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Designing multi-phased CO_2 capture and storage infrastructure deployments

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ABSTRACT

CO_2 capture and storage (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 demonstrate the efficacy of our approach with theoretical analysis and an evaluation using real CCS infrastructure data.

1. Introduction

CO_2 capture and storage (CCS) is the process of capturing CO_2 from large point sources (e.g., power plants, cement manufacturers), transporting that CO_2 via dedicated pipelines, and then sequestering it in the subsurface [1]. In 2018, the Intergovernmental Panel on Climate Change suggested that least-cost pathways that limit the mean global temperature increase to 1.5 or 2 °C require capturing and storing up to 1,200 billion tonnes of CO_2 ($GtCO_2$) by 2100 globally [19,20]. Accomplishing this feat will require CCS infrastructure to handle up to 40 – 60 $GtCO_2$/yr of CO_2 injection [27]. However, as of 2020, existing CCS infrastructure could only support injecting 40 million tonnes of CO_2 per year (40 $MtCO_2$/yr, or 0.04 $GtCO_2$/yr) across nearly 40 projects [9]. Realizing target limits on global temperature increases will require a major investment in CCS infrastructure across many industries.

Planning the large scale deployment of CCS is challenging because it requires concurrently selecting which CO_2 sources to capture from, which locations to store the CO_2, and where to route the transportation pipelines. Large scale CCS projects will inevitably experience variability in their economic conditions, source and reservoir availability, and project objectives over their lifetimes. Many current CCS infrastructure modeling approaches assume a static environment, where the infrastructure design is optimized based on a snapshot of available sources, reservoirs, and their associated economic and capacity parameters that are assumed to remain constant for the entire length of the project. While static models may rely on reasonable assumptions for many applications, there are some where this static assumption is limiting:

1. 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.
2. Government policies, such as increased (or decreased) tax credits (e.g. continuation or increase in 45Q credits in the United States) or modified carbon taxes, that change during the lifetime of a project could lead to increased CCS participation from sources or reservoirs.
3. 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.
4. 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.
5. An increase (or decrease) over time in the target CO_2 capture amount for a CCS project, due to meeting phased capture objectives.

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

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linear program, 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 discuss the theoretical mechanism at play in the multi-phased model's operation and show how it is able to solve more scenarios than the single-phase model is able to solve. We also present an evaluation using real CCS infrastructure data showing that the multi-phased model is in fact able to determine cheaper infrastructure designs than the single-phase model when solving the same problem.

The remainder of this paper is organized as follows. Section 2 discusses relevant work related to infrastructure design and CCS specifically. Section 3 introduces the multi-phased CCS infrastructure design model and discusses its functionality. Section 4 presents the results of an evaluation aimed at quantifying the differences between the multi-phased and single-phase models. Section 5 summarizes the contributions, discusses limitations, and proposes future research efforts.

2. Related work

Optimization of the design of CCS infrastructure is a well-studied problem, with a variety of decision support models described in the literature. Tapia et al. (2018) provides a survey of many CCS decision support models focused on different components of the CCS supply chain and leveraging a variety of optimization techniques [23]. Mathematical programming, and specifically Mixed Integer Linear Programming (MILP), is one of the popular optimization techniques employed in CCS decision support models.

While most MILP-based CCS infrastructure models attempt to concurrently optimize capture, transport, and storage costs, many of the models do so without consideration given to the underlying geography (e.g., population centers, land ownership, topograph). Leonzio et al. formulated a model that assesses the efficacy of various capture technologies but assumes uniform transportation costs [8]. Mohd Nawi et al. introduced the Total Site CO_2 Integration tool that optimizes CO_2 capture and utilization along a predetermined pipeline route sending the remaining CO_2 to storage [15]. Wang et al. developed a decision tree to support matching sources with sinks that considers pipeline costs, but excludes detailed pipeline routing [24]. Zhang et al. does consider some degree of pipeline routing by introducing Steiner points for aggregation of flow into trunk lines [28]. However, this is done at a high resolution and no consideration is given to the underlying geospatial routing requirements of these Steiner point locations. Even though transportation is generally the cheapest component of a capture, transport, and storage CCS project, modelling of pipeline network routing is critical to assessing the efficacy of a proposed project. Pipeline route modelling can actively discover trunk line opportunities, account for geographic variations, and provide more realistic scenario analysis.

Few MILP-based CCS infrastructure models consider the underlying geography in the optimization process and determine pipeline network routes to support the capture or cost objectives. $InfraCCS$ generates pipeline networks, but first clusters capture and storage locations, which results in very low resolutions networks [16]. $ChinaCCUS$ is a China-centric model that does account for pipeline routing [21]. $SimCCS$ is the original MILP-based CCS infrastructure model that accounts for detailed pipeline routing [11,14]. The $SimCCS$ optimization model assumes project parameters do not change throughout the project's lifespan.

Our work expands on $SimCCS$ by leveraging its pipeline network routing capabilities and adding the capability to model infrastructure with parameters that change with time.

Though much of the CCS infrastructure design research to date assumes that the project consists of a single phase, with static parameters, work has been done on multi-phased CCS infrastructure modelling. Two European-centric multi-phased CCS infrastructure design models have been introduced that aim to model the CCS supply chain in Europe over a multi-year time horizon [2,3]. However, neither model allows for variations in capture costs, storage costs, storage capacity, or capture targets across the modelled horizon. They also clusters sources and do not optimize pipeline network routes. Sun et al. introduced a multi-phased model based on $ChinaCCUS$ that does allow for variation in costs and emission quantities, but does not allow for variation in storage amounts and only allows coarse resolution pipeline routing [22]. Middleton et al. incorporated multi-phased modeling into $SimCCS$ without allowing variable costs or capacities [13]. This model also used a discrete pipeline capacity cost function that requires more integer variables in the MILP formulation than our model. Multiple studies have produced multi-phased models that allow for variations in cost and capacity parameters, but do not allow for detailed pipeline routing [4–6].

Our work differs from other multi-phased CCS infrastructure optimization efforts in several substantial ways:

1. Using $SimCCS$'s capabilities, our new model accounts for the underlying geography when designing pipeline network routes at various resolutions.
2. Our new model formulation allows for variations in capture costs, source emission rates, storage costs, annual reservoir capacities, and capture target values across phases.
3. Our new model incorporates a sophisticated pipeline cost function that requires more careful accounting of purchased pipeline capacity, but allows for fewer integer variables than discrete pipeline capacity models, thus enabling more efficient running times.

3. Model formulation

In this section, we introduce the multi-phased CCS infrastructure design model. We consider input consisting of a set of CO_2 emission sources, geologic storage reservoirs, candidate pipeline components, and project phases. Sources are parameterized with phase-specific unit capture costs and annual amounts of capturable CO_2 emissions. Reservoirs are parameterized with phase-specific unit injection costs and annual storage capacities, as well as total lifetime storage capacities.

Candidate pipeline components are the set of possible pipeline locations that the model is allowed to choose from when making deployment decisions. The candidate pipeline components are generated by the existing $SimCCS$ process of calculating paths in a weighted cost surface. The weighted cost surface aggregates numerous properties from the underlying geography (e.g., population, land ownership, land cover, topography, rights of way) and produces a raster quantifying the relative costs of building pipelines between the neighboring cells [7]. Paths between sources and reservoirs are then calculated and sparsified to produce the set of candidate pipeline components [26]. The result of this effort is pipeline network routing at the resolution of the raster grid size. An example of this routing can be seen in Fig. 6 where pipelines are routed around the darker, high cost, region. Pipelines component costs are represented as a set of linear functions (called *trends*) of pipeline capacity versus cost[10]. Fig. 1 shows two linear trend lines covering eleven distinct pipeline capacities. The costs of the distinct pipeline trends were obtained from the NETL Transport Cost Model [17].

Using pipeline trends instead of explicit pipeline capacities (i.e., diameters) reduces the number of integer variables in the model. It is assumed that the capacity of the largest pipeline trend is arbitrarily large. Pipeline construction costs are annualized by way of a capital recovery factor that accounts for project financing. The capital recovery factor includes the amount of time left in the modelled project. In this way, all pipelines are paid off in the project's time period, whether the pipeline opens in a early phase or a late one. The multi-phased CCS infrastructure design problem is formulated as a Mixed Integer Linear Program (MILP) below.

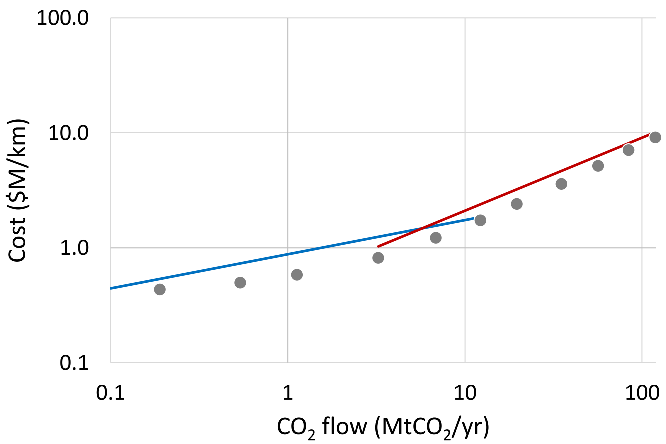


Fig. 1. Two linear pipeline capacity versus cost trends approximating eleven distinct pipeline capacities.

Instance Input Parameters:

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^{src}_{it}	Unit cost to capture from source i in phase t ($/ton)
V^{res}_{jt}	Unit cost to inject in reservoir j in phase t ($/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^{src}_{it}	Annual CO_2 emission rate at source i in phase t (ton/yr)
Q^{res}_{j}	Total lifetime capacity of reservoir j (ton)
Q^{res}_{jt}	Annual capacity of reservoir j in phase t (ton/yr)
$Q^{\min}_{c}$	Minimum annual capacity of pipeline trend c (ton/yr)
$Q^{\max}_{c}$	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:

$y_{kct} \in \{0,1\}$	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:

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

Subject to the following constraints:

$$Q^{min}_c y_{kct} \leq p_{kct} \leq Q^{max}_c y_{kct}, \forall k \in K, \forall c \in C, \forall t \in T \tag{1}$$

$$x_{kct} \leq \sum_{\tau \leq t} p_{kc\tau}, \forall k \in K, \forall c \in C, \forall t \in T \tag{2}$$

$$\sum_{\substack{k\in K:\\ src(k)=n}} \sum_{c\in C} x_{kct} - \sum_{\substack{k\in K:\\ dest(k)=n}} \sum_{c\in C} x_{kct} = \begin{cases} a_{nt} & \text{if n} \in \text{S} \\ -b_{nt} & \text{if n} \in \text{R} \\ 0 & \text{otherwise} \end{cases}, \forall n \in I, \forall t \in T \tag{3}$$

$$a_{it} \leq Q^{src}_{it}, \forall i \in S, \forall t \in T \tag{4}$$

$$a_{i(t-1)} \leq a_{it}, \forall i \in S, \forall t \in T(t > 0) \tag{5}$$

$$\sum_{t\in T} N_t b_{jt} \leq Q^{res}_j, \forall j \in R \tag{6}$$

$$b_{jt} \leq Q^{res}_{jt}, \forall j \in R, \forall t \in T \tag{7}$$

$$\sum_{i\in S} a_i \geq G_t, \forall t \in T \tag{8}$$

Where constraint 1 restricts pipeline capacity by its minimum and maximum values. Constraint 2 ensures that new and existing pipeline capacity is sufficient for the amount of CO_2 to be transported. Constraint 3 enforces conservation of flow at each internal vertex. Constraint 4 ensures that the amount of CO_2 captured at each source is limited by the source's emission rate. Constraint 5 ensures that capture amounts do not decrease between consecutive phases. Constraint 6 limits lifetime storage for each reservoir by its maximum capacity. Constraint 7 limits the annual storage amount in each reservoir to the phase's annual capacity of the reservoir. Constraint 8 ensures each phase's total capture amount meets the phase's target. The version of the model with Constraint 8 is called the CAP version. Constraint 8 can be omitted to form a version of the model called the $PRICE$ version that will only deploy cost negative (i.e., profitable) infrastructure. The $PRICE$ version of the model is useful when considering scenarios with price incentives for CCS projects (e.g., tax credits such as 45Q). These two versions are discussed more in Section 4.

Model Use

The multi-phased model presented above will determine optimal values for the decision variables that minimize the objective function. The model needs to be parameterized with accurate, user-supplied, cost and capacity instance input parameters that constrain the decision variable values and establish the cost model. Determining accurate cost and capacity data for a specific CCS sources and reservoirs is a complicated effort and case study specific. For example, what credit scheme should be applied to reservoirs to model anticipated changes to the 45Q tax credit? Or, how should capture cost estimates change over time to reflect improvements in capture technology. These considerations are case study dependent and are outside of the scope of this work. In Section 4, we present a case study and discuss its associated data collection efforts.

With appropriate input data, the proposed multi-phased model can be used to model all of the scenarios described in Section 1 by manipulating instance input parameters:

1. Source or reservoir unavailability can be modelled by setting their capacities to zero in the phases they are unavailable in.
2. Modifications to tax credits and carbon taxes can be modelled by subtracting the credit amount from the capture or storage costs. If the credit is source dependent (e.g. California's Low Carbon Fuel Standard credit), then the credit should be subtracted from the capture costs of the sources that qualify for the credit. If the credit is reservoir dependent (e.g. 45Q), then the credit should be subtracted from the storage costs of the reservoirs that qualify for the credit. The model is not equipped to manage a credit that is both source and reservoir dependent.

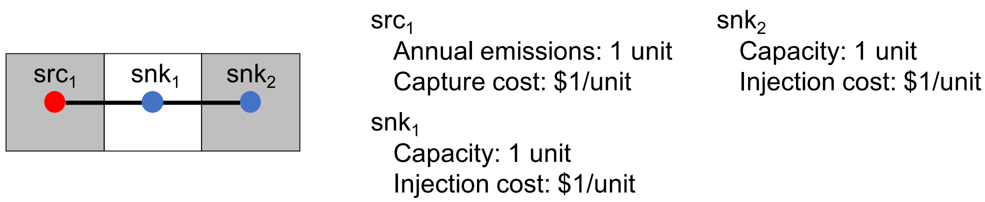


Fig. 2. Consider the objective of capturing one unit per year for a two year project. The single-phased and multi-phased solutions will both capture all emissions from the source and fill all capacity in both sinks. However, the single-phased solution will deploy all sources and sinks at once, and build 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.).

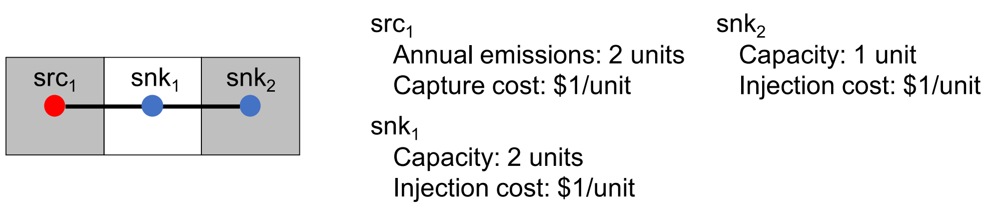


Fig. 3. Suppose there are two available pipeline capacities: 1 unit per year and 2 units per year. Consider a two-phased scenario with an objective of capturing one unit in the first one-year phase and two units in the second one-year phase. Optimal single-phased solutions for each of the phases in isolation 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.

3. Proceeds from sales to EOR fields can be modelled by subtracting the unit (per ton) sales proceeds from the storage costs of each individual EOR field.
4. Phased capture objectives can be modelled by modifying the phase-specific annual CO_2 capture target.

Model Discussion

The multi-phased model presented above is a generalization of an existing single-phase CCS infrastructure design model [14]. 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. Fig. 2 presents a scenario that illustrates this cost saving.
- *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. Fig. 3 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 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. Fig. 4 presents a scenario that illustrates this advantage of concurrently optimizing pipeline routes across multiple phases.

4. Evaluation

As discussed in Section 1, the new multi-phased model is able to model novel scenarios including variations in source and reservoir parameters (e.g., costs, capacities) over the life of a project. However, even without variations in source or reservoir parameters, the multi-phased model has the ability to design lower cost infrastructure than the single-phase model by exploiting the “as needed” deployment of infrastructure. In this section, we present results of simulations comparing the multi-phased model to the single-phase model in identical scenarios to asses the advantages of the multi-phased model and display its ability to find cheaper infrastructure than the single-phase model is capable of finding.

4.1. Data description

The MILP presented in Section 3 was implemented and integrated into *SimCCS*. Source and reservoir data for the evaluation was provided by the Great Plains Institute in support of the National Petroleum Council’s (NPC) 2019 Carbon Capture, Use, and Storage study [18]. The NPC data spans most of the contiguous United States and has a total of 150 potential source and 270 potential sink locations. Source data includes many industries and is the culmination of extensive site-specific economic analysis. Reservoir data includes both deep saline formation storage and enhanced oil recovery (EOR) locations. Saline stor-

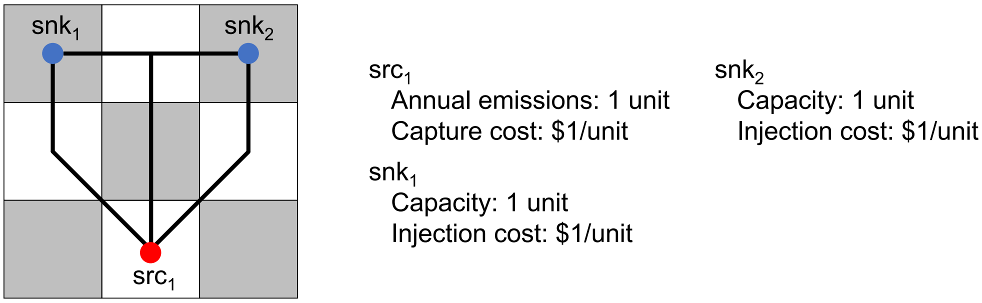


Fig. 4. Suppose pipeline costs are proportional to length. Consider a two-phased scenario with an objective of capturing one unit in the first one-year phase and one unit in the second one-year phase. Optimal single-phased solutions for each of the phases in isolation would result in a direct pipeline 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.

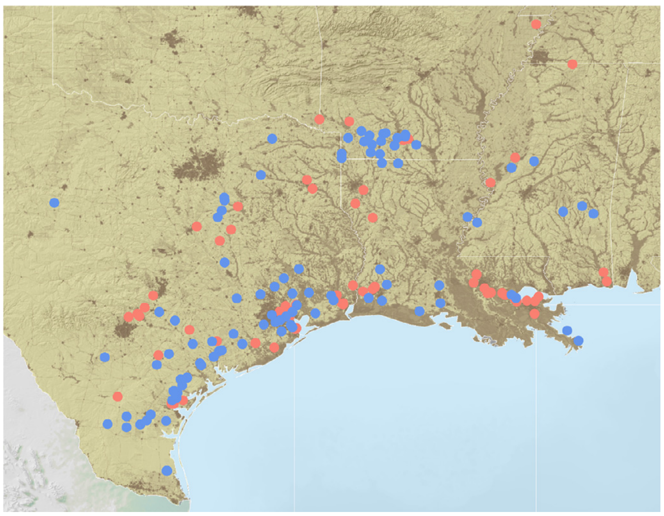


Fig. 5. Locations of source (red circles) and reservoir (blue circles) locations in the Gulf region of the United States used for evaluating the multi-phased CCS infrastructure design model. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

age estimates were generated using the SCO_2T tool [12]. EOR estimates were generated using proprietary data from Advanced Resources International [18]. This evaluation was conducted on 80 sources and 125 sinks, selected from the full NPC data set, centered on the Gulf region. Fig. 5 shows the geographic location of sources and reservoirs used for the evaluation. Candidate pipeline routes were generated in $SimCCS$ using its novel network generation algorithms [26]. The capital recovery factor is set at 10% for all scenarios presented. The time period for all scenarios is 30 years, which the multi-phased model subdivides into six 5-year phases. Scenarios were run in two modes: (1) CAP mode, which includes constraint 8 in the MILP that requires a specified amount of CO_2 to be sequestered, and (2) $PRICE$ mode, which omits that constraint and only sequesters CO_2 that reduces the objective function (i.e., is profitable). Profitable options exist in the scenarios because we include 45Q tax credit amounts of $50 per ton for saline storage and $35 per ton for EOR storage. Because of these tax credits, it is possible for some CO_2 to be captured, transported, and stored for less money than the credit they receive, thus doing so at a profit and deploying in $PRICE$ mode.

4.2. Evaluation results

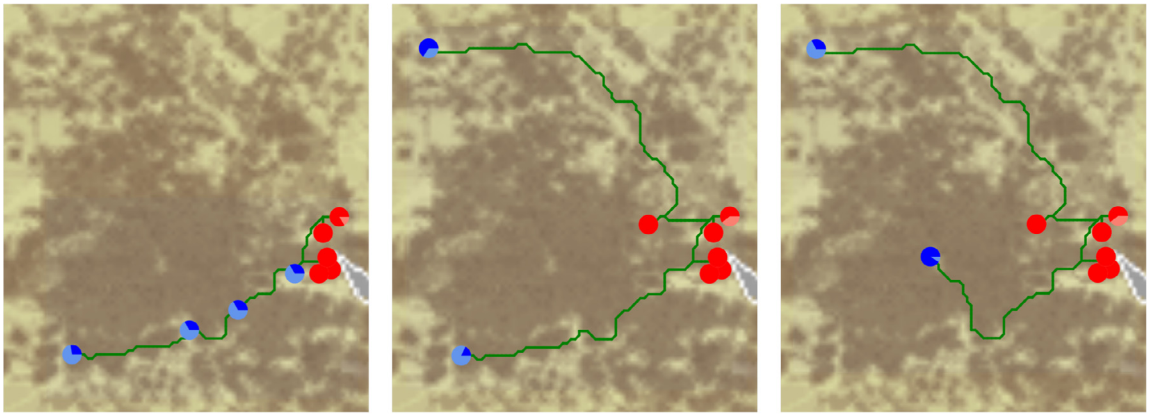
Scenarios were conducted on both the multi-phased and single-phase models in CAP and $PRICE$ modes. Identical costs, capacities, locations, and candidate pipeline networks were used for all scenarios. The only difference between the multi-phased and single-phase model scenarios was the subdivision of the 30-year project length into six 5-year phases. Keeping the data identical allows for any differences in design efficacy to be directly attributable to the multi-phased nature of the new model instead of different data values for different phases. Meaning, cheaper infrastructure found by the multi-phased model indicates it is better at solving the same problem than the single-phase model was designed to solve.

Infrastructure costs and statistics for model solutions run in CAP mode are presented in Table 1. Note that the capture amount for both models is 3 $MtCO_2$/yr, meaning that the two solutions sequester the same amount of CO_2. As seen in the table, capture and storage costs are identical between the single-phase and multi-phased models. The only difference in cost between the models arises with transportation costs. The transportation cost for the full project was $555M for the single-phase model and $363.65M for the multi-phased model, representing a 34% decrease in cost. This decrease in cost is in spite of the fact that the multi-phased model also results in a larger pipeline network at the end of the project.

The multi-phased model was able to decrease transportation costs compared to the single-phase model by exploiting the “as needed” infrastructure deployment capability inherent to segmenting a project into phases. The multi-phased solution began by using source and sink locations that were close to each other. Using sources and sinks that were close to each other resulted in significantly cheaper transportation cost than the single-phase model’s solution that had to utilize its full pipeline network from the start. As phases progressed, the multi-phased model’s solution proceeded to use sink locations that were more expensive to access as the closer sinks filled up. The progression of pipeline development across phases is shown for one small region of the evaluation area in Fig. 6. The iterative development of the pipeline network resulted in increased pipeline deployment in later phases and increased transportation costs, particularly in phase 6 where the annual transportation cost exceeded the single-phase solution’s annual transportation cost. However, by delaying the deployment of the full pipeline network until year 25, the multi-phased solution was able to significantly reduce transportation cost by not operating the full pipeline network for the entire 30-year project.

Infrastructure costs and statistics for model solutions run in $PRICE$ mode are presented in Table 2. Instead of dictating an amount of CO_2 to sequester, as is done in CAP mode, $PRICE$ mode will only sequester CO_2 that can be done so profitably. The solution found by the multi-phased model is both 15% cheaper (i.e., more profitable) and sequestered 5% more CO_2 than the single-phase model. Unlike in the CAP mode results, capture and storage costs, as well as transport costs, varied between the models’ solutions. The multi-phased model was able used more expensive source locations to capture from, but found cheaper storage and transportation solutions. As before, the multi-phased model exploited the “as needed” infrastructure deployment capability of phased designs to reduce transport cost and find more advantageous capture and storage options.

Results from both CAP and $PRICE$ mode scenarios illustrate the ability of the multi-phased model to design solutions that are cheaper than single-phase solutions. These cost savings are present when the multi-phased and single-phase models are asked to do the same thing:



(a) Phases 1 – 3 (b) Phase 4 (c) Phase 5

Fig. 6. Evolution of the multi-phased model solution's pipeline network for one region of the evaluation area. Sources are shown as red circles and storage reservoirs as blue circles. The dark components of the circles indicate the percentage of annual capacity captured from or stored in. The green lines are the pipelines used in those phases. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Infrastructure costs and statistics for the single-phase and multi-phased models in CAP mode.

	Single-Phase	Multi-Phased						
		Full Project	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5	Phase 6
Annual Cost ($M/yr)	−34.8	−41.7	−45.9	−45.9	−45.9	−44.3	−37.2	−31.1
Capture Cost ($M/yr)	126	126	126	126	126	126	126	126
Storage Cost ($M/yr)	−180	−180	−180	−180	−180	−180	−180	−180
Transport Cost ($M/yr)	18.5	12.1	7.94	7.94	7.94	9.51	16.6	22.8
Capture Amount (MtCO_2/yr)	3	3	3	3	3	3	3	3
Pipeline Network Length (km)	333	378	103	103	103	124	205	378

Table 2
Infrastructure costs and statistics for the single-phase and multi-phased models in $PRICE$ mode.

	Single-Phase	Multi-Phased						
		Full Project	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5	Phase 6
Yearly Cost ($M/yr)	-36.8	-42.3	-31.5	-48.0	-48.0	-46.6	-43.8	-36.0
Capture Cost ($M/yr)	120	127.6	75.6	135	135	135	135	150
Storage Cost ($M/yr)	-172	-181.5	-113	-191	-191	-191	-191	-212
Transport Cost ($M/yr)	15.0	11.81	5.33	8.54	8.54	9.95	12.8	25.7
Capture Amount (MtCO_2/yr)	2.87	3.03	1.87	3.19	3.19	3.19	3.19	3.53
Pipe Length (km)	252.3	338	57.8	104	104	124	172	338

Design the cheapest infrastructure possible that captures a set amount of CO_2 (in CAP mode). The scenarios in this evaluation do not exploit the capability of the multi-phased model to consider variations in source and reservoir parameters. Instead, it was a direct comparison of the multi-phased and single-phase models solving the same problem.

5. Conclusion

This research introduced a new modeling approach to CCS infrastructure that considers a project as a series of phases. This new approach was formalized as an MILP and allowed for variations in various source and reservoir parameters. Coupling a phased approach to CCS infrastructure design with source and reservoir parameter variations allows many new problems to be modeled as discussed in Section 1. However, these new capabilities are not the only reason to value the multi-phased model. The multi-phased model is even more effective at solving static scenarios without parameter variations than a single-phase model.

We discussed the theoretical capabilities and rationale for why the multi-phased model is able to find cheaper solutions to static problems than the single-phase model in Section 3. We then presented evidence for these cost savings using real data in Section 4. Not only is the multi-phased model theoretically able to find cheaper CCS infrastructure designs than single-phase models, but it seems to find them in practice as well. This suggests that CCS project studies should strong consider the cost advantages afforded to phased deployments.

The key limitation of the multi-phased model is the dependency on additional integer variables in the MILP formulation compared to the single-phase formulation. This can have significant adverse impacts on computational running time. This can be mitigated by controlling the number of sources and reservoirs considered and by limiting the number of phases considered. There are many reasonable scenarios that will still require employing the single-phase model due to the sheer size of the scenario being run.

There are many future studies that can be motivated by this new multi-phase CCS infrastructure design model:

1. Explore scenarios with variations in source or reservoir parameters (e.g., the impacts of changes to tax credits over time).
2. Employ the multi-phased model in real-world studies in combination with the single-phase model to further quantify differences in solution quality.
3. Employ the multi-phased model to determine realistic construction schedules for a large-scale CCS deployment.

4. Explore alternate solution approaches (e.g., heuristics) in an effort to reduce the impact of the computational complexity costs of having more integer variables, as has been done in other areas of CCS infrastructure design research [25].

Declaration of Competing Interest

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

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