Decomposition methods applied to the design of large-scale CO2 supply chains

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Abstract

Global warming poses a significant contemporary challenge, and one proposed solution in literature is Carbon Capture and Storage (CCS). This study focuses on optimizing a CCS Supply Chain, specifically a multi-period design for Europe encompassing carbon capture, transport, and sequestration with diverse data sources and technologies. The inherent complexity of the resulting Mixed Integer Linear Programming problem for high CO2 reduction targets necessitates exploration of alternative solution methods. To address this, the study proposes an algorithm that combines Generalized Disjunctive Programming and Augmented Lagrangian Relaxation decomposition. The results demonstrate enhanced efficiency and reduced computational time compared to traditional methods, rendering it suitable for large-scale supply chain challenges.

**Keywords**: Carbon Capture and Storage, Augmented Lagrangian Relaxation, Generalized Disjunctive Programming, decomposition, large-scale, supply chain

* 1. Introduction

Global warming has emerged as one of the most significant challenges that society faces today. The battle against climate change and the search for innovative solutions to mitigate its effect has turned into the centre of the researcher’s attention. One potential approach to reduce the global warming effects could be the design of a Carbon Capture and Storage Supply Chain (CCS SC), as proposed by D’Amore and Bezzo (2017). This supply chain design was obtained from the optimisation of a Mixed Integer Linear Program (MILP), minimising the total cost of the CCS SC while simultaneously trying to reach a CO2 reduction target over twenty-year horizon. These considerations lead to a large and complex model (No. Variables > 13 Millions & No. Equations > 8 Millions) which becomes intractable for model instances with CO2 reduction targets exceeding 70%. Furthermore, when introducing new features such as multi-period or parameter uncertainties, it becomes compulsory to explore alternative resolution methods.

In this work, a CCS multi-period supply chain for Europe, based on that presented by D’Amore and Bezzo (2017) , is designed. Post-combustion, oxy-fuel combustion and pre-combustion are considered as possible capture technology options. Data on CO2 emissions and storage sites have been sourced from EDGAR database and CO2Stop Project, respectively. Regarding the CO2 transport between the capture points and the storage locations, two types of pipelines are available—onshore and offshore pipelines. To incorporate the information from these databases into our model, the following data preprocessing steps are required: i) split into regions the Europe territory, ii) classify the regions based on their location (coastal, inland or maritime), and iii) identify the regions associated with both CO2 emissions and the storage sites.

Furthermore, if uncertainty of CO2 emissions with time is considered, it results in an even more complex model to be solve. To overcome the intractability of this model, the CCS supply chain is modelled using both Generalized Disjunctive Programming (GDP) and Augmented Lagrangian Relaxation decomposition. The combination of both techniques is not only useful to reduce the solution time, but also to optimise the supply chain even when the model becomes extremely large and cannot be solve using the classical approaches.

* 1. Model Description

In this contribution a Carbon Capture and Storage (CCS) system is optimized. To achieve this, the territory under consideration must be divided into regions. Once this division is complete, the model's constraints can be established, which can be classified into four groups: capture constraints, transport constraints, sequestration constraints, and logic constraints, which are described below. Each group has, in turn, a principal variable.

Table 1 shows the main parameters and variables of the CCS multi-period supply chain model.

Table 1. Nomenclature used in the equations.

|  |
| --- |
| **Indexes**g: regionst: timec: capture technologiesl: transport formq: transport range: Regions g’ surrounding region g |
| **Parameters**: Capture technology efficiency.: Capture technology 𝑐 unitary cost.: emissions in each region 𝑔.: Reduction target.: Range 𝑞 minimum transported.: Range 𝑞 maximum transported.: Inshore intra-connection cost.: Region 𝑔 size.: Gas pipeline 𝑙 between regions 𝑔 and 𝑔′ fixed cost: Unitary transport cost.: Well injection capacity.: Region 𝑔 storage capacity |
| **Continuous Variables** : Processed  through technology *c* in region *g* at time *t.*: Transported  from region *g* to region *g’* by transport form *l* in a quantity of qat time t.: Sequestered  in region *g* at time *t.* |
| **Binary Variables** |

* + 1. Capture constraints
* **Constraints 1.** The available CO2 in each region sets the upper limit for the total processed CO2.
* **Constraints 2.** Imposes the maximum CO2 that can be processed for each technology in each region.
* **Constraints 3.** Specifies the minimum CO2 that must be processed.
	+ 1. Transport constraints
* **Constraints 4.** Mass balance for each region and time period (eq. ).

|  |  |
| --- | --- |
|  | (1) |

* **Constraints 5.** Defines the upper and lower bounds of the transport ranges. While transported CO2 is a continuous variable, it has been discretized due to the variation of transportation cost with the amount of CO2 being carried.
	+ 1. Sequestration constraints
* **Constraints 6.** Limits the maximum amount of CO2 that can be sequestered in each region based on its storage capacity.
	+ 1. Logic constraints
* **Constraints 7.** Prevents cross-transport between regions (eq. (1)).

|  |  |
| --- | --- |
|  | (2) |

* **Constraints 8.** The primary binary variable *z* depends on five indexes. To simplify optimization, two constraints link the binary variable *z* with two binary variables having a lower number of indexes (and )
* **Constraints 9.** Impedes transport from a region to itself and prohibits direct transport between non-adjacent regions.
* **Constraints 10.** Constraints to prevent transport in specific cases:

Onshore pipelines are disallowed if one of the regions is maritime.

Offshore pipelines are prohibited if one or both of the regions are coastal, and if one of the regions is inland.

* 1. Decomposition methods: Augmented Lagrangian Relaxation

To face the high complexity of the problem, a strategy based on both GDP and Augmented Lagrangian Decomposition has been tested. To apply Augmented Lagrangian Relaxation, it is necessary to identify what are commonly referred to as "complicating constraints. These constraints are the ones that, when relaxed, enable the decomposition of the model into smaller and less complex problems.

In this problem, the complicating constraints are identified within the transport constraints, specifically the mass balances (eq. (1)). These equations work a bond between capture, sequestration, and transport variables, and consequently, between these groups. Without the presence of mass balances, the model could be divided into three separate problems (capture, transport, and sequestration). These problems could further be subdivided based on their indexes (g, l, q, t) if the problem’s structure allows it. This constitutes the first complicating constraint. Additionally, eq. (2) which links each region g with their surrounding regions g’, prevents the decomposition of the transport subproblem into regions. Therefore, it constitutes the second complicating constraint.

Once the complicating constraints have been identified, the subsequent subproblems result from dividing the model through the application of Augmented Lagrangian Relaxation.

* + 1. First subproblem (Capture subproblem)

|  |
| --- |
|  |

|  |  |
| --- | --- |
| *Subject to* |  |
|  | (3) |
|  | (4) |
|  | (5) |

* + 1. Second group of subproblems (Transport subproblems)

|  |
| --- |
|   |

|  |  |
| --- | --- |
| *Subject to* |  |
|  | (6) |
|  | (7) |
|  | (8) |
|  | (9) |
|   |  |

* + 1. Third group of subproblems (Sequestration subproblem)

|  |
| --- |
|  |

|  |  |
| --- | --- |
| *Subject to* |  |
|  | (10) |
|  | (11) |

* + 1. Algorithm

The augmented Lagrangian decomposition method has been applied to our case study following this algorithm:

***Step 1.***Fix an initial value for the multipliers *, = 1,* and variables *, ,= 0 .*

**Step 2.** Compute the first subproblem and obtain .

**Step 3.** = . Compute the second group of subproblems. Whenever subproblems were being solved, the values of and are obtained. These values are used in the subproblems that are not computed yet, being

 = and = .

**Step 4.** Compute the third group of subproblems and obtain.

**Step 5.** Evaluate the value of the complicating constraints at the current iteration.

**Step 6.** Update the penalty parameter :

if , set , otherwise, set

**Step 7.** Update multipliers:

* 1. Results

The computational results obtained using the original and the decomposed formulation are shown below in Table 2 and Table 3, respectively. As can be seen, the computational time has been significantly reduced, even the originally intractable problem has been solved. Furthermore, the gap has been considerably diminished.

Table 2. Computational results of without decomposition.

|  |  |  |
| --- | --- | --- |
|  | Time, s | Gap, % |
| 0.6 | 623 | 1.11 |
| 0.7 | 1530 | 2.06 |
| 0.8 | 3600 | 7.02 |
| 0.9 | Intractable | - |

Table 3. Computational results applying Augmented Lagrangian relaxation.

|  |  |  |
| --- | --- | --- |
|  | Time, s | Gap, % |
| 0.6 | 91 | 0.63 |
| 0.7 | 140 | 0.85 |
| 0.8 | 511 | 1.11 |
| 0.9 | 854 | 3.68 |

* 1. Conclusions

To tackle the challenge of solving large-scale supply chains, we propose an algorithm that integrates both Generalized Disjunctive Programming (GDP) and Augmented Lagrangian Relaxation decomposition. This formulation enables the attainment of a feasible supply chain design for instances that were previously intractable without decomposition techniques, particularly for CO2 reduction targets exceeding 70%. Furthermore, the decomposition algorithm markedly diminishes computation time for instances that are tractable in both approaches.

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