

Misconel, Steffi; Prina, Matteo Giacomo; Hobbie, Hannes; Möst, Dominik; Sparber, Wolfram

Working Paper

How to determine bottom-up model-derived marginal CO₂ abatement cost curves with high temporal, sectoral, and techno-economic resolution?

Suggested Citation: Misconel, Steffi; Prina, Matteo Giacomo; Hobbie, Hannes; Möst, Dominik; Sparber, Wolfram (2022) : How to determine bottom-up model-derived marginal CO₂ abatement cost curves with high temporal, sectoral, and techno-economic resolution?, ZBW – Leibniz Information Centre for Economics, Kiel, Hamburg

This Version is available at:

<https://hdl.handle.net/10419/260472>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

How to determine bottom-up model-derived marginal CO₂ abatement cost curves with high temporal, sectoral, and techno-economic resolution?

Steffi Misconel*, Hannes Hobbie, Dominik Möst,
Chair of Energy Economics, TU Dresden,
Dresden, Germany
*steffi.misconel@tu-dresden.de

Matteo Giacomo Prina, Wolfram Sparber,
Institute for Renewable Energy, EURAC Research,
Bolzano, Italy

Abstract—Marginal CO₂ abatement cost curves derived from bottom-up or top-down models are widely used by policymakers to determine the least-cost sequential order of decarbonization measures and the most effective decarbonization strategies. However, most model-based methods lack high temporal, sectoral, and techno-economic resolution. To address these limitations, this paper presents a linear optimization method with an hourly resolution for a sector-coupled power system to derive step-wise CO₂ abatement cost curves. A step-wise marginal CO₂ abatement cost curve is calculated based on hundreds of hourly dispatch model runs, giving a high level of detail on techno-economic, inter-temporal, and inter-sectoral interactions. Results demonstrate a dynamic relationship between technology-specific CO₂ abatement costs, CO₂ emission reductions, and total system cost development per installed decarbonization measure. Moreover, the results indicate how competing flexibility and decarbonization options interact and how least-cost decarbonization pathways can be reached.

Index Terms—decarbonization measure, flexibility option, linear optimization, marginal abatement cost curve, sector-coupling

I. INTRODUCTION

The European Green Deal calls for achieving carbon neutrality in Europe by 2050. Therefore, the power sector can significantly contribute to achieving this ambitious climate goal, given that it accounts for 25% of all greenhouse gas emissions in Europe [1]. In addition, electrifying demand-side sectors (sector-coupling) makes decarbonization measures and renewable energy sources even more relevant for the power sector. However, the weather dependency of renewable energy sources and the increase in electricity demand due to sector-coupling necessitates balancing of electricity supply and demand, which will lead to an increasing need for power system flexibility by simultaneously pursuing the target of carbon neutrality.

To analyze the complex interactions in the energy system, energy system modeling can support policymakers in defining a feasible and cost-effective energy strategy by identifying the most suitable technology portfolio to achieve specific climate goals. Decision-makers confronted with ambitious CO₂ emission reduction targets need to know which decarbonization

measure to implement in which phase of an abatement strategy and in what order. Therefore, energy system modeling should be more transparent to allow decision-makers to choose between alternative techno-economic solutions depending on their political requirements and identify “no-regret” and “must-avoid” technology options.

Target setting and policy implications can be connected through marginal CO₂ abatement cost (MAC) curves. Different alternative decarbonization solutions can be selected depending on where policymakers decide to locate on the curve [2]. Marginal CO₂ abatement cost curves highlight the cost-effectiveness of decarbonization measures by ranking these options according to their cost per unit of emission reduction, from the lowest to the highest cost measure. Therefore, the estimation of MAC curves is a useful method for policymakers by providing the best energy mix and information on the most cost-effective sequential order. Consequently, MAC curves are not derived to estimate the optimal emission level. Instead, they measure the feasibility and costs of achieving defined emission reduction targets.

Several methods are available for estimating marginal CO₂ abatement costs, each with its own (dis-)advantages. Nevertheless, most approaches lack a high level of temporal, sectoral, and technological resolution. Moreover, model-derived methods often provide smooth or continuous MAC curves that can only be converted into more detailed step-wise MAC curves by decomposition analysis. Additionally, systemic interactions of technologies between sectors are often neglected when calculating marginal costs of CO₂ reduction. This paper aims to overcome these limitations by presenting a bottom-up linear optimization approach with high temporal, sectoral, and techno-economic resolution for deriving step-wise marginal CO₂ abatement cost curves using a case study of the German sector-coupled power system.

This paper proposes a methodological approach that will be applicable and reproducible also for other large-scale electricity system models.

In this paper, the fundamentals of MAC curves are presented in Sect. II, followed by a detailed description of the methodology for deriving step-wise MAC curves in optimization models in Sect. III. A MAC curve for a German

case study is illustrated, and interaction effects of decarbonization measures are discussed in Sect. IV, followed by conclusions in Sect. V.

II. MAC CURVE FUNDAMENTALS

A. Classification of MAC curve approaches

Based on a systematic literature review, 98 publications (1995-2021) are found that can be categorized into MAC curve theory, expert-based, and model-derived MAC curve approaches. Based on the schematic categorization of Huang et al. [3], MAC curve methods can be classified as bottom-up, top-down, or hybrid, as shown in Fig. 1.

The review results indicate that 53% of the MAC curve publications are based on bottom-up methods (22% expert-based financial accounting methods, 31% engineering models), followed by 32% top-down approaches (23% distance functions, 8% computable general equilibrium models). Furthermore, 6% of the identified studies use a hybrid approach, and 9% are MAC curve theory studies.

Bottom-up approaches include financial accounting methods (i.e., expert-based) [4] and engineering optimization models [5]. Based on the techno-economic characteristics of individual sector components, bottom-up approaches calculate the abatement quantity related to direct costs. Using financial accounting methods, break-even abatement costs are calculated based on net present values for each technology. The expert-based approach suffers from a lack of intertemporal, intersectoral, and uncertainty representation. At the same time, the advantage lies in the simplicity of calculation and the clear step-wise MAC curve visualization. Engineering system optimization models consider CO₂ caps or CO₂ prices and reflect technical characteristics on both the supply and demand side of the energy system. The disadvantages of bottom-up methods are the lack of macroeconomic feedback and market behavioral changes.

Top-down approaches are based on economic models such as CGE models [6] and distance function models [7]. Based on market behavior and market-oriented policies, top-down approaches calculate the potential opportunity costs of reaching abatement targets [8]. Distance function models determine a quantity of feasible output under techno-economic conditions to calculate opportunity costs for not producing an incremental unit of desirable products [3]. CGE models employ market-oriented policies for calculating model-endogenous equilibrium prices by considering the interaction of sectors in an economy and balancing supply and demand. Top-down approaches suffer from a lack of dynamic interaction across sectors and technologies.

Hybrid approaches couple bottom-up and top-down models, most commonly an optimization with a CGE model [9]. The hybrid approaches consider techno-economic details of technology portfolios, macro-economic feedback, and market price reactions when determining MAC curves for cost-effective decarbonization pathways. There exist two kinds of model interlinkages, the soft-linked [10] and the hard-linked model coupling [9]. The disadvantages of hybrid approaches are the high complexity and the necessity to simplify one of the two models for computational feasibility.

Model-derived approaches typically produce smooth MAC curves. However, step-wise MAC curves may provide

significant insight into technology-specific interactions during emission reduction. Bottom-up models' technology- and sector-specific CO₂ abatement costs can be interpreted as proxies for CO₂ allowance prices, although carbon prices depend upon various factors. Using a multi-iterative linear optimization approach (without decomposition analysis), a method for deriving step-wise MAC curves with high temporal, sectoral, and techno-economic resolution is described below.

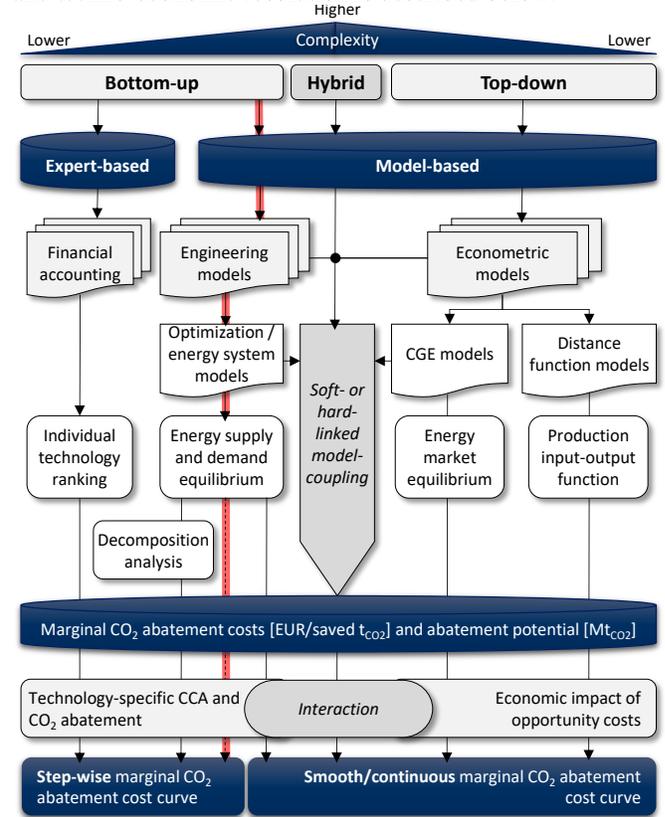


Figure 1. Classification of approaches for deriving marginal CO₂ abatement cost curves based on [3]. The red path represents the applied approach for this paper.

B. Cost of carbon abatement and MAC curve interpretation

The MAC curve graph depicts the costs of CO₂ abatement (CCA) on the y-axis ($EUR/saved\ t_{CO_2}$) along with the cumulative CO₂ emission reductions on the x-axis (Mt_{CO_2}). The CCA is determined by dividing the difference between the total system costs (ΔTC) and CO₂ emissions (ΔCO_2) from a reference system (ref) and a modified system with additional decarbonization measures (m) (Eq. 1). Tab. I illustrates possible relationships between costs and emissions and their resulting CCA. Costs of CO₂ abatement are defined when a CO₂ reduction is achieved by adding an incremental unit of decarbonization measure. The installation of such a measure can result in negative CCA, equal to a net benefit for the system (e.g., through fuel and CO₂ cost savings). Measures that reduce CO₂ emissions without impacting total system costs result in $\approx 0\ EUR/saved\ t_{CO_2}$. Both types of decarbonization options (with $CCA < 0$ or $CCA \approx 0$) are “no-regret” measures that should be integrated into an early phase of decarbonization. Typically, implementing a decarbonization measure in the system results in positive CCA due to additional investments

(“usual” measures). “Must-avoid” measures result in the same or higher CO₂ emissions than the previous system.

$$\begin{aligned} CCA &= \Delta TC / \Delta CO_2 \\ &= (TC_m - TC_{ref}) / (CO_{2,ref} - CO_{2,m}) \end{aligned} \quad \text{Eq. (1)}$$

TABLE I. CATEGORIZATION OF CO₂ ABATEMENT COSTS (CCA) AND DECARBONIZATION MEASURES.

		ΔTC			
		< 0	≈ 0	> 0	
ΔCO ₂	> 0	CCA < 0	CCA ≈ 0	CCA > 0	<div style="display: flex; flex-direction: column; align-items: center;"> <div style="width: 15px; height: 15px; background-color: #003366; margin-bottom: 5px;"></div> “no-regret” measures <div style="width: 15px; height: 15px; background-color: #006699; margin-bottom: 5px; border: 1px solid red;"></div> “usual” measures <div style="width: 15px; height: 15px; background-color: #ff0000; border: 2px solid red; margin-bottom: 5px; display: flex; align-items: center; justify-content: center;"> X </div> “must-avoid” measures </div>
	≈ 0				
	< 0				

Fig. 2 represents the two different visualization modes for a MAC curve: the step-wise (left) and the smooth (right) curve. The technology-specific step-wise MAC curve consists of several rectangular bars corresponding to an individual decarbonization measure. In each bar, the width represents tons of CO₂ reductions, while the height represents the cost of reducing a ton of CO₂ through an incremental unit of a decarbonization measure. In contrast, smooth MAC curves are limited regarding their representation of technological change, detail, and interactions.

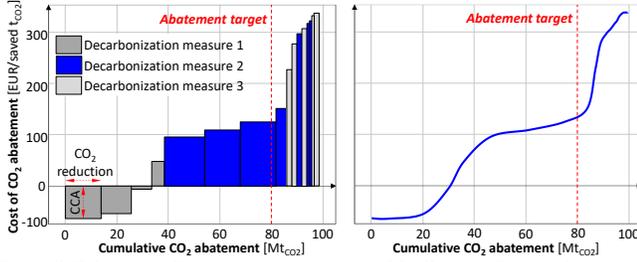


Figure 2. Schematic illustration of a step-wise MAC curve (left) and a smooth MAC curve (right).

III. METHODOLOGY FOR MODEL-DERIVED MAC CURVES

A. Model description

In the electricity system model ELTRAMOD, MAC curves are calculated using operational optimization, and the capacity expansion and curve evaluation are accomplished using an iterative approach. ELTRAMOD is a deterministic linear optimization model that allows electricity market analyses under the assumption of perfect foresight and full competition. The target function minimizes the total cost of electricity provision, which is affected by generation costs based on technology-specific and hourly operational costs, load-change costs, fuel costs, and costs for CO₂ emission allowances. In addition, the cost of load shedding is taken into account (value of lost load). The objective function is subject to several demand and generation constraints. The energy balance is an essential constraint. It ensures power generation and demand equality for each time step and node. The case study of this paper focuses on the German sector-coupled power system in 2030 through the introduction of battery electric vehicles for the transport sector, power-to-heat for the heating sector, and

electrolyzers to cover hydrogen demands of the industry and power sector. The German case study serves as a demonstration, but the proposed method can also be applied to other markets. Further details of ELTRAMOD can be found in, e.g., [11]–[14] and a model validation is presented in the appendix in Tab. IV.

B. Model implementation of step-wise MAC curves

ELTRAMOD calculates the cost-minimal dispatch for 8,760 h per year. For this analysis, ELTRAMOD runs over several hundred iterations. Each iteration step modifies the reference system incrementally by adding another unit of decarbonization measure. A new reference system is selected for each iteration based on the modified reference system that results in CO₂ reduction and the lowest cost of CO₂ abatement (CCA). A case study for the German energy system is used as an exemplary model application. It considers nine mitigation measures: ground-mounted and rooftop photovoltaic, onshore and offshore wind, power-to-heat with heat storages, power-to-H₂-to-power, lithium-ion, and redox-flow batteries, and battery electric vehicles. A step-wise MAC curve is determined from hundreds of hourly dispatch runs, providing a high level of detail on the intertemporal and intersectoral interactions of the sector-coupled power system. This is critical to evaluating the effects of decarbonization options. As illustrated in Tab. II and Fig. 3, step-wise MAC curves can be calculated in optimization models by following five steps:

- (0) Initially, the reference system in ELTRAMOD is defined by calculating the dispatch run for the power system without additional decarbonization measures (Fig. 3). The total system costs (TC^{Ref}) and the CO₂ emissions (CO_2^{Ref}) are saved as reference values for calculating the CCA in subsequent runs with additional decarbonization options.
- (1) The reference system is modified by adding an incremental value (I_m) of a decarbonization measure (Eq. 2). Tab. III lists all decarbonization measures along with their starting values. Additionally, Tab. III shows the incremental values (I_m), which are gradually added to the reference system, and the expansion potential (dV^{Max}) for each measure according to the German climate policy plans. Each incremental value (I_m) is selected in quantity to abate one MtCO₂ in the first iteration.¹ The expansion potential (dV^{Max}) divided by the incremental value (I_m) results in the total number of iterations ($Nsteps_{m,it}$), which gives the number of discrete elements in the MAC curve, approx. ~228 (*it*) (Tab. III).
- (2) In the second step, the model determines the cost-minimal dispatch decision and the CO₂ reduction (Eq. 3) for a modified reference system (e.g., with an additional rooftop PV unit).
- (3) If CO₂ is reduced by adding a decarbonization measure to the reference system, the CCA is determined for the modified system (Eq. 4).
- (4) In the fourth step, the algorithm checks whether the CCA value of the modified system is lower than the CCA value of the previous “best” energy system (Eq. 5). If the condition is true, the modified system with its results is

¹ Except for batteries, since the capacity must be unrealistically high to displace one MtCO₂ for the considered power system.

saved as the new “best” system. The algorithm runs through all nine decarbonization measures (m) in one iteration.

- (5) As a fifth step and in the outer iteration loop, the model validates at the end of each inner iteration loop if the expansion potential (dv^{Max}) of the decarbonization measures will be exceeded in the next step (Eq. 6). A measure that reaches its expansion potential will be removed from the subsequent iterations. In addition, the ‘best’ system with the lowest CCA from the previous iteration step is saved as the new reference system before the iteration loop starts again in step one. ELTRAMOD terminates the calculation when the maximum number of iteration steps ($Nsteps_{it}$) is reached or when all decarbonization measures have achieved their expansion potential (dv^{Max}).

C. Scenario framework for the German sector-coupled power system in 2030

The scenario framework for the case study is based on the revised German climate targets (legislative period 2021-2025) for the sector-coupled power system in 2030. The national climate policy for the electricity sector can be divided into demand-side and supply-side targets. Demand-side targets include implementing at least 15 Mio. battery electric vehicles and 10 GW of electrolyzers by 2030. On the supply-side, the objectives are an 80% vRES share in gross electricity consumption (200 GW PV, 30 GW wind offshore, ~94 GW wind onshore) and the coal phase-out “ideally” by 2030. In addition, ~24 GW of “H₂-ready” gas-fired power plants are expected to be built by 2030. These targets are implemented as constraints or expansion potentials (dv^{Max}) in ELTRAMOD (Tab. III).

TABLE II. SCHEMATIC MODELING ALGORITHM FOR DERIVING STEP-WISE MAC CURVES IN OPTIMIZATION MODELS BASED ON [13]

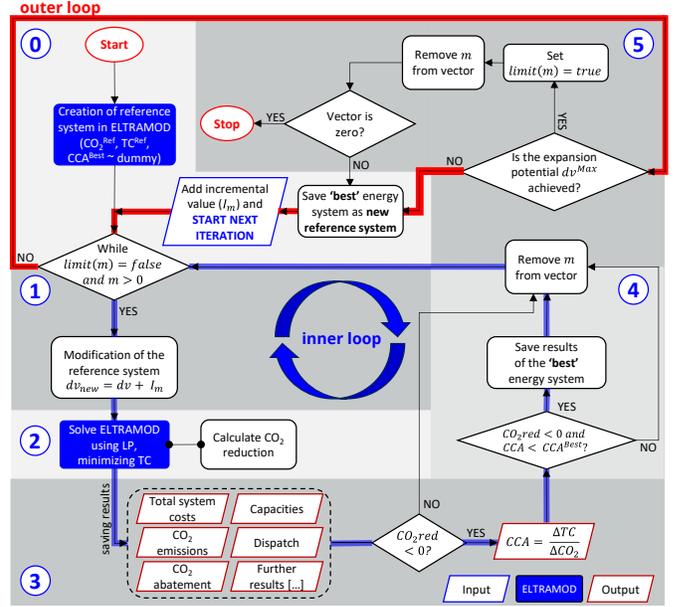
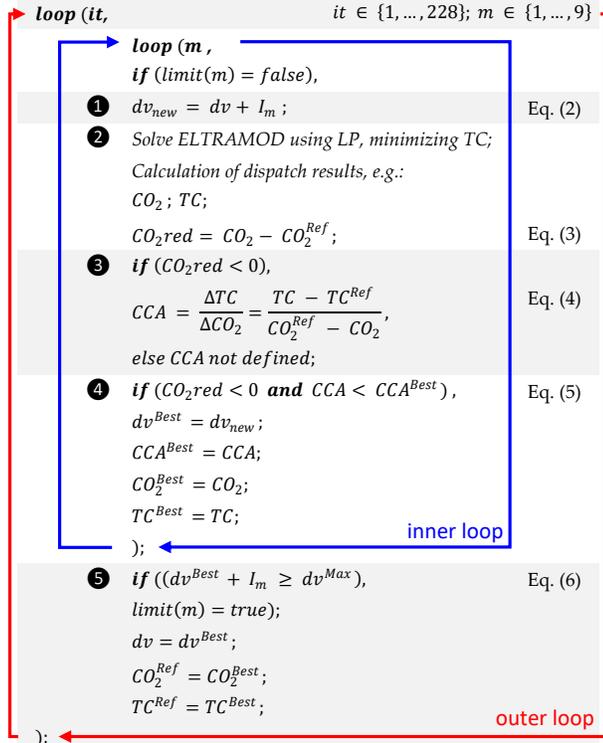


Figure 3. Schematic visualization of the outer and inner iterative loops to derive step-wise MAC curves in optimization models.

TABLE III. STARTING, INCREMENTAL VALUES AND EXPANSION POTENTIALS OF CONSIDERED DECARBONIZATION MEASURES

Decarbonization measure	Unit	Start. value	Incremental value	Policy target	Iteration steps
		dv	I_m	dv^{Max}	$Nsteps_{m,it}$
PV ground-mounted	[GW]	35.2	2.74	90	~20
PV rooftop	[GW]	14.8	2.74	110	~34
Wind onshore	[GW]	52.5	1.60	94	~26
Wind offshore	[GW]	7.6	0.87	30	~25
Battery lithium-ion	[GWh] ^a	0	1.00	20	20
Battery redox-flow	[GWh] ^a	0	1.00	20	20
Power-to-H ₂ -to-power	[GW]	0	0.65	10	~15
Power-to-heat	[GW]	0	0.78	20	~25
Battery electric vehicles	Mio.	0	0.345	15	~43
Total					~228

a. Energy-Power-Ratio 1 MWh/MW

IV. INTERACTION EFFECTS OF DECARBONIZATION MEASURES

As a result of the multi-iterative optimization approach, a step-wise MAC curve for the nine considered decarbonization measures for the German sector-coupled power system is determined and visualized in Fig. 4. The high level of temporal, sectoral, and techno-economic resolution allows for in-depth analysis of interaction effects between the cross-sectoral decarbonization measures.

With each successive step and installed incremental unit of decarbonization measure, the energy system characteristics change. An individual installed decarbonization measure affects every additional measure in terms of CO₂ abatement potential and cost-effectiveness (CCA). The bar plot MAC curve (Fig. 4 a) depicts the optimal solution with the lowest CO₂ abatement costs, while the step-wise point plot MAC

curve² (Fig. 4 b) and the comparison of the technology-specific CO₂ reduction (Fig. 4 c) and total cost development (Fig. 4 d) allows comparing the incremental development of cost-effectiveness for all considered decarbonization measures in every iteration step until the measure's expansion potential is achieved. In this way, relevant dynamics, synergies, and correlations between measures in the decarbonization pathway can be analyzed, and reasons for achieving a particular 'best' technology portfolio can be identified.

Fig. 4 (a) illustrates the CO₂ abatement costs for a specific portfolio of decarbonization measures and their most cost-effective order. According to the first part of the MAC curve, PV ground-mounted and power-to-heat systems are the most cost-efficient decarbonization measures with the lowest and even negative CO₂ abatement costs. A negative CCA indicates that these options lead to a CO₂ reduction by saving total system costs, e.g., through lower conventional generation, and thus fuel and CO₂ costs savings. Increased PV capacity leads to increased vRES surplus generation (i.e., initial curtailment), reducing system benefits and resulting in positive CCA for the last PV units installed until the expansion potential is reached. By implementing battery electric vehicles, including the option of controlled (dis-)charging (power-to-vehicle/vehicle-to-grid), few PV rooftop systems can be integrated. The additional storage capacity of battery electric vehicles boosts cost-effectiveness and reduces CO₂ abatement costs of PV rooftops (Fig. 4 c-d). However, with increasing vRES surpluses due to offshore wind installations, the costs of CO₂ abatement of PV rooftops increase substantially. Wind offshore systems and power-to-H₂-to-power have, next to electric vehicles, the highest CO₂ reduction potential (Fig. 4 c) but are more cost-intensive decarbonization options (Fig. 4 d), which leads to their integration in a later phase of the decarbonization path.

V. CONCLUSIONS & IMPLICATIONS

The outcome of over hundreds of hourly operational optimization model runs using a multi-iterative capacity expansion approach is a step-wise MAC curve that provides a high level of detail on techno-economic, intertemporal, and intersectoral interactions of decarbonization measures. The high-resolution method identifies the most cost-effective carbon reduction pathways and how competing measures interact. Dynamics between technology-specific CO₂ abatement costs, CO₂ reduction, and total cost development per installed decarbonization measure can be determined. Compared to other methods, the integrated approach allows avoiding double counting of CO₂ abatement and costs. Since each incremental CO₂ abatement measure can replace a fossil fuel technology unit once, while the next incremental CO₂ abatement measure must replace another unit of a CO₂ emitting source. As a result, CO₂ abatement measures become even more expensive, since the replaced CO₂ source always tends to have lower CO₂ emissions, leading to a steepening of the MAC curve. Moreover, as presented in this paper, the high-resolution method for deriving step-wise MAC curves is applicable and reproducible for other optimization models and case studies.

However, MAC curves should be interpreted carefully, as the curve's shape depends on the underlying assumptions and excludes external drivers. Thus, a MAC curve should not be applied as the sole instrument for evaluating decarbonization measures and abatement policies. It is a general indication of abatement cost and potential at a given point in a decarbonization pathway. Therefore, MAC curves should be only one element of decision support tools to improve the understanding of emission trading, CO₂ allowance price forecast, investment decisions, and provide insights for policy discussions.

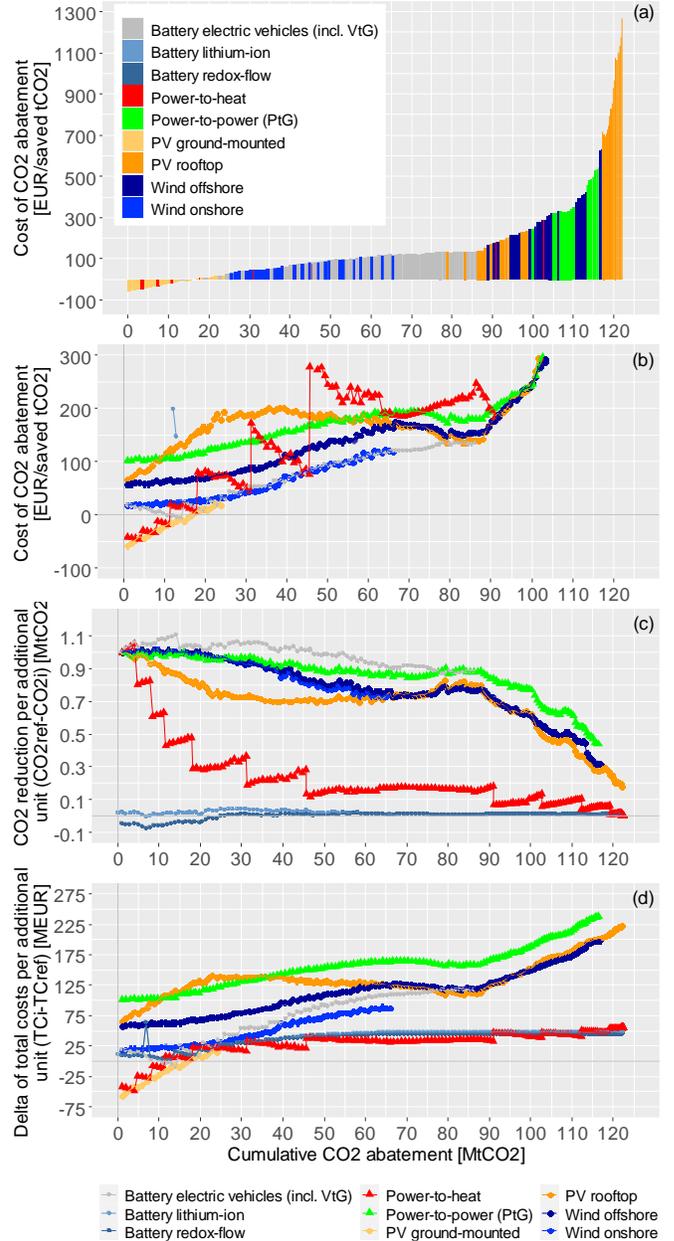


Figure 4. Exemplary marginal CO₂ abatement cost curve in a step-wise bar plot (a), all solutions (zoom) in a step-wise point plot (b), and comparison of technology-specific CO₂ reduction (c) and total cost development (d) based on [13].

² The point MAC curve shows a zoom for the intervals $[-100 < y < 300]$ and $[0 < x < 105]$.

ACKNOWLEDGMENT

The corresponding author gratefully acknowledges the Graduate Academy of TU Dresden funding, making possible the research stay at EURAC Research, Institute for Renewable Energy in Bolzano, from July to September 2021. This contribution is based on conducted research before, during, and after the visit at EURAC Research in Bolzano, Italy.

REFERENCES

- [1] EEA, “GHG emissions by aggregated sector,” 2019. https://www.eea.europa.eu/data-and-maps/daviz/ghg-emissions-by-aggregated-sector-5/#tab-chart_3
- [2] M. G. Prina, F. C. Fornaroli, D. Moser, G. Manzolini, and W. Sparber, “Optimisation method to obtain marginal abatement cost-curve through EnergyPLAN software,” *Smart Energy*, vol. 1, 2021, doi: 10.1016/j.segy.2021.100002.
- [3] S. K. Huang, L. Kuo, and K. L. Chou, “The applicability of marginal abatement cost approach: A comprehensive review,” *Journal of Cleaner Production*, vol. 127, pp. 59–71, 2016, doi: 10.1016/j.jclepro.2016.04.013.
- [4] L. J. Chen, Z. H. Fang, F. Xie, H. K. Dong, and Y. H. Zhou, “Technology-side carbon abatement cost curves for China’s power generation sector,” *Mitigation and Adaptation Strategies for Global Change*, vol. 25, no. 7, pp. 1305–1323, 2020, doi: 10.1007/s11027-019-09909-x.
- [5] K. Van den Bergh and E. Delarue, “Quantifying CO2 abatement costs in the power sector,” *Energy Policy*, vol. 80, pp. 88–97, 2015, doi: 10.1016/j.enpol.2015.01.034.
- [6] J. Morris, S. Paltsev, and J. Reilly, “Marginal Abatement Costs and Marginal Welfare Costs for Greenhouse Gas Emissions Reductions: Results from the EPPA Model,” *Environmental Modeling and Assessment*, vol. 17, no. 4, pp. 325–336, 2012, doi: 10.1007/s10666-011-9298-7.
- [7] X. Zhou, L. W. Fan, and P. Zhou, “Marginal CO2 abatement costs: Findings from alternative shadow price estimates for Shanghai industrial sectors,” *Energy Policy*, vol. 77, pp. 109–117, 2015, doi: 10.1016/j.enpol.2014.12.009.
- [8] Y. H. Ahn and W. Jeon, “Power sector reform and CO2 abatement costs in Korea,” *Energy Policy*, vol. 131, no. October 2018, pp. 202–214, 2019, doi: 10.1016/j.enpol.2019.04.042.
- [9] W. Chen, “The costs of mitigating carbon emissions in China: Findings from China MARKAL-MACRO modelling,” *Energy Policy*, vol. 33, no. 7, pp. 885–896, 2005, doi: 10.1016/j.enpol.2003.10.012.
- [10] A. Schäfer and H. D. Jacoby, “Experiments with a hybrid CGE-MARKAL model,” *The Energy Journal*, vol. 27, no. 2006, pp. 171–177, 2006, doi: 10.2307/23297051.
- [11] S. Misconel, C. Zöphel, and D. Möst, “Assessing the value of demand response in a decarbonized energy system – A large-scale model application,” *Applied Energy*, vol. 299, no. January, 2021, doi: 10.1016/j.apenergy.2021.117326.
- [12] S. Misconel, R. Leisen, J. Mikurda, F. Zimmermann, C. Fraunholz, W. Fichtner, D. Möst and C. Weber, “Systematic comparison of high-resolution electricity system modeling approaches focusing on investment, dispatch and generation adequacy,” *Renewable and Sustainable Energy Reviews*, vol. 153, no. May 2021, 2022, doi: 10.1016/j.rser.2021.111785.

- [13] S. Misconel, M. G. Prina, H. Hobbie, D. Möst, and W. Sparber, “Model-derived step-wise marginal CO2 abatement cost curves to determine least-cost decarbonization pathways for sector-coupled electricity systems”, *Under review*, 2022.
- [14] C.-P. Anke, H. Hobbie, S. Schreiber, and D. Möst, “Coal phase-outs and carbon prices: Interactions between EU emission trading and national carbon mitigation policies,” *Energy Policy*, vol. 144, 2020, doi: 10.1016/j.enpol.2020.111647.
- [15] UBA, “Entwicklung der spezifischen Kohlendioxid-Emissionen des deutschen Strommix in den Jahren 1990 - 2020,” Dessau-Roßlau, 2021. [Online]. Available: <http://www.umweltbundesamt.de/publikationen>

APPENDIX

A. Model validation

The ability of ELTRAMOD to represent market scenarios accounts for its explanatory strength. Several indicators, including electricity generation and CO₂ emissions, can provide valuable insight into the reproducibility of historical power plant dispatch, which can be used to assess the model’s quality. Therefore, ELTRAMOD is calibrated based on historical data from 2020, such as installed capacities, capacity factors, electricity demand, and CO₂ allowance prices. Furthermore, the model is benchmarked to historical data from 2020 regarding electricity generation and emissions [15]. According to Tab. IV, the benchmark model run results are consistent with historical data, confirming the model’s ability to reproduce future markets.

TABLE IV. MODEL VALIDATION REGARDING THE FUEL-SPECIFIC ELECTRICITY GENERATION AND CO₂ EMISSIONS FOR GERMANY [15].

Fuel	Generation [TWh]		CO ₂ emissions [MtCO ₂]	
	ELTRAMOD	UBA	ELTRAMOD	UBA
Oil	0.0	4.0	0.0	3.0
Gas	88.0	87.0	38.0	35.7
Lignite	102.1	83.0	104.9	93.6
Coal	32.9	37.0	25.4	31.2
Nuclear	58.7	58.0	0	0
Others	13.1	25.0	17.3	23.1
Reservoir	0.7	1.0	0	0
Pumped storage	11.8	9.0	0	0
Biomass	50.4	41.0	0	0
Other renewables	1.5	1.0	0	0
Run-of-river	19.2	17.0	0	0
Photovoltaic	47.5	46.0	0	0
Wind offshore	94.1	94.4	0	0
Wind onshore	24.5	24.6	0	0
Total	545	528	186	187