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# Potential of demand response for chlor-alkali electrolysis processes

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***Abstract*—Chlor-alkali electrolysis indicates significant demand response potential, accounting for over 2% of Germany's total electricity demand. To fully analyze this potential, digital models or digital twins are necessary. In this study, we use the IRPopt modeling framework to develop a digital model of an electrolysis process and examine the cost-optimal load shifting application in the day-ahead spot and balancing reserve market for various price scenarios (2019, 2030, 2040). We also investigate the associated $CO_2$ emissions. Combined optimization at both markets results in greater and more robust cost savings of 16.1% but cannibalizes the savings that are possible through optimization separately at each market. In future scenarios, the shares of savings from spot and reserve market could potentially reverse. $CO_2$ savings between 2.5% and 9.2% appear only through optimization at the spot market and could even turn negative if optimized solely at the reserve market.**

***Index Terms*--Demand response, Balancing reserve market, Electricity spot market, Digital model, Chlor-alkali electrolysis**

## I. INTRODUCTION

### A. Background

Electricity supply faces the challenge of continuously balancing supply and demand within a small tolerance window. While day-ahead spot markets optimize the medium term supply and demand balance, supply-side management through markets and regulations, such as balancing reserves and redispatch is applied for short-term balancing[1]–[3]. Demand side management, on the other hand, is also applied through the reserve market and the ordinance for interruptible loads (in Germany: AbLaV - Verordnung zu abschaltbaren Lasten) but with lower contributions [4]. However, energy-intensive industries like the chlor-alkali electrolysis (CAE), responsible for producing chlorine, sodium hydroxide, and hydrogen, indicates great flexibility potential with over 2% share of Germany's total electricity demand and relatively low cost for shifting load [5]. This could potentially reduce overall balancing costs and at the same time electricity procurement costs which are a key factor for industrial competitiveness in times of rising energy costs. The flexibility potential for demand response load shifting (no load shedding) depends largely on intermediate product storage capacity or flexibility of the downstream processes. The flexibility potential can be used to generate cost savings at the day-ahead spot market through increasing electricity consumption and substance production during times of lower electricity prices and vice versa. It can also be used to generate revenues by providing balancing reserve which contributes to further cost savings. Related $CO_2$ emissions will likely also change with the altered load. Determining these potential cost and $CO_2$ savings requires advanced digital multi market optimization models.

### B. Review

Despite numerous existing studies on the savings potential of the spot market, little attention has been paid to the related $CO_2$ emissions (Table I). Since none of the CAE studies analyzed potential $CO_2$ savings one study about the cement industry is added in the review table. No known study analyzed present and future savings potential of a CAE through demand response load shifting optimization at the day-ahead spot and balancing reserve market, including its related $CO_2$ emissions.

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TABLE I. STUDY REVIEW: INDUSTRIAL DEMAND RESPONSE

| | | | | Savings | |
|---|---|---|---|---|---|
| **Industry** | **Ref.** | **Year** | **Author A-Z** | **Electricity cost** | **$CO_2$** |
| CAE | [6] | 2018 | Otashu et al. | 7.3% | - |
| | [7] | 2019 | Roh et al. | 1.9 – 7.3%. | - |
| | [8] | 2014 | Wang et al. | 4.83% | - |
| | [9] | 2019 | Brée et al. | 3.4 – 7.1% | - |
| | [10] | 2008 | Babu et al. | 3.97 – 9.06% | - |
| | [11] | 2020 | Richstein et al. | 12.54 – 18.84% | - |
| Cement | [12] | 2017 | Summerbell et al. | 4.2% | 4% |

### C. *Objective*

In an effort to fill the research gap, this study aims to investigate the savings potential of demand response load shifting at the day-ahead spot and balancing reserve markets, both for present and future scenarios, while also taking into account the associated $CO_2$ emissions. The objective of this study is two-fold:

*1) Present savings:* Determining the maximum electricity cost and related $CO_2$ savings through utilizing the demand response load shifting potential of a CAE at the day-ahead spot and balancing reserve market separately and combined for 2019 price levels in Germany.

*2) Future savings:* Determining *1)* for assumed future day-ahead spot and balancing reserve prices for the key years 2030 and 2040.

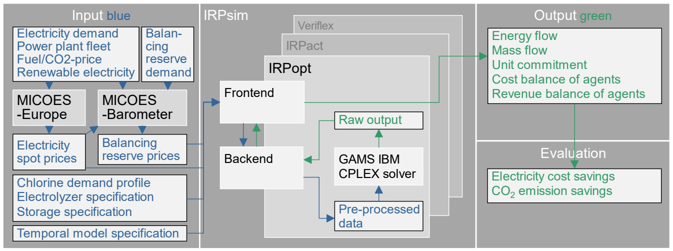
## II. METHOD

### A. *Methodical outline*

The general methodical approach is based on quantitative techno-economic analysis with the help of mathematical optimization modeling. The study utilizes the IRPopt mixed-integer modeling framework [13]–[15] to develop a digital model of an empirical CAE process and optimize it over different markets and scenarios. We focus on key performance indicators such as electricity cost and related $CO_2$ savings, generated by cost optimal load shifting based on the day-ahead spot and balancing reserve market prices. This study considers balancing reserve provision, but not the statistical reserve activation. $CO_2$ emissions are calculated by multiplying the hourly $CO_2$ emission factor of the German electricity system with the hourly (shifted) CAE load. The savings generated through load shifting are compared across different scenarios. The future scenarios for the development of the electricity day-ahead spot and balancing reserve prices and related $CO_2$ emissions are based on previous analyses with the fundamental electricity market models MICOES-Europe and MICOES-Barometer [16], [17].

### B. *Model embedment*

Figure 1 illustrates the embedment of the models and major input and output data flow from the perspective of IRPopt. The input data stream is represented in blue, the output data stream in green. The data of the CAE value chain, along with the electricity spot and balancing reserve prices, serve as input data for IRPopt. Our IRPopt instance is embedded in the IRPsim modeling platform [18], [19]. The raw output data is further processed and then used to evaluate the electricity cost and $CO_2$ savings, which are the key performance indicators of this study.



White outline = models or framework
Black outline = input/output data

Figure 1. Applied modeling framework

### C. *IRPopt modeling framework*

The IRPopt modeling framework allows the design of economic dispatch energy system optimization models. It utilizes a dynamic, deterministic mixed-integer modeling approach, which can be adjusted to varying levels of temporal granularity and rolling horizons. The model framework is implemented in GAMS (General Algebraic Modeling System), utilizing the mixed-integer feature from IBMs CPLEX solver. Its objective is to maximize profit through optimal dispatch of energy carriers and substances (e.g., chlorine) under a wide range of techno-economic constraints. One of the unique features of IRPopt is its ability to build energy systems from a large portfolio of consumer, storage, producer, and distribution technology components, as well as multiple energy carriers, including electricity, heat, hydrogen, and various fossil fuels. Configurable demand response load shifting settings are available for consumer components. Parameters for the components comprise technical (e.g., efficiency, ramp-rate) and economic (e.g., tariffs, variable costs) information. IRPopt has already been applied in the past to answer a wider range of research questions including questions regarding residential demand response potentials [20], [21].

The IRPopt modeling framework and the IRPsim platform are open-source and licensed under GPLv3 [14]. The platform provides back- and frontend structures for a web-based implementation including a graphical user interface. In addition, an expandable multi-scenario database is integrated. IRPopt runs on a 3.35 GHz 32 core CPU with 252 GB RAM. The calculation time for one case varies between 10 minutes and one hour, depending on the complexity of the model. The latest version of IRPopt and IRPsim can be found on GitHub [14], with the version used in this study available under the archived releases [22]. More detailed model descriptions are available under [13], [15].

### D. *MICOES-Europe and -Barometer model*

MICOES-Europe and -Barometer are both fundamental unit commitment models for the electricity market. They are implemented in GAMS using IBM’s CPLEX solver and employ a dynamic, deterministic mixed-integer linear modeling approach with a discrete hourly resolution and an adjustable rolling horizon. More detailed information can be found in [23]–[26]. In the following, the modeling process of the electricity day-ahead spot and balancing reserve prices and related $CO_2$ emissions is briefly summarized. The main input data for both models are electricity demand, technical specifications of the power plant fleet on plant level, commodity prices and renewable electricity generation capacity including the selection of a weather year.

MICOES-Europe determines the cost-optimal unit commitment and dispatch under the main constraint of satisfying electricity demand based on the input of various scenarios. The unit commitment reflects the merit order, and, assuming that operators' bids correspond to their marginal costs, together with electricity demand, sets the clearing price, the day-ahead spot price. MICOES-Barometer uses these modeled spot prices as input data for calculating the balancing reserve prices based on opportunity costs. While the cost-optimal unit commitment for the spot market is determined by MICOES-Europe, MICOES-Barometer determines cost optimal unit commitment for both the spot and balancing reserve market. The difference between the results of both markets represents the opportunity costs. The exogenously balancing reserve demand is calculated beforehand. For the historical 2019 scenario the reserve demand is taken as it was. For the future scenarios 2030 and 2040, the demand is calculated based on a dynamic method [27]. The related $CO_2$ emissions originate from the cost optimal unit commitment. Both MICOES models run on a 2.1 GHz, 8 cores CPU with 48 GB RAM. Calculation time for one case varies between 2 to 5 days.

## III. CASE STUDY

### A. *System*

The techno-economic specifications of the CAE are based on an existing average-sized plant in Germany. An overview of the process steps of the system is given in Figure 2.

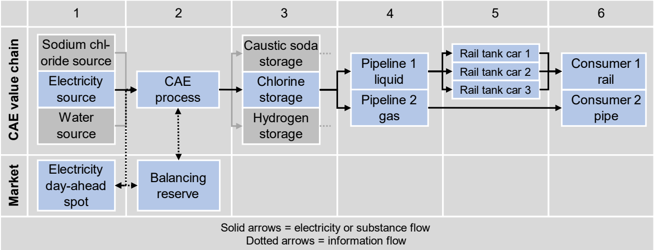


Figure 2. System: CAE value chain

The primary focus of this study is to analyze the potential electricity and $CO_2$ savings through demand response via cost-optimal load shifting at the electricity day-ahead spot and balancing reserve market. Therefore, the input products sodium chloride and water were not included in the analysis, as indicated by the gray shading of the fields. The output products sodium hydroxide and hydrogen were also not included in the analysis. The reason for this is the fixed output mix of the three output products represented by 1 ECU (electrochemical unit), i.e., 1 t chlorine, 1.1 t sodium hydroxide, 0.03 t hydrogen [28], and that the relative chlorine storage capacity is the lowest compared to sodium hydroxide and hydrogen, making the chlorine value chain the bottleneck. The operator of the "CAE process" can buy electricity from the "electricity day-ahead spot market". Depending on CAE efficiency and operating level, chlorine is produced at a specific rate. The chlorine is transported via "Pipeline 1" to "Rail tank Car 1-3", which then delivers it to the aggregated consumer group "Consumer 1". Via "Pipeline 2", the chlorine is transported directly to the aggregated consumer group "Consumer 2". The parameter specification for the various stages of the value chain can be found in Table V. The most important parameters are explained in the following paragraph.

Electricity source: Source of electricity which is not further specified and economically managed through the day-ahead spot market. Utilization: Annual average CAE load divided by its maximum load. The load factor must be less than 100% to leave room for flexible operation. Efficiency: Process conversion efficiency is the number of ECUs produced, divided by the electrical energy consumed. Higher efficiencies lower the utilization of a CAE at a given chlorine demand and therefore provide more room for load shifting. Operating range: Possible operating range of the CAE between its maximum and minimum load. It must be greater than 0% to allow load shifting. Ramp rate: Maximum increase or decrease of the CAE load within the operating range in a given time interval. It must be sufficiently fast to respond to the dynamic prices of the electricity source or the requirements of the balancing reserve products regarding activation time. Start-up cost: Cost of cold start of the CAE process. If the cost is lower, it may make sense to shift the load and shut down the plant at certain time intervals. Chlorine storage capacity: Capacity to store chlorine in the main static storage facility. Within the chlorine value chain, the total storage capacity must be greater than zero to enable load shifting when there is no consumer-side load shifting capacity for chlorine. Rail tank car capacity: Capacity to store chlorine in mobile storage, typically represented by three rail tank cars. Chlorine consumer demand: Chlorine demand over time for each consumer group. A precondition for load shifting is a chlorine demand lower than the maximum production capacity. Electricity day-ahead spot: Electricity market with dynamic prices in hourly resolution. It provides the first financial incentive for triggering load shifting activities through demand response. Balancing reserve: Reserve market with the three products ±FCR (Frequency Containment Reserve, ± positive/negative), ±aFRR (automatic Frequency Restoration Reserves) and ±mFRR (manual Frequency Restoration Reserve). The products are specified in detail in Table VI.

### *B. Scenarios and data*

The present and future electricity spot and balancing reserve prices and the related $CO_2$ emissions originate out of three underlying scenarios called after their target year 2019, 2030 and 2040. 2019 represents the historical reference year while 2030 and 2040 represent the selected future key years. The underlying current and assumed future market conditions are drawn from established publications from Agora, ENTSO-E, European Environment Agency and the German transmission system operators [29]–[32]. Each scenario differs in its national renewable electricity generation, $CO_2$ price, electricity demand (Table II) and reserve demand (Table III), resulting in varying market prices (Table IV).

TABLE II. SCENARIO DATA: GENERAL PARAMETERS

| Parameter | Scenario<br>2019 | <br>2030 | <br>2040 |
|---|---|---|---|
| Renewable electricity generation [TWh] | 237 | 364 | 435 |
| $CO_2$ price [€/t] | 25 | 60 | 80 |
| Electricity demand [TWh] | 490 | 529 | 513 |

Source: Own assumptions and data from [29]–[32].

TABLE III. SCENARIO DATA: RESERVE DEMAND

| Average reserve demand [MW] for Product | Scenario<br>2019 | <br>2030 | <br>2040 |
|---|---|---|---|
| ±FCR | 605 | 430 | 432 |
| +aFRR | 1 903 | 2 092 | 1 308 |
| -aFRR | 1 798 | 1 712 | 1 137 |
| +mFRR | 1 401 | 2 092 | 1 308 |
| -mFRR | 1 026 | 1 712 | 1 137 |

Source: Preparatory model calculations and for 2019 data from [3], [33].

TABLE IV. SCENARIO DATA: PRICES AND $CO_2$ EMISSIONS

| Prices and $CO_2$ emissions<br>Parameter | <br>2019 | <br>±% | Scenario<br>2030 | <br>±% | <br>2040 | <br>±% |
|---|---|---|---|---|---|---|
| Day-ahead spot [€/MWh] | 37.67 | 28 | 60.86 | 33 | 53.11 | 71 |
| CO2 emission factor [t/MWh] | 0.38 | 23 | 0.21 | 39 | 0.19 | 49 |
| ±FCR [€/MW/h] | 13.62 | 33 | 17.91 | 50 | 4.55 | 55 |
| +aFRR [€/MW/h] | 15.04 | 77 | 13.59 | 41 | 8.07 | 58 |
| -aFRR [€/MW/h] | 14.46 | 84 | 0.11 | 191 | 0.00 | 198 |
| +mFRR [€/MW/h] | 24.57 | 123 | 0.22 | 168 | 0.00 | 196 |
| -mFRR [€/MW/h] | 9.27 | 107 | 0.07 | 194 | 0.00 | 200 |

„±%“ = average positive and negative deviation in % (spread)

Source: Calculations with MICOES-Europe and -Barometer
and for 2019 data from [3], [33].

TABLE V. CAE VALUE CHAIN DATA

| Parameter | | Unit | Value |
|---|---|---|---|
| **1** | **Electricity source: day-ahead spot** | | |
| | See Table IV | | |
| **2** | **CAE process** | | |
| | Utilization | % | 82.5 |
| | Capacity max | MW | 56 |
| | Capacity min | MW | 28 |
| | Efficiency | ECU/MWh | 0.434 |
| | Ramp rate up | ECU/h | 122 |
| | Ramp rate down | ECU/h | 244 |
| | Start-up cost | €/pc | 50 000 |
| | Maintenance | h/a | 240 |
| **3** | **Chlorine storage** | | |
| | Capacity | tCl | 960 |
| | Charging rate | tCl/h | 960 |
| | Charging efficiency | % | 100 |
| | Self discharge | %/h | 0.0001 |
| **4** | **Pipeline 1** | | |
| | Capacity | tCl | 124 |
| | Flow rate | tCl/h | 124 |
| | Loss | %/h | 0.0001 |
| | **Pipeline 2** | | |
| | Capacity | tCl | 74.4 |
| | Flow rate | tCl/h | 74.4 |
| | Loss | %/h | 0.0001 |
| **5** | **Rail tank car -each** | | |
| | Capacity | tCl | 124 |
| | Charging rate | tCl/h | 124 |
| | Charging efficiency | % | 100 |
| | Self discharge | %/h | 0.0001 |
| **6** | **Chlorine consumer** | | |
| | Demand | tCl/a | 175 644 |
| | Demand share rail tank car | % | 38 |
| | Demand share pipeline | % | 62 |

Source: Empirical data and [28].

TABLE VI. RESERVE MARKET SPECIFICATION

| **Reserve market specification** | **Product** | | |
|---|---|---|---|
| **Parameter** | **FCR** | **aFRR** | **mFRR** |
| Block bid length [h] | 4 | 4 | 4 |
| Minimum bid capacity [MW] | 1 | 5 | 5 |
| Activation time maximum [min] | 0.5 | 5 | 15 |
| Activation length per incident [min] | 15 | 60 | 60 |
| Obligatory bid (symmetry) | + ∧ - | + ∨ - | + ∨ - |

Source: Cf. [3].

## IV. RESULTS

The study focuses on key indicators such as electricity cost savings and $CO_2$ emissions across different markets (electricity spot, balancing reserve) and scenarios (2019, 2030, 2040). Figure 3 presents the results of the first research objective “present savings”, which analyzes the cost and $CO_2$ savings through cost-optimal load shifting for four market combinations (none, spot only, reserve only, spot & reserve combined) in the present scenario 2019. Spot market optimization leads to electricity cost savings of 5.8% and $CO_2$ emission savings of 2.7%. Reserve market optimization leads to electricity cost savings of 13.3% and $CO_2$ emission savings of -2.7% (negative savings = increase). Optimization combined at both markets leads to the largest electricity cost savings of 16.1% and $CO_2$ emission savings of 2.5%. The cost savings contribution of the reserve market is a bit more than double as much as the one of the spot market.

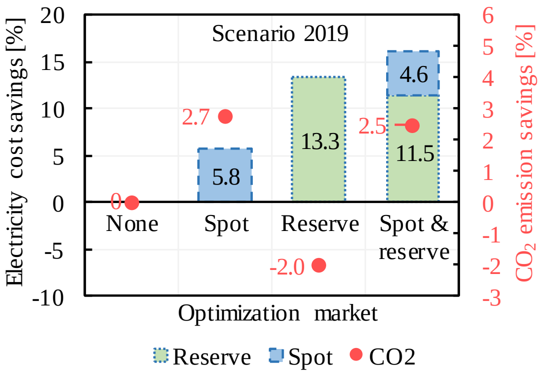


Figure 3. Results 1: present savings

Figure 4 shows the results of the second research objective “future savings”, which analyzes the cost and $CO_2$ savings through cost-optimal load shifting for three market combinations (none, spot only, spot & reserve combined) in the scenarios 2030 and 2040. To ensure efficient comparability, scenario 2019 is shown again here. The costs and emissions of cases with load shifting (spot, spot & reserve) are compared to the reference cases without load shifting (none). Hereby the savings are displayed as changed total electricity costs and $CO_2$ emissions in % compared to the reference cases.

| **[%]** | **Optimization market** | | **Scenario** | |
|---|---|---|---|---|
| | | **2019** | **2030** | **2040** |
| **Electricity cost** | None | 100.0 | 100.0 | 100.0 |
| | Spot | 94.2 | 93.7 | 86.7 |
| | Spot & reserve | 83.9 | 91.0 | 85.4 |
| **$CO_2$ emission** | None | 100.0 | 100.0 | 100.0 |
| | Spot | 97.3 | 93.0 | 90.8 |
| | Spot & reserve | 97.5 | 93.8 | 90.9 |

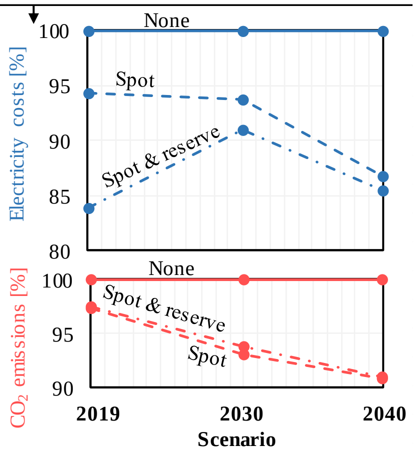


Figure 4. Results 2: future savings

Compared to scenario 2019, scenario 2030:spot shows a slight decrease in costs to 93.7%, while scenario 2040:spot shows a steeper drop in costs to 86.7%. Scenario 2030:spot & reserve shows larger savings than in scenario 2030:spot, but considerably smaller savings than in scenario 2019:spot & reserve. $CO_2$ emissions barely change across spot-reserve market combinations but show a significant decline from 2019 to 2040 in a close to linear manner.

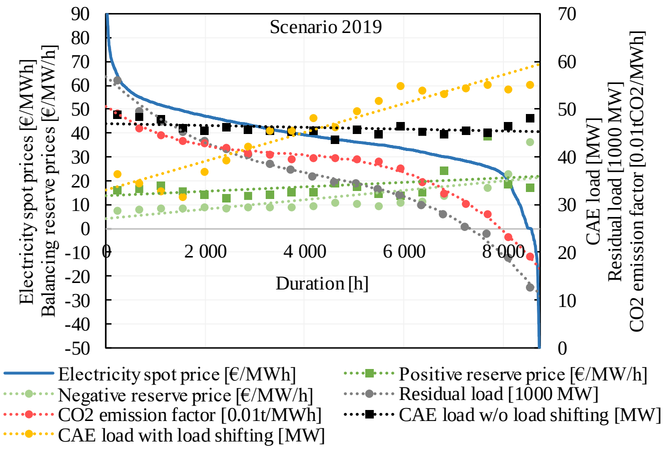
## V. DISCUSSION

The combined optimization of load shifting at the spot & reserve markets yielded the highest electricity cost savings of 16.1% (Figure 3). However, this also led to a cannibalization effect whereby the contribution of each market is reduced. This effect can be attributed to the fact that both incentives, lower electricity prices or higher revenues through reserve provision, compete with each other and provide opportunity costs. For instance, procuring electricity during high price periods to bid and provide +aFRR can result in higher revenue, which can offset the increased electricity costs.

In the case of future spot market optimization (Figure 4), the primary driver of electricity cost savings is not the larger average electricity price, but its fluctuation. The price variability allows the minimization of costs by maximization of production in periods with lower electricity prices. Table IV shows the increasing price deviations in grey alongside average prices over the scenarios. The main reason for the increasing deviations is the variability of residual load through increased shares of renewable electricity capacity in the mix. Both, the price deviations and the electricity cost savings through load shifting based on the spot market slightly increase from 2019 to 2030 and increase significantly more from 2030 to 2040.

The low future prices for -aFRR and ±mFRR assumed in this study (Table IV) led to decreasing cost savings in scenario 2030 and 2040 (Figure 4). One reason for the low prices is the modeling approach of MICOES-Barometer with the assumption of lower reserve demand through the ongoing European reserve market integration and increasing reserve capacity potential like biomass, power-to-heat or gas power plants. These plants have low opportunity costs for reserve provision resulting from the high infeed of renewable electricity (II.D). In the event of a call for balancing reserve, they could generate some additional revenue through the activation which is not considered in this study. The total cost savings of 5.8-16.1% are within the range of the study review of 1.9-18.84% (Table I).

$CO_2$ emission savings seem to relate with spot market optimization because they appear only in spot cases and become negative in the reserve only case (Figure 3). The plausibility of this relationship should be explained with the help of Figure 5. It shows the annual duration curve of electricity spot prices of the year 2019 (blue) and the relating characteristics of further parameters like the $CO_2$ emission factor (red). CAE load w/o load shifting (black) is based on an empirical production profile. CAE load with load shifting (yellow) is the resulting CAE load profile after load shifting based on spot market optimization of scenario 2019. Note that the dots stand for the averages over 438h periods for better visibility. $CO_2$ emission factor (red) relates positively with the electricity spot prices. This means that a shift of load from high price to low price periods (blue) simultaneously leads to lower $CO_2$ emissions. In contrast, the $CO_2$ emission factor (red) shows little to no correlation with the positive (green) and negative (light green) balancing reserve prices. This is the reason that there turned out to be slightly less emission savings in the spot & reserve case than in the spot case and that there is even a 2% increase in emissions in the reserve only case compared to the reference case (Figure 3, Figure 4).



For the sake of visibility, all values are averages over 5%-periods of the year (438 h), except of electricity spot prices. Here, the CAE load with load shifting was optimized at the spot market.

Source: IRPopt model calculations and data from [3], [29], [33].

Figure 5. Annual electricity price duration curve and relating parameters

Limitations of this study are the assumption that 100% of the consumed electricity is bought on the day-ahead spot market (no OTC: over the counter, which is often mixed with day-ahead spot trading) and that the short term price forecasts are 100% accurate. For balancing reserve, only provision and no statistical activation is considered.

## VI. CONCLUSION

The study provides valuable insights into cost savings and $CO_2$ emission reductions achievable through optimized load shifting in different electricity markets (spot and reserve) and scenarios (2019, 2030, 2040). Combined optimization across both markets has the largest savings potential of 16.1% (reserve market: 11.5%, spot market: 4.6%) but leads to cannibalization effects. Cost savings through reserve provision may decrease in the future while savings through spot market optimization could multiply with increasing electricity price spreads. Due to these different developments, offering flexibility combined on both markets can increase savings robustness. Optimization on the spot market can effectively reduce $CO_2$ emissions by 2.7-9.2%. In contrast, optimization only in the reserve market can even increase emissions by 2%.

These savings potentials are new to numerous companies. Policy makers could help to unlock the flexibility potential of energy intensive industries like the CAE through the implementation of supportive initiatives. The study highlights the importance of modeling assumptions in determining the feasibility and cost-effectiveness of load shifting strategies. Therefore, policymakers and companies need to carefully consider the underlying assumptions and uncertainties when evaluating the potential benefits and drawbacks of load shifting strategies. Future upgrades to the digital model, including the integration of automated data connections to create a digital twin, could enable real-time optimization of flexibility use and electricity procurement not only for chlor-alkali electrolysis processes but also for other complex energy-intensive environments. Further research is needed to consider the activation of balancing reserves and the accurate integration of electricity trading mechanisms.

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