OPTIMAL OPERATION OF AN INTEGRATED ENERGY PARK
INCLUDING FOSSIL FUEL POWER GENERATION,
CO₂ CAPTURE AND WIND

A THESIS SUBMITTED TO THE DEPARTMENT OF
ENERGY RESOURCES ENGINEERING
OF STANFORD UNIVERSITY
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR
THE DEGREE OF MASTER OF SCIENCE

Charles Andrew Kang
May 2011
I certify that I have read this thesis and that, in my opinion, it is fully adequate in scope and quality as a thesis for the degree of Master of Science in Energy Resources Engineering.

__________________________________________
(Louis J. Durlofsky)  Principal Co-Adviser

I certify that I have read this thesis and that, in my opinion, it is fully adequate in scope and quality as a thesis for the degree of Master of Science in Energy Resources Engineering.

__________________________________________
(Adam R. Brandt)  Principal Co-Adviser
Abstract

This study considers the operation of an integrated energy park consisting of a baseload coal-fired power station, an MEA-based CO$_2$ capture facility powered by an auxiliary natural gas combustion turbine, and wind generation. Energy park components are modeled using energy and mass balances. A formal optimization procedure is used to determine the optimal hourly dispatch of energy park components to maximize operating profit given fuel prices, hourly electricity price, and hourly wind generation data. The optimization procedure enforces a daily CO$_2$ emission intensity constraint modeled after a California emission performance standard.

Idealized wind and energy price scenarios as well as scenarios from a synthetic year constructed from historical U.S. fuel prices, California electricity prices and Wyoming wind generation data are considered. Several different energy park configurations are studied. For the synthetic year, operating profit excluding maintenance costs for optimized dispatch schedules showed improvement of about 20% over that for schedules derived from a heuristic dispatch procedure. Statistical analysis of aggregate data for the synthetic year indicates that the benefit from optimization is positively correlated with daily electricity price variability and mean wind generation.

Taken in total, this study quantifies the benefit attainable through the flexible operation of an integrated energy park.
Acknowledgements

First, I would like to thank my advisers Prof. Louis Durlofsky and Prof. Adam Brandt who provided advice, supervision, questions and encouragement. Their insights and comments have had an enormous impact on this research, and without them I do not think this work would exist as such. Working with Adam and Lou has been a great experience, and I look forward to continuing to interact with them in the coming years.

I would like to thank Obiajulu Isebor for his help with optimization methods. Though the optimization tool used for the final results in this report is part of a commercial package, much of this work’s earlier development was conducted using Obi’s optimization tools.

I was first introduced to the technology of CO₂ capture and storage in a course taught by Prof. Jennifer Wilcox and Prof. Sally Benson. I would like to thank Jen and Sally for this and subsequent interactions.

The valuable discussions I had with Nicholas Jenkins of Cardiff University and Dale Simbeck of SFA Pacific are gratefully acknowledged.

My office mates Mark McClure, Michael Krause and Obiajulu Isebor have been helpful in ways large and small, from typesetting to coursework to coding.

Support for this work and my studies from the Two Elk Energy Park Integrated Clean Energy Solutions Fund is graciously acknowledged.

Finally, I am grateful to my parents Andy and Nina and my sister Cheryl. They have always supported me and have helped make me the person I am today.
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Chapter 1

Introduction

Two significant challenges are likely to confront electric power systems in the coming years: greenhouse gas (GHG) emissions from fossil fuel combustion will be limited to reduce the risk of climate impacts, and intermittent renewable sources will constitute an increasing fraction of generation on an electric grid that was not originally designed to handle highly intermittent generation.

Many approaches have been proposed to reduce GHG emissions, including fuel switching, carbon dioxide capture and storage (CCS), and expansion of non-fossil power sources (e.g., renewables and nuclear). CCS is appealing because it would enable the use of abundant and low-cost U.S. coal resources while reducing emissions of CO$_2$ to the atmosphere by up to 90%. Unfortunately, capture technologies are expensive. For example, estimates of per-MWh cost penalties for capturing CO$_2$ from new power plants range from $\approx$ 20-40/MWh for a pulverized coal power plant, representing an increase in cost of electricity (COE) of 40-90% over plants without CO$_2$ capture (IPCC, 2005). Capture cost estimates are somewhat lower for NGCC plants, but percentage increases are similar. The energy consumption of CO$_2$ capture, a major contributor to increased cost, is also significant. The energy penalty for capture is estimated at 24-40% for new pulverized coal plants (IPCC, 2005), with a theoretical minimum of about 11% (House et al., 2009).

The intermittency of renewable resources also poses a significant challenge. As
renewable penetration rates rise — a phenomenon driven in part by Renewable Portfolio Standards in at least 27 states in the United States — intermittency could pose challenges for grid operation and reliability. System-level grid modernization and intelligent demand response offer large potential advantages in a grid with significant renewable penetration. Building such a system will, however, be an expensive and lengthy process, as grid improvements are estimated to entail investment of more than $500 billion over 20 years (EPRI, 2004) and will require cooperation among governments, system operators, and utilities across multiple states and provinces. Until improved approaches for handling intermittency are implemented at large scales, significant amounts of renewable resources could be under-utilized. For example, curtailment levels in ERCOT at peak times were 500 to 1000 MW in 2009, sometimes reaching 3000 MW curtailed (Fink et al., 2009).

Given the costly nature of both GHG control and generation intermittency, it is useful to investigate how these problems can be addressed simultaneously. Such strategies are particularly important in light of the clear possibility that both renewables and fossil fuels with CO$_2$ capture will be used simultaneously. Toward this end, in this study we develop a process model of an integrated energy park and apply computational optimization procedures to identify the most beneficial dynamic parameters for integrated operation. The model entails simulation modules representing a baseload pulverized coal power station, a monoethanolamine (MEA)-based CO$_2$-capture unit, a natural-gas-fired combustion turbine to provide heat for carbon capture as well as supplemental electricity, and intermittent wind power. In our model, electricity from wind can be exported to the grid or used for CO$_2$ capture, and CO$_2$-rich MEA solution can be stored to time-shift some of the energy demand. A constraint on the maximum CO$_2$ emission intensity is enforced. With the exception of the coal-fired power unit, all of the modules can be operated quite flexibly. Operating parameters associated with each unit are determined using an optimization procedure to maximize operating profit.

Although the model is intended to be representative of a range of possible integrated-energy-park scenarios, the specific configuration and components are motivated by
a system proposed to operate in the Powder River Basin (PRB) in Wyoming to export power to California (North American Power Group, 2011). Such a system will require some type of CO$_2$ mitigation, as the CO$_2$ intensity of baseload power sold in long term contracts with public utilities in California is required to be less than 499 kg CO$_2$/MWh (SB1368, 2006), while the CO$_2$ intensity of a typical subcritical coal-fired power station burning PRB coal is about 1000 kg CO$_2$/MWh.

Despite the clear need for effective fossil-renewable integration, relatively little previous research has been directed to such combinations. Optimal integration of multiple types of renewable resources has, in contrast, received significant attention (e.g., wind and solar in Celik, 2002 and Habib et al., 1999; wind and hydro in Jaramillo et al., 2004). Among the existing studies addressing integrated fossil-renewable systems, Gouse et al. (1993) considered integration of IGCC systems with solar PV, while Forsberg (2008, 2009) studied nuclear-fossil-renewable combinations. Phadke et al. (2008) explored wind-coal hybrids from an economic perspective. None of these studies, however, applied formal optimization procedures to determine optimal dynamic operating modes and parameters as is accomplished in this work.

A great deal of prior work has been done in considering optimal integration of CO$_2$ capture with coal-fired power stations from a fundamental process design standpoint (Khalilpour and Abbas, 2011; Sanpasertparnich et al., 2010). Other work has been undertaken in assessing different solvents to be used in the separation process (Abu-Zahra et al., 2007; Aroonwilas and Veawab, 2007). These studies have shown that careful integration and design of CCS systems can reduce the energy penalty associated with CCS.

Previous research addressing the flexible operation of integrated coal-fired-power and CCS systems has had the goal of improving economics and reducing the impact on the electric grid. Chalmers and Gibbins (2007) and Chalmers et al. (2009) studied the flexible operation of post-combustion capture systems in an attempt to reduce the costs associated with CCS. In their modeling, solvent regeneration was temporarily shut down to allow increased power output during times of peak power demand and prices. During these times the produced CO$_2$ is either vented (increasing emissions) or stored in rich solution for later regeneration (increasing capital costs).
Similarly, Cohen et al. (2010) optimized the operation of post-combustion CO₂ scrubbing for systems with and without rich solution storage, finding that moderate capacity solution storage allows a 10-30% improvement in operating profits over an inflexible system. The benefits of flexible CCS have been shown to extend to the grid scale as well (Cohen et al., 2010), in that the use of flexible CCS can substantially reduce the amount of lost-capacity replacement required in a CCS-intensive system. The essential finding is that, if carbon capture systems at baseload plants can be turned off for relatively short periods during peak demand, then peak power production capacity is not reduced by the introduction of CCS.

The studies cited above consider systems in which the energy required for CCS is provided by the baseload coal-fired power station (i.e., parasitic operation). An alternative configuration, which has some advantages including the ability to maintain the plant’s existing capacity, is to power CCS using an auxiliary natural-gas-fired unit. Such a system, which is addressed in this work, does not appear to have been considered for optimization in previous studies that consider auxiliary-powered CCS systems, such as those by Bashadi and Herzog (2011) and Gibbins et al. (2011). Our work is also distinct as we explicitly include in our system the usage or sale of wind power, as would be practiced in an integrated wind-coal-gas energy park. Finally, in contrast to previous work, we examine CCS in the context of a CO₂ emission performance standard (EPS) rather than a carbon tax.

This thesis is divided into four chapters including this introduction. Chapter 2 describes the modeling and optimization undertaken in this study: Section 2.1 provides an overview of the energy park configuration considered in this work; our models for the specific units are described in Section 2.2; and the optimization procedure is discussed in Section 2.3. Chapter 3 presents optimization results for a number of cases. These include idealized examples in Section 3.3, realistic scenarios based on wind data from the target location in Wyoming and California electricity prices in Section 3.4, and variations in energy park configuration in Section 3.5. We conclude with a discussion in Chapter 4.
Chapter 2

Modeling and Optimization
Method

2.1 Overview of Energy Park Model

Our model comprises a series of process units or modules. For each of these units we formulate equations describing mass and/or energy flow rates, and the units interact through mass and energy exchanges. All of the modules are characterized by one or more system parameters. Some of these parameters, such as coal consumption rate, are fixed. Others, such as the partial loading of the natural gas combustion turbine, can vary in time and are determined as part of the optimization. Inputs to the model include the available wind power and the electricity price as a function of time. Both the process model and the optimization procedure are implemented in MATLAB.

The overall model is shown schematically in Figure 2.1. It consists of distinct modules for the coal plant (CP), CO₂ capture process, auxiliary natural gas combustion turbine (NGCT), heat recovery steam generator (HRSG, which is used to provide heat to the CO₂ capture unit), and wind power facility. In our model, wind is used primarily for electricity generation but can also be applied to provide heat (via an electric boiler or heat pump) for CO₂ capture when electricity prices do not warrant burning natural gas for this purpose. The modules that contain dynamic decision variables, which are used to optimize system performance, are indicated by
the red stars.

Figure 2.1: Overall process model showing units containing decision variables.

In the CP, coal is burned in air to provide energy to produce steam, which is then used to generate electricity via a steam turbine. CO$_2$-rich flue gas flows from the coal plant into the CO$_2$ capture process, in which some fraction of the flue gas CO$_2$ is separated and compressed. The separation is accomplished using an MEA-based temperature-swing process consisting of two stages, absorption and regeneration. In the absorption stage, CP flue gas interacts with CO$_2$-lean MEA solution, and CO$_2$ absorbs into the solution, causing the exiting flue gas to have a reduced concentration of CO$_2$. In the solvent regeneration stage, heat is applied to the CO$_2$-rich solution to liberate CO$_2$ and return the solution to its lean state. The resultant pure CO$_2$ stream is then compressed in preparation for pipeline transport. We do not model CO$_2$ transport or storage. In our representation of the CO$_2$ capture unit, there is an
option to store CO$_2$-rich solution to allow for time-shifting the heat and work demand associated with regeneration. This introduces the potential for independent operation of absorption and regeneration, as was shown to be useful by Chalmers and Gibbins (2007) and Cohen et al. (2010, 2011).

The heat for the capture process is supplied by heat recovered from the NGCT exhaust via the HRSG, and by the possible conversion to heat of electric power from wind. The work demand for capture is supplied as a parasitic load from the coal power station, NGCT and wind. Electric power generated by the coal power station, NGCT and wind that is not consumed within the system is exported to the electric grid.

To determine operating parameters for a single day, the process model is evaluated under a sequence of steady states assumption using a time discretization of one hour. In the optimization framework, the dynamic parameters are varied until the local maximum of the objective function is found. Bound constraints on the parameters, as well as overall constraints on the system response (e.g., maximum CO$_2$ emission intensity), are enforced. In the general case, four decision variables (indicated in Figure 2.1) determine the system operating behavior in each time period $t$, for a total of 96 optimization parameters per modeled day. These decision variables are the NGCT partial loading, $L_t$, which controls the power output of the NGCT; the wind-to-heat use fraction, $X_t$, which specifies the electric boiler or heat pump duty; the duct firing duty, $D_t$, which controls the amount of natural gas burned in the oxygen-rich NGCT exhaust (duct firing may be used to increase the amount of heat available for CO$_2$ capture); and $S_t$, the fraction of absorbable flue gas CO$_2$ to be stored as rich solution. It is not necessary to include all variables in all optimizations — for example, solvent storage can be set to zero to simulate a system in which this capability is not available.

2.2 Process Model

Each component of the process model incorporates fundamental mass and energy balances. Modules exchange mass and energy with each other and with the outside
world. Quantities exchanged with the outside world include fuel, CO\textsubscript{2} emitted to the atmosphere, CO\textsubscript{2} captured and exported in pure compressed form, and electric power exported to the grid.

### 2.2.1 Coal Plant

The CP model consists of a mass balance and an energy balance. Throughout this study, superscripts indicate the system component or module of interest, and subscripts indicate the flow stream. All variables are defined in a detailed nomenclature section at the end of this thesis.

The mass balance relation provides flue gas flow rate and air intake rate for a given coal combustion rate using the following net chemical reaction:

\[
\dot{n}_a^{CP} (a_1 N_2 + a_2 O_2 + a_3 Ar + a_4 CO_2) \\
+ \dot{n}_c^{CP} (c_1 C + c_2 H + c_3 O + c_4 Cl + c_5 S + c_6 N + c_7 H_2 O + c_8 Ash) \\
\rightarrow \dot{n}_p^{CP} (p_1 N_2 + p_2 O_2 + p_3 Ar + p_4 H_2 O + p_5 NO + p_6 SO_2 + p_7 Cl + p_8 Ash + p_9 CO_2).
\]  

(2.1)

Coefficients \(a_1, \ldots, a_4\) are the molar composition of air; \(c_1, \ldots, c_8\) are the molar composition of the coal; and \(p_1, \ldots, p_9\) are the molar composition of the combustion products. The quantity \(\dot{n}_a^{CP}\) (mol/s) is the molar air intake rate of the CP; \(\dot{n}_c^{CP}\) (mol/s) is the molar coal consumption rate of the CP; and \(\dot{n}_p^{CP}\) (mol/s) is the molar rate of the combustion product, which is further disaggregated into flue gas and solid ash. These molar quantities are used to calculate the mass flow rates for air intake, \(\dot{m}_a^{CP}\) (kg/s), coal consumption, \(\dot{m}_c^{CP}\) (kg/s), flue gas production, \(\dot{m}_{FG}^{CP}\) (kg/s), and ash production, \(\dot{m}_{ash}^{CP}\) (kg/s). Note that \(\dot{m}_{FG}^{CP}\) is a vector because we track multiple flue gas components. The composition of air used here is shown in Table 2.1, and the mass balance relationships used to calculate the combustion products are shown in Table 2.2.

The coal composition used in this work is that of sub-bituminous Wyoming Powder River Basin coal as given in the Integrated Environmental Control Module, or IECM (Rubin et al., 2007). The ratio of \(a_2 \dot{n}_a^{CP}\), the intake rate of oxygen, to \(c_1 \dot{n}_c^{CP}\), the demand rate of oxygen for stoichiometric combustion of the carbon component, is the
2.2. PROCESS MODEL

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Substance</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_1$</td>
<td>N$_2$</td>
<td>0.7808</td>
</tr>
<tr>
<td>$a_2$</td>
<td>O$_2$</td>
<td>0.2095</td>
</tr>
<tr>
<td>$a_3$</td>
<td>Ar</td>
<td>0.0093</td>
</tr>
<tr>
<td>$a_4$</td>
<td>CO$_2$</td>
<td>0.0004</td>
</tr>
</tbody>
</table>

Table 2.2: Air composition

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Substance</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_1  $</td>
<td>N$_2$</td>
<td></td>
</tr>
<tr>
<td>$p_2  $</td>
<td>O$_2$</td>
<td></td>
</tr>
<tr>
<td>$p_3  $</td>
<td>Ar</td>
<td></td>
</tr>
<tr>
<td>$p_4  $</td>
<td>H$_2$O</td>
<td></td>
</tr>
<tr>
<td>$p_5  $</td>
<td>NO</td>
<td></td>
</tr>
<tr>
<td>$p_6  $</td>
<td>SO$_2$</td>
<td></td>
</tr>
<tr>
<td>$p_7  $</td>
<td>Cl</td>
<td></td>
</tr>
<tr>
<td>$p_8  $</td>
<td>Ash</td>
<td></td>
</tr>
<tr>
<td>$p_9  $</td>
<td>CO$_2$</td>
<td></td>
</tr>
</tbody>
</table>

Table 2.2: Product composition in CP combustion

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Substance</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_1  $</td>
<td>N$_2$</td>
<td>$a_1 n_{a CP}$</td>
</tr>
<tr>
<td>$p_2  $</td>
<td>O$_2$</td>
<td>$a_2 n_{a CP} + \frac{1}{2} c_3 n_{c CP} - \left( c_1 + \frac{1}{4} c_2 + c_5 + \frac{1}{2} c_6 \right) n_{c CP}$</td>
</tr>
<tr>
<td>$p_3  $</td>
<td>Ar</td>
<td>$a_3 n_{a CP}$</td>
</tr>
<tr>
<td>$p_4  $</td>
<td>H$_2$O</td>
<td>$\left( \frac{1}{2} c_2 + c_7 \right) n_{c CP}$</td>
</tr>
<tr>
<td>$p_5  $</td>
<td>NO</td>
<td>$c_6 n_{c CP}$</td>
</tr>
<tr>
<td>$p_6  $</td>
<td>SO$_2$</td>
<td>$c_5 n_{c CP}$</td>
</tr>
<tr>
<td>$p_7  $</td>
<td>Cl</td>
<td>$c_4 n_{c CP}$</td>
</tr>
<tr>
<td>$p_8  $</td>
<td>Ash</td>
<td>$c_8 n_{a CP}$</td>
</tr>
<tr>
<td>$p_9  $</td>
<td>CO$_2$</td>
<td>$a_4 n_{a CP} + c_1 n_{c CP}$</td>
</tr>
</tbody>
</table>

Air ratio $\lambda^{CP}$. Here $\lambda^{CP} = 1.2$ (an excess air fraction of 20%) — a typical value for a pulverized coal combustion plant (Kitto and Stulz, 2005).

The elements of $\mathbf{m}_{FG}^{CP}$, the CP flue gas mass flow vector, are given by the product coefficients for species other than ash and Cl after conversion from molar basis to mass basis. For example, for the CO$_2$ component of $\mathbf{m}_{FG}^{CP}$ we have $\dot{m}_{FG,CO_2}^{CP} = p_9 n_{p CP} M_{CO_2}$, where $M_{CO_2}$ is the molecular mass of CO$_2$. Ash does not participate in any chemical reactions in our model, so it is not disaggregated into its constituent compounds. Chlorine is included as part of the ash for simplicity.

We assume that complete combustion occurs. The minor constituents NO and SO$_2$ are determined by the amount of nitrogen and sulfur present in the coal. While these assumptions do not reflect the full complexity of the combustion process, they are acceptable here as the flue gas component of interest is CO$_2$. 
The energy balance for the CP is an efficiency relation
\[ \dot{E}_{CP} = \eta_{CP} \dot{m}_{cCP} \Delta H_{comb}, \quad (2.2) \]
where \( \dot{E}_{CP} \) (W) is the electric power output from the CP, \( \eta_{CP} \) is the overall efficiency of the CP on a higher heating value basis, taken to be 33%, and \( \Delta H_{comb} \) (J/kg) is the higher heating value of the coal.

The baseload CP treated in this model has a \( CO_2 \) emission intensity of 997 kg \( CO_2/MWh \) and a volumetric flue gas \( CO_2 \) concentration of 14.3%.

### 2.2.2 \( CO_2 \) Capture Process and \( CO_2 \)-Rich Solution Storage

#### Basic Capture Process and Energy Requirements

The \( CO_2 \) capture process modeled here is an amine solvent temperature-swing process that uses a 30 wt % MEA aqueous solution. The process and the relevant data are based on the work of Jassim and Rochelle (2006). The data used here are for a process with simple stripping, no vapor recompression, and a stripper approach temperature \( (\Delta T) \) of 10 °C. The capture process is treated as having fixed per-unit mass \( CO_2 \) capture heat and work demands, and the details of process flows and temperatures are not modeled. The per-unit-mass heat and work demands do not vary significantly as a function of the amount of \( CO_2 \) captured, as Ziaii et al. (2009) showed that per-unit-mass heat demand is not a strong function of regeneration load.

In the absorption stage, CP flue gas \( m_{FG}^{CP} \) interacts with \( CO_2 \)-lean solution at low temperature \( (\approx 320 \, K) \), and \( CO_2 \) preferentially absorbs into the solvent at a rate \( \dot{m}_{abs}^{CC} \) (kg \( CO_2/s \)). Absorption fraction can be varied between zero and a maximum absorption fraction \( A_{max} \), typically 0.60 – 0.90. In practice there are several ways to achieve absorption rates between zero and \( A_{max} \). For example, some flue gas might be vented before it reaches a constant-capture rate absorption stage, or the absorption process itself may be operated differently for different desired capture rates. Our treatment of absorption does not distinguish between these different approaches. Lean solution \( CO_2 \) loading is 0.249 mol \( CO_2/mol \) MEA, and rich loading is 0.459 mol
CO$_2$/mol MEA. Absorption has a work requirement $e_{abs} = 0.04$ MJ/kg CO$_2$ to reflect pump work in the whole capture process. This value is representative of the pump duty requirements for configurations presented in Jassim and Rochelle (2006).

In the regeneration stage, CO$_2$-rich solution is heated with steam at 400 K, 0.246 MPa (saturated vapor), which causes CO$_2$ to off-gas at a rate $\dot{m}^r_{CC}$ (kg/s). The steam then condenses to liquid at 400 K, 0.246 MPa (saturated liquid). The CO$_2$ stream contains some water vapor, which is easily removed (water vapor removal is not represented explicitly in the model) to produce a pure stream. Regeneration has a heat demand $e_r = 4.29$ MJ/kg CO$_2$ (Jassim and Rochelle, 2006).

After being separated into a pure stream, the CO$_2$ is compressed to 13.8 MPa for pipeline transport. Compression occurs immediately after separation because it is difficult to store a large volume of low density gas. Hence, $\dot{m}^c_{CC} = \dot{m}^r_{CC}$. The compression stage has a work requirement $e_c = 0.32$ MJ/kg CO$_2$ (Jassim and Rochelle, 2006).

**Storage of CO$_2$-Rich MEA Solution**

Between the absorption and regeneration stage, our model allows storage of some amount of CO$_2$, up to a capacity of $C^r_{CC}$ (kg CO$_2$), in CO$_2$-rich MEA solution. This rich solution storage acts as energy demand storage. It is instructive to consider the mass and volume of solvent involved. Given lean and rich CO$_2$ solvent loading, storing 1 kg of CO$_2$ requires storing 23 kg of rich solution (including the mass of CO$_2$), or approximately 0.0209 m$^3$ solution/kg CO$_2$ Amundsen et al. (2009).

The net CO$_2$ storage rate, $\dot{m}^s_{CC}$ (kg CO$_2$/s), is expressed as

$$\dot{m}^s_{CC} = \dot{m}^CC - \dot{m}^CC_{out}. \quad (2.3)$$

Storage is constrained by a (specified) maximum mass of CO$_2$ that has been absorbed but not yet regenerated and compressed. The stored CO$_2$ at the end of the one-day simulation is required to be less than or equal to the amount of stored CO$_2$ at the beginning of the simulation. No additional cost is associated with CO$_2$-rich solution storage (in future work, storage could be treated with an appropriate capital cost).
CHAPTER 2. MODELING AND OPTIMIZATION METHOD

CO₂ Capture Process Model Formulation

The work supply rates \( \dot{W}_{abs}^{CC} \) and \( \dot{W}_{c}^{CC} \) (W) and heat supply rate \( \dot{Q}_r^{CC} \) (W) requirements for the stages of the CO₂ capture process can be written as functions of the CO₂ capture rate:

\[
\dot{W}_{abs}^{CC} = e_{abs} \dot{m}_{abs}^{CC},
\]  
(2.4)

\[
\dot{Q}_r^{CC} = e_r \dot{m}_r^{CC},
\]  
(2.5)

\[
\dot{W}_{c}^{CC} = e_c \dot{m}_c^{CC}.
\]  
(2.6)

The regeneration rate is controlled by the heat supplied to the capture process from the HRSG and the wind-to-heat facility. All heat supplied is used for regeneration. Thus, the regeneration rate can be written as a function of heat supplied:

\[
\dot{m}_r^{CC} = \frac{\dot{Q}_r^{CC}}{4.29 \text{ MJ}_{th}/\text{kg}},
\]  
(2.7)

where \( \dot{Q}_r^{CC} = \dot{Q}_{HRSG}^{FG} + \dot{Q}_{EH}^{W} \), with \( \dot{Q}_{HRSG}^{FG} \) (W) and \( \dot{Q}_{EH}^{W} \) provided by the HRSG and wind-to-heat modules.

The CO₂-rich solution undergoing regeneration flows out of the storage tank at rate \( \dot{m}_{s_{out}}^{CC} \). The total amount of CO₂ stored in rich solution, \( C_f^{CC} \) (where subscript \( f \) indicates that this is the filled amount of storage filled with rich solution, and \( t \) indicates the time period under consideration), is a function of absorption and regeneration history. The difference between the rate of regeneration of stored rich solution and the excess rate of absorption is the net storage rate \( \dot{m}_{s}^{CC} \) (Equation 2.3). Since mass is conserved, net storage rate must equal the difference between the absorption and regeneration rates:

\[
\dot{m}_{s}^{CC} = \dot{m}_{abs}^{CC} - \dot{m}_r^{CC}.
\]  
(2.8)

In principle any two of the quantities in Equation 2.8 can be chosen freely, and the third calculated. The regeneration rate is calculated elsewhere in the model, so either the storage rate or the absorption rate must be calculated. Within the optimization
framework, as a result of the functional dependencies of the terms in Equation 2.8, it is most convenient to work directly with $\dot{m}_{\text{CC}}$ and to calculate absorption from the other two quantities.

The capture facility is assumed to continually remove solution from storage for regeneration. If there is insufficient stored rich solution available to operate regeneration, as computed from the heat supplied over the time interval (i.e., $C_{CC}^{f,t}/\Delta t < \dot{m}_{r,t}^{CC}$), then additional CO$_2$ is absorbed from the flue gas to make up the difference. Excess CO$_2$ may also be absorbed and the resulting rich solution put into storage at rate $\dot{m}_{\text{CC}}^{s}$. Since $S_t$ (the fraction of maximum absorbable flue gas CO$_2$ to be stored in rich solution) is a decision variable, it is convenient to express Equation 2.8 in the following form, where we use the fact that $\dot{m}_{\text{CC}}^{s} = S_t A_{\text{max}} \dot{m}_{\text{FG,CO}_2}^{CP}$:

$$\dot{m}_{\text{abs,t}}^{CC} = S_t A_{\text{max}} \dot{m}_{\text{FG,CO}_2}^{CP} - \dot{m}_{\text{out,t}}^{CC} + \dot{m}_{r,t}^{CC},$$  \hspace{1cm} (2.9)

where $\dot{m}_{\text{out,t}}^{CC} = \min (\dot{m}_{r,t}^{CC}, C_{f,t}^{CC}/\Delta t)$. The quantities $\dot{m}_{\text{abs,t}}^{CC}$ and $\dot{m}_{r,t}^{CC}$ are then used to calculate $C_{CC}^{f,t+1}$.

### 2.2.3 Natural Gas Combustion Turbine

The NGCT is modeled using mass and energy balances similar to those used for the CP, though here we include the ability to operate at partial load. The mass balance is given by:

$$\dot{n}_a^{CT} (a_1 N_2 + a_2 O_2 + a_3 Ar + a_4 CO_2) + \dot{n}_g^{CT} (c_1 CH_4 + c_2 C_2H_6 + c_3 N_2)$$
$$\rightarrow \dot{n}_p^{CT} (p_1 N_2 + p_2 CO_2 + p_3 H_2O + p_4 O_2 + p_5 Ar).$$  \hspace{1cm} (2.10)

The quantities $a_1, \ldots, a_4$ are the molar air composition given in Table 2.1; $c_1, c_2, c_3$ are the molar natural gas composition given in Table 2.3; and $p_1, \ldots, p_5$ are the molar combustion product composition given in Table 2.4.

As in the CP module, combustion in the NGCT is assumed to proceed to completion. The air intake rate is chosen by using the specific power given in Kim (2004).
Table 2.3: Composition of natural gas

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Substance</th>
<th>Value $^a$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c_1$</td>
<td>CH$_4$</td>
<td>0.834</td>
</tr>
<tr>
<td>$c_2$</td>
<td>C$_2$H$_6$</td>
<td>0.158</td>
</tr>
<tr>
<td>$c_3$</td>
<td>N$_2$</td>
<td>0.008</td>
</tr>
</tbody>
</table>

$a$ - From IECM (Rubin et al., 2007)

Table 2.4: Product composition in NGCT combustion

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Substance</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_1 \dot{n}^{CT}_p$</td>
<td>N$_2$</td>
<td>$a_1 \dot{n}^{CT}_a + c_3 \dot{n}^{CT}_g$</td>
</tr>
<tr>
<td>$p_2 \dot{n}^{CT}_p$</td>
<td>CO$_2$</td>
<td>$a_4 \dot{n}^{CT}_a + (c_1 + 2c_2) \dot{n}^{CT}_g$</td>
</tr>
<tr>
<td>$p_3 \dot{n}^{CT}_p$</td>
<td>H$_2$O</td>
<td>$(2c_1 + 3c_2) \dot{n}^{CT}_g$</td>
</tr>
<tr>
<td>$p_4 \dot{n}^{CT}_p$</td>
<td>O$_2$</td>
<td>$a_2 \dot{n}^{CT}_a - (2c_1 + \frac{7}{2}c_2) \dot{n}^{CT}_g$</td>
</tr>
<tr>
<td>$p_5 \dot{n}^{CT}_p$</td>
<td>Ar</td>
<td>$a_3 \dot{n}^{CT}_a$</td>
</tr>
</tbody>
</table>

The NGCT modeled here has a constant air intake control scheme, so the air intake rate is determined by fuel use at full load. Three turbine types (referred to as B, C and D) are considered. The Type B turbine has specific power 274.2 kJ/kg working fluid, with air intake 54.3 kg air/kg fuel; Type C has specific power 382.5 kJ/kg working fluid with air intake 45.3 kg air/kg fuel; and Type D has specific power 489.1 kJ/kg working fluid with air intake 39.4 kg air/kg fuel (Kim, 2004).

The energy conversion relation for the NGCT is given by

$$\dot{E}^{CT} = \eta^{CT}_{rel}(L)\eta^{CT}_{th} \dot{m}^{CT}_g(L)\Delta H^{comb}_g = \eta^{CT}_{rel}(L)\eta^{CT}_{th} \dot{Q}^{CT}_g(L), \quad (2.11)$$

where the additional efficiency term $\eta^{CT}_{rel}(L)$ is a relative partial load efficiency that reflects the loss in efficiency associated with operation of the turbine at less than full capacity. When the turbine is operated at full capacity, $\eta^{CT}_{rel}(L = 1) = 1$ and the overall efficiency of the turbine is equal to the design thermal efficiency of the turbine $\eta^{CT}_{th}$. The relative partial load efficiency is a function of the partial load $L$, after Kim (2004). Figure 2.2 shows relative efficiency and relative fuel use curves for three turbines. The thermal efficiencies of the three turbines studied are converted to HHV.
basis from the given LHV basis. Type B, described as good but not state-of-the-art, has \( \eta_{th}^{CT} = 0.2813 \) (HHV); Type C, described as state-of-the-art, has \( \eta_{th}^{CT} = 0.3288 \) (HHV); and Type D, described as under development, has \( \eta_{th}^{CT} = 0.3669 \) (HHV) (Kim, 2004; Ganapathy, 2003). NGCT fuel use \( \dot{m}_g^{CT}(L) \) is a nonlinear function of \( L \); for values of \( L < 1 \), decreasing NGCT efficiency entails increased fuel use per MW_e.

Figure 2.2: NGCT partial load relative efficiency and fuel use curves for three turbines.

The temperature of the NGCT flue gas is an important quantity in our model, as this flue gas provides heat for CO\(_2\) capture. An expression relating flue gas temperature and heat per-unit-mass heat addition is obtained by integrating from standard conditions to the final state under the assumption that specific heat capacity varies linearly with temperature; i.e., \( C_{FPFG}^{HRSG}(T) = C_0 + \alpha T \), where \( C_0 = 975.01 \text{ J/kg-K} \) and \( \alpha = 0.2253 \text{ J/(kg-K}^2) \) (Ganapathy, 2003). Multiplying the resulting expression by the flue gas mass flow rate gives an expression relating heat addition rate with flue gas temperature:

\[
\dot{Q}_g^{CT} = \dot{m}_{FG}^{CT} \int_{T_0}^{T_{FG}^{CT}} (C_0 + \alpha T) \, dT = \dot{m}_{FG}^{CT} \left[ C_0 (T_{FG}^{CT} - T_0) + \frac{\alpha}{2} \left( [T_{FG}^{CT}]^2 - T_0^2 \right) \right].
\]  

(2.12)

This equation is solved for \( T_{FG}^{CT} \) (K) to provide an equation for the NGCT flue gas
temperature as a function of heat addition rate $\dot{Q}^C_T$ (W) and NGCT flue gas mass flow rate $\dot{m}^C_{CT}$ (kg/s). Before being used to compute the flue gas temperature, $\dot{Q}^C_T$ is adjusted to account for moisture content. The computed turbine exhaust temperatures are consistent with those given by Kim (2004).

### 2.2.4 Heat Recovery Steam Generator

Burning additional natural gas in the O$_2$-rich NGCT flue gas, referred to as duct firing, is useful when more heat is desired than is available from the NCGT exhaust. The HRSG calculation, which accounts for the possibility of duct firing, proceeds in two steps.

First, duct firing at rate $\dot{m}^H_{HRSG}$ (kg/s) is treated by modifying the mass and energy of the flue gas to account for combustion of the additional gas. Mass balance, energy balance, and flue gas temperature relations are identical to those in the gas turbine, Equations 2.10-2.12. The change in chemical composition of the flue gas due to duct firing is assumed to have negligible impact on its specific heat capacity. The amount of natural gas burned is calculated from $D_t$ as a fraction of the maximum natural gas consumption rate for the HRSG (which is set equal to the maximum natural gas consumption rate of the NGCT for simplicity):

$$\dot{m}^H_{g,t} = D_t \left[ \dot{m}^H_{g,\text{max}} \right].$$  \hspace{1cm} (2.13)

Next, the heat recovery and steam generation process is treated. In the heat recovery process, NGCT flue gas is cooled from approximately 850 K at the NGCT outlet (HRSG inlet) to 423 K at the HRSG outlet (this outlet temperature is chosen to avoid precipitating corrosive fluids in the HRSG, after Ganapathy, 2003). The heat from this cooling process is transferred to the water, which enters the HRSG as saturated liquid at 400 K, 0.246 MPa and leaves as saturated vapor at 400 K. (All heat transfer between the capture process and HRSG occurs at 400 K; only the heat of vaporization of water is used to transfer energy.) The water is assumed to have negligible pressure change between inlet and outlet.

Heat recovery from the flue gas is governed by a relation derived by integrating
the heat capacity of the flue gas between the HRSG inlet and outlet temperatures:

$$
\dot{Q}_{HRSG}^{FG} = \dot{m}_{FG}^{CT} \int_{T_{FG, in}^{HRSG}}^{T_{FG, out}^{HRSG}} C_{P_{FG, out}^{HRSG}}(T) dT,
$$

(2.14)

where $\dot{m}_{FG}^{CT}$ is the mass flow rate of the NGCT flue gas and the HRSG flue gas specific heat capacity function $C_{P_{FG, out}^{HRSG}}(T)$ is taken to be the same as the NGCT flue gas specific heat capacity given above. The mass flow rate of steam generated is then calculated by dividing the rate of heat transfer into the water (equal to the rate of heat removal from the flue gas with a small shell loss) by the heat of vaporization of water at 400 K:

$$
\dot{m}_{H_{2}O}^{HRSG} = \frac{\eta_{sh}^{HRSG} \dot{Q}_{FG}^{HRSG}}{\Delta H_{vap}^{H_{2}O, 400 K}},
$$

(2.15)

where $\eta_{sh}^{HRSG} = 0.97$ is an efficiency term reflecting thermal shell losses in the HRSG.

### 2.2.5 Wind-to-Heat Facility (Heat Pump or Electric Boiler)

The energy park can also produce heat from wind-generated electricity. Although this would not typically be cost effective, there are times when it is preferable to use wind energy for heat rather than to simply curtail (“spill”) it. This could be useful, for example, when high wind generation coincides with low electricity prices.

In the base configuration, the wind-to-heat capability uses an electric boiler; in the alternative scenario we introduce a hypothetical high-lift heat pump. The electric power converted to heat, $\dot{E}^{EH}$ (W), is calculated from the decision variable $X_t$ and the available wind generation:

$$
\dot{E}_t^{EH} = X_t \dot{E}_t^{W},
$$

(2.16)
where $\dot{E}_W^W$ (W) is the wind power generation. The energy conversion relation for the electric boiler is

$$\dot{Q}^{EH} = \eta^{EB} \dot{E}^{EH}, \quad (2.17)$$

where $\eta^{EB}$ is the efficiency of the electric boiler, taken here to be 0.96, a typical value for electric boiler efficiency (Shaalan, 2007).

The energy conversion relation for the hypothetical high-lift heat pump is

$$\dot{Q}^{EH} = \eta^{HP} \left( \frac{T_H}{T_H - T_C} \right) \dot{E}^{EH}, \quad (2.18)$$

where $\left( T_H/(T_H - T_C) \right)$ is the Carnot coefficient of performance for a heat pump acting between hot and cold reservoirs at temperatures $T_H$ and $T_C$ and $\eta^{HP}$ is a constant reflecting practical performance losses. The hypothetical high-lift heat pump acting between 298 K and 400 K with $\eta^{HP} = 0.5$ (chosen so that the heat pump has approximately twice the heat-per-MW$_e$ yield of the electric boiler) has an overall coefficient of performance of 1.96.

The heat provided by the electric boiler or heat pump is applied to water under the same conditions as in the HRSG, and causes a phase change from saturated liquid to saturated vapor at 400 K. As in the HRSG, the water is assumed to have negligible pressure change between inlet and outlet. The mass flow rate of water through the electric boiler or heat pump is given by an expression analogous to Equation 2.15:

$$\dot{m}^{EH}_{H_2O} = \frac{\dot{Q}^{EH}}{\Delta H_{vap, \, 400 \, K}}. \quad (2.19)$$

### 2.2.6 Overall Mass and Energy Flows

The modules described in this section interact with one another through the mass and energy flows. These flows are shown in detail in Figures 2.3 and 2.4. System parameters can be either specified or determined during the optimization.
2.3 Optimization Procedure

For a given fuel price, electricity price and wind generation profile, the integrated energy park model is optimized to maximize operating profit excluding maintenance costs. Decision variables are constrained to fall within feasible bounds, and an overall CO₂ emission intensity constraint is imposed. Capital costs are not included in the model. However, our results can be used to quantify the operating profit for different systems, which can then be compared to incremental capital costs if such cost data are available.

2.3.1 Decision Variables and Objective Function

As discussed earlier, four decision variables are determined in each time interval: NGCT partial load $L_t$, wind-to-heat facility use $X_t$, duct firing natural gas use $D_t$, and absorbable flue gas CO₂ storage fraction $S_t$. This gives a total of 96 decision
variables for a 24 hour period. All decision variables are normalized by their maximum allowable values, so all are bounded by zero and one. The quantities $L_t$, $X_t$ and $D_t$ collectively control the amount of process heat available and thus control CO$_2$-rich solution regeneration $\dot{m}_r^{CC}$. The quantity $S_t$, along with the other decision variables, controls the flue gas CO$_2$ absorption rate. We found that the quality of the search is enhanced significantly if $L_t$ is constrained to avoid low values; specifically $0 < L_t < 0.1$ (this range is in general suboptimal since efficiency is very low). Thus, in our procedure, when $L_t < 0.1$, it is simply set to zero.

An objective function representing the operating profit excluding maintenance costs is formed by subtracting the cost of fuel from the revenues earned from power sales, with an additional regularization cost. The regularization cost reduces abrupt shifts in model settings by penalizing rapid changes in operating parameters. This penalty can be thought of as representing the costs associated with rapid ramping of equipment. Regularization enters the objective function as a specified constant multiplying the sum of the squared changes in the decision variables $L_t$, $X_t$ and $D_t$,
and the normalized absorption rate $A_t = \dot{m}_{abs,t}^{CC} / \dot{m}_{FG,CO_2}$, between successive time periods.

The regularization coefficient $\varepsilon$ is specified as $R/384$, where $R$ is the total daily revenue. This value for $\varepsilon$ is chosen such that a step change from 0 to 1 in all four parameters — i.e., applying the maximum change in all variables from one time period to the next — contributes a penalty of $1/4$ of one hour’s worth of revenues (other values of $\varepsilon$ are considered in the results presented below).

We seek to maximize the objective function $J$:

$$
\max J = \begin{cases}
\sum_{t=1}^{24} (\Delta t) P^E_t \left( \dot{E}_{t}^{CP} + \dot{E}_{t}^{CT} + \dot{E}_{t}^{W} - \dot{W}_{abs,t}^{CC} - \dot{W}_{e,t}^{CC} - \dot{E}_{t}^{EH} \right) \\
- \sum_{t=1}^{24} (\Delta t) P^c \dot{m}_{t}^{CP} + \sum_{t=1}^{24} (\Delta t) P^{NG} \left( \dot{m}_{g,t}^{CT} + \dot{m}_{g,t}^{HRSG} \right) \\
- G
\end{cases}
$$

where $P^E_t$, $P^c$ and $P^{NG}$ are the hourly electricity price, coal price and natural gas price, and where the regularization term $G$ is given by

$$
G = \varepsilon \left[ \sum_{t=2}^{24} (L_t - L_{t-1})^2 + \sum_{t=2}^{24} (X_t - X_{t-1})^2 + \sum_{t=2}^{24} (D_t - D_{t-1})^2 + \sum_{t=2}^{24} (A_t - A_{t-1})^2 \right].
$$

### 2.3.2 General Constraints

As noted above, the decision variables are subject to bound constraints. Two additional constraints apply to the entire time period under consideration: the amount of solvent storage cannot exceed the amount stored initially, and the energy park must meet a CO$_2$ emissions performance standard. There are also two types of general constraints that appear at each time interval, which constitute 48 additional constraints. One set of constraints ensures that CO$_2$ absorption operates within the allowable
range, while the other set ensures that the rich solution storage tank is not overfilled.

The rich solution storage constraint is given by:

\[
C_{f,t_{end}}^{CC} \leq C_{f,t_0}^{CC}.
\]  

(2.22)

It is convenient to express this type of constraint in the form \( h \leq 0 \), where \( h \) is a normalized constraint violation. During the course of the optimization, when \( h \) is zero or less, the constraint is satisfied, in which case we set \( h = 0 \). Otherwise, the value of \( h \) quantifies the degree of constraint violation. Writing the constraint violation in this form we have:

\[
h_{CC}^{C,\text{end}} = \max \left( 0, \frac{1}{C_{CC}^{f,t_{end}} - C_{CC}^{f,t_0}} \right).
\]  

(2.23)

The daily average \( \text{CO}_2 \) emission intensity is constrained to be less than 499 kg \( \text{CO}_2 / \text{MWh} \). This constraint is modeled after the California Emission Performance Standards (SB1368, 2006). Note that in this formulation overall electricity generation and emissions from all park components (CP, NGCT, HRSG, wind farm, and \( \text{CO}_2 \) capture) are combined in calculating \( \text{CO}_2 \) emission intensity. It is unclear whether this would be allowable under current interpretation of the California law, though the optimization procedure could of course be modified to accommodate different interpretations of the emission constraint (see discussion below). This constraint is given by:

\[
-499 \frac{\text{kg} \ \text{CO}_2}{\text{MWh}} + \sum_{t=0}^{23} \left( \dot{m}_{\text{FG,CO}_2}^{CP} - \dot{m}_{\text{abs,t}}^{CC} + \dot{m}_{\text{FG,CO}_2,t}^{HRSG} \right) \frac{\Delta t}{\left( \dot{E}_{t}^{CP} + \dot{E}_{t}^{CT} + \dot{E}_{t}^{W} - \dot{E}_{t}^{CC} - \dot{E}_{t}^{EH} \right) \Delta t} \leq 0.
\]  

(2.24)

Normalizing by the EPS requirement, the constraint violation is as follows:

\[
h^{\text{EPS}} = \max \left( 0, -1 + \frac{1}{499 \frac{\text{kg} \ \text{CO}_2}{\text{MWh}}} \sum_{t=1}^{24} \left( \dot{m}_{\text{FG,CO}_2}^{CP} - \dot{m}_{\text{abs,t}}^{CC} + \dot{m}_{\text{FG,CO}_2,t}^{HRSG} \right) \frac{\Delta t}{\left( \dot{E}_{t}^{CP} + \dot{E}_{t}^{CT} + \dot{E}_{t}^{W} - \dot{E}_{t}^{CC} - \dot{E}_{t}^{EH} \right) \Delta t} \right).
\]  

(2.25)
The absorption rate as described in Equation 2.9 is constrained in each time period such that the absorption rate does not exceed the maximum possible for the capture system. The resulting constraint for each time period is \( \dot{m}_{CC}^{\text{a},t} \leq A_{\text{max}} \dot{m}_{FG,CO_2}^{CP} \). Normalizing by \( \dot{m}_{FG,CO_2}^{CP} \), the constraint violations are:

\[
\frac{\dot{m}_{CC}^{\text{a},t}}{\dot{m}_{FG,CO_2}^{CP}} - A_{\text{max}} \leq 0.
\]

Normalizing by \( \dot{m}_{FG,CO_2}^{CP} \), the constraint violations are:

\[
h_{CC,\text{abs,max},t} = \max \left( 0, \frac{\dot{m}_{CC}^{\text{a},t}}{\dot{m}_{FG,CO_2}^{CP}} - A_{\text{max}} \right). \tag{2.26}
\]

The amount of CO\textsubscript{2} in rich solution storage in each time period is constrained to be less than the maximum rich solution storage capacity. These constraints are expressed as \( C_{CC}^{f,t} \leq C_{CC}^{c} \) and the normalized constraint violations are given by:

\[
h_{CC,\text{C,max},t} = \max \left( 0, \frac{C_{CC}^{f,t}}{C_{CC}^{c}} - 1 \right). \tag{2.27}
\]

The overall constraint violation \( h^{\text{tot}} \) for all of the general constraints is formed by combining the individual constraint violations, where we use a weighting of \( 1/96 \) for each of the 48 constraints that apply in each time period:

\[
h^{\text{tot}} = \sqrt{(h^{EPS})^2 + (h_{CC,\text{end}}^{CC})^2 + \frac{1}{96} \sum_{t=1}^{24} [ (h_{CC,\text{abs,max},t}^{CC})^2 + (h_{CC,\text{C,max},t}^{CC})^2 ]}. \tag{2.28}
\]

When a feasible solution is found, \( h^{\text{tot}} = 0 \). For any infeasible solution, the value of \( h^{\text{tot}} \) gives an indication of the degree of overall constraint violation.

### 2.3.3 Optimization Algorithm

The optimization problem is solved using the \textbf{fmincon} interior point algorithm, a standard function in the MATLAB optimization toolbox. This code is a gradient-based method that enforces general constraints (Equations 2.22-2.27, combined together in 2.28) using a penalty function. Upon convergence, the total constraint violation \( h^{\text{tot}} \) is less than \( 10^{-5} \). Other optimization algorithms including Hooke-Jeeves direct search and a genetic algorithm were also applied, though the best performance was achieved.
using \texttt{fmincon}.

Because our optimization performs a local search, the results are dependent on the initial guess. Therefore, for each optimization problem we run the code four times using random starting points and once starting from a heuristic operating profile (described in Section 3.1). After these five initial runs, 10 additional runs, starting from random perturbations of magnitude 10\% from previously found solutions, are performed. The best result of the 15 total runs is then chosen. Performing additional runs (for example, a total of 30 runs) did not lead to substantially improved results.
Chapter 3

Results for Integrated Energy Park Operation

3.1 Heuristic Operating Profile

We first define a heuristic operating profile as a basis for comparison. This heuristic approach treats the NGCT as a modified peaking plant: the NGCT is operated at a high load when the price of electricity is high enough relative to the price of natural gas to make a profit, and at low load during other times. More specifically, “high” NGCT partial load is the maximum possible load such that all waste heat is used for regeneration. Therefore, peak NGCT partial load produces heat equal to the maximum regeneration heat duty. In times when electricity generation leads to a loss, the NGCT is operated constantly at the minimum load necessary to meet the CO₂ emission performance requirement over the modeled day. In the heuristic case, all available wind energy is exported to the grid. We define optimization benefit $\Delta J$ to be the difference between the profit from the optimized solution $J_{opt}$ and the profit from the heuristic solution $J_{heur}$.
3.2 Base Configuration

Several different configurations are studied in this work. In all configurations, the CP has a generation capacity of 400 MW and is operated at this level constantly. In addition, the NGCT is sized such that recovered NGCT waste heat is sufficient to regenerate CO$_2$-rich solution at a rate equal to 90% of $\dot{m}_{FG,CO_2}$.

The base configuration uses a Type C NGCT of size 327.5 MW$_e$, an electric boiler for the wind-to-heat facility, and has maximum absorption $A_{\text{max}} = 0.65$ (i.e., absorption is undersized compared to regeneration). It has rich solution storage capacity sufficient to hold three hours worth of CP flue gas CO$_2$ at a 90% capture rate (1.196 million kg CO$_2$ in rich solution, or 27,500 m$^3$ of solution).

3.3 Simple Scenarios

Following are four simple scenarios that illustrate system behavior by modifying aspects of the base configuration described in Section 3.2. Input data for these simple scenarios are shown in Figure 3.1. In all of these scenarios, the price of natural gas is $4.60/mmBtu.

3.3.1 Zero Wind, Zero Storage

In this scenario, shown in Figure 3.1(a), the price of electricity rises linearly from $5/MWh to $60/MWh over the course of the day, and wind generation is a constant 0 MW. The maximum CO$_2$ absorption fraction $A_{\text{max}}$ is 0.65. There is no rich solution storage.

As seen in Figure 3.2, the optimized solution has the NGCT turn on in hour 3, rising quickly to 70% for the rest of the day. In the absence of rich solution storage, CO$_2$ absorption and solvent regeneration rates are identical. The NGCT is not dispatched at 100% because the optimization scheme requires that recovered NGCT waste heat be put to use in regeneration. Because there is no storage and absorption is undersized (the NGCT is sized to produce enough heat to regenerate 90% of CP flue gas CO$_2$), the NGCT must be operated at below full load. In this scenario, the
3.3. SIMPLE SCENARIOS

(a) Linear electricity prices with zero wind — Sections 3.3.1 and 3.3.2

(b) Linear electricity prices with constant wind — Section 3.3.3

(c) Wind scenario — Section 3.3.4

Figure 3.1: Input data for wind generation and electricity prices in simple scenarios.

The benefit from optimization for the day is $\Delta J = $14,900 (10.2% improvement over $J_{\text{heur}}$).

3.3.2 Zero Wind, Three Hours Storage

This scenario is the same as that described in Section 3.3.1 except we now include rich solution storage equivalent to three hours of 90% CO$_2$ capture (1.196 million kg...
CO₂). The addition of storage decouples absorption from regeneration, giving the system flexibility to absorb CO₂ at a relatively constant rate but regenerate solvent (which is heat intensive) when electricity prices are more favorable.

As seen in Figure 3.3, NGCT output is reduced in early morning hours while rich solution is accumulated. This NGCT dispatch pattern allows the energy park to take advantage of the higher electricity prices in the later hours of the day while meeting the emissions constraint. This additional flexibility results in an objective function value improvement of \( \Delta J = 59,400 \) (40.5% over \( J_{heur} \)), substantially more than in the previous scenario.

The NGCT is ramped more slowly in this case because of an interaction between the emissions constraint and the CO₂ storage constraint. Because storage is limited, the NGCT must be dispatched earlier in the day to keep rich solution storage from exceeding capacity (as is evident in Figure 3.3, storage is at capacity in hours 7 – 10). \(^1\)

\(^1\)Absent the CO₂ storage constraint, the NGCT would start generating later and ramp up much more quickly (compare the ramp rate in the zero storage scenario) to take advantage of the rising price of electricity; CO₂-rich solution storage would be built up in the first part of the day, and regenerated later with full NGCT load.
Figure 3.3: Results for simple scenario for three hours rich solution storage, zero wind scenario.

### 3.3.3 Constant Wind, Three Hours Storage

This scenario, shown in Figure 3.1(b), differs from the scenario in Section 3.3.2 in that wind generation occurs at a constant 48 MW. Figure 3.4 shows a dispatch schedule that is similar to the scenario without any wind generation, though it differs in that the NGCT starts generating later and ramps up more quickly (the NGCT is not turned on until hour 10). No wind power is used to produce heat in this scenario; electricity prices are high enough that using wind power instead of natural gas to produce heat is economically unfavorable.

The NGCT is ramped up more quickly in this scenario than in the zero wind scenario because the wind power reduces the interaction between the emission constraint and the CO$_2$ storage constraint. Recall that wind generation is counted toward the park’s energy output, which reduces the effective CO$_2$ intensity of the facility. Thus, less CO$_2$ capture is needed, and rich solution storage is sufficient to allow the NGCT to stay idle early in the day when electricity prices are lower. This relates to the concept of “blending” power sources, which we discuss later.

In this scenario, the benefit from optimization is $\Delta J = $ 68,600 (35.6% over $J_{heur}$). The absolute optimization benefit is larger than in the previous scenario because of
CHAPTER 3. RESULTS FOR INTEGRATED ENERGY PARK OPERATION

Figure 3.4: Results for simple scenario with three hours rich solution storage, 48 MW wind scenario.

the increased flexibility afforded by the wind, but it is smaller as a fraction of $J_{heur}$ because the wind also improves the profit in the heuristic case.

3.3.4 Wind-to-Heat Scenario

This scenario, shown in Figure 3.1(c), is constructed to show a situation in which it is favorable to use electric power from wind to produce heat for the CO$_2$ regeneration process. After hour 11, the price of electricity jumps from a constant $5/MWh to a constant $40/MWh, while wind output drops from 120 MW to 0 MW in the same hour. When the electricity price is low, it is economic to use wind instead of natural gas to produce heat.

Figure 3.5 shows that a large fraction (0.4 – 0.9) of wind generation in the first half of the day is used for regeneration heat, and the NGCT is operated at full load in the second half of the day. In this scenario, which is intended to be illustrative, the benefit from optimization is $\Delta J = $91,700 (381.4% over $J_{heur}$). The large relative optimization benefit seen here is due to the special construction of the scenario: electricity prices jump sharply, thus yielding a large benefit from optimal NGCT dispatch; also, electricity prices are very low for an extended period of time, allowing...
3.4. REALISTIC SCENARIOS

Scenarios for each day in a synthetic year are constructed to show the model’s aggregate behavior across a variety of input scenarios. Several assumptions underlie optimization performed on these scenarios. We assume perfect knowledge of electricity prices and wind generation. We further assume that all electricity generated is accepted for export, and that the energy park is a price taker in the market. We neglect all costs and revenues associated with aspects of electricity generation other than energy, such as congestion and auxiliary services. In practice, these assumptions may or may not hold to varying degrees depending on market construction, regulation, weather patterns, and other factors.

Using the base configuration, the optimization problem is solved for every day\(^2\) of a synthetic year, with electricity and natural gas prices from 2010 and wind generation data from 2005.

\(^2\)We exclude the two days affected by daylight saving time changes because these days do not have 24 hours.

Figure 3.5: Results for scenario constructed to demonstrate wind-to-heat usage.

the energy park to exploit the flexibility afforded by the electric boiler.
3.4.1 Data Sources and Treatment

Modeled data for wind power inputs are taken from the NREL Western Wind Dataset (3Tier, 2010), representing generation at four neighboring wind sites in northeastern Wyoming. The data from these four sites were summed. Each of these modeled sites includes 10 three-megawatt turbines, and thus the aggregated data are for 120 MW of wind capacity.

Hourly California electricity prices were obtained from the California Independent System Operator OASIS database (California Independent System Operator, 2010). The prices used are the energy portion of the day-ahead market for a Northern California pricing hub.

Natural gas prices used here are monthly-average natural gas prices delivered to U.S. utilities according to the U.S. Energy Information Administration Short-Term Energy Outlook Custom Table Builder (U.S. Energy Information Administration, 2011). The input Powder River Basin coal has a price of $10/ton across all days. This value is representative of the pre-transport long-run average price of sub-bituminous coal in the United States (U.S. Energy Information Administration, 2009a,b). Variations in coal price can be thought of as increasing or decreasing operating profit by a constant amount (coal consumption is not a decision variable).

3.4.2 Representative Days

Results for two illustrative days are presented in this section. October 18 has electricity price variation, and June 15 has high electricity price variation. Figure 3.6 shows the data for these days.

Low Electricity Price Variation, October 18

Optimization results for October 18 data are shown in Figure 3.7. As is evident in Figure 3.6(a), wind generation is high in the early hours of the day, declining to zero

\(^3\)Wind farm locations 22784 through 22787, all with capacity factor 0.40, were chosen in this study.

\(^4\)Aggregation node TH_NP15_GEN-APND.
Figure 3.6: Model input data for June 15 and October 18. Electricity price data from 2010. Wind generation data from 2005.

at the end of the day, and electricity prices vary from about $30/MWh in the early hours of the day and at the end of the day (with a minimum of $25.79/MWh in hour 2) to about $40/MWh during the rest of the day (with a peak of $42.60/MWh in hour 19).

Figure 3.7: Results for October 18.
In the optimized operating profile, the NGCT is dispatched at near full load when the price of electricity is high, and is turned off when the price is low. CO$_2$-rich solution is built up in the beginning of the day when the NGCT is not running, and is regenerated when the NGCT is running. The wind-to-heat electric boiler is not used, as the price of electricity is never sufficiently low. The benefit from optimization for this day is $\Delta J = $34,800 (14.5% over $J_{heur}$).

High Electricity Price Variation, June 15

From Figure 3.6(b), we see that June 15 electricity prices are low in the early part of the day, with a minimum of $4.15/MWh in hour 4, and are much higher in the middle of the day and in the afternoon, with a peak of $51.20/MWh in hour 15. Optimization results for June 15 are shown in Figure 3.8. The optimized operating profile has the NGCT running at near full capacity when the price of electricity is high, with the exception of hours 18-19, when there is a dip in electricity price. Rich solution storage is built up in hours 0-8, when the electricity price is low, and in hours 18-19. Solvent is regenerated when the NGCT is running. When the price of electricity is very low, as in hours 3 ($4.15/MWh) and 4 ($7.08/MWh), electricity from wind generation is used to produce heat for solvent regeneration.
The benefit from optimization is significant for this day, with $\Delta J = 65,500$, a 61.5% improvement over $J_{heur}$. The June 15 optimization benefit is larger than that in the October 18 scenario because the larger variation in electricity price creates more benefit from variably dispatching the NGCT. The use of wind-to-heat also contributes to $\Delta J$ by reducing the amount of gas that needs to be burned in the NGCT at times with unfavorable electricity price.

### 3.4.3 Aggregate Statistics for Modeled Year

It is of interest to assess the data characteristics that lead to significant optimization benefit. As shown in Figure 3.9, in the base configuration optimization benefit across the modeled year is moderately correlated (correlation coefficient $R = 0.800$) with variability in electricity price and weakly correlated ($R = 0.318$) with mean daily wind generation. Optimization benefit does not exhibit significant correlation with other data characteristics in the modeled year such as wind generation-electricity price correlation, mean electricity price, and wind generation variability.

![Figure 3.9: Optimization benefit in base configuration.](image)

(a) Optimization benefit vs. intra-day variability in electricity price  
(b) Optimization benefit vs. mean daily wind generation

The sources of these correlations can be understood in terms of benefit from flexibility and degree of flexibility. Higher variability in electricity price means that
there is more to be gained from flexible operation — the benefit from operating the
NGCT during times with high price instead of times with low price is large, and if
electricity price ever is sufficiently low, the wind-to-heat capability can be of use as
well. Higher mean wind generation makes the energy park more flexible because the
wind electricity counts toward the emission constraint, freeing the NGCT from being
dispatched in times with the lowest electricity prices.

3.4.4 Sensitivity to Regularization Coefficient

The regularization coefficient $\varepsilon$ described in Section 2.3 is a free parameter for
optimization that was selected to give a 25% penalty for abrupt on-off switching.
Figure 3.10 shows the sensitivity of the objective function to variation in $\varepsilon$ for the
linearly rising electricity price and constant wind generation scenario$^5$ used in Sec-
tion 3.3.3. The relative variation in objective function with $\varepsilon$ is less than 0.7% of
the total objective function value, suggesting that this is not a key factor in the
optimization.

$^5$These runs were conducted with a larger number of perturbations and starting points than in
the standard procedure.
3.5 Impact of Different System Configurations

Two kinds of configurations other than the base configuration are now studied. First, rich solution storage capacity $C_{CC}$ and maximum CP flue gas CO$_2$ absorption fraction $A_{max}$ are varied. Second, components in the base configuration are changed for alternative components.

3.5.1 Variations in Storage and Maximum Absorption

The configurations considered are shown in Table 3.1. The naming scheme indicates the maximum absorption fraction and rich solution storage capacity in terms of number of hours of 90% CP flue gas CO$_2$ capture — for example, Ab65.St0 indicates maximum absorption fraction of 65% with zero hours of rich solution storage.

Table 3.1: Configurations with different rich solution storage capacity and maximum storage fraction

<table>
<thead>
<tr>
<th>Configuration</th>
<th>Max. Abs.$^a$</th>
<th>Store time [hr]$^b$</th>
<th>Store mass [10$^6$ kg CO$_2$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td>0.650</td>
<td>3</td>
<td>1.196</td>
</tr>
<tr>
<td>Ab65.St0</td>
<td>0.650</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Ab65.St1</td>
<td>0.650</td>
<td>1</td>
<td>0.399</td>
</tr>
<tr>
<td>Ab65.St2</td>
<td>0.650</td>
<td>2</td>
<td>0.797</td>
</tr>
<tr>
<td>Ab65.St5</td>
<td>0.650</td>
<td>5</td>
<td>1.993</td>
</tr>
<tr>
<td>Ab775.St0</td>
<td>0.775</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Ab775.St1</td>
<td>0.775</td>
<td>1</td>
<td>0.399</td>
</tr>
<tr>
<td>Ab775.St2</td>
<td>0.775</td>
<td>2</td>
<td>0.797</td>
</tr>
<tr>
<td>Ab775.St3</td>
<td>0.775</td>
<td>3</td>
<td>1.196</td>
</tr>
<tr>
<td>Ab90.St0</td>
<td>0.900</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

$^a$ - Maximum absorption is given by the parameter $A_{max}$

$^b$ - Storage time is computed as $C_{CC} / (1 \text{ hr} \times 0.9 \dot{m}_{FG,CO_2})$

These different configurations are optimized for every fifth day (to save computing time) of the synthetic year described in Section 3.2. Aggregate statistics are shown in Table 3.2. For the base configuration, optimizations were performed using all days...
as well as every fifth day. As can be seen in the first two lines of Table 3.2, aggregate statistics for the two sets of runs differ very little.

Table 3.2: Summary of results for yearlong studies with variation in rich solvent storage and maximum absorption

<table>
<thead>
<tr>
<th>Configuration</th>
<th>$J_{heur}$ Mean (k$/day)</th>
<th>$J_{opt}$ Mean (k$/day)</th>
<th>$\Delta J$ Mean (% of $J_{heur}$)</th>
<th>Correlation Coefficient</th>
<th>$\Delta J$ and Std. Dev.</th>
<th>$\Delta J$ and Mean $E^W$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td>220.7</td>
<td>263.8</td>
<td>19.5</td>
<td>0.800</td>
<td>0.318</td>
<td></td>
</tr>
<tr>
<td>Base (all days)</td>
<td>219.4</td>
<td>262.3</td>
<td>19.6</td>
<td>0.802</td>
<td>0.309</td>
<td></td>
</tr>
<tr>
<td>Ab65_St0</td>
<td>220.7</td>
<td>242.9</td>
<td>10.1</td>
<td>0.238</td>
<td>0.821</td>
<td></td>
</tr>
<tr>
<td>Ab65_St1</td>
<td>220.7</td>
<td>252.8</td>
<td>14.5</td>
<td>0.350</td>
<td>0.711</td>
<td></td>
</tr>
<tr>
<td>Ab65_St2</td>
<td>220.6</td>
<td>257.8</td>
<td>16.8</td>
<td>0.312</td>
<td>0.561</td>
<td></td>
</tr>
<tr>
<td>Ab65_St5</td>
<td>220.7</td>
<td>265.4</td>
<td>20.3</td>
<td>0.835</td>
<td>0.219</td>
<td></td>
</tr>
<tr>
<td>Ab775_St0</td>
<td>221.2</td>
<td>258.8</td>
<td>17.0</td>
<td>0.585</td>
<td>0.457</td>
<td></td>
</tr>
<tr>
<td>Ab775_St1</td>
<td>221.2</td>
<td>262.8</td>
<td>18.8</td>
<td>0.690</td>
<td>0.381</td>
<td></td>
</tr>
<tr>
<td>Ab775_St2</td>
<td>221.2</td>
<td>264.9</td>
<td>19.8</td>
<td>0.768</td>
<td>0.236</td>
<td></td>
</tr>
<tr>
<td>Ab775_St3</td>
<td>221.2</td>
<td>265.8</td>
<td>20.2</td>
<td>0.788</td>
<td>0.249</td>
<td></td>
</tr>
<tr>
<td>Ab90_St0</td>
<td>221.5</td>
<td>264.8</td>
<td>19.6</td>
<td>0.727</td>
<td>0.239</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.2 shows that configurations that are more inflexible, such as Ab65_St0, have optimization benefit moderately correlated with mean wind generation and only weakly correlated with electricity price variability. This is because these configurations derive a great deal of their flexibility from the use of wind in the satisfaction of the CO$_2$ emission intensity constraint. In contrast, configurations that are highly flexible, such as Ab65_St5, exhibit optimization benefit moderately correlated with electricity price variability and weakly correlated with mean wind generation. This is consistent with the expectation that configurations that are designed to be highly flexible benefit when system inputs are highly variable.

The data in Table 3.2 show that larger storage capacity $C_{CC}^{CC}$ and higher maximum absorption fraction $A_{max}$ produce larger optimized profits. This is because storage capacity and oversized maximum absorption fraction represent two different sources of flexibility, and both allow the energy park to shift NGCT operation in time so that the NGCT can be used efficiently when electricity prices are high and turned off when
electricity prices are low. Even when the natural gas – electricity energy conversion makes a loss, it is preferable to produce electricity when electricity prices are higher than when they are lower.

A given profit can be achieved by some combination of absorption level and storage capacity. This means that, for a given profit, there is a tradeoff between absorption tower size and storage tank size: one may choose to have less storage capacity, in which case a larger absorption tower would be required to maintain flexibility, or vice versa. Given that both increased rich solution storage and absorption capacity require additional investment, decisions regarding these components would depend on capital costs. Because these costs are not included in our model, we cannot determine the optimal configuration of the system. However, the marginal change in operating profit from changing the size of a component does provide a way to value that change, and hence our model provides a straightforward way to evaluate capital investment decisions when appropriate cost data are available.

3.5.2 Variations in Energy Park Components

Modifications for two components of the energy park are now considered. First, a high-lift heat pump is substituted for the electric boiler for wind-to-heat capability. Next, the NGCT is exchanged for older (Type B) and newer (Type D) variants, sized to produce enough waste heat for 90% CP flue gas CO\textsubscript{2} capture. The different configurations are shown in Table 3.3. All other parameters in these configurations are the same as in the base configuration. Summary statistics for runs using these configurations are shown in Table 3.4.

<table>
<thead>
<tr>
<th>Table 3.3: Configurations with varying components</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configuration</td>
</tr>
<tr>
<td>------------------------</td>
</tr>
<tr>
<td>Base</td>
</tr>
<tr>
<td>HeatPump</td>
</tr>
<tr>
<td>NGCT_B</td>
</tr>
<tr>
<td>NGCT_D</td>
</tr>
</tbody>
</table>
Table 3.4: Summary of results for yearlong studies with variation in components

<table>
<thead>
<tr>
<th>Configuration</th>
<th>$J_{heur}$ Mean (k$/day)</th>
<th>$J_{opt}$ Mean (k$/day)</th>
<th>$\Delta J$ Mean (% of $J_{heur}$)</th>
<th>Correlation Coefficient $\Delta J$ and Std. Dev. $P^E$</th>
<th>$\Delta J$ and Mean $\hat{E}^W$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td>220.7</td>
<td>263.8</td>
<td>19.5</td>
<td>0.800</td>
<td>0.318</td>
</tr>
<tr>
<td>HeatPump</td>
<td>220.6</td>
<td>264.7</td>
<td>20.0</td>
<td>0.833</td>
<td>0.222</td>
</tr>
<tr>
<td>NGCT_B</td>
<td>192.5</td>
<td>232.8</td>
<td>20.9</td>
<td>0.657</td>
<td>0.524</td>
</tr>
<tr>
<td>NGCT_D</td>
<td>243.8</td>
<td>288.2</td>
<td>18.2</td>
<td>0.843</td>
<td>0.145</td>
</tr>
</tbody>
</table>

The runs using different NGCTs show that the type and size of NGCT has a significant impact on the absolute operating profits of the energy park, but the benefit in relation to the heuristic operating profile shows only a small dependence on NGCT type. The HeatPump and NGCT_D configurations have a high degree of flexibility, as seen in the strong correlation between optimization benefit and electricity price variability and weak correlation between optimization benefit and mean wind generation in these configurations. In contrast, the stronger correlation between optimization benefit and mean wind generation in case NGCT_B is consistent with the fact that, as a result of its lower efficiency, the older Type B turbine provides the park with less flexibility. As with absorption and storage sizing, the choice of NGCT type would depend on capital cost considerations, and the operating profit calculated using the optimization procedure provides a way to evaluate this investment decision.
Chapter 4

Concluding Remarks and Additional Issues

4.1 Summary

This work considered the optimal operation of an integrated energy park. The system included a coal-fired power station, MEA-based CO₂ capture, a natural gas combustion turbine to provide heat for capture and additional electricity, and wind power generation. The ability to (1) operate the NGCT at partial loads, (2) store up to a few hours’ worth of CO₂-rich solution, and (3) convert wind power to heat during times of low electricity prices provides the energy park with considerable operational flexibility. Extensive results demonstrated that the operating economics of the energy park could be improved substantially (by about 20% relative to a heuristic operating mode for the base configuration) through application of formal optimization methods. The benefit of optimal operation in energy park configurations with greater flexibility was shown to be most strongly correlated with electricity price variability, while optimization benefit in systems with less flexible configurations correlated most strongly with mean wind generation.

Although capital costs were not included in this study, results from our procedure can be used to value the impact of different energy park components. These values
can then be compared to the corresponding capital costs to determine the most cost-effective configurations.

This work raises a number of issues of interest in the realm of CCS technology and policy, discussed in Section 4.3.

4.2 An Improved Heuristic

Although application of the optimization procedure developed in this work is expected to provide the best operating parameters, the insight gained from extensive optimization results enables us to suggest an improved heuristic for energy park dispatch. With this new heuristic, the hours of the day are sorted by the price of electricity in descending order starting from the highest price. The NGCT is then dispatched at the maximum possible (heat-limited) partial load to each of the hours in order, until the emission performance standard is met. For configurations with rich solvent storage, NGCT dispatch must be coordinated with solvent storage, which is difficult to accomplish heuristically. One way to approach this would be to first produce an infeasible solution that overuses storage by running the NGCT at full load, and then “back-filling” the needed rich solution. This infeasible solution could then be rendered feasible by successively rescheduling the NGCT until rich solution storage never exceeded capacity.

4.3 Energy Park Concept Policy Implications

An important result arises from the optimization of days with significant wind power inputs: the CO\textsubscript{2} constraint is easier to meet in days with high wind inputs. This is due to the formulation of the CO\textsubscript{2} constraint in our model, which requires power outputs from the entire energy park to, on average, meet the EPS. Because our energy park system includes wind power, and this wind power is assumed to be sold concurrently and indivisibly with the rest of the energy park power, this result makes intuitive sense. However, it is not clear that such power “blending” would meet the requirements of the current California Emission Performance Standards, or of other
In as much as "blending" reduces the potential cost of compliance with GHG regulations and provides additional incentive for the development of wind power, we believe that sensible policy provisions should view this approach as in compliance with regulations. While it could be argued that blending merely “waters down” the emissions from high emitting sources such as coal, it could offer significant economic incentive for wind development (e.g., coal power plant owners may conclude that it is most cost effective to meet EPS requirements by installing large scale wind capacity sufficient to reduce their aggregate emissions from all power sold). Such regulations would need to be designed to avoid double counting of emissions benefits, so that wind power sold as part of a power “blend” could not also be counted towards satisfying some other renewable or emissions standard.

**4.4 Directions for Future Research**

We have shown that application of formal optimization methods can substantially improve the operating economics of an energy park that includes CO$_2$ capture. Future work should extend the optimization framework to include energy park configuration design and capital costs. This will enable quantification of the cost of electricity and the cost of CO$_2$ avoidance.

Other directions for future studies include consideration of real-world market structures and bidding processes, uncertainty in prices and wind data, other timescales of optimization, grid integration issues, and variation in policy. It may also be useful to introduce variable coal power generation into the model in order to quantify the value of flexibility in this key energy park component.
Nomenclature

Abbreviations

CCS CO₂ capture and storage
CP coal plant
EPS emission performance standard
GHG greenhouse gas
HHV higher heating value
HRSG heat recovery steam generator
IECM Integrated Environmental Control Module
MEA monoethanolamine
NGCT natural gas combustion turbine
PRB Powder River Basin

Superscripts

CC CO₂ capture process
CP coal plant
CT natural gas combustion turbine
EB electric boiler
EH wind-to-heat facility
HP heat pump
HRSG heat recovery steam generator

Subscripts

a air
abs absorption
NOMENCLATURE

\( c \)  
compression (mass flows in CO\(_2\) capture process); capacity (rich solution storage in CO\(_2\) capture process); coal (coal plant)

\( FG \)  
flue gas

\( g \)  
natural gas

\( r \)  
regeneration

\( t \)  
time step index

**Decision Variables**

\( D_t \)  
duct firing use decision variable

\( L_t \)  
natural gas combustion turbine partial load decision variable

\( S_t \)  
rich solution storage decision variable

\( X_t \)  
wind-to-heat use decision variable

**Other Optimization-Related Symbols**

\( \Delta J \)  
operating profit improvement due to optimization ($)

\( \varepsilon \)  
regularization penalty coefficient ($)

\( G \)  
regularization penalty ($)

\( h_{CC,abs,max,t} \)  
constraint violation for maximum CO\(_2\) absorption rate

\( h_{CC,end} \)  
constraint violation for returning rich solution storage to original state

\( h_{CC,max,t} \)  
constraint violation for maximum CO\(_2\)-rich solution storage capacity

\( h_{EPS} \)  
constraint violation for emission performance standard

\( h^{tot} \)  
overall constraint violation

\( J_{heur} \)  
operating profit from heuristic dispatch scheme ($)

\( J_{opt} \)  
operating profit from optimized dispatch scheme ($)

\( R \)  
total daily revenue ($)

**Material Flow Rate Quantities**

\( \dot{m}_{CC}^{abs} \)  
CO\(_2\) absorption rate in capture process (kg/s)

\( \dot{m}_{CC}^{reg} \)  
CO\(_2\) regeneration rate in capture process (kg/s)

\( \dot{m}_{s}^{CC} \)  
net rate of CO\(_2\) storage in rich solution (kg CO\(_2\)/s)

\( \dot{m}_{s,in}^{CC} \)  
storage-in rate of CO\(_2\)-rich solution (kg CO\(_2\)/s)

\( \dot{m}_{s,out}^{CC} \)  
storage-out rate of CO\(_2\)-rich solution (kg CO\(_2\)/s)

\( \dot{m}_{c}^{CP} \)  
coal plant coal consumption rate, mass basis (kg/s)
NOMENCLATURE

\( \dot{m}_{FG}^{CP} \) coal plant flue gas production rate, mass basis (kg/s)
\( \dot{m}_{FG,CO_2}^{CP} \) coal plant flue gas \( CO_2 \) production rate, mass basis (kg/s)
\( \dot{m}_{CT}^{n} \) natural gas combustion turbine fuel consumption rate, mass basis (kg/s)
\( \dot{m}_{FG}^{CT} \) natural gas combustion turbine flue gas production rate, mass basis (kg/s)
\( \dot{n}_{H_2O}^{EH} \) wind-to-heat facility steam generation rate (kg/s)
\( \dot{m}_{HRSNG}^{HRSNG} \) heat recovery steam generator duct firing natural gas use rate (kg/s)
\( \dot{m}_{H_2O}^{HRSNG} \) heat recovery steam generator steam generation rate (kg/s)
\( \dot{n}_{a}^{CP} \) molar coal plant air consumption rate (mol/s)
\( \dot{n}_{c}^{CP} \) molar coal plant fuel consumption rate (mol/s)
\( \dot{n}_{p}^{CP} \) molar coal plant product species production rate (mol/s)
\( \dot{n}_{a}^{CT} \) molar natural gas combustion turbine air consumption rate (mol/s)
\( \dot{n}_{g}^{CT} \) molar natural gas combustion turbine fuel consumption rate (mol/s)
\( \dot{n}_{FG}^{CT} \) molar natural gas combustion turbine flue gas production rate (mol/s)

Energy Flow Rate Quantities
\( \dot{E}^{CP} \) coal plant electric power generation (W)
\( \dot{E}^{CT} \) natural gas combustion turbine electric power generation (W)
\( \dot{E}^{EH} \) wind power used to produce heat (W)
\( \dot{E}^{W} \) wind power generation (W)
\( \dot{Q}_{CC}^{R} \) CO₂ capture regeneration heat requirement (W)
\( \dot{Q}_{CT}^{R} \) natural gas combustion turbine heat addition rate (W)
\( \dot{Q}_{EH}^{R} \) wind-to-heat facility heat supply rate (W)
\( \dot{Q}_{HRSNG}^{R} \) heat recovery steam generator flue gas heat recovery rate (W)
\( \dot{W}_{abs}^{CC} \) CO₂ capture absorption work requirement (W)
\( \dot{W}_{c}^{CC} \) CO₂ capture compression work requirement (W)

Other Symbols
\( \alpha \) temperature coefficient for flue gas specific heat capacity (J/kg-K²)
\( \Delta H_{comb}^{C} \) higher heating value of coal (J/kg)
\( \Delta H_{comb}^{G} \) higher heating value of natural gas (J/kg)
\( \Delta H_{vap,400K}^{H_2O} \) heat of vaporization of water at 400 K
NOMENCLATURE

$\Delta t$  
$\eta_{CP}$  
$\eta_{CT}$  
$\eta_{rel}$  
$\eta_{CT}^{th}$  
$\eta_{EB}$  
$\eta_{HRS}^{sh}$  
$\lambda_{CP}$  
$A_t$  
$A_{max}$  
$C_{CC}$  
$C_{CC}^{f,t}$  
$C_0$  
$e_{abs}$  
$e_c$  
$e_r$  
$P_c$  
$P_E$  
$P_{NG}$  
$T_{CT}^{FG}$  
$T_0$  
$T_C$  
$T_H$  
$C_{HRSG}^{PHR}$  
$R$

- time step length (s)
- coal plant efficiency, HHV basis
- natural gas combustion turbine partial load relative efficiency
- natural gas combustion turbine design efficiency
- electric boiler efficiency
- heat recovery steam generator efficiency due to thermal shell losses
- coal plant air ratio
- normalized CO$_2$ absorption rate
- maximum coal plant flue gas CO$_2$ absorption fraction
- total capacity of capture process CO$_2$-rich solution storage (kg CO$_2$)
- mass of CO$_2$ in rich solution storage in time step $t$ (kg CO$_2$)
- heat recovery steam generator flue gas specific heat capacity constant (J/kg-K)
- per-unit-CO$_2$ absorption pumping work requirement in capture process (J/kg CO$_2$)
- per-unit-CO$_2$ regeneration heat requirement in capture process (J/kg CO$_2$)
- per-unit-CO$_2$ compression work requirement in capture process (J/kg CO$_2$)
- price of coal ($/kg)
- price of electricity ($/MWh)
- price of natural gas ($/kg)
- natural gas combustion turbine flue gas temperature (K)
- temperature at reference conditions (K)
- cold reservoir temperature for heat pump (K)
- hot reservoir temperature for heat pump (K)
- specific heat capacity of flue gas in heat recovery steam generator (J/kg-K)
- correlation coefficient
Bibliography

http://www.nrel.gov/wind/integrationdatasets/


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