Optimizing the size of a fully renewable power system to meet energy demand

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OPTIMIZING THE SIZE OF A FULLY RENEWABLE POWER SYSTEM TO MEET HISTORICAL ENERGY DEMAND

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Abstract

In electricity grids, demand and generation must be balanced at all times. Modern electricity is primarily generated by baseload power sources, such as nuclear and coal, and quickly dispatchable sources, such as gas fired power plants, which can be adjusted based on small demand variations. As anthropogenic total CO$_2$ emissions already make up almost 75% of the atmosphere’s total carbon content, governments are increasingly implementing renewable energy mandates. These mandates limit a country’s CO$_2$ emissions and reliance on fossil fuels. Therefore future electricity generation markets will ultimately require variable, renewable power sources that emit no CO$_2$.

Two of the most widely used renewable power sources, wind and solar, cannot always provide energy when there is demand. In order to address this mismatch, either a third dispatchable energy source or an energy storage system has to be included to fully meet demand. This study examines and optimizes a purely renewable energy system to fully meet demand for the town of Minot, North Dakota. The renewable system studied combines wind and solar with CO$_2$ Plume Geothermal as both a third power source and a method of of energy storage.

I find that the renewable power system without energy storage has to be oversized by 400% of maximum demand in order to meet demand for the few constraining hours of the year. System oversizing is greater for summer-peaking demand datasets than for winter-peaking demand datasets. This is explained as winter-peaking demand correlates to CPG power production, which is dispatchable, while summer-peaking demand corresponds to solar power production, which is variable.

Once CO$_2$ Plume Geothermal Energy Storage is introduced, system costs due to over-installation are reduced by 80% compared to the system without energy storage. With CPG Energy Storage the total installed capacity to meet a winter-peaking demand dataset is 2.5 times maximum demand. The sizing to meet a summer-peaking demand dataset is only 2 times maximum demands. Additionally, when using CO$_2$ Plume Geothermal Energy Storage both characteristic demand curves are met with zero CO$_2$ emission. The systems with CO$_2$ Plume Geothermal Energy Storage are currently more expensive than dispatchable, fossil-fuel power sources, but as CO$_2$ costs are introduced the systems become economical.
Acknowledgements

I would like to thank my advisor Benjamin Adams for going above and beyond to help me with my research over the past two years. In addition, Raphael Wu was always willing to help whenever I had an optimization or formatting question. This research would be nowhere near its current state without their constant support.

In addition I would like to recognize my fellow Master's students in the geophysics department, who have worked next to me and with me over the last two years. Their support, the support of my fellow student Adrian Tasistro-Hart, and the support of my family is why I can continue to push myself to work harder.

Finally, I would like the acknowledge the MISO power system and NREL's online databases for making their data available and easy to access.
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1 Introduction

The modern energy grid is defined by two main features: demand and generation. Demand, though largely predictable, fluctuates based on factors that cannot always be predicted or understood. Modern electricity is primarily generated by either base-load sources or quickly dispatchable sources which can be adjusted based on small variations in demand. Examples of these quickly dispatchable sources are gas fired power plants, and examples of base-load sources are coal and nuclear energy. However, as governments are increasingly implementing renewable energy mandates, electricity production is moving towards variable sources. These mandates dictate country wide CO$_2$ emission limits or use of renewable energy. For example, Germany passed the German Renewable Energy Act in 2000, which calls for 80% of German electricity consumption to be renewably generated by 2050 (Barbose et al., 2016).

Further complicating the problem, most renewable sources have fluctuating power output at each moment in time, depending on their natural sources. For example, on a cloudy day, a solar power plant can only produce a fraction of its installed output, meaning it cannot be relied on for quick, adjustable, energy dispatch. This research investigates the combination of fluctuating renewable energy sources, such as wind, solar, and hydropower, to fully and reliably satisfy energy demand.

1.1 Justification

Oil, gas, and coal all have a finite supply on a human time scale, while renewables use replenishing sources such as sunlight and wind. The natural inputs which define renewable energies, like sun cover and solar intensity, are also the fluctuating inputs that make these power sources unreliable (Lofthouse et al., 2015). All the power outputs of the renewable energies previously mentioned depend on complex and difficult to predict weather conditions. The variability of renewable energy output has led to modern reliance on reliable fossil fuels, coal, and nuclear power production. Fossil fuels, while reliable, are also the primary causes for the extreme global increase of CO$_2$ in Earth’s atmosphere.

This increase in atmospheric CO$_2$ is causing the highest acceleration of average temperatures on Earth in the planet’s history. The Paris Agreement, a gathering of the member countries of the United Nations Framework Convention on Climate Change in 2015, called to limit measured global temper-
ature increase to 2.1\(^\circ\) celsius for the year 2050 (United Nations, 2015). Anthropogenic total CO\(_2\) emissions already exceed 1900 Gt, making up almost 75% of the atmosphere’s 2600 Gt total carbon content. To not exceed the 2\(^\circ\) cap, IPCC (Intergovernmental Panel on Climate Change) members have constructed CO\(_2\) models which require limiting additional CO\(_2\) emissions to 860 – 1180 Gt, where the range exists from model uncertainties (Metz et al., 2001). Even the maximum estimate, 1180 Gt, is less than the 1900 Gt emitted in the previous period of forty years. In order to meet such a goal, renewable power needs to be used. As time and money is being invested into developing renewable energy sources, they are becoming more affordable. According to Lazard, the capital cost maximum of rooftop solar photovoltaic cells has decreased from $3,750 to $3,250 between November 2017 – November 2018 (Lazard, 2017, 2018). However, the variability in power generation is a large limitation in the growth of renewable energies. The optimization of variable power sources is thus becoming an important problem to figure out how we can increase the use of and reliance on renewable or carbon neutral power sources to fully meet demand.

This particular study will examine a combination of solar, wind and geothermal as power sources. Geothermal power is the only other renewable energy source aside from hydropower that is dispatchable. Geothermal energy is renewable on a larger time scale, as the diffusion time of heat has to be taken into account. The combination of renewable power sources are optimized to both fully meet demand and also to meet 80% and 50% of maximum demand.

1.2 Background of Renewable Energy Optimizations

Energy Optimization consists of sizing an electricity generation model to meet a timeseries representing electricity demand. Studies which consider renewable energies aim to minimize either CO\(_2\) output, a cost function (capital cost, levelized cost of energy), or to minimize the fraction of energy covered by non-renewables (Allegrini et al., 2015; Baños et al., 2011; Sameti & Haghighat, 2017). The method of this minimization depends on the complexities of the model inputs, the number and types of energy sources taken into account, whether or not transmission methods are included, and different grid sizes and geometries.

Many of these studies thus vary based on the system design in addition to optimization objectives. An optimization study can be critiqued either in terms of the authors’ mathematical methods and
timely solving techniques or from the modeled system construction. This background summary focuses more on the system construction of past work rather than critiquing the mathematical approaches and efficiency of those approaches.

Many methods that do not on the hypothetical ‘grid,’ referencing the global energy trade market. Those that do not are referred to as ‘stand-alone’ systems. An optimization that combines multiple power inputs is referred to as a ‘hybrid’ energy system in the optimization literature. Optimization methods need a location for which to either model demand data or adapt measurements from past years and observations. The more theoretical approaches involve modeling new sources of power from scratch and more applied research looks to retrofitting buildings and existing power supply technologies. Independent, non-retrofitted systems are less constrained in their scope of investigation. Retrofitting is a very involved undertaking for locations larger than a simple group of buildings, and therefore is often only applied to specific building clusters like villages or universities. Studies that tackle larger demand structures, referred to as ‘district-scale’, are not limited to surface area of roofs, or other retrofitted structures, and thus have unbound power source potential to include in the optimization.

The research conducted by Nazir et al. is an example of a retrofitting potential analysis. The authors find supplying electricity to an Indonesian university and its associated building cluster with retrofitted renewable energy technologies to be more expensive than just buying electricity off the general electricity grid. This increased expense is reduced once the authors allow for a window of energy to be bought, and excess energy to be sold to the grid. Nazir et al. conclude that economizing the parameter for CO₂ output (either taxing larger outputs of CO₂ or financially supporting plants with lower carbon output) can be one of the primary ways to justify the extra cost of renewables. Retrofitting existing structures allows for realistic, site specific, energy cost approximations. Unlike a retrofitting study, in this work I undertake a district-scale, unbound power system. This set-up allows me to determine the optimal renewable power source combination with more general, widely applicable results.

Literature reviews like that of Allegrini et al. and Baños et al. compare and contrast past energy optimization studies to provide a succinct summary of which renewable power sources
are considered in many of these studies. A number of studies discussing renewable energies identify geothermal as a potential source for renewable energy growth in the future given its relative dispatchability (Adams & Kuehn, 2012; Baños et al., 2011; Randolph & Saar, 2010). Despite its potential, geothermal is currently considered for heating rather than electricity production because of the < 10% conversion efficiency from thermal energy to electricity. Patišević et al. (2017) show through their optimization method that geothermal district heating can be financially competitive with a non-renewably fueled system. In addition, emissions under the renewably fueled scenario are significantly reduced.

The number of renewably focused optimization projects has drastically increased over the last ten years (Baños et al., 2011). Most authors focus on wind and solar in renewable power supply models (Allegrini et al., 2015). However, wind and solar power sources have a mismatch in the timing of energy supply versus demand (Allegrini et al., 2015; Bernal-Agustín & Dufo-López, 2009; Fleming et al., 2018). In order to reconcile this mismatch, many papers consider batteries or natural mechanical energy storage methods. Allegrini et al. (2015) identify a need for seasonal storage that batteries cannot fill, because they are not efficient enough for effective long term energy storage. An efficient solution for seasonal storage has still not been clearly identified. Based on these shortcomings, Sameti & Haghighat (2017) encourage optimization authors to look toward new energy technologies to solve the energy storage problem.

1.3 CO₂ Plume Geothermal (CPG)

1.3.1 What is CPG?

The CPG system is a geothermal plant, but with CO₂ instead of brine as the primary working fluid. Supercritical CO₂ transfers heat more efficiently than water (Adams & Kuehn, 2012). Refer to figure [1] for the system diagram. A typical geothermal plant taps thermal energy from natural, hot rock reservoirs at depth, while engineered geothermal systems fracture medium porosity geologic features and inject water to be heated at depth before pumped back to the surface (Randolph & Saar, 2010). CO₂ plume geothermal is different than either of these methods, in that it uses a pre-existing medium to high porosity basin with a cap rock through which to circulate CO₂, both displacing the native formation fluid and geologically storing CO₂ in the process (Randolph & Saar, 2011; Adams et al.)
(2015) found that using CO$_2$ as a working fluid rather than brine results in larger geothermal power output from shallow, lower porosity reservoirs. The density changes of CO$_2$ throughout the circulation process create a thermosiphon effect, where it naturally circulates into and out of the reservoir. This effect reduces the system’s power intake, as it the working fluid no longer needs to be artificially pumped in reservoirs at depths of 0.5 – 3 km (Adams et al., 2014).

1.3.2 What are the benefits?

Geothermal energy generation is dispatchable, as a specific amount of power can usually be produced by the turbine, though different pumping pressure and fluid amounts are required depending on ambient temperature. Additional power is required to cool down the hot working fluid after it has been passed through a turbine, and this additional step in the process requires a large amount of power and is heavily temperature dependent. The net geothermal power production is a combination of the power production from the turbine and the cooling power requirement, which thus does have a dependence on uncontrollable natural conditions, although the generation alone does not. Of all the renewable energy sources considered, geothermal is the most viable to cover the base-load of demand since Earth’s heat is always available (Randolph & Saar, 2018). Adams & Kuehn (2012) model CPG energy generation, and because it is demand driven rather than resource driven, they find it can meet 95% of their modeled demand.

A modeled CPG plant with a 50 meter thick reservoir, 700 m well separation, and a pore space CO$_2$ saturation of approximately 42% therefore circulates 2 Megatons of sequestered CO$_2$ (Garapati et al., 2015). The combination of geothermal energy production with sequestered CO$_2$ makes the CO$_2$ sequestration more financially feasible and makes the geothermal energy generation net CO$_2$ negative (Bielicki et al., 2017).
1.4 CO₂ Plume Geothermal with Energy Storage (CPGES)

1.4.1 What is CPGES?

CPGES is an expansion of the CPG design in which energy storage (ES) is added to the power generation plant. The CPGES design requires a shallower, smaller aquifer in addition to the main circulation aquifer. Refer to figure 2 for the CPGES system diagram (Fleming et al., 2019). The characteristic of CPG and geothermal energy which makes it not entirely dispatchable is the energy which is required to cool down the working fluid once it has passed through the turbine and before it is reinjected into the deep aquifer. The CPGES system injects the hot CO₂ into a shallow saline aquifer when energy is needed instead of cooling it, allowing for dispatchable power generation. Later, when there is excess energy production, the CO₂ is pumped up, cooled, and then reinjected into the primary reservoir (Buscheck et al., 2014). Fleming et al. (2019) models a CPGES plant that can behave both as pure CPG and as energy storage depending on system needs. The combined CPGES plant operates in part as a CPG plant constantly producing energy, while the remainder acts as energy storage varying between storage and generation. The fraction of plant behaving as CPG and ES can be adapted hourly by controlling the liquid CO₂ path (Fleming et al., 2018).
1.4.2 What are the benefits?

Including CPGES makes the whole power generation system dispatchable, and thus much more efficient to reliable to satisfy a base-load of power demand. The CPGES system can provide seasonal storage, which is an energy storage mechanism currently missing in literature and important for improving the effectiveness of variable energy sources like solar and wind. It can also be used for daily storage, depending on the system requirements (Fleming et al., 2018). Excess solar and wind energy can be used to drive the CPGES system, therefore harnessing energy that would have otherwise been wasted. CPGES has the potential to be the missing factor for the spread of renewable energies by increasing the reliability of variable power sources. However, Fleming et al. (2019) and Fleming et al. (2018) have not simulated CPGES in a real power system to see if it provides adequate energy storage and generation to meet real demand.

Figure 2: Fleming et al. (2019) propose the CPGES technology represented by the above system diagram. The energy storage is facilitated by the shallow reservoir, where hot CO$_2$ can be stored, temporarily allowing the user to avoid the power loss needed to cool down the fluid. Later, when there is excess energy, the working fluid can be pumped from the shallow reservoir, cooled, and injected into the primary reservoir. The CPG technology is the same system excluding the shallow reservoir. For model simplicity I do not consider the minor cooling tower at step 8 in my CPGES system.
1.5 Thesis Description

This thesis shows the ability of renewable power sources to fully meet a city’s demand by optimizing the sizing of a stand-alone hybrid energy system. Specifically this system combines solar, wind, and geothermal as energy sources in combination with CO$_2$ sequestration and energy storage to meet two characteristic demand curves for North Dakota, USA and the larger midwest region (Figure 3). I use geothermal energy for seasonal storage by including a newly proposed variation on geothermal, CO$_2$ Plume Geothermal (CPG) and CO$_2$ Plume Geothermal with Energy Storage (CPGES), in the modeled energy system. I first approach the problem considering only renewable power sources. I then continue to include energy storage in the model in order to observe how the storage technology improves the efficiency of the system.

Figure 3: The system diagram depicting the energy sources considered in this study. The shallow reservoir is at approximately 1.5 km depth, and the deep reservoir at 2.5 km depth. The features on the surface are not drawn to scale with this depth. The CPGES system uses only one pipe for both CO$_2$ output and input for the shallow reservoir.

1.5.1 Site Location

I optimize the nameplate (installed maximum capacity) for simulated wind, solar, and CPG power plants to satisfy energy demand approximated for Minot, North Dakota. Adams & Kuehn (2012)
first identify Minot, North Dakota as a possible research site for a CPG installation. Minot sits on
the Williston basin, a geologic formation which has been identified by the USGS as a potential site
for CO\textsubscript{2} storage. Thus the permeability and stratigraphy within the basin have been identified as
compatible for modeled CO\textsubscript{2} storage and circulation requirements, which would be necessary for a
CPG plant (Buursink et al., 2012). North Dakota also has both wind and solar generation potential.
Due to this viability, Minot, North Dakota has modeled solar, wind, and temperature datasets from
country-wide research initiatives in the United States directed by the National Renewable Energy
Database (Brower & Corbus, 2009; NREL, 2010).

Demand data are taken from the smaller, more residential town of Rugby, North Dakota (refer to
figure 24) (Adams & Kuehn, 2012). However to also consider industrial demand, demand data for the
Mid-continent Independent Systems Operator (MISO) energy market are also considered. This area
includes North Dakota, Minnesota, Wisconsin, and parts of South Dakota, Iowa, Missouri, Illinois,
and Kentucky (refer to figure 4a). I optimize the solar, wind, CPG, and CPGES system for both
the residential Rugby dataset and the industrial MISO dataset. Generating both results allows for
comparison between the ability of renewables to cover both of these different characteristic demand
scenarios.

1.5.2 Research Questions

This research determines the best way to install combinations of wind, solar, and CPG to satisfy
energy demand in Minot, North Dakota according to various defined scenarios. This will resolve
how to install power sources in order to build an all renewably powered city. It will also
identify how much the proposed CPG power source will factor into such a model. The main questions
of this project are as follows:

- Can a combination of wind, solar, and CPG satisfy unit energy demand for the MISO and
  Rugby areas?

- If so, how do the results change with different optimization goals: minimizing wasted energy,
  energy produced, and capital cost?

- How do the nameplates and costs change when lowering the percentage of demand that has to
  be covered by renewables?
Once energy storage with CPG has been included in the model, how significantly do the nameplates change?

How do the capital costs associated with the CPGES nameplates change?

What does the energy storage system generate and store energy throughout the year, and what does this mean for the developing technology?
2. **Methodology**

This section describes how I acquire and normalize datasets for the specific area, set up the optimization problem, run the optimization problem, and calculate additional representative values. The optimization model will be presented in two sections. The first section describes the optimizations which include only solar, wind, and CPG power sources. The second section then discusses how energy storage is included in the optimization, in addition to the prior three power sources.

2.1 **Nomenclature**

Table 1 documents and describes the variables that are discussed in the following sections.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Meaning</th>
<th>Units</th>
<th>Size</th>
<th>Value range</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\Delta t)</td>
<td>Duration of one timestep</td>
<td>hour</td>
<td>Single value</td>
<td>1</td>
</tr>
<tr>
<td>T</td>
<td>Ambient Temperature</td>
<td>°C</td>
<td>Single value</td>
<td>Various</td>
</tr>
<tr>
<td>(n_s)</td>
<td>Nameplate value for solar</td>
<td>MWe</td>
<td>Single value</td>
<td>≥0</td>
</tr>
<tr>
<td>(n_{snw})</td>
<td>Nameplate value for solar when none is wasted</td>
<td>MWe</td>
<td>Single value</td>
<td>≥0</td>
</tr>
<tr>
<td>(n_w)</td>
<td>Nameplate value for wind</td>
<td>MWe</td>
<td>Single value</td>
<td>≥0</td>
</tr>
<tr>
<td>(n_{wnw})</td>
<td>Nameplate value for wind when none is wasted</td>
<td>MWe</td>
<td>Single value</td>
<td>≥0</td>
</tr>
<tr>
<td>(n_{cpg})</td>
<td>Nameplate value for CPG</td>
<td>MWe</td>
<td>Single value</td>
<td>≥0</td>
</tr>
<tr>
<td>(NO_s)</td>
<td>Normalized hourly output for solar</td>
<td>Unitless</td>
<td>Vector 1x8760</td>
<td>0–1</td>
</tr>
<tr>
<td>(NO_{snw})</td>
<td>Normalized hourly output for solar when none is wasted</td>
<td>Unitless</td>
<td>Vector 1x8760</td>
<td>0–1</td>
</tr>
<tr>
<td>(NO_{cpg})</td>
<td>Normalized hourly output for CPG</td>
<td>Unitless</td>
<td>Vector 1x8760</td>
<td>0–1</td>
</tr>
<tr>
<td>(NO_x)</td>
<td>Refers to any of the considered normalized datasets</td>
<td>Unitless</td>
<td>Vector 1x8760</td>
<td>0–1</td>
</tr>
<tr>
<td>(DO_x)</td>
<td>Refers to any of the considered unnormalized datasets</td>
<td>Various</td>
<td>Various</td>
<td>Various</td>
</tr>
<tr>
<td>demand, unit demand</td>
<td>Normalized demand dataset</td>
<td>MWe</td>
<td>Vector 1x8760</td>
<td>0–1</td>
</tr>
<tr>
<td>solarRS</td>
<td>Solar power production sized by optimization results (NO_s\times n_s) or (NO_{snw}\times n_{snw})</td>
<td>MWe</td>
<td>Vector 1x8760</td>
<td>0–(n_s) or 0–(n_{snw})</td>
</tr>
<tr>
<td>windRS</td>
<td>Wind power production sized by optimization results (NO_w\times n_w) or (NO_{wnw}\times n_{wnw})</td>
<td>MWe</td>
<td>Vector 1x8760</td>
<td>0–(n_w) or 0–(n_{wnw})</td>
</tr>
<tr>
<td>totalP</td>
<td>Total power production of all sources sized by optimization results (solarRS + windRS + NO_{cpg}\times n_{cpg})</td>
<td>MWe</td>
<td>Vector 1x8760</td>
<td>0–((n_s+4n_w+4n_{snw})) or 0–((8n_{snw}+4n_{wnw}+4n_{cpg}))</td>
</tr>
<tr>
<td>(P_{cpg})</td>
<td>The unscaled, calculated hourly power for the modeled CPG plant</td>
<td>MWe</td>
<td>Vector 1x8760</td>
<td>≥0</td>
</tr>
</tbody>
</table>

Table 1: Notation and variable description for the following text
2. METHODOLOGY

2.2 Additional CPGES Nomenclature

Table 2 documents and describes the additional variables that are introduced into the stand-alone energy system when including energy storage.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Meaning</th>
<th>Present vs. Solved vs. Computed After</th>
<th>Units</th>
<th>Size</th>
<th>Value range</th>
</tr>
</thead>
<tbody>
<tr>
<td>$n_{cpges}$</td>
<td>Nameplate value for combined CPGES system</td>
<td>Solved</td>
<td>MWe</td>
<td>Single value</td>
<td>$0 \leq n_{cpges} \leq n_{cpg} + n_{es}$</td>
</tr>
<tr>
<td>$n_{es}$</td>
<td>Nameplate value only ES portion of system</td>
<td>Solved</td>
<td>MWe</td>
<td>Single value</td>
<td>$0 \leq n_{es} \leq f_{SMax} \cdot n_{cpg}$</td>
</tr>
<tr>
<td>$f_{SMax}$</td>
<td>factor by which ES can over and under-produce CPG, from Fleming et al., 2019</td>
<td>Preset at 1.2</td>
<td>Unitless</td>
<td>Single value</td>
<td>$\geq 0$</td>
</tr>
<tr>
<td>$f_{Stor}$</td>
<td>The amount by which the ES system is overproducing or underproducing CPG, limited by $f_{SMax}$</td>
<td>Computed After</td>
<td>Unitless</td>
<td>Single value</td>
<td>$0 \leq f_{Stor} \leq f_{SMax}$</td>
</tr>
<tr>
<td>$P_{ES}$</td>
<td>The power timeseries for the ES system</td>
<td>Solved</td>
<td>MWe</td>
<td>Vector 1x8760</td>
<td>$(-n_{es} \cdot f_{SMax}) – (n_{es} \cdot f_{SMax})$</td>
</tr>
<tr>
<td>$P_{ESprod}$</td>
<td>The power generation timeseries for the ES system</td>
<td>Solved</td>
<td>MWe</td>
<td>Vector 1x8760</td>
<td>$0 – (n_{es} \cdot f_{SMax})$</td>
</tr>
<tr>
<td>$P_{ESstor}$</td>
<td>The power storage timeseries for the ES system</td>
<td>Solved</td>
<td>MWe</td>
<td>Vector 1x8760</td>
<td>$-(n_{es} \cdot f_{SMax}) – 0$</td>
</tr>
<tr>
<td>$P_{cpges}$</td>
<td>The power timeseries for the combined CPG and ES systems</td>
<td>Solved</td>
<td>MWe</td>
<td>Vector 1x8760</td>
<td>$(n_{cpg} - n_{cpg} \cdot f_{SMax}) – (n_{cpges} \cdot f_{SMax})$</td>
</tr>
<tr>
<td>$E_{ES}$</td>
<td>The amount of energy in the reservoir at each hour</td>
<td>Solved</td>
<td>MWe$\cdot$h</td>
<td>Vector 1x8760</td>
<td>$\geq 0$</td>
</tr>
<tr>
<td>$E_{ES0}$</td>
<td>The initial amount of energy in the reservoir at the beginning of the year</td>
<td>Solved</td>
<td>MWe$\cdot$h</td>
<td>Single value</td>
<td>$\geq 0$</td>
</tr>
<tr>
<td>Self Discharge Efficiency (SDE)</td>
<td>The fraction of energy remaining in the reservoir after one hour</td>
<td>Preset at 0.9997</td>
<td>Unitless</td>
<td>Single value</td>
<td>$0 - 1$</td>
</tr>
<tr>
<td>ESbin</td>
<td>Binary variable to indicate if system is producing (1) or storing or off (0)</td>
<td>Solved</td>
<td>Unitless</td>
<td>Vector 1x8760</td>
<td>0, 1</td>
</tr>
<tr>
<td>ESbinStP</td>
<td>Binary variable to indicate if system switches from production to storage</td>
<td>Solved</td>
<td>Unitless</td>
<td>Vector 1x8760</td>
<td>0, 1</td>
</tr>
<tr>
<td>ESbinPtS</td>
<td>Binary variable to indicate if system switches from storage to production</td>
<td>Solved</td>
<td>Unitless</td>
<td>Vector 1x8760</td>
<td>0, 1</td>
</tr>
<tr>
<td>$CO_{2PFL}$</td>
<td>unscaled CO$<em>2$ production flow rate corresponding to $P</em>{cpg}$ for the same temperature dataset</td>
<td>Computed After</td>
<td>kg/s</td>
<td>Vector 1x8760</td>
<td>Various</td>
</tr>
<tr>
<td>$NOCO_{2PFL}$</td>
<td>CO$<em>2$ production flow rate corresponding to $P</em>{cpg}$ scaled to a maximum of 1 MWe production</td>
<td>Computed After</td>
<td>kg/MWe</td>
<td>Vector 1x8760</td>
<td>Various</td>
</tr>
<tr>
<td>RESenvf</td>
<td>CO$_2$ fluid flux into the shallow reservoir due to ES power generation</td>
<td>Computed After</td>
<td>kg/s</td>
<td>Vector 1x8760</td>
<td>$\geq 0$</td>
</tr>
<tr>
<td>RESenvRF</td>
<td>total amount of CO$_2$ in the shallow reservoir at a timestep, only considering influx without outflux</td>
<td>Computed After</td>
<td>kg</td>
<td>Vector 1x8760</td>
<td>$\geq 0$</td>
</tr>
</tbody>
</table>

Table 2: Notation and variable description for the following text

2.3 Data Sources and Normalization

To simulate the meeting of electricity demand with supply, I need demand datasets and generation datasets. I use five datasets in total, three to model solar, wind, and CPG generation, and two to model demand. These two demand datasets represent a residential characteristic demand and an industrial characteristic demand. Each of the two demand datasets is optimized separately with the same three power generation datasets to compare how different system designs are optimal based on the different demand they meet.

To simulate the energy system for a small, residential town (ie. Rugby, ND, population 2,876), I use four datasets from the same year to model the generation supply and demand in the optimization (United States Census Bureau [2010]). Three of these datasets represent the electricity generation of
three different power sources: solar, wind, and CPG. The fourth dataset represents power demand for Rugby, ND. All of these datasets report hourly power values in MWe for the year 2010.

The National Solar Radiation Database reports hypothetical solar power output for a plant in Minot, a town near Rugby (Figure 24). The wind and temperature data are taken from NREL’s Eastern Wind Dataset, which contains power output data for a hypothetical wind power plant just south-west of Minot (Brower & Corbus 2009). I calculate CPG power output from the temperature datasets by a method described in the following section 2.6.

(a) The MISO power supply area covers much of the Midwest including North Dakota, Minnesota, Wisconsin, and parts of South Dakota, Iowa, Missouri, Illinois, and Kentucky.

(b) Rugby, ND is highlighted in a red box along with the nearby town of Minot, ND.

Figure 4: Demand dataset areas

The three power generation datasets used in the MISO simulation are the same as the power generation datasets used in the Rugby simulation. The MISO power supply area covers much of the Midwest including North Dakota, Minnesota, Wisconsin, and parts of South Dakota, Iowa, Missouri, Illinois, and Kentucky (Figure 4a). I use the same hypothetical power datasets because Minot, ND
is within the greater MISO area. This area represents a larger, more industrial focused demand. Demand data from Rugby was only available for the year 2010, so I only use this year for the Rugby simulation. MISO demand data, on the other hand, overlaps the modeled power datasets for the years 2007–2010. Therefore I simulate the MISO power demand versus generation for the whole period of hourly data from 2007–2010. I directly compare the simulation results between the smaller, residential Rugby area and the larger, industrial MISO area for the year 2010. The results for MISO 2007–2009 are used for comparison and yearly variability analyses. Table 3 summarizes the datasets and sources used in this study.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Units</th>
<th>Max.</th>
<th>Min.</th>
<th>Mean</th>
<th>Resolution</th>
<th>Years</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rugby Demand</td>
<td>MWe</td>
<td>13.8 (Winter Peak)</td>
<td>2.4</td>
<td>6.06</td>
<td>Hourly</td>
<td>2010</td>
<td>Otter Tail Power Company (2014)</td>
</tr>
<tr>
<td>MISO Demand</td>
<td>MWe</td>
<td>$10.8 \times 10^4$ (Summer Peak)</td>
<td>$4.31 \times 10^4$</td>
<td>$6.73 \times 10^4$</td>
<td>Hourly</td>
<td>2007–2010</td>
<td>MISO</td>
</tr>
<tr>
<td>Temperature</td>
<td>°C</td>
<td>40.8</td>
<td>-38.9</td>
<td>4.81</td>
<td>5 min.</td>
<td>2007–2010</td>
<td>NREL Western Wind Dataset</td>
</tr>
<tr>
<td>Wind</td>
<td>MWe</td>
<td>2</td>
<td>0</td>
<td>0.864</td>
<td>5 min.</td>
<td>2007–2010</td>
<td>NREL Western Wind Dataset</td>
</tr>
<tr>
<td>Solar</td>
<td>Wh/m²</td>
<td>963</td>
<td>0</td>
<td>168</td>
<td>Hourly</td>
<td>2007–2010</td>
<td>NREL NSRDB</td>
</tr>
</tbody>
</table>

Table 3: All the included datasets, from a variety of sources, include data for the year 2010. This results for this year are the primary focus of the study as it is the latest year for which all data was accessible. The other years of data were not available for Rugby, but only for the MISO region and will be used as a comparison for variability and sensitivity analysis.

However, the demand and generation datasets are uncoupled. To couple them, I first assume all demand and generation timeseries scale linearly. I then scale all the datasets to the same value. The scaled datasets still provide meaningful information about how demand and power output vary throughout the year.

In order to scale these datasets, I normalize them all to a maximum value of one via the following equation, where the subscript \( t \) represents the dataset value at a single timestep:

\[
NO_{x,t} = \frac{DO_{x,t}}{\max(DO_{x})}
\]  

This way the datasets are representative of weather and other power varying inputs rather than on the size of plants or number of people the demand is servicing. I only compare data for the same year, hour of the year, and geographic location. The scaled power output and demand datasets are shown in Figure 5.
Figure 5 also serves as a visualization of the different power and demand trends. The power supply curves, shown in Figure 5A, all have distinct yearly behaviors. Solar energy in Minot, ND has a sinusoidal shape that reaches maximum generation in the summer and minimum in the winter. CPG energy generation has the opposite trend, peaking in the winter and reaching its minimum generation in the summer. This shape reflects the temperature dependence of the energy required to cool down the hot working fluid, which reduces CPG output to zero MWe for particularly hot hours. Wind, on the other hand, has no distinct seasonal behavior but varies seemingly randomly throughout the whole year. Figure 5B shows that demand also has a seasonality. The MISO demand dataset peaks during the summer and has minimal values during the fall and springtime months. The Rugby dataset, on the other hand, peaks in the winter and reaches its minimum during the summer months.

![Figure 5: A. The modeled power output data sets scaled to a maximum of 1. B. The demand datasets for MISO and Rugby scaled to a maximum of 1.](image-url)
2.4 Power Source Resizing

The result of this research is the sizing of the power inputs in order to meet certain conditions of demand. The sizing reflects a scaling of that particular power source by a particular ‘nameplate’ value. The nameplate value indicates the installed maximum power generation for a power plant, which I assign to be the recorded maximum production of a particular power source. The nameplates will represent a constant with units of MWe by which we multiply the unitless datasets in order to mimic that installed size of a power plant.

For example, multiplying the scaled solar dataset NO\textsubscript{s} by a nameplate of 10 MWe will result in a dataset reflecting the behavior of a solar power plant installed to produce a maximum of 10 MWe in 2010. Also, as I only have hourly data, I assume power production is constant across each hour of the year.

I scale demand datasets to a maximum of 1 MWe for the optimization. Therefore I discuss the optimization results in terms of ‘unit power.’ This term represents power datasets that have been scaled to a maximum of 1 MWe. Because the demand data is optimized as a unit power demand, the nameplate results will represent how much times larger power plants have to be sized to meet demand.

In order to meet demand for the whole year, the hourly total power production has to be greater than or equal to the power demand for that hour. The generation and demand varies throughout the year according to its normalized curve shown in Figure 5. The optimization problem therefore linearly scales each power source such that the varying power generation meets varying demand at each hour of the year.

2.4.1 Example Power Source Resizing

Figure 5 illustrates the nameplate scaling process. I scale the plotted demand dataset to a maximum value of 10 MWe for demonstrative purposes. The goal of this optimization problem is to multiply the normalized power datasets by a nameplate value, so the combined sources always generate enough power to meet hourly power demand.
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Figure 6: The power source datasets are scaled by a resulting nameplate value, which is a separate variable for each source, such that the combination of power sources meets demand. Demand actually has a maximum of 1 MWe, but is scaled to 10 MWe in this figure to demonstrate the idea of the source scaling.

2.5 Capital Costs

In order to compare the costs of the system I use capital costs from Lazard (2018) for the wind and solar plants, and values from Adams (2018) for the conceptual CPG plant (Refer to Table 4). Since all the considered renewable power sources have very low operating costs, and the fuel is considered free, I only consider capital costs in this research. The distinction between greenfield and brownfield capital costs reflect whether the CPG plant is being retrofitted to a previous CO\(_2\) storage or engineered geothermal plant (brownfield) versus being built from scratch (greenfield). The greenfield value thus includes the installation costs of all necessary wells, in addition to the wellfield. The brownfield value only includes the cost of production wells. It is assumed that CPG is applied to existing carbon capture and storage sites, so brownfield capital cost values are used in the optimizations and cost calculations.
Table 4: Capital costs per MWe installed are used to calculate power system costs.

### 2.6 CPG Model and Geology

This research targets the Winnipegosis formation in North Dakota for CPG development. The USGS identified the Winnipegosis Formation in North Dakota as a geologic unit with the potential for CO$_2$ sequestration.

The formation has 6—16% porosity and is sealed overhead by the Prairie formation. The Winnipegosis Formation lies at 3.05 kilometers depth and has been estimated by the USGS to have an 11-million acre area, with the potential to sequester 60 Gt CO$_2$ (Buursink et al., 2012). The 10 mD permeability is appropriate for fluid circulation, and with a 275 meter thickness and a 35°C/km gradient, with 10°C at the surface, the temperature and size are suitable for effective heat energy extraction (Buursink et al., 2012). The Winnipegosis formation is topped by the Prairie formation (Figure 7) which serves as an impermeable cap rock, preventing the injected fluid from rising further and ensuring it remains in the formation to be naturally heated and eventually pumped back up to the surface (Buursink et al., 2012).

![Figure 7: The stratigraphic cross section for the Winnipegosis formation and its surrounding formations (Buursink et al., 2012)](image-url)
I calculate the values for CPG power output via the modeled power versus temperature relation:

\[
P_{cpg} = -0.0432 \times (T)^2 - 2.3039 \times (T) + 87.833 \quad (T \leq 0^\circ C) \tag{2}
\]

\[
P_{cpg} = -2.757 \times (T) + 81.939 \quad (T > 0^\circ C) \tag{3}
\]

This relation was modeled specifically for the Winnipegosis Formation by [Adams]\(^\text{[2018]}\) (Figure 8).

(Figure 8) illustrates the temperature dependence of the CPG plant’s power output. The plant has greater power generation when the weather is colder because less power input is needed to cool the hot working fluid. Projecting the linear power versus temperature relationship reveals that there is no net power generation when the ambient temperature is above 29°C.

I insert hourly temperature data into equations 2 and 3 to calculate maximum hourly power output for the modeled CPG power plant. I then normalize the data based on the methods described in the previous section.
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2.6.1 CPGES Model and Temperature Dependence

The CPGES system is introduced because the CPG system generates little to no power when the ambient temperature is high. The CPGES model allows for power generation without temperature dependence, whereas CPG power generation does depend on ambient temperature (Equations 2&3). The temperature dependence of CPG production results from the energy required to cool down the hot CO\textsubscript{2} once it has passed through the turbine and before it is pumped back down into the primary reservoir. However this temperature dependence does not apply for CPGES energy production because the CO\textsubscript{2} is temporarily stored in the shallow reservoir after power generation and does not have to be cooled.

The CPGES system can operate either as a continuous power producer or as complete energy storage, as described by Fleming et al. (2019) in Figure 9.

I simplify the relationship plotted in Figure 9 to a step function without peaks, whose highest production capability is related to the size of the CPG system and the amount by which energy storage can overproduce and underproduce the purely CPG case. This over and underproduction figure is identified in Figure 9 \( f_{SMax} \), and is 1.2 in this CPGES model. The limiting values of the energy storage system are described in the following equations.

\[
-f_{SMax} \cdot n_{cpg} \leq P_{ES} \leq f_{SMax} \cdot n_{cpg}
\]

\( f_{Stor} = f_{Stor} \cdot n_{cpg} \) (5)

\[
-f_{SMax} \leq f_{Stor} \leq f_{SMax}
\]

Equation 5 introduces the variable \( f_{Stor} \), which represents the energy storage portion of the combined CPGES plant. This value is chosen by the optimization problem at each hour timestep.

Temperature variability does not effect the energy storage power production, however it still effects power storage. During the storage phase, CO\textsubscript{2} is extracted from the shallow reservoir, cooled and reinjected into the primary reservoir. Therefore the storage phase depends on temperature in the
same way that CPG power output depends on temperature. I include temperature dependence by multiplying the storage limit by the CPG hourly unit temperature dependence curve, $N_{O_cpg}$.

The maximum hourly energy storage production and storage limits therefore are given in Equation 7.

$$-f_{SMax} \cdot n_{cpg} \cdot N_{O_{cpg}} \leq P_{ES} \leq f_{SMax} \cdot n_{cpg}$$ (7)

The limits of the full, combined CPGES system are defined in Equation 8.

$$n_{cpg} \cdot N_{O_{cpg}} - f_{SMax} \cdot n_{cpg} \cdot N_{O_{cpg}} \leq P_{cpges} \leq n_{cpg} + f_{SMax} \cdot n_{cpg}$$ (8)

Figure 9: Fleming et al. (2019) model the CPGES system that this research bases the energy storage optimization on. The energy storage system is allowed to vary above and below maximum CPG output by $(f_{SMax})*$ (maximum CPG output). The system is also allowed to switch from storage to production once per day, and vice versa. In this study, I approximate $(f_{SMax})$ to be 1.2 based on the above figure.

2.6.2 CO$_2$ Circulation

To better understand our system requirements, we also consider the amount of CO$_2$ that is stored in the shallow reservoir as determined by the optimization. In order to do so we first use the CO$_2$ flow rate data (kg/s) from Adams (2018).

$$CO_{2PFL} \ (kg/s) = -1.7626(T)^2 - 91.458(T) + 7491.7 \quad (T \leq 0^\circ C)$$
\[ \text{CO}_{2\text{PFL}} \, (\text{kg/s}) = -174.55(T) + 7393.4 \quad (T > 0^\circ C) \]

This relationship is illustrated in Figure 10, which identifies the CO\(_2\) flow rate required to get the power output identified in Figure 8 at a particular ambient temperature.

![Figure 10](image)

Figure 10: Adams (2018) also modeled CO\(_2\) flow rates associated with the power output versus temperature (figure 8) for a hypothetical CPG plant on the Winnipegosis formation.

The CO\(_2\) flow rate corresponds to the power generated versus ambient temperature, plotted in Figure 8. As the power output versus Minot ambient temperature is scaled to unit power, I apply the same scaling to the flow rate (Equation 9). I then divide the CO\(_2\) input curve by the maximum CPG Power Generation value, the same way I normalize the CPG power curve. Assuming linear scaling, the maximum CO\(_2\) flow rate value therefore corresponds to unit power output. Mathematically:

\[ \text{NO}_{\text{CO}_{2\text{PFL}}} = \frac{\text{CO}_{2\text{PFL}}(\text{kg/s})}{\text{max}(P_{cpg})(\text{MWe})} \quad (9) \]

I then convert from maximum unit power to actual power based on the solution’s \(P_{ES}\) at each timestep, since the energy storage does not always produce or store to the maximum extent. Since I am only calculating CO\(_2\) input into the shallow reservoir, which corresponds to energy storage energy production, I only consider the positive values of \(P_{ES}\), \(P_{ESprod}\), where the production value is 0 MWe if the system is off or storing. I then multiply \(\text{NO}_{\text{CO}_{2\text{PFL}}}\) by the size and fraction of maximum energy.
the energy storage system actually generates. Since energy storage generation is not temperature dependent, the maximum generation factor equals $f_{S\text{Max}}$, which is set at 1.2 in this study (Figure 9).

$$RES_{co2f}(kg/s) = NO_{co2\text{PFL}} \times \frac{P_{ES\text{prod}} (MWe)}{1.2}$$ (10)

Finally, I integrate this expression over time to calculate the total amount of CO$_2$ in the shallow reservoir.

$$RES_{co2i}(kg) = \sum RES_{co2f} \times \Delta t = \sum RES_{co2f}(kg/s) \times (1 \text{ hr}) \times \frac{3600 \text{ s}}{1 \text{ hr}}$$ (11)

I convert all reservoir CO$_2$ amounts from kg to Megatons for final presentation. This expression only considers CO$_2$ input into the reservoir. To include CO$_2$ output and thus fully constrain the shallow reservoir behavior, we would need to include .03% stored energy loss at each hour of the system. However, we have not yet numerically estimated the relationship between energy loss and CO$_2$ loss from the shallow reservoir. Therefore I limit discussion of shallow reservoir sizing to only how much CO$_2$ is pumped into the reservoir during one year of operation.

### 2.7 CPG Model Scenarios

The three model scenarios (Table 5) do not waste wind and solar energy, minimize total energy, and minimize total capital cost. The first scenario is based on the idea that if wind and solar energy is not used when it is available, it is wasted. Unlike wind and solar, CPG, when not used, remains in the ground as potential energy to be used at a later point in time. Therefore the first optimization scenario involves sizing wind and solar power plants such that they can generate as much energy as possible while still using all the energy they generated. The CPG plant is then sized to cover the remaining demand.

The second scenario allows wind and solar energy to be wasted, and instead minimizes installed nameplates while still meeting demand. The third and final scenario disregards overproduction and minimizes capital cost.

Each of these scenarios is divided into three sub-scenarios. The first of these sub-scenarios requires that demand be met every hour throughout the year. However, in order to meet demand every hour of the year, there is one ‘limiting hour’ during which all three resources have low production.
and that defines the minimum nameplate values calculated. In order to meet energy demand for the
limiting hour, the power sources have to overproduce. I introduce a back-up external power source
so that one limiting hour does not have such a large effect on the total energy production.

Table 5: Scenarios and sub-scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Sub-scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Waste no wind and solar, minimize CPG</td>
<td>1a. Include 0% external power</td>
</tr>
<tr>
<td></td>
<td>1b. Include a 20% external power source</td>
</tr>
<tr>
<td></td>
<td>1c. Include a 50% external power source</td>
</tr>
<tr>
<td>2. Minimize total energy produced</td>
<td>2a. Include 0% external power</td>
</tr>
<tr>
<td></td>
<td>2b. Include a 20% external power source</td>
</tr>
<tr>
<td></td>
<td>2c. Include a 50% external power source</td>
</tr>
<tr>
<td>3. Minimize capital costs</td>
<td>3a. Include 0% external power</td>
</tr>
<tr>
<td></td>
<td>3b. Include a 20% external power source</td>
</tr>
<tr>
<td></td>
<td>3c. Include a 50% external power source</td>
</tr>
</tbody>
</table>

2.8 CPG Optimization Problem

The method of Mixed Inter Linear Programming for optimization takes as input an objective function
and a constraint function, of the form:

$$\begin{align*}
\text{minimize } & \quad c^T(x) \\
\text{subject to } & \quad f_i(x) \leq b_i
\end{align*}$$

and then minimizes the objective function ($c^T(x)$) through various techniques, where $^T$ indicates
the transpose. I model the optimization problem with YALMIP in MATLAB R2018a and solve it using Gurobi 8.0 with a 0.5% optimality gap (Lofberg, 2004) (MATLAB (R2017a)) (Gurobi Optimizer
Reference Manual, 2018). Modeling the problem consists of defining the variables to be optimized,
the objective functions, and the constraint functions. When considering CPG, solar, and wind power,
the optimized variables are the individual nameplates for each power source. The objective and
constraint functions are outlined in Table 5.
2. METHODOLOGY

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Objective function (maximize/minimize)</th>
<th>Constraint function</th>
<th>Variables solved</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Waste no wind or solar (2 Optimizations)</td>
<td>1. max. ( \sum (n_{snw} \times NO_{s} + n_{wnw} \times NO_{w}) \times \Delta t )</td>
<td>1. solarRS + windRS ( \leq ) demand, ( n_{snw}, n_{wnw} )</td>
<td>1. ( n_{snw}, n_{wnw} )</td>
</tr>
<tr>
<td></td>
<td>2. min. ( \sum (n_{cpg} \times NO_{cpg}) \times \Delta t )</td>
<td>2. ( \text{totalP} \geq \text{demand} ), ( n_{cpg} )</td>
<td>2. ( n_{cpg} )</td>
</tr>
<tr>
<td>2. Waste some wind and solar, minimize energy</td>
<td>min. ( \sum (n_{s} \times NO_{s} + n_{w} \times NO_{w} + n_{cpg} \times NO_{cpg}) \times \Delta t )</td>
<td>( \text{totalP} \geq \text{demand} ), ( n_{s}, n_{w}, n_{cpg} )</td>
<td>( n_{s}, n_{w}, n_{cpg} )</td>
</tr>
<tr>
<td>3. Waste some wind and solar, minimize capital cost</td>
<td>min. ( \sum (n_{s} \times cc_{s} + n_{w} \times cc_{w} + n_{cpg} \times cc_{cpg}) \times \Delta t )</td>
<td>( \text{totalP} \geq \text{demand} ), ( n_{s}, n_{w}, n_{cpg} )</td>
<td>( n_{s}, n_{w}, n_{cpg} )</td>
</tr>
</tbody>
</table>

Table 6

Once I include external power, the objective functions remain the same but the constraint functions change to the equations shown in Table 7. I allow two scenarios in which demand is not fully met. The first scenario allows that on each day, the energy generated can be short of demand by 20% of maximum demand. The second scenario allows for energy production to be short of demand by 50% of the maximum demand. I discuss results in terms of unit power, therefore 20% of maximum demand corresponds to 0.2 MWe and 50% to 0.5 MWe, which is the maximum hourly limit of the external source’s power production.

<table>
<thead>
<tr>
<th>Sub-scenario</th>
<th>Constraint</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meet all demand</td>
<td>( \text{totalP} \geq \text{demand} )</td>
</tr>
<tr>
<td>Meet at least 80% of max. demand</td>
<td>( \text{totalP} \geq \text{demand} \geq \frac{2}{5} )</td>
</tr>
<tr>
<td>Meet at least 50% of max. demand</td>
<td>( \text{totalP} \geq \text{demand} \geq \frac{1}{2} )</td>
</tr>
</tbody>
</table>

Table 7

2.9 CPGES Storage Model Details and Scenarios

In order to model the CPGES system, the optimization problem had to be updated with the addition of new variables and constraints. Refer to Table 2 for descriptions of the newly introduced variables in order to define the CPGES system.

The results from the CPG Scenario 1 (never overproducing wind or solar power) reveal that the CPG system cannot be relied on alone to fully satisfy a remainder of demand. Since this scenario proves infeasible, I do not carry it into my consideration of CPGES. The energy storage scenarios therefore consist of minimizing total energy production and minimizing capital cost (Table 8).

I choose to consider energy minimization as only the minimization of the energy storage production and not of storage. I choose this method, expressed in the objective equation in Table 8, because CPG power storage only absorbs excess energy from the solar, wind, and CPG sources, and these...
sources of production are already being considered in the minimization. Since the ES system is intrinsically linked to the CPG technology, the cost minimization objective function only considers the combined CPGES technology. The nameplate of this system reflects the maximum power production of the CPG added to the ES power curves. Therefore the CPGES nameplate can also be represented as the peak production in plot 9. Fleming (in review) calculated the capital cost for the combined CPGES system used in this research.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Description</th>
<th>Objective Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>4. Waste some wind and solar and include energy storage</td>
<td>Meet all demand while minimizing total energy generated</td>
<td>( \min \sum (n_s \cdot NO_s + n_w \cdot NO_w + n_{cpg} \cdot NO_{cpg} + P_{ESprod}) )</td>
</tr>
<tr>
<td>5. Waste some wind and solar and include energy storage</td>
<td>Meet all demand while minimizing capital costs</td>
<td>( \min \sum (n_s \cdot cc_s + n_w \cdot cc_w + n_{cpges} \cdot cc_{cpges}) )</td>
</tr>
</tbody>
</table>

Table 8

### 2.10 CPGES Optimization

I add energy storage into the optimization by creating a new hourly variable, \( P_{ES} \), which represents the power output of the ES system at each hour timestep. \( P_{ES} \) varies between the production maximum, represented as positive output, and the storage maximum, represented as negative output, as described in equation (7). In order to replicate the behavior of the storage system, I also place the following constraints on the ES optimization:

- Allow the ES system to store excess power from other power sources in a particular hour
- limit the ES system to switch from production to storage only once per day and vice versa
- Include a loss of stored energy every hour
- Include a loss of stored energy every hour

Table 9 shows the mathematic expression of these constraints.
2. METHODOLOGY

<table>
<thead>
<tr>
<th>Goal</th>
<th>Constraint functions</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Define the ES system</td>
<td>[ -n_{cpg} \cdot NO_{cpg} + f_{sMax} \leq P_{ES} \leq n_{cpg} \cdot f_{sMax} ]</td>
<td>1. Define storage and production limits of ES, where only storage has temperature dependence</td>
</tr>
<tr>
<td>Limit storage</td>
<td>[ (n_{s} \cdot NO_{s} + n_{w} \cdot NO_{w} + n_{cpg} \cdot NO_{cpg} + P_{ES}) \geq 0 ]</td>
<td>2. Ensure ES storage is limited to what is generated in the same timestep</td>
</tr>
<tr>
<td>Limit ES switch from storage to production and vice versa only once per day</td>
<td>( \sum_{24hrs} (ESbin_{PtS}) \leq 1 ) ( \sum_{24hrs} (ESbin_{StP}) \leq 1 )</td>
<td>11. Limit the switch in any day to 1 for prod. to stor. 12. Limit the switch in any day to 1 for stor. to prod.</td>
</tr>
<tr>
<td>Include storage reservoir loss</td>
<td>[ E_{ES}(t) = SDE \cdot E_{ES}(t-1) - P_{ES}(t) ] for all ( t &gt; 1 ) [ E_{ES}(1) = SDE \cdot E_{ES}(0) - P_{ES}(1) ] [ E_{ES}(0) = E_{ES}(t = t_{final}) ]</td>
<td>13. Ensure the energy stored in the ES system is non-negative 14. Define timeseries as the energy from the previous hour multiplied by the SDE plus the power input from that hour 15. Define the energy in the reservoir for the first hour 16. Ensure that the initial energy in the reservoir equals the final</td>
</tr>
</tbody>
</table>

Table 9

2.11 Cost of Avoided CO₂

A fully renewable power system is currently more expensive than a fossil fuel or nuclear power system. However, a renewable system releases no CO₂. The cost of avoided CO₂ is the additional system price of a renewable system per ton of CO₂ that an equivalent non-renewable system would emit in its lifetime. In a carbon-neutral future, companies that emit CO₂ also have to pay to have it sequestered. The cost of avoided CO₂ is therefore compared to the price of CO₂ sequestration per ton of CO₂ emitted.

To constrain the cost increase of a purely renewable system, I calculate the carbon abatement costs for the optimized power systems. I compare the cost of the renewable system, calculated from optimization results and the capital costs in table 4 to a unit natural gas power plant. Natural gas power has carbon emissions of 0.51 tons/MWe-h, reported by Lazard (2017). The renewable sources of energy have no carbon output.

I assume the 20% and 50% external energy used in scenarios 2b, 2c, 3b, and 3c is a natural gas plant. I then calculate the CO₂ output of the natural gas power plant and the external energy sources over a hypothetical 30 year system lifetime. I finally calculate the capital cost difference between the more expensive renewable system and the cheaper natural gas dispatchable energy source. The cost difference divided by the CO₂ output differences results in a carbon abatement figure, or a price per ton of carbon avoided.

In order to consider greenfield cost values as well, I also run the optimization and calculate the carbon abatement cost for the more expensive greenfield CPG and CPGES systems.
The Intergovernmental Panel on Climate Change’s projected carbon costs are used for comparison (Metz et al., 2001). This comparison represents choosing to initially pay more not to release CO$_2$ (cost of avoided CO$_2$), or to purchase a cheaper system and pay additionally throughout its lifetime to sequester the CO$_2$ that it emits (IPCC carbon cost).
3 Results & Discussion

This section presents the optimization results and analyses of the fully renewable CPG and CPGES systems. Each optimization, according to the scenario guidelines, generates nameplate sizes for every considered power source. In addition to the nameplate results, I also discuss cost results, yearly power behavior, and the sensitivity and variability of these results.

I present the results using two new variables. The first is the Nameplate Oversize Ratio (NOR). This value indicates how many times greater the resulting nameplate for a particular power source is compared to maximum demand. Since we optimize for unit demand, the NOR values are the same as the nameplate results to satisfy unit demand. However, the NOR variable presents nameplate results in a manner which is more accessible to varying demand datasets for future analysis.

The second value is the Ratio to Maximum Demand (RMD). RMD is similar to NOR, but is used to present the power production time series in reference to maximum demand. RMD can also be considered as the multiplication of the NOR results with that particular power source’s normalized output curve ($N_{O_x}$) at a particular timestep. Both RMD and NOR have units of $\frac{\text{MW}_e}{\text{MW}_e}$ and are thus unitless.

3.1 CPG Optimization Results

Figures 11 and 12 show the nameplate results considering solar, wind, and CPG power sources for the considered optimization scenarios.
Both the Rugby and MISO unit demand datasets are met primarily by solar and CPG power generation. Additionally, the nameplates required to meet unit demand for both demand datasets decrease with increasing use of external power. The largest sizing of power sources optimized for
Rugby demand is solar, around 2.4 times maximum demand in scenario 2a. The largest sizing for MISO demand, however, is approximately 6.1 times maximum demand, also for solar in scenario 2a and 3a.

The Rugby and MISO optimized power systems have similar power distribution between sources and trends with increasing external power. However, the Rugby NOR values are almost three times smaller than MISO NOR values, though both the MISO and Rugby demand datasets have a maximum of 1 MWe.

These nameplate results will be further broken down and analyzed in the following sections.

3.1.1 Scenario 1 Results

The most noticeable features in the Scenario Results are the lack of CPG nameplate results for Rugby scenarios 1a. and 1b. and for all three MISO subscenarios. These results depict the infeasibility of not wasting wind or solar energy. The wind and solar resources are sized as large as possible such that their energy is always completely used to satisfy demand, and then CPG is relied on to satisfy the remainder of demand. However, the temperature dependence of CPG causes the power source to not always be able to produce enough energy to completely meet demand. On many hours in the year, the temperature exceeds the CPG production limit of approximately 30°C, when CPG does not generate any power (Figure 8) (Equation 3).

This temperature production limit indicates when more energy is required to cool the CO₂ than the system’s turbine generates. As long as CPG generates at least a little energy, it can be sized to meet demand. However when no energy is generated, the system fails to meet demand.
Figure 13 shows the remainder of demand after wind and solar production has been included, plotted in blue for MISO scenario 1. This hourly demand remainder is compared to the hourly temperatures, plotted in red, and the temperature CPG production limit. On the hours when temperature is above the CPG production limit, CPG cannot meet the remainder of demand therefore the optimization is not solveable.

Scenario 1c has a solution for Rugby unit demand only because the 50% external power source generates enough energy to cover the demand remainder on the hours when CPG cannot. Even the 50% external, however, cannot compensate for the hours with no CPG generation for the MISO demand dataset.

These results indicate that CPG cannot be relied on to meet a portion of demand by itself. The CPG power output’s temperature dependence means a certain degree of wasting wind and solar resources has to be accepted to always meet demand in this particular system set up.
3. RESULTS & DISCUSSION

3.1.2 Scenario 2 & 3 Results

A significant difference between Figures 11 and 12 are the differences in the total sizes of installed systems to satisfy the same unit power. The Nameplate Oversize Ratio indicates how much larger than maximum demand the installed power systems would have to be.

The Rugby and MISO demand curves are satisfied by primarily CPG and solar energy, however the MISO unit power solar and CPG nameplates are approximately three times greater than the Rugby unit power nameplates. This difference is caused by the seasonal behavior of the datasets. The Rugby dataset peaks in the winter and corresponds closely with the CPG production seasonal behavior. MISO demand peaks in the summer and most closely corresponds to solar power generation (Figure 5). It is the reliability and relative dispatchability of CPG versus the non-dispatchable, variable, nature of solar power that causes this sizing difference between the MISO and Rugby unit power results. On a cloudy day, solar energy can dip down to 25% production of its installed capacity even on an hour during the peak summer season. CPG, on the other hand, only dips to 65% of production during its peak winter season.

The variability of solar power is caused by the nature of its production—when the sun is not shining, solar energy cannot be harnessed. Earth’s thermal energy, however, is constantly available. This thermal energy can always be harnessed, though sometimes the nature of the system means that the continued energy generation requires more energy input than is actually generated.

Based on the different system NOR values for MISO and Rugby unit demand, we see that the system design with solar, wind and CPG energy sources most efficiently covers demand for areas represented by the Rugby demand. The Rugby demand dataset represents primarily residential areas with winter-peaking power demand.

Another striking feature about the Scenario 2 and 3 results is the similarity in the nameplate across the different objectives. Specifically, the nameplate results for Rugby Scenarios 2a. and 2b. are the same as the results from 3a and 3b. The MISO 2a, 2b, and 2c results are also the same as the MISO 3a, 3b, and 3c results. The results which are the same across scenario 2 and 3 show that in many cases minimizing cost and energy lead to the same optimal system setup. CPG is by far the most expensive of the power sources (Table 4), roughly 1.5 times more expensive than solar. However, CPG plays such an integral role in power supply that even reducing the CPG nameplate by 0.01
during certain hours would require a significant increase in either the solar or wind to meet demand, such that there would no longer be an economic benefit. This consistency in resulting nameplate values across optimization objective shows the effect that a few particular hours, henceforth called ‘limiting hours,’ constrain the optimization results.

The only case which is not constant across scenario 2 and 3 is Rugby scenarios 2c and 3c. The 2c result is also unique in that it excludes all wind and solar power, opting to only rely on 50% CPG power and 50% external power production. However, when cost is minimized rather than energy, scenario 3c, we see that utilizing only CPG and external is no longer the optimal configuration, as CPG is still more expensive than the other renewable energy sources.

3.1.3 Cost Results

Figures 14 and 15 compare the capital costs for satisfying unit power for a Rugby characteristic demand curve versus for a MISO characteristic demand curve. The increased system size to satisfy MISO unit demand, due to the timing of the peak demand during the year, also corresponds to a much higher capital cost compared to the cost for Rugby unit demand.

Figure 14: Total cost for MISO and Rugby energy minimized power scenarios, scaled by maximum demand
3. RESULTS & DISCUSSION

Figure 15: Total cost for MISO and Rugby cost minimized power scenarios, scaled by maximum demand

The differences in NOR results between scenario 2 and scenario 3 for Rugby demand are barely visible in the price differences of the two systems (Figure 14). The MISO NOR results were the same across scenario 2 and 3 and therefore the costs for scenarios 2 and 3 are also the same.

In both scenarios 2 and 3, it is always over two times more expensive to build a solar, wind, and CPG power system to satisfy MISO unit demand than to satisfy Rugby unit demand. Since both demand datasets have the same maximum value, these price differences, which correspond to nameplate size differences, are a result of the temporal variability and seasonality of the demand datasets. The price difference comes from the temporal correlation between the demand datasets and the different unit power generation datasets.

The pricing of both systems decreases with increasing external power. The Rugby system price, however, decreases much more significantly than the MISO system price. Specifically, with 50% external power (2c, 3c) the Rugby system price decreases to only 30% of the 0% subscenarios (2a, 3a). The MISO 2c and 3c system price only decreases to approximately 45% of the 0% external subscenario price.

The capital cost of solar power is only 1.1 million dollars per MWe installed (Table 4). However, because solar is a variable power source it has to be sized to over 2 times maximum demand for Rugby and over 6 times maximum demand for MISO in order to have fully renewable power generation.
A diesel engine is only 0.65 million dollars per MWe installed (Table 4), and because it is quickly dispatchable it only has to be built with the same nameplate as maximum demand. A diesel engine power supply alone would therefore only cost 0.65 million dollars, whereas renewable solar, wind, and CPG systems for Rugby and MISO are 30 million and 70 million dollars, respectively. Even with 50% external power, the Rugby optimized power system costs 5 million and the MISO system costs 35 million dollars, still much more expensive than the diesel power supply. This cost increase for the renewable systems have to therefore be justified either by their lack of CO₂ emission, or a new feature has to be introduced that lowers the system cost.

3.1.4 External Power Behavior

I include external power usage in the optimization, measured by the percentage of maximum demand it can generate, in order to reduce the effect of ‘limiting hours’ on the system’s overproduction. These are the hours when all the energy sources are at a low percentage of nameplate production, and therefore have to be significantly oversized in order to meet demand. Including external as an option allows a little leeway so the sources do not have to fully meet demand during these hours.
Figure 16: This figure demonstrates the benefit of including sub-scenarios in which not all energy demand is met. Figure A shows total energy production versus demand, while Figure B shows the distribution of the hourly energy production. The power sources are overproducing based on the limitations defined by one hour for which all sources have low production. However, when we allow 20% of maximum demand to be covered by some external source, not by the given renewables, the overproduction lessens (shown in C and D).

Figure [16] demonstrates that allowing energy production to only meet 80% of maximum demand lowers the energy overproduction average to 35 times maximum demand from the previous 45 times excess (Figure [16]). The demand that is not met can be assumed to be filled by some sort of dispatchable energy system, which we have referred to as the external energy.
Figure 17: The temporal behavior of the external power source for each Rugby subscenario, where the dashed black line indicates the external energy limit set in the particular subscenario.

Figure 17 shows how the external power is used for Rugby throughout the year as a back up source, whose production is limited to either 20% or 50% of maximum demand. Another way to think about the external is that for unit power, our external sources could only generate 0.2 MWe-h for subscenario b and 0.5 MWe-h for subscenario c. Figure 17 shows how external power is included by the optimization to satisfy Rugby unit demand in both scenarios 2 and 3. Figures 17A and 17C have approximately the same very low use of external, where it is only used at 1.6% of its capacity, only producing 275 MWe-h throughout the whole year. Still, however, such a small usage of an external power source can decrease the overproduction by ten times. Figures 17B and 17D show how the external power with 0.5 MWe-h maximum is used for scenarios 2c and 3c, respectively. The external energy usage plots show how the system uses external power source almost constantly, especially during the summer and winter, to meet Rugby demand. This usage illustrates the temporal
offset between the Rugby demand characteristic and the CPG characteristic production curve. Since there is no wind or solar installed in the Rugby 3c sub-scenario, we know that whenever external power is used, it is filling the gap between CPG generation and demand.

Figure 18: The temporal behavior of the external power source for each MISO subscenario, where the dashed black line indicates the external energy limit set in the particular subscenario.

Figure 18 shows how the external power is used for MISO unit demand throughout the year. The external power usage to meet MISO unit energy demand is entirely limited to the summer. The total yearly external power usage is much less for MISO unit demand than for Rugby unit demand (Figure 12).

The summer-peaking characteristic of MISO demand and its large use of solar during the summer leads to just a few summer hours, when solar power production is low, during which the system has to be significantly upscaled to meet demand. Once external power is introduced, it only has to generate during a few of these hours to greatly minimize the size of the required power system. The extreme
overproduction caused by those few limiting hours is what therefore causes very limited external use to vastly lower the power sources’ NOR values for MISO unit demand.

However, Rugby unit demand uses the external source more throughout the year than the MISO demand, and thus the external has a greater effect on Rugby nameplate sizing. Both Rugby scenarios 2c and 3c have less than 1 MWe total installed nameplates across all three renewable power sources. The efficient use of the external power in the Rugby optimization leads to the more significant decrease in the system’s total costs for Rugby with increasing external power that we saw in the previous section.

The summer only use of external energy to satisfy MISO unit demand, in combination with the oversizing of the system, reveal the importance of seasonal storage for variable energy. In the off-peak seasons the system under generates, while during the peak seasons certain hours with large demand require oversizing the system. Therefore if energy could be stored during the off-peak seasons and discharged during the extreme hours the renewable system would greatly increase in efficiency.

3.1.5 Yearly Variability

So far, many of the results have been dependent on the ‘limiting hours’ of the system. In order to understand the sensitivity of the optimization results to the timing of these hours I also ran the optimization for the three years before 2010, 2007-2009. These additional results allow comparison to see how weather fluctuations on particular hours and days would effect the sizing of the system over the whole year. Figures 19 and 20 plot how the nameplate sizing changes between years.
Figure 19: The optimization NOR results vary across each year of MISO data, where the whole 4-year dataset results lie within the range of results from all four individual years.

The optimization nameplate results vary significantly, with CPGES and solar varying by over 30% for scenario 2 and 3 results. Wind and Solar variations are greatest when minimizing capital cost (Figure 19B). Solar power nameplates vary by 2–4 NOR between all cost subscenarios, CPG varies 1–2 NOR, and wind varies by 4–15 NOR between all cost subscenarios. Again, the NOR indicates how many times greater the installed power source size is compared to maximum demand. The wind plant size variation is therefore between 4 times and 15 times greater than maximum demand.

The variation in power source NOR for energy minimization is much lower, with solar NOR varying between 1–2.5, CPG varying 1–3, and wind varying 0.25–1. This difference reflects the price difference between the cheaper wind and solar power sources versus the more expensive CPG power source (Table 4). The energy minimization optimization is only concerned with which power source best fits demand (scenario 2), while the cost minimization is only concerned about lowering the total capital cost (scenario 3). Scenario 3 therefore tries to satisfy the majority of demand with the wind and solar, however these are also the two most variable power sources while CPG is more consistent. The variation differences therefore represent the trade-off between a more expensive, but more reliable system (Figure 19A) and a cheaper, more variable system (Figure 19B).
This extreme variation decreases as soon as external energy is introduced, because external energy reduces the impact of a year’s limiting hours on the whole system sizing.

I also optimized the system to cover the whole 4-year period, the results of which are plotted in comparison to each individual year’s optimization results in Figure 20.

Figure 20: All of the 4-year datasets optimized together meet demand at each hour for all four years, whereas the individual year results only have to worry about the limiting hours from that particular year.

The time series plotted in figure 20 show the limiting hour for the entire 4-year dataset. The hour at which sized power generation exactly meets demand, the limiting hour, is during the summer season with particularly high demand. On that hour solar efficiency is low, and because it is summer CPG is also low, so all three power sources have to be oversized in order to meet the high demand.
3. RESULTS & DISCUSSION

3.1.6 CPG Results Moving Forward

The CPG, solar, and wind system works best for winter peaking, residential datasets (Rugby), however summer peaking industrial datasets (MISO) are more representative of a larger portion of the country’s electricity demand. Therefore we want to explore ways by which we can make the CPG, solar, and wind system more efficiently meet a MISO-characteristic demand.

The first observation on how to improve the system efficiency is that introducing external energy has a large impact on MISO nameplates, even when it only operates at 0.01% of its total capacity. We therefore turn to a renewable energy storage method which is able to behave similarly to the quickly dispatchable external energy (Figures 17 and 18), but with a higher generation capacity.

3.2 CPGES Optimization Results

CPGES harnesses overproduced energy from previous hours within the renewable solar, wind, and CPG power generation system. In this section I include the energy storage system in the optimization with the aim of reducing the effect of limiting hours on the power system size and size variability. Introducing CPGES is a renewable alternative to including an external source that emits CO₂, as assumed in the previous CPG results section.

3.2.1 ES behavior

Figures 21, 22, and 23 show the year long behavior of the energy storage technology for the Rugby 2010, MISO 2010, and MISO 2007–2010 optimizations.
Figure 21: The energy storage and generation behavior of the ES system to meet MISO demand, as determined by the optimization for the energy minimization (scenario 4) and cost minimization (scenario 5)
Figure 22: The energy storage and generation behavior of the ES system to meet Rugby demand, as determined by the optimization for the energy minimization (scenario 4) and cost minimization (scenario 5)
The ES system output behaves similarly to the external power source from the CPG results. The system stores primarily during the off-peak seasons, in winter for the MISO dataset and in summer for the Rugby dataset. In addition to seasonal storage, the ES system has the capability for daily switches between generation and storage, allowing the system to avoid large reservoir losses. The 4-year MISO ES time series (Figure 23) shows how ES technology on a 4-year timescale is used primarily as seasonal storage, working as energy storage in the winter and energy generation in the summer.

### 3.2.2 Nameplate Results with and without ES

Introducing energy storage into the power supply system reduces the nameplates for both the cost and energy minimizations significantly compared to the all-renewable scenario 2a and 3a sizes for both MISO and Rugby.
The MISO total installed nameplates decrease from 11 NOF without external, 4.5 NOF with 50% external, to 2 NOF with energy storage. Energy storage satisfies demand with fully renewable energy and the smallest total installed nameplates. Therefore ES more effectively reduces the optimal nameplate sizing than including a 50% external power source for MISO unit demand.

Figure 24: A comparison of the NOR values resulting from the optimization with and without ES for MISO energy minimization (scenario 4), the ES plot has no subscenarios because the storage takes the place of the external power considered in scenarios 1–3
Figure 25: A comparison of the NOR values resulting from the optimization with and without ES for MISO cost minimization (scenario 5), the ES plot has no subscenarios because the storage takes the place of the external power considered in scenarios 1–3

The nameplate distribution between solar, wind, and CPGES power is similar to the distribution of the 50% external (2c, 3c) power system. This distribution has CPGES and solar power equally covering the majority of demand. However, in the ES results wind power plays a larger role than it did in any of the scenarios 1–3 (Figures 24 and 25).

The Rugby energy storage optimization results for both cost and energy minimization rely primarily on CPGES (Figures 26 and 27). Unlike MISO unit demand, Rugby unit demand is more effectively satisfied by including 50% external with CPG, solar, and wind energy generation, exemplified by subscenario 2c and 3c, rather than including CPGES.
Figure 26: A comparison of the NOR values resulting from the optimization with and without ES for Rugby energy minimization (scenario 4)
3. RESULTS & DISCUSSION

Figure 27: A comparison of the NOR values resulting from the optimization with and without ES for Rugby cost minimization (scenario 5)

3.3 How does the ES affect the price

The MISO cost minimization carbon abatement results for scenarios 3 and 5 (cost minimization), with both greenfield and brownfield capital cost values, are shown in Figure 28. According to the IPCC projection, within the next eighty years both the ES scenario and 50% external subscenario will be more cost efficient than building a cheaper natural gas plant and paying to sequester the emitted CO$_2$. This carbon cost reflects how the IPCC predicts future governments will place prices on CO$_2$ emission due to global warming.
Figure 28: the cost of CO\textsubscript{2} avoidance for MISO, considering both brownfield and greenfield CPG capital costs

Only the Energy Storage brownfield scenario is below the 2050 carbon price, which means that based on iPCC predictions, by the year 2050 it will be more economical to spend money initially and install the more expensive ES plant than to install a cheaper natural gas power plant and pay to sequester the carbon it releases.

To meet the Rugby unit demand, subscenario 3c greenfield, which includes 50% external, is actually the cheapest option for CO\textsubscript{2} avoidance while still minimally using external fossil power sources (Figure 29).
These results indicate it is most financially efficient to equip existing carbon sequestration plants with CPGES capabilities (brownfield cost values) for MISO type demand. For Rugby demand it is similarly efficient to equip existing plants or build new CPGES from scratch. Both of these options, brownfield and greenfield ES plants, are equal to or under the 2050 predicted CO$_2$ price.

### 3.3.1 How does ES affect the yearly variability

Introducing CPG energy storage greatly decreases the magnitude of yearly sizing variability. However, each power source nameplate still varies around 20% of the average NOR because the nameplates are so small (Figures 30 and 31).
Figure 30: Introducing ES greatly decreases the amplitude of NOR variances between different years of MISO energy minimization optimizations (scenario 2,5)
3. RESULTS & DISCUSSION

Figure 31: Introducing ES greatly decreases the amplitude of NOR variances between different years of MISO energy minimization optimizations (scenario 3,6)

The variance indicates that using past years to predict future energy source sizing is not the most effective method. However, future energy demand prediction is the subject of different research which focuses solely on the future energy market. To make this study more applicable, incorporating a method of predicting future demand can be explored instead of just using past observations.

3.3.2 CO₂ Reservoir Input

Figure 32 shows the input of CO₂ into the shallow reservoir. The CO₂ amount constrains the maximum required size of the shallow reservoir to reproduce the optimization results from this research.
Figure 32: The influx of CO$_2$ into the shallow reservoir each hour, shown in the top plot, corresponds to CPGES power generation. The bottom plot shows the cumulative amount of CO$_2$. Both these plots use data from the MISO 2010 energy minimization (scenario 5).

We see that across the 2010 year, the energy minimized MISO demand-modeled energy storage system pumps just over 1 Mt CO$_2$ into the shallow reservoir. Unfortunately the CO$_2$ extraction from the reservoir, corresponding to storage, is not yet calculated because the relationship between reservoir loss and CO$_2$ loss has not yet been modeled. Presumably, as the energy storage model requires that the energy stored in the reservoir returns to the initial value by the end of the year (Table 9), in a one year cycle this CO$_2$ is pumped out incrementally whenever the system charges.
4 Conclusions

As a result of my simulations, I can draw the following conclusions. The objective of the first scenario, not wasting wind or solar energy, proves that though CPG is dispatchable, it cannot be relied on to meet a constant demand. This result stems from the fact that on the hottest hours of the year, the CPG system has no net power output. The CPG system can always generate power, however an equal or greater amount of power is required to cool down the hot working fluid on these particular hours. Therefore this research focuses mostly on the results from scenarios 2 and 3, when wind and solar are allowed to overproduce.

**Fully meeting demand with the renewable system results a system total installation that is over 400% of maximum demand.** To cover all Rugby demand with renewables in scenario 2a and 3a, the CPG, solar, and wind combination power systems require installing renewable power sources capable of generating at least 4.25 times maximum demand, at a cost of 29 million dollars. For MISO 2010 demand, the total system has to be installed 11.5 times larger than the maximum demand, costing 74 million dollars. Conversely, installing a diesel engine to meet the same demand would cost 0.65 million dollars, which is over forty times cheaper than the Rugby system, which is in turn a third the price of the MISO system. However, the more expensive, renewable systems have no CO₂ emissions.

When an external power source is used, it decreases oversizing and therefore the total price of the optimized systems. For Rugby, allowing an external source to cover up to 50% of maximum demand decreases the total system size to 0.5 times maximum demand at a cost of 8 million dollars (sub-scenario 3c). For MISO, the installed system with 50% external power generation is only 4 times maximum demand, but costs 31 million dollars.

**In the results both optimization scenarios 2 and 3, the system designed to meet the Rugby demand costs less than the system defined to meet the MISO demand dataset.** This feature corresponds seasonal mismatch of the different demand datasets and the availability of the variable power sources. For instance, Rugby peaks in the winter, which correlates best to the more reliable CPG dataset. MISO, on the other hand, peaks in the summer, which corresponds to solar power, but solar power output fluctuates more than that of CPG. Thus, systems designed to satisfy a winter-peaking demand will tend to have larger CPG utilization and lower costs.
Including energy storage provides a way to efficiently meet summer-peaking demand. When using energy storage, no external generation is needed, and thus no CO\textsubscript{2} is emitted. Once ES is introduced into the system, the fully renewable, cost minimized Rugby power system is reduced to 2 times maximum demand, costing 10.9 million dollars (scenario 5). Though this price is still more expensive than the Rugby system with external energy (sub-scenario 3c), it releases no CO\textsubscript{2}. The MISO 2010 power system with ES included only needs 2.5 times maximum demand power installation, which costs 16.4 million dollars (scenario 5). For MISO unit demand, ES provides the cheapest renewable power system with the least overproduction.

We see that the optimization results without CPG vary significantly for the same location across different years of observation. This is especially true for the cost minimization model, which heavily relies on the more variable solar and wind power sources. However once ES is introduced, it stabilizes the optimization sizing results across the different years. To design a reliable power system, the demand and power source data have to be modeled across several years, rather than just considering average values.

Though including CPGES significantly reduces the cost of the entire system, all the power systems still cost much more than 0.65 million dollars, which is the capital cost of a diesel engine capable of fully meeting demand. However, as worldwide attention focuses on combatting global warming, governments have begun attaching prices to CO\textsubscript{2} emissions and setting emission limits. Therefore, while not currently economically practical, the proposed all-renewable systems are only going to become more economical as CO\textsubscript{2} costs are included.

Finally, CPG and CPGES can provide dispatchable power and energy storage on both short and seasonal time scales. This storage can stabilize variable renewably generation such that demand can be reliably met. Thus, CPGES can enable a transition from fossil fuels to renewable energy.
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