AN ECONOMIC STUDY OF CARBON CAPTURE AND STORAGE SYSTEM DESIGN AND POLICY

A Dissertation

by

DARMAWAN PRASODJO

Submitted to the Office of Graduate Studies
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

May 2011

Major Subject: Agriculture Economics

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Approved by:

Co-Chairs of Committee,	Bruce A. McCarl
	Jianbang Gan
Committee Members,	David A. Bessler
	James W. Richardson
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ABSTRACT

An Economic Study of Carbon Capture and Storage System Design and Policy.

(May 2011)

Darmawan Prasodjo, B.S.; M.S., Texas A&M University

Co-Chairs of Advisory Committee: Dr. Bruce A. McCarl
Dr. Jianbang Gan

Carbon capture and storage (CCS) and a point of electricity generation is a promising option for mitigating greenhouse gas emissions. One issue with respect to CCS is the design of carbon dioxide transport, storage and injection system. This dissertation develops a model, OptimaCCS, that combines economic and spatial optimization for the integration of CCS transport, storage and injection infrastructure to minimize costs. The model solves for the lowest-cost set of pipeline routes and storage/injection sites that connect CO2 sources to the storage. It factors in pipeline costs, site-specific storage costs, and pipeline routes considerations involving existing right of ways and land use. It also considers cost reductions resulting from networking the pipelines segment from the plants into trunk lines that lead to the storage sites. OptimaCCS is demonstrated for a system involving carbon capture at 14 Texas coal-fired power plants and three potential deep-saline aquifer sequestration sites. In turn OptimaCCS generates 1) a cost-effective CCS pipeline network for transporting CO_2

from all the power plants to the possible storage sites, and 2) an estimate of the costs associated with the CO_2 transport and storage. It is used to examine variations in the configuration of the pipeline network depending on differences in storage site-specific injection costs. These results highlight how various levels of cooperation by CO_2 emitters and difference in injection costs among possible storage sites can affect the most cost-effective arrangement for deploying CCS infrastructure.

This study also analyzes CCS deployment under the features in a piece of legislation – the draft of American Power Act (APA) - that was proposed in 2010 which contained a goal of CCS capacity for emissions from 72 Gigawatt (GW) by 2034. A model was developed that simulates CCS deployment while considering different combinations of carbon price trajectories, technology progress, and assumed auction prices. The model shows that the deployment rate of CCS technology under APA is affected by the available bonus allowances, carbon price trajectory, CCS incentive, technological adaptation, and auction process. Furthermore it demonstrates that the 72GW objective can only be achieved in a rapid deployment scenario with quick learning-by-doing and high carbon price starting at $25 in 2013 with a 5% annual increase. Furthermore under the slow and moderate deployment scenarios CCS capacity falls short of achieving the 72 GW objective.

DEDICATION

To my late father Brig Gen TNI Sadja Moeljoredjo, whom I promised that I would get this Ph.D degree;

To Diny my wife for being my rock, my sanity and my strongest believer;

To Dylan and Dykstra for giving me hope for a brighter future;

To my mother whose constant thoughts and prayers resonate in my heart;

To my brother and sister who always keep me grounded.

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Special thanks go to Vicki Heard and Dee Cochran who helped me navigate the maze of paperwork and procedure required to get to this point. My thanks go out to all of the other professors and support staffs in Texas A&M's Department of Agricultural Economics who have made my entire graduate experience wonderful.

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And last but certainly not the least, I have been sustained throughout this tremendous amount of work by three powerful forces in my life: my supportive wife, my two sons and my family back home. Their presence in my life and never-ending concern are the reason that I’m here today. I thank and love you all dearly.

NOMENCLATURE

American Electric Power	Utility company, operates Pirkey and Oklaunion power plants
ANP	Utility company, operates Coleto Creek power plant
APA	American Power Act
ArcGIS	Geographic information system software
BBA	Amount of CO_2 captured beyond bonus allowance
Bituminous	Black coal (higher quality than lignite coal)
Bonus Allowance	CO_2 allowancethat compensates for CCS expense
Bonus Price	The amount ($) of CCS incentive for one metric ton of CO_2
Bonus Ratio	Ratio of bonus price to carbon price
Btu	British thermal unit
Coleto Creek	Power plant, operated by International Power near Goliad TX
CO_2	Carbon dioxide
CCS	Carbon capture and storage
CPS Energy	Utility company, operates J.T Deely and J.K Spruce power plants

eGrid	Emissions & Generation Resource Integrated Database, a comprehensive source of data on the environmental characteristics of electric power generated in the U.S.
EPRI	Electric Power Research Institute
ESRI	Geographical information system software company
Fayette Power Project	Power plant, operated by Colorado River Authority near La Grange TX
GAMS	General Algebraic Modeling System
Gibbons Creek	Power plant, operated by Texas Municipal Power Agency
GIS	Geographic information system
Granite Wash	Saline aquifer in northwest Texas
GHG	Greenhouse gas
Harrington	Power plant, operated by Xcel Energy near Amarillo TX
CPLEX Optimizer	Software that incorporates IBM-ILOG simplex methodology
Frio	Largest saline aquifer in the US, south Texas
IGCC	Integrated gasification combined cycle
J.T Deely	Power plant, operated by CPS Energy
Lignite	Lowest grade of coal, sometimes referred to as brown coal
Limestone	Power plant, operated by NRG Energy
Lower Colorado River Authority	Utility company, operates Fayette Power Project power plant

Luminant Energy	Utility company, operates Monticello, Martin Lake, and Sandow No 4 power plants. Formerly TXU Energy.
Martin Lake	Power plant, operated by Luminant Energy near Longview TX
Monticello	Power plant, operated by Luminant Energy near Mount Pleasant TX
Mtons/year	Million metric tons per year
MILP	Mixed-integer linear programing
NEMS	National Energy Modeling System
NRG Energy	Utility company, operates Limestone and W.A Parish power plants. NRG Energy acquired the retail operations of Reliant Energy in May 2009.
Oklaunion	Power plant, operated by American Electric Power and Oklahoma Municipal Power Authority
Optimum	Select criteria from a given domain that yields the minimum CCS infrastructure cost
PC	Pulverized coal
Pirkey	Power plant, operated by American Electric Power Co near Hallsville TX
Sandow Station Unit 4	Power plant, operated by Luminant Energy near Rockdale TX

San Miguel	Power plant, operated by San Miguel Electric near Jourdanton TX
San Miguel Electric	Utility company, operates San Miguel power plant
Separable Programming	Methodology that uses linear programming to approximate convex nonlinear equations Spruce Power plant, operated by CPS Energy
Texas Municipal Power	Utility company, operates Gibbons Creek power plant
Tolk	Power plant, operated by Xcel Energy near Muleshoe TX
Ton	Metric ton (1000 kg)
UBA	Amount of CO_2 captured under bonus allowance
W.A Parish	Power plant, operated by NRG energy near Houston TX
Woodbine	Saline aquifer in northeast Texas
Xcel Energy	Utility company, operates Harrington and Tolk power plants
$/ton	Dollars per metric ton
¢/kW	Cents per kilowatt-hour

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1. INTRODUCTION

As a reliable and affordable source of domestic energy, coal has in large part powered the American economy for decades and the trend is likely to continue. Coal-fired power plants accounted for 27% of fossil fuel consumed and 50% of electricity generated in the U.S. during 2008 (U.S. Energy Information Administration 2009). According to the American Coal Foundation, the U.S. has the world's largest supply of recoverable coal reserves—about 275 billion tons—and can accommodate national demand for 250 years at the current rate of consumption (The American Coal Foundation 2010). Coal is an advantageous energy source because of its significantly lower cost relative to available options. It provides energy at \$1-\$2 per million Btu with the next most inexpensive fuel source being natural gas at \$4-\$6 per million Btu. Given its durable economic advantage, it's reasonable to assume that coal will remain an important component of the U.S. energy supply for decades. Nevertheless, coal-fired power plants will almost certainly need to reduce carbon dioxide emissions in the not-to-distant future. The Intergovernmental Panel on Climate Change (IPCC) has outlined how carbon capture and storage (CCS) technology can reclaim carbon dioxide emitted during fossil fuel combustion (Barker, et al. 2007).

This dissertation follows the style of the *American Journal of Agricultural Economics.*

Considering the growing concern that surrounds greenhouse gas emissions, CCS technology offers the electricity-generating sector a potential path to a low-carbon future.

1.1 Dissertation Objectives

CCS is in a relatively early phase of development. Several major key issues remain unresolved, including the development of means and approaches for large complex infrastructure design, estimation of site dependent transportation and injection costs, and determination of the level of incentives required to gain deployment in the face of high initial CCS cost. In analyzing the issue, the energy modeling community generally uses uniform CCS costs across regions because of the absence of an accurate CCS cost analysis. As a result, CCS economic analyses depict a mostly uniform economy-wide impact, ignoring the fact that future CCS deployment would be regionally differentiated depending on regional geologic formations, amount of CO_2 captured, level of collaboration among CO_2 source operators, and region-specific geography/land ownership patterns. In addition several questions, such as how CCS deployment is going to be affected by the interaction of economic criteria of prevailing market carbon price, CCS cost, and available CCS bonus allowance under different cap and trade policy, remain largely unexplored.

This study examines CCS system and policy design issues by developing economic modeling approaches to these CCS issues. The overall objective is to generate economically based information and tools that will support of efforts to prepare for CCS implementation. More specifically the study pursues two sub objectives:

- To examine economically optimal CCS network design. To do this a model to design an economically optimal CCS system, from capture through conveyance to injection is developed. In turn case studies are done on the sensitivity of the design to problem framing and data assumptions
- To assess the economically justified amount of CCS technology deployment by considering carbon price, CCS technology cost, subsidy amounts, and the availability of CCS bonus allowance.

1.2 CCS Network Design Study

A pipeline network is the only feasible solution to transport large volumes of CO_2. Due to its complex characteristics, the design and economics of CCS infrastructure has not been extensively examined in the CCS research community. Designing the most cost-effective CCS infrastructure is an economic cost minimization problem. Hence, we develop an economic model to design an optimized CCS infrastructure by globally minimizing both the pipeline construction costs and injection costs. In developing the CCS network model we consider:

- the most cost-effective CCS pipeline network design for transporting and injecting CO_2
- site specific costs associated with CO_2 transportation and injection
- possible cost reductions from collaboration on pipeline construction by power plant operators

- relationships between site-specific injection costs and the resultant CCS infrastructure.

1.3 CCS Policy Study

The technologies required to perform CCS (capture, transportation and storage) already exist. But today CCS cost is high and a supportive national policy is needed to assist utility companies and investors in initial deployment. I use economic modeling to analyze different paths of CCS technology deployment under a national energy policy. To do this I develop an economic model (herein named CCSDeployment) to simulate various CCS deployment scenarios under a cap and trade framework. In researching the CCS policy, I perform different economic procedures:

- identifying the CCS economic path in reaching 72 GW net CCS capacity
- quantifying net CCS capacity under different scenarios
- quantifying the amount of CO_2 captured
- quantifying the bonus ratio
- identifying the deployment stage schedule

1.4 Background

Carbon capture cost depends on the how power is generated, what type of coal is used, the capacity of plant, how much CO_2 is captured, and which particular capture technology is implemented. Several studies estimate current capture cost to be $40-160/ton (Dooley, Dahowski, et al. 2006b) (Al-Juaied and Whitmore 2009). Yet, transportation and injection costs are highly variable and determined by a combination of several dynamic factors such as the spatial arrangement of CO_2 sources, quantity of

CO_2 transported, location of sequestration sites, injection costs, and the level of cooperation among power plant operators. Currently, CCS analysis often assumes a total transportation and injection cost of $10-15/ton due to the lack of more accurate information (Dooley, Dahowski, et al. 2006b). Because these costs vary so greatly in response to regional and geographic factors, the Department of Energy (DOE), Environmental Protection Agency (EPA), Electric Power Research Institute (EPRI) and other research institutes have all given high priority to developing a more comprehensive cost-calculation system.

Meaningful reductions in CO_2 emissions require the development of a large-scale CCS infrastructure, but its design involves a complex set of decisions. For example, a straight line pipeline between two points may not be the optimal pipeline route as geographic features or land ownership patterns may render a less direct route to be superior. Hence, spatial optimization considering such factors is required. In addition, costs can be reduced if clusters of power plants feed CO_2 into shared transport pipelines. A pipeline network must be built for delivering captured CO_2 to aquifer storage sites. As CCS infrastructures scales up, it requires a more robust modeling methodology that can determine optimal routing of captured CO_2 to available sequestration sites. Previous CCS optimization models are based on fewer variables, older technology, and did not include site-specific geologic information. This research project designs a cost-minimizing CCS infrastructure to transport CO_2 to sequestration sites with fuller input variables and better algorithmic sensitivity to input criteria than previous modeling efforts.

According to the report by the Interagency Task force on Carbon Capture and Storage (2010), even though the required technologies (capture, transmission and storage) to perform CCS already exist, the major barrier for CCS deployment is the lack of comprehensive climate change legislation (Interagency Task Force on Carbon Capture and Storage 2010). A supportive national policy will assist utility companies in overcoming the incremental costs of adopting CCS and create a stable and reliable framework for private investors. Until such policy is enacted, CCS technology is not an economically viable investment.

There have been a series of discussions on energy policy related to CCS deployment. The current federal administration has outlined a plan to implement an economy-wide cap-and-trade program to reduce greenhouse gas emissions by 80 percent before 2050 that also supports clean-coal technology. In June 2009, the U.S. House of Representatives passed the American Clean Energy and Security Act (ACES) which promotes a market similar to the European Union's Emission Trading Schemes (Waxman and Markey 2009). However, the bill died in the Senate and never became law.

In May 2010, Senators Kerry and Lieberman released a draft of the American Power Act (APA) (Kerry and Lieberman 2010). This proposed legislation stalled in the national legislature and also failed to become law. The goal of this proposed legislation was to increase U.S. energy security, create clean energy jobs, decrease dependence on foreign fuel, and reduce greenhouse gas (GHG) emissions such as carbon dioxide (CO_2).

Since the release of APA, there have been many analyses that considered features therein by various organizations. The EPA's analysis emphasizes the economy-wide impact and short term impact of APA by using ADAGE[1] and IPM[2] energy models respectively (U.S. Environmental Protection Agency 2010). In addition, there are a series of analyses, mostly in environmental blogs and newspaper articles, which cover a broad range of topics, including: how the current economic climate impacts the feasibility of APA, how the allocation of allowances would affect certain industries, and how cap and trade fits into the current and future political situation. However, no analysis has been done to understand the economic conditions that would lead to CCS deployment by considering how the interaction of carbon price, CCS technology progress, the reverse auction process and constraint of CCS bonus allowance availability will affect the progress of CCS deployment. The second part of the study is to analyze how those parameters might affect CCS deployment under a cap and trade framework.

1.5 Plan of Dissertation

This Dissertation consists of two main analysis sections along with an introduction and conclusion. The first analysis section addresses CCS system design developing a model and using it in a Texas case study. The second analysis section examines CCS deployment under cap and trade policy.

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[1]ADAGE, Applied Dynamic Analysis of the Global Economy (ADAGE) model developed by RTI
[2] IPM, The Integrated Planning Model developed by ICF International

2. AN ECONOMIC STUDY OF CCS SYSTEM DESIGN

2.1 Introduction

Between 2007 and 2008, global CO_2 emissions from coal combustion increased by 3% and represented 12.6 billion tons CO_2 (International Energy Agency 2010b). Without additional measures, the *2010 World Energy Outlook* report projects that emissions from coal will grow to 18.6 billion tons CO_2 in 2030 (International Energy Agency 2010a). The Intergovernmental Panel on Climate Change (IPCC) states that CCS (Figure 1) can be used to store carbon dioxide from the combustion of fossil fuels (Barker, et al. 2007). Applying CCS to the generation of electricity using fossil fuels can result in significantly reduced emissions of greenhouse gases to the atmosphere. It is one of many processes which can help reduce greenhouse gas emissions (called low-emission coal technology).

Carbon capture and storage can be considered as a bridge to the future considering that we simply cannot shut down coal-fired power plants and replace them with renewable energy or alternatives. According to Williams, Keith and Rhodes, the carbon releases from biomass conversion might also be captured and stored using CCS technology (Williams 1998) (Keith and Rhodes 2002). Hence, the biomass energy system with CCS has the potential to deliver CO_2 negative energy carriers. If this ambitious system is widely applied, the global energy system as a whole could become an instrument to remove CO_2 emissions from the atmosphere on a continuous basis

(Azar, et al. 2006). One possible way to sustain our energy supply while reducing emissions is to make fossil-fuel-based power generation more environmentally friendly.

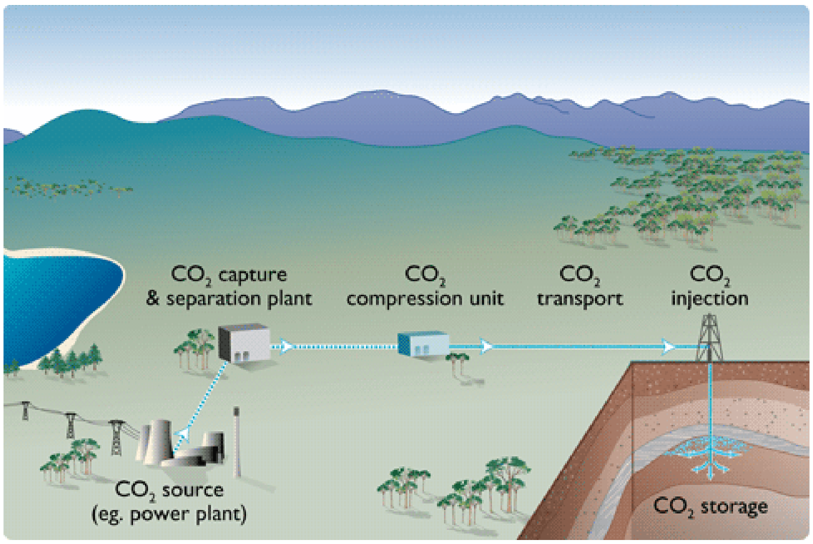

Figure 1. Schematic diagram of CCS systems

Notes: (courtesy of http://www.co2crc.com.au/aboutccs/)

2.2 Literature Review

To effectively mitigate adverse climate change, CCS needs to be deployed on a large scale (Pacala and Socolow 2004). Haszeldine argues that reliable, cost-effective capture by clusters of CCS power plants must emerge, national pipeline networks must be developed, and aquifer storage capacity must be validated (Haszeldine 2009).

Designing large-scale CCS infrastructures is a complex process that needs to incorporate both spatial and economic data in order to achieve optimization. For example, costs can be reduced if clusters of power plants use shared CO_2 transport pipelines. Therefore, the ability to scale up a CCS infrastructure requires a model that can determine the most cost-effective way of transporting CO_2 to storage sites.

The current techniques used to model and design large-scale CCS infrastructures do not lead to complete optimization. Early CCS system designs used dedicated pipelines to connect one CO_2 source to one storage site (IEA Greenhouse Gas R&D Programme 2005). McCoy and Rubin formulated an engineering-economic model that estimates the cost of CO2 transport for different regions in the US. They estimated the CO2 transport cost of a 100 km pipeline constructed in the Midwest and transporting 5 mtons/year to be $1.16/ton CO2. This value is $0.39/ton lower than the estimated transport cost of a pipeline built in the Central US and $0.20/ton higher the one built in the Northeast (McCoy and Rubin 2008). Chandel et al. developed a model that derives the levelized cost of transporting CO_2 per km based on different mass flow rates, additional energy use, and varying distance (Chandel, Pratson and Williams 2010). Herzog et al. created a model that matches CO_2 sources and sequestration sites using spatial optimization and independent site-to-source pipelines (Herzog, et al. 2007). Some models make the broad assumption that the pipelines will be straight (Illinois State Geological Survey 2005), or that there is a minimum and maximum distance between sources and reservoirs (Dooley, Dahowski, et al. 2006a). Still, other studies evaluate the regional match between CO_2 sources and available gross pore space in geologic formations (Dooley, Dahowski and Davidson 2009). Middleton & Bielicki perform a spatial and economic optimization at once by optimizing CCS infrastructure on

California based on premise of uniform injection cost, limited pipeline merging and hypothetical selection of CO_2 sources and sinks (Middleton and Bielicki 2009). Quantified relationships between input factors (e.g. site-specific injection cost and the degree of the cooperation among CO_2 emitters) and resultant spatial arrangement of CCS infrastructure have been relatively unexplored in any of those studies.

2.3 CCS System Design as an Economic Problem

The design of CCS systems consists of several key economic elements including the selection of power plants with CCS potential, the economic characterization of sinks, the spatial relationships between sources and sinks, the cost of CCS movement and injection, the harnessing of economies of scale through pipeline merging, and the implementation of a comprehensive cost optimization across the system.

The economic feasibility of CCS technology for a specific CO_2 source depends on the generating technology (different generations of pulverized coal technology or integrated gasification combined cycle technology), the size of the plant, the type of coal used, the location, possibility of pipeline convergence, and the availability of sequestration sinks in proximity. Identification of economically feasible CO_2 sources with the potential to be retrofitted with CCS technology requires consideration of the economic tradeoffs between CCS retrofit (and possibility of receiving CCS subsidy), retirement, and the purchase of emission allowances at prevailing carbon market price. This study uses an enhanced NEMS model equipped with National Energy Technology Laboratory (NETL) CCS retrofits code and different predictive scenarios of supportive policies.

It is by nature that the spatial arrangement of CO_2 sources and potential sinks are spatially scattered. Developing a pipe route between two points requires a spatial-economic optimization to place the most cost-effective route that considers both the distance and also the level of difficulty of constructing a pipeline through various types of terrain. Terrain considerations include the geographical features of an area as well as the area's social and political data. Each proposed movement path should reflect the most cost-effective route between two points.

The nature of pipeline engineering allows it to benefit from economies of scale in which transporting CO_2 through a larger diameter pipe is more efficient than transporting it through a smaller diameter pipe. This means that collaboration among CO_2 source operators facilitates the possibility of pipeline convergence and reduces the overall CCS infrastructure cost. The economic decision is to identify whether the additional distance associated with pipeline merging can be offset with the economic efficiency gain associated with larger pipe or cheaper injection costs. To facilitate the possibility of cost saving we design our economic model to consider a CO_2 source not only as a source, but also as a possible hub in which a series of smaller pipes can merge to become a bigger pipe to gain efficiency and reduce the overall infrastructure cost.

Each sequestration site is unique in terms of spatial location and mean cumulative injection cost. We should select the most cost-effective sequestration site for each power plant. It is an economic decision whether to select a sink with a more expensive injection cost but closer in proximity (and cheaper transportation cost) or to select a sink with a cheaper injection cost but at a greater distance (and more expensive transportation cost). For each CO_2 source, we should match sink with the lowest combination of both transportation cost and injection cost.

To design the most cost-effective CCS infrastructure, comprehensive cost minimization covering not only the pipeline construction cost but also the site-specific injection cost has to be performed. Previous CCS modeling efforts using partial cost minimization considering only pipeline construction cost while assuming uniform injection costs unfortunately results in a sub-optimal infrastructure design. The use of comprehensive cost minimization (over partial cost minimization) potentially improves the cost-effectiveness of the resultant CCS infrastructure.

Once the most cost-effective CCS infrastructure is designed, marginal CO_2 transportation and the injection costs can be computed. The availability of individual transportation and injection costs enables national energy economic modeling efforts (NEMS, Adage, IPM etc.) to identify the impact of supportive policy on the most efficient energy generation on specific regions (instead of uniform economy-wide analysis). Current energy economic modeling efforts rely on uniform transportation and injection cost because of the absence of a comprehensive CCS infrastructure economic model.

In short, beyond the complexity of spatial data and pipeline engineering, the design of the most cost-effective CCS pipeline network is a complex economic problem with multiple key elements that have to be solved simultaneously.

2.4 Toward a Model

A next logical step is to create a CCS infrastructure model that employs comprehensive optimization that accounts for site-specific storage costs, full-scale pipeline merging, and more realistic selection of CO_2 sources and sinks. Such a model should also be capable of analyzing the impact of how different local factors (e.g. site-specific injection cost and the degree of the cooperation among CO_2 emitters) alter the spatial arrangement of CCS infrastructure.

In this study, we introduce a comprehensive spatial-engineering-economic CCS infrastructure optimization model (OptimaCCS) that simultaneously considers all components of CCS infrastructure. The model will identify the spatial arrangement resulting in the most effective transportation and injection cost. We identify potential CO_2 sources by using the Nicholas Institute's version of NEMS that has been enhanced with a CCS scenario code (built by National Energy Technology Laboratory) (Geisbrecht 2009) and coupled with a particular climate policy (accommodating a certain emission penalty and CCS incentive). We use injection costs into saline formations identified by Eccles et al. (Eccles, et al. 2009). Saline formations are used because they have a larger potential capacity as compared to other geologic formations.

2.5 Model Setup

Given sets of CO_2 sources and sequestration sites, OptimaCCS minimizes cost with consideration of multiple key decision points simultaneously. The algorithm behind OptimaCCS identifies every single pipeline segment candidate through a spatial permutation process. Each segment candidate is already spatially optimized (using

ArcGIS) to minimize construction cost by considering environmental impact through sensitive areas (e.g. national park, state park, national forest), and the higher costs associated with building pipelines through urban areas, water road-crossings, railroads, and different elevations. OptimaCCS recognizes that a CO_2 source is not only a source but also a potential hub in which small pipelines can merge to become a trunk pipeline to give the advantage of economies of scale. In this way, costs are reduced for the entire network. OptimaCCS can design the best pipeline network for distributing CO_2 from a set of sources to a set of sequestration sites to minimize the total cost of CO_2 transportation and sequestration.

We demonstrate OptimaCCS using 14 coal-fired power plants in Texas as the set of CO_2 sources, and three saline formations as the set of storage sites. OptimaCCS application highlights the importance of systematic planning for CCS infrastructure by examining how different levels of cooperation between CO_2 sources and different sets of injection cost would affect the sensitivity of the optimized CCS infrastructure.

2.5.1 Pipeline Engineering Principle

Chandel et al. developed a pipeline model that yields the design parameters and costs for a trunkline based on the diameter pipe required to transport different mass flows of CO_2, the number and spacing of booster pumps needed to keep the CO_2 supercritical, the power required to accomplish this high-pressure transport, and specific costs of CO_2 transport (e.g. pipeline costs, pump costs, operation and management costs, and the cost of electricity for transport) (Chandel, Pratson and Williams 2010). Chandel's study derived the pipeline cost from existing natural gas pipelines published in 2004 (Parker 2004). The costs are adjusted to reflect 2008 by using the Global Steel Price Index for materials and the Chemical Engineering Plant Cost Index (PCI) for labor and miscellaneous costs. OptimaCCS utilizes the pipeline engineering principle from this study.

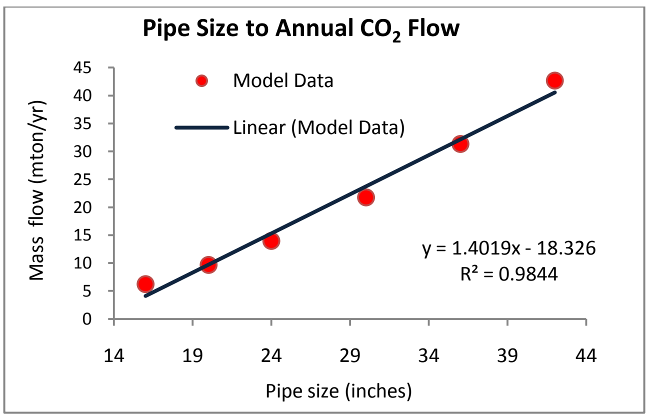

Figure 2. Mass flow in million tons for different pipe diameters

Figure 2 shows the relationship between pipe diameter and the mass flow of CO_2 assuming that CO_2 is kept in a supercritical state. As the pipe size increases, the mass flow is expected to increase as well. The largest commercially available pipe in Chandel's study is 42 inches diameter. However, larger-diameter pipes may be available in the future if demand grows.

OptimaCCS models cost minimization through a series of constraints. One such constraint is to transform mass flow of CO_2 to pipe size in a linear fashion. To estimate this linear relationship between pipe size and CO_2 mass flow, a linear regression is performed on the Chandel pipeline model data with dependent variable Y_i (mass flow mtons/year) and the independent variable X_i (pipe size in inches).

$$y_i = \beta_0 + \beta_1 x_1 + \varepsilon_i \qquad [1]$$

A linear regression model assumes that the relationship between the dependent variable y_i and the ρ-vector of regressors x_i is approximately linear (Equation 1) (Weisberg 2005). This approximate relationship is modeled through a so-called "disturbance term" ε_i, an unobserved random variable that adds noise to the linear relationship between the dependent variable and regressors.

$$CO_2MassFlow_i = 1.4019\, PipeSize_i - 18.326 \qquad [2]$$

The regression between pipe size and mass flow is represented in equation (2). It has an R^2 of 0.9844, which means equation (2) is a good fit to estimate the relationship between pipe size and mass flow.

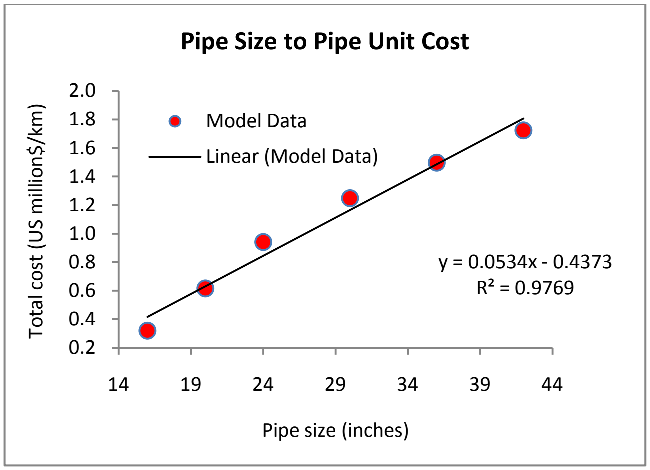

Figure 3. Capital cost ($/km) for different pipe diameters

The cost minimization requires another constraint to transform pipe size to baseline development cost per kilometer of pipeline by using the pipeline model developed by Chandel et al. (Figure 3). The model data chart in figure 3 shows that total baseline pipeline development cost per kilometer increases as the pipe size increases. The regression between pipe size and the baseline cost is captured in equation (3) with R^2 of 0.9769 which means it is also a good fit estimate.

$$PipeCostKm_i = 0.0534\,PipeSize_i - 0.4373 \qquad [3]$$

The CCS analysis in this study is designed to analyze a medium-sized power plant or bigger with CO_2 captured of at least 0.75 million tons per year. These preconditions require a pipe size of at least 13.6 inches in diameter. In that regard, the negative intercepts of equations (2) and (3) can be justified.

2.5.2 OptimaCCS: CCS Infrastructure Two-stage Optimization Model

Given a set of points where CO_2 is captured, designing a cost-minimizing CCS pipeline and injection network requires consideration of four key decision variables to minimize cost: 1) Storage site selection, 2) Assignment of CO_2 sources to storage sites, 3) Selection of pipeline route including convergence points for pipelines, and 4) Selection of size of pipes. Due to the complexity of the pipeline design, it became clear that no single modeling program or spatial analysis software could consider all of these decisions simultaneously. The solution employed herein is to create an algorithm that combines the capabilities of both ArcGIS[3] spatial optimization and mathematical programming based cost minimization (Figure 4).

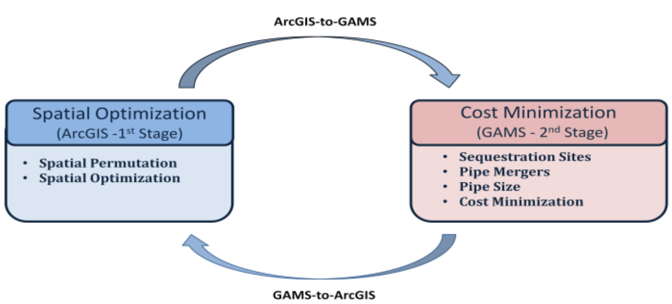

Figure 4. Two-stage CCS infrastructure optimization consists of spatial optimization and cost minimization

[3] ArcGIS is a software program used to perform spatial analysis

ArcGIS contains features (e.g. CostDistance and CostPath) for calculating the cost-minimizing route from one point to another based on the cost of traversing parts of the region represented. The cost of traversing a route represents both the distance and the level of difficulty of building a pipeline between two points. Mathematical programming modeling (implemented through GAMS equipped with IBM ILOG CPLEX Optimizer) provides a flexible, high-performance mathematical programming solver for selecting cost minimizing routes, pipe sizes and pairing of sources to storage areas.

The combination of the software packages harnesses both strengths to achieve comprehensive CCS infrastructure optimization. Thus, Two-Stage Optimization involving ArcGIS and GAMS will be used to design cost-minimizing pipeline networks to connect a group of power plants to a group of geologic sequestration sites.

2.5.2.1 Stage 1- Spatial Optimization

Once a set of CCS-equipped power plants (as CO_2 sources) and CO_2 storage areas destination locations are identified, GIS can be used to identify every possible combination of pipeline segments (Figure 8) and to spatially optimize the cost of each pipeline segment. For simplicity, the model assumes that once a pipeline is connected to a sink, all the CO_2 flowing through the pipe would be sequestered into that sink.

A cost surface[4] is utilized to represent the relative difficulty of constructing a pipeline through various types of terrain by considering both the geographical features as well as social and political data. The cost surface was constructed as a raster layer of the continental United States with 500 meter-square cells. The cell values were designed to reflect a multiplier of the relative cost of pipeline baseline cost. The baseline pipeline cost (cost multiplier of 1) assumes that a pipeline traverses a flat surface (without any obstacles) which includes the fixed cost of material, labor, and miscellaneous costs. The multiplier adjusts cost by factoring in the contribution of geographical features, social impact, and right of way to the pipeline cost such as: 1) flat surface/baseline 2) slope/elevation 3) land use (agriculture, forest, national park, and urban areas) 4) water crossing, and 5) right of way (Table 1 and Figure 5).

Table 1. 8-Layer Cost Surface with Geographic, Social, and Right-of-Way Features

No	Features	Description	Multiplier
1	Flat Surface/baseline	Grassland, barren, dessert	100%
2	Slope/elevation	Low - high slope	+0-15%
3	Predominant agriculture land use	Agricultural land	+20%
4	Predominant Forest Land Use	Needs additional clearing effort	+30%
5	National forest/national Park	Prohibited	+Infinity
6	Urban areas	Light – highly populated	+20-200%
7	Need for water Crossing	Needs additional infrastructure (bridge)	+100%
8	Right of way	Existing – new	+0-10%

[4] A three-dimensional 'contour model' representing the variation in costs multiplier over an area

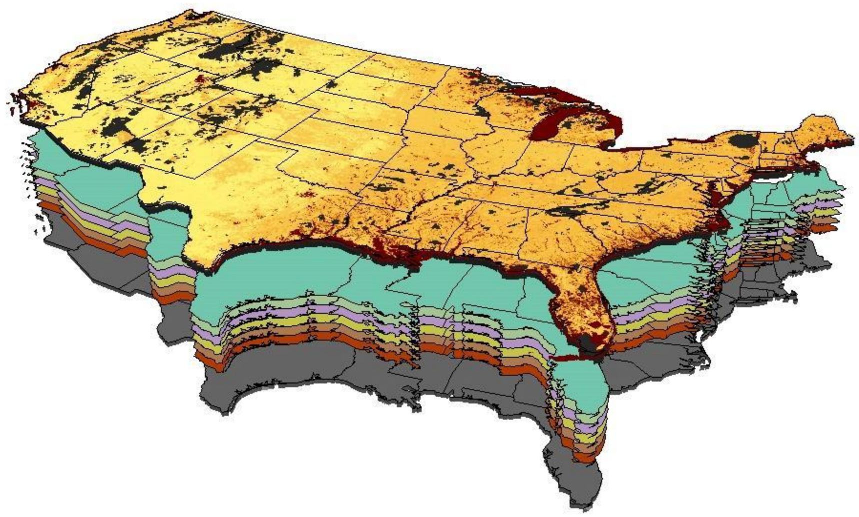

Figure 5. 8-Layer cost surface

Barren terrain, dessert, and grassland provide ideal conditions for pipeline construction, and thus any cells classified as barren or grassland were given values of cost multiplier of 1 and are treated as a baseline cost (Table 1).

In the case of the slope of a cell, the average slope of the terrain within a cell was calculated. Based on the average slope, a cost multiplier was assigned to that cell. The slope data layer was developed from a 500 meter resolution digital elevation model

(DEM) from the U.S. Geological Survey[5]. If the cell had an average slope of less than 10 degrees the cell was given an increased value of 0%. If the average slope was greater than 10 degrees but less than 20 degrees, the cell was given an increased value of 5%. Cells with an average slope greater than 20 degrees but less than 30 degrees were given an increased value of 10%, and any cells with an average slope greater than 30 degrees were given an additional value of 15% (Table 1).

Cells dominated by agricultural areas were given a value of 20% increase to reflect the additional difficulties of navigating the pipeline around farming infrastructure and property. Cells predominantly forested areas require additional preparation work which increases the cost of pipeline construction by approximately 30 percent. We try to avoid developing pipeline that crosses any national park and national forest (Table 1).

Lightly developed urban areas were given an increase of 20%, representing similar concerns with navigating the pipeline route around existing infrastructure as with agricultural areas. More densely developed urban areas were given an increase of 200%, representing the extreme costs that would be necessary to construct a pipeline through dense urban environments, and to discourage (though not prohibit) routing through these cells based on discussions with pipeline experts (Table 1).

Cells dominated by wetlands were given a value of 100% increase to reflect the even greater preparation work necessary in these sensitive areas. Cells that were

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[5] Digital Elevation Model(DEM), U.S. Geological Survey. (http://edc2.usgs.gov/geodata/index.php)

predominantly water were also given an additional value of 100% due to the additional structures (e.g. bridge) and costs required to cross a body of water (Table 1).

The cost surface considers the additional costs that would be associated with obtaining a new right of way for pipeline construction relative to building along an existing right of way. If a cell had an existing right of way in it, a value of 0% was added to the cell. If no existing right of way was present the cell was given an additional value of 10% (Table 1).

Once all of the variables had been assigned the values for each cell were added to the base value to give each cell their final cost surface value. The final value represents the relative cost of constructing a pipeline through that cell over the baseline cost (Figure 5).

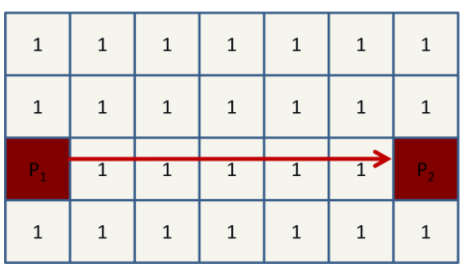

Figure 6. A direct pipeline between two points on the baseline uniform cost surface

Dijkstra developed an algorithm that can establish the shortest path problem in a graph setting (Dijkstra 1959). ESRI ArcGIS implemented the modified Dijkstra algorithm (to take into account cost surface) as spatial functionalities (e.g. CostDistance and CostPath) to identify the least-cost path between two points. The CostDistance function is designed to identify the total cost and also provides a way to trace back the back link grid between two points. The CostPath function uses the intermediate output from CostDistance to come up with the optimized route (represented as a vector) between two points. The combination of these two functions enables the modeling of least-cost path between two points which is exactly what we need in CO_2 pipeline development.

For instance, we have two points (P1 and P2) on a uniform cost surface with each pixel having a level difficulty multiplier of 1 (baseline), such as a desert (Figure 6). Since it is a uniform cost surface, the Dijkstra algorithm identifies a least-cost path between P1 and P2 as a straight line path with normalized distance of 5 units.

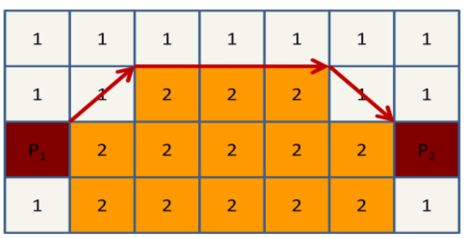

Figure 7. Geographic considerations contribute to determination of pipeline route (for a given cost surface)

In another instance, we have two points (P1 and P2) located on a mixed cost surface area (Figure 7). This surface area contains some pixels with a pipeline development multiplier of 2 (e.g. urban areas), which means that those areas are twice as expensive as the baseline development cost. Using the least-cost path from P1 to P2 results in a pipeline route that avoids high-cost development areas. A normalized distance is used to reflect both the distance and the multiplier related to building a pipeline over varying terrain. For example, if it is twice as difficult to build a pipeline over a 1 km stretch of terrain, the normalized distance for that 1 km distance is 2. Under the mixed cost surface, a straight line route results in a normalized distance of 10 units, while the spatially-optimized, least-cost path is almost half as much at a normalized distance of 5.9 units (Figure 7). Using these two examples, the use of the modified Dijkstra algorithm, cost surface, and normalized distance is proven to be robust in identifying the least-cost path between two points.

One crucial step in the process of cost minimization is the identification of pipeline segment candidates. OptimaCCS uses a brute-force spatial permutation algorithm by combining all possible beginning and ending points of segments (Figure 8). The algorithm eliminates any segment that has the same beginning and ending points to avoid any unnecessary computation. Once a pipeline reaches a sequestration site, all the CO_2 is sequestered in that site, which means there is no additional pipeline needed.

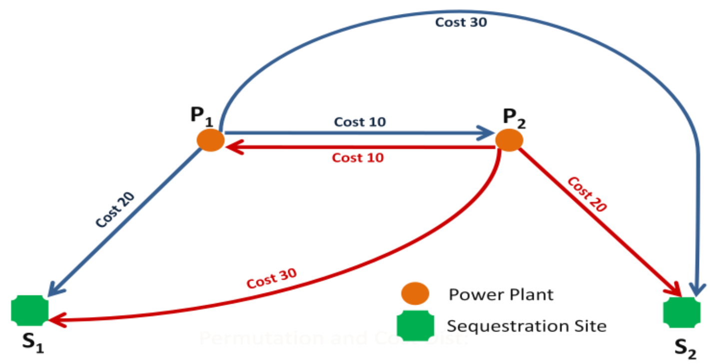

Figure 8. Spatial permutation operation on two sources and two sinks

Table 2. Spatial Permutation Outcome

No	Beginning Point	Ending Point	Normalized Distance
1	P1	P2	10
2	P1	S1	20
3	P1	S2	30
4	P2	P1	10
5	P2	S1	30
6	P2	S2	20

The outcome of spatial optimization and permutation operation on spatial arrangement of 2 CO_2 sources and 2 sinks (Figure 8) can be seen in Table 2 which contains six possible pipeline segments. The number of possible pipeline segments can be counted by multiplying the number of beginning and ending points. Let's say that we have n CO_2 sources and s sequestration sites. The number of pipeline segment beginning points is simply the number of CO_2 sources which is n. Pipeline segment ending points could be either another CO_2 source with (n-1) possibilities or a sequestration site with s possibilities with total count of (n-1+s). Hence, the number of exhaustive spatial permutations (which reflects the number of pipeline segment candidates) is the product of the number of beginning points multiplied by the number of ending points: (n x (n+s-1)). In our example in figure 8, we have 2 CO_2 sources and 2 sinks with total number of pipeline segments (2 x (2-1+2)) which is equal to 6. Exhaustive spatial permutation facilitates the cost minimization process by considering every possible pipeline convergence.

2.5.2.2 Stage 2 – Mathematical Modeling

The core engine of OptimaCCS is a cost minimization optimization formulated as a mixed-integer programming (MIP) model. The model is an extension of the basic transportation problem discussed by McCarl et al (McCarl and Spreen 2003). The model determines the volume of CO_2 flow across a pipeline segment and the pipe size, plus whether or not to build a pipeline segment between two nodes. The OptimaCCS model is a MIP because it combines continuous decision variables for CO_2 flows and pipe size that can take on any value greater or equal to zero and binary integer decision variables on whether or not to build a segment that can take on a value of 0 or 1.

The objective function of OptimaCCS (equation (4)) is to globally minimize both pipeline development plus operating cost, and CO_2 injection cost over the CCS time horizon (infrastructure lifespan) which enables the design of the most cost-effective CCS infrastructure. The setup of global cost minimization also facilitates an active search of the best configuration which decides whether a sink with a more expensive injection cost but closer in proximity is more cost-effective than another sink with a cheaper injection cost but greater distance, or vice versa. This setup also determines whether the cost associated with a trunkline's greater distance is offset by savings from engineering efficiencies of bigger pipe diameter. Hence, pipeline convergence is facilitated to reduce overall pipeline cost during the cost minimization process. The objective function also contains a mechanism to accommodate a step function to identify whether a pipeline segment between two nodes should be built using the XBuild binary variable.

$$\text{MINIMIZE} \sum_{i}\sum_{j} NormDist_{i,j}\, XCostPerKm_{i,j} +$$

$$\sum_{R}\sum_{S} XFlow_{S,R}\, RCost_{R} * THorizon + \sum_{i}\sum_{j} XBuild_{i,j} \qquad [4]$$

S.T

$$\sum_{i} XFlow_{i,k} + SCapture_{k} - \sum_{j} XFlow_{k,j} \leq 0 \qquad \forall\ k \in S \qquad [5]$$

$$XFlow_{i,j} - M * XBuild_{i,j} \leq 0 \qquad \forall\ i, j \in P \text{ where } i \neq j \qquad [6]$$

$$XFlow_{i,j} - 1.402 * XSize_{i,j} + 15.326 * XBuild_{i,j} = 0$$

$$\forall\ i, j \in P \text{ where } i \neq j \qquad [7]$$

$$0.053 * XSize_{i,j} - XCostKm_{i,j} - 0.437 * XBuild_{i,j} = 0$$

$$\forall\ i, j \in P \text{ where } i \neq j \qquad [8]$$

$$XSize_{i,j} \leq MaxSize \qquad \forall\ i, j \in P \text{ where } i \neq j \qquad [9]$$

$$\sum_{i} XFlow_{i,k} * THorizon \leq RCapacity_{k} \qquad \forall\, k \in R \text{ and } i \in S \qquad [10]$$

Sets:

S	stationary CO_2 sources
R	reservoir (sinks)
P,i,j,k	point which may include sources + reservoirs

Parameters:

$SCapture_S$	annual CO_2 captured in source S (ton/year)
$RCapacity_R$	maximum amount of CO_2 stored in reservoir R
$RCost_R$	marginal injection costs of reservoir R
$NormDist_{i,j}$	normalized distance between point i and j

Scalars:

THorizon	life time of a CCS project (30 years)
MaxSize	maximum pipe size (inches)
M	arbitrarily large number

Continuous Decision Variables:

$XFlow_{i,j}$	mass flow between point i and j (mtons/year)
$XSize_{i,j}$	pipe size between point i and j (inches)
$XCostPerKm_{i,j}$	pipeline baseline unit cost per km between point i and j ($/km)

Binary Decision Variable:

$$XBuild^{i,j} \begin{cases} 1 \text{ if pipeline is constructed from point i to j} \\ 0 \text{ otherwise} \end{cases}$$

The flow constraint equation (5) ensures that the flow of CO_2 coming to a point plus the CO_2 captured at that point is less than or equal to the flow of CO_2 coming out. Equation (5) facilitates a mechanism that a power plant is considered not only as a CO_2 source but also as a potential hub in which several smaller pipelines merge to become a bigger pipeline to gain efficiency. Equation (6) ensures that there is a CO_2 flow (between point i and j) only when a pipeline segment is built between point i and j (e.g. $XBuild^{i,j} = 1$). This is an implementation of step function as a constraint with M as an arbitrarily large number (Schoomer 1964). Equation (7) relates CO_2 flow to pipe size through a linear transformation (which is derived from equation (2)). Equation (8) is used to relate pipe size to pipe unit cost per km (which is derived from equation (3)). The use of $XBuild^{i,j}$ in equation (7) and (8) is to make sure that when a pipeline segment between point i and j is not built (e.g. $XBuild^{i,j} = 0$), then the values of $XFlow^{i,j}$, $XSize^{i,j}$ and $XCostPerKm^{i,j}$ are all zero. This is to represent the fact that we cannot transport CO_2 through a pipeline that does not exist. Equation (9) imposes a maximum pipe size. Equation (10) makes sure that the sequestration site chosen has capacity to store the total accumulated CO_2 for at least the time span of the CCS project. Building a pipeline involves high initial capital investment. Once the pipeline is built it is not cost-effective to dismantle it due to a sink being full.

OptimaCCS is non-temporal with the assumption that pipeline infrastructure is used to its constructed capacity over time. The total injection cost is computed using average cost over the lifetime of the CCS system (30 years in this study).   In addition, the storage capacity of geologic formations is given as a maximum total volume rather than as an annual injection limit. Hence, the amount of CO_2 injected is in total CO_2 volume for the whole time span of the CCS system. More refined site-specific maximum injection rate data availability may open up a possibility for model enhancement to express a constraint in terms of maximum annual injection capacity without much revision of data definition and model structure.

2.5.2.3 CCS Infrastructure Economies of Scale

The drive for carbon capture and storage (CCS) development is in part because of the potential of the technology to have a great impact on reducing CO_2 emissions. In order to do so, CCS must be deployed at a large scale. We recognize that CCS will be subject to a series of challenges including regulatory, climate policy, legal and social acceptance, but the degree of CCS deployment will also be determined by the economy of scale of CCS technology itself. CCS technology achieves economies of scale if the increase in the amount of CO_2 captured and the possibility of cooperation between CO_2 emitters will lower the average cost of capturing, transporting, and sequestering per unit ton of CO_2. The economy of scale of CCS technology is important for understanding and designing the CCS spatial organization, cooperation between sources, and the scale of the technology deployment.

These economies of scale can be derived from pipeline engineering principles as used in the Chandel et al. study (Chandel, Pratson and Williams 2010), which can be characterized by the decreasing of average cost of transporting a unit ton of CO_2 per unit distance as the pipe diameter increases (Figure 9). The average cost-per-ton per km of CO_2 decreases at a decreasing rate as the diameter increases. This means that there is an incentive to aggregate CO_2 flow from multiple sources into larger diameter pipelines to reduce costs. A CCS system will require many pipeline segments, each of which can exhibit increasing returns to scale.

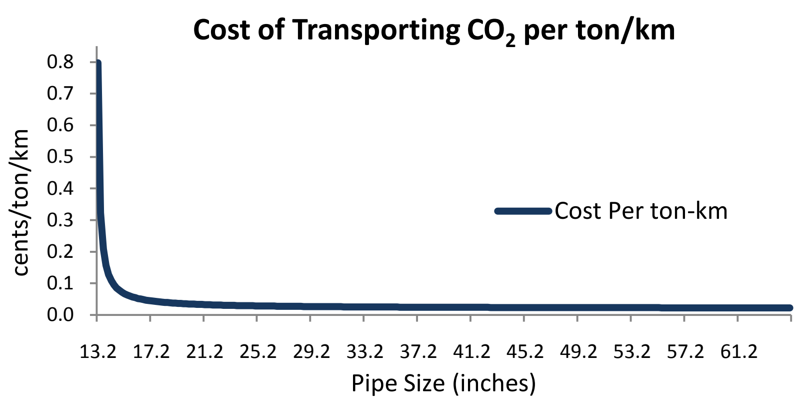

Figure 9. Pipe diameter vs average CO_2 transport cost

This phenomena can be explained by the fact that the amount of fluid that can flow through a pipeline is dictated by the cross-sectional area of the pipeline which is, in turn, determined by the square of pipe diameter ($\pi * D^2$). The change of flow increases in a proportion greater than the increase in the diameter, and thus larger diameter pipelines result in a cheaper marginal transportation cost per unit ton of CO_2 per km (Chandel, Pratson and Williams 2010). Chandel et al. also identifies that increasing the pipe diameter increases the interval distance at bigger relative at which booster pumps are needed to keep the CO_2 pressurized to stay in liquid form. Increasing the pipe diameter also leads to a larger corresponding relative decrease in the friction factor. It can be safely assumed that the costs to compress or pressurize a fluid are linearly related to the pressure drop, which means that increasing the pipe diameter will result in a much smaller marginal transportation cost. All of these engineering considerations dictate that as the pipeline diameter increases, the cost of transporting a unit of CO_2 per unit distance also decreases, illustrating the economies-of-scale phenomena.

2.6 OptimaCCS Application: Texas Case Study

Now attention is focused on applying OptimaCCS to a case study of CO_2 sources and sequestration sites in Texas. First, we use it to develop a CCS infrastructure that globally minimizes development and injection costs for a system that serves all sources and sinks given their spatial distribution. OptimaCCS is then configured to ignore injection costs to mimic the considerations of previous CCS modeling efforts. Additionally, we analyze different injection costs to see how this affects the spatial arrangement of the CCS infrastructure. Finally, we configure OptimaCCS to model an infrastructure in which each CO_2 source uses an unshared pipeline to access the sequestration reservoir so that we can quantify economic efficiencies that result from scaling up the infrastructure.

2.6.1 Data Development

2.6.1.1 Texas CO_2 Sources Identification

We use the Nicholas Institute's version of NEMS (NI-NEMS) to determine coal-fired power plants that are retrofitted with CCS technology (National Energy Technology Laboratory 2008). Subsequently, 14 existing coal-fired power plants are identified (table 3, figure 10) and the NEMS database also provides a captured CO_2 volume.

Table 3. 14 Existing Coal-fired Power Plants in Texas Identified by NI-NEMS to have CCS potential

No	Plant Name	Operator	County	Capacity (GW)	Emission (mtons/year)	Captured (mtons/year)
1	Limestone	NRG Energy	Limestone	1.85	0.72	6.48
2	Harrington	Xcel Energy	Potter	1.08	0.30	2.66
3	Tolk	Xcel Energy	Lamb	1.14	0.38	3.41
4	Pirkey	American Electric Power	Harrison	0.72	0.51	4.56
5	Gibbons Creek	Texas Municipal Power Agency	Grimes	0.45	0.37	3.35
6	J T Deely & Spruce	CPS Energy	Bexar	1.50	0.79	7.14
7	W A Parish	NRG Energy	Fort Bend	3.97	0.47	4.27
8	Monticello	Luminant Energy	Titus	1.98	0.66	5.93
9	Fayette Power Project	Lower Colorado River Authority	Fayette	1.69	0.16	1.48
10	San Miguel	San Miguel Electric Coop Inc	Atascosa	0.41	0.17	1.52
11	Oklaunion	American Electric Power	Wilbarger	0.72	0.08	0.72
12	Martin Lake	Luminant Energy	Rusk	2.38	0.68	6.11
13	Sandow No 4	Luminant Energy	Milam	1.14	0.45	4.08
14	Coleto Creek	International Power	Goliad	0.60	0.57	5.09
		Total			**6.31**	**56.80**

Table 3 and Figure 10 show the 14 power plants identified as having CCS potential. They have a total capacity of 19.3 GW and potential CO_2 capture of 56.8 million tons/yr.

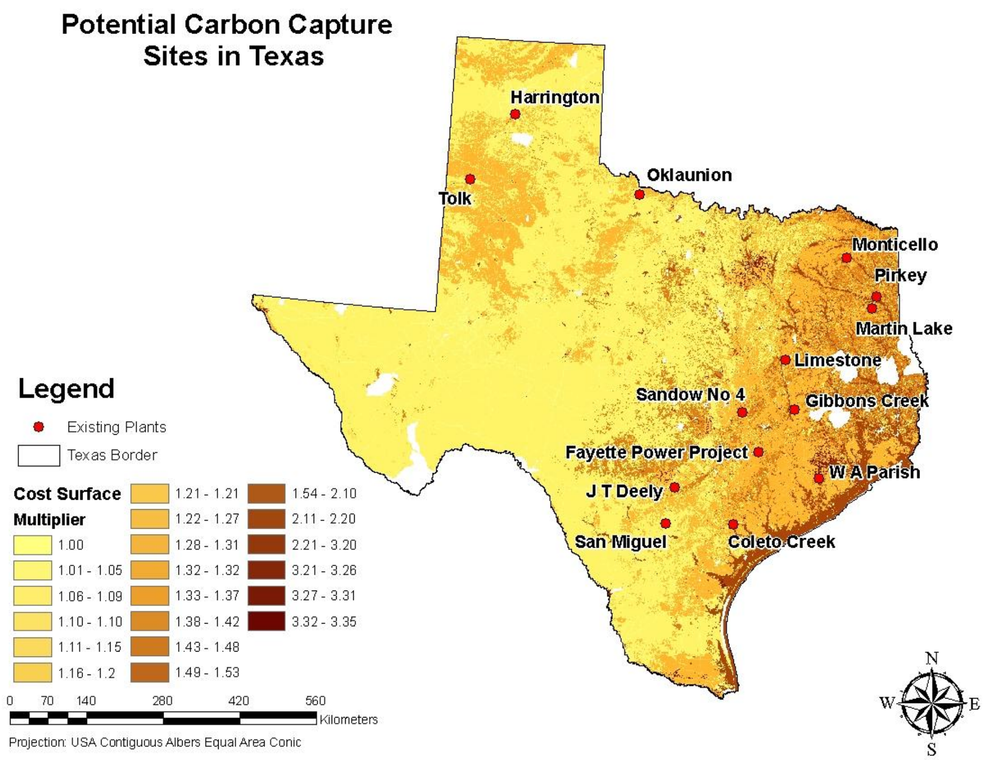

Figure 10. 14 power plants identified by NI-NEMS as being CCS candidates

2.6.1.2 Three Saline Aquifers in Texas

The Southeast Regional Carbon Sequestration Partnership (SECARB) reports indicate that saline formations located along the U.S. gulf coast have the potential to store 350–1,400 billion tons/yr of CO_2 (National Energy Technology Laboratory 2010). Texas has three deep saline formations with large capacities for storing CO_2: Frio basin, Woodbine basin, and Granite Wash basin. The U.S. Department of Energy (DOE) funded the Frio Brine pilot site CO_2 injection tests in 2004 and 2006 in order to characterize the Frio saline formation. Both tests showed promising results regarding the feasibility of injecting CO_2 into high-permeability, high-volume sandstone present at

5,000 ft depth (Holtz, et al. 2005). Eccles et al. performed a reservoir characterization study of 12 saline aquifers which included Frio, Woodbine and Granite Wash (Figure 11) (Eccles, et al. 2009) and gave estimates of the capacity, injection rate, and the marginal CO_2 injection cost for each reservoir.

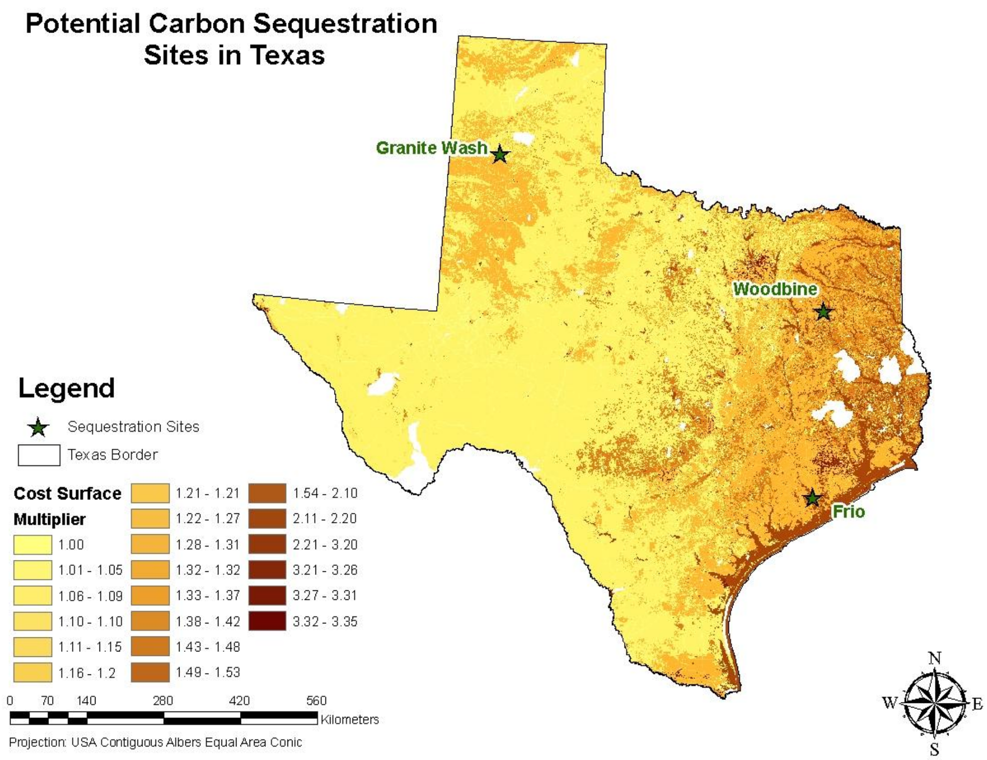

Figure 11. Saline formations with sequestration potential

The potential maximum CO_2 capture from these 14 power plants is 56.8 million tons annually. If we consider emissions to be constant over time and a system lifespan of 30 years, total capture amounts to approximately 1.7 billion tons of CO_2. Matching the amount of total CO_2 captured with a CO_2 capacity supply curve for Granite Wash, Woodbine and Frio, we calculate the average marginal injections cost in Table 4. Woodbine and Granite Wash both have average CO_2 injection costs of $4.5/ton if we inject a total of 1.7 billion tons over 30 years. Frio has a distinct economic advantage with an injection cost of only $0.75/ton for the same amount of CO_2 over the same time span.

Table 4. Average Marginal CO_2 Injection Cost Estimate (Eccles, Pratson, Newell, & Jackson, 2009).

No	Saline Aquifers	Avg Marginal Injection Cost ($/ton)
1	Frio	$0.75/ton
2	Granite Wash	$4.50/ton
3	Woodbine	$4.50/ton

2.6.2 OptimaCCS Comprehensive Optimization

We use OptimaCCS to determine a cost minimizing CCS infrastructure for this particular set of 14 sources and three sinks with the assumption of full cooperation between plant owners. Under this run, we consider not only the pipeline construction cost but also the site-specific injection cost to come up with the most cost-effective CCS infrastructure.

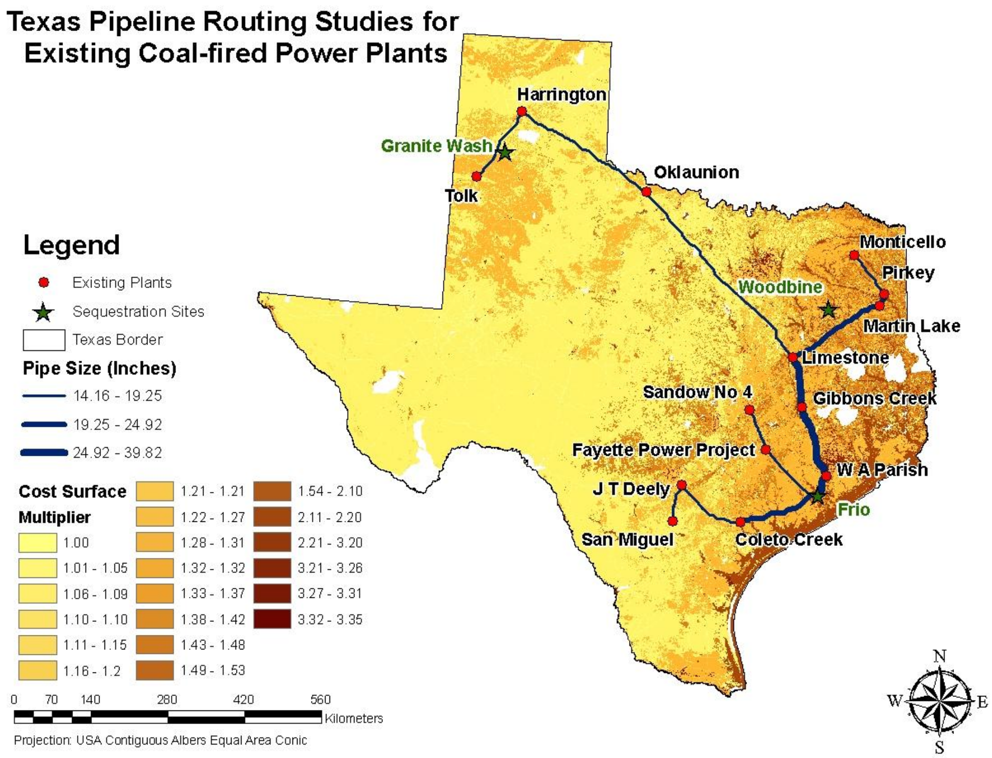

Figure 12. Optimized pipeline network under comprehensive optimization

Figure 12 exhibits the output map and shows that Frio is specified as the only sink, meaning that the costs of the other two sequestration sites (Granite Wash and Woodbine) are so expensive that it makes sense to add pipeline costs to get to the cheaper frio. CO_2 supply from panhandle plants (Tolk, Harington, and Oklaunion) flows along a trunkline to Limestone where it joins the main line. CO_2 from northeast Texas plants (Monticello, Pirkey, and Martin-Lake) flows along a second trunkline that also converges at Limestone, which serves as a central hub receiving 29.9 mtons/yr CO_2. Here, the trunkline capacity is expanded and it flows to Gibbons Creek and WA Parish, delivering 37.5 mtons/yr CO_2 from these 9 plants. In southern Texas, CO_2 flow from San Miguel is transported to the JK Spruce/JT Deely plant where a trunkline begins. Flow continues to Colleto Creek and then reaches Frio to deliver 13.7 mtons/yr CO_2. In central Texas, flow from Sandow No. 4 is transported to Fayette Power Project and combined onto a direct pipeline to Frio, delivering 5.6 mtons per year CO_2.

Table 5. Pipeline Segments for an Optimized Infrastructure

No	Beginning Point	Ending Point	Distance (km)	Flow (mtons/year)	Pipe Size (inches)	Segment Cost ($ millions)
1	Limestone	Gibbons Creek	95	29.9	34.38	$172.12
2	Harrington	Oklaunion	283	6.1	17.4	$154.06
3	Tolk	Harrington	151	3.4	15.51	$66.48
4	Pirkey	Martin Lake	26	10.5	20.56	$25.11
5	Gibbons Creek	W A Parish	141	33.2	36.77	$271.79
6	J T Deely	Coleto Creek	136	8.7	19.25	$95.15
7	W A Parish	Frio*	41	37.5	39.82	$96.31
8	Monticello	Pirkey	93	5.9	17.31	$61.86
9	Fayette Power Project	Frio*	130	5.6	17.04	$82.75
10	San Miguel	J T Deely	71	1.5	14.16	$26.80
11	Oklaunion	Limestone	415	6.8	17.92	$238.07
12	Martin Lake	Limestone	194	16.6	24.92	$221.60
13	Sandow No 4	Fayette Power Project	82	4.1	15.98	$42.48
14	Coleto Creek	Frio*	159	13.7	22.88	$160.87
		Total	**2017 km**			**$1,715.42**

Table 6. Economic Analysis of an Optimized Infrastructure

No	Power Plant	Annual Capture (mtons/year)	30 yrs Capture (million tons)	Injection Site	Marginal Injection Cost ($/ton)	Injections Cost ($ millions)	Pipeline Cost ($ millions)
1	Limestone	6.5	194.4	Frio	$0.75	$145.82	$107.00
2	Harrington	2.7	79.7	Frio	$0.75	$59.74	$204.26
3	Tolk	3.4	102.4	Frio	$0.75	$76.82	$329.15
4	Pirkey	4.6	136.9	Frio	$0.75	$102.64	$147.11
5	Gibbons Creek	3.3	100.4	Frio	$0.75	$75.33	$35.99
6	J T Deely	7.1	214.1	Frio	$0.75	$160.59	$161.93
7	W A Parish	4.3	128.1	Frio	$0.75	$96.11	$10.97
8	Monticello	5.9	178.1	Frio	$0.75	$133.54	$253.25
9	Fayette Power Project	1.5	44.4	Frio	$0.75	$33.27	$22.00
10	San Miguel	1.5	45.7	Frio	$0.75	$34.29	$61.37
11	Oklaunion	0.7	21.7	Frio	$0.75	$16.30	$37.34
12	Martin Lake	6.1	183.2	Frio	$0.75	$137.38	$182.30
13	Sandow No 4	4.1	122.5	Frio	$0.75	$91.86	$103.23
14	Coleto Creek	5.1	152.6	Frio	$0.75	$114.42	$59.51
			Total			**$1,278.10**	**$1,715.42**

In this configuration, total pipeline length is 2017 km and the network delivers 56.5 mtons/yr to Frio from these 14 plants (Table 5). The total cost of this pipeline network is $1.7 billion (Table 6) and the injection costs for 56.5 mtons/yr of CO_2 for 30 years are roughly $1.3 billion. The total CCS infrastructure plus injection costs would be approximately $3 billion.

Table 7. Individual Marginal Transportation and Injection Cost Under Comprehensive Optimization

No	Plant Name	CO2 Captured (mtons/year)	Transportation Cost ($/ton)	Injection Cost ($/ton)	Total Cost ($/ton)
1	Limestone	6.5	$2.64	$0.75	$3.39
2	Harrington	2.7	$12.31	$0.75	$13.06
3	Tolk	3.4	$15.43	$0.75	$16.18
4	Pirkey	4.6	$5.16	$0.75	$5.91
5	Gibbons Creek	3.3	$1.72	$0.75	$2.47
6	J T Deely	7.1	$3.63	$0.75	$4.38
7	W A Parish	4.3	$0.41	$0.75	$1.16
8	Monticello	5.9	$6.83	$0.75	$7.58
9	Fayette Power Project	1.5	$2.38	$0.75	$3.13
10	San Miguel	1.5	$6.44	$0.75	$7.19
11	Oklaunion	0.7	$8.25	$0.75	$9.00
12	Martin Lake	6.1	$4.78	$0.75	$5.53
13	Sandow No 4	4.1	$4.05	$0.75	$4.80
14	Coleto Creek	5.1	$1.87	$0.75	$2.62

Marginal transportation cost over a segment is computed by taking the annualized capital cost of developing a pipeline (plus annual maintenance cost) divided by the total of amount CO_2 transported annually. The transportation costs for each plant are computed by taking the tons moved multiplied by the costs of the plant segments used. Table 7 exhibits the total marginal transportation and injection cost for each power plant, which ranges from $1.16/ton to $16.18/ton. WA Parish has the cheapest transportation cost because it is closest to the Frio sink and Tolk has the highest cost because it is the farthest. Only two plants (Harrington and Tolk) have transportation and injection costs greater than $10/ton. The consensus within the energy modeling community is that a combined transportation and injection cost below $10/ton makes a CO_2 source a good candidate for inclusion into a larger CCS infrastructure.

2.6.3 OptimaCCS Least-cost Path Optimization

OptimaCCS is configured next to design the CCS infrastructure's pipeline network with the sole consideration given to minimizing pipeline construction costs. The least-cost path algorithm develops pipeline routes that connect CO_2 sources to nearest sinks while excluding site-specific sequestration costs. This mimics two previous CCS modeling efforts that also use a least-cost path algorithm: 1) Herzog et al. analyzed cost in the WESTCARB report (Herzog, et al. 2007), and 2) Middleton and Bielicki designed a CCS pipeline in California while assuming that site-specific injection costs are uniform (Middleton and Bielicki 2009).

Ignoring injection costs, the 14 power plants are connected to the closest sequestration sites (Figure 13) and result in three pipeline networks each feeding a separate sequestration site. The Granite Wash pipeline network (Tolk, Harrington, Oklaunion plants) has a construction cost of about $156 million, total length of 440 km, and total CO_2 delivery of 6.8 mtons/yr. The Woodbine pipeline network (Monticello, Pirkey, Martin-Lake, Limestone, Gibbons Creek plants) has a total construction cost of about $243 million, length of 339 km, and CO_2 delivery of 20.5 mtons/yr. The Frio pipeline network (Sandow No 4, Fayette Power Project, W.A Parish, J.K Spruce, J.T Deely, San Miguel, Coleto Creek plants) has a construction cost of about $440 million, a length of 616 km, and CO_2 delivery of 23.58 mtons/yr.

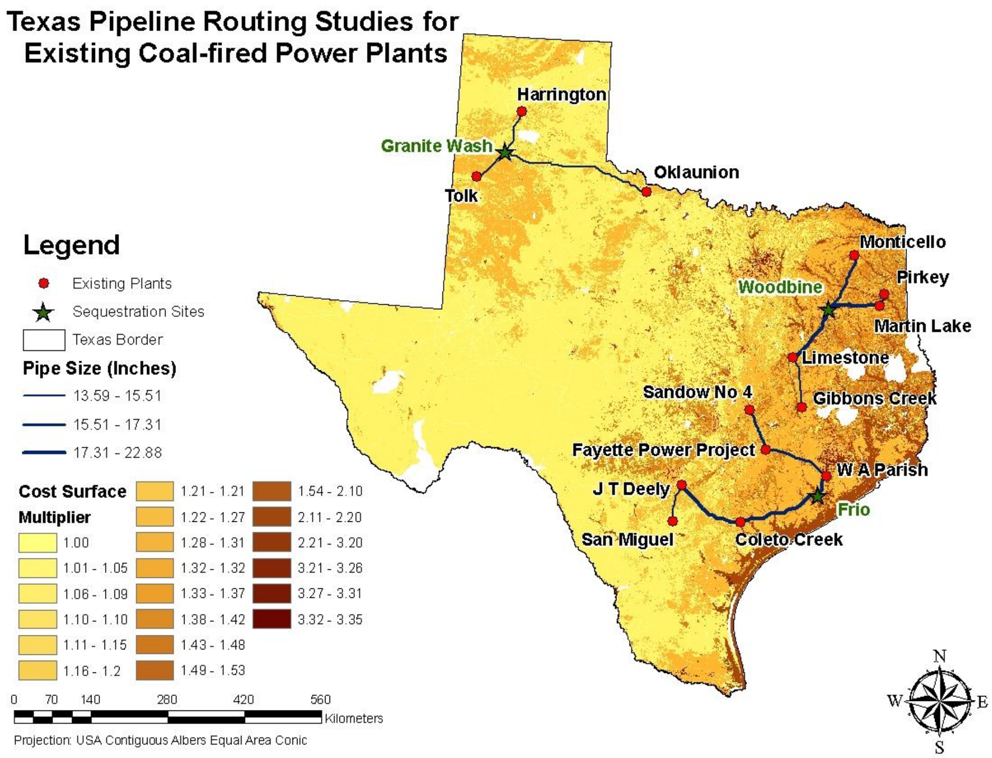

Figure 13. Pipeline network transport cost only optimization

These three smaller pipeline networks have a total of 1510 km of pipeline that connect all 14 power plants to their closest sequestration sites (Table 8). Even though OptimaCCS only considers transport costs in designing the physical pipeline network, the site-specific injection costs are included in the total CCS costs. In this framework, the pipeline construction cost and injection cost are \$0.9 billion and \$5 billion respectively (Table 9). The total CCS cost is over \$5.9 billion or is roughly twice as expensive as the more comprehensive framework that considers injection costs and gives a \$3 billion final cost (Table 9, Table 6).

Table 8. Pipeline Segments Under Transport Cost Only Optimization

No	Beginning Point	Ending Point	Distance (km)	Flow (mtons/year)	Pipe Size (inches)	Segment Cost ($ millions)
1	Limestone	Woodbine*	119	9.8	20.1	$91.51
2	Harrington	Granite Wash*	82	2.7	15.0	$32.23
3	Tolk	Granite Wash*	75	3.4	15.5	$34.02
4	Pirkey	Martin Lake	26	4.6	16.3	$16.52
5	Gibbons Creek	Limestone	95	3.3	15.5	$47.79
6	J T Deely	Coleto Creek	136	8.7	19.3	$95.15
7	W A Parish	Frio*	41	9.8	20.1	$36.23
8	Monticello	Woodbine	114	5.9	17.3	$75.01
9	Fayette Power Project	W A Parish	127	5.6	17.0	$78.49
10	San Miguel	J T Deely	71	1.5	14.2	$26.80
11	Oklaunion	Granite Wash*	283	0.7	13.6	$90.03
12	Martin Lake	Woodbine*	99	10.7	20.7	$87.43
13	Sandow No 4	Fayette Power Project	82	4.1	16.0	$42.48
14	Coleto Creek	Frio*	159	13.7	22.9	$160.87
		Total	**1510 km**			**$914.54**

Table 9. Economic Analysis of Transport Cost Only Optimization

No	Power Plant	Annual Capture (mtons/year)	30 yrs Capture (million tons)	Injection Site	Marginal Injection Cost ($/ton)	Injection Cost ($ million)	Pipeline Cost ($ million)
1	Limestone	6.5	194.4	Woodbine	$4.50	$874.9	$60.3
2	Harrington	2.7	79.7	Granite Wash	$4.50	$358.4	$32.2
3	Tolk	3.4	102.4	Granite Wash	$4.50	$460.9	$34.0
4	Pirkey	4.6	136.9	Woodbine	$4.50	$615.8	$53.9
5	Gibbons Creek	3.3	100.4	Woodbine	$4.50	$452.0	$79.0
6	J T Deely	7.1	214.1	Frio	$0.75	$160.6	$161.9
7	W A Parish	4.3	128.1	Frio	$0.75	$96.1	$15.7
8	Monticello	5.9	178.1	Woodbine	$4.50	$801.2	$75.0
9	Fayette Power Project	1.5	44.4	Frio	$0.75	$33.3	$26.3
10	San Miguel	1.5	45.7	Frio	$0.75	$34.3	$61.4
11	Oklaunion	0.7	21.7	Granite Wash	$4.50	$97.8	$90.0
12	Martin Lake	6.1	183.2	Woodbine	$4.50	$824.3	$50.0
13	Sandow No 4	4.1	122.5	Frio	$0.75	$91.9	$115.2
14	Coleto Creek	5.1	152.6	Frio	$0.75	$114.4	$59.5
			Total			**$5,015.9**	**$914.5**

2.6.4 Injection Cost Sensitivity

Clearly, the outcome of the comprehensive optimization depends heavily on the site-specific injection costs (derived from Eccles et al.) which may shift due to site-specific factors (e.g. more granular geologic data, higher well-drilling costs). In addition, the outcomes of the comprehensive optimization do not lend themselves to a straightforward understanding of the relationship between site-specific injection cost and the output of a single sequestration site's CCS infrastructure.

Here, we progressively decrease the relative difference of injection cost between Frio and the two other sequestration sites (Granite Wash, and Woodbine), to see how low those costs need to become before the resultant CCS infrastructure uses three separate sequestration sites and find these relative costs need to fall below $1.98 (Table 10).

Table 10. Relative Difference of Marginal Injection Costs to Frio Baseline Cost with Frio Serving as a Single Sequestration Site

No	Saline Aquifers	Avg Marginal Injection Cost ($/ton)
1	Frio	Baseline
2	Granite Wash	Baseline + $1.99/ton
3	Woodbine	Baseline + $1.98/ton

This shows that OptimaCCS considers site-specific marginal injection costs when determining infrastructure configuration. By analyzing these input factor sensitivities, we are less dependent on current absolute values of marginal injection cost for each sequestration site. Many researchers argue that future geologic data will be more accurate and granular, and these results show how much this would need to change to bring those sinks into play.

2.6.5 Tolk Power Plant: Unshared vs Trunkline Pipe

To analyze the economics of a CCS infrastructure restricted to using individual source-to-sink pipelines, we solve OptimaCCS by prohibiting pipeline convergence. The resulting infrastructure costs can now be compared to those of the trunkline design. Here, we are attempting to quantify the economic gains from a fully-scaled-up infrastructure. This scenario uses the source (Tolk) that is farthest from its sink (Frio) as an example. Tolk has the potential to capture 3.41 million tons of CO_2 annually at its current level of power generation.

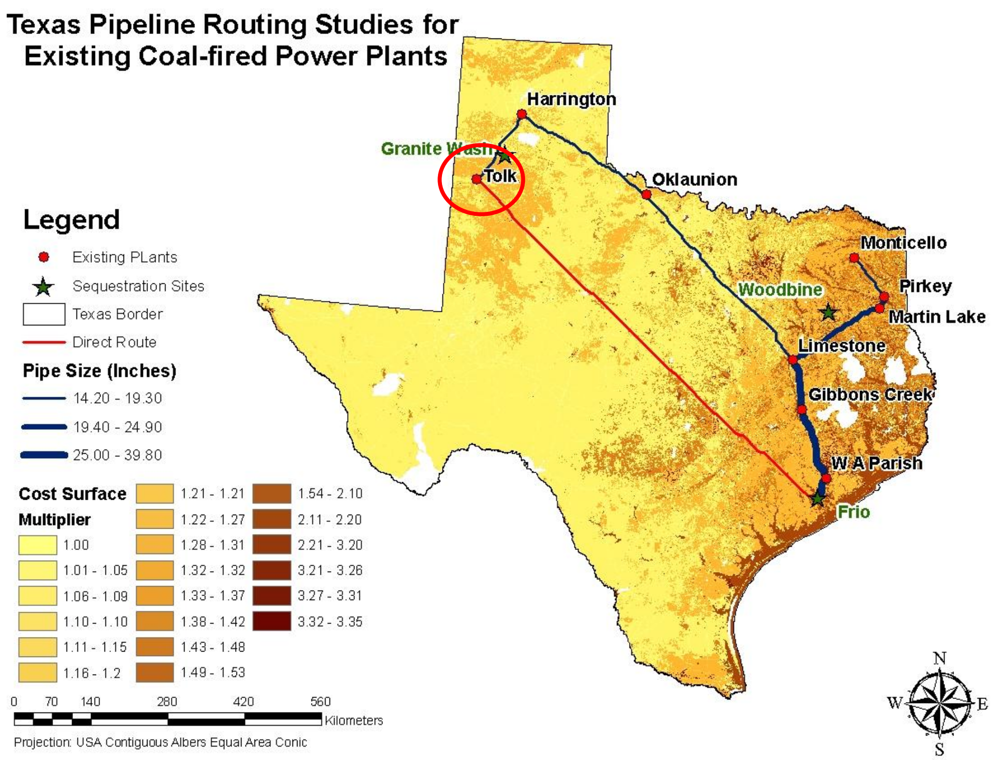

Figure 14. Comparison of individual pipeline vs trunkline service for Tolk

Table 11. Cost Share for Trunkline Service to Tolk

No	Beginning Point	Ending Point	Distance (km)	Flow (mtons/year)	Pipe Size (inches)	Segment Cost ($ millions)	Tolks Share ($ millions)
1	Tolk	Harrington	151	3.4	15.5	$66.48	$66.48
2	Harrington	Oklaunion	283	6.1	17.4	$154.06	$86.66
3	Oklaunion	Limestone	415	6.8	17.9	$238.07	$119.64
4	Limestone	Gibbons Creek	95	29.9	34.4	$172.12	$19.67
5	Gibbons Creek	W A Parish	141	33.2	36.8	$271.79	$27.93
6	W A Parish	Frio*	41	37.5	39.8	$96.31	$8.77
	Total		**1126 km**				**$329.15**

Table 12. Comparison of Pipeline Characteristics for Individual vs Trunkline Service to Tolk

No	Characteristics	Individual	Trunkline (network)
1	Distance (km)	863	1126
2	Biggest Pipe size(inches)	15.51	39.82
3	Pipeline Cost (million $)	393	329
4	Transportation Cost ($/ton)	$18.42	$15.43

Figure 14 shows alternative CO_2 delivery configurations (trunkline vs individual) between Tolk source and Frio sink. A direct Tolk-to-Frio pipeline would cover 863 km and cost $393 million (Table 12). Trunkline delivery involves a series of pipe diameter increases as CO_2 flow converges at Harrington, Oklaunion, Limestone, Gibbons Creek, and finally WA Parish plants. The Tolk-to-Frio trunkline delivery system covers 1126 km and the Tolk's pipeline share would cost $329 million (Table 11, Table 12).

OptimaCCS's pipeline configuration analysis helps isolate cost savings that can result when the proximity of sources facilitates trunkline flow. Our model determines whether the cost associated with a trunkline's greater length is offset by savings from engineering efficiencies for CO_2 flow as pipe diameter scales up. Economic analysis of pipeline service to Tolk determines $64 million cost savings result from choosing a trunkline configuration instead of direct source-to-sink pipelines. This cost reduction represents the value of cooperation by plant owners and it results from several component efficiencies that are gained when scaling up the infrastructure.

2.6.6 Tolk Power Plant, Granite Wash vs Frio

Under the comprehensive cost minimization, OptimaCCS selects the best configuration of sequestration sites that minimizes the overall total transportation and injection cost across the entire network. To do so it weighs the economic tradeoffs in deciding whether to select a sink with a more expensive injection cost but a closer proximity (and cheaper transportation cost) or a sink with a cheaper injection cost but a greater distance (and more expensive transportation cost). For Tolk power plant the decision is between 1) Granite Wash, which is more expensive but closer in proximity, and 2) Frio, which is cheaper but requires a longer distance pipeline.

Table 13. Comparison of Granite Wash vs Frio

No	Costs	Granite Wash ($ millions)	Frio ($ millions)
1	Pipeline Cost	$34	$329
2	Injection Cost	$461	$77
4	Total Cost	$495	$451

For Tolk, the pipeline cost to connect to Granite Wash is $34 million and the total injection cost is $461 million with total CCS cost of $495 million (Table 13). On the other hand, to connect to Frio the pipeline cost is $329 and the injection cost is $451 with total cost of $451 million (Table 13). Even though the pipeline cost to connect to Granite Wash is cheaper than the cost to connect to Frio, the injection cost of Granite Wash is relatively more expensive than that of Frio. The result is that the total CCS cost of Frio ($451 million) is cheaper than that of Granite Wash ($495 million). Hence, Frio is selected as the best sequestration site for Tolk power plant. In this fashion, OptimaCCS selects the best configuration of sequestration sites that minimizes system-wide transportation and injection cost.

2.7 Conclusion of OptimaCCS Development and Application

We used OptimaCCS to perform an economic analysis of CCS infrastructure considerations and then determine the optimal configuration of a full-scale deployment. Our model links 14 sources and three potential sinks.

We analyze the model's sensitivity to input criteria such as site-specific injection cost, pipeline construction cost, and coordination among plant owners. Finally, our economic analysis quantifies these distinct cost-sensitivities and potential savings.

Economic optimization determines a multi-trunkline configuration that benefits from economies of scale in both construction and operation costs. The model successfully identified the best transport plus injection cost minimizing pipeline configuration for transporting all CO_2 to the Frio sequestration reservoir (Figure 12) and quantified construction and injection costs of the resultant multi-trunkline route (Table 6). This configuration yields a total cost of $3 billion. To illustrate the cost savings due to the OptimaCCS modeling improvements over previous efforts, we compare the costs of a model that only looks at pipeline costs versus one that considers both pipeline and injection costs. We find that comprehensive optimization yields a $2.9 billion potential cost savings.

3. ANALYSIS OF CAP AND TRADE SUPPORTIVE POLICY

Practical experience and detailed technical and engineering cost studies demonstrate that CCS is both technologically and potentially economically feasible. According to a report by the Interagency Task force on Carbon Capture and Storage published this August (Interagency Task Force on Carbon Capture and Storage 2010) the required technologies (capture, transmission, and storage) to perform CCS already exist. The real-world barrier to CCS development is the lack of a supportive environmental regulation[6]. A supportive national policy will assist utility companies in overcoming the incremental costs of adopting CCS and creating stable and reliable frameworks for private investments.

In the past, environmental law and regulation was dominated by command-and-control approaches. In the 1990s this approach shifted and policy makers increasingly explored environmental policy instruments which provided economic incentives for firms and individuals to reach environmental goals. For instance, the 1990 Clean Air Act Amendment that proposed controlling acid rain with a cap and trade program is cited by "The Economist" magazine as the greatest green success story of that decade. Following the success of the 1990 Clean Air Act, the U.S. has attempted to take actions

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[6] In addition, further studies need to discern the environmental impact, the perceived investment risks of different technologies, and uncertainty as to how quickly the cost of CCS will be reduced through R&D and learning-by-doing.

to reduce carbon dioxide and other greenhouse gas emissions linked with global climate change using market-based instruments.

In June, 26, 2009, the U.S. House of Representatives approved a comprehensive climate energy legislation known as the American Clean Energy and Security Act (ACES) or HR 2454. However, the bill died in the Senate and never became law. On May, 2010, Sen. John Kerry (D-MA) and Sen. Joe Lieberman (I-CT) introduced similar comprehensive energy legislation, the American Power Act. This proposed legislation also stalled in the national legislature and failed to become law. To analyze the economic feasibility of CCS technologies under cap and trade instruments we developed a model to simulate the different scenarios of CCS deployment by considering different combinations of carbon price trajectories, technological progress, and allowance auction. The model is based on the premise that CCS costs is high ($80-$150/ton) and that the expected carbon price is much lower ($15-$25/ton with a 5% annual increase). Under these assumptions, installing CCS technology without a government subsidy is economically unfeasible. The real constraint of CCS deployment under cap and trade policy is the availability of CCS bonus allowances, a form of government subsidy. However, the relationship between bonus allowances and tons of CO_2 captured is not linearly one-to-one. The amount of CO_2 captured (and permanently sequestered) is recognized by a quantity of bonus allowances that are awarded with respect to the current carbon price.

Based on this premise, we propose, design, and develop a model that simulates the distribution of a guaranteed CCS bonus allowance by considering the dynamics of carbon pricing, the progress of CCS technology, and the availability of CCS bonus allowances under cap and trade policy. This study uses the American Power Act (APA) for a case study in systematic modeling. First we identify the features of the APA such as the available bonus allowance and the characteristics of each phase. Second, we identify the empirical interrelationship between available bonus allowance and the amount of CO_2 captured coupled with carbon price trajectories and CCS technological progress. Third, we translate this understanding (model requirement) into an economic model. We consider three scenarios: rapid, moderate, and slow deployments. We aim to model, explain, and assess the likelihood of achieving the goal of 72 GW of deployment by 2034.

3.1 Cap and Trade Literature Review

Cap and trade can be traced back to Coase's idea of negotiated solutions to externality problems (Coase 1960). Crocker (Cocker 1966) and Dales (Dales 1968) independently developed the idea of using transferable discharge permits (TDP) to allocate the pollution-control burden among pollution sources. Dales' work focuses on water pollution permitting while Crocker's focuses on air pollution permitting (even though they use the same system). Montgomery (Montgomery 1972) provides the extension of proof that such a system could provide a cost-effective policy instrument by defining an emission based permit system (EPS). Tietenberg (Tietenberg 1985) suggests that a cost-effective solution may be achieved by the EPS approach, which allows for unit-for-unit trades among any sources in the same airshed (in the case of air pollution).

From these literature sources, it can be deduced that the allocation method of allowances (free distribution or auction) does not influence firms' production and emission reduction decisions. Montgomery (Montgomery 1972) emphasizes that firms face the same emissions cost regardless of the allocation method. When using an allowance, whether it was received for free or purchased through auction, a firm loses the opportunity to sell that allowance, and thereby recognizes this "opportunity cost" in deciding whether to use the allowance. Consequently, the allocation choice will not influence a cap's overall costs.

3.2 American Power Act Literature Review

After the release of the APA (Kerry and Lieberman 2010) on May 12,2010, there have been an array of APA analyses done by various organizations. EPA's analysis emphasizes the economy-wide impact and short term impact of using ADAGE (RTI n.d.) and IPM (ICF International n.d.) energy models respectively (U.S. Environmental Protection Agency 2010). In addition, there is a series of analyses, mostly in environmental blogs and newspaper articles, which cover a broad range of topics including: how the current economic situation impacts the feasibility of the APA, how the allocation of allowances would affect certain industries, and how cap and trade sits in the current and future political situation. However, no analysis has been done to understand how the interaction of carbon price, CCS technological progress, the reverse auction process, or the constraints of CCS bonus allowance availability will affect the progress of CCS deployment. The emphasis of this study is on demonstrating how those parameters are going to affect CCS deployment under a cap and trade framework.

3.3 Cap and Trade Economic Theory

This section revisits the economic theory of cap and trade which is an adaptation of the basic cap and trade theory discussed in Hanley et al. (Hanley, Shogren and White 1997). Let's consider a CO_2-polluting coal-fired power plant that faces an increasing marginal pollution abatement cost curve (Figure 15). Without any regulation, the plant will choose to abate zero units of carbon and avoid the abatement costs represented by the area underneath the marginal abatement cost curve: B + C + D. Suppose a benefit-cost analysis has determined that optimal abatement occurs at the blue dot where the marginal benefit and marginal cost curves intersect. The resulting level of emissions is e* (Figure 15).

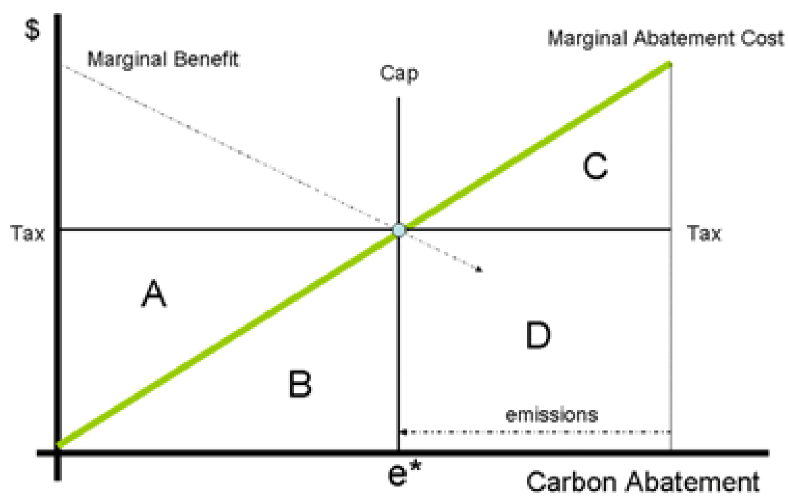

Figure 15. Cap and trade vs carbon tax for single polluting coal-fired power plant (Hanley, Shogren, & White, 1997)

Using cap and trade, the government is to set a cap where marginal benefit equals marginal abatement cost. The efficient abatement level is achieved at e*, and the total abatement cost to the pollution firm is the area of B (Figure 15).

Alternately, in the case of a carbon tax, the government is to set a tax where marginal benefit equals marginal abatement cost. Firms operating coal fired power plants will notice that it is cheaper to abate carbon emissions as long as the marginal abatement cost is lower than the tax. Since the tax bill (A + B) is greater than the marginal abatement cost bill (B) to the left of the vertical "cap" line, the coal-fired power plant firms will choose to abate. To the right of the "cap" line, the marginal abatement cost bill (C + D) is greater than the tax bill (D) so the firm will choose to pay the tax and continue to pollute. As a result, the efficient abatement level is achieved at e*. The total abatement cost to firms operating coal-fired power plants is the total area of B + D, with total government revenue being D (Figure 15).

To understand the logic of trading carbon allowances between coal-fired power plants, a two-panel diagram is needed to illustrate the increasing marginal abatement costs of two coal-fired power plants (Figure 16). One plant utilizes Pulverized Coal (PC) technology with higher abatement cost (in blue) that goes right to left with abatement. The other plant uses Integrated Gasification Combined Cycle (IGCC) technology which has a lower abatement cost (in green) that goes left to right with abatement. The width of the horizontal axis is the abatement that must be achieved to reduce the overall emissions to an efficient level.

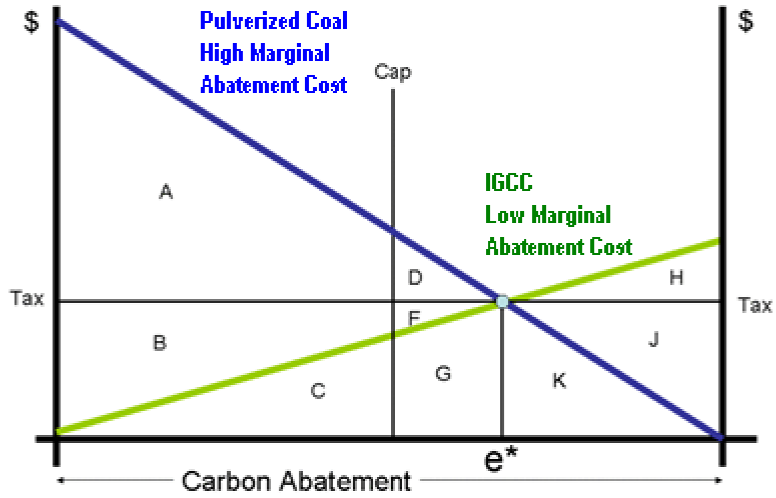

Figure 16. Cap and trade vs carbon tax for two coal-fired plants

The intersection of the two marginal abatement costs is where economic efficiency is achieved. The total costs of achieving the efficient abatement/emissions level is C + G + K. The efficient emissions level, e*, shows that the low-abatement-cost power plant should allow for greater reductions in emissions than the high-abatement-cost power plant (Figure 16).

Under a cap and trade framework, a government body sets a carbon cap by issuing carbon permits to coal-fired power plants. Each permit gives the plant the right to emit one unit of carbon. For simplicity's purpose, we can do it "fairly" by giving each plant the same amount of permits. The abatement cost for the low-abatement-cost (IGCC) plant is equal to area C. The abatement cost for the high-abatement-cost (PC) plant is D + F + G + K (Figure 16). At some point, the high-cost power plant might rather have a permit than pay those high costs. If it recognizes that the marginal abatement cost is higher than the marginal abatement cost of the low-cost plant, it could propose a trade. In effect, the blue line over area D, F and G is a demand curve for permits, and the green line is a supply curve for permits. Anywhere in between the blue and green line is a permit price that is mutually agreeable between both plants. A competitive permit market will result in a permit price equivalent to the efficient carbon tax. Trading reduces overall abatement costs by the area of D + F. The efficient abatement level is achieved at e*. The abatement cost to the polluting plants, C + G + K, is minimized (Figure 16).

3.4 An Overview of CCS Technology Development

A coal plant with CCS will cost more than a similar plant due to the additional cost to build and operate the capture facility. The capture process also requires additional energy which is referred to as an "energy penalty" (Al-Juaied and Whitmore 2009). The high cost and energy penalty burdens, as well as the lack of full-scale experience with CO_2 capture at coal-fired plants are two of the many obstacles to the adoption of CCS. As time and technology progress, the reliability of the technology will improve, decreasing the costs of deploying CO_2 capture with coal-fired power plants along with the attendant energy penalties.

The CCS community agrees that the first several full-scale operations at coal-fired power plants will perform inconsistently as CCS technology will still be in early development. The Energy Information Agency uses the National Energy Modeling System (NEMS) to configure a network of only 4 power plants for an initial deployment of CCS to minimize risk and to maximize the learning process (U.S. Energy Information Administration 2010). Kuuskraa (Kuuskraa 2007) refers to this initial stage as the

"Smaller Scale Program" and Thompson et al. (Thompson, et al. 2010) call it the "Pioneer Phase." Both agree that a larger-scale CCS project is needed to reduce the cost of CCS and Thompson et al. labels this subsequent stage as the "Cost Reduction Phase." Our CCS technology development framework builds upon and refines these earlier efforts. Our model categorizes the development of the CCS industry as moving through four key phases: The CCS Startup Phase, the Early Adopter Phase, The Cost Reduction Phase, and The Full Scale CCS Deployment Phase (Figure 17).

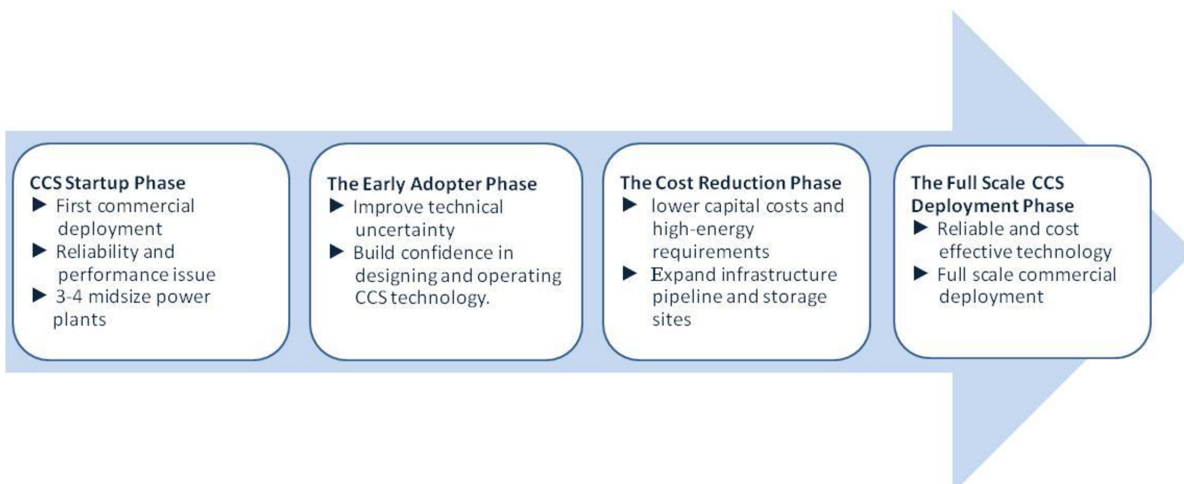

Figure 17. CCS technology development phase

3.4.1 The CCS Startup Phase

Prior to the startup phase, CCS technology has been developed on a laboratory scale or pilot project scale but has not been implemented on a full commercial scale. The first few commercial-scale CCS plants can be categorized as the 1st generation of

CCS technology and they may face uncertainty regarding reliability and performance. The emphasis during this phase is to focus resources on critical reliability issues by identifying significant risks to CCS implementation as early as possible. The CCS startup phase should be designed to ensure that the incursion into new full-scale CCS technology territory will be a successful venture.

3.4.2 The Early Adopter Phase

The early adopter phase is characterized by technical improvements that lead to a better generation of CCS technology with fewer questions about reliability and performance. This phase is aimed at building confidence and experience in selecting, designing and operating integrated CO_2 capture and storage systems. At the end of the early adopter phase, reliable cost and performance expectations for CO_2 capture, transport and injection technology will be achieved.

3.4.3 The Cost Reduction Phase

In the cost reduction phase, experience gained from the early adopter phase, along with the on-going development of CCS technology, will contribute to further reductions in the high capital costs of installing CO_2 capture technologies. Technological progress will likely reduce high energy requirements and loss of power generation output. The cost reduction will take place by traversing learning curves and expanding infrastructure such as pipelines and storage sites to support CCS growth. The cost reduction phase could transform CCS from a technology only affordable to a select few coal-fired plants to a cost-effective GHG mitigation option with global impact.

3.4.4 The Full Scale CCS Deployment Phase

Due to the progress achieved during the previous phases, CCS technology becomes technically reliable, cost-effective, and widely accepted resulting in full-scale CCS deployment. By this time the technology is ready to face rapid commercial deployment and expansion to a scale that makes deep reductions in carbon dioxide emissions possible by mid-century.

3.5 Components of CCS Abatement Cost

The components of CCS – capture, transport, and injection – already exist in mature markets for certain industrial applications but the technology has yet to be used in commercial-scale coal-fired power plants. For example, oil companies capture CO_2 from the ground, use pipelines to transport it to mature oil fields, and then inject it into wells in order to perform enhanced oil recovery.

Table 14 gives the current capture cost, which ranges from $45 to $130 per ton of CO_2 depending on the generating technology and type of coal used (Al-Juaied and Whitmore 2009). By 2030, after several generations of technological advancement, the future cost of capture is expected to drop by $25-$80 per ton of CO_2.

The transportation cost varies based on the distance to available reservoirs and the scale of the pipeline. Using economies of scale, costs can be reduced by creating a network of pipelines that funnel into increasingly large pipes as shown in the previous part of this study. In this way CO_2 can be piped as far as 1,000 km at a cost of less than $8/ton (Chandel, Pratson and Williams 2010).

Table 14. Estimates of CCS capture cost compiled by Harvard Kennedy School of Public Policy (Al-Juaied & Whitmore, 2009)

No	Estimate Source	Current Marginal Cost (2009- $/ton)	Future Marginal Cost (2030 - $/ton)
1	Boston Consulting Group (2008)	70	45
2	McKinsey (2008)	80–115	40–60
3	S&P (2007)	—	40–80
4	BERR (2006)	—	40
5	Shell (2008)	130	65 or below
6	Chevron (2007)	>100	N/A
7	Vattenfall (2007)	45	25–45

For sequestration, the last leg of the CCS process, costs can range from $1-$1,000 per ton of CO_2 depending on the nature of geological reservoir sites (Eccles, et al. 2009). Palo Alto Research Center estimates the sequestration cost component must be less than $5 per ton of CO_2 in order for CCS to be cost-effective (Palo Alto Research Center 2008). Geological reservoirs with injection costs less than this sequestration cost of $5 per ton of CO_2 will be utilized first with higher cost reservoirs becoming more feasible as technology matures.

The high cost of CO_2 capture and uncertainty surrounding sequestration make CCS unfeasible for market penetration under current conditions. Given the right incentives, though, certain coal-fired power plants will be able to invest in and develop technologies to be implemented in the future by the industry at large.

3.6 American Power Act Features

Now I review features of the APA that must be considered in its analysis.

3.6.1 Bonus Allowance and CCS Technology Stages

To facilitate the deployment of carbon capture and storage (CCS) technology the APA provides for a bonus allowance to create incentives for operators to install CO_2 capture facilities in retrofit power plants or to build new plants with carbon capture capabilities. The percentage of the national cap for CCS starts at 0.8% in 2017 and reaches 10% in 2034 (Figure 20). Since the national cap (Figure 18) decreases yearly, the actual value of the allowance for CCS also varies yearly, starting at about 50 million tons per year in the beginning and stabilizing between 300 and 350 million tons per year after 2022 (Figure 21).

The allocation of CCS bonus allowances in the APA will greatly impact CCS deployment and the progress of CCS technology. Hence it is important to analyze the availability of CCS bonus allowance allocations (Figure 21) under the framework of CCS technology development put forth in the CCS Technology Development Framework.

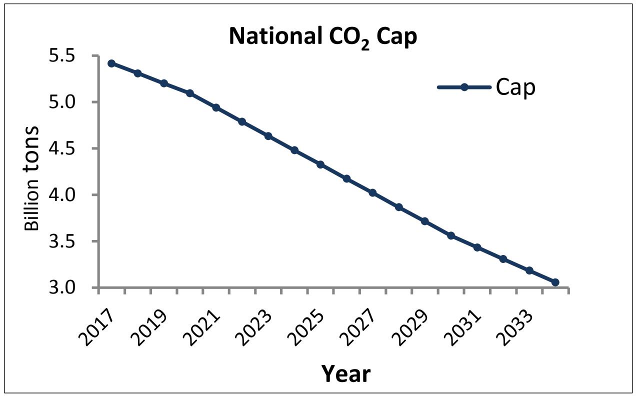

Figure 18. National CO_2 cap under American Power Act

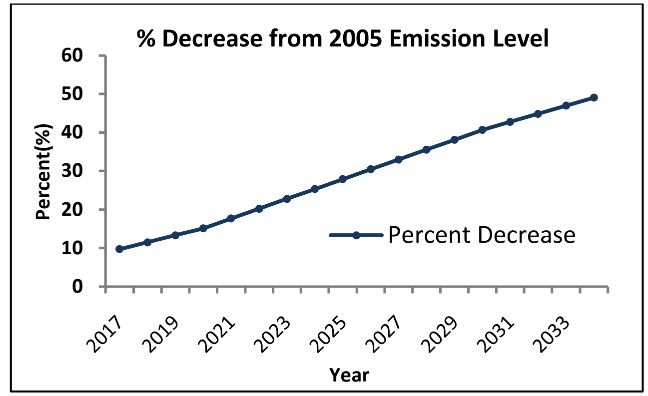

Figure 19. Percent decrease from 2005 emission level under American Power Act

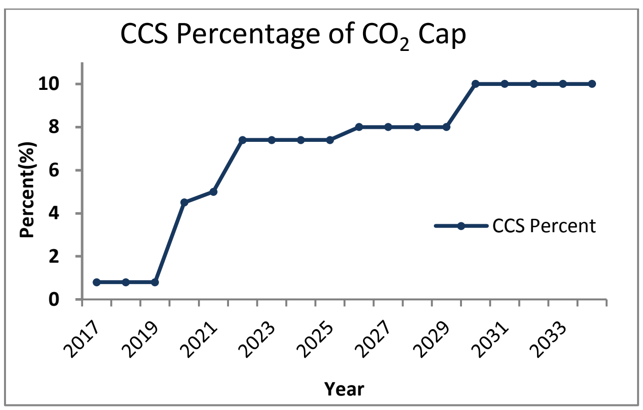

Figure 20. CCS bonus allowance as a percentage of CO2 cap

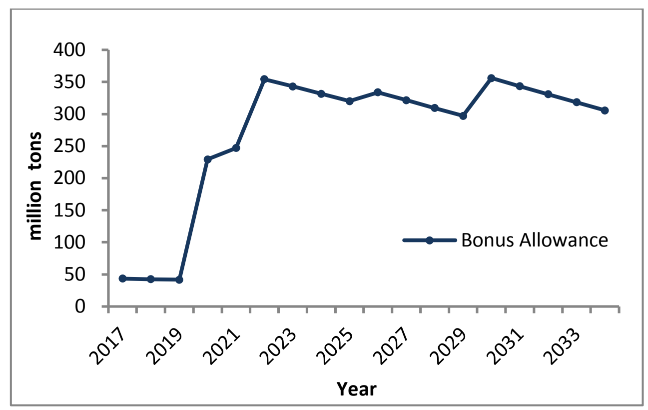

Figure 21. CCS bonus allowance in million tons

3.6.1.1 APA - The CCS Startup Phase

The APA recognizes the high technological risk related to the startup phase by providing less than 50 million tons of bonus allowance during the period of 2017 to 2019. The limited number of bonus allowances coupled with a low carbon price (range between $18/ton to $30/ton) during this period will restrict the number of pioneer plants that are able to participate in the program to only two or three mid-size power plants (300-500 MW). A small number of power plants installing CCS will minimize the risk and at the same time maximize the learning process. It is expected that critical reliability issues with mid-size (300-500) power plants will be resolved during the CCS startup phase in the span of three years.

3.6.1.2 APA - The Early Adopter Phase

In the startup phase, the CCS community will learn a great deal about 1st generation technology across the spectrum of capture, transportation, and sequestration. However, many technological uncertainties will remain due to different sized power plants, different generation technologies, and different geologic formations. The APA increases the amount of bonus allowance from 50 million tons to around 250 million tons during the period of 2020 to 2022. The additional bonus allowance allows additional power plants with different sizes and technologies to join the CCS program. These additional power plants will enable the process to improve the reliability of CCS technology, making it dependable for different combinations of power plant sizes, generation technologies, capture technologies and sequestration sites.

3.6.1.3 APA - The Cost Reduction Phase

CCS cost eventually has to be reduced in order for CCS to play a big role in mitigating CO_2 emission in a cost-effective way. The APA facilitates such a cost reduction by allocating more bonus allowances – 300 to 350 million tons – from 2023 to 2034. The additional bonus allowance coupled with the higher carbon price during the same period will add additional power plants to the system and expand the CCS infrastructure further. The speech of Secretary Steven Chu in Charleston, West Virginia, captures the essence of this development, when he states "Engineers and scientists do remarkable things and costs are driven down." (Chu 2010). The cost reduction phase could transform CCS from a technology only affordable to a select few coal fired plants to a cost-effective GHG mitigation option with global impact.

3.6.1.4 APA - The Full Scale CCS Deployment Phase

The APA expects that the CCS technology will reach maturity at the end of this program, creating broad public acceptance of CCS and enabling a transition to full commercial deployment to achieve GHG reduction objectives. The start of full-scale CCS deployment is contingent on both the success of the previous “cost reduction phase” and on carbon pricing. Full-scale deployment could start before 2030 if the program is successful from a technological, political, and societal perspective, or it could be delayed beyond 2034 if the progress of CCS deployment is slow.

3.6.2 APA CCS Deployment Phases

To progressively adopt CCS technology the CCS deployment program under the APA is divided into two phases:

3.6.2.1 Phase I

Phase one is mainly designed to overcome CCS technological challenges and is further divided into two tranches.

3.6.2.1.1 Tranche 1

In tranche one, the pioneer firms are rewarded with a CCS incentive in the form of bonus allowances. Starting from $50 per ton of equivalent bonus allowance for 50% CO_2 captured and sequestered, a company could receive at most $96 per ton for 90% or above of CO_2 avoided. The goal of tranche one is to eliminate the potential risks associated with CCS early deployment (Table 15). The pioneer power plants are expected to establish reliable cost and performance expectations of CCS, building confidence and experience in designing and operating CCS.

3.6.2.1.2 Tranche 2

Once the electric generating units reach the capacity of 10 GW, Phase one will move forward into tranche 2. The second tranche is similar to the first tranche, the only difference is the CCS incentive is $85 per ton instead of $96 per ton of CO_2 emissions avoided. With ten more GWs of electric generating capacity the plants in the second tranche could further lower the high capital costs through learning, thus extending CCS infrastructure and market penetration while establishing even more reliable expectations of cost and performance (Table 15).

Table 15. CCS Deployment Phase and CCS Technology Progress

No	Phases	Major Policy Instrument	Scale	Emphasis	Characteristics Expectation
1	Phase I-Tranche I	Bonus Allowance ($50 - $96/ton)	Smaller	Improve reliability and performance issues	Unreliable cost and performance expectation High cost
2	Phase I-Tranche II	Bonus Allowance ($50 - $85/ton)	Small	Improve reliability and decrease cost	More reliable medium/high cost
3	Phase II	Reverse Auction	Larger	Decrease cost through expanding CCS infrastructure Wide public acceptance	Reliable Low/medium cost
4	Post 2034	Cap and Trade	Full Scale	Commercialization	Low cost and reliable performance Widely accepted

3.6.2.2 Phase II

During the second phase, the more mature technology will give operators an accurate expectation of cost and performance for building plants with CCS capability. On the policy side, instead of giving CCS incentives with fixed value, the central authority will distribute the bonus allowances based on reverse auction, meaning that only the companies with lowest bid can acquire the allowance. This procedure will favor the plants with efficient CCS technology which are able to capture and sequester carbon emissions with the lowest cost. Reverse auction will facilitate the adoption of efficient CCS technology and assist the utility sector in transitioning to commercial CCS deployment (Table 15).

3.6.3 Reverse Auction: APA Second Phase

Phase II of the APA sets the amount of CCS incentive per ton of CO_2 emissions avoided through reverse auction. The reverse auction allows fossil fuel plants with CCS technology to offer bids to capture and store a ton of CO_2 for a price. While traditional auctions involve a single seller and many buyers, a reverse auction generally involves many sellers, which in this case are the power companies, and one buyer, in this case the authority that distributes bonus allowances. In a first price reverse auction, the winner is the bidder who submits the lowest bid, and is paid the bonus price equal to his or her bid (Milgrom and Weber 1982). Alternately, in a second price reverse auction, the winner is the bidder who submits the lowest bid, and is paid a bonus price equal to the next lowest submitted bid (Milgrom and Weber 1982).

Power plants that can offer the lowest $/ton bids will win the auction and receive the associated bonus allowances. This policy ensures that incentive is available to enhance the likelihood of commercial CCS deployment. However, bonus allowances are only issued to those projects which can sequester CO_2 at the lowest cost. Without a reverse auction, plants are likely to hold out on installing or retrofitting plants with CCS technology until the price of carbon reaches a "breakeven price" where the cost of capturing and sequestering a ton of CO_2 is equal to the cost of one allowance. Most studies have indicated that this is around $40/ton of CO_2, a price not reached until 2030 for most of the APA allowance price trajectories.

When power companies abate one ton of CO_2, they have to incur the marginal cost of capturing, transporting, and injecting it noted below in equation (11) as CCS_{Cost}.

During Phase II of a reverse auction, the APA provides a CCS subsidy in the amount of the Auction Price. In this scenario the total cost born by power companies is (CCS_{cost} – $Auction_{price}$). On the other hand, power companies have the option to keep emitting CO_2 by purchasing CO_2 permits at the prevailing market price. Power companies are indifferent in regards to choosing between going online with CCS or emitting CO_2 by buying carbon permits when the total cost of CCS born by utility companies $(CCS_{cost} - Auction_{Price})$ is equal to carbon price as dictated in equation (11):

$$CCS_{cost} - Auction_{Price} \leq Carbon_{Price} \qquad [11]$$

With simple math we can rearrange equation (11) to become equation (12) and determine the minimum bids that a power plant is willing to submit. Equation (12) implies that the auction price should be higher than the total of CCS cost minus the carbon price.

$$Auction_{Price} \geq CCS_{cost} - Carbon_{Price} \qquad [12]$$

Each coal-fired power plant has a unique CCS cost depending on their coal technology, the amount of CO_2 capture, the spatial arrangement of the facility, and the sequestration site. It is pointed out in game theory that, during a bidding process, bidders have a dominant strategy to bid their true values which can be derived from equation (12) (Milgrom and Weber 1982). This is an important fact when firms are submitting their bids in a reverse auction, because those with the lowest costs are more likely to submit a lower price to win the bidding process. Since the winning bidder's value is the minimum among all the values, the winning bid conveys a low bound on all the loser's signaling the least incentive needed to install CCS technology at that point in time. Reverse auction ensures that the bonus allowance is only issued to the most efficient plant with the lowest capture and sequestration cost (Kuuskraa 2007). In this way, the APA can achieve a low-carbon economy with the lowest societal cost.

3.7 The CCS Deployment Model

Our CCS deployment model factors in real-world considerations for CCS implementation. We achieve this by considering how the interaction of carbon price, CCS technology progress, the reverse auction process, and constraint of CCS bonus allowance availability will affect the progress of CCS deployment under cap and trade. We use the American Power Act as a case study.

Our model is developed in two stages. In the first stage we translate the legal language of American Power Act into colloquial English by having extensive discussions with Jonas Monast, an environmental lawyer associated with The Nicholas Institute for Environmental Policy Solutions at Duke University. The resulting text is a summary of this collaboration:

- This model analyzes CCS deployment under a cap and trade climate policy framework. In this study, the model is specifically applied to the Kerry-Lieberman American Power Act (Kerry and Lieberman 2010).

- The model iterates each year from 2017 until 2034 to select eligible power plants[7]. Allocation of the available CCS bonus allowance set by the APA is made to the greatest possible number of coal-fired power plants based on the cost of CCS technology and carbon price trajectory.
- There is a 90% carbon capture rate for all installed CCS units.
- The model simulates reverse auction allocations which are dependent on CCS cost, carbon price, and the resulting auction price. Remaining bonus allowances after allocation are added to the following year. No new CCS installations will receive allowances after 2034.
- The model is contract-based, which means that for each power plant participating in the program, it predicts the amount CO_2 captured for the next 10 years and the amount of allowance needed to cover those captured emissions based on the predicted bonus ratio. This is necessary because the APA framework treats each contract differently depending on when power companies implement CCS (first phase, first or second tranche, second phase, etc).
- The participation of additional power plants in any given year will depend on the number of allowances made available under the emissions cap, the bonus price or auction price, the aggregate amount of CO_2 emitted that year, and the carbon price at that time.

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[7] We assume a generic power plant of 500 MW with average of 3 million tons CO2 emission annually.

- 10 years of allowances are reserved for each additional plant to cover captured emissions. Power plants will be withdrawn from the CCS program after ten years of receiving bonus allowance and the bonus allowances tied to the plants are available for other power plants.
- Allowance allocation is optimized with perfect knowledge of future carbon price trajectory and future technological progress.
- The model stops picking an additional plant when remaining bonus allowances for that year are allocated; or remaining allowances until 2034 cannot cover the amount necessary for 10 years of capture.

In the second stage we translate this model requirement into an economic simulation program (Appendix D and E). In this study, we run the model with different combinations of carbon price trajectories, technological progress, CCS costs, and auction prices.

3.8 Empirical Model Setup

Now empirical assumptions to set up the APA model are reviewed including 1) relationship between bonus allowance and CO_2 captured, 2) carbon price trajectories, 3) the relationship between carbon price and deployment scenarios, and 4) indicator of CCS economic plausibility.

3.8.1 Relationship Between Bonus Allowance and CO_2 Captured

Our model is based on the premise that the relationship between bonus allowances and tons of CO_2 captured is not one to one. CO_2 that is captured and permanently sequestered is recognized by a quantity of bonus allowances that are awarded with respect to the current carbon price. The purpose of this conversion is so that the administrator can issue bonus allowances that will have a market value equivalent to the bonus price promised by the legislation (i.e. $96/ton during first tranche, $85/ton during second tranche and auction price during second phase.). For example, if the price of a ton of CO_2 emission on the open market is $12/ton and the CCS bonus price is $96/ton (the bonus price promised by the legislative framework during first tranche) then the administrator would be required to give 8 bonus allowances (to match $96) for each ton captured, this is referred to as the "bonus ratio".

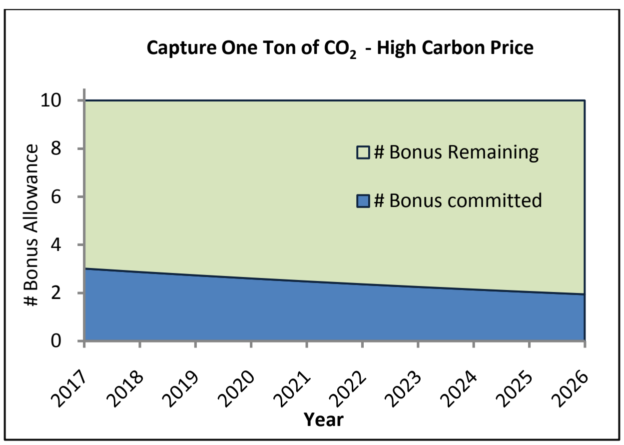

Figure 22. 10 tons of bonus allowance to capture one ton of CO_2 for 10 years under high carbon price trajectory

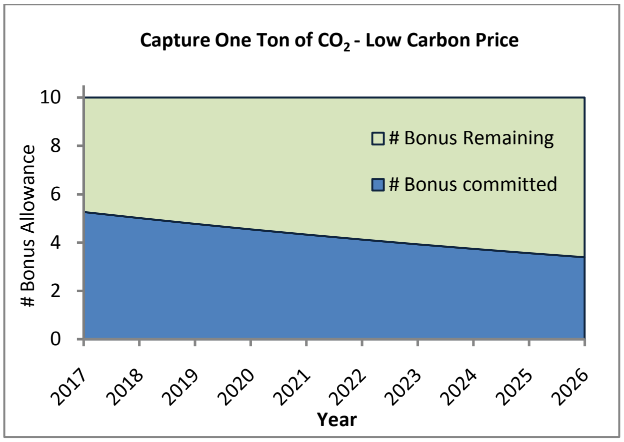

Figure 23. 10 tons of bonus allowance to capture one ton of CO2 for 10 years under low carbon price trajectory

Similarly, if the price of a carbon permit is \$36/ton and the bonus price is \$96/ton then 3 bonus allowances would be issued (to match the \$96 bonus price) per ton of CO_2 captured and sequestered. Hence the same quantity of available CCS bonus allowance may cover different amount of CO_2 captured depending on different carbon price trajectories as described in Figure 22 and 23.

3.8.2 Carbon Price Trajectories

Our CCS deployment model uses allowance prices of \$15, \$20, and \$25 per ton of CO_2 starting in 2013 and increasing annually by 5% (Figure 24). This rate is consistent with other energy-economic models and with the U.S. Environmental Protection Agency's (EPA) recent analysis of the American Power Act (U.S. Environmental Protection Agency 2010). In their base case scenario of the bill they use \$16 and \$17 per tCO_2 in 2013, which falls between our slow and moderate CCS deployment scenarios. Initial allowance prices in the EPA's analysis range from $18-40 for their scenarios.

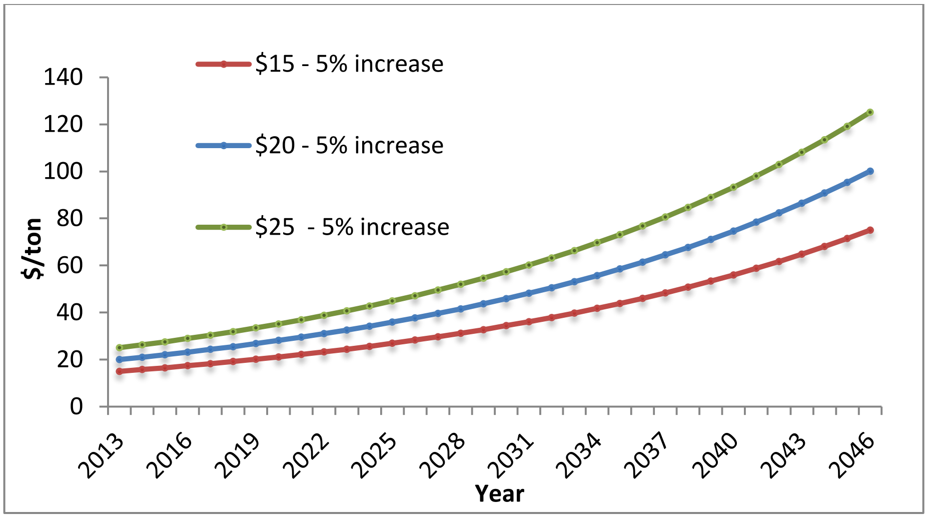

Figure 24. Different carbon price scenarios

3.8.3 Carbon Price and Deployment Scenarios

Our CCS deployment model combines three carbon permit price trajectories with three CCS technology development trajectories in order to represent slow, moderate, and rapid CCS deployment scenarios (Table 16). The difference between CCS cost and carbon price directly influences the auction price of an allowance during the reverse auction of Phase II (equation 12). The implication of this relationship is that if CCS technology progresses quickly costs and auction prices are minimized. On the other hand, if technology develops slowly CCS costs and auction prices will remain high.

Table 16. Different CCS Deployment Scenarios under American Power Act

No	Market Penetration Scenarios	Carbon Price in 2013	CCS Technology Progress	Auction Price
1	Slow Deployment	$15 increasing at 5% annually	Slow Technology Progress High CCS Cost	$70
2	Moderate Deployment	$20 increasing at 5% annually	Moderate Technology Progress Moderate CCS Cost	$50
3	Rapid Deployment	$25 increasing at 5% annually	Rapid Technology Progress Low CCS Cost	$30

3.8.3.1 Slow Deployment Scenario

The initial carbon price is set low at $15/ton in 2013 and slow technological progress results in high CCS costs. This scenario leads to a large difference between CCS costs and carbon prices and a high auction price. Our model sets the auction price at $70/ton (Table 16).

3.8.3.2 Moderate Deployment Scenario

The initial carbon price is set at $20/ton in 2013, a midrange value, and moderate technological progress results in moderate CCS costs. Because this scenario produces less of a difference between CCS costs and carbon prices than the slow deployment scenario a lower auction price of $50/ton is set (Table 16).

3.8.3.3 Rapid Deployment Scenario

The initial carbon price is set high at $25/ton in 2013, and rapid technological progress results in significant efficiency gains and greatly reduced CCS costs. This scenario leads to a small difference between CCS costs and carbon prices and a low auction price. Our model sets the auction price at $30/ton (Table 16).

3.8.4 Indicator of CCS Economic Plausibility

During the process of CCS deployment, the energy modeling community would greatly benefit from a CCS economic plausibility index to allow analysis of the economic performance of CCS technology and facilitate predictions of future performance. In this study, we propose the use of bonus ratio which is the ratio between the CCS incentive and carbon price (equation 13).

$$\text{Bonus Ratio} = \frac{\text{CCS Incentive}}{\text{Carbon Price}} \qquad [13]$$

Bonus ratio also represents the quantity of bonus allowance issued to cover one ton of CO_2. In this section we explain why the ratio between CCS incentive and carbon price conveys the degree of economic plausibility of CCS technology and can be very informative.

Table 17. Computation of Bonus Ratio in Phase I and II under American Power Act

	Phase I Tranche 1	**Phase I Tranche 2**	**Phase II Reverse Auction**
Bonus Ratio	$\frac{\$96}{\text{Carbon Price}}$	$\frac{\$85}{\text{Carbon Price}}$	$\frac{\text{Auction Price}}{\text{Carbon Price}}$

With the assumption of a CO_2 capture rate of 90%, the APA sets the CCS incentive for tranche 1 and tranche 2 at \$96/ton and \$85/ton respectively (Table 17). It is clear that the bonus ratio during the first phase is purely determined by the market carbon price because the bonus price is fixed.

In the second phase, the amount of CCS incentive is not mandated. Instead it is determined through the process of reverse auction and is called auction price (Table 17). This reflects the more dynamic nature of the bonus ratio at this time as it will be affected by both the auction price and the carbon price. Additionally, according to equation (12), the auction price is dictated by the difference of CCS cost and carbon price. This means that the bonus ratio during the reverse auction framework of phase 2 is indirectly influenced by CCS cost and directly influenced by the carbon price.

One indication of full-scale CCS commercialization is when CCS technology is a cost- effective solution in mitigating climate change. It also means that CCS technology will be installed regardless of whether there is a CCS incentive. Equation (14) characterizes conditions when a power plant is indifferent whether to install CCS technology.

$$\mathrm{CCS_{cost}} - \mathrm{Incentive} \le \mathrm{Carbon\,Price} \qquad [14]$$

If there is no CCS incentive and a power plant is still indifferent whether to install CCS technology, we can derive equation(14) to become equation(15) by replacing CCS incentive by zero.

$$\mathrm{CCS_{cost}} \le \mathrm{Carbon\,Price} \qquad [15]$$

The full-scale CCS commercial deployment is dictated by equation(15) where marginal CCS_{cost} is less than carbon price. This can be achieved with a successful CCS technology development and in the same time high carbon price.

When CCS incentive is small (or close to zero), equation(13) can be derived to become equation(16) .

$$Bonus_{Ratio} = \frac{\sim 0}{\text{Carbon}_{\text{Price}}} \qquad [16]$$

$$Bonus_{Ratio} = \sim 0 \qquad [17]$$

Equation (16) holds only when equation (15) also holds. These two conditions signal that CO2 source operators are willing to install CCS technology without any form of CCS subsidy. Hence, the signal of full scale CCS commercial deployment is indicated by low value of bonus ratio. Bonus ratio less than one signals a progressive situation for CCS deployment. However, bonus ratio equal to zero means that CCS technology is trully a cost-effective solution to mitigate CO_2 even without government incentive/subsidy.

3.9 APA Analysis

Now an analysis will be done on aspects of the APA including 1) the discussion of how the output of bonus ratio will affect the timing of APA phases, and 2) the discussion of how the bonus ratio will affect cumulative CCS Net Capacity and Amount of CO2 Captured.

3.9.1 Bonus Ratio and Timing

This model is able to identify different path of bonus ratio depending on different scenarios. Using the framework of bonus ratio analysis (discussed in previous section), we can explain how different scenarios will affect the different path of bonus ratio which will affect the timing of each phase of CCS deployment.

The slow CCS deployment scenario is characterized by a low carbon price and high CCS cost which will dictate a high bonus ratio. A higher bonus ratio will enable CCS participants to receive more bonus allowance for each ton of CO_2 emission avoided. Therefore, the bonus allowance available each year will be used up quickly, limiting the number of plants that are able to join the program. A higher bonus ratio will require more time to complete each tranche and proceed to the second phase (Figure 25, figure 26). Considering that the CCS program in the APA ends in 2034, the prolonged first phase will shorten the amount of time the second phase has to enforce a reverse auction that is able to further decrease the bonus ratio. A shorter second phase leaves little time for the market to transition to full-scale deployment, and the bonus ratio remains high (Figure 25). The result is that auction price remains high and technological progress is still slow, which further impedes the implementation of the APA CCS program. A high bonus ratio also signals that there is not enough incentive to install CCS technology because of a low carbon price and high CCS cost. As a result, the plausibility that any power plant will install CCS technology without the guaranteed bonus incentive is low.

On the contrary, rapid CCS deployment is characterized by a high carbon price and low CCS cost due to rapid CCS technology development. As a result, bonus ratio is low, and CCS participants will receive less bonus allowance for each ton of CO_2 emission avoided (Figure 25 and figure 26). This will allow more plants to participate in the program which, in turn, will allow for more learning by doing. This rapid deployment will expedite the completion of the 1st and 2nd tranches and give more time to perform the reverse auction in phase two (Figure 25 and figure 26). The longer second phase will give the market more time to transition to full-scale commercial deployment, which could further lower the auction price and contribute to rapid technological progress. As explained in the previous section, low bonus ratio also means that there is a good incentive for power plants to install CCS technology even without a guaranteed bonus incentive.

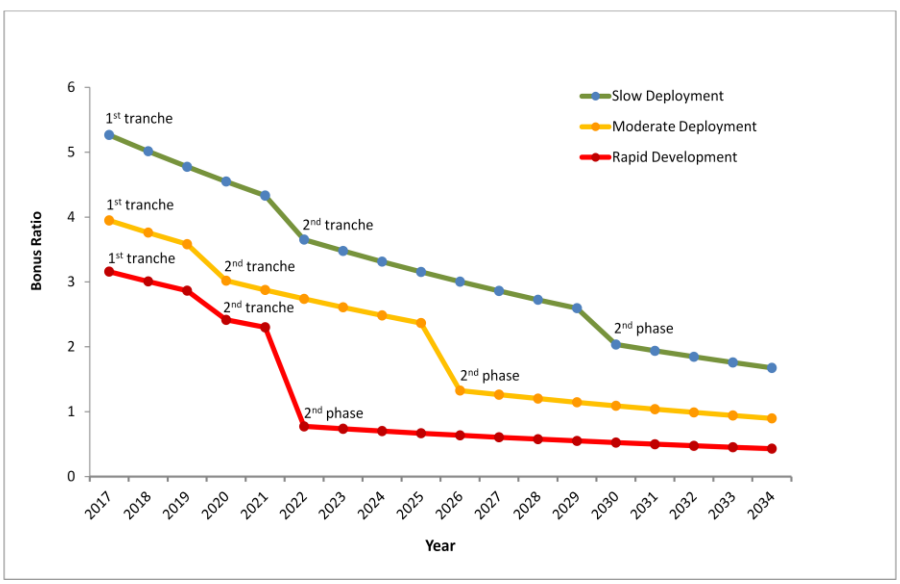

Figure 25. Bonus ratio trajectories under three deployment scenarios

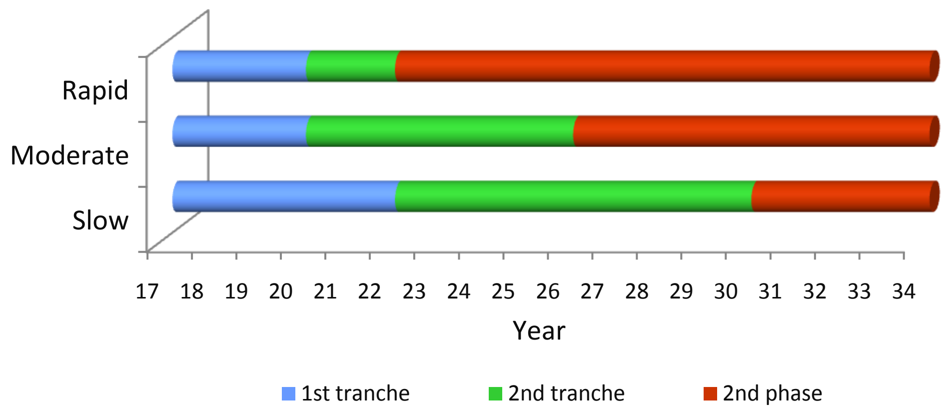

Figure 26. Timing of CCS deployment under different scenarios

Full scale CCS commercial deployment will be achieved when CCS technology can serve as a cost-effective solution for capturing CO_2 with little or no additional government incentive. Absolute full-scale CCS commercial deployment means that the technology deployment is self-propelled and bonus allowance is not needed, meaning that the bonus ratio is equal to zero (see previous section). Rapid deployment scenario results in low bonus ratio (less than one) which indicates that CCS deployment is progressing well, demonstrating that there is a strong incentive for industries to adopt the technology. On the other hand, slow deployment scenario results in high bonus ratio (greater than one) which indicates that there are little incentives for utility companies to adopt CCS technology unless there is a high subsidy.

3.9.2 Cumulative CCS Net Capacity and Amount of CO2 Captured

Now an analysis will be done on aspects of the cumulative CCS net capacity and the amount of CO_2 captured.

3.9.2.1 Cumulative CCS Net Capacity

The APA sets an objective of having 72 GW of CCS net capacity deployed by 2034. This is in agreement with the energy modeling community consensus that full-scale CCS commercial deployment is reached when the CCS capacity is around 62-72 GW. This study is able to identify the capacity of CCS installed depending on different scenarios. Our analysis also explains how bonus ratio (as the indicator of CCS deployment plausibility) drives the final CCS capacity installed.

Under slow deployment, APA has a slow start since the number of power plants participating is constrained by the number of bonus allowances available (and high bonus ratio is high as demonstrated in the previous section) and bonus allowance is used up quickly. The slow start in the beginning also slows down the learning-by-doing process, which means that the CCS cost is likely to stay high. During the reverse auction, the auction price and bonus ratio are high, which also limits the number of additional power plants that can participate in the program. It is not a surprise that under slow deployment, our model estimates only 24.5 GW of CCS net capacities by 2034 (Table 18 and figure 27).

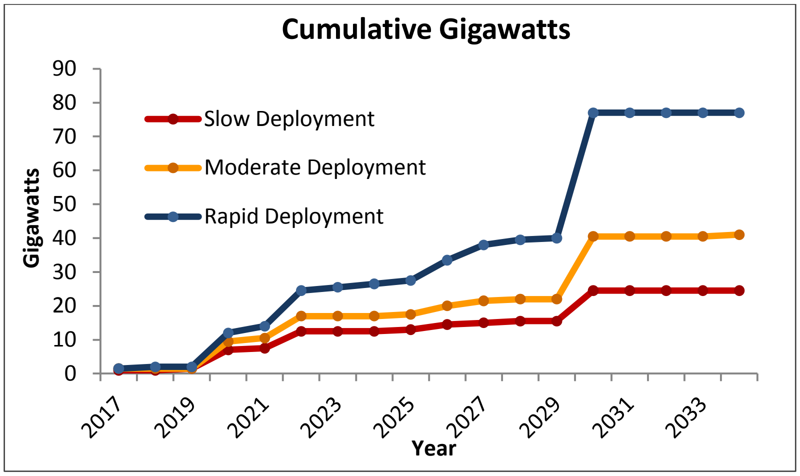

Figure 27. Trend of installed CCS capacity under different scenarios

Table 18. Net CCS Cumulative Capacity Under Different Deployment Rates

No	Deployment Scenario	Net CCS Capacity (Gigawatt)
1	Slow Deployment	24.5
3	Moderate Deployment	41.0
3	Rapid Deployment†	77.0

Under the rapid deployment scenario, the bonus ratio is low, enabling APA to cover more CO_2 and get a quick start during the 1st and 2nd tranche. This smooth implementation of CCS technology during the first phase makes the CCS cost drop further during the second phase. At the same time, carbon prices continue to increase. The combination of low CCS cost and high carbon prices make the auction price low (around \$30) which further decreases the bonus ratio to less than one. As a result, a lot of net CCS capacity is installed during the period after 2030. The cumulative CCS net capacity under rapid deployment according to our model scenario could reach 77 GW by 2034, which is in line with APA's objective of 72 GW by 2034. However, the slow and moderate deployment scenarios come up short, with 24.5 GW and 41 GW CCS net capacity at the end of 2034 (Figure 27, Table 18).

3.9.2.2 Amount of CO_2 Captured

This model is able to identify the exact amount of CO_2 captured depending on the predicted scenario. The amount of CO_2 captured is linearly comparable to the total CCS net capacity. Additionally, the amount of CO_2 captures depends on the time span CCS systems operate. The longer the CCS system operates, the larger the amount of CO_2 captured. We assume that the CCS technology installed will keep capturing CO_2 for the time span of 40 years.

While the APA commits to bonus allowances for only ten years, we assume that CCS technology will operate for the next 40 years. Hence, this study divides the CO_2 captured into two different categories, as follows:

- CO_2 captured under bonus allowance

  Refers to the CO_2 captured while the coal-fired power plant still receives bonus allowance under the first ten years of CCS operation.

- CO_2 captured beyond bonus allowance

  Refers to the CO_2 captured over the following 30 years, while the coal-fired power plant is not receiving bonus allowance.

Because the length of time covered by the second category (CO_2 captured beyond bonus allowance) is three times that of the first (CO_2 captured under bonus allowance), the amount of CO_2 captured under the second category is likewise three times the amount captured under the first.

As depicted in our model output, the graphs show that under the slow deployment scenario (Figure 28 and Table 19), the total CO_2 captured under bonus allowance and beyond bonus allowance are 1.8 billion tons and 5.3 billion tons respectively. The total of CO_2 captured under slow deployment scenario is 7.1 billion tons in the span of 2017 to 2070 (Figure 28 and Table 19). Our model does not take into account CO_2 captured without the incentive of bonus allowance. Under the slow deployment scenario where carbon price is low and CCS cost is high, the chance that commercial power plants will install CCS technology without bonus incentive is very slim.

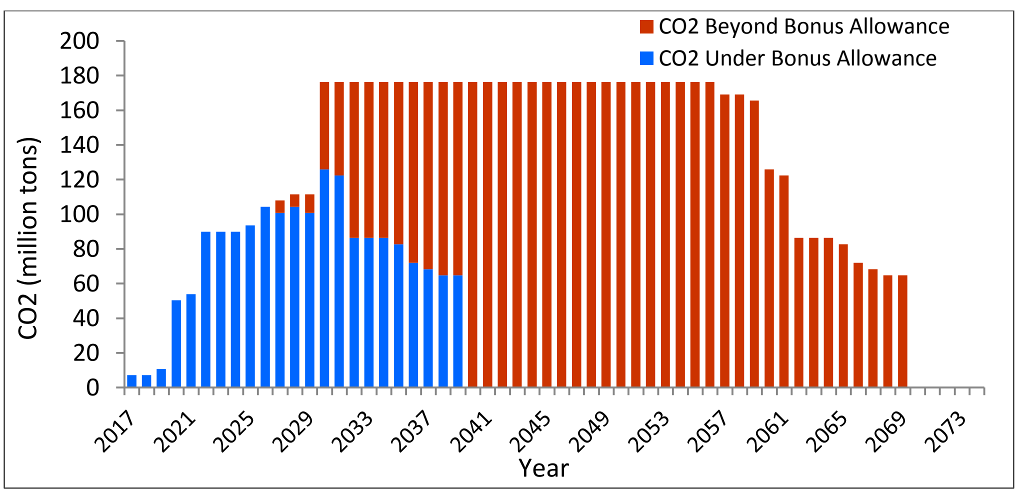

Figure 28. CO_2 captured under slow deployment scenario

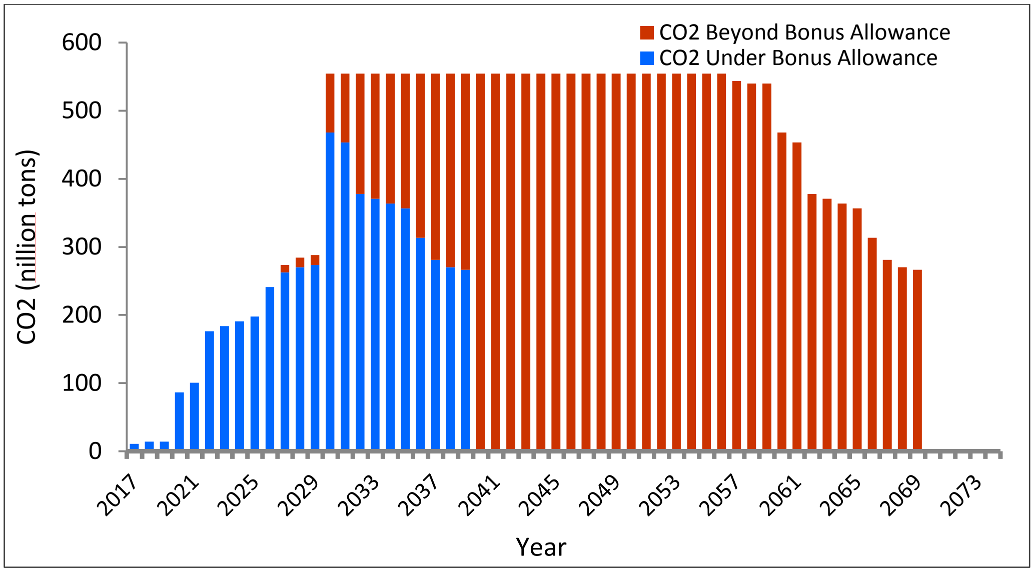

Figure 29. CO_2 captured under rapid deployment scenario

Table 19. CO_2 Captured Under Different CCS Deployment Scenario

No	Market Penetration	CO_2 Captured UBA[8] (billion tons)	CO_2 Captured BBA[9] (billion tons)	CO_2 Captured Total (billion tons)
1	Slow Deployment	1.8	5.3	7.1
2	Moderate Deployment	3.0	8.9	11.9
3	Rapid Deployment	5.5	16.6	22.1

Under the rapid deployment scenario, the CO_2 captured under bonus allowance and beyond bonus allowance are 5.5 billion tons and 16.6 billion tons respectively, with a total of 22.1 billion tons of CO_2 in the time span between 2017 and 2070 (Figure 29

[8] UBA: Under Bonus Allowance
[9] BBA: Beyond Bonus Allowance

and Table 19). The rapid deployment scenario dictates a low bonus ratio (less than one), especially after 2030 (Figure 25). A low bonus ratio signals that the CCS technology is in the process of reaching full-scale commercial deployment. Hence, under the rapid deployment scenario, there might be a possibility that there are several coal-fired power plants that are willing to install efficient CCS technology even without APA bonus allowance assistance. Our model does not take into account these additional quantities of CO_2 captured which means that our rapid deployment estimate is a low estimate.

3.10 Conclusions of American Power Act Modeling

According to the consensus within CCS community, 62 - 72 GW of installed CCS capacity is the milestone which, when reached, signals full commercial CCS deployment. It is simply impossible, however, for there to be instantaneous large commercial adoption of CCS. Carbon price alone will be insufficient to support large scale CCS deployment due to the initial CCS technology barrier. The APA uses a combination of incentives for research and development, demonstration projects, and CCS incentives to overcome these barriers. The APA deployment policy is designed to focus on spurring innovation in addition to increasing CCS deployment. According to our model, full CCS commercial deployment can only be reached under rapid a deployment scenario, with cumulative capacity reaching 77GW by 2034. Under this scenario, five years are required to complete the first phase and about 12 years are required in a reverse auction. However, the scenario requires a carbon price starting at \$25 in 2013. For utility companies, this assumption is harsh and will increase operating costs by \$75 million in order to purchase CO_2 allowances for a plant with 500MW capacity in the first year alone. Although the slow and medium-deployment scenarios may put less stress on the operators, they will fall short of meeting the APA CCS programmatic goal of 72GW of CCS deployment by 2034.

4. GENERAL CONCLUSIONS

TECHNOLOGY, ECONOMY AND POLICY

4.1 Conclusion

The significant wealth invested in fossil fuel infrastructure combined and the stong and growing energy demand coupled with the currently limited inventory of alternative energy resources (e.g. solar power, wind, and biomass) indicate that the world's economies will continue to consume significant fossil fuel resources in the foreseeable future. Efforts to stabilize CO2 have been widely called for and if pursued must be done in an economically efficient manner. The availability of CCS in the wide portfolio of options for reducing greenhouse gas emissions may help facilitate the achievement of GHG emission reduction goals.

The future economic feasibility of CCS is critically dependent on CCS cost, future energy policy (e.g. CO_2 tax or cap and trade) and its relative economic competitiveness over other mitigation options. The IPCC report on CCS indicates that CCS systems will be competitive with other large-scale mitigation options such as nuclear power and renewable energy technologies (Intergovernmental Panel on Climate Change 2005).

In order to assess the economic potential of CCS technology we must answer two questions, how are we going to design the CCS infrastructure and how much will it cost. Due to limited CCS modeling capability, the energy economic modeling community simply uses uniform costs which, unfortunately, mask the complexity of the realistic deployment of CCS and the fact that CCS potential differs by region. For instance, regions with low CCS cost (due to the availability of cheap sequestration sites in close proximity, among other factors) will be likely to harness CCS as an economically affordable option, while other regions with high CCS cost will have to consider different types of generating technologies (nuclear, wind, solar, etc). This work develops a procedure, OptimaCCS, for least cost CCS transport and injection system design. It considers optimal pipeline routing, injection site selection and pipeline sizing. Additionally, OptimaCCS's capability to incorporate individual transportation and injection costs at the national level will enable the energy modeling community to identify CCS's relative economic advantage over other mitigation options with much greater accuracy.

Due to the high cost of CCS technology, the real-world barrier to CCS development is the lack of supportive environmental regulation. Unless there is a CCS incentive, utility companies will quickly not implement it. Under cap and trade, the less CO_2 utility companies release to the air, the more of their carbon permits they can sell (or the fewer carbon permits they have to purchase). However, a cap-and-trade system is unlikely to result in a sufficiently high market price for CO_2 (less than \$30 per ton) in the early years of a carbon control regime to assure that all coal plant developers adopt CCS systems. At lower carbon prices CO_2 source operators are likely to conclude that it is more economical to let plants operate uncontrolled and purchase credits to offset their emissions. Features in the draft of the APA fix this situation by allocating CCS bonus allowances. This study examines CCS deployment under cap and trade finding that it is constrained by the availability of CCS bonus allowances. Based on this premise, the model is used to study different paths of CCS deployment depending on differing combinations of carbon price, technological progress, and the availability of bonus allowances. We discern the signal of the economic plausibility of CCS deployment by analyzing bonus ratio (i.e. the ratio between bonus price/auction price and carbon price). Full scale CCS commercialization is indicated when the technology is deployed regardless of if there is any incentive. A lower bonus ratio means more CCS technology will be more economically plausible. This study explains how different predictive scenarios lead to different levels of bonus ratios which, in turn, affect the path of CCS deployment. Another contribution of the study is to set up the CCS technological progress framework, to relate potential progress with CCS cost, and to assess the resultant dynamic of CCS deployment.

4.2 Limitations

OptimaCCS is a model that approximates CO_2 flow through pipeline, in addition to pipe size, pipe cost and the location of pipeline. These approximations are inherently inexact. This section discusses model limitations.

The Texas case study uses NEMS to evaluate the tradeoffs between retrofitting, retiring, and purchasing emissions allowances. NEMS assumes uniform transportation and injection costs when processing these decision tradeoffs. In reality, the transportation and injection costs are determined by complex dynamic interactions involving the amount of CO_2 captured, the level of CO_2 source operator collaboration, the proximity of the source to the injection site, and the site-specific injection cost. Once

OptimaCCS identifies these unique individual power plant transportation and injection costs, we can use these costs to redo the power plant selection with much greater accuracy.

We use linear regression to approximate the relationship between pipe diameter and the mass flow, and the relationship between pipe diameter and the mass flow of CO_2. Even though both linear regressions are good-fits for certain ranges, they both have negative intercepts. Further detailed analysis and empirical testing reveals that our estimate is not accurate for pipe sizes smaller than 13.6 inches, which is translates to a CO_2 flow of 0.75 million tons per year.

We use continuous pipe size, which is not readily available in the market. However, different pipe sizes may be manufactured if there is a growing demand. In addition, the model can also be reconfigured with additional binary variables representing the exact industry standard pipe size.

We use a cost surface which represents a pipeline cost multiplier considering 8 layers of geographical features as well as social and political data. These parameters are empirically determined through extensive discussions with pipeline engineers from ConocoPhillips which reflect some degree of uncertainty. Cost calibration is needed to identify the magnitude of cost difference between a real past project and an OptimaCCS estimate. Additionally, we can include more environmental impacts such as endangered species, other social data, etc.

Despite these limitations, OptimaCCS is a very powerful tool for designing the most cost-effective CCS infrastructure. In addition, OptimaCCS is able to determine the change in the resultant spatial arrangement caused by changes in model input or parameters, such as the level of collaboration between CO_2 source operators and site-specific injection costs.

Our CCSDeployment model takes into account coal-fired power plants that install CCS technology under APA bonus allowance assistance. On the other hand, the rapid deployment scenario dictates a low bonus ratio (less than one), especially after 2030 (Figure 25) which signals that the CCS technology is in the process of reaching full-scale commercial deployment. Hence, under the rapid deployment scenario, there might be a possibility that there are several coal-fired power plants that are willing to install efficient CCS technology even without APA bonus allowance assistance. Our model does not take into account these additional quantities of CO_2 captured which means that our rapid deployment estimate is a low estimate.

4.3 Future Research

OptimaCCS is continuing to be improved with further research and development. A post-processing module is under development to account for incremental trunkline expansion based on standardized pipeline diameters and therefore allow more accurate construction cost estimates. The model can also be reconfigured with additional binary variables representing the exact industry standard pipe size. Spectra Energy is helping us calibrate OptimaCCS by establishing the appropriate calibration multiplier for each land segment. We do this by modeling past pipeline projects and comparing our results with real-world results. We are also working to enhance OptimaCCS's pipeline engineering components by factoring in requirements to keep CO_2 liquefied and determining the locations of booster stations along the pipe routes.

This model is non-temporal and therefore assumes that pipeline components are built simultaneously. These modeling scenarios also assume that all 14 power plants would bring CCS technology online concurrently. We are developing the ability to increment CO_2 capture retrofit deployments as they occur and to determine the correct sequence of segmented infrastructure expansions for economic efficiency.

Finally, we are exploring how OptimaCCS can be configured to design a national-scale CCS infrastructure. Using NI-NEMS and eGrid, a national database of power plants with retrofit potential can be identified. Our literature review characterizes 12 saline formation sequestration sites that can be expanded to region-specific smaller sequestration sites (or Enhanced Oil Recovery facilities). Consequently with the availability of a national database, sequestration site characterization, and OptimaCCS modeling, it is now possible to design a national-level CO_2 pipeline network and to estimate unique individual power plant CCS costs. The current use of uniform CCS transportation and injection cost nationwide in energy modeling efforts is acceptable for initial high-level planning. However, the availability of unique (more accurate) individual power plant CCS cost on the national level will enable a new spectrum of energy spatial analysis and enhance the current analysis of CCS technology.

In conclusion, the availability of CCS in the portfolio of options for reducing greenhouse gas emissions may help facilitate the achievement of atmospheric CO_2 concentration stabilization. This study facilitates large-scale deployment by answering the questions of how to design the CCS infrastructure and how much it will cost under varying scenarios. In addition, this study identifies a specific path to reach full-scale CCS deployment. This new information is critical to devising efficient policy planning at a high level and intelligent low-level strategic business planning for utility companies.

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APPENDIX A. OPTIMACCS IMPLEMENTATION AND GRAPHICAL USER INTERFACE

In this study, OptimaCCS is implemented as an *add-on* module of ArcMap 9.3.1 which means it can be installed to any ArcGIS software package. Because of its multi-platform characteristics, OptimaCCS is an integrated software package that includes different components: ArcGIS 9.3.1, ArcObject (C++ Com Objects), GAMS 23.2.1, Microsoft Access VBA Script and Microsoft Excel VBA Script. The cost minimization is implemented as a Mixed-Integer Linear Programming (MILP) under a GAMS environment with a solver that is based on a leading mixed-integer optimizer (IBM's ILOG CPLEX). Because of OptimaCCS's requirement of intensive computation and large memory usage, the system platform specifies 64-bit servers to achieve full-scale performance gains from multi-core technologies and enhanced memory management techniques of 48 gigabyte RAM configuration.

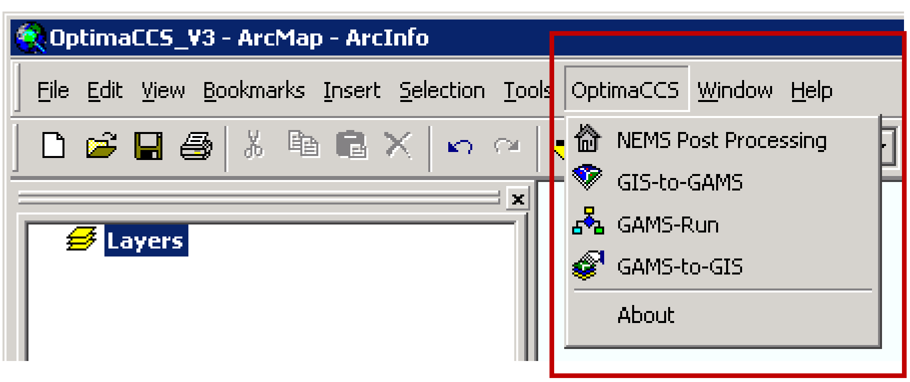

Figure 30. OptimaCCS menu

There are four modules developed:

- NEMS Post Processing Module

  The NEMS original output is embedded inside complex relationships of different Microsoft Access tables. Transforming those tables into a CO_2 source map through manual steps may involve a series of lengthy database manipulations and GIS arrangements. On the other hand, NEMS Post Processing module translates those complex tables into CO_2 sources map (shapefile) with one click of a button.

- GIS-to-GAMS Module

  The GIS-to-GAMS module translates the maps (in a form of shapefiles) of CO_2 sources and sequestration sites into mathematical modeling parameters.

- GAMS-Run Module

  The GAMS cost-minimization object is embedded inside "GAMS Run" functionality to mask the complexity of running GAMS mathematical models.

- GAMS-to-GIS Module

  The GAMS-to-GIS module transforms output from the GAMS mathematical modeling into GIS pipeline routes.

All the functionalities are designed for ease of use. We embedded the GAMS modeling inside ArcGIS functionality so that modelers/users are not required to have prior GAMS experience in order to implement OptimaCCS functionalities. Complete specifications of the software bundle are proprietary and have not been released.

APPENDIX B. CCS CASE STUDY

VIDEO PRESENTATION

We have used Google Earth to create this animated presentation that shows pipelines, power plants, and the Frio sequestration site in our Texas-based case study of CCS infrastructure in figure 12. We thank Brooks Rainy Pearson, Esq. of the Nicholas Institute for Environmental Policy Solutions at Duke University for lending her voice to this video presentation. The movie is part of the supplemental video file.

APPENDIX C. 14 COAL-FIRED POWER PLANTS WITH CCS POTENTIAL IN TEXAS

NI-NEMS identified 14 power plants having the potential to be retrofitted with CCS technology and with a collective generation capacity of 19.3 GW, potential CO_2 capture of 56.8 million tons per year, and total CO_2 emission of 6.3 million tons annually.

Figure 31. Limestone station

1) Limestone Station

The Limestone Electric Generating Station, owned by NRG Texas, is a large utility coal-fired steam electric power plant located in Limestone County with 1.85 GW nameplate capacity. Limestone fires a blend of Texas lignite and Powder River Basin coal. In our scenario, the unit would capture 6.48 million tons of CO_2 each year.

Figure 32. Harrington station

2) Harrington Station

Harrington Station is a coal-fired, steam-electric generating station with three operating units located northeast of Amarillo, Texas. The plant is operated by Xcel Energy (formerly Southwestern Public Service Company) and has current generation capacity of 1.08 GW. The plant fires mostly low-sulfur coal supplied primarily from Wyoming's Powder River Basin and would capture 2.66 million tons of CO_2 annually.

Figure 33. Tolk station

3) Tolk Station

Tolk Station is a coal-fired, steam-electric generating station located southeast of Muleshoe, Texas. The plant is operated by Xcel Energy with generation capacity of 1.14 GW. It fires low-sulfur coal supplied primarily from Wyoming's Powder River Basin and would capture 3.41 million tons of CO_2 per year.

Figure 34. Pirkey station

4) Pirkey Station

Pirkey is a single-unit, coal-fired power plant operated by American Electric Power Co. Inc. with generation capacity of 0.72 GW. The station fires lignite and is located in Harrison County (approx. 140 miles east of Dallas). According to our scenario, this plant would capture 4.56 million tons of CO_2 per year.

5) Gibbons Creek Station

Gibbons Creek is a coal-fired, steam-electric plant operated by Texas Municipal Power Agency with generation capacity of 0.45 GW. The plant burns low-sulfur coal shipped from Wyoming's Powder River Basin. Approximately 6000 tons of coal per day travels from the pile on a conveyor belt system to silos on the boiler. Noteably, the plant was converted from lignite to low-sulfur coal in 1996. Our scenario shows that Gibbons Creek would capture 3.35 million tons of CO_2 annually.

Figure 35. J.T Deely station

6) J.T Deely and Spruce Stations

J.T Deely and Spruce are jointly operated by CPS Energy, a gas and electricity utility owned by the City of San Antonio. The plants have a combined generation capacity of 1.5 GW and are located Bexar County, potentially capturing 7.14 million tons of CO_2 per year.

Figure 36. W.A Parish station

7) W.A. Parish Station

W.A. Parish is operated by NRG Energy and is located 25 miles southwest of downtown Houston. It has significantly larger nameplate generation capacity of 3.97 GW and would capture 4.27 million tons of CO_2 per year. NRG Energy received $167 million from the DOE in March 2010 to implement a clean CCS demonstration project to capture and sequester 400,000 tons of CO_2 annually. NRG will provide additional funding for a project total of $334 million. While this dissertation assumes that the CO_2 captured from these 14 Texas plants would be injected into underground saline formations, this particular project uses the CO_2 capture to enhance production at mature oil fields in Texas' gulf coast region.

Figure 37. Monticello station

8) Monticello Station

The Monticello station is located in Mount Pleasant in Titus County, about 260 miles north of Houston. There are three units at the station with total capacity of 1.98 GW. The plant burns lignite coal from nearby mines, supplemented by low-sulfur sub-bituminous coal from the Wyoming's Powder River Basin. It is owned and operated by Luminant Energy, a subsidiary of Energy Future Holdings (formerly TXU). According to our NEMS scenario, the plant would capture 5.93 million tons of CO_2 annually.

Figure 38. Fayette Power Project station

9) Fayette Power Project Station

Fayette Power Project is owned and operated by the Lower Colorado River Authority and is located seven miles east of La Grange, Texas. The plant has a capacity of 1.69 GW, gets its cooling water from Lake Fayette, and serves more than 1 million people in Central Texas. The main fuel source is low-sulfur coal from the Powder River Basin of Wyoming, which burns more cleanly than other types of coal or lignite. According to our scenario, the plant would capture 1.48 million tons of CO_2 every year.

10) San Miguel Station

The San Miguel plant was brought online in 1982 and is located in Jourdanton, Texas, about 40 miles south of San Antonio. It is owned and operated by San Miguel Electric, a generation and transmission cooperative formed in 1977 specifically for this plant. The plant has a capacity of 0.41 GW and would capture 1.42 million tons of CO_2 annually in our NI-NEMS scenario.

Figure 39. Oklaunion station

11) Oklaunion Station

The Oklaunion Power Station is a 670-megawatt, coal-fired plant located in Vernon, Wilbarger County, Texas. The plant is owned and operated by American Electric Power and the Oklahoma Municipal Power Authority. In our NI-NEMS scenario, Oklaunion captures 0.72 million tons of CO_2 per year.

Figure 40. Martin Lake station

12) Martin Lake Station

The 2.38-gigawatt- Martin Lake plant is located south of Longview . The plant fires locally-mined lignite and sub-bituminous Powder River Basin coal transported from Wyoming by Burlington Northern and Santa Fe Railway. In our NI-NEMS scenario, the plant captures 6.11 million tons of CO_2 per year.

13) Sandow Station Unit 4

Sandow Station Unit 4 is a 1.14-GW, coal-fired power station owned and operated by Luminant Energy. Sandow units 1, 2 and 3 are owned and operated by Alcoa. It is near Rockdaleand, fires lignite from the Three Oaks mine, and captures 4.08 million tons of CO_2 in our NI-NEMS scenario.

14) Coleto Creek Power Station

Coleto Creek Power Station is a 0.6-GW, coal-fired plant located in Goliad County, Texas. The plant is owned and operated by International Powers and captures 5.09 million tons of CO_2 each year in our NEMS scenario.

APPENDIX D. CCS DEPLOYMENT SIMULATION GRAPHICAL USER INTERFACE

The CCS deployment simulation has three assumptions: 1) carbon price inflation rate of 5%; 2) CO_2 capture rate of 90%; 3) CCS technology lifespan of 40 years.

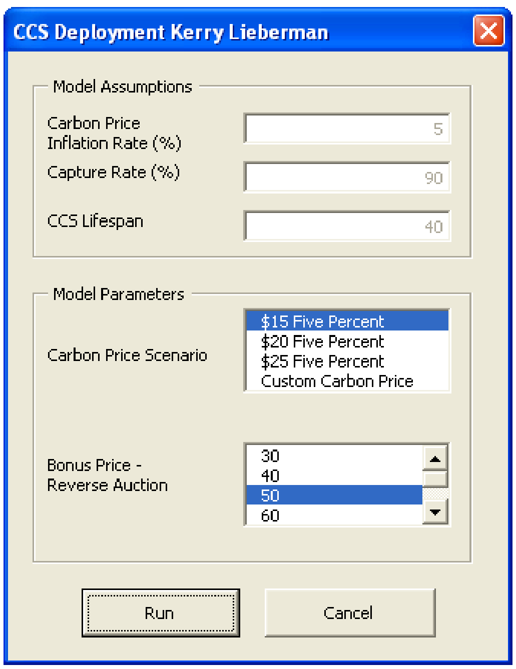

Figure 41. Graphical user interface of CCS deployment simulation

The simulation has two parameters 1) carbon price trajectory and 2) reverse auction price which reflects the progress of CCS technology. The code of this simulation module is in APPENDIX E.

APPENDIX E. CCS DEPLOYMENT PROGRAM IN MICROSOFT EXCEL VBA

- Global Variables

```
'Bidding Price
Public dblBiddingPrice As Double

'Index of power plant
Public iPlantNum As Integer

'Index of year
Public iMaxYear

'The list of power plants
Public strArrPlant(200) As String
Public dblArrCost(200) As Double
Public dblArrEmm(200) As Double
Public dblArrFalse(200) As Boolean

'Bonus Allowance and Carbon Price Structure
Public dblBonusAllowance(100) As Double
Public dblCarbPrice(100) As Double

'structure for big picture
Public dblStructPlant(100, 300) As String
Public dblStructEmission(100, 300) As Double
Public iStructNumPlant(100) As Integer
Public dblStructBonusPrice(100, 300) As Double
Public dblStructRatio(100, 300) As Double
Public dblStructBonus(100, 300) As Double
Public dblStructCost(100, 300) As Double

'The list of plant participated during a particular year
Public yearArrPlant(50, 200) As String
Public yearArrEmission(50, 200) As Double
Public yearArrCost(50, 200) As Double
Public yearArrPhase(50, 200) As Integer
Public yeariPlant(50) As Integer
Public yearArrBonusPrice(50, 200) As Double
Public yearArrBonusRatio(50, 200) As Double

'Track phase
Public iPhase As Integer  '1= Tranche 1, 2=Tranche 2, 3=Phase 3
Public dblBonusPrice(4) As Double
Public dblCurrRatio As Double
Public strPhaseYear(4) As String
Public iPhaseYear(4) As String

Public dblRemaining(50) As Double
Public dblRemainingNon(50) As Double
Public dblCumGig As Double 'Cumulative Gigawatts
```

```
Public dblMinEmmission As Double

'Bonus Allowance Amortization
Public dblAmortRemain(20) As Double
Public dblAmortTotal As Double
Public dblAmortPercent As Double
Public dblNPV

Public perCarbonPrice As Double
Public indexPlantOutput  As Integer

Public BoolBorrow As Boolean
```

- F.2 VBA Form

```
'Developer : Darmawan Prasodjo
'Design:
'1. This module is designed to model Carbon Capture and Storage deployment under American Power Act (APA)
'2. The module is to distribute available bonus allowances to generic power plant from year 2017 to 2034
'3. Generic power plant is 500 MW with annual CO2 emission of 3 million tons/year
'4. The parameters are:
'   a. Carbon price trajectories (low, medium and high)
'   b. Bonus allowance auctin price ($70, $50 and $30)
Private Sub cmdRun_Click()
Dim i, j As Integer
Dim year As Integer
Dim tt As Integer
Dim iMid As Integer
If ListBox2.Text = "" Then
dblBiddingPrice = 50
Else
dblBiddingPrice = CDbl(ListBox2.Text)
End If
indexPlantOutput = 2
iMid = 9
Sheets("Amort").Select
Call deletePlantOutput
Call Initialize
Call ReadAllowancePrice
Call ReadOrderPowerPlant
If BoolBorrow = True Then
'iterate through time
For year = 1 To iMaxYear
'For year = 1 To 10
Call GetPowerPlant(year)
Call AdjustBonusCommitmentNew(year)
Call DumpPowerPlant(year)
Next year
Call DumpPhase
Else
MsgBox "Non Borrowing is under construction"
```

```
'For year = 1 To 9
'Call GetPowerPlantNonBorrow(year)
'Call AdjustBonusCommitmentNew(year)
'Call DumpPowerPlant(year)
'Next year
'For year = 10 To iMaxYear
'Call GetPowerPlant(year)
'Call AdjustBonusCommitmentNew(year)
'Call DumpPowerPlant(year)
'Next year
'Call DumpPhase
End If
Sheets("Simulation").Select
Application.Worksheets("Simulation").Cells(6, 14) = ListBox1.Text
Application.Worksheets("Simulation").Cells(6, 15) = dblBiddingPrice
Call computeCapture
Call phaseChart
Call PhaseTable
MsgBox "Horay Complete !!!"
End Sub

Private Sub PhaseTable()
If ListBox1.Text = "$15 Five Percent" Then
Application.Worksheets("CPhase").Cells(3, 3) = strPhaseYear(1)
Application.Worksheets("CPhase").Cells(3, 4) = strPhaseYear(2)
Application.Worksheets("CPhase").Cells(3, 5) = strPhaseYear(3)
Application.Worksheets("CPhase").Cells(3, 6) = dblBiddingPrice
Application.Worksheets("CPhase").Cells(9, 3) = dblCumGig
Application.Worksheets("CPhase").Cells(9, 4) = dblBiddingPrice
ElseIf ListBox1.Text = "$20 Five Percent" Then
Application.Worksheets("CPhase").Cells(4, 3) = strPhaseYear(1)
Application.Worksheets("CPhase").Cells(4, 4) = strPhaseYear(2)
Application.Worksheets("CPhase").Cells(4, 5) = strPhaseYear(3)
Application.Worksheets("CPhase").Cells(4, 6) = dblBiddingPrice
Application.Worksheets("CPhase").Cells(10, 3) = dblCumGig
Application.Worksheets("CPhase").Cells(10, 4) = dblBiddingPrice
ElseIf ListBox1.Text = "$25 Five Percent" Then
Application.Worksheets("CPhase").Cells(5, 3) = strPhaseYear(1)
Application.Worksheets("CPhase").Cells(5, 4) = strPhaseYear(2)
Application.Worksheets("CPhase").Cells(5, 5) = strPhaseYear(3)
Application.Worksheets("CPhase").Cells(5, 6) = dblBiddingPrice
Application.Worksheets("CPhase").Cells(11, 3) = dblCumGig
Application.Worksheets("CPhase").Cells(11, 4) = dblBiddingPrice
ElseIf ListBox1.Text = "Custom Carbon Price" Then
Application.Worksheets("CPhase").Cells(6, 3) = strPhaseYear(1)
Application.Worksheets("CPhase").Cells(6, 4) = strPhaseYear(2)
Application.Worksheets("CPhase").Cells(6, 5) = strPhaseYear(3)
Application.Worksheets("CPhase").Cells(6, 6) = dblBiddingPrice
Application.Worksheets("CPhase").Cells(12, 3) = dblCumGig
Application.Worksheets("CPhase").Cells(12, 4) = dblBiddingPrice
Else
End If
End Sub
```

```

Private Sub phaseChart()
iPhaseYear(0) = 0
Dim i, j As Integer
For i = 1 To iMaxYear
Application.Worksheets("CRatio").Cells(i + 1, 4) = dblCarbPrice(i)
Next i
For j = 1 To 3
For i = iPhaseYear(j - 1) + 1 To iPhaseYear(j)
Application.Worksheets("CRatio").Cells(i + 1, 2) = strPhaseYear(j)
Application.Worksheets("CRatio").Cells(i + 1, 3) = dblBonusPrice(j)
Next i
Next j
End Sub

Private Sub computeCapture()
Dim dblCaptureUBA(100) As Double
Dim dblCaptureBBA(100) As Double
Dim iLifeSpan As Integer
Dim dblCapture As Double
Dim iCommit As Integer
iCommit = 10
Dim i, j As Integer
iLifeSpan = CInt(txtLifespan.Text)
For i = 1 To 99
dblCaptureUBA(i) = 0
dblCaptureBBA(i) = 0
Next i
For i = 1 To iMaxYear
dblCapture = Application.Worksheets("Simulation").Cells(i + 1, 8)
For j = 1 To iCommit
dblCaptureUBA(i + j - 1) = dblCaptureUBA(i + j - 1) + dblCapture
Next j
For j = 11 To iLifeSpan
dblCaptureBBA(i + j - 1) = dblCaptureBBA(i + j - 1) + dblCapture
Next j
Next i
For i = 1 To iMaxYear + iLifeSpan
Application.Worksheets("CCaptured").Cells(i + 1, 2) = dblCaptureUBA(i)
Application.Worksheets("CCaptured").Cells(i + 1, 3) = dblCaptureBBA(i)
Next i
End Sub

Private Sub deletePlantOutput()
Dim i As Integer
For i = 1 To 100
Application.Worksheets("PlantsOutput").Cells(i + 1, 1) = ""
Application.Worksheets("PlantsOutput").Cells(i + 1, 2) = ""
Application.Worksheets("PlantsOutput").Cells(i + 1, 3) = ""
Application.Worksheets("PlantsOutput").Cells(i + 1, 4) = ""
Application.Worksheets("PlantsOutput").Cells(i + 1, 5) = ""
Application.Worksheets("PlantsOutput").Cells(i + 1, 6) = ""
Next i
```

```
End Sub

Private Sub DumpPhase()
Application.Worksheets("Simulation").Cells(2, 14) = strPhaseYear(1)
Application.Worksheets("Simulation").Cells(3, 14) = strPhaseYear(2)
Application.Worksheets("Simulation").Cells(4, 14) = strPhaseYear(3)
Dim i As Integer
For i = 1 To iMaxYear
Application.Worksheets("Simulation").Cells(i + 1, 5) = dblCarbPrice(i)
Next i
End Sub

Private Sub DumpPowerPlant(iYear As Integer)
Dim ii As Integer
Dim strPlant As String
Dim dblEmission As Double

'Public yearArrPlant(50, 200) As String
'Public yearArrEmission(50, 200) As Double
'Public yearArrCost(50, 200) As Double
'Public yeariPlant(50) As Integer
'Public yearArrBonusPrice(50, 200) As Double
'Public yearArrBonusRatio(50, 200) As Double
dblEmission = 0
For ii = 1 To yeariPlant(iYear)
strPlant = strPlant + " " + yearArrPlant(iYear, ii)
dblEmission = dblEmission + yearArrEmission(iYear, ii)
Application.Worksheets("PlantsOutput").Cells(indexPlantOutput, 1) = yearArrPlant(iYear, ii)
Application.Worksheets("PlantsOutput").Cells(indexPlantOutput, 2) = yearArrEmission(iYear, ii)
Application.Worksheets("PlantsOutput").Cells(indexPlantOutput, 3) = yearArrCost(iYear, ii)
Application.Worksheets("PlantsOutput").Cells(indexPlantOutput, 4) = 2016 + iYear
If yearArrPhase(iYear, ii) = 1 Then
Application.Worksheets("PlantsOutput").Cells(indexPlantOutput, 5) = "Tranche 1"
ElseIf yearArrPhase(iYear, ii) = 2 Then
Application.Worksheets("PlantsOutput").Cells(indexPlantOutput, 5) = "Tranche 2"
Else
Application.Worksheets("PlantsOutput").Cells(indexPlantOutput, 5) = "Phase 2"
End If
Application.Worksheets("PlantsOutput").Cells(indexPlantOutput, 6) = yearArrBonusPrice(iYear, ii)
indexPlantOutput = indexPlantOutput + 1
Next ii
Application.Worksheets("Simulation").Cells(iYear + 1, 6) = strPlant
Application.Worksheets("Simulation").Cells(iYear + 1, 7) = CStr(yeariPlant(iYear))
Application.Worksheets("Simulation").Cells(iYear + 1, 8) = CStr(dblEmission)
Application.Worksheets("Simulation").Cells(iYear + 2, 9) = dblRemaining(iYear + 1)
Application.Worksheets("Simulation").Cells(iYear + 1, 11) = dblCumGig
End Sub

Private Sub GetPowerPlantNonBorrow(iYear As Integer)
Dim ii As Integer
Dim dblRealRemain As Double
```

```
Dim dblRemainingYear As Double
Dim tt As Integer
Dim dblAmort As Double
If iYear = 14 Then
tt = 1
End If
'Call AmortInitialize(iYear)
dblCurrRatio = dblBonusPrice(iPhase) / dblCarbPrice(iYear)
dblRemainingYear = dblRemaining(iYear)
Call copyRemaining
For ii = 1 To iPlantNum
dblRealRemain = dblRemainingYear / dblCurrRatio
If (dblArrEmm(ii) >= dblMinEmmission) And (dblArrEmm(ii) <= dblRealRemain) And (dblArrFalse(ii) = False) Then
tt = 1
If nonBorrowCheck(dblArrEmm(ii), iYear) Then
dblArrFalse(ii) = True
'Call AmortUpdate(iYear, dblArrEmm(ii), dblBonusPrice(iPhase))

yeariPlant(iYear) = yeariPlant(iYear) + 1
yearArrPlant(iYear, yeariPlant(iYear)) = strArrPlant(ii)
yearArrPhase(iYear, yeariPlant(iYear)) = iPhase
yearArrEmission(iYear, yeariPlant(iYear)) = dblArrEmm(ii)
yearArrCost(iYear, yeariPlant(iYear)) = dblArrCost(ii)
yearArrBonusPrice(iYear, yeariPlant(iYear)) = dblBonusPrice(iPhase)
yearArrBonusRatio(iYear, yeariPlant(iYear)) = dblCurrRatio
dblRemainingYear = dblRemainingYear - (dblArrEmm(ii) * dblCurrRatio)
dblRealRemain = dblRemainingYear / dblCurrRatio
dblCumGig = dblCumGig + dblArrEmm(ii) / 7200000#
If ((dblCumGig < 15) And (dblCumGig > 9.7) And (iPhase = 1)) Then
iPhase = iPhase + 1
dblCurrRatio = dblBonusPrice(iPhase) / dblCarbPrice(iYear)
strPhaseYear(1) = "2017-" + CStr(iYear + 2016)
strPhaseYear(2) = CStr(2016 + iYear) + "-"
ElseIf ((dblCumGig < 25) And (dblCumGig > 19.7) And (iPhase = 2)) Then
iPhase = iPhase + 1
dblCurrRatio = dblBonusPrice(iPhase) / dblCarbPrice(iYear)
strPhaseYear(2) = strPhaseYear(2) + CStr(2016 + iYear)
strPhaseYear(3) = CStr(2016 + iYear) + "-2035"
End If
End If
End If
Next ii
tt = 1
End Sub

Private Sub copyRemaining()
Dim i As Integer
For i = 1 To 49
dblRemainingNon(i) = dblRemaining(i)
Next i
End Sub
```

```
Private Function nonBorrowCheck(dblEmm As Double, year As Integer) As Boolean
Dim passBool As Boolean
Dim i As Integer
Dim dblRatio As Double
Dim dblRealEmm As Double
' dblRemaining(iYear)
passBool = True
For i = 1 To 10
dblRatio = dblBonusPrice(iPhase) / dblCarbPrice(year + i - 1)
dblRealElm = dblEmm * dblRatio
If dblRealElm > dblRemainingNon(year + i - 1) Then
passBool = False
GoTo outside
End If
Next i
outside:
If passBool = True Then
For i = 1 To 10
dblRemainingNon(year + i - 1) = dblRemainingNon(year + i - 1) - dblEmm * dblBonusPrice(iPhase) / dblCarbPrice(year + i - 1)
Next i
End If
nonBorrowCheck = passBool
End Function

Private Sub GetPowerPlant(iYear As Integer)
Dim ii As Integer
Dim dblRealRemain As Double
Dim dblRemainingYear As Double
Dim tt As Integer
Dim dblAmort As Double
If iYear = 14 Then
tt = 1
End If
Call AmortInitialize(iYear)
dblCurrRatio = dblBonusPrice(iPhase) / dblCarbPrice(iYear)
dblRemainingYear = dblRemaining(iYear)
For ii = 1 To iPlantNum
dblRealRemain = dblRemainingYear / dblCurrRatio
If (dblArrEmm(ii) >= dblMinEmmission) And (dblArrEmm(ii) <= dblRealRemain) And (dblArrFalse(ii) = False) Then
tt = 1
dblAmort = Amortize(iYear)
If (dblArrEmm(ii) < dblAmort) Then
dblArrFalse(ii) = True
Call AmortUpdate(iYear, dblArrEmm(ii), dblBonusPrice(iPhase))
yeariPlant(iYear) = yeariPlant(iYear) + 1
yearArrPlant(iYear, yeariPlant(iYear)) = strArrPlant(ii)
yearArrPhase(iYear, yeariPlant(iYear)) = iPhase
yearArrEmission(iYear, yeariPlant(iYear)) = dblArrEmm(ii)
yearArrCost(iYear, yeariPlant(iYear)) = dblArrCost(ii)
yearArrBonusPrice(iYear, yeariPlant(iYear)) = dblBonusPrice(iPhase)
yearArrBonusRatio(iYear, yeariPlant(iYear)) = dblCurrRatio
```

```
dblRemainingYear = dblRemainingYear - (dblArrEmm(ii) * dblCurrRatio)
dblRealRemain = dblRemainingYear / dblCurrRatio
dblCumGig = dblCumGig + dblArrEmm(ii) / 7200000#
If ((dblCumGig < 10.8) And (dblCumGig > 9.3) And (iPhase = 1)) Then
iPhaseYear(1) = iYear - 1
iPhase = iPhase + 1
dblCurrRatio = dblBonusPrice(iPhase) / dblCarbPrice(iYear)
strPhaseYear(1) = "2017-" + CStr(iYear + 2016)
strPhaseYear(2) = CStr(2016 + iYear) + "-"
ElseIf ((dblCumGig < 20.8) And (dblCumGig > 19.3) And (iPhase = 2)) Then
iPhaseYear(2) = iYear - 1
iPhaseYear(3) = iMaxYear
iPhase = iPhase + 1
dblCurrRatio = dblBonusPrice(iPhase) / dblCarbPrice(iYear)
strPhaseYear(2) = strPhaseYear(2) + CStr(2016 + iYear)
strPhaseYear(3) = CStr(2016 + iYear) + "-2035"
End If
End If
End If
Next ii
tt = 1
End Sub
Private Sub AmortInitialize(iYear)
Dim j As Integer
For j = 1 To 10
dblAmortRemain(j) = dblRemaining(iYear + j - 1)
Next
End Sub
Private Sub AmortUpdate(iYear As Integer, dblEmm As Double, dblBonusPrice As Double)
Dim j As Integer
Dim dblRatio As Double
Dim dblRemainNonMax As Variant
If iYear = 14 Then
j = 1
End If
If iYear > 9 Then
nonMaxYear = iMaxYear - iYear + 1
dblRatio = dblBonusPrice / dblCarbPrice(iYear)
dblRemainNonMax = getRemaining(iYear, dblEmm, nonMaxYear, dblBonusPrice, dblRatio)
For j = 1 To 10
dblAmortRemain(j) = dblAmortRemain(j) - dblRemainNonMax(j)
Next j
Else
For j = 1 To 10
If iYear + j - 1 <= 18 Then
dblRatio = dblBonusPrice / dblCarbPrice(iYear + j - 1)
dblAmortRemain(j) = dblAmortRemain(j) - (dblEmm * dblRatio)
Else
dblRatio = 1
dblAmortRemain(j) = 0
```

```
End If
Next j
End If
j = 1
End Sub

Private Function AmortizeNonBorrow(iYear) As Double
Dim j As Integer
Dim k, l As Long
Dim dblGuess As Double
Dim tt As Integer
Dim dblGuessRes As Double
Dim dblDiff As Double
Dim dblDiffS As Double
Dim up As Boolean
Dim step As Integer
Dim delta As Double
Dim pos As Boolean
Dim nonMaxYear As Integer
dblNPV = 0
Amortize = 0
For j = 1 To 10
dblNPV = dblNPV + dblAmortRemain(j)
Next j
Application.Worksheets("Amort").Cells(4, 1) = dblNPV
SolverOK SetCell:=Range("AmortOutput"), MaxMinVal:=3, ValueOf:=dblNPV, ByChange:=Range("AmortInput")
SolverSolve userFinish:=True
Amortize = Application.Worksheets("Amort").Cells(1, 3) / dblCurrRatio
SolverFinish KeepFinal:=1
Dim dblCheck As Double
dblCheck = Application.Worksheets("Amort").Cells(1, 3)
If iYear = 14 Then
tt = 1
End If
End Function

Private Function Amortize(iYear) As Double
Dim j As Integer
Dim k, l As Long
Dim dblGuess As Double
Dim tt As Integer
Dim dblGuessRes As Double
Dim dblDiff As Double
Dim dblDiffS As Double
Dim up As Boolean
Dim step As Integer
Dim delta As Double
Dim pos As Boolean
Dim nonMaxYear As Integer
dblNPV = 0
Amortize = 0
For j = 1 To 10
```

```
dblNPV = dblNPV + dblAmortRemain(j)
Next j
Application.Worksheets("Amort").Cells(4, 1) = dblNPV
SolverOK SetCell:=Range("AmortOutput"), MaxMinVal:=3, ValueOf:=dblNPV,
ByChange:=Range("AmortInput")
SolverSolve userFinish:=True
Amortize = Application.Worksheets("Amort").Cells(1, 3) / dblCurrRatio
SolverFinish KeepFinal:=1
Dim dblCheck As Double
dblCheck = Application.Worksheets("Amort").Cells(1, 3)
If iYear = 14 Then
tt = 1
End If
End Function

Private Sub delay()

Dim kk, ll, mm As Integer
For kk = 1 To 1000
For ll = 1 To 1000
mm = 1
Next ll
Next kk
End Sub
Private Sub AdjustBonusCommitmentNew(ByVal iYear As Integer)
Dim i, ii, tt As Integer
Dim j, jj, k As Integer
Dim structNum As Integer
Dim dblRemainNonMax As Variant
'Has total 10 years of bonus allowance
If iYear < 10 Then
For jj = 1 To yeariPlant(iYear)
'compute the bonus allowance commitment for 10 year
For i = 1 To 10
iStructNumPlant(iYear + i - 1) = iStructNumPlant(iYear + i - 1) + 1
structNum = iStructNumPlant(iYear + i - 1)
dblStructPlant(iYear + i - 1, structNum) = yearArrPlant(iYear, jj)
dblStructEmission(iYear + i - 1, structNum) = yearArrEmission(iYear, jj)
dblStructBonusPrice(iYear + i - 1, structNum) = yearArrBonusPrice(iYear, jj)
dblStructRatio(iYear + i - 1, structNum) = yearArrBonusPrice(iYear, jj) / dblCarbPrice(iYear + i
- 1)
dblStructBonus(iYear + i - 1, structNum) = dblStructRatio(iYear + i - 1, structNum) *
dblStructEmission(iYear + i - 1, structNum)
dblRemaining(iYear + i - 1) = dblRemaining(iYear + i - 1) - dblStructBonus(iYear + i - 1,
structNum)
Next i
Next jj
'Forward the remaining to the following year
dblRemaining(iYear + 1) = dblRemaining(iYear + 1) + dblRemaining(iYear)
dblRemaining(iYear) = 0
Else
'has less than 10 years bonus allowance
nonMaxYear = iMaxYear - iYear + 1
```

```
'Compute NPV of total Emission
'Divide into the nonMaxYear
'Decrease the remaining by the division
For jj = 1 To yeariPlant(iYear)
'Since the remaining year is less than 10 years, we need to adjust the commitment
dblRemainNonMax = getRemaining(iYear, yearArrEmission(iYear, jj), nonMaxYear, yearArrBonusPrice(iYear, jj), yearArrBonusRatio(iYear, jj))
tt = 1
For i = 1 To 10
If (iYear + i - 1) < 19 Then
iStructNumPlant(iYear + i - 1) = iStructNumPlant(iYear + i - 1) + 1
structNum = iStructNumPlant(iYear + i - 1)
dblStructPlant(iYear + i - 1, structNum) = yearArrPlant(iYear, jj)
dblStructEmission(iYear + i - 1, structNum) = yearArrEmission(iYear, jj)
dblStructBonusPrice(iYear + i - 1, structNum) = yearArrBonusPrice(iYear, jj)
dblStructRatio(iYear + i - 1, structNum) = yearArrBonusPrice(iYear, jj) / dblCarbPrice(iYear + i - 1)
dblStructBonus(iYear + i - 1, structNum) = dblStructRatio(iYear + i - 1, structNum) * dblStructEmission(iYear + i - 1, structNum)
dblRemaining(iYear + i - 1) = dblRemaining(iYear + i - 1) - dblRemainNonMax(i)
End If
Next i
Next jj
'Forward the remaining to the following year
dblRemaining(iYear + 1) = dblRemaining(iYear + 1) + dblRemaining(iYear)
dblRemaining(iYear) = 0
End If
End Sub

Private Function getRemaining(ByVal iYear As Integer, ByVal dblEm As Double, ByVal nonMaxYear As Integer, ByVal bonusPrice As Double, ByVal BonusRatio As Double) As Variant
Dim retArr As Variant
Dim vv As Variant
Dim dblTotNPV As Double
Dim jj As Integer
dblTotNPV = 0
For jj = 1 To 10
dblTotNPV = dblTotNPV + dblEm * (BonusRatio / ((1 + perCarbonPrice) ^ (jj - 1)))
Next jj
ReDim retArr(1 To 10)
retArr(1) = 9#

'after calling this function, the
Call AmortizeNonMaxYear(dblTotNPV, nonMaxYear)
For tt = 1 To nonMaxYear
retArr(tt) = Application.Worksheets("Amort").Cells(tt, 3)
Next tt
getRemaining = retArr
If iYear = 14 Then
tt = 1
End If
End Function
Private Sub AmortizeNonMaxYear(dblTotNPV As Double, year As Integer)
```

```
Dim tt As Integer
Dim strRange As String
Dim v As Variant
Dim iAdd, iRow As Integer
iAdd = 4
iRow = iAdd + year
ReDim v(1 To 10)
For tt = 1 To 10
v(tt) = 0
Next tt
strRange = "Amortize" + CStr(year)
Application.Worksheets("Amort").Cells(4, 1) = dblTotNPV
SolverOK SetCell:=Application.Worksheets("Amort").Cells(iRow, 1), MaxMinVal:=3, ValueOf:=dblTotNPV, ByChange:=Range("AmortInput")
SolverSolve userFinish:=True
SolverFinish KeepFinal:=1
End Sub
Private Sub Initialize()
Dim i, j As Integer
If CheckBox1.Value = True Then
BoolBorrow = True
Else
BoolBorrow = False
End If
Dim tt As Integer
tt = 1
dblCumGig = 0
iMaxYear = 18
iPhase = 1
' The bonus price
' First tranche is $96
dblBonusPrice(1) = 96#
' Second tranche is $85
dblBonusPrice(2) = 85#
' Second Phase is with Reverse auction
dblBonusPrice(3) = 50#
dblBonusPrice(3) = dblBiddingPrice
For i = 1 To 49
dblRemaining(i) = 0
For j = 1 To 199
yearArrPlant(i, j) = ""
yearArrEmission(i, j) = 0
yeariPlant(i) = 0
Next j
Next i
For i = 1 To 99
For j = 1 To 99
dblStructPlant(i, j) = ""
dblStructEmission(i, j) = 0
iStructNumPlant(j) = 0
Next j
Next i
For i = 1 To 100
```

```
dblBonusAllowance(100) = 0
dblCarbPrice(100) = 0
Next i
dblMinEmmission = (7200000#) / 5#
perCarbonPrice = CDbl(TextBox1.Text) / 100#
Application.Worksheets("Amort").Cells(2, 1) = 1# + perCarbonPrice
iPhase = 1   '1= Tranche 1, 2=Tranche 2, 3=Phase 3
dblCurrRatio = 0
For i = 1 To 3
strPhaseYear(i) = ""
Next i
tt = 1
End Sub
Private Sub ReadAllowancePrice()
Dim i, j As Integer
'Public dblBonusAllowance(100) As Double
'Public dblCarbPrice(100) As Double
For i = 1 To iMaxYear
dblBonusAllowance(i) = Application.Worksheets("Simulation").Cells(i + 1, 4) * 1000000#
If ListBox1.Text = "$15 Five Percent" Then
dblCarbPrice(i) = Application.Worksheets("CarbP").Cells(i + 6, 6)
ElseIf ListBox1.Text = "$20 Five Percent" Then
dblCarbPrice(i) = Application.Worksheets("CarbP").Cells(i + 6, 7)
ElseIf ListBox1.Text = "$25 Five Percent" Then
dblCarbPrice(i) = Application.Worksheets("CarbP").Cells(i + 6, 8)
ElseIf ListBox1.Text = "$Floor Five Percent" Then
dblCarbPrice(i) = Application.Worksheets("CarbP").Cells(i + 6, 3)
ElseIf ListBox1.Text = "$Ceiling Five Percent" Then
dblCarbPrice(i) = Application.Worksheets("CarbP").Cells(i + 6, 4)
ElseIf ListBox1.Text = "Custom Carbon Price" Then
dblCarbPrice(i) = Application.Worksheets("CarbP").Cells(i + 6, 9)
End If
dblRemaining(i) = dblBonusAllowance(i)
Next i
Dim tt As Integer
tt = 1
End Sub
Private Sub ReadOrderPowerPlant()
Dim strTempPlant  As String
Dim dblTempCost As Double
Dim dblTempEmm As Double
Dim iMax As Integer
Dim i, j As Integer
Dim dblMin As Double
Dim dblCurr As Double
Dim iMin As Integer
For i = 1 To 1000
If Application.Worksheets("Plants").Cells(i + 1, 1) = "" Then
GoTo outside
End If
Next i
outside:
iMax = i - 1
```

```
For i = 1 To iMax
strArrPlant(i) = Application.Worksheets("Plants").Cells(i + 1, 1)
dblArrEmm(i) = Application.Worksheets("Plants").Cells(i + 1, 2)
dblArrCost(i) = Application.Worksheets("Plants").Cells(i + 1, 9)
dblArrFalse(i) = False
Next i
For i = 1 To iMax
dblMin = dblArrCost(i)
For j = i To iMax
dblCurr = dblArrCost(j)
If dblMin > dblCurr Then
strTempPlant = strArrPlant(j)
dblTempCost = dblArrCost(j)
dblTempEmm = dblArrEmm(j)
strArrPlant(j) = strArrPlant(i)
dblArrCost(j) = dblArrCost(i)
dblArrEmm(j) = dblArrEmm(i)
strArrPlant(i) = strTempPlant
dblArrCost(i) = dblTempCost
dblArrEmm(i) = dblTempEmm
dblMin = dblCurr
End If
Next j
Next i
For i = 1 To iMax
Application.Worksheets("Plants").Cells(i + 1, 11 + 1) = strArrPlant(i)
Application.Worksheets("Plants").Cells(i + 1, 12 + 1) = dblArrEmm(i)
Application.Worksheets("Plants").Cells(i + 1, 13 + 1) = dblArrCost(i)
Application.Worksheets("Plants").Cells(i + 1, 14 + 1) = dblArrFalse(i)
Next i
iPlantNum = iMax
Dim tt As Integer
tt = 1
End Sub

Private Sub CommandButton1_Click()
Unload frmKerryLib
End Sub
Private Sub Label1_Click()
End Sub
Private Sub Label4_Click()
End Sub
Private Sub ListBox2_Click()
End Sub
Private Sub UserForm_Initialize()
ListBox1.Clear
ListBox1.AddItem "$15 Five Percent"
ListBox1.AddItem "$20 Five Percent"
ListBox1.AddItem "$25 Five Percent"
ListBox1.AddItem "Custom Carbon Price"
'ListBox1.AddItem "$Floor Five Percent"
'ListBox1.AddItem "$Ceiling Five Percent"
ListBox1.Text = "$15 Five Percent"
```

```
ListBox1.Value = "$15 Five Percent"
ListBox2.AddItem "30"
ListBox2.AddItem "40"
ListBox2.AddItem "50"
ListBox2.AddItem "60"
ListBox2.AddItem "70"
ListBox2.AddItem "80"
ListBox2.AddItem "90"
ListBox2.Text = "50"
ListBox2.Value = "50"
perCarbonPrice = 0.05
End Sub
```

VITA

Mr. Darmawan Prasodjo received his Bachelor of Science in Computer Science with a minor in Industrial Engineering from Texas A&M University in 1994. He then served as a researcher for the Indonesian Ministry of Research and Technology and the World Bank's Project Support Group in Jakarta. He returned to Texas A&M and completed a Master of Science in Computer Science with specialization in software development in 2001. After several years of professional consulting, he began a doctoral program in Agriculture Economics that focuses on natural resource economics, economic modeling, spatial optimization, and energy economics. This doctoral program supports other research for mitigating climate change associated with large-scale power generation. As a doctoral candidate, he gained expertise in economic modeling that combines theory with real-world parameters. His core strengths are in the use of GAMS and GIS to model economic scenarios. He received his Ph.D in May 2010

He currently holds a research position at Duke University's Nicholas Institute for Environmental Policy Solutions. His work has contributed to the development of OptimaCCS for designing CCS infrastructures that have optimal economic characteristics. His secondary research is in the development of an optimized U.S. transportation model (SIMTrave) by porting the European partial-equilibrium TREMOVE model to fit U.S. policy. Mr. Darmawan Prasodjo can be reached at Nicholas Institute for Environmental Policy Solutions, Duke University, NC 27705. His email is dprasodjo@gmail.com.