# *Projecting future costs of direct air capture for deep decarbonization*

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## Overview

According to the IPCC, all mitigation pathways to limit global temperature rise to well below 2°C include negative emissions technologies (NETs) for carbon dioxide (CO2) removal [1]. Direct air carbon capture and storage (DACCS) is a promising NET as it permanently and measurably removes CO2 from the air and stores it in aquifers or basalts [2]. However, capture costs of DACCS are high, with current estimates ranging from \$300 to \$3000/t$CO_2$ [3]. The large-scale deployment of DACCS will therefore largely depend on the reduction of costs [4]. To make informed investment decisions a clear understanding of cost reduction potentials, including projections of future costs is needed. For energy technologies a proven method is to use experience curves, based on the empirical observation that costs decrease by a fixed percentage for each doubling of cumulative installed capacity [5]. However, cost projections are inherently uncertain [6], with experience rate parameters being a major source of uncertainty that can significantly impact cost projections [7]. For several established low-carbon technologies, including solar PV [8] and batteries [9], historical deployment data has been used to extrapolate experience rates.

Due to the limited deployment history of nascent technologies such as DACCS, it is not possible to derive empirical experience rates from past deployment data. Therefore, previous studies used experience rates of other low-carbon technologies to project DACCS costs [10], [11]. Yet, this approach may result in significant over- or underestimation of costs due to differences in experience rates between technologies [12]. An arbitrary approach in choosing an experience rate and failing to account for uncertainties in cost projections can lead to a false sense of precision. This can lead to erroneous, incomplete, or misleading policy conclusions [13]. To address this gap, we use a component-based experience curve approach [14], assigning individual experience rates to each key component of the technology. We conduct expert interviews to evaluate the technology-inherent characteristics of the components, based on which we assign experience rates. We thus derive probabilistic cost projections based on bottom-up cost estimates and theoretically grounded component-based experience curves.

## Methods

We propose a framework to project the future cost of DACCS using experience rates derived from theoretical principles. The experience rates are determined by assessing the design complexity and customization needs of the technical components and the overall system through expert interviews. We assess three different DACCS archetypes. We then conduct cost projections through a bottom-up cost analysis, utilizing experience rates and Monte Carlo simulation to derive probabilistic cost projections for DACCS.

## Results

Our preliminary findings demonstrate that there are substantial differences in the cost reduction potentials of the three DACCS technologies under assessment, with the exact magnitude currently being quantified and presented at the conference. Our expert interviews indicate variations in experience rates for the different DACCS technologies and their components, with the highest experience rates occurring for novel components. Our modeling shows that cost shares shift from capital expenditures (CAPEX) to variable operating expenditures (OPEX) as the DACCS technologies move down the experience curve, emphasizing the need for affordable renewable energy to make DACCS economically viable.

**Conclusions**

Our results suggest that it is unlikely for any of the three assessed DACCS technologies to achieve cost reductions below \$100/tCO2 at a Gt-scale. Therefore, supporting the deployment of both existing and novel DACCS methods is crucial to achieving mid-century net-zero targets and closing the carbon dioxide removal gap [15]. Our study offers valuable insights for modelers, researchers, and policymakers to understand the influence of technology-inherent characteristics of DACCS systems on the potential for cost reductions. Our results can serve as inputs for energy system models to evaluate the costs of DACCS against other greenhouse gas mitigation methods, to assess the contribution of DACCS towards achieving net-zero emissions.

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