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Using CO_2-Plume geothermal (CPG) energy technologies to support wind and solar power in renewable-heavy electricity systems

Anna C. Van Brummen [a,*], Benjamin M. Adams [a], Raphael Wu [b], Jonathan D. Ogland-Hand [a], Martin O. Saar [a,c,*]

[a] ETH Zurich, Geothermal Energy and Geofluids Group, Department of Earth Sciences Zurich, Switzerland
[b] ETH Zurich, Reliability and Risk Engineering, Department of Mechanical and Process Engineering, Zurich, Switzerland
[c] University of Minnesota, Department of Earth and Environmental Sciences, Minneapolis, MN, USA

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ABSTRACT

CO_2-Plume Geothermal (CPG) technologies are geothermal power systems that use geologically stored CO_2 as the subsurface heat extraction fluid to generate renewable energy. CPG technologies can support variable wind and solar energy technologies by providing dispatchable power, while Flexible CPG (CPG-F) facilities can provide dispatchable power, energy storage, or both simultaneously. We present the first study investigating how CPG power plants and CPG-F facilities may operate as part of a renewable-heavy electricity system by integrating plant-level power plant models with systems-level optimization models. We use North Dakota, USA as a case study to demonstrate the potential of CPG to expand the geothermal resource base to locations not typically considered for geothermal power. We find that optimal system capacity for a solar-wind-CPG model can be up to 20 times greater than peak-demand. CPG-F facilities can reduce this modeled system capacity to just over 2 times peak demand by providing energy storage over both seasonal and short-term timescales. The operational flexibility of CPG-F facilities is further leveraged to bypass the ambient air temperature constraint of CPG power plants by storing energy at critical temperatures. Across all scenarios, a tax on CO_2 emissions, on the order of hundreds of dollars per tonne, is required to financially justify using renewable energy over natural-gas power plants. Our findings suggest that CPG and CPG-F technologies may play a valuable role in future renewable-heavy electricity systems, and we propose a few recommendations to further study its integration potential.

Nomenclature for this manuscript is provided in Table 1.
Word Count: 7,147

1. Introduction

1.1. Motivation and background

Current climate concerns require transitioning from the present electricity system to one that emits much less carbon dioxide (CO_2) as an electricity generation byproduct [1–4]. Wind turbines and solar photovoltaics (PVs) will likely generate a substantial portion of electricity in the future, but there is increasing evidence that least-cost decarbonized electricity systems will also include other technologies and processes to complement variable renewable energy production. For example, energy storage (e.g., batteries) can reduce the required energy generation by storing excess electricity generation and then dispatching that stored electricity hours or months later when it is in demand [5–8]. Technologies that can provide dispatchable, or "firm," electricity when the wind is not blowing or the sun is not shining (e.g., geothermal power plants), also have potential to reduce the cost of decarbonizing electricity by reducing system sizes and increasing reliability [9–11]. CO_2 capture and storage (CCS), which is the process of capturing CO_2 that would otherwise be emitted to the atmosphere and injecting it into geological formations for permanent storage, may also provide cost-conscious options for decarbonizing electricity [1,2,4,12].

CO_2-Plume Geothermal (CPG) technology could be used in these roles to support variable renewable energy technologies by *using* geologically stored CO_2 [13–18]. For example, CPG power plants can provide dispatchable power: CO_2 that was geologically sequestered in a sedimentary basin geothermal resource is intentionally produced to the land surface and the geothermal energy in the CO_2 is used to generate electricity in a geothermal power plant. After power production, the

* Corresponding authors.
E-mail addresses: anna.vanbrummen@gmail.com (A.C. Van Brummen), saarm@ethz.ch (M.O. Saar).

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Table 1
The above table lists all the nomenclature used in the following text.

Variable	Units	Name
n_S	[MW/MW$_{max\ demand}$]	Normalized Capacity of Solar Energy Technologies
n_W	[MW/MW$_{max\ demand}$]	Normalized Capacity of Wind Energy Technologies
n_{CPG}	[MW/MW$_{max\ demand}$]	Normalized Capacity of CPG Power Plants
n_{CPG-F}	[MW/MW$_{max\ demand}$]	Normalized Capacity of CPG-F Facilities
$NO_{s,t}$	[dim]	Hourly Capacity Factor of Solar Energy Technologies in hour t
$NO_{w,t}$	[dim]	Hourly Capacity Factor of Wind Energy Technologies in hour t
$NO_{CPG,t}$	[dim]	Hourly Capacity Factor of CPG Energy Technologies in hour t
ND_t	[MW/MW$_{max\ demand}$]	Normalized Electricity Demand in hour t
$P_{ESprod,t}$	[MW/MW$_{max\ demand}$]	Normalized Power Produced by the CPG-F Facility Operating To Provide Energy Storage in hour t
cc_s	[\$/MW$_e$]	Specific Capital Cost of Solar Energy Technologies
cc_w	[\$/MW$_e$]	Specific Capital Cost of Wind Energy Technologies
cc_{CPG}	[\$/MW$_e$]	Specific Capital Cost of CPG Power Plants
cc_{CPG-f}	[\$/MW$_e$]	Specific Capital Cost of CPG-F Facilities
cc_{ng}	[\$/MW$_e$]	Specific Capital Cost of Natural Gas Power Plants
X	[dim]	Percent of Normalized Electricity Demand that Can be Met-with the External Power Source
D	[MWh/yr-MW$_{max\ demand}$]	Total Annual Normalized Electricity Demand
G	[MWh/yr-MW$_{max\ demand}$]	Total Annual Normalized Generation From External Power Source
R	[tCO$_2$/MWh]	Natural Gas Power Plant CO_2 Emission Rate
Y	[Years]	Assumed Lifetime of Power System

produced CO_2 is cooled, condensed, and re-injected into the subsurface reservoir. As a result, none of the produced CO_2 is emitted to the atmosphere.

Additionally, CPG technology can use geologically stored CO_2 to provide energy storage, or both energy storage *and* dispatchable power simultaneously, with Flexible CPG (CPG-F) facilities [19,20]. In CPG-F facility operation, geothermally heated CO_2 is produced to the surface and expanded through a turbine to generate dispatchable electricity, like in a CPG power plant, and then this CO_2 is either a) injected into a second, shallower sedimentary basin geothermal resource for temporary storage, or b) expanded through another turbine to generate more dispatchable electricity, before being cooled and re-injected into the primary subsurface reservoir. Any CO_2 temporarily stored in the shallower reservoir is later produced back to the land surface, cooled, and re-injected into the primary reservoir. This temporary storage allows operators to provide energy storage because it time-shifts the parasitic cooling and pumping power loads. Because it is possible to only divert a portion of the CO_2 to the second reservoir for temporary storage, it is possible for CPG-F facilities to provide energy storage and dispatchable power *simultaneously* (Fig. 1).

In addition to the capability of CPG technology to support variable wind and solar energy technologies, there are other unique benefits of CPG that may be valuable to electricity system decarbonization efforts. First, sedimentary basins, which is the broad name for the saline aquifers targeted for CCS and CPG, are ubiquitous (e.g., underlying half of North America [21,22]), but they have not conventionally been used for geothermal power generation because they are generally colder than conventional geothermal resources. For example, the 2019 U.S. D.O.E. GeoVision report excluded these resources when estimating the geothermal electricity generation potential of the U.S. [23]. In addition, prior work has shown that the heat in the sedimentary basins can be more efficiently extracted if CO_2 is used as the heat extraction fluid instead of brine [15,24]. CPG technology could expand the geothermal energy base to locations where geothermal power plants are not typically considered options for cost-competitive electricity generation, thus expanding the contribution that geothermal power may make for supporting variable renewable energy technologies [25].

Second, CPG-F facilities operating for energy storage can generate power during hot hours of the year. The dispatchability of any thermal

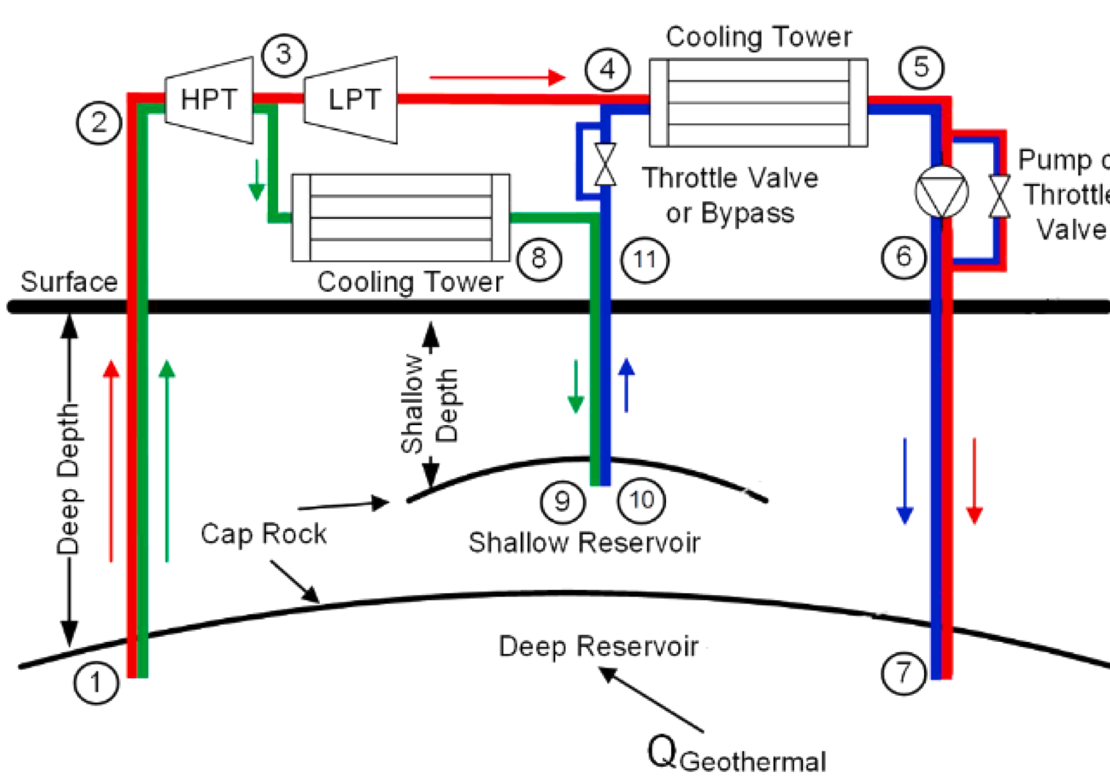

Fig. 1. The above figure is taken with permission from Fleming et al. [19] on modeling and determining the efficacy of CPG-F systems. Steps 1–7 represent the CPG-only system, while steps 8–11 can be added to transform a CPG system into a CPG-F system.

generation technology (i.e., fossil-fuel power plant, geothermal power plant, nuclear power plant) can be constrained on hot days if the temperature difference between the heat source (i.e., geothermal heat, fossil fuel burn) and heat sink (i.e., atmosphere) is too low. This constraint is a larger issue for geothermal power plants compared to fossil-fuel power plants, for example, because the subsurface is colder than the temperature at which fossil fuels burn [26]. But, when CPG-F facilities operate to provide energy storage, the CO_2 is not immediately cooled because it is temporarily stored in the second reservoir [19,20]. As a result, the turbine back pressure of the CPG-F facility is independent of the ambient air temperature and CPG-F can generate electricity during hot days. In other words, CPG-F facilities could support variable wind and solar energy technologies on hot days when geothermal power generation would otherwise be constrained to a low, or zero, capacity factor.

Third, CPG-F facilities are also capable of providing long-duration energy storage over seasonal timescales because sedimentary basins have more than sufficient pore-volumes to store weeks or months worth of compressed CO_2, and thus energy. While there is growing recognition that long-duration energy storage could provide value in renewable-heavy electricity systems by time-shifting electricity generation over seasonal timescales [7,8], there are limited technologies available to provide this service. CPG technology could provide energy storage services over durations that other energy storage approaches cannot, thus supporting variable renewable energy technologies in a way that is currently lacking.

1.2. Scope and contributions of paper

In this paper, we investigate the potential that CPG technology may have for supporting variable renewable energy technologies by finding the capacity of solar, wind, and CPG energy generation technologies to meet the electricity demand under a variety of electricity demand and external power option scenarios. This contribution is novel in multiple ways. First, it is the first study to investigate the feasibility of using CPG technology in a location not typically considered for having geothermal resources amenable to power generation. Thus, it is the first study to investigate the ability of CPG technology to expand the geothermal resource base. Second, it is also the first study to model CPG power plants and CPG-F facilities operating as part of the electricity system. Our prior work has designed and optimized CPG power plants and CPG-F facilities, but no one has studied what role these technologies may play as components of the electricity system. Section 2 describes the models that we built and integrated for this purpose and the case study we picked to highlight the potential of CPG technologies to provide geothermal electricity generation in locations where geothermal resources are not considered viable (i.e. economic). We present and discuss our results in Section 3 and summarize our primary conclusions and avenues for future work in Section 4.

2. Methodology

We integrate results from plant-scale geothermal power generation simulations with grid-level linear, or mixed-integer linear, optimization models to investigate the capacities of wind, solar, and geothermal energy technologies needed to supply annual electricity demand for three different objectives: 1) no curtailment of electricity generated by wind or solar energy technologies, 2) minimize the total electricity generated, and 3) minimize total capital cost. Within each scenario, we include three cases of how much of the total electricity demand must be met with wind, solar, or CPG energy technologies: a) 100%, b) 80%, and c) 50%. We include these cases because it is likely that future decarbonized electricity systems will include non-renewable energy technologies such as flexible nuclear power plants or fossil-fuel power plants equipped with CO_2 capture and (geologic) storage (CCS) [9,10]. Because CPG-F facilities can be operated to provide energy storage services and energy storage can change the optimal deployment and dispatch of electricity systems [6,27], we also include a case when total electricity generation or total capital costs are minimized under 100% renewable electricity scenarios where CPG-F facilities are available instead of conventional CPG power plants.

In the cases where capital costs are minimized, we calculate a break-even CO_2 tax. This metric estimates the CO_2 tax required to equate the cost of meeting demand by electricity generated with renewable energy technologies to the cost of electricity generated using natural-gas turbines, assuming the cost of natural-gas power plants increases proportionally to the rate at which they emit CO_2. A positive break-even CO_2 tax implies that a CO_2 tax would be required to justify, on a cost basis, using renewable energy technologies to meet demand instead of natural-gas power plants. For this calculation, we also assume the external power providing up to 20% or 50% of electricity demand was generated by natural-gas power plants.

We use Rugby, North Dakota, USA, as a location case study for two reasons. First, Rugby is the geographic center of the North American continent and is not well-known for its geothermal resources, despite having sedimentary basin geothermal energy resources favorable for electricity generation with CPG technology. In other words, we chose Rugby, ND to illuminate the ability of CPG technology to expand the geothermal energy resource base to locations that do not currently use geothermal energy resources for electricity generation. Secondly, the population of Rugby, ND primarily relies on electricity for heat supply, which results in an electricity demand profile that is at a maximum in the winter (i.e., "winter-peaking"). While this seasonal electricity demand relationship is in contrast to most of the United States, where peak demand occurs in the summer (i.e, "summer-peaking") because fossil-fuel is burned for heat, it is possible that winter-peaking demand will become more common as a result of electrification of the heating sector [28], or of deep penetration of solar PV [29]. As a result, investigations into winter-peaking demand electricity systems may become more important in future decarbonized energy and electricity systems. An example is Switzerland, where electricity demand is higher in the winter than in the summer, at least in part due to ground-sourced heat pumps' electricity demand [30]. In addition, we execute our framework using electricity demand data from Midcontinent Independent System Operator (MISO), which peaks in the summer, because many parts of North Dakota are within the area that is managed by MISO. As a consequence of using both winter-peaking demand and summer-peaking demand data, we maximize the generalizability of our findings across uncertainties in future electricity peak demand.

Section 2.1 describes the optimization models that we created and used to estimate the capacity of wind, solar, and CPG energy technologies needed to meet demand and Section 2.2 describes the method used to estimate the break-even price of CO_2. Section 2.3 presents the data that we generated or obtained to characterize the optimization models for our case study. Section 2.4 describes our sensitivity analysis, which included executing our framework across different weather-years for the summer-peaking demand data.

2.1. Estimated capacity of wind, solar, and geothermal energy technologies required to meet demand

We built and used different optimization models to estimate the renewable energy capacity in each scenario: no curtailment of electricity generated by wind and solar energy technologies (Section 2.1.1); minimize total electricity generation (Section 2.1.2); and minimize total capital costs (Section 2.1.3). These optimization models are simple and transparent, which is appropriate for this study considering that the primary methodological contribution is the integration of the CPG plant-scale results with grid-level optimization models. For example, we follow prior work and do not account for power transmission losses or unit-level constraints in the optimization and assume perfect foresight of demand and weather conditions [31,32]. The primary inputs in all optimizations were the normalized annual electricity demand and the annual capacity factors of wind, solar, and CPG power plants. We normalized the input demand data by the maximum annual demand to simplify the comparison of our results across the winter-peaking (i.e., Rugby) and summer-peaking (i.e., MISO) electricity demand scenarios.

2.1.1. No curtailment of electricity generated by wind or solar energy technologies

In the first scenario, we investigate the capacity of wind, solar, and geothermal energy technologies that are needed to avoid curtailing any electricity generated by wind and solar energy technologies by performing two optimizations. In the first optimization, we find the maximum capacity of wind and solar energy technologies that do not generate more electricity than is demanded by maximizing the capacities of wind and solar energy technologies:

$$\max \sum_{t=1}^{T} n_s \times NO_{s,t} + n_w \times NO_{w,t} \tag{1}$$

subject to:

$$n_s \times NO_{s,t} + n_w \times NO_{w,t} \le ND_t \qquad \forall t = 1, \ldots, T \tag{2}$$

where n_s and n_w are the decision variables and represent the normalized capacities of solar and wind energy technologies, respectively [MW/MW$_{\text{max demand}}$]. $NO_{s,t}$ and $NO_{w,t}$ are the hourly capacity factors for wind and solar energy technologies, respectively, throughout the year [dim], and ND_t is the normalized electricity demand for every hour of the model horizon [MW/MW$_{\text{max demand}}$]. These three variables are inputs to the model.

We then use the capacity estimates (i.e., n_s and n_w) in a second optimization to estimate the capacity of geothermal energy technologies needed to meet demand without curtailment by minimizing the capacity of CPG power plants:

$$\min \sum_{t=1}^{T} n_{cpg} \times NO_{cpg,t} \tag{3}$$

subject to:

$$n_s \times NO_{s,t} + n_w \times NO_{w,t} + n_{cpg} \times NO_{cpg,t} \ge ND_t \qquad \forall t = 1, \ldots, T \tag{4}$$

The only decision variable in this second optimization is the normalized capacity of CPG power plants, n_{cpg} [MW/MW$_{\text{max demand}}$]. $NO_{cpg,t}$ are the hourly capacity factors of geothermal energy generation throughout the year, an input to the model. Executing this optimization finds the minimum capacity of CPG power plants required to supply electricity in the hours that it cannot be met with wind and solar energy generation alone.

2.1.2. Minimize electricity generation

In the second scenario, curtailment of electricity generated by wind and solar energy technologies is allowed and we minimize the total amount of electricity generated:

$$\min \sum_{t=1}^{T} n_s \times NO_{s,t} + n_w \times NO_{w,t} + n_{cpg} \times NO_{cpg,t} \tag{5}$$

subject to:

$$n_s \times NO_{s,t} + n_w \times NO_{w,t} + n_{cpg} \times NO_{cpg,t} + X \ge ND_t \qquad \forall t = 1, \ldots, T \tag{6}$$

where n_s, n_w, and n_{cpg} are decision variables that represent the normalized capacities of solar energy technologies, wind energy technologies, and CPG power plants, respectively [MW/MW$_{\text{max demand}}$]. $NO_{s,t}$, $NO_{w,t}$, $NO_{cpg,t}$, and ND_t are inputs to the model and remain unchanged from Eq. (4). X is also an input to the model and is the percent of electricity demand that can be met with an external power source in any given hour of the year (e.g., $X = 0.2$ for the 80% renewable energy scenarios).

The optimization model is different in the case where CPG-F facilities are available instead of CPG-only power plants to account for the operational flexibility of CPG-F facilities. In the CPG-F case, the objective function changes to:

$$\min \sum_{t=1}^{T} n_s \times NO_{s,t} + n_w \times NO_{w,t} + n_{cpg} \times NO_{cpg,t} + P_{ESprod,t} \tag{7}$$

where $P_{ESprod,t}$ is an additional decision variable and is the normalized power produced by the CPG-F facility operating to provide energy storage during hour t [MW/MW$_{\text{max demand}}$]. Modeling the CPG-F facility in the optimization model also required adding many more constraint equations compared to the optimizations with CPG-only power plants and we provide a full description of these equations in the Appendix.

2.1.3. Minimize capital cost

In the third and final scenario, curtailment of electricity generated by wind and solar energy technologies is allowed and we minimize the total capital costs of the electricity system:

$$\min \sum_{t=1}^{T} n_s \times cc_s + n_w \times cc_w + n_{cpg} \times cc_{cpg} \tag{8}$$

subject to:

$$n_s \times NO_{s,t} + n_w \times NO_{w,t} + n_{cpg} \times NO_{cpg,t} + X \ge ND_t \qquad \forall t = 1, \ldots, T \tag{9}$$

where n_s, n_w, and n_{cpg} are the decision variables, representing the normalized capacities of solar energy technologies, wind energy technologies, and CPG power plants, respectively [MW/MW$_{\text{max demand}}$]. Variables cc_s, cc_w, and cc_{cpg} are the capital costs of the different energy technologies [$/MW] and are inputs to the model. The other inputs to this optimization remain unchanged from the optimizations performed in the scenarios where electricity generation is minimized (Section 2.1.2).

In the case where CPG-F facilities are included, the objective function changes to:

$$\min \sum_{t=1}^{T} n_s \times cc_s + n_w \times cc_w + n_{cpg-f} \times cc_{cpg-f} \tag{10}$$

where n_{cpg-f} is the normalized capacity of the CPG-F facility, which is a decision variable [MW/MW$_{\text{max demand}}$], and cc_{cpg-f} is an input to the model and is the capital cost of the CPG-F facility [$/MW]. The other decision variables and inputs remain unchanged from the case where CPG-only power plants are used (Eq. (8)). This optimization model is solved using the same constraint equations as the optimization model with CPG-F facilities in Section 2.1.2, which are provided in the Appendix.

2.2. Estimated break-even CO_2 tax

In this study, we define the break-even CO_2 tax, A [$/t$CO_2$], with Eq. (11):

$$A = \frac{n_s \times cc_s + n_w \times cc_w + n_{cpg} \times cc_{cpg} + n_{cpg-f} \times cc_{cpg-f} - (1 - X) \times cc_{ng}}{(D - G) \times R \times Y} \tag{11}$$

where cc_{ng} is the assumed capital cost of natural gas power plants [$/MW], D is the total annual normalized electricity demand [MWh/yr-MW$_{\text{max demand}}$], G is the total annual normalized generation from the external power source as estimated with the optimization model [MWh/yr-MW$_{\text{max demand}}$], R is the assumed CO_2 emission rate from natural gas power plants [tCO_2/MWh], and Y is the assumed lifetime of the system [years]. Only a portion of the variables in Eq. (11) may be needed to calculate the break-even CO_2 tax in any given renewable energy percentage case. For example, when 100% of electricity demand must be met with renewable energy sources, X and G are zero. While both CPG-only power plants and CPG-F facilities rely on using geologically stored CO_2 to provide electricity generation or energy storage, we do not assume that the capital cost of these technologies decreases for providing CO_2 storage services, which could be a significant income source. Similarly, we assume no cost of condensed CO_2.

For this study, we assume the system lifetime, Y, is 30 years and the natural-gas CO_2 emission rate, R, is 0.51 tCO_2/MWh [33].

2.3. Data

2.3.1. Electricity demand and capacity factors of wind and solar energy technologies

Electricity demand data for the city of Rugby (North Dakota, USA) from 2010 was obtained from the Otter Tail Power Company (OTPC) [34]. We used 2010 data specific to Minot, ND (about 60 miles east of Rugby) from the Western Wind Dataset and National Solar Radiation Database to obtain wind and solar energy technology capacity factors because this was the closest available location to Rugby in those datasets [35,36]. Capacity factors are defined as the percent of total capacity that is available in any hour to generate electricity. For example, a 20 MWe wind farm can produce 10 MWe of power in instances (in this study, hours) when the capacity factor is 50%.

We designated these 2010 datasets as baseline data. A summary of our baseline datasets is given in Table 2. In this study, we use a time resolution of one hour because the solar and demand datasets were available with this resolution. We used averages across the hour for any input dataset that was available at resolutions finer than one hour.

2.3.2. Capacity factors of CO_2 plume geothermal (CPG) power plants

We generate hourly capacity factor data to input to the optimizations using a CPG power plant model from our prior work [15,25] and the ambient air temperature data from the Western Wind Dataset [35]. The CPG power plant model was characterized with data specific to our Rugby case study and used to determine the power output as a function of ambient air temperature. Then the ambient air temperature data from the Western Wind Dataset was used to estimate the capacity factor of a CPG power plant operating in Rugby over the year using curve fit approximations of the data [25].

To characterize the CPG power plant model, we assumed that all CPG power plants were constructed so they use the Winnepegosis sedimentary basin geothermal resource, which underlies the area near Rugby. The Winnepegosis basin is large (i.e., 11-million acre formation with the potential to sequester 60 $GtCO_2$) and we assumed homogeneous subsurface reservoir properties of 3.05 km depth, 275 m thickness, 10 mD permeability, and a temperature of 117 °C, based on a geologic temperature gradient of 35 °C/km and a 10 °C mean annual surface temperature [37].

In our model, we also limit the condensing temperature of the wet cooling tower to a minimum of 7 °C to safely keep it from freezing in subzero ambient air temperature conditions. Thus, the approach temperature difference of the condensing tower is allowed to increase above 7 °C for ambient air temperatures below 0 °C. This results in lower cooling tower parasitic fan loads in subzero ambient air temperatures, but with a maximum gross turbine power generated. In other words, these assumptions mean than the CPG power plants we model in this study cannot fully utilize the low ambient air temperature. The use of a dry cooling tower during subzero operation would allow for condensing temperatures less than 0 °C, but we assumed wet cooling towers because dry cooling towers cost substantially more, both in capital cost and parasitic power requirements.

We did not simulate CPG-F facilities in as much detail as the CPG-only power plants in this study. Instead, we followed our prior work that suggests CPG-F facilities when operating for energy storage could generate or store up to 1.2 times more electricity than could be generated with a CPG power plant operating with 100% capacity factor [19,20]. As a result, we used this 1.2 multiplication factor and the estimated CPG capacity factors to constrain CPG-F facilities in our optimizations. This prior work also suggests that the cooling tower that is used when the CPG-F facility is generating electricity while operating to provide energy storage services is used much less than the cooling tower that is used when the CPG-F facility is storing energy. As a result, the turbine backpressure of the CPG-F facility is independent of ambient air temperature because the CO_2 is stored in the shallow reservoir and not immediately cooled. In other words, we assumed that the ambient air temperature constraints of CPG-only power plants do not apply to CPG-F facilities when they are generating electricity while operating to provide energy storage services.

Table 2
Overview of baseline data.

Dataset	Units	Max.	Min.	Mean	Source
Demand	MWe	13.8	2.4	6.06	OTPC [34]
Temperature	°C	40.8	-38.9	4.81	NREL [35]
Wind	MWe	2	0	0.864	NREL [35]
Solar	Wh/m^2	963	0	168	NREL [36]

2.3.3. Costs

The specific capital costs we assumed for this study are given in Table 3.

We include two capital costs for CPG power plants (i.e., brownfield and greenfield) because we estimate the break-even CO_2 tax using both cost estimates to understand how this assumption may change the CO_2 tax required to justify using renewable energy technologies instead of natural-gas power plants. The brownfield cost estimate assumes that the CPG power plant is constructed on a pre-existing geologic CO_2 storage site and the greenfield cost estimate assumes the CPG power plant is constructed at a site with no prior CO_2 injection. With the exception of the few break-even CO_2 taxes that we calculated with greenfield cost estimates, all results presented in this study assume brownfield capital cost estimates of CPG-only power plants and CPG-F facilities.

2.4. Sensitivity analysis: Different weather-years

There is a growing understanding that the results of models that investigate renewable-heavy electricity systems are substantially sensitive to weather-year [27,39–42]. As a result, we performed a sensitivity analysis in this study by executing our optimization framework across different years of data when electricity demand peaks in the summer. Specifically, we apply our optimization framework using data from 2007, 2008, 2009, and an additional run using all four years together (i.e., 2007–2010) because these were additional years for which MISO demand data, solar capacity factors, wind capacity factors, and ambient air temperature data were available. Electricity demand data were not available outside 2010 for Rugby and as a result our sensitivity analysis does not incorporate winter-peaking electricity demand conditions. We

Table 3
Capital Costs Assumed for this Study. Unlike other technologies that can provide energy storage services, CPG-F facilities only have a power capital cost because there is no fuel cost [19]. All considered energy productions (solar, wind, CPG, CPG-F) have a fuel cost of $0/MWh.

Energy Technology	Variable	Capital Cost ($/MW)	Data Source
Solar	cc_s	$1.1\text{x}10^6$	Lazard [38]
Wind	cc_w	$1.35\text{x}10^6$	Lazard [38]
CPG (brownfield)	cc_{cpg}	$17\text{x}10^6$	Adams et al. [25]
CPG (greenfield)	cc_{cpg}	$29\text{x}10^6$	Adams et al. [25]
CPG-F	cc_{cpg-f}	$1.4 \cdot cc_{cpg}$	Fleming et al. [20]
Natural Gas	cc_{ng}	$0.85\text{x}10^6$	Lazard [38]

have not included (heat or electric) power performance or sensitivity analyses of CPG or CPG-F systems in the publication here, as we addressed such performance analyses in Randolph and Saar [14], Adams et al. [15], Garapati et al. [17], Ezekiel et al. [43], Ezekiel et al. [44], Fleming et al. [24] and Fleming et al. [19]. Furthermore, we conducted CPG parameter sensitivity analyses regarding power generation [45] as well as both power generation and reservoir heat depletion rates [18].

3. Results & discussion

The optimal capacities of wind and solar energy technologies, CPG-only power plants, and CPG-F facilities and the break-even CO_2 taxes are both a result in part of the hourly CPG capacity factors. As a consequence, we first describe the results of our plant-scale CPG-only model and our estimated hourly CPG capacity factors (Section 3.1) before presenting the optimal capacities required to supply the electricity demand, the results of our sensitivity analysis (Section 3.2), and the break-even CO_2 taxes (Section 3.3).

3.1. Estimated hourly CO_2 plume geothermal capacity factors

Fig. 2 shows the calculated net power generation of a CPG-only power plant operating in the Winnipegosis formation as a function of ambient air temperatures with relevant simulation equations . There is a discontinuity at 0 °C because we only allowed the approach temperature difference of the condensing tower to increase above 7 °C for ambient air temperatures below 0 °C. As a result of this discontinuity, we used two separate equations to approximate the relationship between net power generation and ambient air temperature.

Fig. 3 shows the hourly capacity factors and the normalized demand profiles for the 2010 baseline data that were input to the optimization models. The capacity factors for CPG-only power plants are zero during the hours of the year that have ambient air temperatures greater than 30 °C because the potential capacity of a CPG-only power plant at these temperatures is negative (Fig. 2). There were approximately ten “limiting hours” throughout the year in which ambient air temperatures were low that also coincided with low solar and wind capacity factors. The hourly capacity factors for CPG-only power plants are generally highest in the winter months because that is when ambient air temperature is lowest.

One reason we chose Rugby, ND as a case study was because the state of North Dakota does not have well-known geothermal resources favorable for electricity generation. The results in Figs. 2 and 3 suggest that North Dakota may have potential geothermal resources that could be used for power production using CPG technology. As a result, energy system modelers should be aware of CPG technology because it is likely more broadly deployable compared to other geothermal energy technologies. But future modelers should also be mindful that CPG power plants, like all geothermal power plants, may be unable to provide electricity to meet demand during hot days because the gross electricity generation is a function of the turbine backpressure, which in turn is a function of the ambient air temperature [26].

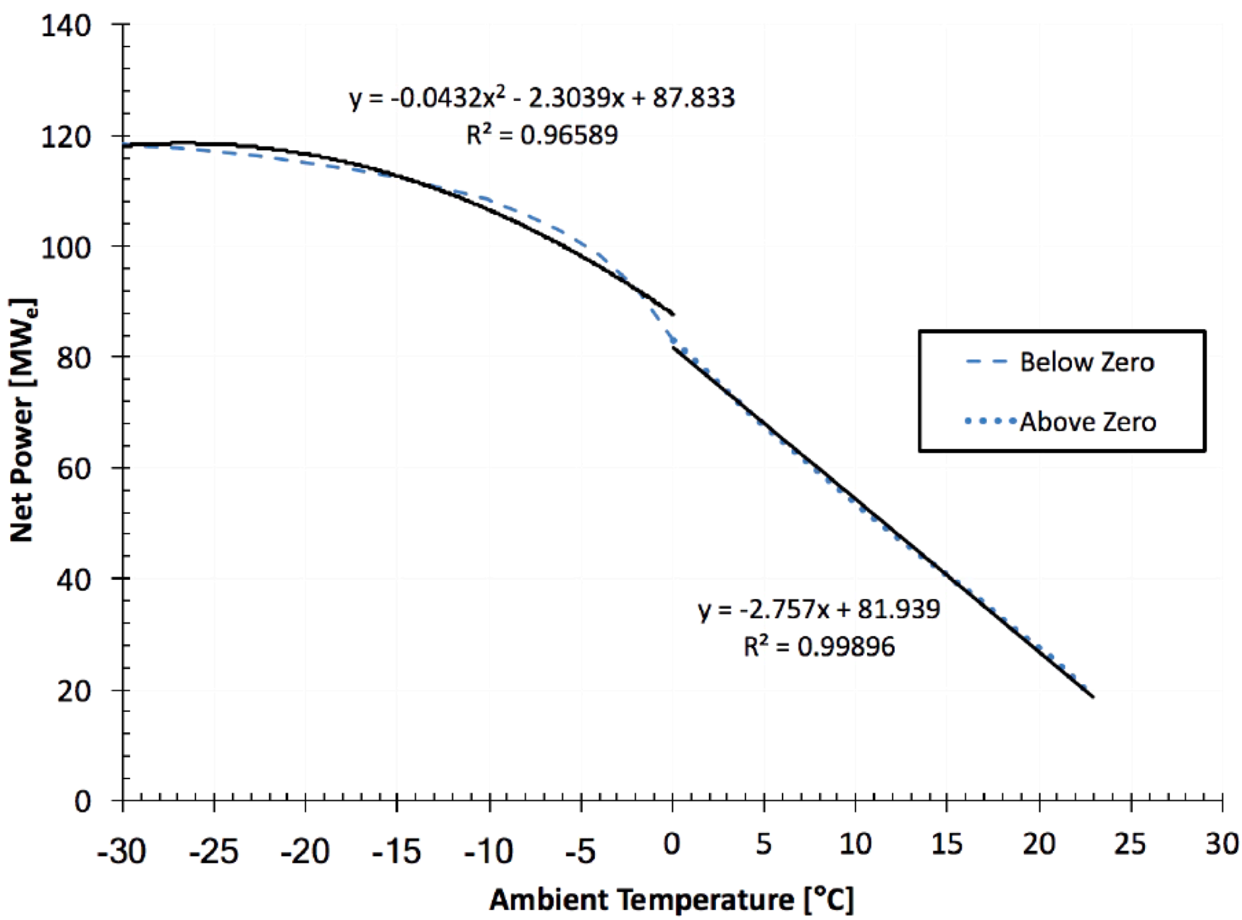

Fig. 2. Simulated power generation of a CPG-only power plant in the Winnipegosis Formation as a function of ambient air temperature (blue dotted and dashed line) and the curve fit approximations used to estimate CPG-only capacity factors in Rugby, ND (black lines) are plotted above. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

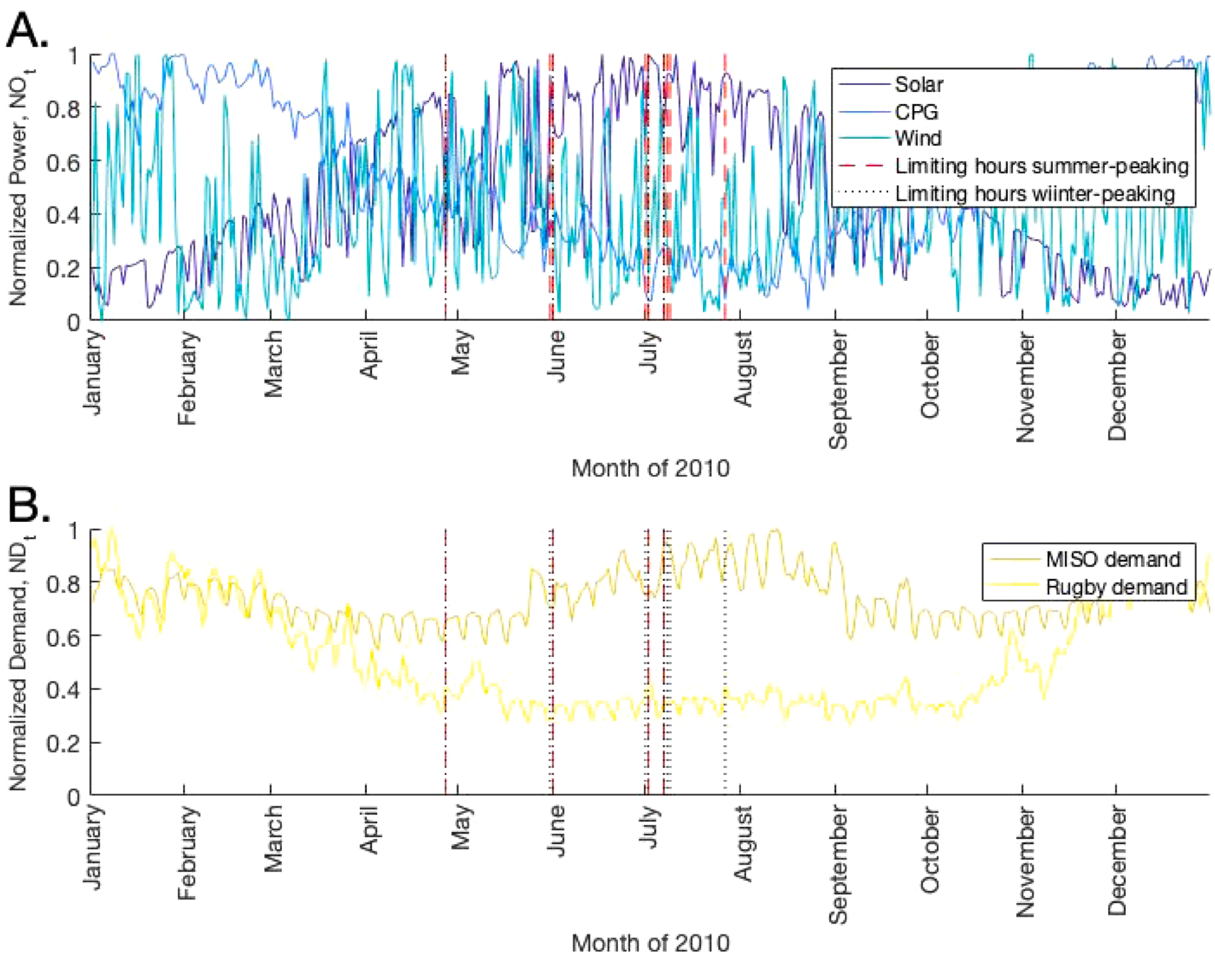

Fig. 3. The normalized A) capacity factors across the year for wind, solar, and CPG-only energy technologies and B) electricity demand are represented above.

3.2. Estimated optimal capacities of wind, solar, and CPG energy technologies

Fig. 4 shows the normalized capacities (e.g., n_s) of the power systems for each optimization that we performed using baseline data. Except for one case, all optimizations that did not allow curtailment of electricity generated with wind or solar energy technologies failed because there were hours in the summer during which the CPG power plants could not generate electricity due to ambient air temperatures exceeding 30 °C (Fig. 3). These temperature constraining hours did not cause the optimization to fail in the winter-peaking demand scenario in which 50% of demand could be met with external power because the demand was low enough during these summer hours that 50% of demand could be supplied by electricity generated with wind and solar energy. As a consequence, our results suggest that curtailment may be necessary for electricity systems that rely primarily on renewable energy technologies, even in locations with geothermal energy resources that are favorable to power generation.

In the other two optimization model scenarios, the total capacity required to meet demand was typically higher than peak-demand. For example, when electricity generation was minimized, the total normalized capacity of the entire system was about 5x and 11.5x higher than peak-demand in the winter-peaking and summer-peaking demand scenarios, respectively. This total capacity was much higher than peak-demand primarily because of a few “limiting hours” during which wind, solar, and geothermal capacity factors were all low or zero. As a result, the total installed capacity must be much greater than peak-demand so that there is sufficient supply of electricity during these hours.

The other two optimization model scenarios also show that total capacity was highest in the scenarios in which CPG power plants, wind energy technologies, and solar energy technologies supplied 100% of electricity demand. This relationship is also a result of the “limiting hours.” For example, as shown in Fig. 5, these “limiting hours” occur in the summer for the summer-peaking demand data, but have less influence on the overall system capacity when renewable energy technologies do not have to meet 100% of demand because the external electricity lessens the extent to which the limiting hours define the capacity of the system.

As shown in Fig. 4, in every case of all scenarios, the optimal power capacities were larger when demand peaked in the summer compared to when demand peaked in the winter. This occurred primarily because the hourly CPG power plant capacity factors were largest in the winter months compared to the summer months. For example, the CPG power plant capacity factors are at a minimum 65% across the winter months and as a result, if 1 normalized MWe of CPG-only power plant capacity was deployed, then CPG-only power plants could meet at least 65% of all electricity demand in the winter (Fig. 3). This finding suggests that CPG power plants could become more valuable for decarbonizing electricity if winter-peaking demand becomes more common.

Fig. 4 also shows that the optimal capacity mix is a function of the predefined percentage of electricity that must be supplied by renewable energy technologies. This result suggests that a predefined percentage of electricity generation that must come from renewable energy sources (e.g., a renewable portfolio standard) will likely influence the optimal mix of renewable energy sources deployed or dispatched. For example, as the percent of demand met with an external source increases, the capacity of CPG power plants decreases less compared to the capacity of solar energy technologies. As a result, the value that CPG may have in any

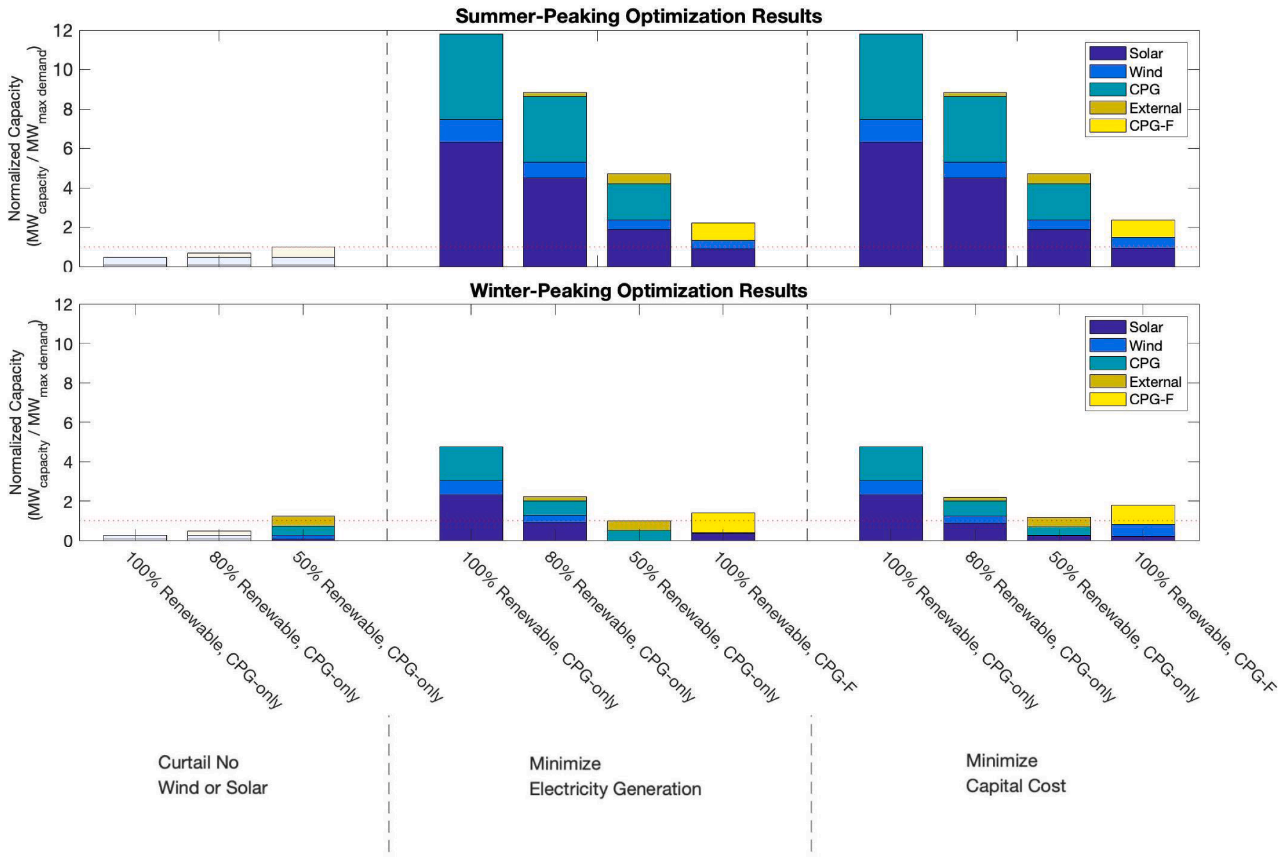

Fig. 4. This figure illustrates the normalized optimal capacities that are required to supply summer-peaking demand (top) and winter-peaking demand (bottom). The transparent bars in the no wind or solar curtailment scenarios indicate failed optimizations. Wind and Solar could be optimized, as plotted, but CPG could not fill in the remaining demand, and thus is not plotted. These results were generated using baseline data as inputs in the optimization models. The horizontal dashed line indicates the normalized peak demand.

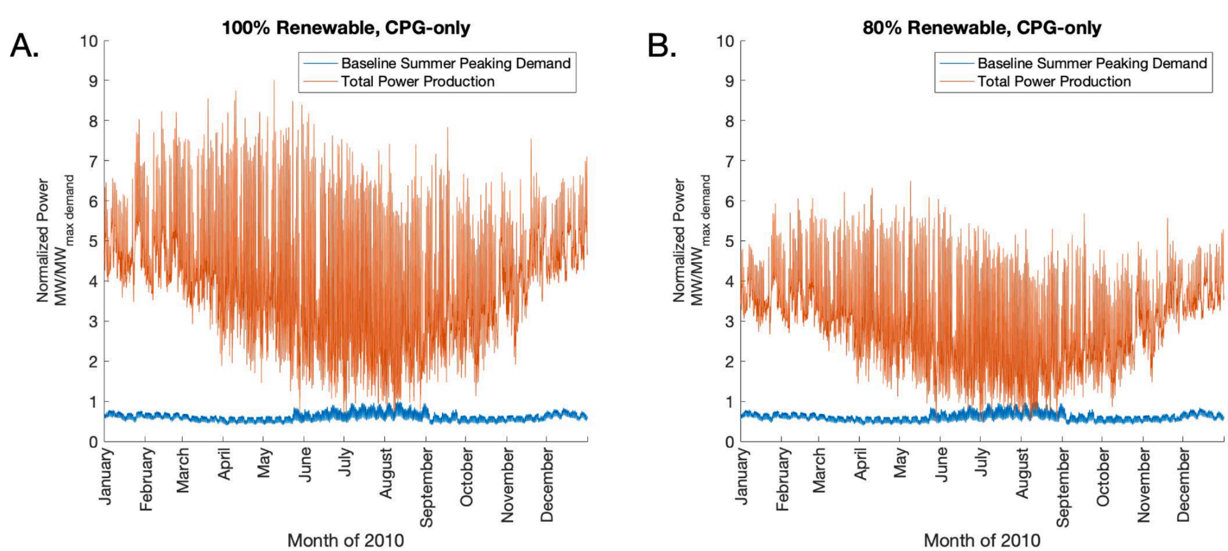

Fig. 5. Normalized total demand and power production for summer-peaking demand when electricity generation is minimized.

electricity system will be a function of the renewable energy target, if one exists, in addition to other factors like the electricity demand, the seasonal availability of renewable energy resources, and the cost of using those resources to generate electricity.

Finally, Fig. 4 also suggests that the total installed capacity substantially decreases when CPG-F facilities are available instead of CPG-only power plants. Fig. 6 can be used to demonstrate why CPG-F facilities affected the total capacity in this way.

First, CPG-F facilities could reduce total power capacities because the operational flexibility is dispatched to avoid the ambient air temperature constraints of CPG-only power plants, thereby reducing the sensitivity of the total system capacity to the otherwise "limiting hours."

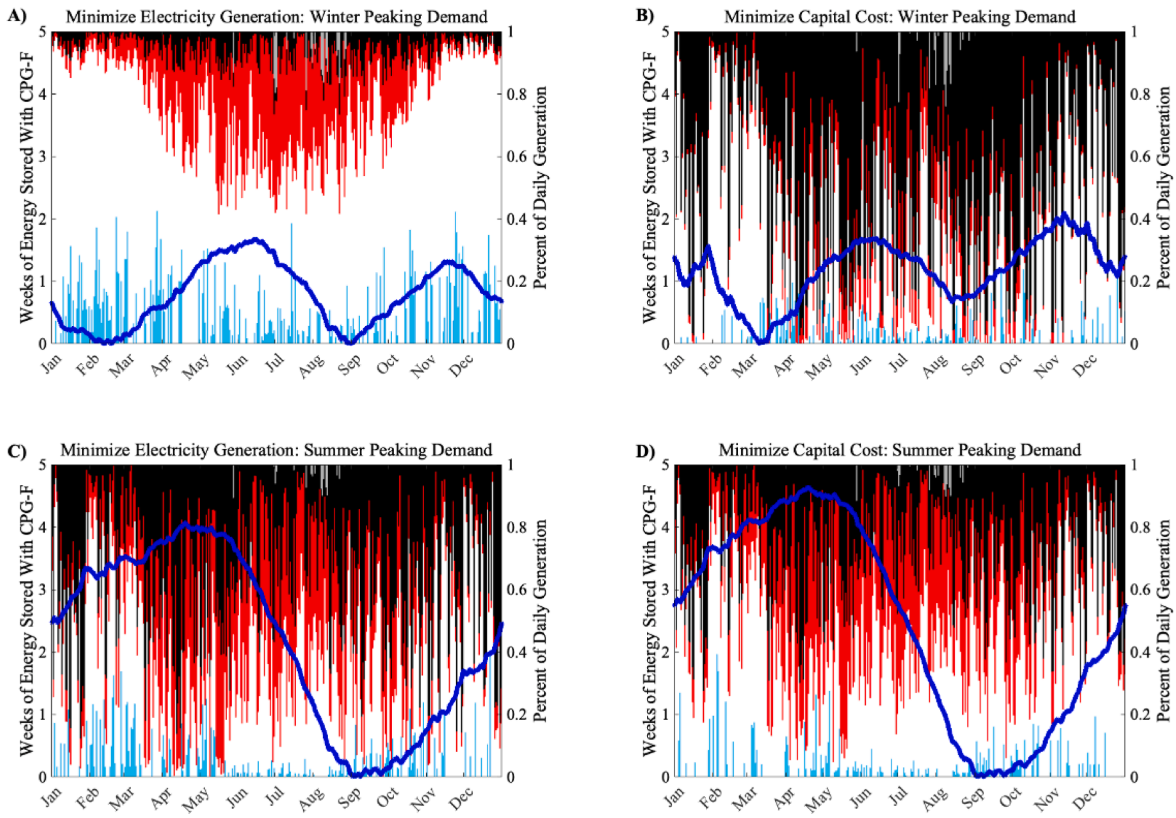

Fig. 6. The left axis plots weeks of stored energy with CPG-F Facilities (dark blue line). On the right axes, the stacked bar charts show the daily percent of electricity generation from CPG-F facilities operating to provide only dispatchable power (light blue), CPG-F facilities providing both dispatchable power and energy storage services simultaneously (white), solar energy technologies (red), wind energy technologies (black), and CPG-F facilities providing only energy storage services (grey). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 6 shows CPG-F facilities operated to provide 1) only dispatchable power (light blue bars), 2) only energy storage (grey bars), and 3) both energy storage and dispatchable power simultaneously (white bars) on different days throughout the year in all four optimizations. When providing only energy storage (grey bars), the CPG-F facilities operated to dispatch electricity and never to consume (store) electricity. In contrast, CPG-F facilities consume (store) electricity that is generated while providing dispatchable power (white bars), which occurs because that stored electricity can be generated later, regardless of the ambient air temperature.

Second, CPG-F facilities could also reduce total power capacities by providing long-duration energy storage over seasonal time scales. Fig. 6 shows that the weeks of energy stored with CPG-F facilities follow a seasonal cycle in all optimizations. For example, when the electricity demand peaked in the winter, CPG-F facilities stored energy from March to June and from September to mid November (northern hemisphere) to dispatch in the following 3 months. When electricity demand peaked in the summer, electricity was stored from September to May to dispatch from May to September. As a result, approximately 4 weeks (minimize electricity generation) or 4.5 weeks (minimize capital cost) of energy storage capacity is needed when electricity demand peaks in the summer and approximately 1.5 weeks (minimize electricity generation) or 2 weeks (minimize capital cost) of energy storage capacity is needed when electricity demand peaks in the winter.

Fig. 6 shows that more energy storage capacity is needed when electricity demand peaks in the summer compared to when it peaks in the winter. This relationship further demonstrates the implications of the ambient air temperature constraint for CPG power plants. From a seasonal storage perspective, it makes sense to store energy during the off-peak season to dispatch during the season when electricity demand is highest. But in our results, this relationship is not observed when demand peaks in the winter: stored energy is dispatched during the summer months in addition to the winter months. This result occurs when electricity demand peaks in the winter because CPG-F facilities are being used to provide energy storage services to both a) meet peak-demand in the winter, and b) meet demand in the summer when CPG capacity factors are lowest. This result may not be as pronounced for systems with lower summer ambient air temperatures or higher geothermal reservoir temperatures.

Overall, there is a growing recognition that long-duration energy storage could provide value in renewable-heavy electricity systems by time-shifting electricity generation over seasonal timescales [7,8], but there are limited technologies available to provide this service. Most prior studies in this area either a) model generic energy storage approaches and discuss that no widely available technology exists that can deliver the required energy capacity [31], or b) constrain their models based on specific energy storage technologies, thereby limiting the potential energy capacity required [46]. As a consequence, our results are somewhat unique in that we do not constrain the energy capacity in our model, and yet the technology under consideration (i.e., a CPG-F facility) is technically able to achieve the hours, or in this case weeks, of required energy storage capacity because sedimentary basins have more than sufficient volumes required to store weeks to months worth of compressed CO_2, and thus energy. Further, our results suggest that there is value in being able to simultaneously provide dispatchable power and energy storage services, which is another unique characteristic of CPG-F facilities compared to other power plant or energy storage technologies.

3.2.1. Sensitivity analysis: Different weather-years when electricity demand peaks in the summer

The results generated with our baseline data (Fig. 4), suggest that the normalized capacities are relatively similar when electricity generation is minimized as to when capital costs are minimized. This relationship occurs in part due to the "limiting hours" throughout the year, and as shown in Table 4, is relatively unique to our baseline weather-year. When different weather-years were used, the "limiting hours" were different and thus the two different optimizations resulted in differing total normalized capacities: the total capacity was generally larger when capital costs were minimized compared to total electricity generation. For the same reason, the amount of wind, solar, and CPG power plants that comprised the total capacity also varied across different weather-years and optimization objective functions. Despite these differences, these results do confirm our primary findings from our baseline results: even with CPG power plants, over-capacity in excess of peak-demand is required to supply electricity demand in renewable-heavy electricity systems.

Additionally, the results from our sensitivity analysis support our finding that CPG-F facilities can substantially reduce the required power capacities by providing long-duration energy storage over seasonal time-scales. In fact, across the variability in total normalized power capacity for the different weather-years and optimization objective functions, the results were comparatively constant for the scenarios in which CPG-F facilities were available instead of CPG-only power plants (Table 4). For example, across all combinations, the total normalized power capacity was either 2.1, 2.2, or 2.3 of which the CPG-F facilities comprised 0.9 or 1.0 $MW/MW_{max\ demand}$. And as shown in Fig. 7, across all weather-year combinations, the CPG-F facility was primarily operated to store electricity from fall to spring, and then dispatch that stored electricity during the summer months when demand was highest.

Table 4
Normalized Capacity [$MW/MW_{max\ demand}$]: Total (Solar, Wind, CPG or CPG-F).

		Minimize Electricity Generation	Minimize Capital Cost
2010 (baseline)	100% Renewable, CPG	11.8 (6.3,1.2,4.3)	11.8 (6.3,1.2,4.3)
	80% Renewable, CPG	8.6 (4.5,0.8,3.3)	8.6 (4.5,0.8,3.3)
	50% Renewable, CPG	4.2 (1.9,0.5,1.8)	4.2 (1.9,0.5,1.8)
	100% Renewable, CPG-F	2.2 (0.9,0.4,0.9)	2.3 (0.9,0.5,0.9)
2007	100% Renewable, CPG	13.6 (5.6,1.6,6.4)	29.6 (9.7,17.0,2.9)
	80% Renewable, CPG	10.0 (4.3,0.9,4.8)	21.7 (7.4,12.2,2.1)
	50% Renewable, CPG	5.0 (2.3,0.5,2.2)	9.1 (3.6,4.3,1.2)
	100% Renewable, CPG-F	2.2 (0.9,0.4,0.9)	2.2 (0.7,0.6,0.9)
2008	100% Renewable, CPG	8.9 (4.2,0.7,4.0)	10.5 (6.2,0.7,3.6)
	80% Renewable, CPG	6.4 (3.0,0.5,2.9)	6.6 (3.3,0.5,2.8)
	50% Renewable, CPG	3.4 (1.5,0.3,1.6)	3.4 (1.5,0.3,1.6)
	100% Renewable, CPG-F	2.1 (0.9,0.3,0.9)	2.2 (0.7,0.6,0.9)
2009	100% Renewable, CPG	9.5 (3.8,1.6,4.1)	13.4 (6.8,4.2,2.4)
	80% Renewable, CPG	6.3 (2.3,1.3,2.7)	8.1 (3.7,2.7,1.7)
	50% Renewable, CPG	2.6 (1.3,0.1,1.2)	3.5 (1.9,0.6,1.0)
	100% Renewable, CPG-F	2.0 (0.7,0.3,1.0)	2.3 (1.1,0.2,1.0)
2007–2010	100% Renewable, CPG	12.8 (5.6,0.8,6.4)	17.2 (9.2,3.7,4.3)
	80% Renewable, CPG	9.5 (4.3,0.5,4.7)	12.4 (7.1,2.0,3.3)
	50% Renewable, CPG	4.7 (2.3,0.2,2.2)	5.5 (3.2,0.5,1.8)
	100% Renewable, CPG-F	2.1 (0.9,0.2,1.0)	2.2 (0.9,0.3,1.0)

Despite the consistency in power capacity, Fig. 7 shows that the required power capacity did vary by up to almost three weeks across weather-years and up to about half a week across optimization objective functions. This variability mostly occurred because the CPG-F facility was primarily operated to provide long-duration energy storage over seasonal timescales and energy storage capacity is more important than power capacity for time-shifting seasonal amounts of electricity. Further, the energy capacities did not vary as much across optimization objective functions in part because CPG-F facilities do not have an energy capital cost. It is likely that the two different optimization objective functions would have resulted in more different energy capacities had the energy capital cost of CPG-F facilities not been free.

3.3. Break-Even CO_2 tax

Fig. 8 shows the break-even CO_2 taxes that we estimated using the capital-cost minimized optimal power capacities and assuming the external power source was a natural-gas power plant. The break-even CO_2 taxes are positive for every case, which suggests that a CO_2 tax is required to justify using renewable energy instead of natural gas power plants. A CO_2 tax is always required to justify deploying renewable energy compared to natural-gas power plants on a cost-basis because a) the capital costs we assumed for natural-gas power plants were less than the capital costs we assumed for any renewable energy technology (Table 3) and b) much more total capacity is needed compared to total demand when renewable energy technologies are relied upon to supply substantial portions of the power demand (Fig. 4). For example, the break-even CO_2 taxes were always larger when the power demand peaked in the summer compared to when demand peaked in the winter because more capacity is needed when demand peaks in the summer compared to the winter (Fig. 4).

Fig. 8 also suggests that in the hypothetical scenario where CO_2 tax increases with time, it may become less costly to use a CPG-F facilities with wind and solar energy technologies to provide 100% of electricity demand than CPG-only with wind and solar. CPG-F facilities are 1.4 times more costly than CPG-only power plants (Table 3) but require much lower installation power capacities than CPG-only due to their increased flexibility. For example, when electricity demand peaks in the summer and assuming the price trajectories from the IPCC, it will become less expensive to meet 100% of power demand with wind, solar, and CPG-F technologies compared to using natural-gas sometime before it becomes less costly to meet only 50% of power demand with wind, solar, and CPG-only power plants. Overall, this result demonstrates the value of long-duration energy storage in renewable-heavy electricity supply systems, which is how CPG-F facilities were generally operated to provide electricity in our optimizations (Fig. 6).

4. Conclusions and recommendations for future work

In this study, we investigated the potential that CO_2 Plume Geothermal (CPG) power plants and flexible, capable of storing energy, CPG facilities (CPG-F) may have for supplying electricity demand as part of a renewable-heavy electricity system. We simulate CPG power generation using a plant-scale model and use those results to characterize power grid-level optimization models to find the optimal power capacity of wind and solar energy technologies, CPG-only power plants, or CPG-F facilities under three different objectives: 1) no curtailment of electricity generated by wind and solar energy power plants, 2) minimize electricity demand, and 3) minimize capital cost. We execute these optimizations over both winter peaking and summer peaking demand profiles and perform a sensitivity analysis to investigate how robust our findings are across different weather-years. We find that:

1. CPG technology can enable geothermal electricity generation in places like North Dakota, but the dispatchability of CPG power plants is constrained during hot days. As a result, our findings suggest that some power generation may still be curtailed when CPG power plants are used to support

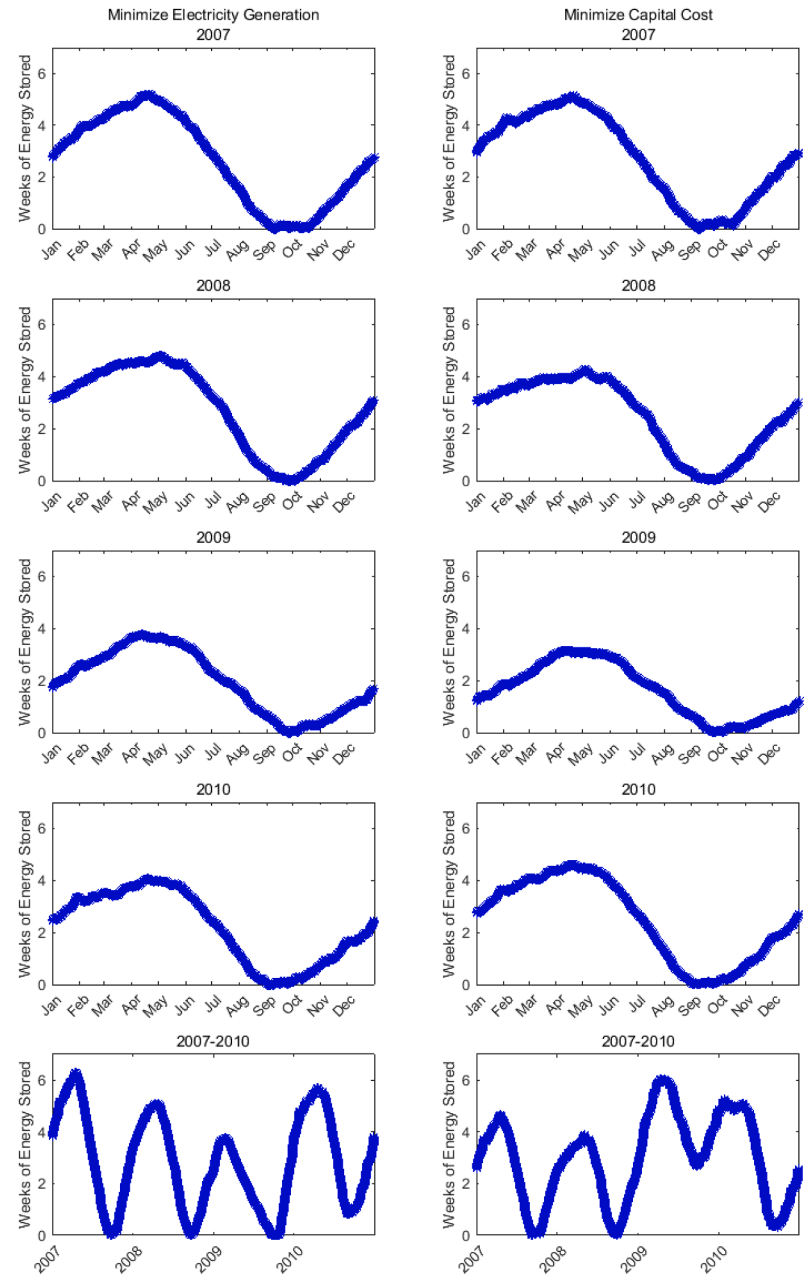

Fig. 7. The above figure illustrates weeks of energy stored by CPG-F facilities in all sensitivity analysis scenarios.

wind and solar energy technologies. In our Rugby, ND case study, CPG power plants could generate electricity at ambient air temperatures below approximately 30 °C, but this maximum air temperature will increase in locations with hotter sedimentary basin geothermal resources.

2. The optimal capacities required to meet demand changed across scenarios that depend on when peak demand occurs, renewable energy penetration target, and weather-year, but were greater than peak demand due to a handful of "limiting hours" in the spring or summer when renewable energy technology capacity factors were low.

3. CPG-F facilities substantially reduce the total system capacity required to meet demand compared to CPG power plants by providing long-duration energy storage over seasonal timescales. In other words, CPG-F facilities were able to reduce the sensitivity of the total system capacity to the "limiting hours."

4. The operational flexibility of CPG-F facilities was primarily leveraged to bypass the ambient air temperature constraint of CPG power plants by storing electricity that it generated while operating to provide both dispatchable power and energy storage. As a result, our findings suggest there is at least one application in which there is value for simultaneously providing energy storage and dispatchable electricity with CPG-F facilities.

5. Using the capital costs assumed in this study, policy is needed to justify using renewable energy technologies on a cost-basis compared to natural-gas power plants. Across all optimizations, we found that a CO_2 tax on the order of hundreds to thousands of dollars per tCO_2 emitted to the atmosphere would be required before renewable energy technologies are less expensive than using natural-gas power plants.

4.1. Future work

Overall, given the ability of CPG power plants and CPG-F facilities to support variable renewable energy technologies, future work should continue to investigate the role(s) that these technologies could play in different grid-integration contexts. Here, we suggest a few ideas for such

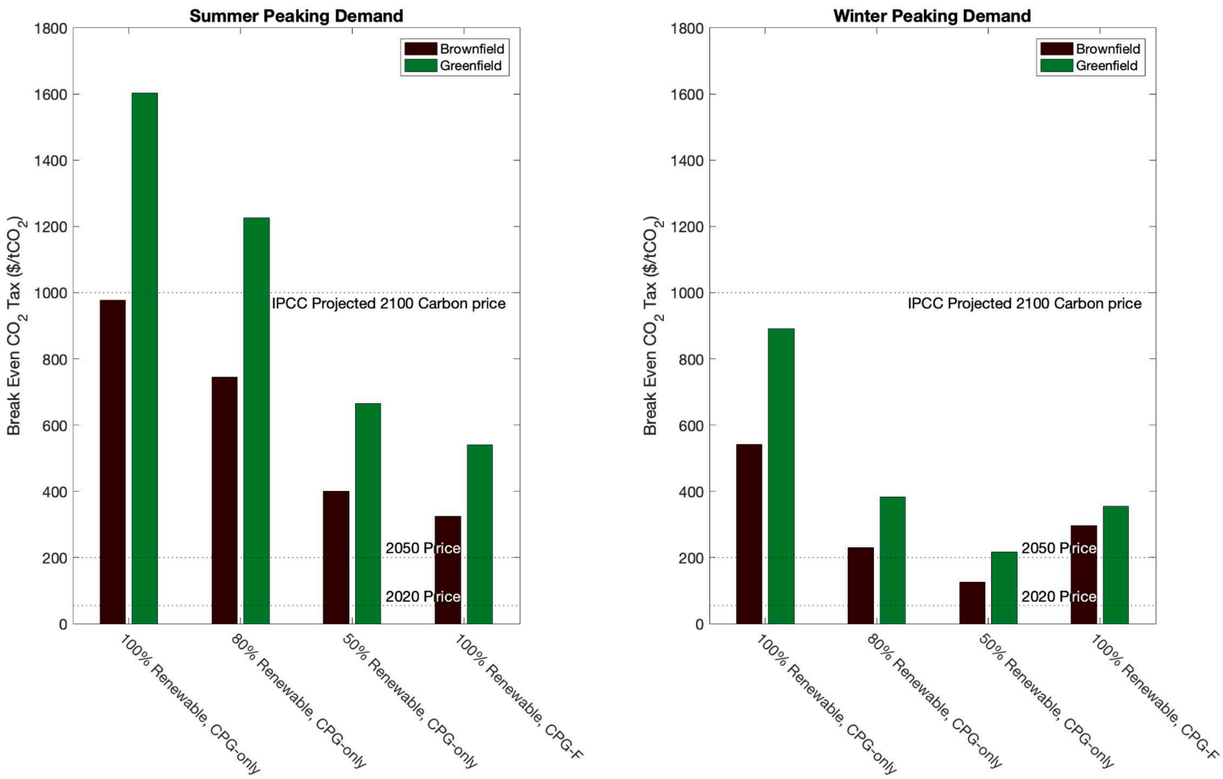

Fig. 8. Break-even CO_2 taxes are plotted above, assuming both Greenfield and Brownfield CPG Capital Costs. The dashed lines reference the projected CO_2 prices that the Intergovernmental Panel on Climate Change (IPCC) suggest may be needed to address climate change [47].

studies that were beyond the scope of this paper but would build off our findings:

- *Estimate CPG power generation across larger geospatial areas, especially in those locations where electricity demand peaks in the winter (e.g. in Switzerland), or may peak in the winter due to future heating electrification.* As sedimentary basins are ubiquitous, CPG technology could expand the geothermal resource base to other locations like North Dakota that are not conventionally considered for having geothermal resources suitable for cost-competitive electricity generation. If CPG power generation was estimated over large enough geospatial areas that cost-capacity supply curves could be created, more robust integration studies could be performed, for example, adding CPG power plants to capacity expansion models of the electric power system under future scenarios of high electrification.
- *Investigate scenarios where CPG technologies are financially compensated for providing* CO_2 *storage services.* If a CO_2 policy was enacted that increased the cost of natural-gas power plants, it is also likely that CPG power plants and CPG-F facility operators would receive additional revenue from storing CO_2. In this case, the break-even CO_2 taxes that we estimated would decrease because the cost of CPG technologies (in the numerator of Eq. (11)) would go down by the rate that CO_2 is stored. This could substantially reduce the break-even CO_2 taxes because CPG power plants may require around 2 to 7 $MtCO_2/MW_e$ of reusable but eventually permanently geologically stored CO_2 to generate electricity, depending on the subsurface geology and power capacity of the power plant [25].
- *Investigate how a CPG-F facility is optimally dispatched in different grid-integration contexts.* In this study, we assumed CPG-F facilities were operated from a grid-scale perspective, which likely resulted in significantly different operation scenarios compared to assuming a more realistic, profit-maximizing, perspective. Future work could investigate how operators should use the immense flexibility of CPG-F facilities for a specific application (e.g., power transmission or generation capacity deferral [48,49], energy arbitrage [50,51]).
- *Optimize CPG-F facility design to provide long-duration energy storage over seasonal time scales.* Despite the potential for CPG-F facilities to be operated differently in different contexts, this study suggests that a primary application of CPG-F facilities is seasonal energy storage and prior work suggested that the value of providing seasonal energy storage will likely increase with decreasing energy capital costs or increasing round-trip efficiencies [8]. As CPG-F facilities have zero energy capital costs and round-trip efficiencies above 100% due to the geothermal heat flux [19,20], they may provide tremendous value, and thus designing a CPG-F facility specifically for this service would likely be of financial and climate-mitigation interest. The assumptions around CPG-F facilities that we used for this study were based on our prior work, which used a relatively generic CPG-F system design [19,20]. There are many ways this design could be changed (e.g., increasing the number of wells and the location of those wells, changing the diameter of wells, sizing the surface power plant equipment) that would change the performance and capital cost of the CPG-F facility [18]. As a result, the design could be optimized to provide seasonal energy storage services, thereby increasing the value of CPG-F facilities for this application.

CRediT authorship contribution statement

Anna C. Van Brummen: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft. **Benjamin M. Adams:** Conceptualization, Methodology, Writing – original draft, Supervision. **Raphael Wu:** Methodology, Formal analysis, Writing – review & editing. **Jonathan D. Ogland-Hand:** Visualization, Writing – original draft. **Martin O. Saar:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Full specification of optimization models with CPG-F facilities

A1. Optimization model nomenclature

We begin by defining notation for the optimization model.

A1.1. Sets and parameters

T - the number of hours in the planning horizon
$NO_{s,t}$ - the hourly capacity factors for solar energy technologies, $t = 1, \ldots, T$
$NO_{w,t}$ - the hourly capacity factors for wind energy technologies, $t = 1, \ldots, T$
$NO_{cpg,t}$ - the hourly capacity factors for CPG power plants and CPG-F facilities, $t = 1, \ldots, T$
cc_s - the capital cost of solar energy technologies [$/MW]
cc_w - the capital cost of wind energy technologies [$/MW]
cc_{cpg-f} - the capital cost of CPG-F facilities [$/MW]
ND_t - the normalized electricity demand over hour t [$MW/MW_{\text{max demand}}$], $t = 1, \ldots, T$
f_{SMax} - the factor by which the CPG-F facility can generate or consume (store) more electricity compared to CPG power plants.
M - a large number
Q - the number of hours in a day (i.e., 24).
η - the fraction of energy stored by CPG-F facility operating to provide energy storage services that remains available to be discharged after hour t.

We model the operation of CPG-F facilities operating with wind and solar energy technologies to supply 100% of electricity demand over T hourly time periods. The amount of electricity available from solar and wind renewable energy technology is constrained by the capacity factors $NO_{s,t}$ and $NO_{w,t}$. The capacity factor for CPG power plants also influences the operation of CPG-F facilities, but not as directly the capacity factors of wind and solar energy technologies because we assumed CPG-F facilities were not constrained by ambient air temperature when generating electricity while operating to provide energy storage services. In the scenario where capital costs are minimized, the assumed capital costs cc_s, cc_w, and cc_{cpg-f} influence the optimal capacity of each technology. CPG-F facilities generating electricity while operating to provide energy storage can dispatch more electricity than a CPG power plant because some of the parasitic loads associated with the CPG power plant are not applied. Instead, these loads are applied later to consume (store) electricity. As a result, a CPG-F facility operating to provide energy storage can generate or consume f_{SMax} more electricity than a CPG power plant or a CPG-F facility operating to provide dispatchable power. For this study, we assume f_{SMax} was equal to 1.2 [20]. We also assumed that a CPG-F facility operating to provide energy storage services can only switch from consuming electricity to generating electricity, or vice-versa, one time per day, or one time per Q hours. Lastly, only η percent of the energy stored by the CPG-F facility at the start of hour t was available at the end of hour t. For this study, we assume η was equal to 99.97%.

A1.2. Decision variables

n_s - the normalized capacity of solar energy technologies [$MW/MW_{\text{max demand}}$]
n_w - the normalized capacity of wind energy technologies [$MW/MW_{\text{max demand}}$]
n_{cpg} - the normalized capacity of CPG power plants [$MW/MW_{\text{max demand}}$]
n_{cpg-f} - the normalized capacity of CPG-F facilities [$MW/MW_{\text{max demand}}$]
$P_{ESProd,t}$ - the normalized power produced by CPG-F facilities operating to provide energy storage services in hour t [$MW/MW_{\text{max demand}}$]
$P_{ES,t}$ - the normalized electricity generated or stored by CPG-F facilities operating to provide energy storage services in hour t [$MW/MW_{\text{max demand}}$]
$ESbin_{store,t}$ - a binary variable that is 1 when the CPG-F facilities are consuming (storing) electricity when operating to provide energy storage during hour t
$ESbin_{prod,t}$ - a binary variable that is 1 when the CPG-F facilities are generating electricity when operating to provide energy storage during hour t
$ESbin_{storecheck,t}$ - a binary variable that is 1 when the CPG-F facilities switches from storing energy to generating electricity after hour t
$ESbin_{prodcheck,t}$ - a binary variable that is 1 when the CPG-F facilities switches from generating electricity to storing energy after hour t
E_t - the cumulative amount of energy, or "state of charge" of the CPG-F facilities at the end of hour t

When the CPG-F is operating to provide energy storage services, $P_{ESProd,t}$ is equal to $P_{ES,t}$ when electricity is being generated and zero otherwise. $ESbin_{storecheck,t}$ and $ESbin_{prodcheck,t}$ are counters that track how often the CPG-F facility switches from generating to consuming (storing) electricity when operating to provide energy storage services. E_t represents the state of energy in the CPG-F facility at the end of hour t.

A1.3. Optimization model formulation

The problem is formulated as minimizing the amount of electricity generated (Eq. (A.1)) or as minimizing the capital cost (Eq. (A.2)), depending on the scenario.

$$\min \sum_{t=1}^{T} n_s \times NO_{s,t} + n_w \times NO_{w,t} + n_{cpg} \times NO_{cpg,t} + P_{ESprod,t} \tag{A.1}$$

$$\min \sum_{t=1}^{T} n_s \times cc_s + n_w \times cc_w + n_{cpg-f} \times cc_{cpg-f} \tag{A.2}$$

subject to:

$$n_s \times NO_{s,t} + n_w \times NO_{w,t} + n_{cpg} \times NO_{cpg,t} + P_{ESprod,t} \geq ND_t \qquad \forall t = 1, \ldots, T \tag{A.3}$$

$$-n_{cpg} \times NO_{cpg,t} \times f_{SMax} \leq P_{ES,t} \leq f_{SMax} \times n_{cpg} \qquad \forall t = 1, \ldots, T \tag{A.4}$$

$$n_{cpg-f} \geq n_{cpg} \times NO_{cpg,t} + P_{ES,t} \qquad \forall t = 1, \ldots, T \tag{A.5}$$

$$n_{cpg-f} \geq -\left(n_{cpg} \times NO_{cpg,t} + P_{ES,t}\right) \qquad \forall t = 1, \ldots, T \tag{A.6}$$

$$n_s \times NO_{s,t} + n_w \times NO_{w,t} + n_{cpg} \times NO_{cpg,t} + P_{ES,t} \geq 0 \qquad \forall t = 1, \ldots, T \tag{A.7}$$

$$P_{ESprod,t} \geq P_{ES,t} \qquad \forall t = 1, \ldots, T \tag{A.8}$$

$$P_{ESprod,t} \geq 0 \qquad \forall t = 1, \ldots, T \tag{A.9}$$

$$M = 100 \tag{A.10}$$

$$-M \times ESbin_{store,t} \leq P_{ES,t} \qquad \forall t = 1, \ldots, T \tag{A.11}$$

$$M \times ESbin_{prod,t} \geq P_{ES,t} \qquad \forall t = 1, \ldots, T \tag{A.12}$$

$$ESbin_{trans,t} >= ESbin_{prod,t} \tag{A.13}$$

$$ESbin_{trans,t} <= 1 - ESbin_{store,t} \tag{A.14}$$

$$ESbin_{prodcheck,t} >= ESbin_{trans,t} - ESbin_{trans,t-1} \tag{A.15}$$

$$ESbin_{prodcheck,t} >= 0 \tag{A.16}$$

$$ESbin_{storecheck,t} >= ESbin_{trans,t} - ESbin_{trans,t-1} \tag{A.17}$$

$$ESbin_{storecheck,t} >= 0 \tag{A.18}$$

$$\sum\nolimits_{t=1}^{Q} \left(ESbin_{storecheck,t}\right) \leq 1 \qquad \forall t = 1, 1+Q, 1+2 \times Q, \ldots, T-Q-1 \tag{A.19}$$

$$\sum\nolimits_{t=1}^{Q} \left(ESbin_{prodcheck,t}\right) \leq 1 \qquad \forall t = 1, 1+Q, 1+2 \times Q, \ldots, T-Q-1 \tag{A.20}$$

$$E_t \geq 0 \qquad \forall t = 1, \ldots, T \tag{A.21}$$

$$E_t = \eta \times E_{t-1} - P_{ES,t} \qquad \forall t = 1, \ldots, T \tag{A.22}$$

$$E_{t=1} = \eta \times E_{t=0} - P_{ES,t=1} \tag{A.23}$$

$$E_{t=0} = E_{t=T} \tag{A.24}$$

Objective function (A.1) minimizes the amount of electricity generated to meet 100% of normalized electricity demand from wind and solar energy technologies and CPG-F facilities. Objective function (A.2) minimizes the capital cost of the electricity system that supplies 100% of electricity demand using wind and solar energy technologies and CPG-F facilities. Constraints (A.3) ensure that the total electricity generated is greater than the normalized demand. Constraints (A.4) limit the total amount of electricity consumed (stored) and generated by the CPG-F facility operating to provide energy storage services to a multiple of the amount of electricity that can be generated by the CPG power plant. These constrains along with constraints (A.5) and constraints (A.6) link the capacity and functioning of CPG-F facility to the CPG power plant capacity factors. Constraint (A.7) ensures that the system can only store energy from solar, wind, or cpg produced that hour. Constraint (A.8) and constraint (A.9) ensure that the production element of CPG-F is always positive, and that it will always be equal to the total CPG-F output, or greater than the total CPG-F output when storage is occurring. Constraint (A.10) defines a large M, allowing the optimization to create various following binary variables. Constraint (A.11) defines a binary variable at each time step which indicates whether the system is storing (1) or not (0). Constraint (A.12) defines a binary variable at each time step which indicates whether the system is producing (1) or not (0). Constraints (A.13) and (A.14) define a binary variable at each time step which is 1 whenever the system is producing or off and 0 when storing or off. Constraints (A.15) and (A.16) define a binary variable of length (T - 1) which indicates whether or not between each time step the CPG-F system has switched from storing to producing. Constraints (A.17) and (A.18) define a binary variable of length (T - 1) which indicates whether or not between each time step the CPG-F system has switched from producing to storing. Constraint (A.19) limits the system to only switching from storing to producing once per day. Constraint (A.20) limits the system to only switching from producing to storing once per day. Constraint (A.21) ensures that E_t, which represents the potential energy sequestered in the reservoir at each time step, is never negative. Constraint (A.22) updates the energy in the reservoir such that it equals the energy stored at the last timestep multiplied by the self discharge factor η, with whatever energy was produced removed from the total. Constraint (A.23) defines the energy in the reservoir at the first time step (t = 1). Constraint (A.24) requires that the energy stored at the end of the year equals the energy in the reservoir at the beginning of the year.

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