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Optimal design of a distributed energy resource system that economically reduces carbon emissions

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HIGHLIGHTS

- Analysis on minimum cost to reduce carbon emissions using optimization is explored.
- Novel utility rate, generator state, and transportation constraints are presented.
- The effect of export price of electricity is explored.
- The cost to reduce CO_{2e} emissions is determined for different technology scenarios.
- Optimal technology adoption trajectories are established for the same scenarios.

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ABSTRACT

Distributed energy resources (DER) are commonly associated with reduced CO_{2e} emissions. The decision to design such a system that reduces emissions typically results in increased costs. In order to economically select and operate a DER system that also reduces CO_{2e} emissions, a mixed integer linear program for sizing and dispatching a DER system was developed and used with real data to determine the optimal DER design that reduces emissions at the lowest cost. The optimization program includes a novel formulation of constraints that govern utility natural gas, generator operation, and interaction with fleet vehicles. The results show that the least expensive way of reducing CO_{2e} is through the use of renewable gas in a conventional combined heat and power engine (i.e., a gas turbine), resulting in a cost to reduce emissions of between \$120 and \$150 per CO_{2e} tonne. Reducing emissions further requires the adoption of higher efficiency generators, or renewable generators, increasing cost of CO_{2e} by up to \$475 per tonne. Allowing for electrical export and the offset of grid operations results in the purchase of less energy storage, reducing the cost of CO_{2e} to \$190 per tonne under retail electricity rates, or \$230 per tonne when the DER operator sends excess renewables back to the utility grid for free. Finally optimization results for this particular case indicate that changes to the transportation system occur last since the marginal costs of changing fleet vehicles is highest versus the CO_{2e} reduction benefit.

1. Introduction

In 2013, the University of California system committed to "…emitting net zero greenhouse gases (GHG) from its buildings and vehicle fleets by 2025…" [1]. This commitment was made in support of California State Law aimed at reducing GHGs [2], and to address the "…growing environmental crisis…" created by climate change [1]. In order to reach this goal, the UC system is considering numerous on- and off-campus options aimed at reducing GHG emissions, including the use of solar power on- and off-campus, and the use of biogas fuel.

Ideally, the path towards carbon neutrality would simultaneously consider all University of California campuses, medical centers, and national laboratories. However, major decisions are made at the campus level, and the resolution required for some decisions, such as the types and quantities of renewable distributed energy resources (DER) to adopt at each institution, require a more granular approach. DER includes distributed generation (DG), including small gas turbines (GT) and fuel cells (FC) with waste heat recovery through a heat recovery unit (HRU), solar photovoltaics (PV), combined with various types of electrical and/or thermal energy storage (EES and TES, respectively). Considering that many institutions and communities around the world also desire to reduce their GHG emissions in a cost-effective manner, it is important to understand the technology mixes that help reduce GHGs at the campus or community level for the lowest

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Nomenclature

agg	aggregated
Bldg	building
Boil	boiler
cap	capital cost
chrg	charging (energy storage)
con	conventional vehicle
dchrg	discharging (energy storage)
ex	electrical export
DER	distributed energy resource
DERopt	distributed energy resource optimization
DG	distributed generation
EES	electric energy storage
EVSE	electric vehicle supply equipment
FC	fuel cell
GHG	greenhouse gas
GT	gas turbine
HRU	heat recovery unit
MILP	mixed integer linear program
ng	natural gas
NEM	net energy metering
OM	operations and maintenance
PEB	plugin electric bus
PV	photovoltaic
req	required
rng	renewable natural gas
SCE	Southern California Edison
SCG	Southern California Gas
TES	thermal energy storage
TOU	time of use
UC	unconstrained
UCI	University of California, Irvine
VC	vapor compression
veh	vehicle

possible cost.

Current literature presents numerous methods for DER system design and dispatch. Heuristic design and dispatch methods have been developed to use statistical [3] or physical models [4] to evaluate systems, design dynamic dispatch strategies [5,6], and to also quickly examine the performance of different DER system configurations in different climate zones [7–9]. Also, extensive DER system and dispatch work that uses optimization methods have been presented. Models using linear programming have been developed to optimize the design of DER systems [10–12], as well as DER system operation [13]. Linear formulations have also been to proposed to minimize cost and GHGs associated with an energy demand while accounting for demand stochasticity and DER reliability [14].

One of the most popular methods for DER system design and operation optimization is mixed integer linear programming (MILP). This type of formulation can be used to capture the combination of discrete (i.e., number of generators purchased) and continuous (i.e., DG part load power setting) decisions that form a DER optimization problem. Dispatch models have been produced using MILP to minimize operating cost [15–17] and GHG emissions [16]. Prior MILPs that do not explicitly address GHG emissions account for the design of additional utility systems [18,19], legal constraints on DER system design [20], coproduction of chemicals [21], DG part load efficiencies [22], and renewable energy source [23] or electrical energy storage (EES) [24]. MILP formulations that include GHG emissions in the cost function [25–27], or as a constraint for limiting total emissions [28] have been presented. One popular and widely used formulation is known as the Distributed Energy Resource – Customer Adoption Model, which includes combined cooling heat and power components, renewable energy sources, EES, TES, electric vehicle interactions [29–37]. The cost function used by DER-CAM allows for minimization of cost, GHG emissions, or a combination of both through the use of weighting factors.

Finally, other nonlinear formulations have been presented that include DG part load efficiency [38–40] and nonlinear TES behavior [40]. Pruitt et al. [40] in particular, showed that optimal DER system design models can be improved through the inclusion of physical phenomena that affect DER operation. However, while the additional complexity generally produces more robust and realistic results, computational time is usually increased [40].

The current work expands upon prior DER system optimization work with the desire to address the University of California net zero GHG commitment. Since the focus of this work is DER technologies, some options, such as purchasing wholesale electricity from renewable sources (which are being evaluated by the University of California [41]), are not addressed. Also, it is assumed that energy efficiency measures have already been widely implemented since these technologies tend to be cost-effective ways of reducing energy demand. For example, the University of California, Irvine campus has deployed deep energy efficiency measures to reduce demand by more than 50% [42].

In this work, a MILP called the Distributed Energy Resource optimization (DERopt) model is developed to minimize the cost of energy. DERopt includes a novel formulation for utility natural gas cost, TES, GT and FC operational state, and interaction with fleet vehicles, such as public transportation buses.

Solar PV systems, renewable gas, electrical export, and alternative fuel vehicles are considered for possibly reducing GHG emissions. The MILP is then exercised using real data for the University of California, Irvine (UCI) campus to determine the optimal DER system for adoption that minimizes cost while reducing GHG emissions.

2. Models

For the purpose of this work, all GHG emissions are quantified in terms of the equivalent amount of carbon dioxide emissions, CO_2 equivalent, or CO_{2e}.

2.1. UCI campus energy model

2.1.1. Central plant & building energy demand dynamics

A central cogeneration plant is currently operated at UCI to meet nearly all of the campuses electrical, heating, and cooling demands. The central plant consists of a 13.5 MW gas turbine, heat recovery steam generator, 5.5 MW steam turbine, eight vapor compression chillers that have a combined capacity of 16,680 tons of cooling, and a cold TES with 60,000 ton-hours of storage [43,44]. The central plant supplies hot and cold water to the campus through a district heating and cooling system that delivers energy to all of the major buildings on campus. In addition to the central plant, over 4 MW of solar PV has been installed across the campus.

Extensive monitoring equipment has been installed throughout the plant and across the campus. This monitoring capability has led to the collection of 15 min averaged electrical, heating, and cooling demand for the entire UCI campus from 2009 to the present. The amount of captured data would be difficult to directly use in the MILP proposed in Section 2.3. Instead, k- medoids clustering method that uses a similar structure to a typical facility location problem was built based on the work presented in [45] was built and used to filter the large set of data to a smaller, but representative data set. The filtering method reduces 12 months of 15 min data down to three months, allowing for the