	711	34	45	616
Baton Rouge	Hybrid	BH	284	22	28	629
Baton Rouge	Hybrid	BCH	1,641	307	1,874	352
Baton Rouge	Hybrid	BCHR	1,641	307	1,874	352
Baton Rouge	Hybrid	BCHRJ	1,641	307	1,874	352
Baton Rouge	Renewable	B	2,751	1,253	8,229	-
Baton Rouge	Renewable	BC	3,106	1,047	8,182	-
Baton Rouge	Renewable	BH	2,857	1,173	8,215	-
Baton Rouge	Renewable	BCH	3,107	1,047	8,182	-
Baton Rouge	Renewable	BCHR	3,107	1,047	8,182	-
Baton Rouge	Renewable	BCHRJ	3,107	1,047	8,182	-

Note: B= Bill Savings; C= Climate; H= Health; R=Resilience; J=Jobs

Table A.6: Economics

Location	Scenario	Objective*	NPV ($)	BAU LCC ($)	Optimum LCC ($)	Net Capital Costs ($)	Lifecycle O&M Costs ($)	Lifecycle Utility Costs ($)
Austin	Diesel	B	(842,524)	8,552,007	9,394,531	325,219	152,735	8,552,007
Austin	Hybrid	B	(384,429)	8,552,007	8,936,436	1,729,836	365,690	6,582,095
Austin	Hybrid	BC	354,741	10,740,947	10,386,206	3,158,808	548,610	5,263,255
Austin	Hybrid	BH	(6,528)	9,518,036	9,524,564	2,587,662	448,508	5,797,755
Austin	Hybrid	BCH	934,640	11,706,975	10,772,335	3,833,839	633,013	4,745,742
Austin	Hybrid	BCHR	5,794,371	16,566,706	10,772,335	3,833,839	633,013	4,745,742
Austin	Hybrid	BCHRJ	12,570,379	16,566,706	3,996,327	3,833,839	633,013	4,745,742
Austin	Renewable	B	(4,840,942)	8,552,007	13,392,949	10,883,745	1,132,004	1,377,200
Austin	Renewable	BC	(2,896,459)	10,740,947	13,637,406	10,883,745	1,132,004	1,380,706
Austin	Renewable	BCH	(2,012,179)	11,706,975	13,719,154	10,883,745	1,132,004	1,384,539
Austin	Renewable	BCHR	2,847,552	16,566,706	13,719,154	10,883,745	1,132,004	1,384,539
Austin	Renewable	BCHRJ	21,757,058	16,566,706	(5,190,352)	10,883,745	1,132,004	1,384,539
Petaluma	Diesel	B	(625,799)	12,797,510	13,423,309	257,872	121,107	12,797,510
Petaluma	Hybrid	B	4,009,112	12,797,510	8,788,398	4,434,281	603,653	3,678,517
Petaluma	Hybrid	BC	4,926,698	14,031,680	9,104,982	4,664,253	629,941	3,446,033
Petaluma	Hybrid	BH	4,314,842	13,226,664	8,911,822	4,481,189	610,789	3,638,709
Petaluma	Hybrid	BCH	5,247,393	14,460,834	9,213,441	4,706,113	635,709	3,416,811
Petaluma	Hybrid	BCHR	8,544,189	17,757,630	9,213,441	4,706,113	635,709	3,416,811
Petaluma	Hybrid	BCHRJ	16,082,769	17,757,630	1,674,862	4,706,113	635,709	3,416,811
Petaluma	Renewable	B	2,800,033	12,797,510	9,997,477	7,271,416	686,736	2,039,326
Petaluma	Renewable	BC	3,879,672	14,031,680	10,152,008	7,303,425	696,406	2,001,276
Petaluma	Renewable	BCH	4,266,164	14,460,834	10,194,670	7,315,134	699,828	1,992,817
Petaluma	Renewable	BCHR	7,562,960	17,757,630	10,194,670	7,315,134	699,828	1,992,817
Petaluma	Renewable	BCHRJ	19,445,114	17,757,630	(1,687,484)	7,315,134	699,828	1,992,817
Baton Rouge	Diesel	B	(842,524)	4,779,954	5,622,478	325,219	152,735	4,779,954
Baton Rouge	Hybrid	B	(842,524)	4,779,954	5,622,478	325,219	152,735	4,779,954
Baton Rouge	Hybrid	BC	(583,769)	7,239,616	7,823,385	1,509,986	411,775	3,780,995
Baton Rouge	Hybrid	BH	(857,656)	5,861,639	6,719,295	810,427	254,541	4,318,702

Baton Rouge	Hybrid	BCH	(784,356)	8,321,301	9,105,657	4,218,479	699,132	2,556,783
Baton Rouge	Hybrid	BCHR	4,075,375	13,181,032	9,105,657	4,218,479	699,132	2,556,783
Baton Rouge	Hybrid	BCHRJ	10,098,920	13,181,032	3,082,112	4,218,479	699,132	2,556,783
Baton Rouge	Renewable	B	(7,766,796)	4,779,954	12,546,750	10,516,924	1,033,416	996,410
Baton Rouge	Renewable	BC	(6,073,200)	7,239,616	13,312,816	10,823,261	1,167,133	978,316
Baton Rouge	Renewable	BH	(6,974,621)	5,861,639	12,836,260	10,587,057	1,073,254	1,047,212
Baton Rouge	Renewable	BCH	(5,097,941)	8,321,301	13,419,242	10,823,336	1,167,160	984,335
Baton Rouge	Renewable	BCHR	(238,210)	13,181,032	13,419,242	10,823,336	1,167,160	984,335
Baton Rouge	Renewable	BCHRJ	12,952,414	13,181,032	228,618	10,823,336	1,167,160	984,335

Note: B= Bill Savings; C= Climate; H= Health; R=Resilience; J=Jobs

Table A.7: Emissions

Location	Scenario	Objective*	Climate Lifecycle Cost ($)	Health Lifecycle Cost ($)	Year 1 CO2 Emissions [lb.]	Year 1 NOx Emissions [lb.]	Year 1 SO2 Emissions [lb.]	Year 1 PM2.5 Emissions [lb.]
Austin	Diesel	B	2,248,297	1,038,875	4,523,275	2,781	2,978	191
Austin	Hybrid	B	1,702,452	791,921	3,425,108	2,061	2,285	145
Austin	Hybrid	BC	1,225,329	467,356	2,465,199	1,383	1,253	97
Austin	Hybrid	BH	1,425,674	473,053	2,868,268	1,645	1,153	110
Austin	Hybrid	BCH	1,068,110	319,897	2,148,895	1,191	736	79
Austin	Hybrid	BCHR	1,068,110	319,897	2,148,895	1,191	736	79
Austin	Hybrid	BCHRJ	1,068,110	319,897	2,148,895	1,191	736	79
Austin	Renewable	B	262,190	126,816	527,492	247	385	23
Austin	Renewable	BC	240,951	91,913	484,762	209	259	20
Austin	Renewable	BCH	241,768	77,097	486,405	213	196	19
Austin	Renewable	BCHR	241,768	77,097	486,405	213	196	19
Austin	Renewable	BCHRJ	241,768	77,097	486,405	213	196	19
Petaluma	Diesel	B	1,274,356	546,089	2,563,835	1,095	305	93
Petaluma	Hybrid	B	342,573	159,826	689,211	324	91	26
Petaluma	Hybrid	BC	298,198	123,156	599,935	248	69	21
Petaluma	Hybrid	BH	319,099	110,010	641,985	216	60	20
Petaluma	Hybrid	BCH	289,314	99,753	582,062	196	54	18

Petaluma	Hybrid	BCHR	289,314	99,753	582,062	196	54	18
Petaluma	Hybrid	BCHRJ	289,314	99,753	582,062	196	54	18
Petaluma	Renewable	B	164,935	64,492	331,826	125	25	14
Petaluma	Renewable	BC	150,901	49,285	303,593	93	16	11
Petaluma	Renewable	BCH	147,826	39,065	297,406	70	10	10
Petaluma	Renewable	BCHR	147,826	39,065	297,406	70	10	10
Petaluma	Renewable	BCHRJ	147,826	39,065	297,406	70	10	10
Baton Rouge	Diesel	B	2,519,019	1,162,839	5,067,932	3,557	2,880	278
Baton Rouge	Hybrid	B	2,519,019	1,162,839	5,067,932	3,557	2,880	278
Baton Rouge	Hybrid	BC	1,865,863	849,275	3,753,870	2,608	2,094	205
Baton Rouge	Hybrid	BH	2,227,186	1,017,733	4,480,803	3,128	2,510	245
Baton Rouge	Hybrid	BCH	1,056,456	409,740	2,125,449	1,403	911	114
Baton Rouge	Hybrid	BCHR	1,056,456	409,740	2,125,449	1,403	911	114
Baton Rouge	Hybrid	BCHRJ	1,056,456	409,740	2,125,449	1,403	911	114
Baton Rouge	Renewable	B	412,103	177,313	829,096	509	436	46
Baton Rouge	Renewable	BC	344,107	124,581	692,297	377	272	39
Baton Rouge	Renewable	BH	397,485	128,738	799,688	439	266	42
Baton Rouge	Renewable	BCH	337,426	106,984	678,857	368	212	37
Baton Rouge	Renewable	BCHR	337,426	106,984	678,857	368	212	37
Baton Rouge	Renewable	BCHRJ	337,426	106,984	678,857	368	212	37

Note: B= Bill Savings; C= Climate; H= Health; R=Resilience; J=Jobs

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