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An Improved Cascade Analysis for The Dual Carbon Goals

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Renewable energy and carbon dioxide capture and storage can cut carbon dioxide emissions, and negative emissions technologies are effective methods of carbon dioxide removal. The integration of the three is an important approach to mitigate surface temperature rise and achieve the climate change vision. This paper presents an improved algebraic targeting approach for multi-period energy planning integrating fossil energy, renewable energy, carbon capture and storage, and negative emission technologies. In this work, the risk hedging effect of negative emission technologies and the operational lifetime of carbon capture and storage are considered to reduce the amount of carbon capture and storage deployed. The approach can reduce the economic costs, environmental costs, and likelihood of stranded assets in low-carbon energy planning. This multi-period algebraic targeting approach is demonstrated through a case study. The results show that multi-period low-carbon energy planning can achieve better deployment of resources and technologies and reduce the pressure to reduce carbon emissions in the early stages of planning.

1. Introduction

The tipping point of climate catastrophe is approaching. Achieving the 1.5°C temperature control temperature targets of the Paris Agreement will require more urgent and ambitious action on deep CO_2 reductions. One important way to reduce CO_2 is to promote a transition from fossil to renewable energy sources (You and Kakinaka, 2022). However, the current role of fossil energy cannot be completely replaced. carbon capture and storage (CCS) can allow the use of fossil fuels while significantly reducing the amount of CO_2 emitted into the atmosphere. These two carbon reduction measures cannot really achieve net zero emissions. The importance of carbon dioxide removal (CDR) has emerged. Negative emission technologies (NETs) is the predominant means of delivering CDR. NETs can remove pre-existing CO_2 from the atmosphere and offset carbon emissions from hard-to-decarbonise sectors (Pires, 2019). The maturity of NETs is currently limited, but timely deployment of NETs can better play their risk-hedging role in energy planning and contribute to safe and sustainable achievement of climate goals. All three of these approaches play an integral role in mitigating climate change, and there is a growing body of research on the integration of carbon reduction and decarbonisation technologies. Carbon Emission Point Analysis (CEPA) has been established in recent years and is widely used. Originally developed by Tan and Foo (2007), CEPA is based on traditional pinch analysis principles to provide policy makers with information on sustainable energy deployment (Andiappan et al., 2019). Subsequently, a graphical targeting method known as the Energy Planning Pinch Diagram (EPPD) was developed to analyse the minimum required amount of renewable energy resources while considering the maximum amount of conventional fossil fuels that could be used (Tan and Foo, 2007). Later, approaches such as cascade analysis (Foo et al., 2008), the automated targeting model (Lee et al., 2009), and algebraic target approaches (Sahu et al., 2014) have been developed, which overcome some of the limitations of graphical approaches. Nair et al. (2021) recently developed a generic algebraic targeting approach for integrating renewable energy, CCS, and NETs. This

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approach eliminates the iterative procedure needed during the graphical targeting approach (Nair et al., 2020) ,enabling more convenient handling of large data sets (Nair et al., 2021).
The above-mentioned work can only carry out low-carbon energy planning for a certain country or sector within a year. In past work, Ooi et al. (2014) proposed multi-cycle retrofit planning, but they only considered the addition of CCS to the power generation sector planning. In practice, different carbon reduction targets are usually set at different stages, such as China's commitment to work towards carbon peaking by 2030 and carbon neutrality by 2060. In other words, due to factors such as the maturity of carbon reduction measures and CDR, the reduction process must be a gradual one. A multi-period low-carbon energy planning that integrates various carbon reduction measures and CDR is a more reasonable option.
This work proposes an improved multi-period algebraic targeting approach that enables the integration of fossil energy, renewable energy, CCS and NETs on the one hand, and joint multi-cycle planning on the other. This multi-period energy planning incorporates the concept of time periods, which allows for a more optimal deployment of resources and technologies by taking into account the input time of NETs and the operational lifetime of CCS systems. At the same time, multi-stage energy planning can also alleviate the pressure to reduce carbon emissions in the early stages.
The paper is organised as follows. A formal problem statement is given in the next section. Section 3 gives the general procedure for the multi-period algebraic targeting approach. Section 4 illustrates the use of the approach with a case study of the enhanced NDC policy scenario in China. Finally, the paper ends with the conclusion and an outlook for future work.

2. Problem Statement

The following is the statement of multi-period low-carbon energy planning problem.

- Given a set of time intervals $t \in T$, the time intervals can be formulated by planners according to the energy planning goals or policies of a given region/sector, it is assumed that there are a total of H time intervals.
- Given a set of energy sources $i \in I$, comprised of fossil energy sources and renewable energy sources. Each energy source has a given energy supply $F_{St,i}$ and its respective carbon emission factor $C_{S,i}$. The product of its modified supply $F_{Xt,i}$ and $C_{S,i}$in t is its carbon emission load $\Delta m_{St,i}$. The total carbon emission load of all energy sources in t is Δm_{Zt}.
- Given a set of energy-producing NETs (EP-NETs) $a \in A$ and energy-consuming NETs (EC-NETs) $b \in B$. The carbon emission factor of EP-NET and EC-NET are $C_{NP,a}$ and $C_{NN,b}$. The energy produced and consumed in t are $F_{NPt,a}$ and $F_{NNt,b}$.
- Carbon emission factors for NETs that generate/consume insignificant amounts of energy, such as afforestation, are assumed to be zero and are not entered in the cascade table. Total carbon emissions absorbed in t is Δm_{Nt}.
- Given a set of regions/sectors $j \in J$. The total energy demand in t is $\sum_j F_{Dt,j}$ and the carbon emission constraint is Δm_{Lt}.
- The sum of Δm_{Lt} and Δm_{Nt} in t is the modified carbon emission constraint Δm_{Xt}. The difference between Δm_{Zt} and Δm_{Xt} is the amount of carbon emissions Δm_{Rt} that needs to be reduced in t. The quotient of Δm_{Xt} and $F_{Dt,j}$ is the target carbon emission factor $C_{Dt,j}$ in t.
- It is assumed that it is not necessary to wait until NET is available on a large scale before deploying it, but rather deployment is done as soon as possible (Obersteiner et al., 2018), i.e., integrating the selected NETs into the energy planning process as soon as they have a predicted potential value.
- It is assumed that the operating lifetimes (LT), parasitic power losses (X) and removal rates (RR) of the CCS equipment remain constant.

3. Multi-period algebraic targeting approach

In this approach, the energy loss due to CCS is compensated by additional energy from renewable sources. Table 1 shows the basic structure of the cascade table, which presents the data from the calculations of the algebraic targeting approach. The calculation framework is shown in Figure 1.
Two illustrations of the cascade table are as follows.

a. Each row in the cascade table represents a level k.
b. Emission factors are filled in the cascade table in ascending order. Fill in the last level in column C_k with an arbitrarily large value for calculation purposes.

The flow chart is illustrated in Figure 1.

(S1) The carbon emission factor(C_k) for the energy sector after the CCS retrofit is calculated in the first step.

(S2) The formula in yellow box ① gives the corrected energy supply ($F_{Xt,i}$) in t, i.e. the supply of fossil energy after being offset or increased by the NETs, and the carbon load that still needs to be reduced in t (Δm_{Rt})
(S3) The formula in green box ② gives the theoretical deployment ($F_{TR,k}$) and the actual deployment ($F_{AR,k}$) of CCS in t.
(S4) The formula in blue box ③ gives the demand for compensatory energy (F_{COMPt}), the supply of energy in the energy sector after completion of the CCS deployment ($F_{Alt,k}$) and the final net supply of energy ($F_{Nt,k}$).
(S5) The formula in red box ④ gives the energy cascade($\delta_{t(k)}$) and the emission cascade ($\varepsilon_{t(k)}$) in t.
(S6) In the absence of an intentional explanation, i or k takes the values n-1, n-2,…2.
(S7) The first step calculates the carbon emission factor for source i after retrofitting with CCS.

Table 1: Basic structure of a cascade table for multi-period algebraic targeting approach

T	C_k	$\sum_j F_{Dt,j}$	$F_{NPt,b}$	$F_{St,i}$	$F_{NNt,b}$	$F_{Xt,i}$	$F_{TR,k}$	$\Delta F_{TR,k}$	$F_{AR,k}$	$F_{Alt,k}$	$F_{Nt,k}$	$\delta_{t(k)}$	$\varepsilon_{t(k)}$	ΔC_k
												δ_1=0		
	C_1		$F_{NP1,1}$		$F_{NN1,a}$	$F_{X1,1}$					$F_{N1,1}$		$\varepsilon_{1(1)}$=0	
												$\delta_{1(1)}$		ΔC_1
	C_2		$F_{NP1,2}$		$F_{NN1,2}$	$F_{X1,2}$					$F_{N1,2}$		$\varepsilon_{1(2)}$	
												$\delta_{1(2)}$		ΔC_2
	…		…	…	…	…	…	…	…		…		…	
												…		…
t_1	…	$\sum_j F_{D1,j}$	…	…	…	…	…	…	…	$F_{Al1,k}$	…		…	
												…		…
	…		…	…	…	…	$F_{TR,n-2}$	$\Delta F_{TR,n-2}$	$F_{AR,n-2}$	$F_{Al1,n-2}$	$F_{N1,n-2}$		…	
												…		…
	C_{n-1}		$F_{NP1,n-1}$	$F_{S1,n-1}$	$F_{NN1,n-1}$	$F_{X1,n-1}$	$F_{TR,n-1}$	$\Delta F_{TR,n-1}$	$F_{AR,n-1}$	$F_{Al1,n-1}$	$F_{N1,n-1}$		$\varepsilon_{1(n-1)}$	
												$\delta_{1(n-1)}$		ΔC_{n-1}
	C_n												$\varepsilon_{1(n)}$	
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
t_n	…	…	…	…	…	…	…	…	…	…	…	…	…	…

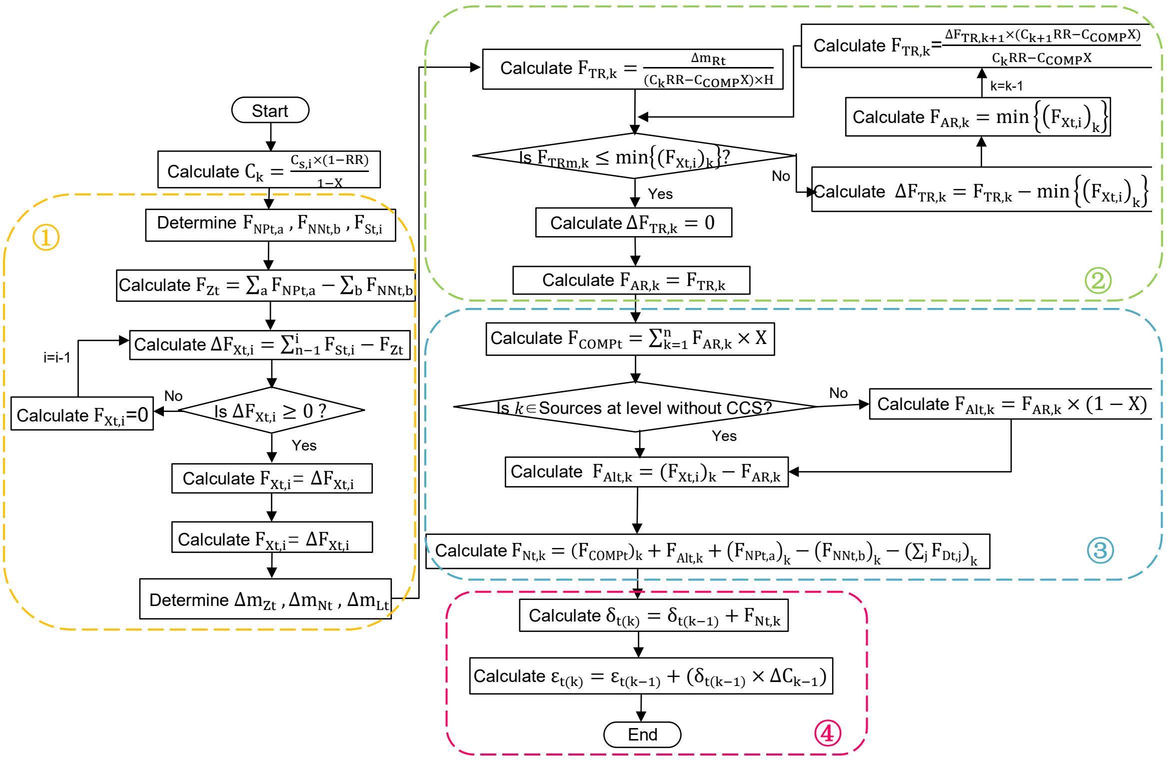

Figure 1: Flow chart of the computational process of the multi-period algebraic targeting approach

4. Case Study

This section uses China's enhanced 2030 Nationally Determined Contribution (NDC) target as a study case. The case is divided into two periods, the first (t_1) from 2021 to 2025 and the second (t_2) from 2026 to 2030. The data for energy demand and carbon emission constraints for this scenario are from the synthesis report (PCRPT, 2020). Data on the potential of EP-NETs comes from the report by Cai et al. (2021). The amount of carbon sequestered by AR is extrapolated from de Jong (2021) and the amount of carbon sequestered by SCS is extrapolated from Zhou et al. (2021). The emission factors for fossil energy are obtained from Tan et al. (2009). The carbon emission factors for NETs are from Ng et al. (2020), and the emission factor for renewable energy is zero (House et al., 2011). Due to the limited research on EC-NETs in China under this scenario, their role in energy planning is ignored. In other words, EC-NETs are not considered in the calculation process of this case for the time being. Table 2 and Table 3 includes raw (C_k, $\sum_j F_{Dt,j}$, $F_{NPt,b}$, ΔC_k), process ($F_{Xt,i}$, $F_{TR,k}$, $\Delta F_{TR,k}$, $F_{AR,k}$, $F_{Alt,k}$) and result ($F_{Nt,k}$, $\delta_{t(k)}$, $\varepsilon_{t(k)}$) data for each of two periods (t_1 and t_2) of low carbon energy planning. All data are entered in Table 2 and Table 3 according to their specific meaning corresponding to the row in which their carbon emission factor is located.

Table 2: First period energy cascade table for case studies

T (y)	C_k(Gt/ PWh)	$\sum_j F_{Dt,j}$ (PWh)	$F_{NPt,b}$ (PWh)	$F_{St,i}$ (PWh)	$F_{Xt,i}$ (PWh)	$F_{TR,k}$ (PWh)	$\Delta F_{TR,k}$ (PWh)	$F_{AR,k}$ (PWh)	$F_{Alt,k}$ (PWh)	$F_{Nt,k}$ (TWh)	$\delta_{t(k)}$ (PWh)	$\varepsilon_{t(k)}$ (Gt)	ΔC_k
											0.00		
	-0.61		$2.05*10^{-3}$		$2.05*10^{-3}$					$2.05*10^{-3}$		0.00	
											$2.05*10^{-3}$		0.23
	-0.38		$8.71*10^{-2}$		$8.71*10^{-2}$					$8.71*10^{-2}$		$4.70*10^{-4}$	
											$8.92*10^{-2}$		0.38
	0.00			38.14	38.14	0.00	0.00	0.00	38.14	55.15		$3.44*10^{-2}$	
											55.24		0.13
	0.13								1.33	1.33		7.25	
											56.57		0.04
t1	0.17								95.06	95.06		9.64	
											151.63		0.09
	0.26	212.50			212.50					-212.50		23.31	
											-60.87		0.35
	0.61			20.88	20.88	0.00	0.00	0.00	20.88	20.88		2.20	
											-40.00		0.13
	0.74			38.87	38.87	1.56	0.00	1.56	37.31	37.31		-3.00	
											-2.69		0.24
	0.98			114.61	114.52	113.02	1.18	111.84	2.69	2.69		-3.65	
											0.00		9.02
	10.00											-3.65	

Table 3: Second period energy cascade table for case studies

T (y)	C_k(Gt/ PWh)	$\sum_j F_{Dt,j}$ (PWh)	$F_{NPt,b}$ (PWh)	$F_{St,i}$ (PWh)	$F_{Xt,i}$ (PWh)	$F_{TR,k}$ (PWh)	$\Delta F_{TR,k}$ (PWh)	$F_{AR,k}$ (PWh)	$F_{Alt,k}$ (PWh)	$F_{Nt,k}$ (TWh)	$\delta_{t(k)}$ (PWh)	$\varepsilon_{t(k)}$ (Gt)	ΔC_k
											0.00		
	-0.61		$6.15*10^{-3}$		$6.15*10^{-3}$					$6.15*10^{-3}$		0.00	
											$6.15*10^{-3}$		0.23
	-0.38		0.23		0.23					0.23		$1.41*10^{-3}$	
											0.24		0.38
	0.00			52.46	52.46	0.00	0.00	0.00	52.46	69.47		$9.25*10^{-2}$	
											69.71		0.13
	0.13								1.33	1.33		9.20	
											71.04		0.04
t_2	0.17								95.06	95.06		12.21	
											166.10		0.11
	0.28	233.64			233.64					-233.64		30.75	
											-67.54		0.33
	0.61			28.15	28.15	0.00	0.00	0.00	28.15	28.15		8.77	
											-39.40		0.13
	0.74			40.96	40.96	1.56	0.00	1.56	39.40	39.40		3.65	
											0.00		0.24
	0.98			112.08	111.84	113.02	1.18	111.84	0.00	0.00		3.65	
											0.00		9.02
	10.00											3.65	

In this scenario, the CCS removal rate (RR), parasitic power loss (X) and operating lifetime (LT) (Gao et al., 2020) are assumed to be: 0.85, 0.15, and 20 y. Energy losses caused by CCS systems are compensated by renewable energy sources.

After energy correction, the total demand for fossil energy decreased by 0.33 PWh (=(2.05+87.17+6.15 +233.44)*10^{-3} PWh) in the two periods, equivalent to a direct reduction of 0.32 Gt (=0.33*0.98 Gt) of carbon emissions. Since the assumed CCS operational lifetime (LT) is greater than the total duration of the two periods, the CCS can be deployed for two periods of continuous emission reduction. Therefore, CCS retrofits for the same energy source sector for different periods are calculated uniformly. The calculated theoretical CCS retrofit for both periods of coal sector is 113.02 PWh (=94.145/(0.98*0.85) PWh), and the available transformation of coal sector in the second period is less than this value. To meet the continuous use time of CCS as much as possible and reduce the one-time investment, the CCS retrofit of coal sector for both periods was 111.84 PWh (i.e. the total energy supply from the corrected coal sector in the second period).The remaining 2.69 PWh (=114.524-111.836 PWh) of coal sector from the first period was not retrofitted, but rather the oil sector from both periods was retrofitted and the CCS retrofit for oil sector was 1.56 PWh (=1.18*(0.98*0.85)/(0.74*0.85) PWh). The CCS deployment is reduced by 0.80 PWh (=1.18*2-1.56 PWh) compared to retrofitting the remaining coal sector from the first period. The energy cascade in column twelve of Table 2 and Table 3 shows that the energy supply for the first and second periods exactly meets the energy demand for both periods. The emissions cascade in column thirteen of Table 2 and Table 3 shows that the emissions for the first period are 3.65 Gt more than the carbon constraint for that period, while the emissions for the second period are 3.65 Gt less than the emissions constraint for that period. According to Table 4 of the overall cascade table, it can be obtained that the last item in the column where the emissions cascade is located is zero. This means that in this case scenario the CO2 emissions meet the emission constraint.

Table 4: The overall energy cascade table for the case study

C_k(Gt/PWh)	$F_{N,k}$(PWh)	$\delta_{(k)}$(PWh)	$\varepsilon_{(k)}$(Gt)	ΔC_k
		0.00		
-0.61	8.20*10^{-3}		0.00	
		8.20*10^{-3}		0.23
-0.38	0.32		1.89*10^{-3}	
		0.33		0.38
0.00	124.62		0.13	
		124.95		0.13
0.13	2.66		16.44	
		127.61		0.04
0.17	190.12		21.85	
		317.73		0.09
0.26	-212.50		50.49	
		105.23		0.02
0.28	-233.64		52.75	
		-128.41		0.33
0.61	49.02		10.97	
		-79.39		0.13
0.74	76.70		0.64	
		-2.69		0.24
0.98	2.69		0.00	
		0.00	(Pinch)	9.02
10.00			0.00	

5. Conclusions

In this work, an improved multi-period algebraic target approach for the integration of fossil energy, renewable energy, CCS and NETs was developed. The case study showed that a total of 0.33 PWh of fossil energy demand was offset by deploying NETs as soon as possible. In addition, the NETs were able to capture additional atmospheric CO_2, increasing the carbon emission constraint, reducing the need for CCS deployment and better plays the risk hedging role of NETs. Multi-period energy planning can consider the lifetime of the CCS, effectively reducing the risk of stranded assets, as shown in the case study, where the unified deployment of two periods reduced the one-off deployment of CCS by 0.80 PWh. The case study also showed that the 3.65 Gt of excess carbon emissions from t_1 can be offset in t_2, which presented that the multi-period energy planning also mitigates the pressure to reduce carbon emissions upfront.

Most NETs are currently in the research phase and projections of the future potential of NETs are limited, so the data on NETs in this work may not be entirely accurate. As negative emission technologies become more mature, their potential will be more accurately predicted. Such techno-economic uncertainties need to be factored into planning models. In addition, the variety of NETs that can be used on a large scale will become more and more diverse. The integration of NETs in energy planning can be considered in terms of the impact of the preference of the selection of NETs (e.g., economic, sustainability) and the number of NETs selected on the technical and economic feasibility of energy planning when multiple NETs can be used.

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