EFFECTS OF TAX CREDITS ON CARBON CAPTURE AND SEQUESTRATION IN A MULTI-PHASED MODEL

by

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NOMENCLATURE

CCS	Carbon Capture and Storage
MILP	Mixed Integer Linear Program
NOP	Network Optimization Problem
CO_2	Carbon Dioxide
source	Carbon emitting power plant
sink	Reservoir for carbon storage / sequestration
45Q	Carbon Capture and Sequestration Tax Credit ("Section 45Q")
CQP	Credit Qualification Period
Mt/CO_2	Millions of Tons of CO_2
M/$	Millions of dollars

ABSTRACT

Studies have consistently shown that the increase of CO_2 in the atmosphere is correlated to rising temperatures. In order to stop the rise in global temperatures, climate change mitigation strategies will need to be deployed at scale. All of the plans that meet the goal of staying below 2° C include CO_2 capture and storage (CCS) as one of those strategies. CCS is a climate change mitigation strategy aimed at reducing the amount of CO_2 vented into the atmosphere by capturing CO_2 emissions from industrial sources, transporting the CO_2 via a dedicated pipeline network, and injecting it into geologic reservoirs. Designing CCS infrastructure is a complex problem requiring concurrent optimization of source selection, reservoir selection, and pipeline routing decisions. Current CCS infrastructure design methods assume that project parameters including costs, capacities, and availability, remain constant throughout the project's lifespan. In this research, we introduce a novel, multi-phased, CCS infrastructure design model that allows for analysis of more complex scenarios that allow for variations in project parameters across distinct phases. We also apply this new model to a study exploring the impacts of modifying CCS tax credits on the economic viability of CCS projects.

CHAPTER ONE

INTRODUCTION

Carbon Capture and Storage (CCS) is a critical tool for combating climate change by reducing CO_2 emissions into the atmosphere. CCS is the process of capturing CO_2 emissions from industrial sources (e.g., power generation stations), transporting those emissions via a dedicated pipeline network, and injecting them into geologic reservoirs for long-term sequestration. Industrial sources generate CO_2 as a byproduct of burning fossil fuels for power generation. CO_2 can be captured before, during, or after the burning process occurs. Once CO_2 is captured, it needs to be transported. Pipelines are connected directly to industrial sources to allow for transportation to geologic reservoirs. The CO_2 can be injected into these geologic reservoirs, which store the CO_2 with overlying seals, pressure changes, and through chemical reactions. To have a meaningful impact on global CO_2 emission targets, CCS projects must be deployed on a wide scale across many industries and geographic regions. CCS infrastructure modeling is a critical tool to support CCS adoption by providing stakeholders with objective evaluations of potential deployment scenarios. Modeling CCS infrastructure is the process of concurrently determining the most appropriate emission sources to capture from, the storage locations to inject into, and the pipeline transportation network. The objective of this optimization problem is to deploy minimal cost infrastructure that achieves some goal.

Current CCS infrastructure modeling approaches assume that the sources, reservoirs, pipelines, and objectives remain constant throughout a project. For example, if a source can capture CO_2 for $30 per ton on day one, it is assumed that value does not change for the entire 30-year project. While static models may be reasonable for many applications, there are some applications where a static assumption is limiting:

- Sources or reservoirs may not be available throughout the entire project length, instead coming online after project initiation, or becoming inactive prior to project completion.
- Government policies, such as increased (or decreased) tax credits or modified carbon taxes, that change during the lifetime of a project could lead to increased CCS participation from sources or reservoirs.
- Fluctuations in the price of oil could incentivize or disincentivize enhanced oil recovery (EOR) fields to purchase CO_2 from a CCS project over the life of the project, thereby impacting CO_2 sales prices.
- Financial constraints of the CCS project may require phased construction of the infrastructure over a significant period of time (e.g. 20 years) instead of construction all at once.
- An increase (or decrease) over time in the target CO_2 capture amount for a CCS project, due to meeting phased capture objectives.
- Technology changes are continuously reducing the cost of CO_2 capture from many industries, driving a dynamic capture cost over the lifetime of a 30-year project.

None of these scenarios can be adequately addressed by a single-phase, static, infrastructure design model without significant degradation in solution quality. In this research, we propose a novel multi-phased CCS infrastructure design model, formulated as a mixed integer linear program (MILP), that concurrently optimizes the design across multiple phases to construct a solution that is globally optimal for the full project instead of locally optimal for individual phases. We note that the solving of our MILP as an optimization problem is NP-Hard, the complexity of MILPs is discussed further in Section 2.1. The

MILP that represents our new model is very versatile and allows for considering complex scenarios, including the ones detailed above. One timely application we explore is the impacts of modifying tax credits on the viability of CCS adoption.

Section 45Q of the U.S. Tax Code details a tax credit for CCS projects that includes a variable credit amount targeted at specific emission thresholds. The goal of 45Q is to incentivize CCS development, but wide-scale development has not yet been realized. 45Q includes both a credit amount (\$ per ton of CO_2 captured) and period of time that credit can be claimed. As of July 2021, there have been multiple proposals submitted to Congress that would modify 45Q to increase credit amounts and extend credit qualification periods. Some of these proposals would remove or change restrictions on requirements for receiving 45Q tax credits. Any changes to 45Q would impact economic and infrastructure planning and will have dramatic effect on possible CCS projects. Projects that were not viable with the original credit amounts may now be viable if the credits are increased enough.Modeling these scenarios is important to the CCS community to ensure long-term economic viability of CCS projects. To accurately model the impacts of changes to 45Q on CCS project viability, a CCS infrastructure design model must be able to account for variations in credit amounts over the life of a project. We use our new multi-phased CCS infrastructure design model to quantify the impacts of possible changes to 45Q on CCS adoption. Results using the new multi-phased model will give policy makers a more accurate look at the long-term impacts of changes to the tax policy.

The rest of this thesis is organized as follows: Chapter 2 details previous research relating to designing optimal CCS infrastructure. Chapter 3 formulates the multi-phased model as a mixed integer linear program. Chapter 4 uses the new multi-phased model to quantify the impacts of tax credit changes on CCS project viability. Chapter 5 summarizes contributions, limitations, and future potential works based on this research.

CHAPTER TWO

RELATED WORKS

2.1 Infrastructure Modeling

Infrastructure modeling is important across industries as accurate planning is needed for the implementation of complex systems [1] [2] [3] [4] [5]. Infrastructure models can be represented more simply as network optimization problems (NOPs) [6]. NOPs can be formally represented as MILPs.

We note that MILPs can be the formal definition of decision and optimization problems. MILPs as decision problems are NP-Complete and as optimization problems are NP-Hard. NP-Complete problems are decision problems meaning that they have solutions but these solutions are not necessarily achievable in polynomial time. Polynomial time solutions are generally looked at as the benchmark for how fast algorithmic problems are solved. NP-Hard problems are at least as hard as NP-Complete problems but are not necessarily decision problems. If a problem cannot be solved in polynomial time it could take an extraordinary amount of time for a computer to solve the problem, ranging anywhere from days to millions of years.

NOPs were initially focused on telecommunications infrastructure but have been expanded to cover infrastructure in multiple industries [7] [8]. (Mah and Shacham, 1978)'s NOP closely reflects a CCS optimization problem as they use Networks to represent a system of pipelines [9]. MILPs have been used to solve a multitude of different NOPs. (Lin et al., 2011) create a MILP to model and coordinate urban traffic networks [10]. (Trodden et al., 2012) formulate a MILP that simultaneously decides boundaries of islands for power networks [11]. (Hong et al., 2019) Showed that MILPs can also be used for gathering pipeline networks with the consideration of hydraulic characteristics [12]. (Wedzik et al., 2016) Formulated a MILP to simultaneously optimize a wind farms network layout [13]. (Zhang et al., 2017) Proposed a MILP to find an optimal offshore oilfield gathering system [14]. (Wang et al., 2017) formulate a MILP to design a multi-period natural gas transmission network in order to find pipeline routes and sites of compressor stations [15].

After optimal networks are established, the scaling and growth of these networks is important. Scaling and growth can be represented in multi-phased models. Computational models are being utilized to find multi-phased solutions [16] [17]. These models can be used to plan and estimate costs of large scale infrastructure projects that operate over long periods of time [18] [19].

2.2 Carbon Capture and Storage Modeling

Many decision support models have been created to utilize mathematical programming in order to model CCS. Some of the initial research done surrounding CCS, was on the best means of transportation. (Svensson et al., 2004) found that inland operations were most cost effective when using pipelines to transport CO_2 [20]. Once pipelines were chosen as the transportation method, the problem was morphed into a NOP, and many other solutions began to spring up.

(Tapia et al., 2018) perform tool categorization, sorting projects by their focus on capture, utilization, storage, or transportation [21]. There exist quite a few CCS tools that optimize capture but cannot be considered fully integrated solutions as they do not support pipeline routing capabilities. (Odenberger et al., 2008) searched for optimal economic solutions for CCS, but used a pre-defined network of pipelines connecting sources to reservoirs [22]. (Mohd Nawi et al., 2016) present the Total Site CO_2 Integration tool, which optimizes CO_2 capture and utilization but also used predetermined pipelines [23]. (National Energy Technology Laboratory, 2018) created the FE/NETL CO@ Transport Cost Model, which estimated pipeline costs and pressure losses, but did not perform detailed routing or source and sink selection [24]. (Wang et al., 2016) developed a decision tree to support matching sources with sinks that considers pipeline costs, but also excludes detailed routing [25].

(Middleton et al., 2009) were the first to create a fully integrated system for modeling CCS, *SimCCS* [26]. *SimCCS* was released in 2009 and redesigned in 2020 [27]. *SimCCS* is a fully integrated tool for CCS, it includes multivariate optimization, economic modeling, uncertainty analysis, and pipeline geo-location. (Middleton et al., 2012) created a methodology for generating specific pipeline routing in a five step process [28]. The process has since been updated twice, the first being computationally expensive [29]. *SimCCS* currently uses Delaunay triangulation to generate specific pipeline routes [30].

The model is further described in the Problem section. *SimCCS* was an incredibly novel solution to the problem of CCS, and sparked other groups to begin research. The first notable project being The JRC InfraCCS [31]. InfraCCS used clustering algorithms to improve computational complexity by reducing the number of sources and sinks. By doing this they stop their solution from being optimal. (Sun and Chen, 2017) developed ChinaCCUS, which focuses on China based sources and sinks. MARKAL, is a CCS modeling project that optimizes a MILP for CO_2 reduction in the Netherlands [32]. OptimaCCS is a CCS focused on coal producing power plants in Texas [33]. (DaneshFar et al., 2021) utilize the SimCCS technology to generate optimal solutions for a CCS network in Oklahoma [34]. Most models that concurrently optimize source and sink selection, as well as pipeline routing are based on SimCCS [26].

For the majority of related projects, the optimization goal was to reach a given capture target. A different approach to the problem led to the creation of SimCCS^{PRICE} (Kuby et al., 2011a) [35]. SimCCS^{PRICE} altered the MILP to optimize for infrastructure profitability rather than a given capture amount. CCS systems can become profitable when given tax credits that cover and surpass the costs for capture, injection, and transportation. (Han and Lee, 2011) created work similar to SimCCS^{PRICE}, which was a framework for CCS that optimized profits based on post capture utilization [36].

A couple of projects include a multi-phased structure. An updated InfraCCS, which modeled the decarbonisation of Europe from 2015 through 2050 utilizing clustering and the Delaunay triangulation algorithms to create optimal pipeline generation [37]. InfraCCS allows for multiple phases of pipeline route creation but does not seem to be able to adjust pricing or capture goals across time periods. (Johnson and Ogden, 2011) created a model with a multi-phased aspect to model deployment of a CCS in Colorado and Texas. This model expanded multi-phased pipeline construction and capture from 2016 to 2050. This model similar to some of the aforementioned papers relies on existing Natural gas pipelines to establish pipeline routes [38]. Neither of these papers include the formalized description of their optimization problem.

CHAPTER THREE

MULTI-PHASED MODEL FORMULATION

In this chapter, we first present a common, single-phase, version of the CCS infrastructure design model. The reason to show this model is to be able to highlight differences between it and the new multi-phased model. We then introduce the new multi-phased model and discuss its theoretical functionality and capabilities.

3.1 Single-Phase Model

The CCS model discussed in this paper is constructed with carbon emitting plants (sources), injection reservoirs (sinks), and the network of potential pipelines that exist between them. The information known about the sources is the amount of capturable CO_2 emitted from the plant, the variable cost per ton of CO_2 captured, and its geographical location. Similar information is known about the sinks, including the total capacity of the sink, the variable cost per ton of injecting CO_2, and the sinks geographical location. Information relating to the pipeline network includes a cost vs capacity model used to determine the cost of a pipeline component hosting a given capacity. This cost is broken into a fixed construction cost and variable (i.e., quantity dependent) utilization cost. The cost model is a piecewise function composed of linear components called trends. The pipeline costs approximated by the cost model are from the National Energy Technology Laboratory's CO_2 Transport Cost Model [24]. The pipeline cost model based on trends, instead of explicit pipe diameters, reduces the number of integer variables in the Integer Linear Program model with minimal impacts on the realism of the model [39]. The set of possible pipeline locations (termed the *candidate network*) is calculated based on shortest paths in a weighted-cost surface. This cost surface incorporates many geospatial factors (e.g., populations centers, land ownership) to influence routing decisions [30]. Various routing algorithms have been explored to calculate the candidate network, though an algorithm based on Delaunay triangulation is most commonly used [29].

The data described above is used to parameterize a Mixed Integer Linear Program (MILP) model that aims to minimize CCS infrastructure cost subject to various deployment constraints. The basic version of this model is presented below.

Instance Input Parameters:

Variable	Description
V_i^s	Variable cost for capturing CO_2 from source i (\$/tCO_2)
V_j^w	Variable cost for injecting CO_2 at reservoir j (\$/tCO_2)
S	Set of sources
R	Set of reservoirs
I	Set of all graph nodes
K	Set of candidate pipeline arcs
C	Set of pipeline capacity trends
Q_i^s	CO_2 production rate at source i (MtCO_2/yr)
Q_j^r	Capacity or reservoir j (MtCO_2)
Q_{kc}^{max}	Maximum capacity of pipeline k with trend c (MtCO_2/yr)
Q_{kc}^{min}	Minimum capacity of pipeline k with trend c (MtCO_2/yr)
α_{kc}	Cost to transport one tonne of CO_2 on pipeline k with trend c
β_{kc}	Cost to build pipeline k with trend c

MILP Decision Variables:

Variable	Description
$y_{kc} \in \{0, 1\}$	Indicates if pipeline k with trend c is built
$a_i \in \mathbb{R}$	Amount of CO_2 captured at source i (tCO_2/yr)
$b_j \in \mathbb{R}$	Amount of CO_2 injected into reservoir j (tCO_2/yr)
$p_{kc} \in \mathbb{R}$	Amount of flow in pipeline k with trend c (tCO_2/yr)

The MILP is driven by the objective function:

$$\min \overbrace{\sum V_i^s a_i}^{\text{capture cost}} + \overbrace{\sum_{k\in K}\sum_{c\in C}\alpha_{kc}p_{kc}}^{\text{pipeline use cost}} + \overbrace{\sum_{k\in K}\sum_{c\in C}\beta_{kc}y_{kc}}^{\text{pipeline build cost}} + \overbrace{\sum_{j\in R}V_j^w b_j}^{\text{storage cost}}$$

The objective function calculates and minimizes the total infrastructure cost. If capture, transport, and storage all incur a cost, then the optimal solution will be to deploy nothing at a cost of zero. However, if there are negative costs in the system, then the objective function can possibly be decreased beyond zero representing a profitable project. The two sources of negative costs are tax credits that exist to encourage CCS adoption and proceeds from CO_2 sales for industrial use.

The objective function is subject to the following constraints:

$$Q_{kc}^{min}y_{kc} \leq p_{kc} \leq Q_{kc}^{max}y_{kc}, \forall k \in K, \forall c \in C \tag{3.1}$$

$$\sum_{c\in C} y_{kc} \leq 1, \forall k \in K \tag{3.2}$$

$$\sum_{\substack{k\in K:\\ src(k)=i}}\sum_{c\in C}p_{kc} - \sum_{\substack{k\in K:\\ dest(k)=i}}\sum_{c\in C}p_{kc} = \begin{cases} a_n & \text{if n} \in \text{S} \\ -b_n & \text{if n} \in \text{R}, \forall n \in I \\ 0 & \text{otherwise} \end{cases} \tag{3.3}$$

$$a_i \leq Q_i^s, \forall i \in S \tag{3.4}$$

$$b_j \leq Q_j^r, \forall j \in R \tag{3.5}$$

Constraint (3.1) ensures a pipeline is built before transporting CO_2 and its capacity works for the amount of flow. Constraint (3.2) allows at most one linear-piece (i.e., trend) pipeline between any two nodes. Constraint (3.3) enforces conservation of flow at each non-source or sink node. Constraint (3.4) ensures each source is limited to capture at most its maximum production. Constraint (3.5) caps storage for each reservoir by its maximum capacity [27]

This model allows users to determine least-cost CCS infrastructure for simulations of deployment scenarios. The model will return relevant metrics such as how much CO_2 the scenario captured, how much it cost, which sources and sinks were used, and which pipelines were built. The assumptions made by this model are that all of the sources and sinks immediately start capturing and storing CO_2, the pipelines are immediately built, and that the costs relative to capturing CO_2 maintain constant (excluding inflation) over the timeline of the project. As discussed in Chapter 1, this model assumes that input parameters are static for the lifetime of the project. For some modeling applications this assumption is adequate, but for others it is not. In the next section, we present a multi-phase CCS infrastructure design model that enables more sophisticated scenario modeling by allowing parameters to vary throughout the lifetime of the project.

3.2 Multi-Phased Model

The multi-phased model includes sources, sinks, and a candidate pipeline network, just like in the single-phase model. The multi-phased model differs from the single-phase model by considering the project lifespan as being broken up into a set of discrete *phases*. These phases are periods of time that aggregate together to form the entire project. The key contribution of the model is to allow entity costs and capacities to vary across phases. As before, an instance consists of a set of CO_2 emitting plants (sources), a set of storage reservoirs (sinks), a candidate pipeline, and project phases. Capture and injection costs, capacities, and credit amounts are able to have different values for each phase. We introduce the new multi-phased CCS infrastructure design model below as a MILP.

Instance Input Parameters:

Variable	Description
S	Set of sources
R	Set of reservoirs
I	Set of vertices (S, R, and pipeline junctions)
K	Set of candidate pipeline components
C	Set of pipeline trends
T	Set of project phases
V_{it}^{src}	Unit cost to capture from source i in phase t (\$/ton)
V_{jt}^{res}	Unit cost to inject in reservoir j in phase t (\$/ton)
α_{kc}	Unit cost to transport on pipeline component k with trend c (\$/ton)
β_{kc}	Annualized cost to build pipeline component k with trend c (\$M/yr)
Q_{it}^{src}	Annual CO_2 emission rate at source i in phase t (ton/yr)
Q_{j}^{res}	Total lifetime capacity of reservoir j (ton)
Q_{jt}^{res}	Annual capacity of reservoir j in phase t (ton)
Q_{c}^{min}	Minimum annual capacity of pipeline trend c (ton/yr)
Q_{c}^{max}	Maximum annual capacity of pipeline trend c (ton/yr)
N_t	Number of years in phase t (years)
G_t	Annual target CO_2 capture amount during phase t (ton/yr)

MILP Decision Variables:

Variable	Description
$y_{kct} \in \{0,1\}$	Indicates if pipeline k with trend c is built in phase t
$a_{it} \in \mathbb{R}_{\geq 0}$	Annual amount of CO_2 captured at source i (ton/yr)
$b_{jt} \in \mathbb{R}_{\geq 0}$	Annual amount of CO_2 injected in reservoir j in phase t (ton/yr)
$x_{kct} \in \mathbb{R}_{\geq 0}$	Annual amount of CO_2 in pipeline k with trend c in phase t (ton/yr)
$p_{kct} \in \mathbb{R}_{\geq 0}$	Annual CO_2 capacity of pipeline k with trend c in phase t (ton/yr)

The MILP is driven by the objective function representing the cost of the full project across all phases:

$$\min \overbrace{\sum_{i\in S}\sum_{t\in T} V_{it}^{src} a_{it} N_t}^{\text{capture cost}} + \overbrace{\sum_{k\in K}\sum_{c\in C}\sum_{t\in T}\left((\alpha_{kc} p_{kct} + \beta_{kc} y_{kct})\sum_{\tau\geq t} N_\tau\right)}^{\text{transport cost}} + \overbrace{\sum_{j\in R}\sum_{t\in T} V_{jt}^{res} b_{jt} N_t}^{\text{storage cost}}$$

Subject to the following constraints:

$$Q_c^{min} y_{kct} \leq p_{kct} \leq Q_c^{max} y_{kct}, \forall k \in K, \forall c \in C, \forall t \in T \tag{3.6}$$

$$x_{kct} \leq \sum_{\tau\leq t} p_{kc\tau}, \forall k \in K, \forall c \in C, \forall t \in T \tag{3.7}$$

$$\sum_{\substack{k\in K:\\ src(k)=n}} \sum_{c\in C} x_{kct} - \sum_{\substack{k\in K:\\ dest(k)=n}} \sum_{c\in C} x_{kct} = \begin{cases} a_{nt} & \text{if n} \in \text{S} \\ -b_{nt} & \text{if n} \in \text{R} \\ 0 & \text{otherwise} \end{cases}, \forall n \in I, \forall t \in T \tag{3.8}$$

$$a_{it} \leq Q_{it}^{src}, \forall i \in S, \forall t \in T \tag{3.9}$$

$$a_{i(t-1)} \leq a_{it}, \forall i \in S, \forall t \in T (t > 0) \tag{3.10}$$

$$\sum_{t\in T} N_t b_{jt} \leq Q_j^{res}, \forall j \in R \tag{3.11}$$

$$b_{jt} \leq Q_{jt}^{res}, \forall j \in R, \forall t \in T \tag{3.12}$$

$$\sum_{i\in S} a_i \geq G_t, \forall t \in T \tag{3.13}$$

The objective function calculates and minimizes the total project's infrastructure cost across all phases of the project, similarly to what is done in the single-phase version. Constraint 3.6 ensures that a pipeline is built before transporting CO_2 and that the pipeline's capacity is appropriate for the amount of flow. Constraint 3.7 ensures the new and existing pipeline capacity is sufficient for the amount of CO_2 to be transported. Constraint 3.8 enforces conservation of flow at each internal vertex. Constraint 3.9 ensures that amount of CO_2

captured at each source is limited by the source's emission rate. Constraint 3.10 ensures that capture amounts do not decrease between consecutive phases. Constraint 3.11 limits lifetime storage for each reservoir by its maximum capacity. Constraint 3.12 limits the annual storage amount in each reservoir to the phase's annual capacity of the reservoir. Constraint 3.13 ensures each phase's the total capture amount meets the phase's target.

The multi-phased model can be used to give a more accurate depiction of the implementation of CCS infrastructure across time periods. These new abilities are listed below.

1. Allows for the alteration of tax credits over time. Described in Chapter 1 and again in Chapter 4, tax policies surrounding CCS are constantly changing, in order to accurately represent these changes a multiple-phased model is required.
2. Allows us to manually determine availability of capture and storage locations. We need to be able to model when power plants close as well as if it takes a plant a longer time to join the network as building infrastructure takes time.
3. Allows us to include the reduction of capture costs. As time goes on scientists are generating cheaper and more efficient CO_2 capture solutions [40], which will make CCS more economically feasible for power plants, we can only display the effects of reductions in these costs model them over time.
4. Model the changes in goals for CO_2 capture. With many countries and companies aiming to be Carbon neutral, the assumption is more CO_2 will need to be captured to achieve this goal, a phased model is needed to show increases in CO_2 capture goals.

These improvements allow users to model more complex scenarios while generating higher accuracy solutions based on the current information that is known surrounding CCS. In order to correctly model the effect that changes to tax policy surrounding CCS projects, a multi-phased model is needed. Not only in scenarios when tax policies change, but to model current policy in which the amounts of tax credit are increasing and leveling off after a certain number of years. In addition, the infrastructure for these projects does not spring up over night. The pipelines connecting sources to sinks are generally going to be built incrementally, this can all be displayed when using the multi-phased model.

3.3 Model Discussion

The multi-phased model presented above is a generalization of an existing single-phase CCS infrastructure design model [27]. In the single-phase version of the model, the instance input parameters and MILP decision variables are constant throughout the entire project length while the objective of minimizing infrastructure cost remains the same. The infrastructure design for a multi-phase CCS project can be naïvely approximated by sequential solutions of the single-phase model:

1. Find optimal infrastructure to support phase 1.
2. Mark opened infrastructure as purchased and find optimal additional infrastructure needed to support phase 2.
3. Repeat for remaining phases.

The limitation of this iterative approach is that infrastructure deployed in each phase is done without consideration given to future phases. This can lead to sub-optimal solutions for the full project. Instead of designing infrastructure one phase at a time, the multi-phased model concurrently optimizes infrastructure for all phases. This results in infrastructure designs that are globally optimal for the full project instead of locally optimal for the individual phases. The multi-phased model leverages three techniques for generating globally optimal solutions that improve upon iterative single-phase solutions:

- *As-needed Infrastructure Deployment.* In single-phase models, any infrastructure that is opened needs to be opened during the entire (single-phased) project. Alternatively, in the multi-phased model, infrastructure can open (and close) over the course of the project. This flexibility can lead to cost savings when infrastructure is only opened when necessary. Figure 3.1 presents a scenario that illustrates this cost saving.

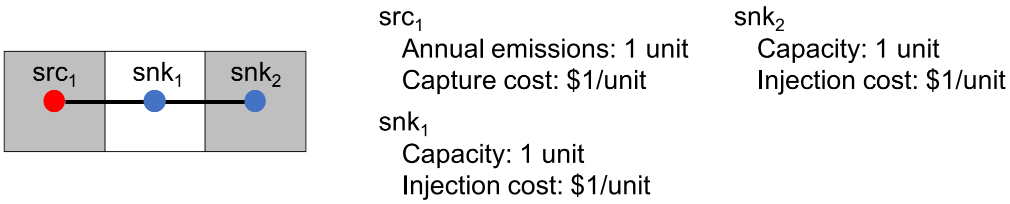
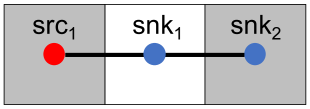


Figure 3.1: Consider the objective of capturing one unit per year for a two year project. The single-phased and multi-phased solutions will both capture all emissions from the source and fill all capacity in both sinks. However, the single-phased solution will deploy all sources and sinks at once, and build a one-capacity pipeline from src_1 to snk_1 and one half-capacity pipeline from snk_1 to snk_2. Alternatively, the multi-phased solution will build a one-capacity pipeline from src_1 to snk_1 and fill snk_1 in the one-year phase one followed by an additional one-capacity pipeline from snk_1 to snk_2 to fill snk_2 in the one-year phase two. This will result in a cheaper solution since pipeline cost functions are subadditive (i.e., two one half-capacity pipelines are more expensive than a single one-capacity pipeline.)

- *Infrastructure Overprovisioning.* The aggregate of optimal single-phased solutions does not allow for overprovisioning early phases in anticipation of future phases. Since the multi-phased model concurrently optimizes all phases, a pipeline can be deployed in one phase with a larger capacity (i.e., diameter) than is necessary if a larger capacity will be required in a future phase. This can provide beneficial economies of scale by constructing a single large pipeline in an early phase instead of multiple smaller pipelines across multiple phases. Figure 3.2 presents a scenario that illustrates the power of overprovisioning in early phases.

- *Targeted Routing.* Optimal pipeline routing for a single phase without consideration given to future phases will not necessarily result in an optimal solution across all



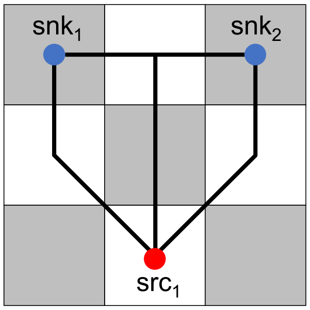
src_1
Annual emissions: 2 units
Capture cost: \$1/unit

snk_1
Capacity: 2 units
Injection cost: \$1/unit

snk_2
Capacity: 1 unit
Injection cost: \$1/unit

Figure 3.2: Suppose there are two available pipeline capacities: 1 unit per year and 2 units per year. Consider a two-phased scenario with an objective of capturing one unit in the first one-year phase and two units in the second one-year phase. Optimal single-phased solutions for each of the phases in isolation would result in a one-capacity pipeline connecting the source to snk_1 in phase 1 and a two-capacity pipeline connecting the source to snk_1 and one-capacity pipeline connecting snk_1 to snk_2 in phase 2. This would require building two pipelines over the life of the project between the source and snk_1. Alternatively, the optimal multi-phased solution would build a single two-capacity pipeline between the source and snk_1 initially in phase 1. This pipeline would be overprovisioned for phase 1, but would not require new construction in phase 2.

phases. Instead, it may be advantageous to select a routing that is sub-optimal for the current phase, but leads to cheaper pipeline networks in subsequent phases. By concurrently optimizing all phases, the multi-phase model will find globally optimal pipeline routes across all phases. Figure 3.3 presents a scenario that illustrates this advantage of concurrently optimizing pipeline routes across multiple phases.



src$_1$
Annual emissions: 1 unit
Capture cost: \$1/unit

snk$_1$
Capacity: 1 unit
Injection cost: \$1/unit

snk$_2$
Capacity: 1 unit
Injection cost: \$1/unit

Figure 3.3: Suppose pipeline costs are proportional to length. Consider a two-phased scenario with an objective of capturing one unit in the first one-year phase and one unit in the second one-year phase. Optimal single-phased solutions for each of the phases in isolation would result in a direct pipeline between the source and snk_1 and the source and snk_2 for a total pipeline length of 4.83. Alternatively, a cheaper pipeline network can be selected by using the shared pipeline from src_1 to the cell between snk_1 and snk_2, and then pipelines from that cell to snk_1 and snk_2 for a total pipeline length of 4.

CHAPTER FOUR

CASE STUDY

The multi-phased model can be used to model deployment scenarios to give power plants, owners of reservoirs, and policy makers better insight into how changes in policy can influence CO_2 capture amounts and deployment strategies. In this case study we explore the impacts of tax credit modifications on the feasibility of CCS projects in California and Kansas. We use the multi-phased model to determine deployment infrastructure for various credit portfolios. The goal of this case study is to determine how changes to tax credit amounts and credit qualification periods impact project profit and the amount of CO_2 processed.

4.1 45Q Tax Credit

Section 45Q of the U.S. Tax Code, commonly referred to as 45Q, details a tax credit for operators who capture and store CO_2 in a qualified manner. The tax credit was originally introduced in 2008 by the Energy Improvement and Extension Act to incentivize the adoption of CCS across many industries [41]. 45Q initially provided a \$20 credit for captured CO_2 permanently stored in a saline reservoir, and \$10 credit for CO_2 used for direct economic benefit, most commonly enhanced oil recovery (EOR) [1]. These credits were to increase to \$23.82 and \$11.91 respectively by 2020. Credit would be available until a CO_2 emitting plant had captured and stored 75 million tons of CO_2, with a plant being required to capture at least 500,000 metric tons per year [42].

45Q was updated in 2018, increasing the credits to \$31.77 for saline stored and \$20.22 for

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[1] Enhanced oil recovery is the process of injecting CO_2 into oil fields to increase production. Oil fields will pay for CO_2 for this purpose, so the capture facility will collect proceeds from sale of CO_2 to the oil field in addition to any tax credits.

EOR. These credits increase to \$50 and \$35 respectively in 2026, with the credits increasing after 2026 in accordance with inflation. These credits are available to a plant for 12 years after the facility begins capturing. Plants that emit at least 500,000 metric tons annually must capture at least 500,000 metric tons per year or 25,000 metric tons for plants that emit less. Capture efforts must commence by January 1, 2026.

As of 2021 there are multiple proposals for changes to 45Q, the primary proposal being the Coordinated Action to Capture Harmful Emissions (CATCH) Act. The CATCH Act would increase the credit amounts to \$85 for saline stored and \$60 for EOR [43]. In this case study, we use the new multi-phased model and real CCS infrastructure data from California and Kansas to quantify the impacts of modifications to the 45Q tax credit. The modifications we consider are (1) additional credit amounts and (2) increased credit qualification periods. We quantify the impacts of modifications by using (1) project cost and (2) project CO_2 capture amounts.

4.2 Data Description

Data for this case study was collected as part of the US Department of Energy funded Carbon Utilization Storage Partnership (CUSP) project. California and Kansas data sets both contain sets of CO_2 emitting sources from various industries including coal power, natural gas power, cement production, ethanol production, fertilizer production, and petroleum refineries. Sinks include both saline and EOR locations. EOR sales proceeds vary by location and values were estimated by subject matter experts.

The California data has 75 CO_2 sources, that emit 58.4479 $MtCO_2$/yr. Natural gas power plants account for 27.47 $MtCO_2$/yr, with 9.07 $MtCO_2$/yr coming from combined heat and power, 7.04 $MtCO_2$/yr from cement, 9.6 $MtCO_2$/yr from hydrogen, 4.6 $MtCO_2$/yr from petroleum, and 0.57 $MtCO_2$/yr from ethanol. 100 sinks were considered for long term CO_2 storage in California. These sinks have the total storage capacity of 37,103.91 $MtCO_2$. This allows for ample storage of the CO_2 emitted by the 75 sources. 36,270.15 $MtCO_2$ of this total capacity is located in the 91 Saline reservoirs while 833.76 $MtCO_2$ is located in nine EOR reservoirs. The geographic distribution of sources and sinks from the California data set is presented in Figure 4.1.

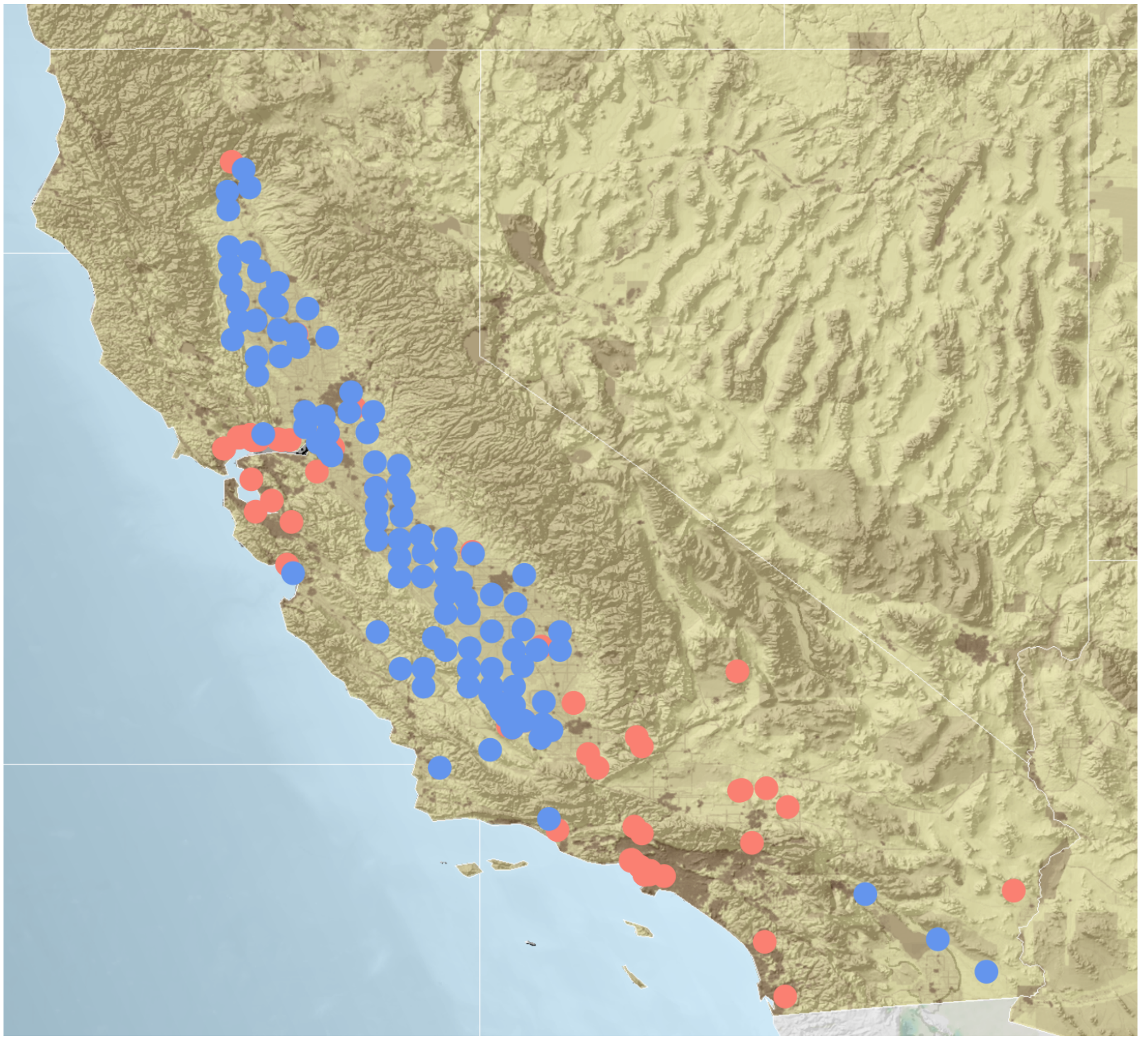

Figure 4.1: Geographic distribution of source (red) and sink (blue) locations in the state of California.

The Low Carbon Fuel Standard (LCFS) is an additional tax incentive for CCS available in California [44]. LCFS credit qualification amounts vary across industries and credit amounts are dependent on current market values. For example, ethanol production facilities receive 100% of the full credit value, while petroleum refineries receive roughly 80% of the full credit value. Since the credit was created in 2017, it's value has ranged from \$70 to \$218, but has not dipped lower than \$158 since 2019 [45]. In our simulations we used recommendations from subject matter experts to set the full LCFS credit value to be a conservative \$100. Since the actual LCFS credit amount received by individual sources depends on numerous factors including industry type, sources in our simulations received a range of LCFS credit values.

The Kansas data has 26 sources emitting a total of 33.76 $\mathrm{MtCO_2/yr}$. 22.14 $\mathrm{MtCO_2/yr}$ is from coal burning power plants. Petroleum refineries make up another 3.88 $\mathrm{MtCO_2/yr}$, the rest made up by cement, ethanol, fertilizer, and natural gas plants. Kansas contains 56 potential sinks with a total storage capacity of 1,505.05 $\mathrm{MtCO_2}$. 46 of the 56 storage locations are for EOR, but only make up 126.05 $\mathrm{MtCO_2}$ of the total capacity while the 10 Saline reservoirs account for 1379 $\mathrm{MtCO_2}$ of total storage. The geographic distribution of sources and sinks from the Kansas data set is presented in Figure 4.2.

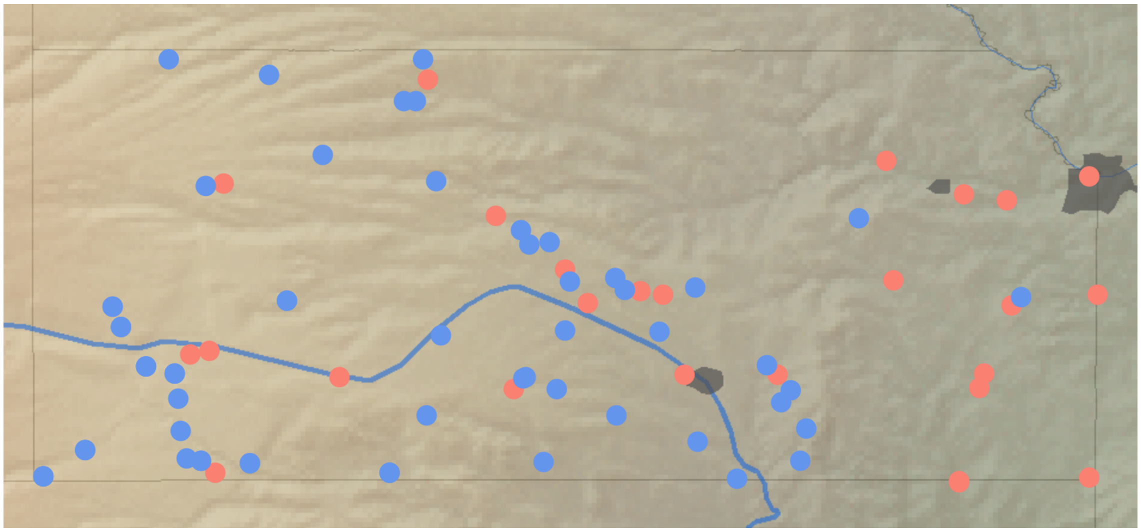

Figure 4.2: Geographic distribution of source (red) and sink (blue) locations in the state of Kansas.

4.3 Study Descriptions

Our study focused on two states, California and Kansas. For both studies we assumed a 20-year project length, as advised by subject matter experts. The current 45Q tax credit qualification period is 12 years. Meaning, projects can only receive the 45Q tax credits for a total of 12 years, even if the project extends beyond 12 years.

In both California and Kansas, we independently considered increases in tax credit amount and extensions to the credit qualification periods (CQP). We considered the current 45Q credit amounts as the baseline for our study: \$50 per ton for saline storage and \$35 per ton for EOR storage. We considered additional credit amounts ranging from \$0 to \$25 in \$5 dollar increments, and from \$25 to \$100 in \$25 increments. When credit amounts were changed, the CQP was fixed at the current 45Q period of 12 years for the 20-year project.

The study then considered extensions of the CQP from 12 years to 20 years in increments of 2 years. In these scenarios, the credit amounts were fixed at current 45Q levels of \$50 per ton for saline storage and \$35 per ton for EOR storage. The number of years that this credit was received corresponded to the CQP for that scenario. So for the first scenario, those credit amount were received for 12 years, and then no credit was received for the remaining 8 years of the project. This ratio of credit-receiving years to credit-free years is what we changed from 12/8 up to 20/0 in increments of 2 years.

In Kansas we included an additional study involving additional credits and extended CQPs. The need for the last study was established while running scenarios. At this time we realized that the extensions of credits were not sufficient to capture a significant portion of Kansas's CO_2 as current credits are not large enough to cover the costs of capturing CO_2 at many of the largest plants in Kansas. In order to account for the capture costs, we included additional credits of \$10 and \$20 and applied the credits in conjunction with the CQP extensions. Extensions were applied from 12 to 20 years in increments of 2 years the same way from the original CQP study.

4.4 SimCCS

The Scalable Infrastructure Model for CCS (*SimCCS*) is a popular CCS infrastructure design software based on integer linear programming models [26]. *SimCCS* ingests capture, storage, and transport data and formulates a cost-minimizing MILP. *SimCCS* then uses IBM's CPLEX optimization software to solve the MILP [46]. The solution is then parsed by *SimCCS* and displayed for the user in terms of costs, capacities, and geospatial results. *SimCCS*'s open-source nature encourages modifications and extensions to the *SimCCS* framework. We implemented the new multi-phased model and integrated it into *SimCCS*. This required modifying *SimCCS*'s data reading functions to account for multiple parameter values across various phases as well as modifying the solution parsing and display process. This enabled the use of *SimCCS* for this specific 45Q study, but will also enable future phased study efforts.

4.5 Results

We have included tables and graphs to display the impacts of our study and how changes to tax policies can be used to incentivize CCS. In all of these studies we mention capture amounts and profits. Capture amounts are figures that represent $MtCO_2$ being captured and stored in geologic reservoirs. Profits represent amounts paid to industrial sources for capturing and storing CO_2 that would otherwise be emitted into the atmosphere. The money paid to industrial sources is given as tax credits, meaning that profits are costs for the government and the taxpayer. We note that all of our studies were run with *SimCCS*. Each study was run within a 5% margin of error to the optimal solution. When running CPLEX it displays an estimated margin of error from the optimal solution, and allows a user to terminate a run before the optimal value is reached.

Table Key

CQP - Credit Qualification Period

Y_{NC} - Years during study without credit

LCFS - Amount of LCFS credit

S_C - Amount of credit per ton for storage in a saline reservoir

EOR_C - Amount of credit per ton for EOR utilization

A_C - Credit in Addition to Tax Credit 45Q

CAP - Amount of CO_2 Captured and Stored in $MtCO_2$

$PROFIT$ - Profit \$M

CAP_Y - Amount of yearly CO_2 Captured and Stored in $MtCO_2$/yr

$PROFIT_Y$ - Amount of yearly profit

Chart Key

All studies are based on a 20 year project length

All entries with associated dollar amounts are in billions of dollars

All entries with associated capture amounts are in $MtCO_2$

xC - A study with x years of credit and $(20 - x)$ years without credit

xAC - A study with 12 years of credit and 8 years without credit and \$$x$ additional credit

xC_yAC - A study with x years of credit and $(20-x)$ years without credit and \$$y$ of additional credit

4.5.1 California Results

Results for the California scenarios are presented in Table 4.1. The scenarios present are the additional credit amounts and the CQP extensions. CQP indicates the number of years that credit was received and Y_{NC} indicates the number of years that no credit was received by industrial sources. The baseline credit amounts from the 45Q study of $50 for saline storage and $35 for EOR storage were used. In California LCFS credits, as described in Section 4.2, are received in both phases. A_C represents additional credit. CAP represents the amount of CO_2 captured and stored, PROFIT represents profit for industrial sources.

Table 4.1: Table to describe the CQP with additional credit study on the profits and captured CO_2 in California

CQP	Y_{NC}	LCFS	S_C	EOR_C	A_C	CAP	$PROFIT$
12	8	100	50	35	0	375.566	$11,837.10
12	8	100	50	35	5	375.566	$12,959.63
12	8	100	50	35	10	391.852	$14,113.19
12	8	100	50	35	15	413.33	$15,296.59
12	8	100	50	35	20	413.33	$16,536.84
12	8	100	50	35	25	413.33	$17,779.98
12	8	100	50	35	50	518.536	$24,475.37
12	8	100	50	35	75	607.288	$32,999.13
12	8	100	50	35	100	1017.008	$45,236.47
12	8	100	50	35	0	375.566	$11,829.34
14	6	100	50	35	0	375.566	$13,186.88
16	4	100	50	35	0	391.852	$14,563.60
18	2	100	50	35	0	412.2005	$15,296.59
20	0	100	50	35	0	412.2005	$17,932.48

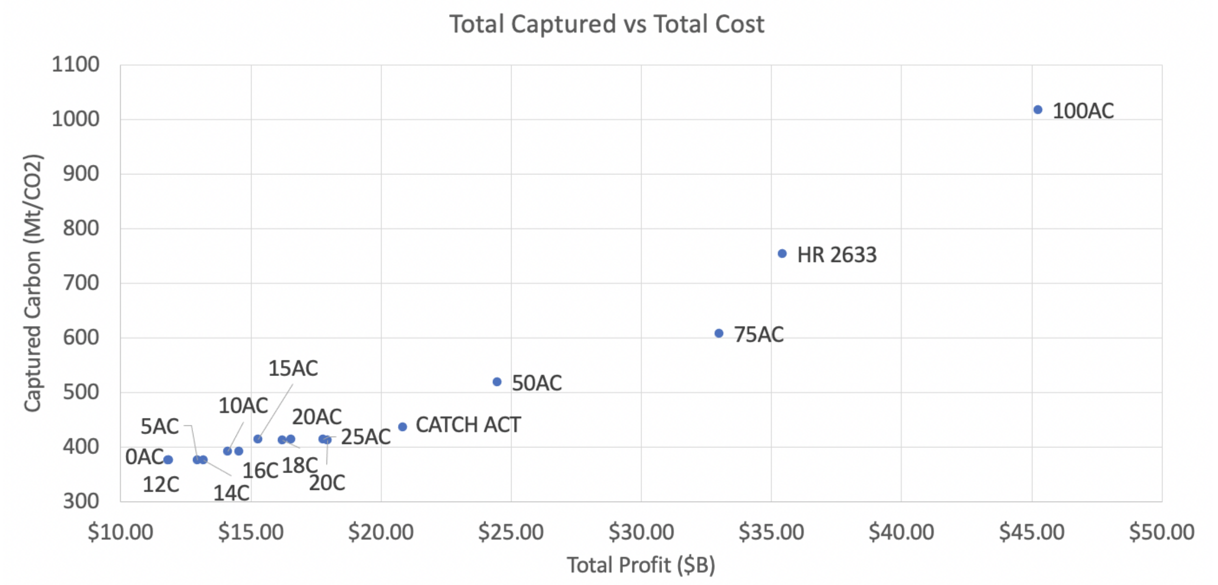

Figure 4.3: A comparison of total profit and amount of CO_2 captured for the state of California. 20AC indicates a scenario with $20 per ton additional credit and 20C indicates a scenario with 20 years of credit qualification period. CATCH ACT and HR 2633 indicate static scenarios representing proposals to change 45Q discussed in Section 4.6

The California data had similar capture and profit output across the additional credit and CQP study up to the $25 additional credit mark, shown in Table 4.1 and Figures 4.6 and 4.4. Our studies also found that at the maximum CQP of 20 years, that slightly less CO_2 was captured than at the added credit of $25, while the project with the higher CQP realized higher profits. All of this can be seen in Table 4.1, and visualized in Figures [4.4 - 4.7]

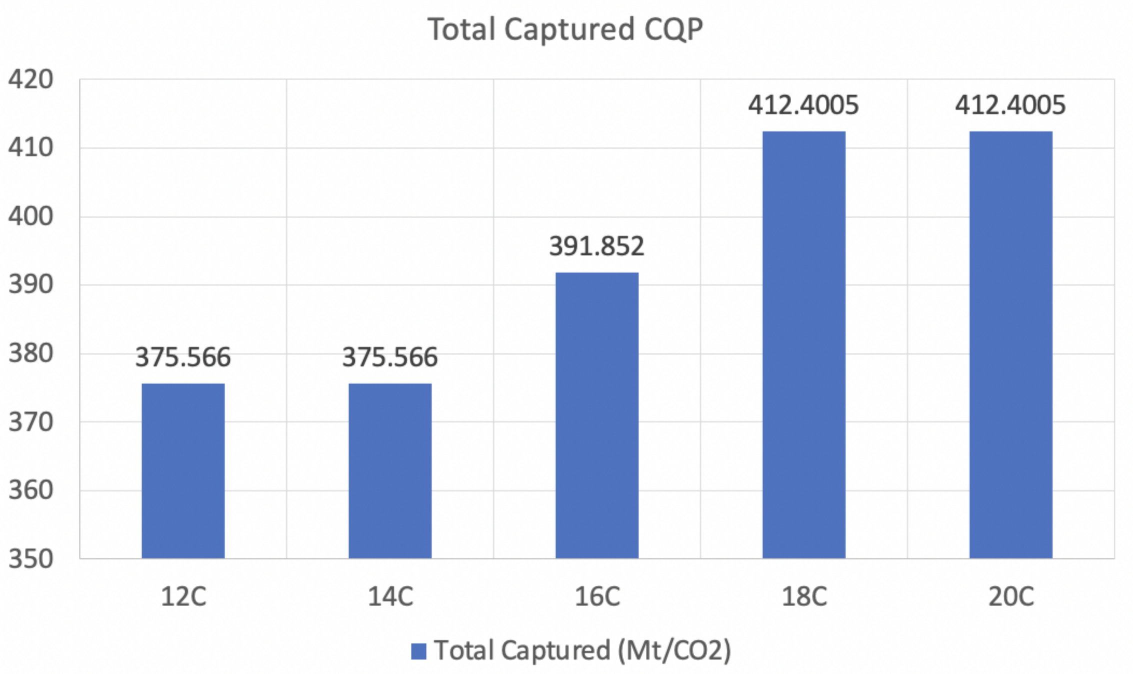

Figure 4.4: A comparison of total captured for the California CQP study.

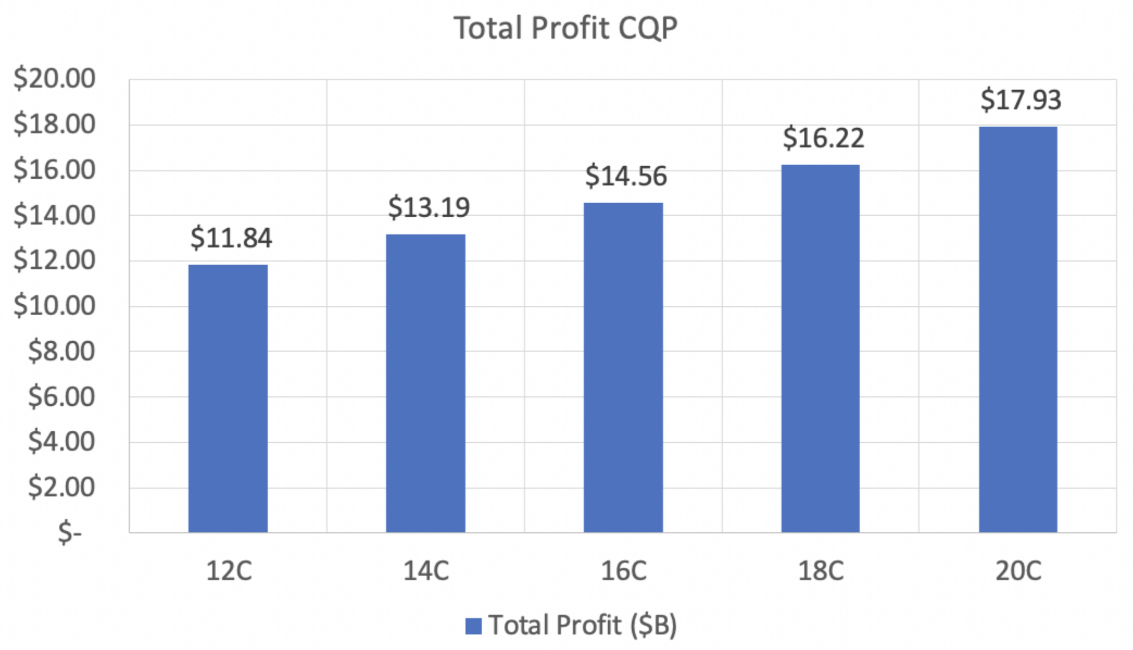

Figure 4.5: A comparison of total profit for the CQP study in California.

The maximum amount of CO_2 that could potentially be captured in California is about 58 Mt/CO_2 per year as stated in Section 4.2. Over the course of a 20 year timeline this is equivalent to about 1,160 Mt/CO_2. Our study showed that using only the baseline 45Q credit amounts, \$50 per ton for saline and \$35 per ton for EOR, around 32% of the CO_2 was captured, resulting in almost \$12B of profit. The CQP studies show jumps from the 32% amount (375.566 MtCO_2) to 391.82 MtCO_2 and then again to 412.4 MtCO_2, about 35% of the total amount. The profit generated for the scenario that captures 412.4 MtCO_2 is around \$18B. Credit amounts increase linearly, while capture amounts increase more similarly to steps on a staircase, shown in Figures 4.4 and 4.5. The increased profits amount to a 3% increase in total CO_2 captured. Which is a modest increase for the additional \$6B dollars in government tax credit that it would require to accomplish.

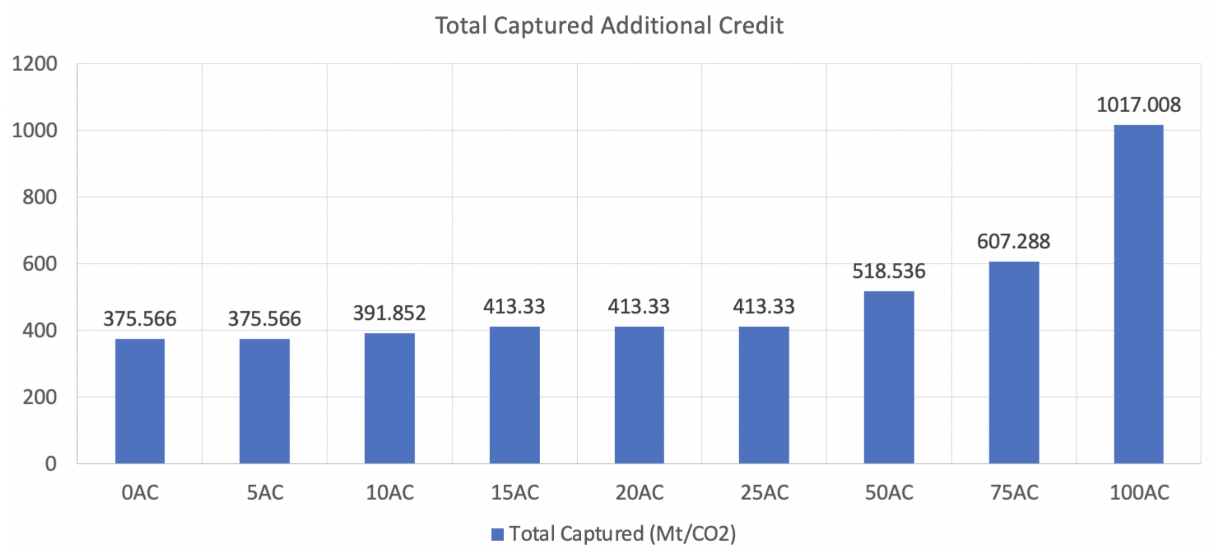

Figure 4.6: A comparison of total captured for the additional credit study in California.

The additional credit study, shown in Figures 4.6 and 4.7 shows large increases in CO_2 captured. The initial data point in the study, 12 years of credit and 8 years with no

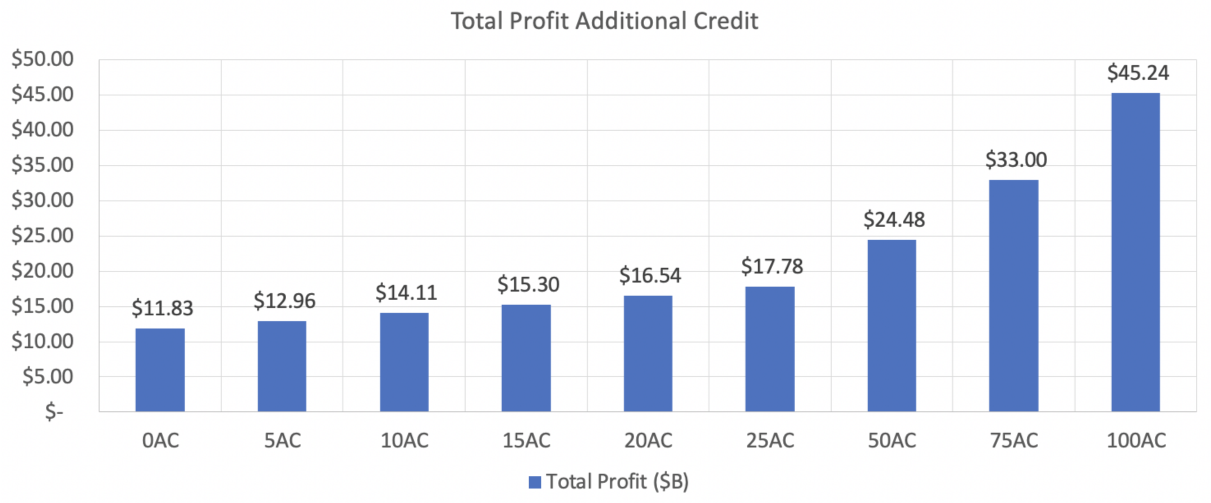

Figure 4.7: A comparison of total profit for the additional credit study in California.

credit captures 375.566 $MtCO_2$ with a profit of almost \$12B[2]. The study hits what looks like a local maximum from \$15 to \$25 of additional credit but is able to break out at \$50 additional credit, shown in Figure 4.6. The \$50 additional credit captures 518.536 $MtCO_2$. Following that the study with \$100 of additional credit given captures 1017.008 Mt/CO_2 which amounts to 87% of the total CO_2 emitted. Admittedly this study would result in a profit of about \$60B, which is a very high price tag for CO_2 capture incentives. Depending on California's emission targets credits may need to be raised in order to capture a larger portion of the available CO_2. Shown in the above graphs, with the correct combination of CQP and additional credit, California can achieve most capture targets that they would like to set.

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[2] The base case of 12 years of credit and 8 years of no credit with no additional credit is the same across the additional credit and the CQP studies.

4.5.2 Kansas Results

Results for the Kansas scenarios are presented in Table 4.2. The scenarios present are the additional credit amounts, CQP extensions, and CQP extension with additional credits. CQP indicates the number of years that credit was received and Y_{NC} indicates the number of years that no credit was received by industrial sources. The baseline credit amounts from the 45Q study of \$50 for saline storage and \$35 for EOR storage were used, when credits were being received. The amount of credit in addition to the baseline A_C is also shown. CAP represents the amount of CO_2 captured for that scenario and PROFIT represents the cost of the project (i.e., the total system profit).

Table 4.2: A table that describes the effects of the additional credit, CQP, and CQP with additional credit studies on the profits and captured CO_2 in the state of Kansas

CQP	Y_{NC}	S_C	EOR_C	A_C	T_{CAP}	T_{PROFIT}
12	8	50	35	0	82.50	\$1,080.41
12	8	50	35	5	108.25	\$1,354.37
12	8	50	35	10	108.65	\$1,679.39
12	8	50	35	15	114.80	\$2,011.92
12	8	50	35	20	114.80	\$2,355.65
12	8	50	35	25	114.80	\$2,700.72
12	8	50	35	50	335.00	\$6,177.64
12	8	50	35	75	613.55	\$12,375.89
12	8	50	35	100	674.95	\$22,237.04
12	8	50	35	0	82.50	\$1,080.41
14	6	50	35	0	114.80	\$1,420.44
16	4	50	35	0	114.80	\$1,817.12
18	2	50	35	0	114.40	\$2,212.13

20	0	50	35	0	114.40	$2,612.40
12	8	50	35	10	108.65	$1,679.39
14	6	50	35	10	114.80	$2,219.48
16	4	50	35	10	114.80	$2,375.52
18	2	50	35	10	280.50	$3,254.89
20	0	50	35	10	334.80	$4,819.18
12	8	50	35	20	114.80	$2,355.65
14	6	50	35	20	114.80	$3,029.02
16	4	50	35	20	334.80	$4,400.94
18	2	50	35	20	339.00	$6,311.06
20	0	50	35	20	363.60	$8,281.33

The results from the extended CQP in Kansas showed that the credit amount was not large enough in order for an extension of the credit to make a difference. This is displayed by the cluster of points towards the bottom left of the chart in 4.8. Also in the aforementioned cluster of points exist the values from the additional credit study. Both of these sets of points get stuck at around the value 114.80 (Mt/CO_2). The CQP and the additional credit study get stuck at this point with 14 years of credit and 6 years of no credit and with $15 additional credit respectively. By adding credits to the credit study past the $25 mark, the MILP was able to capture more CO_2 shown in . In the CQP with additional credit study we found that capture amounts broke out of this point. The sticking point is also shown in Figure 4.9.

A closer look into the CQP with additional credit study, in Figure 4.11, shows steady upward growth for both studies. Rather than capping out at the 114.8 value, the CQP study with $10 additional credit reaches a value of 334.48 (Mt/CO_2) captured, while the $20

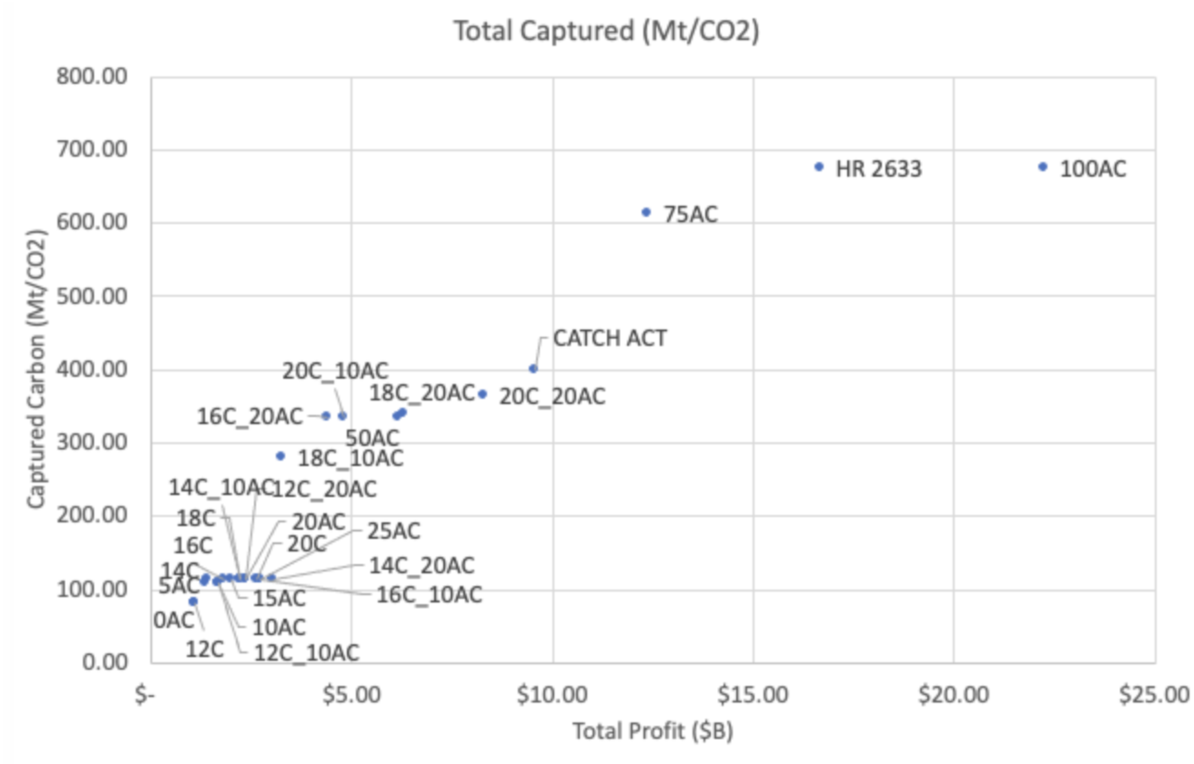

Figure 4.8: A comparison of total profit and amount of CO_2 captured for the state of Kansas. 10AC indicates a scenario with $10 per ton of additional credit, 16C indicates a scenario with 16 years of credit qualification period and 4 years with no credit, 14C_10AC indicates a scenario with 14 years of credit qualification period, 6 years with no credit and $10 per ton of additional credit. The remaining scenarios follow those formats with the exception of the CATCH ACT and HR 2633. The CATCH ACT and HR 2633 indicate static scenarios representing proposals to change 45Q discussed in Section 4.6

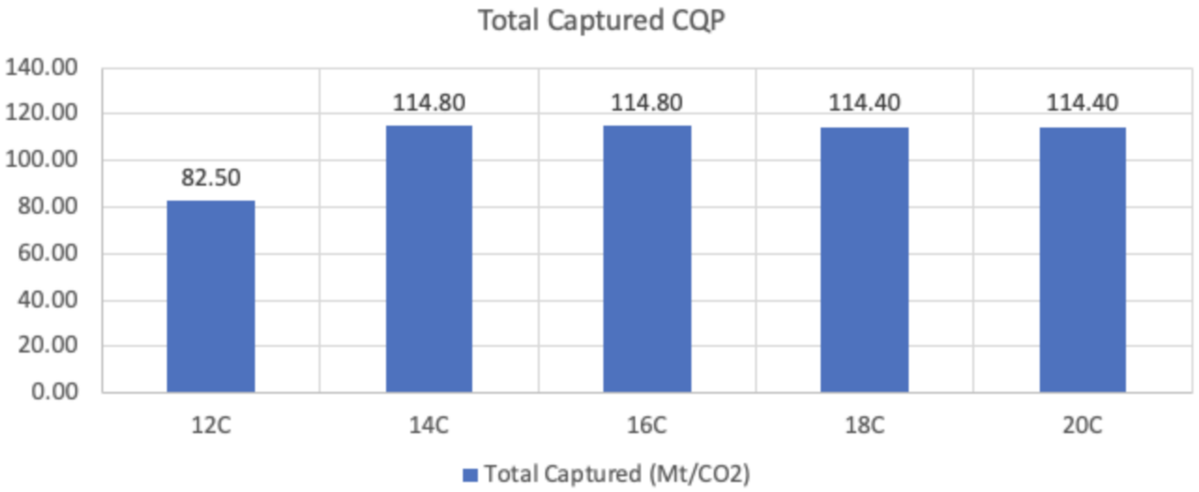

Figure 4.9: Total Capture amounts from the CQP study

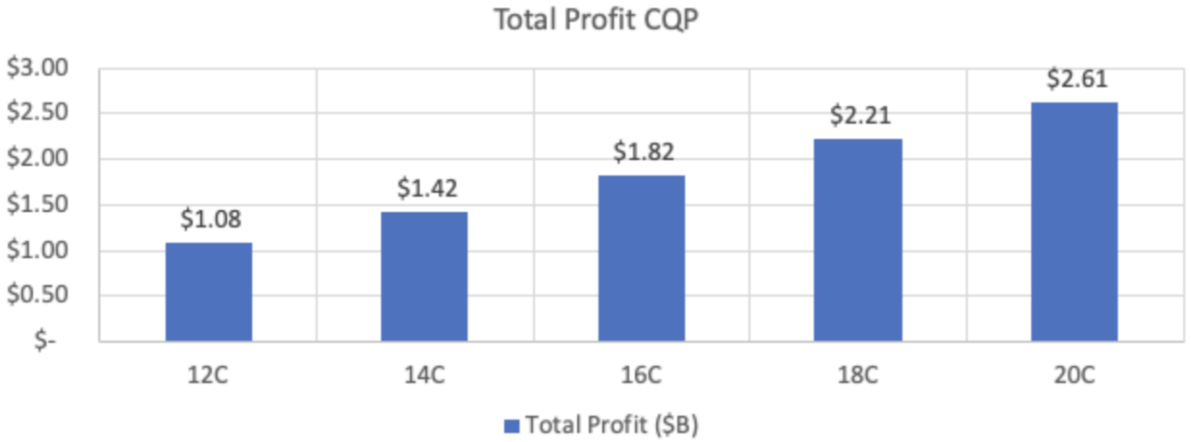

Figure 4.10: Total Profit from the CQP study

study captures that amount at its 14 years of credit 6 years without credit, and captures its maximum at \$363.60. The profit for the maximum captured amount in the \$10 study is \$4.8B while the profit for the maximum captured amount in the \$20 study is \$8.2B/\$, found in Figure 4.12. This is an example of a large increase in profit without a significant improvement in CO_2 captured. Demonstrating that 20 years of credit, with \$10 of additional credit, is a significantly better credit and CQP portfolio than 20 years of credit with \$20 of additional credit.

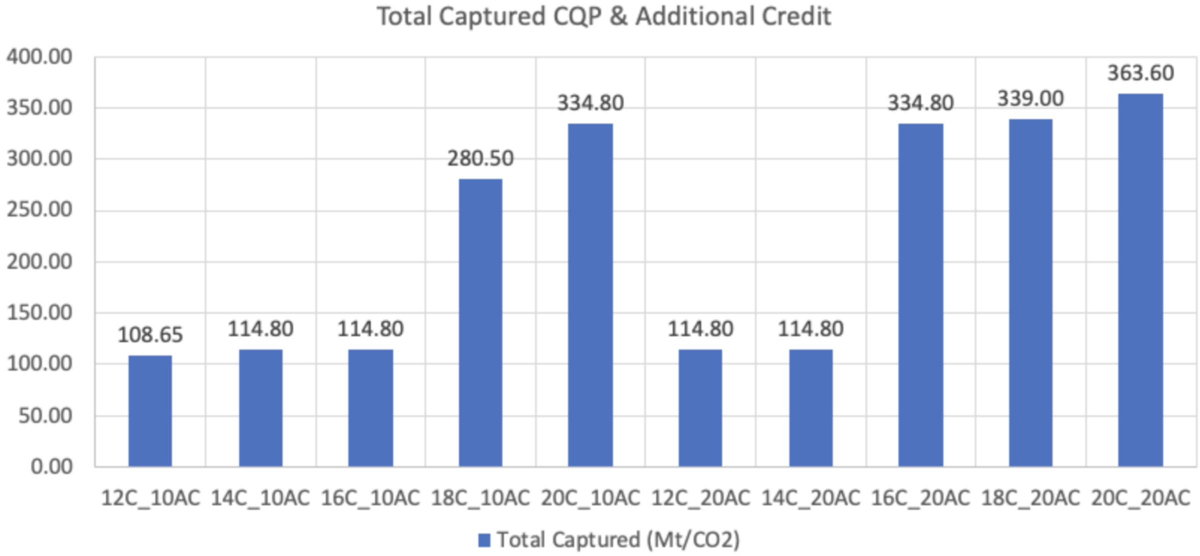

Figure 4.11: Total Capture amounts from the CQP with additional credit study

At the low end of the additional credit study, the Kansas models captured 82.50 Mt/CO_2 at the high end, captured 674.95 Mt/CO_2, costing \$1.08B and \$22.2B respectively, shown in Figures 4.13 and 4.14. The lowest amount captured was with the current 45Q tax credits and the largest with \$100 of additional credit. The maximum amount of CO_2 that could be captured per year in Kansas was 33.76 Mt/CO_2 making the upper bound for captured CO_2 675.2 Mt/CO_2. In the \$100 additional credit study (100AC) 99.9% of the available CO_2 was captured costing \$22.2B. In the \$75 additional credit study 613.55 Mt/CO_2 was

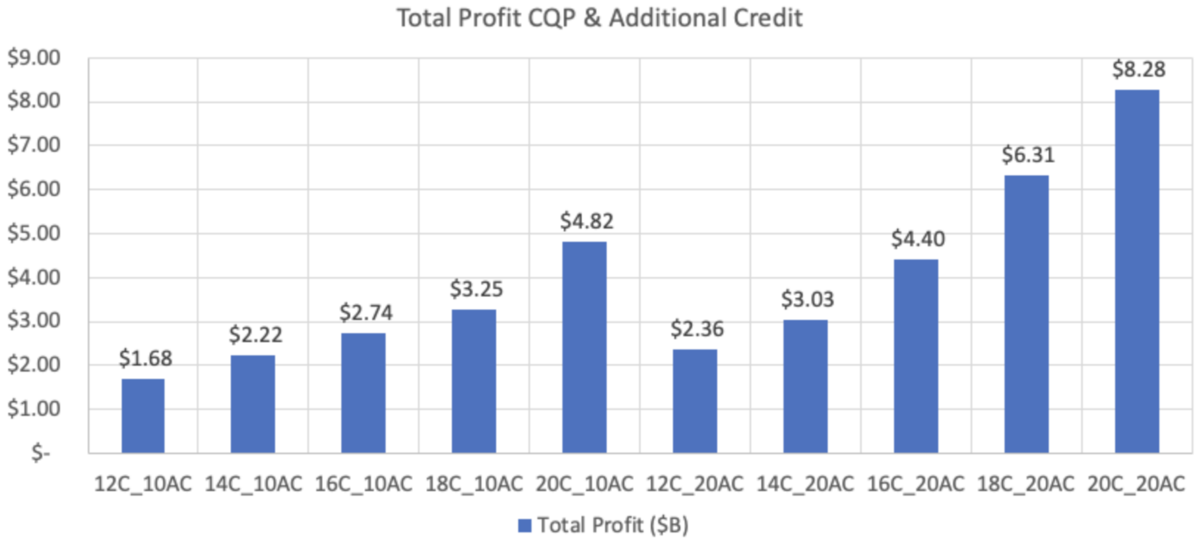

Figure 4.12: Total Profit from the CQP with additional credit study

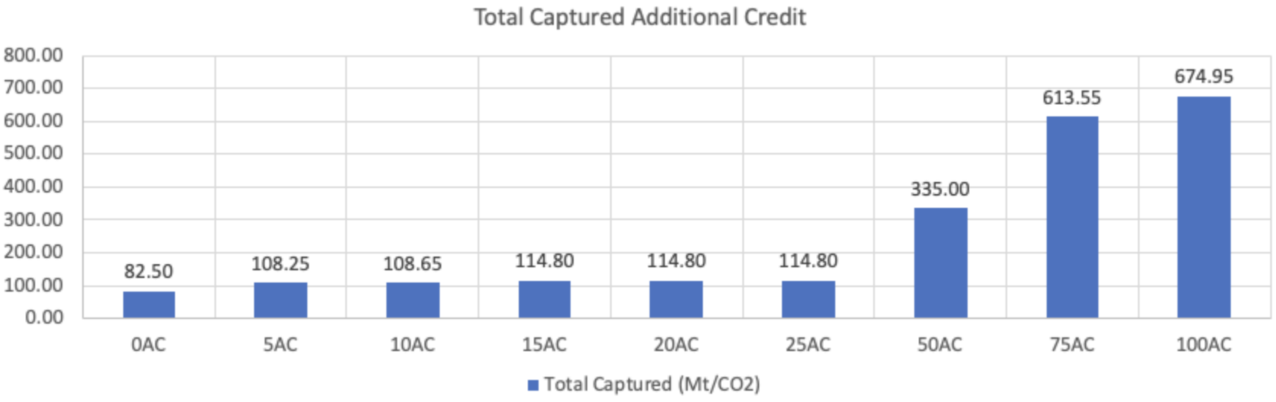

Figure 4.13: Total Capture amounts from the additional credit study

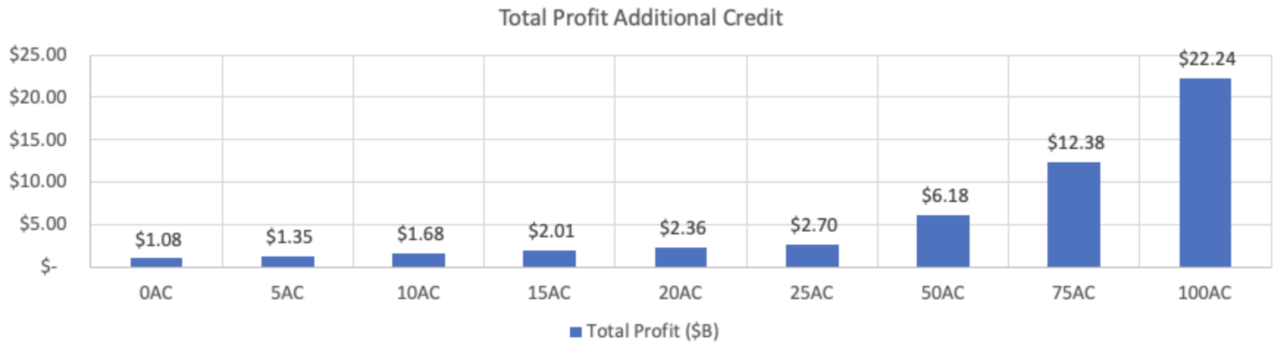

Figure 4.14: Total profit from the additional credit study

captured costing \$12.3B. This study was able to capture 90.8% of the total available CO_2. This \$75 additional credit study would result in \$10B profit reduction with respect to the 100AC study while still capturing 90% of Kansas's CO_2. Deciding between a \$75 and \$100 additional credit could be a potential trade-off policymakers would have to consider when generating optimal credit portfolios.

4.6 Impacts of Current Proposals to 45Q

There are currently seven proposals to amend 45Q [43]. Here we address two similar proposals and model their effects on the California and Kansas data. The first proposal is the Coordinated Action to Capture Harmful Emissions (CATCH) Act mentioned in Section 4.1. The CATCH Act does not change the credit's current time constraints. The CATCH Act increases the credit for saline stored CO_2 to be \$85, and increases credit for EOR utilization per ton of CO_2 to \$60.

The second is H.R. 2633 which aims to amend the Internal Revenue Code of 1986 to increase and expand the credit for CO_2 sequestration (HR 2633). HR 2633 removes the requirement to begin construction within a specified time period. HR 2633 also proposes an extension from the current 12 year limit on the credit qualification period to 20 years. HR 2633 increases the credit for saline stored CO_2 to be \$85, and increases credit for EOR utilization per ton of CO_2 to \$50.

Each proposal was run against the California and Kansas data. HR 2633 was run on a 20 year timeline and the CATCH Act was run on a 12 year timeline. These runs did not use the multi-phased model as these credits, if implemented, would become available immediately.

4.6.1 Proposal Results

Table 4.3 describes the results of the CATCH Act study and the HR 2633 study. These tables include the State name and Proposal title. The CQP column indicates how many years the industrial sources received credits. LCFS describes the additional credit received by sources located in California. S_C describes the amount of credit given to sources per ton of CO_2 captured and stored in saline reservoirs. EOR_C describes the amount of credit given per ton of CO_2 captured and stored in EOR reservoirs. CAP represents the amount of CO_2 captured for that scenario and PROFIT represents the cost of the project (i.e., the total system profit). CAP_Y represents the amount of $MtCO_2$ captured. $PROFIT_Y$ represents the amount of yearly profit generated for industrial sources.

Table 4.3: A table to describe the results of implementing two proposed amendments to 45Q in California and Kansas, the CATCH Act (An \$85 credit for saline storage and a \$60 credit for EOR storage), and HR 2633 (An \$85 credit for saline storage and a \$50 credit for EOR storage). These proposals are described in more detail in Section 4.6.

State	Proposal	CQP	LCFS	S_C	EOR_C	CAP	$PROFIT$	CAP_Y	$PROFIT_Y$
CA	CATCH	12	100	85	60	436.88	\$20,854.93	36.4	\$1737.91
CA	HR 2633	20	100	85	50	753.898	\$35,438.01	37.7	\$1,771.90
KS	CATCH	12	0	85	60	663.60	\$9,539.93	33.23	\$794.99
KS	HR 2633	20	0	85	50	675.20	\$16,662.48	33.76	\$833.12

In California and Kansas the HR 2633 proposal captured more CO_2 than the CATCH Act as seen in Table 4.3. This was expected as the credits in the HR 2633 were available for 20 years, while the CATCH Act's credits are available for 12.

In California and Kansas, the HR 2633 proposal captured more CO_2 year over year compared to the CATCH Act. This result occurs because the longer credit terms reduce the average capture cost over time, allowing for more sources and sinks to participate in the network. In Kansas the HR 2633 study captured 100% of the total CO_2 available for capture from industrial sources in our study. This happened in HR 2633 but not in the CATCH Act because the CATCH Act's larger credit amount for EOR storage led to higher EOR utilization. In turn this caused the MILP to not use the same saline reservoirs that allowed for the capture of some smaller sources in HR 2633. This demonstrates that with the correct additional credit and CQP, that most capture targets can be reached.

The effects of these studies relative to additional credit and CQP studies are shown in Figure 4.1 and Figure 4.2. The studies performed very well in comparison to the other studies, which was to be expected as neither of the two scenarios needed to pay for a secondary phase without credits.

4.7 Case Study Discussion

The analysis in Section 4.5 show that policy makers can optimize tax credits and CQPs to capture target amounts of CO_2. In Section 4.6.1 we demonstrated that tax credits can encourage CO_2 capture up to 100% of the total available CO_2 for capture in regards to the industrial sources in our study. It was also shown that scenarios find more optimal solutions through additional credit amounts rather than through increased CQPs. The extension of time to current policy may seem like a more pallet-able solution to the general public but after analysis it was more expensive and less effective than an increase in tax credits.

The majority of the experiments were set up in two phases, where tax credits (excluding

LCFS) were only available in the first phase. One of the constraints of the MILP was that capture amounts could not decrease across phases. This meant projects needed to earn enough revenue in their first phase to cover the expenses of capture in the second phase. The experiment set up and constraints led to capture amounts, with respect to total captured CO_2 each year, being static across phases.

All of the results trended upward as tax credits and qualification periods increased, which was consistent with our assumptions. The model was able to give insight into how potential changes to tax policy over time can influence CO_2 capture amounts. Current tax credits have not been as influential as desired and these results show that current tax credits are too low to incentivize wide spread adoption. Experiments with additional tax credits demonstrated that higher economic incentives could lead rationally acting agents to adopt CCS.

The modeled tax increases lead to the capture of 87% of the emitted CO_2 in California, and 100% of the emitted CO_2 in Kansas. These are vast improvements relative to the model's suggested CO_2 capture amounts with tax credit 45Q (32% and 12% respectively). These credits could lead to a reduction of hundreds of millions of tons of CO_2 emitted by each state over the lifetime of these projects.

CHAPTER FIVE

CONCLUSION

In this dissertation we have developed a system for multi-phased modeling of CCS infrastructure. We have demonstrated a need for this model by establishing deficiencies in the current model. The multi-phased model, implemented in $SimCCS$, creates optimal solutions for complex scenarios with changing constraints over time. We can use this model to guide us in the generation of scenarios that optimize credit and capture goals. These optimal solutions can be used by policy makers to influence credits to help achieve goals related to CO_2 reduction.

Future practical work could focus on expanding scenarios to more accurately match tax policy. Future scenarios could include the ramping of credits over time, the reduction in CO_2 capture costs, and the phased replacement of credits with taxes. Interested parties can also formulate potential scenarios in order to find the highest impact credits to generate the implementation of CCS infrastructure. Scenarios can be built based on arbitrary constraints to demonstrate the effectiveness of increased tax credits on CCS deployment. These scenarios could range from changing tax credits to lowered costs of carbon capture.

Future theoretical work could include expanding the multi-phased model to include constraints relative to specific source/sink pairings. This expansion would require a large reconstruction of the current MILP, as for most NOPs we are not certain as to which sources transport carbon to which sinks. Meaning we know source A captures x CO_2 and source B stores y CO_2, but it is not know how much of the CO_2 from x is stored in y. Quick, computationally efficient, ways to approximate the multi-phased model could also be developed, as has been done for the single-phase variant [47].

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