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Planning minimum regret CO_2 pipeline networks

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ABSTRACT

The transition to a low-carbon economy necessitates effective carbon capture and storage (CCS) solutions, particularly for hard-to-abate sectors. Herein, pipeline networks are indispensable for cost-efficient CO_2 transportation over long distances. However, there is deep uncertainty regarding which industrial sectors will participate in such systems. This poses a significant challenge due to substantial investments as well as the lengthy planning and development timelines required for CO_2 pipeline projects, which are further constrained by limited upgrade options for existing infrastructure. The economies of scale inherent in pipeline construction exacerbate these challenges, leading to potential regret over earlier decisions. While numerous models were developed to optimize the initial layout of pipeline infrastructure based on known demand, a gap remains in addressing the incremental development of infrastructure in conjunction with deep uncertainty. Hence, this paper introduces a novel optimization model for CO_2 pipeline infrastructure development, minimizing regret as its objective function and incorporating various upgrade options, such as looping and pressure increases. The model's effectiveness is also demonstrated by presenting a comprehensive case study of Germany's cement and lime industries. The developed approach quantitatively illustrates the tradeoff between different options, which can help in deriving effective strategies for CO_2 infrastructure development.

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Carbon capture and storage; strategic planning; scenarios; regret; network design

1. Introduction

Carbon capture and storage (CCS) represents a pivotal technique in mitigating climate change by capturing CO_2 emissions directly from industrial sources and sequestering them in suitable geological formations. CCS will most likely be used by certain industries such as cement and lime, which are classified as hard-to-abate sectors due to their unavoidable process emissions (Abdelshafy et al., 2022). Therefore, CCS has been integrated as a key technique in several industrial transformation roadmaps (IEA., 2018). The European Commission also introduced in 2023 the Net Zero Industry Act (European Commission, 2023), which proposes an EU-wide goal of providing CO_2 injection capacity at around 50 million tonnes by 2030. Germany recently outlined the key points for CCS development in its Carbon Management Strategy (BMWK, 2024).

To make CCS economically viable, there arises the need to transport large quantities of CO_2 over long distances from the emitters to potential sinks. Therefore, the International Energy Agency (IEA) outlines CO_2 transport and storage as one of the key working fields (IEA., 2023). Abdelshafy et al. (2022) show that pipelines will play a crucial role as they are the most cost-effective transportation mode compared to trucks or trains. To reach the ambitious climate goals, the planning and installation of the pipeline infrastructure must begin now. However, pipelines also come with high initial investment costs as well as ongoing operational and maintenance costs. These high costs go along with other challenges. Besides the associated techno-economic risks, there are several uncertainties regarding carbon prices, political support, and social opposition (Abdelshafy et al., 2022). Also, there are still controversies regarding the CCS demand of some sectors (e.g., steel) as there are other alternative decarbonization technologies (e.g., hydrogen direct reduction) (Material Economics, 2019; IEA., 2020). Additionally, due to the immense size of the prospective networks, they are going to be established incrementally. For example, the studies of Morbee et al. (2011) and Morbee et al. (2012) show that the CO_2 network in Europe will expand gradually over the next three decades. Therefore, based on the effectiveness of the planning approach, each construction phase can impact the next one either positively or negatively.

These ambiguities are specifically hindering fast developments using current planning methods. Decision makers need approaches that allow them to secure their investment against the uncertain environment. Herein, no-regret and

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low-regret are two terms often used in the discussion (ZEP, 2020; Agora Energiewende & AFRY Management Consulting, 2021; IN4climate.NRW (Ed.),), 2021). However, this concept is so far mainly addressed from a qualitative perspective, and instead of dealing with regret as an abstract concept, there is a genuine need to quantify and minimize it, thereby supporting the decision-making process. This poses the question of whether there are planning methods that lead to minimum regret for CO_2 pipeline planning under uncertain demand. In this regard, demand refers to certain industries or countries joining the system at different times.

Here, the main challenge is the economic features of pipeline construction projects. As pipeline construction has nonlinear cost functions and constraints (Benrath et al., 2020; Parker, 2003), economies of scale play a major role in minimizing the construction costs. Also, once the pipeline is built, it cannot be upgraded to a bigger diameter later without incurring extremely high costs. The application-oriented literature (e.g., Mischner et al. (2015)) contains several techno-economic aspects of enhancing capacity within natural gas (NG) networks. This may involve methods such as adding more pumping stations and compressors along the existing pipeline to increase the pressure, or building parallel lines. However, the expenses associated with such measures remain significantly higher compared to initially building the pipeline with a high capacity. Thus, it might be advantageous to build bigger pipelines in earlier phases even if they are not yet fully utilized. Nonetheless, oversizing poses risks as the potential emitters may decide not to join the network at a later stage. In such a case, oversized pipelines would incur unnecessary costs in construction, operation, and maintenance.

Given the high uncertainty surrounding which emitters will join the system, it is essential to optimize for multiple scenarios within a single model. This necessitates deriving a regret-minimizing, multi-period model that addresses nonlinear cost functions and constraints while considering only specific upgrade options in subsequent periods. The planning should also account for geographic features and model numerous future demand scenarios. This paper proposes such a model and demonstrates its efficacy via a case study. In terms of paper structure, the following section provides an overview of related research and states how our contribution fits into it. Afterwards, we describe our methodology in Section 3 and lay out the formal model in Section 4. In Section 5, we present a case study to demonstrate the model and discuss the results, as well as a sensitivity analysis. Finally, we conclude the paper with Section 6, highlighting the main outcomes and an outlook for future research.

2. Related research

Due to the crucial role of CCS, the relevant supply chains and infrastructure systems have emerged as important themes in the literature. Tapia et al. (2018) provide a comprehensive review of decision support systems for CCS. The study demonstrates the wide range of methods that have been developed to address the different operations along the CCS supply chain, i.e., CO_2 capture, transportation, and storage. For pipeline network design, there are also various approaches. There is an abundance of literature on NG as well as for the underlying graph problems, e.g., the Minimum Fixed Charge Network Flow Problem (FCNFP). However, we focus this section specifically on strategic planning methods of mid-to-long-distance CO_2 pipeline networks. Based on the modeling requirements mentioned in the previous section, we divide the literature analysis into four parts: general design and scalability, approaches to geographic accuracy, considerations of uncertainty, and how our contribution fits into the literature.

2.1. General design and scalability

Pipeline design and operation involve nonlinear constraints, which make overly detailed models hard to manage and tract. Therefore, all subsequent publications incorporate assumptions and simplifications to address this challenge. In order to build a pipeline network, the planner has to select appropriate pipeline sizes. Thus, a common approach is to model discrete pipeline sizes with an assigned flow as a Mixed Integer Linear Program (MILP) (Bennæs et al., 2024; Middleton & Bielicki, 2009; Sun & Chen, 2017). The MILP-based models can be either single-period or multi-period models. The multi-period models (e.g., Jones et al. (2022)) incorporate a stepped approach of building the network incrementally. Middleton et al. (2020) improved their model by using a piecewise linear approximation, aiming to make the optimization more scalable. This advancement has been further expanded upon by Jones et al. (2022). Whitman et al. (2022) also demonstrate that modeling CCS infrastructure design as an FCNFP is feasible. Since this poses an NP-hard problem, they provide several heuristics for it. Some earlier models (e.g., Elahi et al. (2014)) adopt a simplified approach with a combination of fixed and linear costs. Following Parker (2003), a quadratic cost function based on the inner pipeline diameter can be used as an approximation of the discrete sizes. Herein, a squared cost function can be employed to determine the CO_2 flow. Yeates et al. (2021) model the problem as a minimum cost flow problem and provide a comparison of different available heuristics as well as their own heuristic.

2.2. Geographic accuracy

Geographic features such as slopes, population density, and existing infrastructure must be considered. Onyebuchi et al. (2018) conclude that CO_2 is neither toxic nor explosive, but it could still pose a risk for humans. Moreover, building CO_2 infrastructure close to residential areas may face opposition from the local community. Elevation profiles also pose significant challenges not just for building the pipeline but also for technical limitations on how CO_2 is transported through pipelines. Therefore, integrating geodata during the design phase of the pipeline networks is essential. Herein, there are various approaches with different accuracy levels to account for the geographic factors. The conventional method is assuming straight lines between the emitters (Elahi et al., 2014; Sun & Chen, 2017). Bennæs et al. (2024) have advanced this approach by using offshore and onshore detour factors. Middleton et al. (2012) consider geographic features like slopes, waterways, national parks and state parks, as well as infrastructure like highways and railroads. They also make a distinction between wetlands and urban areas. Yeates et al. (2024) also adopt the same approach and incorporate more factors. They integrate population density and consider existing NG pipelines as a positive factor, based on the assumption that construction is cheaper to build where pipeline infrastructure already exists.

2.3. Uncertainty

Uncertainty has also emerged as a crucial aspect in the relevant models. While many studies have typically assumed known demands, various models consider variables such as uncertain sink capacity (Middleton & Yaw, 2018). For the specific use case of enhanced oil recovery (EOR), several multistage, stochastic models are proposed (Abdoli et al., 2023; Tapia et al., 2016). The study of d'Amore et al. (2019) also incorporates uncertain storage capacities and emission targets. Han and Lee (2012) consider uncertain amounts of CO_2 emissions, product prices, and operating costs in their multistage stochastic model. There are also multiple models that account for fluctuating carbon prices, either by using a multistage stochastic model (Elahi et al., 2017) or qualitative analysis (Sun & Chen, 2022). Demand uncertainty was not covered sufficiently, except for some publications such as Nicolle and Massol (2023). The latter paper also introduces the concept of regret. However, while it shows that building for certain demand and then upgrading later leads to the maximization of regret over multiple periods, they do not examine the network layout, but rather general pipeline construction.

2.4. Knowledge gaps & our contribution

While significant research has been conducted on the aforementioned aspects, pipeline network models still require more upgrades and integration. As shown in Table 1, most of the enhancements have focused on the geodata and routing, followed by considering multi-period optimization. Additionally, there is no study that addresses these aspects combined. Also, stochastic models have been the primary approach for addressing uncertainties such as storage capacities and CO_2 prices. However, to the best of our knowledge, there are no stochastic values or historical data available that could be used to determine emitter participation. Furthermore, regulatory mandates (e.g., on third-party access (European Parliament, 2018)) might require a pipeline operator to adjust its network in future periods and include everyone interested in joining. This, along with other potential regulations and long-term viability considerations, may force decision makers to be very conservative. Having a model that shows the worst-case outcomes can inform policymakers how impactful it would be to add or exclude certain industries from a potential network, as well as show the impact of regulations. Herein, there is a research gap for worst-case optimization considering uncertain emitter scenarios. Furthermore, *min-max* regret as a target function as well as the use of upgrade functions as in Mischner et al. (2015) were, to our best knowledge, never used in the context of CO_2 pipeline network planning. To close this gap, we propose a novel two-stage multi-scenario optimization model that uses *min-max* regret as a target function. The derived approach also aims for comprehensive analyses by considering all relevant aspects listed in Table 1. We are building on the general ideas of Middleton et al. (2020) and Yeates et al. (2024) for geographic data, as well as using piecewise linear approximation. Similar to Jones et al. (2022), we follow an approach to develop the network over multiple periods. We further make use of upgrade functions, inspired by Mischner et al. (2015).

3. Method

We have a set of scenarios $\mathcal{S}$. Each scenario $s \in \mathcal{S}$ has a set of nodes $\mathcal{V}'$ that are CO_2 emitters (sources) with an amount of emissions or sinks with a maximum capacity. We select an initial scenario $s_1 \in \mathcal{S}$ to start building the pipelines ($t = 0$). After a period of n_1 years, we take another set of investment decisions ($t = 1$). After this stage, we still consider running the pipeline network for the next n_2 years.

For our optimization model, we consider geographical accuracy to derive a graph and a cost function for building and maintaining a pipeline section.

To connect the nodes $\mathcal{V}'$ in a geographically accurate way, we follow the approach to incorporate geographic data outlined by Middleton and Bielicki (2009) that was improved and applied for Germany by Yeates et al. (2024).

Table 1. Comparison of selected models

	Model	Geodata & Routing	Multi-Period	Uncertainty	Upgrade & Regret
Middleton etal. (2020)	MILP	√	×	×	×
Sun and Chen (2017)	MILP	×	√	×	×
Whitman etal. (2022)	Heuristic	√	×	×	×
Yeates etal. (2024)	Heuristic	√	×	×	×
Bennæs etal. (2024)	MILP	√*	×	×	×
Middleton and Yaw (2018)	MILP	√	×	Sinks	×
Abdoli etal. (2023)	MILP	×	√	Sinks	×
This model	MILP	√	√	Emitters	√

*Using different detour factors for overland and sea pipeline.

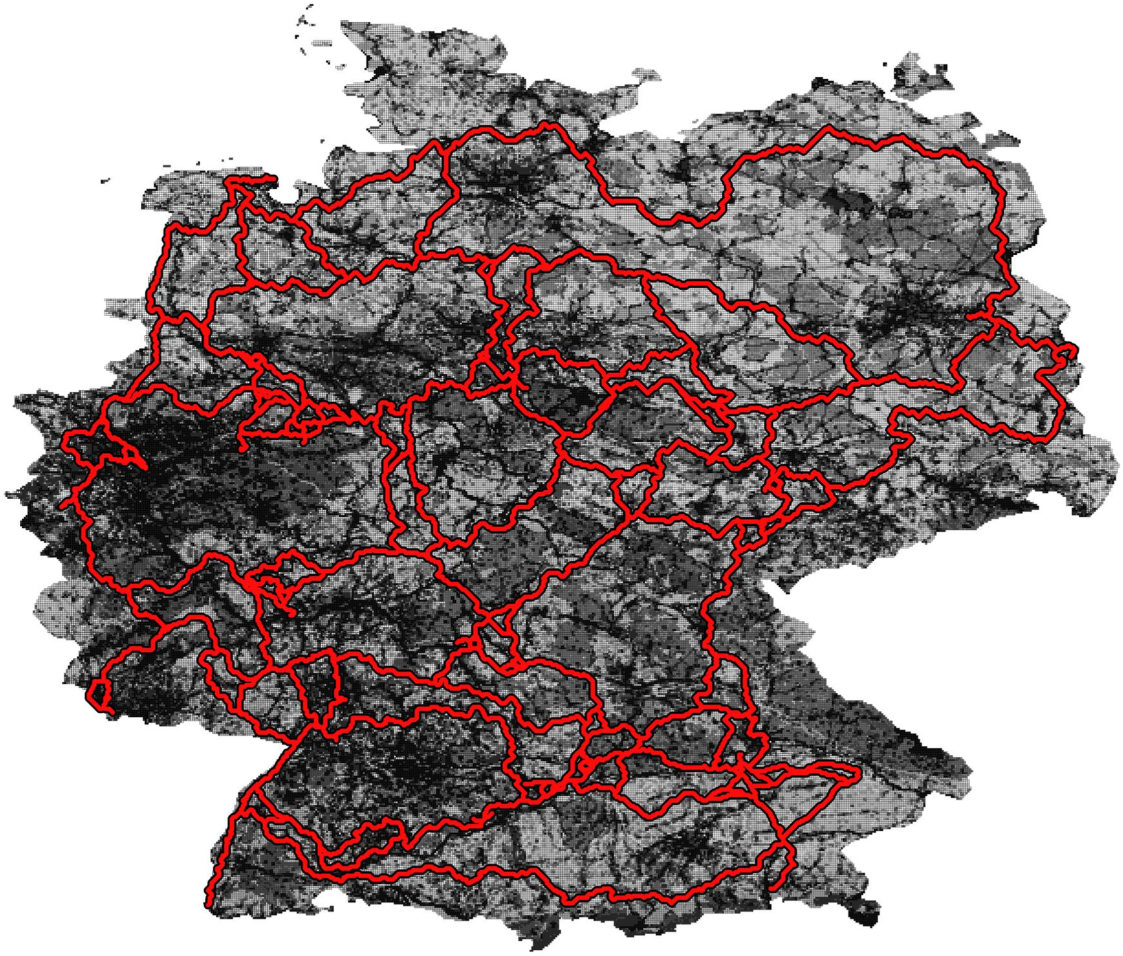


Figure 1. Raster map, lighter = better conditions, darker = worse conditions, and network graph (lines).

In short, we create a raster map with squares with a side length of 1.5 km. Then, for geographical features like terrain, rivers, existing infrastructure, population density, or national parks, we apply multipliers to the squares, creating a penalty on each square. From one node to another, we compute the least penalized way through the raster map. We then reduce the found routes to a common graph by introducing transport nodes where the routes merge. A detailed description of the approach can be found in Appendix A.

This results in a directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{A})$, where $\mathcal{V}'$ is a subset of $\mathcal{V}$ that is extended by the transport nodes. For an example, see Figure 1. Furthermore, for each arc $(i,j) \in \mathcal{A}$, we get the length l_{ij} following the exact geographic line.

Each node $i \in \mathcal{V}$ has a demand d_{is} depending on the scenario s. All transport nodes have $d_{is} = 0$. Sinks have negative demands $d_{is} < 0$ and sources have positive demands $d_{is} > 0$. Sources that are not present in another scenario are transport nodes in that scenario.

For costs, we are using the cost function given by Yeates et al. (2024), which is a slightly simplified version of Parker (2003):

$$cost(D) = (C1 \cdot D^2 + C2 \cdot D + C3) \cdot l_{ij}$$

$C1$, $C2$, and $C3$ are cost constants, D is the inner diameter of the pipe, and l_{ij} is its length. To get this inner diameter, we use the following function of Benrath et al. (2020):

$$D = \sqrt{\frac{F}{v \cdot \pi \cdot 0.25 \cdot p}}$$

$$D \text{ inner diameter}, F \text{ flow rate}, v \text{ velocity}, p \text{ density}$$

Following the approach of Yeates et al. (2024), we fix the pressure and temperature of the gas. We derive the density of the gas p, and we also fix the velocity v inside the pipeline. We can now derive a maximum flow for a given pipeline diameter D, and so derive the cost function based on a given flow rate F:

$$cost(F) = \left(\frac{F}{v \cdot \pi \cdot 0.25 \cdot p} \cdot C1 + \sqrt{\frac{F}{v \cdot \pi \cdot 0.25 \cdot p}} \cdot C2 + C3 \right) \cdot l_{ij}$$

As this function is nonlinear, we approximate it with a set of piecewise linear functions, called linear cost segments $\mathcal{C}$. For each linear cost segment, we derive a linear part m_c and a fixed part y_c. An example of how this approximation looks can be seen in Figure 2. Yearly operation and maintenance costs are taken as a percentage of the initial investment costs, as in Benrath et al. (2020). Future costs are discounted using a discount rate τ.

Based on the cost function and the graph, we can compute a network in $t = 0$: For each arc $(i,j) \in \mathcal{A}$, we have to decide whether to build a pipeline with a specific linear cost segment $c \in \mathcal{C}$ and, if so, how much maximum gas flow we have on that arc.

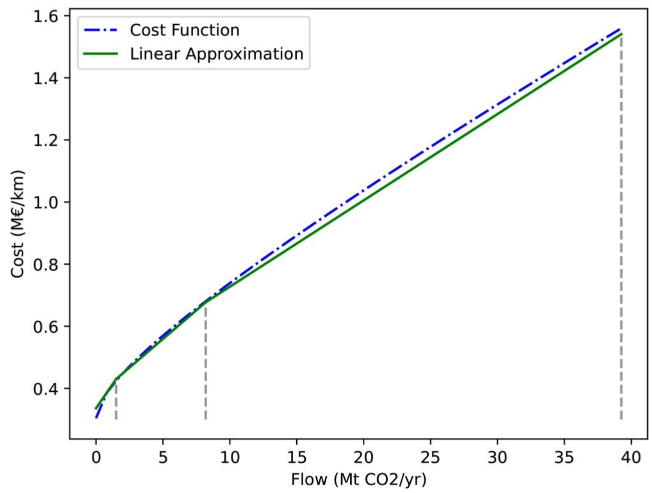


Figure 2. Cost function and approximation, three linear cost segments.

The following decisions have to be taken in $t = 1$, e.g., five years after $t = 0$: How do we extend the already given network in a cost-optimal way? For this, we have a set of upgrade operations $\mathcal{O}$ that we derived from Mischner et al. (2015). This includes building parallel lines ($o = 1$) (also called looping), and a pressure increase on an existing line ($o = 2$). For the pressure increase, we allow an extra flow, taking the original flow in $t = 0$ multiplied by $o_2^{\max}$. This comes at a cost factor of o_2^{cost} times the original price.

Our main focus is a regret model; however, to determine its efficacy, we need two complementary models.

The first model (M1) assumes perfect information of the scenarios s_1 and s_2 in a phased approach. This leads to a layout in $t = 0$ that can be easily extended in $t = 1$. The successive information model (M2) computes an optimal network for a scenario s_1 without anticipation of scenario s_2, which can lead to heavy interventions and regret of the decisions.

For the regret model, we then assume that all scenarios can become active in the following investment period $t = 1$. We define a *min-max* regret target function that considers the costs of all possible outcomes and computes the regret against the best solution, if the scenario outcome was known (M1). This gives the solution for $t = 0$ that can be built, knowing the regret over all possible realizations in $t = 1$ is minimal.

Our model is tractable compared to other publications, as we reduce the economic model significantly. We do not include sink opening costs, sink sequestration costs, or investment costs at the emitter side. Each scenario assumes that all participants need to handle all CO_2. The focus is on the pipeline construction, operation, and maintenance costs. This is possible as we assume a necessity to sequester certain CO_2 amounts to reach climate neutrality. The tractability also relies on using solutions, like the results from the perfect information model (M1), as starting points.

4. Formal model

In this section, we describe the complete formal model. In addition to the main two-stage regret model, we employ two benchmark models (M1 and M2) to evaluate solution quality under different information structures. These are needed to compute best known solutions for certain scenario combinations and to evaluate the benefit of the regret model. The following index sets, parameters, and variables are in common, but the complementary models omit some of them.

Index Sets	
$\mathcal{V}$	nodes
$\mathcal{A}$	arcs
$\mathcal{S}$	scenarios
$\mathcal{C}$	linear cost segments
$\mathcal{O}$	operations

Parameters	
l_{ij}	length of an arc from node i to j
m_c, y_c	cost for building a pipeline with linear cost segment c
Q_c^{max}	maximum diameter of pipeline with linear cost segment c
Q_c^{min}	minimum diameter of pipeline with linear cost segment c
d_{is}	demand of node i in scenario s (negative for sinks)
d_{i1s}	demand of node i in scenario s in period 1
n_1	years between the first and second investment period
n_2	years between the first investment period and the end of the planning horizon
OM	factor for operation and maintenance
τ	discount rate
o_2^{max}	maximum pressure increase factor
o_2^{cost}	cost for pressure increase

Variables	
b_{ijc}	pipeline build on arc (i,j) with linear cost segment c in period 0
p_{ijc}	flow on arc (i,j) with linear cost segment c in period 0
b_{ijcs}	pipeline build on arc (i,j) with linear cost segment c in period 1 considering scenario s
p_{ijcs}	flow on arc (i,j) with linear cost segment c in period 1, considering scenario s
f_{ijs}	total flow on arc (i,j) in period 1, considering scenario s
r_{ijs}	restructure cost for arc (i,j) in period 1, considering scenario s
u_{oijs}	use operation o on arc (i,j) in period 1, considering scenario s
x	system regret

4.1. First stage

In the first stage, the model decides on the general layout of the network. It decides if to build a pipeline on an arc (b_{ijc}) and how much flow is put on that arc (p_{ijc}).

(1) to (3) ensure that the piecewise linear cost segments are respected. This also includes that a flow is only allowed on an arc on which a pipeline is built. (4) ensures that all demand in the system is handled, and that flow is conserved throughout the pipeline network.

$$Q_c^{\min} b_{ijc} \le p_{ijc} \qquad (i,j) \in \mathcal{A}, c \in \mathcal{C} \tag{1}$$

$$Q_c^{\max} b_{ijc} \ge p_{ijc} \qquad (i,j) \in \mathcal{A}, c \in \mathcal{C} \tag{2}$$

$$\sum_{c \in \mathcal{C}} b_{ijc} \le 1 \quad (i,j) \in \mathcal{A} \tag{3}$$

$$\sum_{(i,j)\in\mathcal{A}} \sum_{c\in\mathcal{C}} p_{ijc} - \sum_{(j,i)\in\mathcal{A}} \sum_{c\in\mathcal{C}} p_{jic} \ge d_{js} \;\; j \in \mathcal{V}, s = s_1 \tag{4}$$

$$b_{ijc} \in \{0,1\} \qquad (i,j) \in \mathcal{A}, c \in \mathcal{C} \tag{5}$$

$$p_{ijc} \ge 0 \qquad (i,j) \in \mathcal{A}, c \in \mathcal{C} \tag{6}$$

4.2. Second stage

In the second stage of the model, all decision variables are indexed by s, so decisions are made for all possible realizations.

For each pipeline segment (i, j), a binary decision u_{oijs} is made if a certain upgrade function o is used in scenario s. The upgrade functions are not mutually exclusive, meaning we could increase the pressure of the old pipeline as well as build a parallel one next to it. Similar to (4), constraint (7) ensures that all demand is satisfied and flow conservation. A variable f_{ijs} is introduced as this is possible to achieve by multiple different operations. This is manipulated by each operation with indicator constraints.

$$\sum_{(i,j)\in A} f_{ijs} - \sum_{(j,i)\in \mathcal{A}} f_{jis} \geq d_{j1s} \qquad j \in V, s \in \mathcal{S} \tag{7}$$

$$u_{oijs} \in \{0,1\} \qquad (i,j) \in \mathcal{A}, s \in \mathcal{S}, o \in O \tag{8}$$

$$f_{ijs} \geq 0 \qquad (i,j) \in \mathcal{A}, s \in \mathcal{S} \tag{9}$$

If option $o = 1$ is selected (indicated by $u_{1ijs} = 1$), the model can build a parallel or a new line on an arc (i, j). This is modeled analogously to the first stage, but with scenarios and adding up both pipeline flows in (10).

$$(u_{1ijs} == 1) \Rightarrow f_{ijs} = \sum_{c\in\mathcal{C}} p_{ijc} + p_{ijcs} \qquad (i,j) \in \mathcal{A}, s \in \mathcal{S} \tag{10}$$

$$\sum_{c\in\mathcal{C}} b_{ijcs} \leq 1 \qquad (i,j) \in \mathcal{A}, s \in \mathcal{S} \tag{11}$$

$$Q_c^{\min} b_{ijcs} \leq p_{ijcs} \qquad (i,j) \in \mathcal{A}, c \in \mathcal{C}, s \in \mathcal{S} \tag{12}$$

$$Q_c^{\max} b_{ijcs} \geq p_{ijcs} \qquad (i,j) \in \mathcal{A}, c \in \mathcal{C}, s \in \mathcal{S} \tag{13}$$

$$b_{ijcs} \in \{0,1\} \qquad (i,j) \in \mathcal{A}, c \in \mathcal{C}, s \in \mathcal{S} \tag{14}$$

$$p_{ijcs} \geq 0 \qquad (i,j) \in \mathcal{A}, c \in \mathcal{C}, s \in \mathcal{S} \tag{15}$$

By selecting option $o = 2$ (indicated by $u_{2ijs} = 1$), we allow increasing an already existing capacity by a factor $o_2^{\max}$ by increasing the pressure in the pipeline (16). Constraint (17) enforces a restructuring cost r_{ijs} on this.

$$(u_{2ijs} == 1) \Rightarrow f_{ijs} = \sum_{c\in\mathcal{C}} p_{ijc} \cdot o_2^{\max} \qquad (i,j) \in A, s \in \mathcal{S} \tag{16}$$

$$(u_{2ijs} == 1) \Rightarrow r_{ijs} = I_{ij}^0 \cdot o_2^{cost} \qquad (i,j) \in A, s \in \mathcal{S} \tag{17}$$

To compute the system regret x, we need to calculate investment costs I, operating and maintenance costs O, and restructuring costs R for each scenario. I, as well as O occurring in $t = 0$, are the same for all scenarios, but differ for $t = 1$. As investments done in $t = 1$ are not entirely written off at the end of the planning horizon, we need to calculate the remaining value and subtract it from I^1. To compute the regret value, we further need the best solution for the case where we assume full knowledge, which scenario occurs in $t = 1$. To compute this best solution value B_s, we are using the complementary model $M1$ (see section 4.3.1).

The target function (18) in conjunction with constraint (19) forces a *min-max* regret optimization.

$$\min\ x \tag{18}$$

$$I^0 + O^0 + \frac{n_2 - n_1}{n_2} I_s^1 + O_s^1 + R_s - B_s \leq x \qquad s \in \mathcal{S} \tag{19}$$

$$x \geq 0 \tag{20}$$

with:

$$I^0 = \sum_{(i,j)\in A} \sum_{c\in\mathcal{C}} (p_{ijc0} \cdot m_c + b_{ijc0} \cdot y_c) \cdot l_{ij}$$

$$O^0 = \sum_{n=1}^{n_1} OM \cdot \frac{I^0}{(1+\tau)^n}$$

$$I_s^1 = \sum_{(i,j)\in A} \sum_{c\in\mathcal{C}} (p_{ijcs} \cdot m_c + b_{ijcs} \cdot y_c) \cdot l_{ij}$$

$$R_s = \sum_{(i,j)\in A} r_{ijs}$$

$$O_s^1 = \sum_{n=n_1}^{n_2} OM \cdot \frac{I^0 + I_s^1 + R_s}{(1+\tau)^n}$$

$B_s =$ Best solution for scenario s with perfect information

4.3. Complementary models

As noted in earlier sections, we employ two complementary models that support the development and evaluation of the regret model. Both serve as benchmarks, with the solution from model M1 used to calculate regret values.

4.3.1. Perfect information model (M1)

This model M1 is used to calculate the best known solutions (B_s) and to compute initial solutions for the regret model. It assumes full knowledge of scenarios $s1$ and $s2$. It will make its investment decisions in $t = 0$, already considering all necessary upgrades for $t = 1$. For the second stage, the set S just contains one scenario $s2$. The following objective function is used with $s = s2$, subject to (1) - (17).

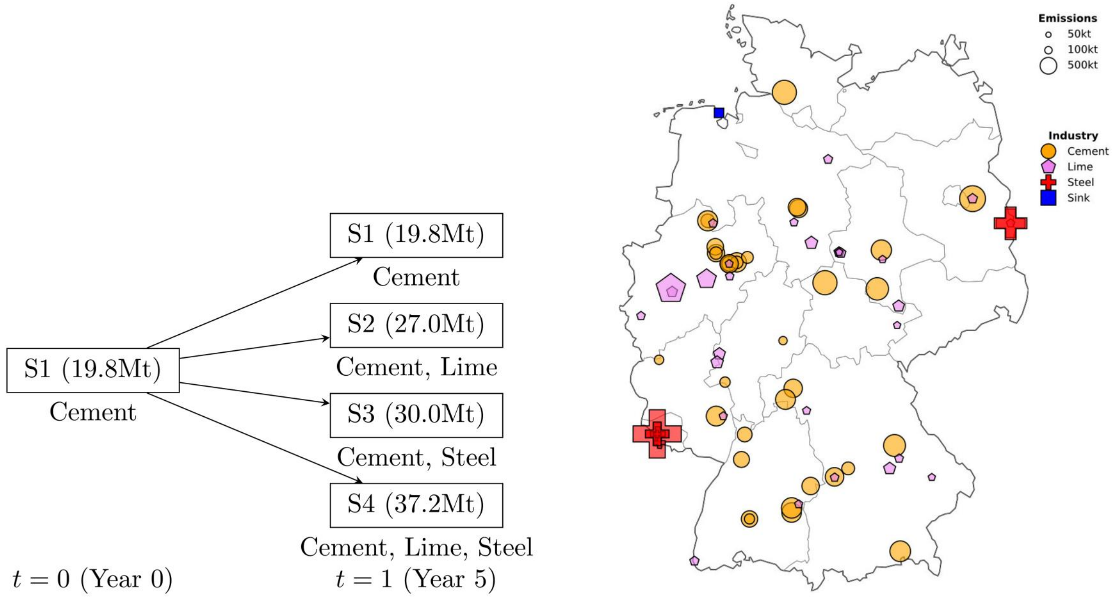
$$\min\ z_{M1} = I^0 + O^0 + \frac{n_2 - n_1}{n_2} I_s^1 + O_s^1 + R_s \tag{21}$$

4.3.2. Successive information model (M2)

This model M2 is used to benchmark the regret solutions as well as the M1 solutions. It works in two steps. It first computes the optimal solution network for one scenario $s1$ and for one period $t = 0$. It assumes that the pipeline is used consistently for an amount n_2 of years. This problem resembles nearly the first stage decision problem in Section 4. The following target function is minimizing investment cost I^0. This suffices, as operation and maintenance costs are directly dependent on this, and there are no further changes to the layout. The target function is subject to (1) - (6).

$$\min\ z_{t0} = \sum_{(i,j)\in\mathcal{A}} \sum_{c\in\mathcal{C}} (p_{ijt} \cdot m_c + b_{ijc} \cdot y_c) \cdot l_{ij} \tag{22}$$

In a second step, more information becomes available, namely the scenario $s2$ happening in $t = 1$. All first stage



(a) Scenario tree (b) Geographical distribution of emitters

Figure 3. Scenarios.

variables $(b_{ijc}, p_{ijc} \quad (i,j) \in A, c \in C)$ become parameters, set to the outcome values of the first optimization. It then finds the optimal network for $t = 1$ and scenario $s2$. The following objective function is used, subject to (7) - (17).

$$\min\ z_{t1} = \frac{n_2 - n_1}{n_2} I_s^1 + O_s^1 + R_s \tag{23}$$

5. Case study

To demonstrate our model, we present a case study on the development of a CO_2 pipeline network in Germany. The cement producers are assumed to be the first consumers of the initial network. This is attributed to the indispensability of CCS to decarbonize the sector due to the hard-to-abate process emissions (IEA., 2018). Additionally, the sector's ongoing activities planning of the relevant infrastructure demonstrate a clear and determined vision regarding the technology deployment (OGE., 2024; VDZ., 2024). Therefore, the uncertainty surrounding CCS demand is relatively minimal compared to other industrial sectors. Afterwards, four scenarios are considered for the network development (Figure 3a).

The first scenario (S1) assumes that no additional emitters are added to the network. The second (S2) and third (S3) scenarios assume that either the lime or steel emitters are added to the network, respectively. Finally, both the lime and steel emitters join the network in the fourth scenario (S4). An overview of the scenarios and their respective plant count and emissions can be found in Table 2 (DEHSt, 2023). The geographic distribution of the emitters is also depicted in Figure 3b. The analyses consider the emitters with more than 100 kt CO_2 as well as the steel plants located far away from the planned national hydrogen network. The study also considers a North Sea harbor (Wilhelmshaven) as a potential sink, based on VDZ. (2024). All parameters can

Table 2. Scenario details

Scenario	Description	Emitters	Emissions [Mt/a]
S1	Cement	35	19.8
S2	Cement, Lime	64	27.0
S3	Cement, Steel	44	30.0
S4	Cement, Lime, Steel	73	37.2

Table 3. Total system costs

Scenarios	z_{M1}[Mio €]	z_{M2}[Mio €]	z_R[Mio €]
Cement (S1)	3,141.325	3,141.325	3,584.782
Cement, Lime (S2)	3,976.254	4,997.963	4,294.844
Cement, Steel (S3)	3,946.124	4,422.603	4,313.799
Cement, Lime, Steel (S4)	4,648.960	5,585.506	4,913.010

Table 4. Potential savings, regret, and benefit

Scenarios	Potential[Mio €]	Regret[Mio €]	Benefit[Mio €]
Cement (S1)	0.000	443.458	−443.458
Cement, Lime (S2)	1,021.710	318.591	703.119
Cement, Steel (S3)	476.479	367.675	108.804
Cement, Lime, Steel (S4)	936.546	264.049	672.497

be found in Appendix B. This also includes all the data sources for geographic features, population density, etc., as well as gas density, velocity, discount rate, and cost parameters. The calculations are performed with Gurobi version 12, on Intel Xeon 8468 Sapphire Rapids CPUs with 36 cores, with a base speed of 2.1Ghz and 96GB of RAM. Running the case study (including M1, M2, and the regret model) needs around 168 hours of computation. Additional information on run times and solution quality is provided in Appendix C.

The results of the case study and the resulting layouts are provided in Tables 3 and 4 as well as Figures 4–6. Table 3 presents the system costs for the three different models computed for the case study: the regret model, the perfect information model (M1), and the successive information model (M2). The perfect information model (M1) and the

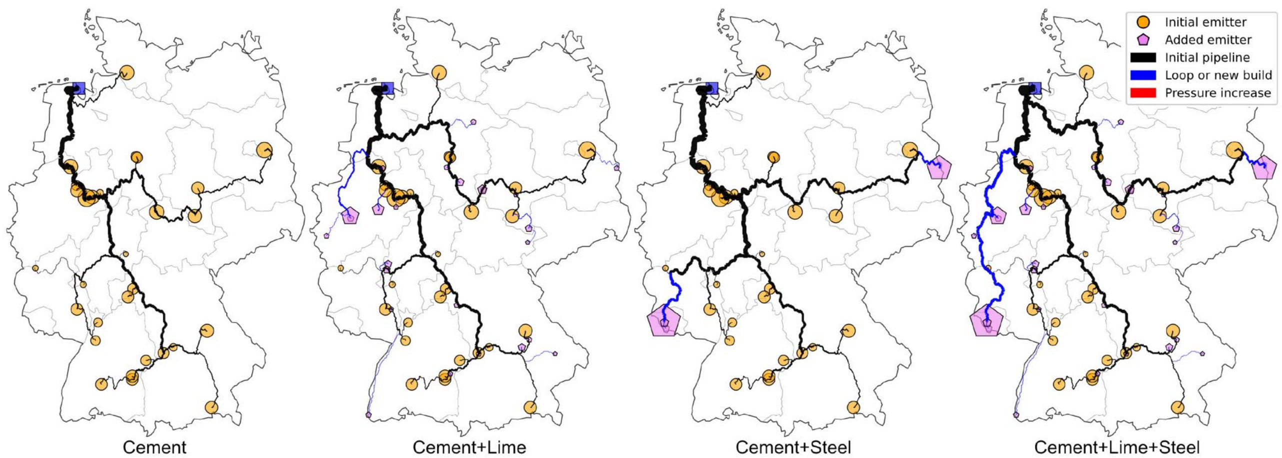


Figure 4. Perfect information model result layouts.

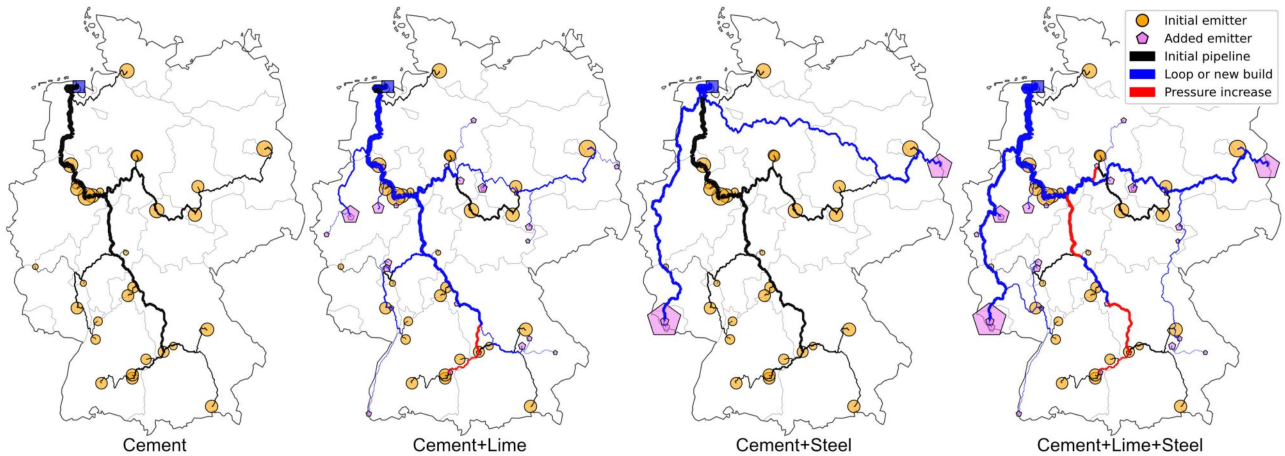


Figure 5. Successive information model result layouts.

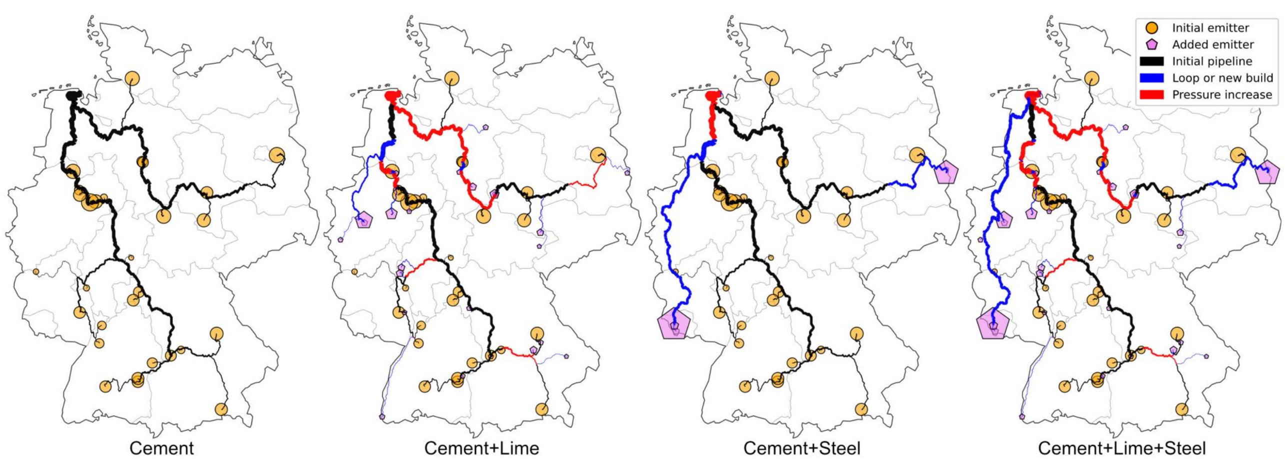


Figure 6. Regret model result layouts.

successive information model (M2) were run for each scenario combination separately. Table 4 also shows the potential savings through perfect knowledge, the regret, and the benefit of the regret optimization. Herein, potential savings mean the difference between the results of the perfect information model and the successive information model; benefit means the difference between the results of the regret model and the successive information model.

The layouts in Figures 4–6 are visualized to show both investment periods in the same map. For $t = 0$, circles represent the emitters and black lines show the pipeline build. For the second period, the pentagons indicate the added emitters. The other lines either illustrate the construction of a new pipeline or a parallel line (upgrade option 1) or show that the pressure in the pipeline is increased (upgrade option 2).

For the perfect information model (M1), the system costs of the different scenarios range between 3,141 Mio. and 4,648 Mio. €. The outcomes of the perfect information model are characterized by oversizing to accommodate all requested demands. Subsequently, only the connecting pipelines to the existing network are built in t = 1. As shown in Figure 4, no parallel lines or pressure increases were used. Using the successive information model (M2), the initial network of scenario S1 is constructed first and then upgraded at t = 1. Therefore, as expected, this approach exhibits significant increases in cost. In the cement and lime scenario (S2), the cost increases from 3,976 Mio. € to 4,998 Mio. € (+1,022 Mio. €). For the cement, lime, and steel scenario (S4), there is an analogous increase of 937 Mio. € from 4,649 Mio. € to 5,586 Mio. €. In the cement and steel scenario (S3), there is also an increase of 476 Mio. €, which is significantly lower compared to the other scenarios.

Figure 5 depicts the layout changes of the successive information model. Compared to Figure 4, significant interventions throughout the network are observed. Herein, a mixture of pressure increases, parallel lines, and new pipelines is used in S2. Contrariwise, the initial layout is ignored in S3, with new lines being built primarily in areas where no existing pipeline is present. For S4, nearly no pressure increase is used. One new eastern trunk is established, which also connects to sources in Bavaria. From east to west, the new trunk mostly follows the initial layouts, but sometimes establishes new lines in areas not used before.

Using the regret model, the scenarios S2, S3, and S4 perform better than with the successive information model, with S2 and S4 having improvements of over 500 Mio. €. S3 has a smaller benefit of around 109 Mio. € and S1 leads to an extra cost of 443 Mio. €, which also represents the biggest regret. The network presented in Figure 6 showcases a rather clean layout. In many sections, the network is just oversized to allow simple connections in t = 1. However, the network makes use of pressure increases in specific parts of the network (S2, S3). The network in t = 0 looks very similar to the perfect knowledge model for S4.

5.1. Sensitivity analysis

To strengthen our results, we conduct a sensitivity analysis. Hereby, we investigate the following economic parameters: construction cost, pressure increase cost, and expected years of operations in conjunction with the years between the two investment periods. Furthermore, we consider a scenario where pipelines are only built along the existing NG network.

5.1.1. Construction cost

The construction cost it is varied by 10 %. While this change impacts the solution values, it has no impact on the final layout. The length of the network stays the same. Also, there are only very minor changes in diameter.

5.1.2. Pressure increase cost

In the original case study, we assume $o_2^{cost} = 15\%$. This is based on NG pipelines, which have different economics than CO_2; therefore we also investigate other values (10% and 20%).

The outcomes are nearly identical. In the perfect information model, still, no pressure increase is used, which implies oversizing remains the best strategy. In the successive information model, the changes are minimal. In most cases, the increased flow on a given pipeline segment exceeds 10%, making looping the preferred option over pressure increase.

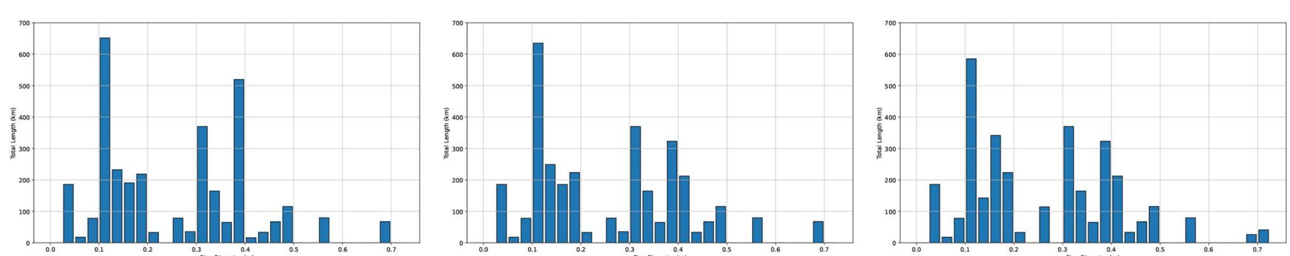
Although the length and layout of the network stay the same, there are some changes in the diameter. Having the pressure increase at lower prices allows building slightly smaller diameters in some parts of the network. However, the difference in the distribution of pipeline sizes is relatively small, as shown in Figure 7.

While a better regret value is obtained, this can be attributed to the slightly smaller diameters and lower refactoring cost rather than to better layouts.

5.1.3. Years of operation

In terms of years of operation, we consider different durations ($n_2 = 20$, $n_2 = 30$, $n_2 = 40$) in addition to the original 25 years. Furthermore, we examine the impact of changing the second stage to $n_1 = 10$ years after the initial investment, instead of 5. The different settings are denoted as '$n2 - n1$'. E.g. '$20 - 10$' means 20 years of operation and 10 years until the next investment.

Figure 8 shows the layout changes for the perfect information model for scenario S4. In the '$20 - 10$' case, oversizing is used significantly less. A new trunk is built in the second investment period in western Germany, stretching nearly completely to the north. Compared to the '$25 - 5$' base case, the trunk length is significantly reduced. For '$30 - 5$', most of the west trunk is already built in $t = 0$



(a) $o_2^{cost} = 10\%$ (b) $o_2^{cost} = 15\%$ (base case) (c) $o_2^{cost} = 20\%$

Figure 7. Distribution of pipeline size for different pressure increase costs.

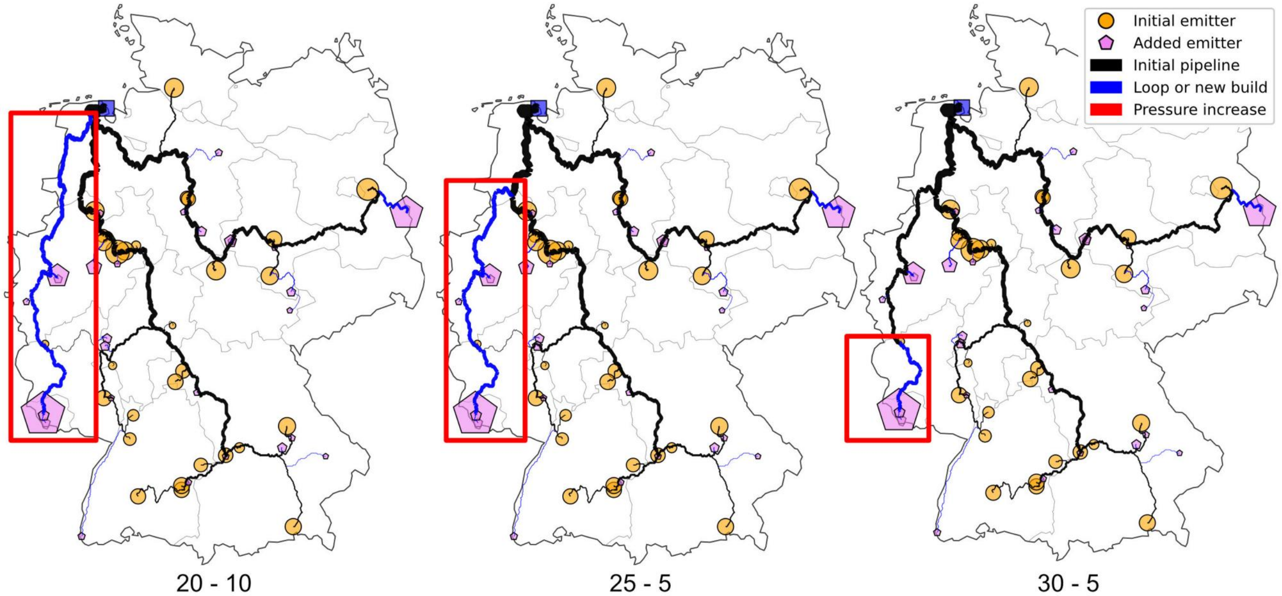


Figure 8. Impact of years of operation (n_2) and years until second investment period (n_1) [$n2 - n1$], comparison of layout of perfect information model S4, rectangle highlights major difference.

except for the last connection. (The other sensitivity runs '$30 - 10$' and '$40 - 10$', have an equal layout to '$25 - 5$', while '$40 - 5$' has the same layout as '$30 - 5$'.)

In the regret optimization, investments are also delayed in the '$20 - 10$' case. This, combined with the overall lower regret value, suggests that delaying the second investment period leads to less regret.

5.1.4. Geographic multipliers

As mentioned above, existing pipeline infrastructure is a crucial component in planning a new network. Industry studies (e.g., VDZ. (2024)) plan the whole network solely based on the existing NG network. We can replicate this setting by changing the multiplier for 'pre-existing pipelines' to 0. If we need to connect to the existing network, we still use the other values as in Table 5.

Figure 9 shows the two $t = 0$ regret layouts for the case study. The layouts are vastly different. Overall, this setting incurs higher costs for all models, amounting to around 200 Mio. € on average. The regret, however, is slightly lower for the NG grid case with 419 Mio. € compared to 443 Mio. € in the base case.

5.1.5. Summary

In summary, the sensitivity analysis indicates that the construction and the pressure increase cost have little impact. However, the choices of years of operation and the second investment period lead to significant layout changes. Also geographic multipliers have a significant impact.

6. Conclusion

We propose a novel regret-minimizing optimization model for designing CCS pipeline networks. In a case study, we demonstrate that our model is able to identify networks that are adaptable to changing scenarios over time. It computes the tradeoffs of these adapted and oversized layouts. Thus, the study holds strong relevance for policy making as it directly addresses the challenges of planning and financing CO_2 transport infrastructure under uncertainty. The framework enables decision makers to assess and quantify these tradeoffs, ultimately making informed decisions. By introducing an optimization model that accounts for phased development and minimizes the risk of regret from premature or misaligned investments, it provides the stakeholders with a practical framework for designing flexible, future-proof infrastructure strategies. Such insights are crucial for ensuring that public and private resources are allocated efficiently, while supporting long-term climate goals and enabling hard-to-abate industries to transition toward a low-carbon economy. Therefore, the outcomes are also valuable for policy frameworks, for example, the EU Net Zero Industry Act (European Commission, 2023), which aims to accelerate decarbonization in hard-to-abate sectors.

The case study results demonstrate that oversizing the pipeline is clearly the preferred option if perfect information is available. Contrariwise, building without considering potential future scenarios is not a viable option, as it proves to be highly inefficient. Indeed, both models represent two extreme cases. On the one hand, it is strategically naive to overlook the potential future changes. That is why the initial layout of the successive information model undergoes significant changes to allow the integration of additional emitters. On the other hand, the potential changes are also associated with several uncertainties, which is why the perfect knowledge model is not effective in real applications. Herein, the regret optimization model emerges as a viable approach to tackle this dilemma. As the results of the regret optimization model demonstrate, the required alterations are significantly lower than with the successive information

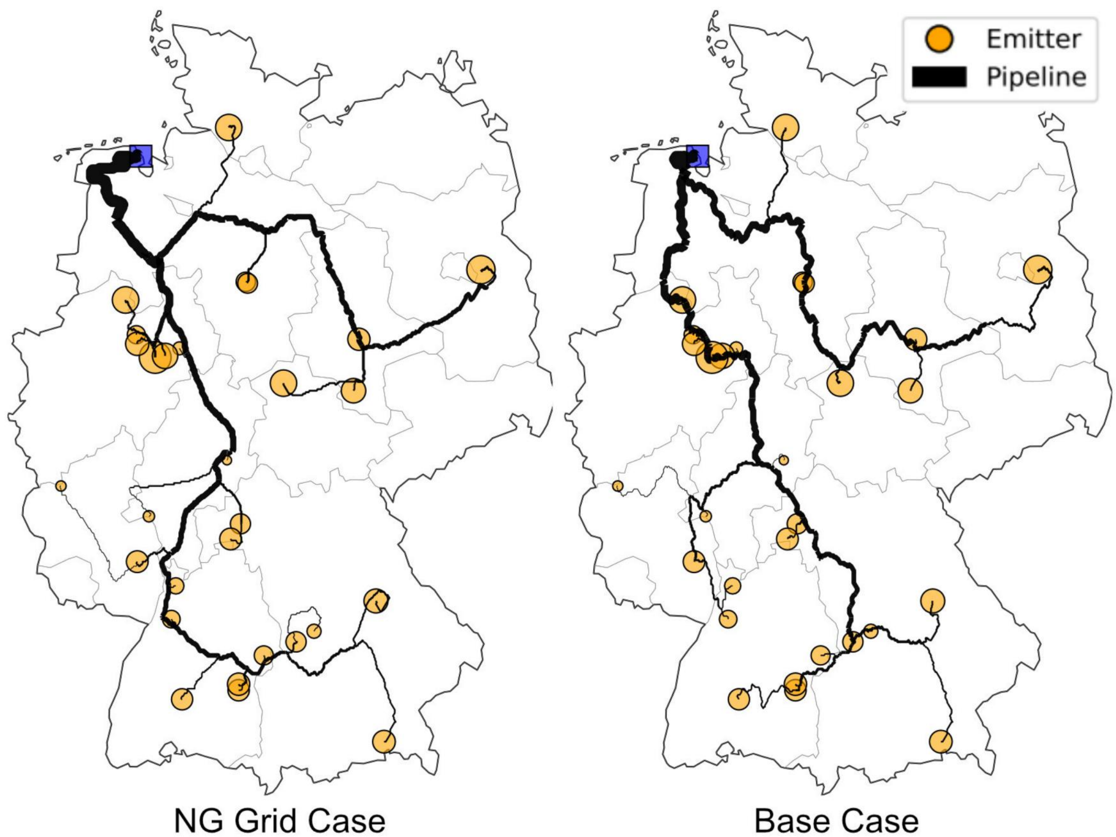


Figure 9. Comparison of different geographical multipliers, built according to the NG grid versus the base case, regret model at $t = 0$.

model (M2). It should be highlighted that the regret model will still incur alterations, as it is impossible to eliminate uncertainties. Nonetheless, while there may not be a solution without regret, the model can serve as the optimal approach to minimize it.

Looking ahead, the model can undergo upgrades in different directions. Firstly, exploring multi-stage or extended investment periods could provide a better understanding of long-term dynamics and potential outcomes. Secondly, considering reduction scenarios in our framework can also be a useful integration. While the model can theoretically handle decreasing values, sensible aggregated scenario rules would need to be determined, as well as downgrade options for the pipelines. Thirdly, investigating alternative transportation connections, such as rail, could offer insights into diversifying infrastructure options and mitigating risks associated with reliance on single modes. Fourthly, the chosen worst-case optimization might be overly cautious. Contrasting our results with more optimistic settings could provide valuable insights. Lastly, increasing the model's scalability can enhance the effectiveness of our approach. While the model's performance is satisfactory at present, its capacity reaches its limit with industry-scale cases. Hence, improving scalability to incorporate additional cases, scenarios, and data inputs will be crucial for sustaining the model's utility and relevance in increasingly complex decision-making environments.

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Data availability statement

The data (including the source code) that support the findings of this study are openly available in 'Zenodo' at http://doi.org/10.5281/zenodo.15812995, Reference Bogs et al. (2025).

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Appendix A. Graph from geographic data

With the following steps, we derive the candidate graph from the geographic data and emitters

1. Split the geographic area into $1.5km \cdot 1.5km$ squares.
2. Apply multipliers for: Population density, slope, CDDA Zones and nature parks, lakes and waterways, infrastructure like existing pipelines, motorways, and railroads.
3. Inject emitters and sinks into the grid, this also includes emitters that are not present in all the scenarios to ensure a consistent graphs between the time periods. All emitters located in the same square are treated as a single node, with their emissions summed together.
4. Use Delaunay triangulation between all emitters (including hypothetical ones) and sinks.
5. Calculate the shortest path between the triangulated points. For this, we consider each square a node in a graph. Each orthogonal neighbor is connected with an edge that has the weight according to the multiplier. Each diagonal neighbor has an arc that has the weight multiplied with $\sqrt{2}$.
6. We save the shortest paths with their nodes into a new undirected graph.
7. In the new graph, merge all nodes with a degree of two, thus only remaining nodes are with a degree greater equal three (transport nodes or emitters, sinks) or one (just emitters and sinks).
8. Convert the undirected graph into a directed graph.

Appendix B. Case study parameters

For nearly all parameters, we follow Yeates et al. (2024). Gas density of $p = 900\frac{kg}{m^3}$ and a velocity of $v = 3\frac{m}{s}$. We use Parker (2003) formula adjusted by inflation to 2022 and a discount rate of 5%. The second stage decisions are made after $n_1 = 5$ years. We assume a $n_2 = 25$-year operational period which is the official write-off period for pipelines in Germany (Bundesfinanzministerium, 1995).

For the generation of the graph we use the data listed in Table 6 and the multipliers listed in Table 5.

Table 5. Multipliers used

Criterion	Multiplier
Population density/km^2 (<250)	1
Population density/km^2 (250-500)	4
Population density/km^2 (500-2000)	9
Population density/km^2 (2000-4000)	16
Population density/km^2 (4000-8000)	25
Population density/km^2 (>8000)	36
Pre-existing pipelines	0.25
Railroads	3
Motorways	3
Rivers, lakes, and transitional waters	10
CDDA protected areas (excl. National parks)	10
National parks	30
Terrain slope [0°-90°]	1-20

Table 6. Datasets used

Data	Source
Geographic outlines	Eurostat (2021)
Pre-existing pipelines	Kunz et al. (2017)
Population density	Batista e Silva et al. (2021)
CDDA protected areas and national parks	European Environment Agency (2020)
Road and rail infrastructure	Kelso (2024)
Topography	European Union's Copernicus Land Monitoring Service information (2022)
Waterways, lakes, transitional waters	Kelso (2024)

Appendix C. Computational results

The calculations are performed using Gurobi version 12 on Intel Xeon 8468 Sapphire Rapids CPUs with 36 cores with base speed of 2.1Ghz and 96GB of RAM.

Given the long planning horizon of our model, extended computation times are acceptable. For both models M1 and M2, we set a timeout of 72 hours, targeting an optimality gap of 1%, while accepting solutions with gaps of up to 2%. For the problem sizes considered in our study, most instances were solved significantly faster, with only one exception. An overview of the runtimes and solution quality is provided in Table 7.

Considering the structure of the regret model, it generally does not find a lower bound. Thus, it does not terminate but rather runs into a given timeout. Nevertheless, the solutions obtained at the 72-hour timeout seem to be a very suitable compromise solution.

Table 7. Runtimes and solution quality: an optimality gap is only given next to the solution value if gap $\geq 1\%$

Model	Scenario	Time[s]	Solution Value	Approximation Error
M1	S1	1860	3117.848	0.75%
	S2	258900	3932.599 (1.54%)	1.10%
	S3	4632	3850.085	2.43%
	S4	54646	4514.342	2.90%
M2	S1	1860	3117.848	0.75%
	S2	19251	4983.108	0.30%
	S3	5	4339.724	1.87%
	S4	4593	5500.763	1.52%
Regret		258900	350.477 (-%)	20.97%

C1. Impact of piecewise linear approximation

As our approach uses a piecewise linear approximation, it is necessary to determine the number of linear cost segments that offer a good tradeoff between runtime and solution quality. To that end, we tested our case study using one, two, or three linear cost segments.

Figure 10a shows the error between the real solution value and the approximate solution value for both the M1 and M2 models. As expected, the error decreases significantly with each additional linear cost segment. E.g., the average error decreases from 10.09% with one linear cost segment to 1.55% with two linear cost segments, and further down to 0.52% with three linear cost segments. However, as shown in Figure 10b, this reduction in error comes at a notable increase in the runtime. The average is going up from 33 minutes with one linear cost segment to 14 hours with two linear cost segments and 23 hours with three linear cost segments.

When comparing the real solution values (see Figure 11), adding linear cost segments yields improved solutions, though the gains are relatively minor (less than 1%). Consequently, the incremental benefit of using more than one linear cost segment appears limited.

However, for the regret model, the high error with one linear cost segment poses a problem. The best-known solution values from M1 are highly inaccurate. As these are inputs for the regret model, running it with them does not yield any sensible results. In contrast, utilizing two or three linear cost segments does not create a similar problem.

Examining the solution quality of the regret model, going from two to three linear cost segments reduces the error in the solution value from 21% to 5%. However, the real solution quality only improves by 17.4 million € (4.1%). In summary, using one linear cost segment is not feasible within the regret model due to unacceptable errors. Moreover, while three linear cost segments provide slightly more accurate values and better solutions compared to two linear cost segments, the modest improvement does not justify the substantially higher runtime.

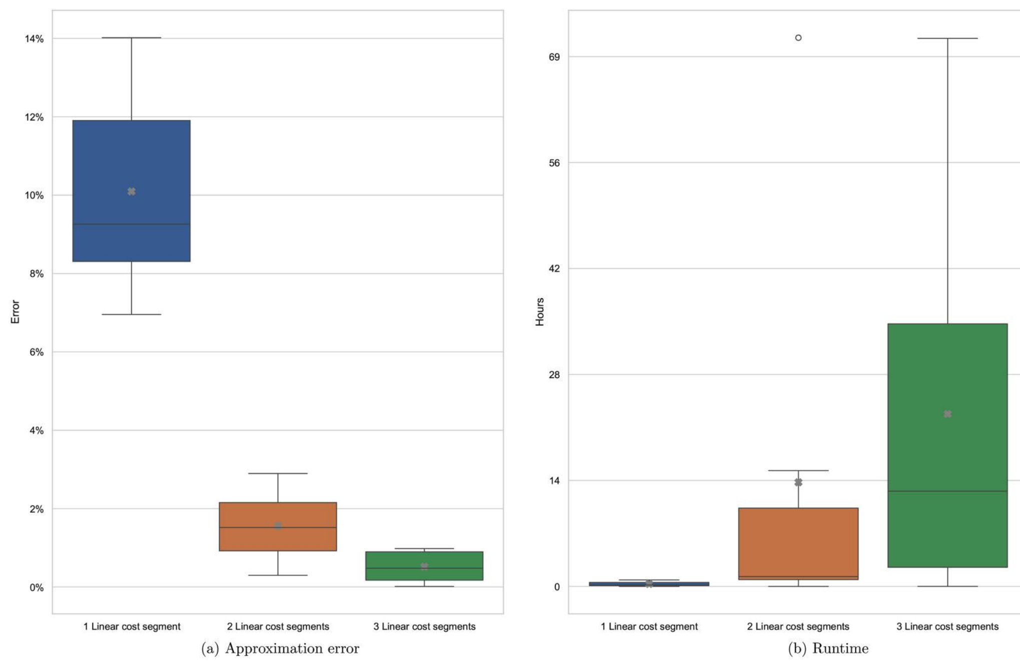

Figure 10. Approximation error versus runtime.

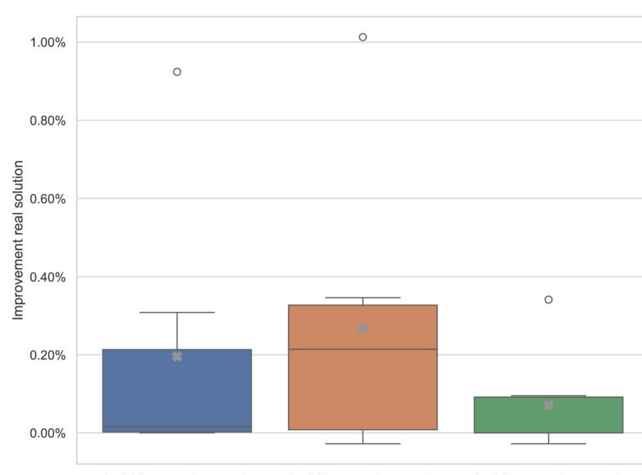

Figure 11. Improvements in real solution value adding more linear cost segments.